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Editorial Note

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Understanding time-varying systematic risks in Islamic and conventional sectoral indices

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ABSTRACT

This paper examines the nature of time-varying systematic risk for both Islamic and non-Islamic sectoral indices. The novelty lies in the analysis of behavioural changes in beta according to the global economic state. Using daily stock market return data on 10 global sectors, we show that both Islamic and conventional indices follow a similar cyclical pattern over time. The sectoral beta turns out to be smaller for the Islamic market compared to the conventional market. These results remain robust to multiple additional tests. On this basis, we argue that a lower systematic risk of Islamic equities can offer portfolio diversification opportunities.

Keywords: *Beta; Systematic Risk; Equity Indices; Islamic Finance.*
JEL Classification: D40, G21, Z12

1. INTRODUCTION

In this paper, we examine the nature of time-varying systematic risk for both Islamic and non-Islamic sectoral indices using time-series data. After the 2007 financial crisis, interest in exploring alternative asset classes for risk diversification and risk mitigation has increased dramatically. This renewed focus has reinvigorated interest in systematic risks in financial markets. That Islamic capital markets have become an important asset class over the last decade or so (see S&P Global, 2017; Ernest & Young, 2016 and GIFR, 2017) has further simulated interests in systematic risks. As the survey article on Islamic banking and finance by Narayan and Phan (2017) demonstrates, there is now a defined focus on comparing Islamic markets with non-Islamic (conventional) markets. Our paper builds on this agenda by specifically examining the behaviour of systematic risks in these two types of markets.

Our investigation is important because understanding systematic risks in markets helps in investment decision making. To this end, while there are some studies (Dewandaru, Bacha, Masih and Masih 2015 and Sensoy 2016) that examine systematic risks in Islamic stock markets, nothing has been attempted in terms of understanding time-varying risks. For example, Dewandaru et al. (2015) and Sensoy (2016) undertake a comparative analysis indicating Islamic sectoral indices have significantly lower beta than non-Islamic (conventional) indices. A limitation of these studies is that they undertake a static analysis of estimating beta whereby the systematic risk is estimated for the entire sample only. Static beta fails to capture the shifting risk structures of firms in conjunction with the macroeconomic environment. This makes it more appropriate to capture the time varying properties of beta by capturing the dynamic beta. Jagannathan and Wang (1994), Chan and Chen (1988) and Longstaff (1989) show that a constant beta estimate fails to capture the changes over time in non-diversifiable (systematic) risk.

The current study extends the existing literature on systematic risks along multiple lines. First, our study adds to the limited research on the comparative analysis of systematic risks in Islamic and conventional markets by studying time-varying risks as opposed to static analysis of risks. The key advantage of modelling dynamic risk over static risk is that it allows one to understanding risk over time, noting phases of risk clustering. The type of dynamic risk modelling we propose also allows us to understand behavioural changes in risk according to global economic state. We define the economic states as phases of economic recessions and expansions. This definition of recessions and expansions follows Rizvi, Dewandaru, Bacha and Masih (2014), Arshad, Rizvi and Ibrahim (2014) and Alam, Arshad and Rizvi (2016). These studies suggest using global events to define recessions.

Third, our work complements Sensoy (2016) by studying short term and long term components of systematic risks. Sensoy (2016) only analyses systematic risk over the long run. Understanding risk over short run is equally important for portfolio management strategies and for day traders and speculative investment amongst others. . Lastly, we examine systematic risk at the sector level. Our motivation for sectoral risk analysis has roots in a large body of research that shows that particular sectors of the market behave very differently compared to other sectors and indeed the market itself. This type of behaviour has been documented across a range of firm behaviors. For example, Westerlund and Narayan (2015), Bannigidadmath and Narayan (2016), Narayan and Bannigidadmath (2015), Phan, Sharma and Narayan (2015a, 2015b), and Narayan and Sharma (2011) show that stock return predictability (regardless of the type of predictors) is sector-dependent. These studies show that as a result of the predictive ability (which is stronger for some sectors compared to others) trading strategies can be more successful in some sectors than others. Specifically, on Islamic financial markets, a sector-based analysis has been undertaken with respect to stock return predictability (Narayan, Narayan, Phan, Thuraisamy, and Tran 2016) and the profitability of the Indian stock market which has a fair representation of Islamic stocks (Narayan, Ahmed, Sharma, and Prabheesh 2014). These studies show that sectoral predictability and profits are sector-dependent. The overall message emerging from all these sector-based studies is that sectors are homogeneous thus likely to behave differently compared to the market. In order to bring out this heterogeneity it is important that hypotheses test is conducted at the sector-level.

The objectives this study are to: (1) analyse whether systematic risk behaves differently for Islamic and conventional sectors across economic states; and (2) assess whether Islamic sectors are less risky over an extended period of time.

Our approaches to addressing the proposed research questions follow a multi-step process. First, to extract time-varying risk (beta) for Islamic and conventional sectoral indices, we run a time-series regression of sectoral daily returns on the global Islamic index returns, and on the global conventional market index returns. Second, we utilise the wavelet decomposition technique to decompose sectoral indices (of both market types) into short- and long-term horizons. Third, we identify economic states based on Alam et al. (2016). Fourth, we estimate the beta of Islamic and conventional sectoral indices by running a regression of each sector's excess daily return over a rolling window of 36 months. Fifth, we use the F-test and t-test to find statistical differences in the betas of the indices. Last, using exponential generalized autoregressive conditional heteroscedastic (EGARCH) model, we calculate the time-varying volatility of both sectorial indices.

Our approaches lead to three new results. First, across all sectors and time periods, the Islamic sectoral beta tends to be smaller than conventional beta, implying a subdued reaction to stock market changes. This adds to the general volatility of stock return literature (in the Islamic finance space) from the systematic risk perspective. Second, we observe that across all sectors, the beta of Islamic equities had relatively similar volatility during the crisis and post-crisis periods compared to their conventional counterparts. Third, in our analysis, we observe that the beta of health care, oil & gas, and technology sectors have a remarkably lower volatility in the post-crisis period, especially in the long term.

Our findings contribute to three different strands of the literature. First, our finding of time-varying risk in Islamic market, its evolution over the post-crisis period, and how it is different from conventional markets connects to the literature more broadly on time-varying analysis of Islamic markets, such as those on price discovery. For example, Narayan, Phan, Sharma, and Westerlund, (2016) estimate time-varying price discovery for a large sample of Islamic stocks and show that this time-varying price discovery predicts Islamic stocks returns. Bannigidadmath and Narayan (2016) show that sectoral stock returns of the Indian market are predictable (using a range of financial ratio predictors) and that the average of the time-varying profits (obtained using a mean-variance utility function) are economically meaningful.

Second, our study contributes to a relatively recent strand of literature on the impact of systematic risk on Islamic stock markets. Relating to the global financial crisis of 2007-2009, several studies argue that Islamic indices offered more stability compared to most conventional indices (Girad and Hassan, 2008; Charles, Pop and Darne 2011). Moreover, Islamic stocks are often low-leverage stocks with high asset backing, thus characterised by a lower beta (see Sensoy, 2016; Dewandaru, et al. 2015). Our findings support the notion that firms with higher debt to equity ratio have significantly negative relation between return and stock volatility as compared to those with lower debt/equity ratios (Black, 1976; Christie, 1982). In recent related literature on Islamic equities unique findings are documented. While Narayan and Bannigidadmath, (2015) reach the conclusion that Islamic stocks are more profitable than their conventional counterparts, in another study Narayan et al. (2016) argue that the credit quality of Islamic stocks matter for profitability.

Third, our estimates of risks suggesting that sectoral indices are different complements recent literature on sectoral heterogeneity, (see Hong, Torous and Valkanov 2007; Narayan, Mishra and Narayan 2011; Narayan and Sharma, 2011; Rapach, Strauss, Tu, and Zhou 2014). Moreover, by showing that systematic risk is time-varying we complement the broader literature that has documented time-varying systematic risk in conventional stocks (See Oh and Patton 2017; Babenko, Boguth and Tserlukech 2017 etc.). In the literature on Islamic stocks, our study is the first to document time-varying systematic risk for decomposed short-term and long-term components. This is a significant contribution as evidence of time varying systematic risk can have several investment/risk management-oriented implications. The main implication in this regard is that a lower systematic risk of Islamic equities can offer diversification opportunities for optimization of portfolios. Moreover, the relatively lower beta of the Islamic markets arising out of lower debt suggests a benefitting long position during recessions but similar long positions in Islamic stocks will be a disadvantage in expansions. It is important to note that while we do not specifically test this hypothesis, it is something that future studies will find worthy of investigation.

To reaffirm our results, the empirical analysis is subjected to three robustness checks. First, we recalculate time-varying beta at a different (weekly) frequency, and our results are broadly consistent with those obtained using daily data. This suggests that our results are insensitive to data frequency. Second, we split the sample period in different economic states and study the systematic risk, and observe similar patterns as our full 18 year period. Third, instead of time-varying beta, we proxy volatility with the GARCH variance term extracted from an exponential GARCH(1,1) model, and find trivial changes in our main results.

Following the introduction, Section 2 explores the data. The methodologies used are discussed in Section 3 and then an empirical analysis in Section 4. Lastly, the conclusion is presented in Section 5.

2. DATA

Following the works of Kong, Rapach, Strauss, and Zhou (2011), Narayan et al. (2014), Phan et al. (2015b) and Alam et al. (2016), we focus on sectors of the market. Specifically, we have10 sectoral global indices for both conventional and Islamic counterpart from January 1, 1996 to December 31, 2015, spanning 4957 observation days. The indices have been extracted from the Dow Jones Index for both Islamic and conventional. The indices are value-weighted indices; for details and motivation, see Narayan and Bannigidamath (2017) and Narayan, Phan, Narayan and Bannigidadmath (2017). Daily returns are calculated using the equation , $r_t = \ln(P_t) - \ln(P_{t-1})$. Here, $r_{t\,t}$ and P_t denote daily return and price at the business day t, respectively. For robustness checks, we use other data frequencies, as recommended by Narayan and Sharma (2015), namely, weekly and monthly returns.

We have restricted our sample to ten major sectors based on two filters. Firstly, the sectoral index should at least constitute 30 stocks comprising of at least 10 markets. This filter has been placed to ensure the global nature of the analysis as well as to remove any small sector bias in our analysis. The second filter is to ensure that sectors from both Islamic and conventional markets are represented. This has been imposed to address the objective of undertaking comparisons between Islamic and conventional sectoral indices. It follows that applying both filters provided us with 10 sectors. The sectors are listed in Table 1 along with the number of firms making up each sectoral index.

[TABLE 1 HERE]

For a robust understanding of the behaviour of the efficiency of these sectoral comparisons, wedivided our data into five major time periods to factor in the distinct phases the global markets have gone through over the sample period. The first sample is 1996-2000, which is marked by a global economic boom, coupled with financial liberalization phases across the world. This liberalization opened the markets, removed restrictions for investments, and assisted in developing the stock markets. This era witnessed a few crises which were contained domestically or regionally; however, internationally this period was marked as stability and growth.

This is followed by 2001–2002, when markets in developed countries went through turmoil in the aftermath of the corporate scandals like Enron and WorldCom and the September 2001 World Trade Centre bombings, all of which had a significant impact on our sampled sectors. In the post-2002 (2002-2006), the markets experienced a normal phase of steady economic growth. In this period, global economies picked up and no major stock market or economic or financial market crashes were witnessed. This period is classified as a normal boom period. Post this period (2007-2009) has been classified as the crisis period, which originated in US and translated into a global economic slowdown followed by the Euro crisis. The period from 2010 onwards marked the recovery and stabilization phases, where countries globally began to slowly recover from the effects of the crisis and proceed to economic growths.

3. METHODOLOGY

The following section details the two main methodologies used in this paper. Firstly, wavelet decomposition is used to divide the sectoral indices of both Islamic and conventional markets into short-term and long-term horizons. Next, the beta value is estimated by running the regression of each sector’s daily returns on the respective global index returns for Islamic and conventional markets over a rolling window of 36 months.

3.1. Wavelet Decomposition

Following the calculation of the return series for all sectors in our sample, wavelet analysis is used to separate each return series into its fundamental multiresolution (multihorizon) components. To do this, the Maximum Overlap Discrete Wavelet Transformation (MODWT) is applied on the daily return series through sampling of the returns at uniformly spaced points in time. Converting the return series from time domain into scale (interval) domain will allow us to understand the frequency at which the activity in the time series occurs.

The daily return series are sampled at different scale crystals (j) as follows: *d*4 (16-32 day), d5 (32–64 days), and d6 (>64 days). A non-decimated orthogonal MODWT with symmlet 8 is used as a wavelet function to obtain the multiscale decomposition of the return series. The MODWT has the advantage of a time invariant property and on the flexibility of data length (it does not require the integral power of two). The wavelet symmlet 8 is considered most appropriate for financial series owing to its ability to get the least asymmetric property. The transformed returns series $r(t)$ will then be represented as a linear combination of wavelet function:

$$r(t) \approx \sum_k s_{J,k}\, \boldsymbol{\phi}_{J,k}(t) + \sum_k d_{J,k}\, \boldsymbol{\psi}_{J,k}(t) + \sum_k d_{J-1,k}\, \boldsymbol{\psi}_{J-1,k}(t) + \cdots \sum_k d_{1,k}\, \boldsymbol{\psi}_{1,k}(t) \qquad (1)$$

where:

$J\ is\ the\ number\ of\ scale\ crystals\ (intervals\ or\ frequencies)$

$k\ is\ the\ number\ of\ coefficients\ in\ the\ specified\ component$

$and\ the\ coefficients\ s_{j,k} and\ d_{j,k} represent\ the\ underlying\ smooth\ behaviour\ of\ the\ data$

$and\ \phi_{j,k(t)} and\ \psi_{j,k(t)}\ are\ the\ father\ and\ mother\ orthogonal\ wavelet\ pair\ that\ are\ given$

$respectively\ by$:

$$\phi_{j,k}(t) = 2^{-j/2}\phi\left(\frac{t-2^j k}{2^j}\right)\ for\ j = 1\ to\ J \qquad (2)$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right)\ for\ j = J\ to\ 1 \qquad (3)$$

$s_{J,k}$ are the coefficients for the father wavelet at the maximal scale called the 'smooth' coefficients that represent the underlying smooth behaviour of the series. While $d_{J,k}$ are called the 'detail' coefficients that represent the scale deviations from the smooth process obtained from the mother wavelet at all scales from 1 to *J*. *F(t)* is reconstructed containing the separate components of the original series at each frequency *j*.

These coefficients are measures of the contribution of the corresponding wavelet function to the total series. After we decompose the return series into *j* crystals, the crystals *dj* are recomposed into a time domain. The entire return series is replicated in multi-resolution decomposition as follows:

$$\widehat{r^j} = D_1 + \ \ldots\ldots D_j + S_j \qquad (4)$$

where *Dj* is the recomposed series in the time domain from the crystal *dj* and S_J is the recomposition of the residue. The reconstituted return series $\hat{r}^j$ contain the separate components of the original series at each frequency *j*. *Dj* represent the contribution of frequency *j* to the original series.

The wavelet method is beneficial as it provides us with a multiresolution analysis for correlation. Hence allowing us to study the correlation's dependence on a time scale. This is important because different investors have different investment horizons and wavelet analysis can be used to improve decision making in the practical situations of risk management, portfolio allocation and asset pricing.

Following the works of Arshad et al. (2016), Arshad and Rizvi (2015), we use the summation of the decomposed scale d1 (2–4 days) and d2 (4–8 days) to represent the short term investor horizon, while the d5 (32–64 days) and s5 (>64 days) represent the long term investor horizon for our study. The intuition behind this method allows the authors to split the return series in its long term and short-term component. The argument lies in the belief that the short-term component of the return series would also comprise speculative and arbitrage traders, which may distort the prices from its fundamental value based return which is identified in the long term component.

3.2. Systematic Risk

Following traditional works in finance, the beta is the measure of the systematic risk. For each country, we estimate the beta value by running the regression of each sector's daily returns on the respective global index returns for Islamic and conventional markets over a rolling window of 36 months following the work of Dewandaru et al (2014). To obtain beta of each firm within a country, we roll this regression on a thirty-six month window.

4. EMPIRICAL ANALYSIS

Figure 1 shows the betas for all sectoral indices that have been calculated over the period of 1996-2015. Interestingly, the betas for the original data and decomposed data show significant variation for some indices, both in terms of scale within Islamic and conventional counterparts, as well as within short and long-term components. We use the F-test and *t*-test to check for difference in variance and sample. We find that apart from the technology sector, conventional and Islamic betas are statistically different with different means and variances. The results for the tests on original betas are presented in Table 2[1]. Following the literature (See, for instance, Rizvi et al. 2014; Arshad et al. 2016; Alam et al. 2016) the short-term component represents the beta for investors with more speculative holding in the stock market while long term investors are fundamental-based investments. From Figure 1, we notice that while industrial and consumer services sectors tends to show more stability in their betas, other sectors exhibit high volatility. A clear visual difference in betas is observed in the case of the financial sector of Islamic and conventional indices. This finding is similar to the results in Sensoy (2016).

[FIGURE 1 HERE]

However, this graphical analysis has relatively limited analytical value and thus we firstly refer to Table 2, which provides the mean and standard deviation of the betas for each sector. Interestingly, we notice that the betas for Islamic sectors across the full sample and the decomposed shorter and longer horizons, on average, are lower than their conventional counterparts. This is in line with the findings of Dewandaru et al. (2015), who argue that the Islamic sectoral indices have a lower static beta than its conventional counterpart thus translating into lower systemic risk for Islamic investors. This can be attributed to the relatively smaller number of constituents, which may comprise of relatively less liquid stocks. This is highly possible as the screening criterion, which classifies stocks as Islamic depends heavily on the debt to equity ratios. Large equity firms in developing countries tend to be more illiquid and family owned, thus a lower average beta may arise from that. Likewise, the lower systematic risk can also be attributed to the lack of Islamic stocks and thus longer term holding of these stocks by Shariah compliant funds (Rizvi and Alam, 2016).

[TABLE 2 HERE]

However, the analysis on the average beta does not provide the complete picture, and a cursory look at the volatility of the beta tells a different story. Apart from the technology sector, the betas of the Islamic sectors are relatively more volatile across the board, with a stark difference especially in long-term component. This does not bode well from an investment strategy aspect. This may be attributable to the smaller size of the constituent list, which gives rise to less diversification opportunities.

Any analysis at this point may be limited in drawing conclusions as the sample period undertaken covers a longer duration, where multiple economic phases were experienced. Following the works of Rizvi et al. (2014) and Alam et al. (2016), we split our sample

[1] For the other pairs of conventional and Islamic are available with the author on request. They are not included in the paper for brevity reasons

accordingly and analyse our results for each period separately. The betas are presented in the Table 3. The general trend follows similar to the graphical plots in Figure 1, with Islamic indices closely following the conventional markets in most sectors.

However, across all sectors and time periods, the Islamic sectoral beta tends to be smaller than their conventional counterparts which implies a damper reaction to stock market changes. This is in line with Sensoy (2015), who argues that this is a sign of less riskiness of the Islamic equity markets. However, in the case of the utilities and financial sectors, especially during the economic boom of 2003-2006, the beta of the Islamic sector for the long-term component is visibly less than its conventional counterparts. This may be due to the relatively small constituent list owing to the debt screening. Utility firms globally tend to be debt intensive projects, which do not pass the shariah screening criteria. Similarly, as the financial sector core business is considered un-Islamic, its universe is limited and comprises of relatively illiquid stocks. Most of the findings conform to Sensoy (2016), who explored a similar sample size but for a full-length period. These findings cautiously support Dewandaru et al. (2015) of Islamic markets as less risky in terms of their systematic risks.

[TABLE 3 HERE]

We follow a similar methodology to explore the volatility of betas using EGARCH presented in Table 4. The results suggest a similarity between the pair of indices across different economic states. An interesting observation is that in all indices from 2007-2015 covering the recent financial crisis and recovery the betas have a lower volatility as compared to pre-2007. This can be explained via the increase in number of investors and through more widespread technology driven information flow. With the stability aspect between Islamic and conventional sectors, apart from the health care, oil & gas, and technology sectors, the Islamic indices tend to be have a higher volatility, which we argue owes to the smaller constituent list.

[TABLE 4 HERE]

For further robustness checks, we pursue two more aspects of analysis. Firstly, we recalculate our betas for the sample period using weekly returns. The results of average beta for the 1996-2015 period, and for different economic states are presented in Table 5(a, b). The results concur with our earlier findings. For a further conformity check of our findings, we also calculate the betas for both daily returns and weekly returns using the alternative calculation of systematic risk using the covariance formula, and findings are similar to earlier conclusions. The results of average beta are appended in Table 6(a, b ,c ,d). (The results of volatility for the robustness checks, are available from the author on request and not included here for brevity).

5. CONCLUSION

The main objective of this study is to explore and compare the aggregate systemic risk profiles of conventional and Islamic equity markets using sectoral level time series data. The sample comprises of ten sectoral indices and over a period of nineteen years. The key contribution primarily stems from the comparative analysis of the betas as systematic risk proxy and across different global economic states.

In majority of the cases, we observed that the conventional and its counterpart Islamic sectoral indices follow a similar pattern overtime. However, upon additional analysis, we found that

Islamic sectors' aggregate risk in the case of the financial and utilities sectors is much less. This does reflect the argument that they may provide a lower risk to investors. Nevertheless, this lower beta of the Islamic sectors also means that investors focusing on Islamic sectors would have lower returns as compared to their conventional counterparts in economic booms.

Our findings complement recent literature comparing Islamic and conventional financial markets as surveyed in, for example, Narayan and Phan (2017). Our study adds a risk-oriented dimension toward understanding Islamic markets vis-à-vis conventional markets from the point of view of sectors.

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Table 1: World Equity Market Sectors in Sample

This table records the number of companies used and their descriptive statistics for the daily returns of the 10 sectors in sample. Column 3 and 4 provide the number of companies in each sector for Islamic and conventional indices respectively.

Sector	Sector Code	No. of Companies	
		Islamic	Conventional
Basic Materials	BM	225	1121
Consumer Goods	CG	480	1464
Consumer Services	CS	267	1355
Financial	FIN	134	2576
Health Care	HC	373	854
Industrial	IND	606	2474
Oil and Gas	O&G	110	641
Technology	TECH	348	1065
Telecom	TELECOM	60	189
Utilities	UTL	36	375

Table 2: Mean and Volatility for full sample

This table reports the mean for the betas of our 10 Islamic and conventional sectors (Panel A) and the standard deviation (Panel B). The betas are calculated by running the regression of each sector's daily return on the respective global index for Islamic and conventional markets over a rolling window of 36 months. The 10 sectors are differentiated between Islamic and conventional indices, where they are further assorted into 3 time horizons, i.e. actual, short-term and long-term. Columns 2 and 5 denote the actual series prior to decomposition. Columns 3 and 6 show the descriptive statistics for short-term representing a horizon of 2-8 days. Columns 4 and 7 provide the statistics for long-term horizons which covers any period more than 32 days. The last column shows the t-stats for the original series beta to observe if the betas of the Islamic and conventional indices are statistically unique. The critical value for the t-stat is 1.960.

Panel A: Mean							
	Islamic			Conventional			
	Actual	Short-Term	Long-Term	Actual	Short-Term	Long-Term	T-stat
Basic Materials	1.001	0.955	1.111	1.052	1.024	1.161	27.700
Consumer Goods	0.681	0.68	0.676	0.76	0.755	0.763	73.715
Consumer Services	0.893	0.906	0.803	0.932	0.933	0.918	31.215
Financial	0.751	0.682	1.026	1.137	1.117	1.142	86.731
Health Care	0.779	0.807	0.643	0.804	0.834	0.655	25.939
Industrial	0.967	0.93	1.057	1.021	0.999	1.071	48.313
Oil and Gas	0.996	1.003	1.065	0.974	0.983	1.079	-12.791
Technology	1.343	1.369	1.339	1.346	1.374	1.365	1.671
Telecom	0.794	0.756	0.85	0.923	0.924	0.892	62.320
Utilities	0.56	0.524	0.614	0.637	0.658	0.607	25.545
Panel B: Volatility							
	Islamic			Conventional			
	Actual	Short-Term	Long-Term	Actual	Short-Term	Long-Term	T-stat
Basic Materials	0.392	0.285	0.342	0.257	0.239	0.321	1.435
Consumer Goods	0.195	0.336	0.536	0.275	0.283	0.358	1.258
Consumer Services	0.154	0.233	0.442	0.202	0.202	0.279	1.540
Financial	0.373	0.297	0.417	0.169	0.172	0.195	5.134
Health Care	0.241	0.317	0.543	0.360	0.340	0.524	1.036
Industrial	0.139	0.179	0.209	0.136	0.133	0.176	2.267
Oil and Gas	0.415	0.278	0.363	0.295	0.276	0.377	1.245
Technology	0.398	0.213	0.284	0.237	0.232	0.305	0.788
Telecom	0.202	0.275	0.437	0.266	0.240	0.441	1.142
Utilities	0.258	0.362	0.610	0.405	0.371	0.668	1.374

Table 3: Average Beta for Each Sector

This table provides the average beta for each of the 10 sectors (Panel A-J). The betas are calculated by running the regression of each sector's daily return on the respective global index for Islamic and conventional markets over a rolling window of 36 months. The betas are presented for Islamic and conventional sectoral indices for the actual, short term and long term time horizons. The first column shows the overall time period (first row) and the 5 different economic states during our sample period. The * represents recessionary economic global states.

Panel A: Basic Materials						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	1.001	0.955	1.111	1.052	1.024	1.161
1996-2000	0.546	0.558	0.691	0.676	0.699	0.877
2001-2002*	0.680	0.638	0.635	0.784	0.750	0.714
2003-2006	1.118	1.031	1.292	1.231	1.174	1.421
2007-2009*	1.406	1.338	1.481	1.275	1.239	1.346
2010-2015	1.158	1.111	1.292	1.188	1.149	1.262
Panel B: Consumer Goods						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.681	0.680	0.676	0.760	0.755	0.763
1996-2000	0.663	0.664	0.648	0.773	0.799	0.694
2001-2002*	0.429	0.426	0.454	0.525	0.509	0.599
2003-2006	0.684	0.685	0.659	0.819	0.804	0.852
2007-2009*	0.665	0.656	0.765	0.701	0.684	0.743
2010-2015	0.787	0.788	0.753	0.831	0.816	0.848
Panel C: Consumer Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.893	0.906	0.803	0.932	0.933	0.918
1996-2000	0.950	0.935	0.854	0.968	0.952	0.924
2001-2002*	0.879	0.891	0.874	1.009	1.003	1.101
2003-2006	0.933	0.965	0.712	0.965	0.979	0.887
2007-2009*	0.831	0.845	0.800	0.871	0.876	0.910
2010-2015	0.865	0.887	0.815	0.893	0.901	0.895
Panel D: Financial Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.751	0.682	1.026	1.137	1.117	1.142
1996-2000	0.697	0.501	1.673	1.073	1.018	1.200
2001-2002*	0.403	0.291	0.658	1.075	1.055	1.100
2003-2006	0.672	0.622	0.604	1.045	1.036	0.967
2007-2009*	1.187	1.219	1.134	1.365	1.344	1.221
2010-2015	0.744	0.740	0.820	1.171	1.173	1.193
Panel E: Health Care						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.779	0.807	0.643	0.804	0.834	0.655
1996-2000	0.909	0.935	0.623	0.972	0.997	0.672
2001-2002*	0.572	0.558	0.542	0.619	0.603	0.534
2003-2006	0.764	0.815	0.619	0.788	0.850	0.663
2007-2009*	0.610	0.630	0.573	0.622	0.644	0.608
2010-2015	0.862	0.890	0.759	0.863	0.896	0.712
Panel F: Industrial						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.967	0.930	1.057	1.021	0.999	1.071
1996-2000	0.826	0.771	0.987	0.931	0.909	1.016

2001-2002*	0.985	0.960	1.251	1.077	1.081	1.109
2003-2006	0.947	0.894	1.020	1.035	1.004	1.099
2007-2009*	1.052	1.016	1.136	1.036	1.009	1.127
2010-2015	1.039	1.022	1.018	1.054	1.032	1.047
Panel G: Oil & Gas						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.996	1.003	1.065	0.974	0.983	1.079
1996-2000	0.585	0.590	0.601	0.645	0.656	0.683
2001-2002*	0.613	0.606	0.636	0.654	0.652	0.671
2003-2006	1.098	1.102	1.307	1.030	1.031	1.384
2007-2009*	1.353	1.384	1.335	1.185	1.219	1.243
2010-2015	1.194	1.193	1.301	1.195	1.198	1.266
Panel H: Technology						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	1.343	1.369	1.339	1.346	1.374	1.365
1996-2000	1.665	1.724	1.767	1.611	1.641	1.720
2001-2002*	1.994	2.040	1.841	2.107	2.174	1.998
2003-2006	1.328	1.337	1.262	1.370	1.387	1.384
2007-2009*	0.996	1.022	0.940	1.003	1.039	0.914
2010-2015	1.067	1.075	1.077	1.052	1.071	1.087
Panel I: Telecom						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.794	0.756	0.850	0.923	0.924	0.892
1996-2000	0.893	0.845	0.896	1.020	0.972	0.985
2001-2002*	0.883	0.874	1.078	1.115	1.149	1.161
2003-2006	0.855	0.808	0.804	0.930	0.936	0.840
2007-2009*	0.843	0.835	0.849	0.843	0.874	0.783
2010-2015	0.609	0.551	0.766	0.818	0.819	0.816
Panel J: Utilities						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.560	0.524	0.614	0.637	0.658	0.607
1996-2000	0.378	0.328	0.444	0.464	0.505	0.377
2001-2002*	0.332	0.291	0.256	0.391	0.392	0.382
2003-2006	0.449	0.431	0.387	0.724	0.742	0.670
2007-2009*	0.902	0.893	0.963	0.737	0.749	0.795
2010-2015	0.659	0.607	0.813	0.746	0.761	0.727

Table 4: Average Volatility of Beta

This table provides the average volatility of the beta for each of the 10 sectors (Panel A-J). The volatilities are obtained using EGARCH and are presented for Islamic and conventional sectoral indices for the actual, short term and long term time horizons. The first column shows the overall time period (first row) and the 5 different economic states during our sample period. The * represents recessionary economic global states.

Panel A: Basic Material						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000470	0.000467	0.001011	0.000414	0.000399	0.001108
1996-2000	0.000499	0.000500	0.001733	0.000424	0.000395	0.001552
2001-2002*	0.000379	0.000392	0.000652	0.000339	0.000362	0.000822
2003-2006	0.000538	0.000520	0.000978	0.000447	0.000426	0.001229
2007-2009*	0.000526	0.000522	0.000737	0.000561	0.000512	0.000903
2010-2015	0.000403	0.000403	0.000719	0.000336	0.000341	0.000875
Panel B: Consumer Goods						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000167	6.39E-28	0.000367	0.000126	0.00014	0.000219
1996-2000	0.000239	6.41E-28	0.000613	0.000152	0.000175	0.000403
2001-2002*	0.000204	6.41E-28	0.000271	0.000154	0.000178	0.000199
2003-2006	0.000157	6.38E-28	0.000303	0.000123	0.000136	0.000194
2007-2009*	0.00015	6.38E-28	0.00041	0.00012	0.000122	0.000165
2010-2015	0.000113	6.37E-28	0.000226	0.000102	0.00011	0.000122
Panel C: Consumer Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.00029	0.00030	0.00055	0.00014	0.00000	0.00025
1996-2000	0.00036	0.00039	0.00082	0.00018	0.00000	0.00031
2001-2002*	0.00033	0.00031	0.00036	0.00020	0.00000	0.00018
2003-2006	0.00033	0.00032	0.00075	0.00014	0.00000	0.00036
2007-2009*	0.00031	0.00032	0.00042	0.00014	0.00000	0.00017
2010-2015	0.00019	0.00020	0.00033	0.00010	0.00000	0.00019
Panel D: Financial Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.001335	0.001566	0.002147	0.000257	0.000289	0.000446
1996-2000	0.002607	0.003156	0.003742	0.000286	0.000325	0.000501
2001-2002*	0.000981	0.001104	0.001629	0.000229	0.000261	0.000269
2003-2006	0.000759	0.00083	0.001897	0.000226	0.000251	0.000599
2007-2009*	0.002068	0.002367	0.001932	0.000374	0.000415	0.000482
2010-2015	0.000464	0.00055	0.00133	0.000207	0.000231	0.000343
Panel E: Health Care						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000297	0.00027	0.000635	0.000349	0.000362	0.000728
1996-2000	0.00041	0.000401	0.000987	0.00052	0.000577	0.001139
2001-2002*	0.000333	0.000278	0.000444	0.000481	0.000437	0.000523
2003-2006	0.00032	0.000266	0.000622	0.000376	0.000354	0.000859
2007-2009*	0.000232	0.000207	0.000468	0.000227	0.000251	0.000486
2010-2015	0.000214	0.000198	0.000512	0.000212	0.000227	0.000505
Panel F: Industrial						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000134	0.000145	0.000194	8.93E-05	8.88E-05	0.000162
1996-2000	0.000167	0.000202	0.000141	8.97E-05	9.95E-05	0.000175

2001-2002*	0.00018	0.000195	0.000221	0.000177	0.000143	0.000162
2003-2006	0.000142	0.000147	0.00028	8.68E-05	9.28E-05	0.000206
2007-2009*	0.000119	0.000127	0.000162	8.25E-05	8.53E-05	0.00011
2010-2015	9.44E-05	9.28E-05	0.000187	6.46E-05	6.16E-05	0.000149
Panel G: Oil & Gas						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000593	0.000613	0.001496	0.000746	0.000773	0.002116
1996-2000	0.0007	0.000796	0.001288	0.000837	0.000929	0.0013
2001-2002*	0.000599	0.000641	0.000878	0.00074	0.00082	0.001156
2003-2006	0.000803	0.000776	0.002581	0.001148	0.001089	0.004939
2007-2009*	0.000531	0.000486	0.000814	0.000717	0.000712	0.00167
2010-2015	0.000396	0.000415	0.001486	0.000423	0.000455	0.001424
Panel H: Technology						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000503	0.000541	0.00102	0.000813	0.000908	0.001273
1996-2000	0.000767	0.000937	0.00152	0.001291	0.001532	0.001803
2001-2002*	0.000635	0.00065	0.000714	0.001394	0.00153	0.001619
2003-2006	0.000578	0.000543	0.001233	0.000852	0.00084	0.002135
2007-2009*	0.000362	0.000345	0.00072	0.000484	0.000538	0.000467
2010-2015	0.000271	0.000289	0.000735	0.00038	0.000438	0.000568
Panel I: Telecom						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000454	0.000464	0.000916	0.000368	0.000368	0.000722
1996-2000	0.000445	0.00046	0.000792	0.00048	0.000472	0.000855
2001-2002*	0.000507	0.00049	0.000869	0.000651	0.000551	0.001425
2003-2006	0.000585	0.000564	0.001414	0.000383	0.000388	0.000714
2007-2009*	0.000413	0.000414	0.000336	0.000267	0.000292	0.000311
2010-2015	0.000379	0.000416	0.000989	0.000225	0.00025	0.000595
Panel J: Utilities						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.000483	0.000595	0.001202	0.000277	0.000277	0.000795
1996-2000	0.000579	0.00086	0.001338	0.000264	0.000276	0.000526
2001-2002*	0.000516	0.000556	0.001599	0.000338	0.000344	0.000685
2003-2006	0.000479	0.000523	0.001255	0.000299	0.000288	0.00124
2007-2009*	0.000554	0.000612	0.00082	0.000278	0.000282	0.000724
2010-2015	0.000362	0.000437	0.001117	0.000253	0.000244	0.000783

Table 5a: Mean and Volatility of Sectoral Indices using Weekly Returns

This table presents the mean (Panel A) and volatility (Panel B) of the beta of the 10 sectoral indices for the actual, short-term and long-term time horizons. Weekly data is used as a robustness test for our analysis using the entire sample period, 1996-2015. The average of the beta is shown in Panel A for the mean, while standard deviation is used to find the volatility presented in Panel B.

Panel A: Mean						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.596	0.583	0.600	0.655	0.639	0.623
Consumer Goods	0.993	0.951	1.040	1.028	1.001	1.070
Consumer Services	0.764	0.750	0.824	0.921	0.909	0.957
Financial	0.463	0.422	0.537	0.710	0.702	0.732
Health Care	0.844	0.819	0.779	0.852	0.813	0.801
Industrial	0.859	0.871	0.869	0.883	0.894	0.885
Oil and Gas	0.542	0.522	0.557	0.528	0.503	0.548
Technology	0.638	0.612	0.642	0.600	0.568	0.616
Telecom	0.665	0.632	0.752	0.733	0.707	0.784
Utilities	0.624	0.568	0.670	0.844	0.792	0.792
Panel B: Volatility						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.293	0.285	0.342	0.257	0.239	0.321
Consumer Goods	0.334	0.336	0.536	0.275	0.283	0.358
Consumer Services	0.260	0.233	0.442	0.202	0.202	0.279
Financial	0.312	0.297	0.417	0.169	0.172	0.195
Health Care	0.341	0.317	0.543	0.360	0.340	0.524
Industrial	0.172	0.179	0.209	0.136	0.133	0.176
Oil and Gas	0.298	0.278	0.363	0.295	0.276	0.377
Technology	0.226	0.213	0.284	0.237	0.232	0.305
Telecom	0.293	0.275	0.437	0.266	0.240	0.441
Utilities	0.343	0.362	0.610	0.405	0.371	0.668

Table 5b: Average Beta of Sectoral Indices

This table provides the average volatility of the beta for each of the 10 sectors (Panel A-J) using weekly data. The volatilities are obtained using EGARCH and are presented for Islamic and conventional sectoral indices for the actual, short term and long term time horizons. The first column shows the overall time period (first row) and the 5 different economic states during our sample period. The * represents recessionary economic global states.

Panel A: Basic Material						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.596	0.583	0.600	0.655	0.639	0.623
1996-2000	0.440	0.391	0.561	0.631	0.571	0.666
2001-2002*	0.825	0.766	0.685	0.893	0.846	0.729
2003-2006	0.616	0.586	0.541	0.631	0.602	0.536
2007-2009*	0.542	0.570	0.583	0.550	0.579	0.585
2010-2015	0.655	0.676	0.650	0.662	0.679	0.631
Panel B: Consumer Goods						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.993	0.951	1.040	1.028	1.001	1.070
1996-2000	0.731	0.623	0.778	0.863	0.771	0.967
2001-2002*	1.127	1.029	1.292	1.224	1.219	1.257
2003-2006	1.021	1.001	1.066	0.984	0.967	0.975
2007-2009*	1.178	1.170	1.119	1.219	1.188	1.223
2010-2015	1.043	1.041	1.107	1.028	1.039	1.074
Panel C: Consumer Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.764	0.750	0.824	0.921	0.909	0.957
1996-2000	0.622	0.642	0.671	0.814	0.809	0.929
2001-2002*	0.694	0.708	0.952	0.802	0.820	0.866
2003-2006	0.657	0.639	0.607	0.880	0.872	0.838
2007-2009*	0.860	0.811	0.947	1.055	1.015	1.019
2010-2015	0.922	0.894	0.983	1.005	0.989	1.059
Panel D: Financial Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.463	0.422	0.537	0.710	0.702	0.732
1996-2000	0.157	0.100	0.381	0.626	0.629	0.663
2001-2002*	0.542	0.479	0.560	0.764	0.764	0.816
2003-2006	0.510	0.481	0.447	0.796	0.762	0.743
2007-2009*	0.394	0.362	0.508	0.593	0.599	0.708
2010-2015	0.681	0.647	0.729	0.761	0.752	0.764
Panel E: Health Care						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.844	0.819	0.779	0.852	0.813	0.801
1996-2000	0.566	0.521	0.539	0.546	0.477	0.588
2001-2002*	0.962	0.970	0.977	0.941	0.911	0.986
2003-2006	0.809	0.776	0.697	0.774	0.747	0.677
2007-2009*	1.093	1.027	0.991	1.153	1.093	1.048
2010-2015	0.923	0.927	0.850	0.964	0.952	0.866
Panel F: Industrial						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.859	0.871	0.869	0.883	0.894	0.885
1996-2000	0.886	0.863	0.902	0.924	0.923	0.956
2001-2002*	0.861	0.837	0.801	0.816	0.807	0.846

2003-2006	0.822	0.889	0.850	0.856	0.887	0.828
2007-2009*	0.824	0.851	0.840	0.882	0.895	0.864
2010-2015	0.879	0.886	0.893	0.893	0.904	0.892
Panel G: Oil & Gas						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.542	0.522	0.557	0.528	0.503	0.548
1996-2000	0.382	0.348	0.498	0.388	0.346	0.533
2001-2002*	0.543	0.479	0.645	0.537	0.471	0.613
2003-2006	0.522	0.510	0.402	0.473	0.452	0.353
2007-2009*	0.589	0.606	0.628	0.562	0.593	0.591
2010-2015	0.659	0.640	0.641	0.657	0.628	0.645
Panel H: Technology						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.638	0.612	0.642	0.600	0.568	0.616
1996-2000	0.434	0.401	0.452	0.357	0.321	0.392
2001-2002*	0.480	0.458	0.489	0.442	0.418	0.448
2003-2006	0.551	0.550	0.535	0.536	0.522	0.488
2007-2009*	0.885	0.839	0.856	0.861	0.804	0.831
2010-2015	0.787	0.758	0.808	0.755	0.728	0.827
Panel I: Telecom						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.665	0.632	0.752	0.733	0.707	0.784
1996-2000	0.571	0.550	0.724	0.579	0.528	0.697
2001-2002*	0.579	0.578	0.558	0.579	0.608	0.467
2003-2006	0.555	0.532	0.616	0.652	0.630	0.794
2007-2009*	0.809	0.795	0.967	0.908	0.900	0.959
2010-2015	0.770	0.701	0.823	0.873	0.836	0.865
Panel J: Utilities						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.624	0.568	0.670	0.844	0.792	0.792
1996-2000	0.571	0.550	0.724	0.579	0.528	0.697
2001-2002*	0.579	0.578	0.558	0.579	0.608	0.467
2003-2006	0.555	0.532	0.616	0.652	0.630	0.794
2007-2009*	0.809	0.795	0.967	0.908	0.900	0.959
2010-2015	0.770	0.701	0.823	0.873	0.836	0.865

Table 6a: Alternative Mean and Volatility of Sectoral Indices Using Daily Returns

This table presents the mean (Panel A) and volatility (Panel B) of the beta of the 10 sectoral indices for the actual, short-term and long-term time horizons. The betas are calculated using the covariance formula in Excel. The average of the daily betas is shown in Panel A for the mean, while standard deviation is used to find the volatility presented in Panel B.

Panel A: Mean						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.985	0.941	1.094	1.035	1.008	1.143
Consumer Goods	0.670	0.670	0.665	0.749	0.744	0.752
Consumer Services	0.879	0.892	0.791	0.917	0.919	0.904
Financial	0.739	0.671	1.010	1.119	1.100	1.124
Health Care	0.767	0.794	0.633	0.792	0.821	0.645
Industrial	0.952	0.915	1.040	1.005	0.983	1.054
Oil and Gas	0.981	0.987	1.049	0.959	0.968	1.063
Technology	1.322	1.348	1.319	1.325	1.352	1.344
Telecom	0.782	0.744	0.837	0.909	0.909	0.878
Utilities	0.551	0.516	0.605	0.627	0.648	0.598
Panel B: Volatility						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.386	0.362	0.601	0.322	0.306	0.605
Consumer Goods	0.192	0.199	0.337	0.171	0.181	0.257
Consumer Services	0.152	0.156	0.418	0.122	0.125	0.263
Financial	0.367	0.408	0.798	0.162	0.169	0.305
Health Care	0.237	0.233	0.462	0.233	0.235	0.454
Industrial	0.137	0.146	0.237	0.091	0.096	0.190
Oil and Gas	0.408	0.400	0.718	0.366	0.353	0.785
Technology	0.392	0.413	0.584	0.442	0.463	0.655
Telecom	0.199	0.209	0.466	0.186	0.177	0.464
Utilities	0.254	0.259	0.597	0.217	0.217	0.471

Table 6b: Average Beta of Sectoral Indices Using Daily Returns

This table provides the average beta for each of the 10 sectors (Panel A-J). The beta is obtained using covariance formula and are presented for Islamic and conventional sectoral indices for the actual, short term and long term time horizons. The first column shows the overall time period (first row) and the 5 different economic states during our sample period. The * represents recessionary economic global states.

Panel A: Basic Material						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.985	0.941	1.094	1.035	1.008	1.143
1996-2000	0.538	0.550	0.680	0.665	0.688	0.864
2001-2002*	0.669	0.628	0.625	0.772	0.738	0.703
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	1.384	1.317	1.459	1.255	1.220	1.326
2010-2015	1.169	1.116	1.278	1.189	1.148	1.249
Panel B: Consumer Goods						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.670	0.670	0.665	0.749	0.744	0.752
1996-2000	0.653	0.654	0.638	0.761	0.786	0.683
2001-2002*	0.422	0.420	0.447	0.517	0.501	0.590
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.655	0.646	0.753	0.691	0.673	0.731
2010-2015	0.771	0.774	0.726	0.806	0.794	0.812
Panel C: Consumer Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.879	0.892	0.791	0.917	0.919	0.904
1996-2000	0.935	0.920	0.841	0.953	0.938	0.910
2001-2002*	0.865	0.878	0.861	0.993	0.987	1.084
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.819	0.832	0.787	0.858	0.863	0.896
2010-2015	0.843	0.866	0.790	0.871	0.879	0.864
Panel D: Financial Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.739	0.671	1.010	1.119	1.100	1.124
1996-2000	0.686	0.493	1.647	1.056	1.003	1.182
2001-2002*	0.397	0.287	0.647	1.058	1.039	1.083
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	1.169	1.201	1.116	1.344	1.324	1.202
2010-2015	0.732	0.715	0.849	1.137	1.139	1.167
Panel E: Health Care						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.767	0.794	0.633	0.792	0.821	0.645
1996-2000	0.895	0.920	0.613	0.957	0.982	0.662
2001-2002*	0.563	0.549	0.534	0.609	0.594	0.526
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.600	0.620	0.564	0.612	0.634	0.599
2010-2015	0.828	0.858	0.732	0.822	0.854	0.688
Panel F: Industrial						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.952	0.915	1.040	1.005	0.983	1.054
1996-2000	0.813	0.759	0.972	0.917	0.895	1.000
2001-2002*	0.970	0.946	1.232	1.060	1.064	1.092

2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	1.036	1.000	1.119	1.020	0.994	1.110
2010-2015	1.027	1.010	1.015	1.040	1.018	1.039
Panel G: Oil & Gas						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.981	0.987	1.049	0.959	0.968	1.063
1996-2000	0.576	0.580	0.591	0.635	0.645	0.672
2001-2002*	0.604	0.597	0.626	0.644	0.642	0.661
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	1.332	1.363	1.314	1.167	1.200	1.224
2010-2015	1.185	1.187	1.261	1.178	1.184	1.225
Panel H: Technology						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	1.322	1.348	1.319	1.325	1.352	1.344
1996-2000	1.640	1.697	1.740	1.587	1.616	1.693
2001-2002*	1.964	2.009	1.813	2.075	2.141	1.967
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.981	1.006	0.925	0.988	1.023	0.900
2010-2015	1.036	1.042	1.068	1.021	1.037	1.071
Panel I: Telecom						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.782	0.744	0.837	0.909	0.909	0.878
1996-2000	0.879	0.832	0.882	1.004	0.957	0.970
2001-2002*	0.870	0.861	1.062	1.098	1.131	1.144
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.830	0.822	0.836	0.830	0.860	0.771
2010-2015	0.611	0.562	0.757	0.804	0.814	0.805
Panel J: Utilities						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.551	0.516	0.605	0.627	0.648	0.598
1996-2000	0.373	0.322	0.437	0.457	0.497	0.371
2001-2002*	0.327	0.286	0.252	0.385	0.386	0.377
2003-2006	1.101	1.016	1.272	1.212	1.156	1.399
2007-2009*	0.888	0.879	0.948	0.726	0.738	0.782
2010-2015	0.671	0.624	0.833	0.736	0.754	0.718

Table 6c: Alternative Mean and Volatility of Sectoral Indices Using Weekly Returns

This table presents the mean (Panel A) and volatility (Panel B) of the beta of the 10 sectoral indices for the actual, short-term and long-term time horizons. The betas are calculated on weekly returns using the covariance formula in Excel. The average of the daily betas is shown in Panel A for the mean, while standard deviation is used to find the volatility presented in Panel B.

Panel A: Mean						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.965	0.916	1.026	1.009	0.962	1.072
Consumer Goods	0.629	0.615	0.624	0.721	0.703	0.704
Consumer Services	0.818	0.820	0.741	0.867	0.848	0.848
Financial	0.761	0.717	0.946	1.062	1.049	1.054
Health Care	0.711	0.733	0.593	0.734	0.763	0.604
Industrial	0.933	0.893	0.975	0.964	0.941	0.989
Oil and Gas	0.888	0.918	0.983	0.849	0.886	0.996
Technology	1.193	1.235	1.237	1.179	1.231	1.261
Telecom	0.795	0.735	0.784	0.878	0.861	0.823
Utilities	0.585	0.534	0.567	0.576	0.578	0.561
Panel B: Volatility						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
Basic Materials	0.470	0.442	0.566	0.389	0.369	0.571
Consumer Goods	0.215	0.218	0.318	0.202	0.199	0.242
Consumer Services	0.248	0.228	0.394	0.178	0.179	0.248
Financial	0.574	0.561	0.753	0.245	0.230	0.288
Health Care	0.278	0.284	0.435	0.281	0.313	0.429
Industrial	0.185	0.206	0.223	0.136	0.138	0.179
Oil and Gas	0.503	0.481	0.677	0.459	0.442	0.741
Technology	0.427	0.461	0.551	0.448	0.501	0.617
Telecom	0.313	0.291	0.440	0.309	0.274	0.438
Utilities	0.323	0.365	0.564	0.273	0.279	0.444

Table 6d: Average Beta of Sectoral Indices Using Weekly Returns

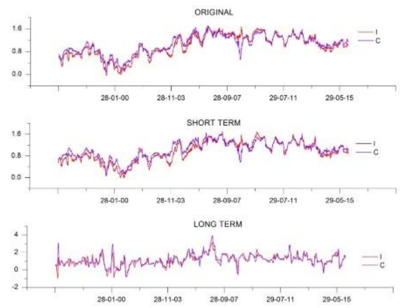
This table provides the average beta for each of the 10 sectors (Panel A-J). Weekly returns are used as a robustness. The beta is obtained using covariance formula and are presented for Islamic and conventional sectoral indices for the actual, short term and long term time horizons. The first column shows the overall time period (first row) and the 5 different economic states during our sample period. The * represents recessionary economic global states.

Panel A: Basic Material						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.965	0.916	1.026	1.009	0.962	1.072
1996-2000	0.436	0.445	0.638	0.603	0.594	0.811
2001-2002*	0.747	0.693	0.585	0.793	0.732	0.658
2003-2006	1.081	1.017	1.195	1.186	1.115	1.314
2007-2009*	1.442	1.343	1.367	1.303	1.211	1.243
2010-2015	1.140	1.082	1.198	1.137	1.104	1.171
Panel B: Consumer Goods						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.629	0.615	0.624	0.721	0.703	0.704
1996-2000	0.551	0.529	0.599	0.685	0.696	0.640
2001-2002*	0.427	0.423	0.418	0.523	0.504	0.551
2003-2006	0.652	0.633	0.609	0.807	0.773	0.787
2007-2009*	0.614	0.603	0.707	0.656	0.642	0.685
2010-2015	0.751	0.743	0.681	0.791	0.761	0.761
Panel C: Consumer Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.818	0.820	0.741	0.867	0.848	0.848
1996-2000	0.883	0.857	0.788	0.890	0.861	0.853
2001-2002*	0.879	0.892	0.807	1.010	0.955	1.017
2003-2006	0.796	0.828	0.655	0.888	0.870	0.818
2007-2009*	0.721	0.750	0.739	0.772	0.795	0.840
2010-2015	0.811	0.796	0.741	0.836	0.812	0.810
Panel D: Financial Services						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.761	0.717	0.946	1.062	1.049	1.054
1996-2000	0.792	0.611	1.543	1.032	0.987	1.107
2001-2002*	0.510	0.541	0.608	1.031	1.043	1.015
2003-2006	0.567	0.570	0.558	0.918	0.952	0.892
2007-2009*	1.223	1.156	1.046	1.341	1.291	1.127
2010-2015	0.718	0.736	0.795	1.053	1.042	1.094
Panel E: Health Care						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.711	0.733	0.593	0.734	0.763	0.604
1996-2000	0.794	0.822	0.574	0.851	0.887	0.620
2001-2002*	0.681	0.598	0.502	0.730	0.632	0.495
2003-2006	0.727	0.791	0.570	0.729	0.839	0.612
2007-2009*	0.539	0.551	0.529	0.567	0.573	0.561
2010-2015	0.732	0.759	0.686	0.730	0.752	0.645
Panel F: Industrial						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.933	0.893	0.975	0.964	0.941	0.989
1996-2000	0.814	0.747	0.911	0.881	0.851	0.938
2001-2002*	1.006	0.976	1.153	1.057	1.053	1.021

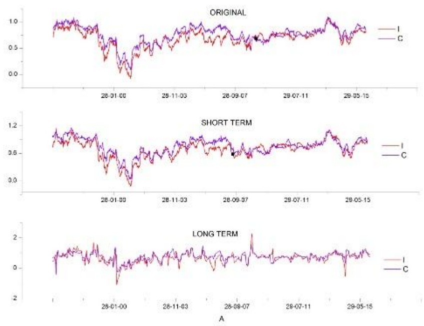
2003-2006	0.900	0.844	0.943	0.982	0.943	1.016
2007-2009*	1.016	0.990	1.048	0.979	0.966	1.040
2010-2015	0.983	0.963	0.952	0.979	0.959	0.974
Panel G: Oil & Gas						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.888	0.918	0.983	0.849	0.886	0.996
1996-2000	0.429	0.399	0.555	0.490	0.488	0.630
2001-2002*	0.471	0.566	0.581	0.494	0.555	0.614
2003-2006	1.026	1.092	1.211	0.900	0.940	1.282
2007-2009*	1.214	1.244	1.231	1.051	1.104	1.146
2010-2015	1.135	1.168	1.182	1.115	1.165	1.148
Panel H: Technology						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	1.193	1.235	1.237	1.179	1.231	1.261
1996-2000	1.616	1.727	1.632	1.545	1.666	1.588
2001-2002*	1.673	1.740	1.704	1.645	1.778	1.850
2003-2006	1.097	1.084	1.162	1.154	1.155	1.275
2007-2009*	0.829	0.857	0.868	0.834	0.857	0.844
2010-2015	0.943	0.964	1.002	0.921	0.942	1.005
Panel I: Telecom						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.795	0.735	0.784	0.878	0.861	0.823
1996-2000	0.822	0.763	0.827	1.011	0.956	0.909
2001-2002*	0.855	0.772	0.999	1.038	1.015	1.077
2003-2006	0.967	0.825	0.739	0.902	0.874	0.771
2007-2009*	0.790	0.827	0.784	0.763	0.804	0.722
2010-2015	0.643	0.594	0.709	0.762	0.753	0.755
Panel J: Utilities						
	Islamic			Conventional		
	Actual	Short Term	Long Term	Actual	Short Term	Long Term
1996-2015	0.585	0.534	0.567	0.576	0.578	0.561
1996-2000	0.455	0.342	0.410	0.411	0.405	0.348
2001-2002*	0.337	0.326	0.234	0.344	0.267	0.351
2003-2006	0.527	0.424	0.357	0.684	0.677	0.618
2007-2009*	0.849	0.921	0.888	0.669	0.746	0.734
2010-2015	0.676	0.635	0.780	0.665	0.668	0.674

Figure 1: Plots of Betas for each Sector

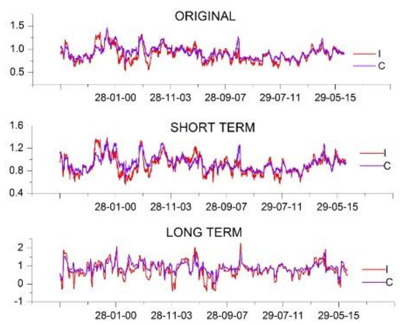
Plot of Beta of Basic Materials



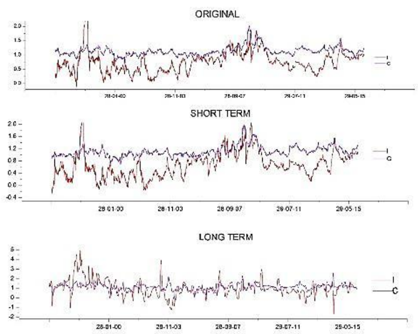
Plot of Beta of Consumer Goods



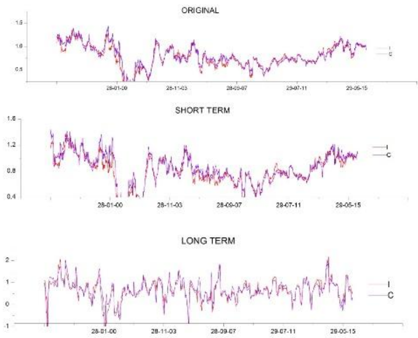
Plot of Beta of Consumer Services



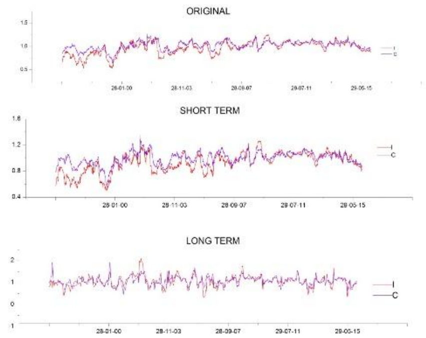
Plot of Beta of Financials



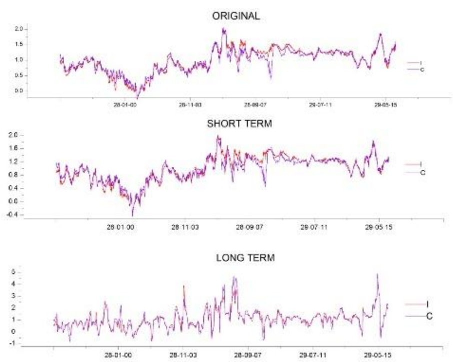
Plot of Beta of Health Care



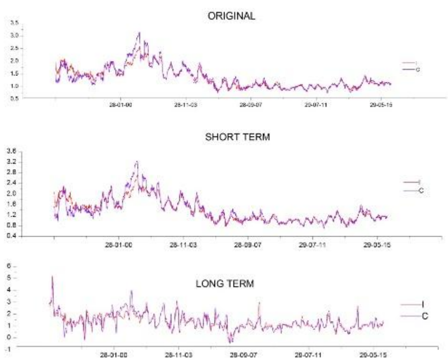
Plot of Beta of Industrial



Plot of Beta of Oil and Gas



Plot of Beta of Technology



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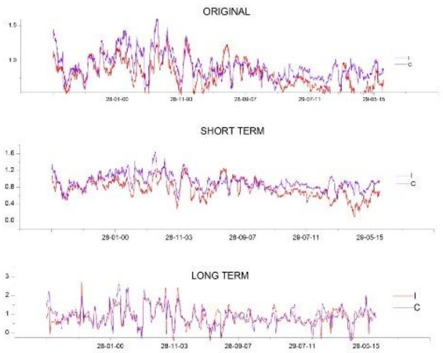	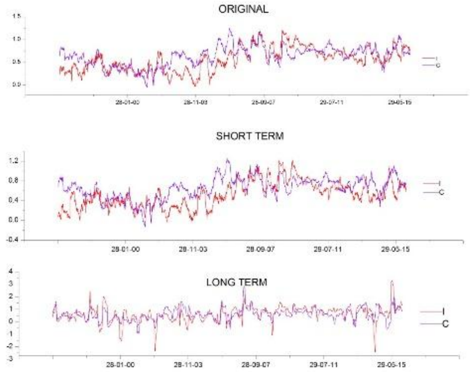

The Dynamic Linkage between Exchange Rate, Stock Price and Interest Rate in India

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ABSTRACT

This study analyses dynamic linkage between stock price, exchange rate and interest rate for India using maximum overlap discrete wavelet transform (MODWT) which is very much appropriate when the variables are in discrete in nature. We use monthly data on stock return, exchange rate and interest rate from January 2000 to December 2014. Our major findings indicate that the empirical relationship between these variables is not significant at lower scales. As we go on higher scales, there is a clear linkage between them and three markets are associated with each other. Moreover, the direction and type of the relationship depends on the frequency bands and finally with the help of Granger causality tests we established a lead/lag relationship between stock price, exchange rate and interest rate.

Keywords: Exchange Rate, Stock Price, Interest Rate, modified overlap discrete wavelet transform (MODWT), India

JEL Codes: C22, G15

1. Introduction

The post-liberalization era in India particularly since 2000 has increased the interdependence between key financial markets. There are ample of studies in the literature, which examine pair-wise dynamic linkage between exchange rates and stock prices, stock prices and interest rates, and exchange rates and interest rates for both developed and developing countries; see for example, Abdalla and Murinde (1997), Ajayi et al. (1998), Granger et al. (2000), Smyth and Nandha (2003) Phylaktis and Ravazzolo (2005), Moore (2007), Walid et al. (2011), Tsai (2012), Lin (2012), Hacker et al. (2012) and Moore and Wang (2014). The results are mixed because of diverse assumptions in the theoretical models and plethora of techniques in empirical analysis. The examination of co-movements between exchange rate, interest rate and stock prices are important from economic policies perspective as each financial market react quickly to the changes of economic fundamentals. Further, examining the dynamic relationship between stock market, foreign exchange market and capital market in case of emerging countries like India is more relevant because negative or positive shocks affecting one market may be transmitted quickly to another through contagious effect. Besides, it would be interesting to verify whether or not transmissions between the foreign exchange market, the equity market, and capital markets behave differently during crisis periods.

Fundamentally the dynamic linkage between stock prices and exchange rates is based on three main theoretical approaches. First, the flow-oriented approach by Dornbusch and Fischer (1980). According to them the flow-oriented models of exchange rates focus on the trade balance or current account balance. The proponents of these models state that changes in exchange rates affect international competitiveness and thus influence real output. Furthermore, because stock price can be interpreted as the present value of future cash flows of firms or industries, hence, it reacts to exchange rate changes. Second, the stock-oriented approach by Frankel (1983) and Branson (1983), postulate that decrease in stock prices affect aggregate demand through wealth and liquidity effects, which in turn leads to a lower demand for money with ensuing lower interest rates. The low interest rates always discourage capital inflows of domestic country, which causes in depreciation of home currency against the foreign currency. Thus, through stock-oriented approach, exchange rate may be affected by stock price movements. Third, based on Mundell (1963) - Fleming (1962) model, an increase in interest rate is necessary to stabilize the exchange rate depreciation and to curb the inflationary pressure. The high interest rate policy raises the attractiveness of domestic financial assets as a result of which capital inflow takes place and thereby limiting the exchange rate depreciation. The higher interest rates also reduce the net value of future returns from the assets and hence reduce the stock prices.

A series of empirical papers focused on the relationship between stock returns and exchange rate using both cross-country and country-specific data. Some studies have indicated there are long-term equilibrium relation between stock price index and exchange rate (see: Smith, 1992; Abdall and Murinde, 1997; Granger et al., 2000; Ibrahim and Aziz, 2003; Kim, 2003; Patnaik et al., 2011; Katechos, 2011; Inci and Lee, 2014). Other studies have stated that the relationship between exchange rate and stock price is exists in short-run (see: Bahmani-Oskooee and Sohrabian, 1992; Nieh and Lee, 2001; Smyth and Nandha, 2003). Some propose that stock price and exchange rate are positively related (See: Phylaktis and Ravazzolo, 2005; Sevuktekin and Nargelecekenler, 2007; Diamandis and Drakos, 2011; Sensoy and Cihat, 2014).

Another strand of the literature examines the relationship between the interest rates and exchange rates (see: Baxter, 1994; Chinn and Meredith, 2004; Bautista, 2006; Choi and Park, 2008; Hacker et al., 2012). Exchange rates and interest rates are connected by the uncovered interest rate parity (UIP): Risk-neutral investors will be indifferent among the available interest rates in two countries since the exchange rate between these two countries is expected to adjust resulting in an elimination of a potential interest rate arbitrage. An exchange rate determination model in the flexible-price monetary tradition indicates a positive relationship between the interest rate differential and the exchange rate (Hacker et al., 2012). Chinn and Meredith (2004) found a positive relationship between interest rates and exchange rates was observable when using long-maturity data but the opposite occurred when using short maturity data for G7 countries. Similarly, Choi and Park (2008) evaluated the causal relationship between interest rates and exchange rates during the Asian crisis period.

There are few studies that examined the dynamic relationship between stock market and foreign exchange market in the context of India. Mishra (2004) using Granger's Causality test and Vector Auto Regression technique on monthly stock return, exchange rate and interest rate found a unidirectional causality between the exchange rate and interest rate, but no Granger's causality between the exchange rate return and stock return. Narayan (2009) apply several variants of the EGARCH model to examine the role of depreciation of the Indian rupee on India's stock market. The results found that volatility persistence has been high and appreciation of Indian rupee over the 2002 to 2006 has generated more stock returns and less volatility. Andries et al. (2014) investigate the co-movement of interest rate, stock price and exchange rate in India in the period between July 1997 and December 2010 using the cross-wavelet power, the cross-wavelet coherency, and the phase difference methodologies. They found that there exists co-movement among these three variables and relationship depends on the frequency bands.

Based on these ambiguity results between exchange rates, stock prices and interest rates, which have found from the existing review literature, this paper makes an attempt to examine the dynamic linkage among these three variables in India using the Wavelets analysis. Our paper differs from the existing literature in three ways. First, though bulk of studies in India examined pair-wise relationship among these three variables using standard VAR, Cointegration, Granger causality approachs, there is hardly any study except (Andries et al., 2014), which check the relationship in the presence of frequency domains. Second, Andries et al. (2014) use the continuous wavelet analysis using monthly data. But our paper uses maximum overlap discrete wavelet transform (MODWT) which is very much appropriate when the variables are in discrete in nature. We use monthly data on stock price, exchange rate and interest rate which are discrete in nature and hence motivate us to see whether the findings from our study are similar or divergent to Andries et al. (2014). Third, our study uses data of more recent years i.e. till December 2014 as compared to Andries et al. (2014) which used data till December 2010. Though the global financial crisis started in 2008, but the failure of decoupling hypothesis was actually noticed in India after 2010, particularly from 2011 to 2013. Therefore, an examination of the dynamic relationship between three markets in India is very much crucial particularly beyond 2010. Our major findings indicate that the empirical relationship between these variables is not significant at lower scales. As we go on higher scales, there is a clear linkage between them and three markets are associated with each other. Moreover, the direction and type of the relationship depends on the frequency bands and finally with the help of Granger causality tests we established a lead/lag relationship between stock price, exchange rate and interest rate.

The rest of the paper is organized as follows. Section 2 explains the detailed methodology of the maximum overlap discrete wavelet transform (MODWT) and data sources. Section 3 presents the empirical results and the last section is the conclusion. Conclusions are found in Section 4.

2. Methodology

Wavelets have the ability to decompose any time series into several sub-series which are associated with particular time scale. Processes at these different time-scales, which otherwise could not be distinguished, can be separated using wavelet methods and then subsequently analysed with ordinary time series methods. Gençay et al. (2002) argue that wavelet methods provide insight into the dynamics of economic/financial time series beyond that of standard time series methodologies. Financial time series are most complex in nature. However, we can consider some facts like stock price, exchange rates, and interest rates indices are discontinuous in nature and stationarity does not easily hold. Wavelets work naturally in the area of non-stationary time series, unlike Fourier methods which are crippled by the necessity of stationarity. In recent years the interest for wavelet methods has increased in economics and finance. This recent interest has focused on multiple research areas like exploratory analysis, density estimation, analysis of local in homogeneities, time scale decomposition of relationships and forecasting (Crowley, 2007). This is possible because of the capability of wavelets to decompose on different time scales yet still preserve the time localization.

Gençay et al. (2001) investigate the scaling properties of foreign exchange rates using wavelet methods. They use the maximal overlap discrete wavelet transform estimator of the wavelet variance to decompose variance of the process and find that foreign exchange rate volatilities are described by different scaling laws on different horizons. Similar wavelet multi scale studies are also analysed by Gençay et al. (2001, 2003, 2005), Gençay & Selçuk(2004), and Gençay & Fan (2009). The maximal overlap discrete wavelet transform (MODWT) is one, which is a modification of the ordinary discrete wavelet transform (Percival and Walden, 2000). This transform loses orthogonality but acquires attributes suitable for economic research like smoothness and possibility to analyse non-dyadic processes (processes that are not multiples of two). Kim and In (2005, 2006, 2007) have conducted many studies in finance using the wavelet variance, wavelet correlation and cross-correlation. Kim and In (2005) study the relationship between stock markets and inflation using the MODWT estimator of the wavelet correlation. They conclude that there is a positive relationship between stock returns and inflation on a scale of one month and on a scale of 128 months, and a negative relationship between these scales.

2.1. Modified Overlap Discrete Wavelet Transform

A wavelet is essentially a small wave which grows and decays in a limited time period. There are two main classes of wavelets: the continuous wavelet transforms (CWT) and its discrete counterpart (DWT).As noted by Percival and Walden (2000), the majority of the wavelet analysis applications in the economic field concentrate exclusively on the DWT because it is a more natural way of handling discrete time series such as those commonly used in economics and finance. The Maximal Overlap Discrete Wavelet Transform (MODWT) is similar to the Discrete Wavelet Transform (DWT) in that high pass and low-pass filters are applied to the input signal at each level. However, in the MODWT, the output signal is not subsampled (not decimated). Instead, the filters are up sampled at each level. As pointed by Gallegati (2012), the wavelet coefficients can be straightforwardly manipulated to achieve several recognizable statistical quantities such as wavelet variance, wavelet correlation, and wavelet cross-correlation. The wavelet variance decomposes the variance of a time series on a scale by-scale basis and constitutes a useful tool for determining what time scales are the dominant contributors to the overall variability of a series (Percival and Walden, 2000).

Let X_t be a stationary stochastic process with variance σ_X^2. If $\sigma_X^2(\lambda_j)$ denotes the wavelet variance at scale λ_j, then the following relationship holds:

$$\sigma_X^2 = \sum_{j=1}^{\infty} \sigma_X^2(\lambda_j) \qquad (1)$$

where $\sigma_X^2(\lambda_j)$ represents the contribution of the changes at scale λ_j to the total variance of the process. This relationship states that the wavelet variance provides an exact decomposition of the variance of a time series into components associated to different time scales.

An estimator for wavelet correlation is constructed using the MODWT. This estimator was introduced by Percival (1995), Whitcher (1998) and Whitcher et al. (2000). An estimator for wavelet cross-correlation is a natural extension of the estimator of wavelet correlation and has similar properties. The MODWT coefficients indicate changes on a particular scale. Thus, applying the MODWT to a stochastic time series produces a scale-by-scale decomposition. The basic idea of wavelet variance is to substitute the notion of variability over certain scales for the global measure of variability estimated by sample variance (Percival and Walden 2000). Same applies to wavelet covariance. The wavelet covariance decomposes sample covariance into different time scales. In other words, wavelet covariance on a particular time scale indicates the contribution of covariance between two stochastic variables from that scale. The wavelet covariance at scale $\lambda_j \equiv 2^{j-1}$ can be expressed as (Gençay et al. 2002)

$$cov_{xy}(\lambda_j) = \frac{1}{\breve{N}} \sum_{t=L_j-1}^{N-1} d_{j,t}^X d_{j,t}^Y \qquad (2)$$

where $d_{j,t}^I$ are the MODWT wavelet coefficients of variables l on a scale λ_j. $\breve{N}_j$ = N - L_j + 1 is the number of coefficients unaffected by the boundary, and $L_j = (2^j-1)(L-1) + 1$ is the length of the scale λ_j wavelet filter. An estimator of the wavelet covariance can be constructed by simply including the MODWT wavelet coefficients affected by the boundary and renormalizing. This covariance is, however, to some degree biased. Because covariance is dependent on the magnitude of the variation of time series, it is natural to introduce the concept of wavelet correlation. The wavelet correlation is simply made up of the wavelet covariance for
$\{X_t, Y_t\}$ and the wavelet variance for $\{X_t\}$ and $\{Y_t\}$.The MODWT estimator of the wavelet correlation can be expressed as

$$\rho_{XY}(\lambda_j) = \frac{cov_{xy}(\lambda_j)}{\sqrt{V_X(\lambda_j) V_Y(\lambda_j)}} \qquad (3)$$

where

$$V_l(\lambda_j) = \frac{1}{\breve{N}} \sum_{t=L_j-1}^{N-1} [d_{j,t}^X]^2 \qquad (4)$$

I = X, Y is the wavelet variance of stochastic process (Percival, 1995).

2.2. Granger Causality Analysis

Finally, the Granger causality analysis (GCA) is used to investigate whether one time series can correctly cause another (Granger, 1969).

If we have two time series *X* and *Y*, the paired model is as following:

$$Y_t = \sum_{n=1}^{p} A_n X_{(t-p)} + \sum_{n=1}^{p} B_n Y_{(t-p)} + CZ_t + E_t \tag{7}$$

$$X_t = \sum_{n=1}^{p} A_n^{'} Y_{(t-p)}^{'} + \sum_{n=1}^{p} B_n^{'} X_{(t-p)}^{'} + C^{'} Z_t + E_t^{'} \tag{8}$$

X_t and Y_t represent the two time series at time *t*. $X_{(t-p)}$ and $Y_{(t-p)}$ represent the time series at time *t-p, p* representing the number of lagged time points (order). A_n and $A_n^{'}$ are signed path coefficients. B_n and $B_n^{'}$ are auto regression coefficients and E_t and $E_t^{'}$ are residual.

2.3. Data

This paper uses monthly data on Real Effective Exchange Rate, monthly average closing prices of NSE S&P CNX index and call money rate of the Reserve Bank of India as interest rate over the period January 2000 to December 2014. All the variables are collected from Handbook of Statistics on Indian Economy published by RBI and CEIC database published by Euro money Institutional Investor Company. We considered the stock prices in the return form while both the interest rates and exchange rates are in their level form.

3. Results and Discussion

We presented the descriptive statistics of all three variables in Table 1. In terms of standard deviations, the volatility of stock market is higher than that of exchange market, so the investment risk of stock market is higher than exchange market.

Table 1: Descriptive statistics

	Interest Rate	Stock Returns	Exchange Rates
Mean	6.94	0.92	103.60
Median	6.64	1.96	102.14
Maximum	54.32	18.14	115.87
Minimum	0.17	-27.03	96.67
Std. Dev.	4.32	6.17	4.81
Skewness	7.56	-0.75	0.74
Kurtosis	82.33	5.08	2.41
Jarque-Bera	48641.96***	48.7***	19.11***

*** indicates 1% level of significance.

The mean monthly return over the study period is positive for stock returns implying an increasing trend. The measure of skewness and kurtosis indicate that both interest rate and exchange rate are positively skewed, whereas, the stock return is negatively skewed. Similarly, we also notice that interest rate series is highly leptokurtic and exchange rate is platykurtic with respect to normal distribution. The Jarque-Bera statistic rejects the normality for each of the series at 1% level. Before doing any analysis, it is important to test the stationary property of a variable. We apply both Augmented Dicky Fuller (ADF) and Phillips and Perron (PP) unit root tests and we find that interest rate and stock returns are stationary at level, whereas, the exchange rate series are non-stationary at level but stationary at first differenced form[2].

Figure 1(a): Plot of call money rate

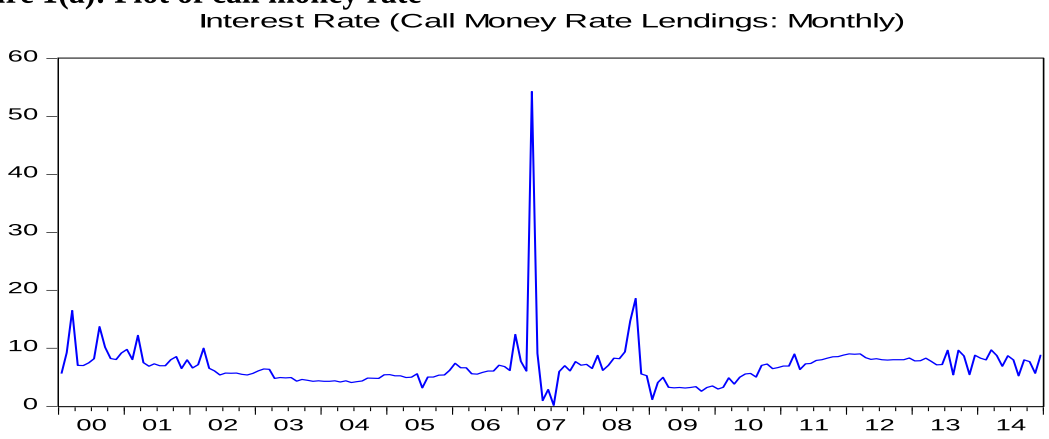


Figure 1(b): Plot of stock returns

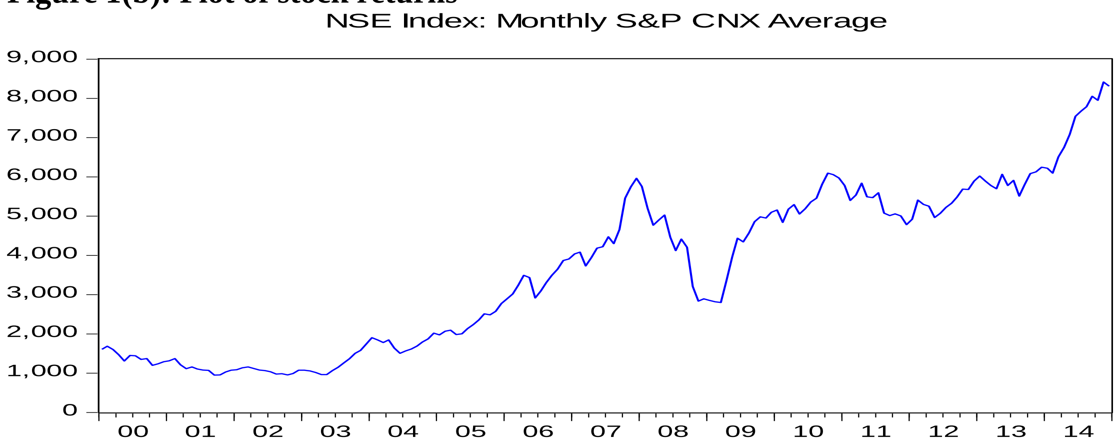
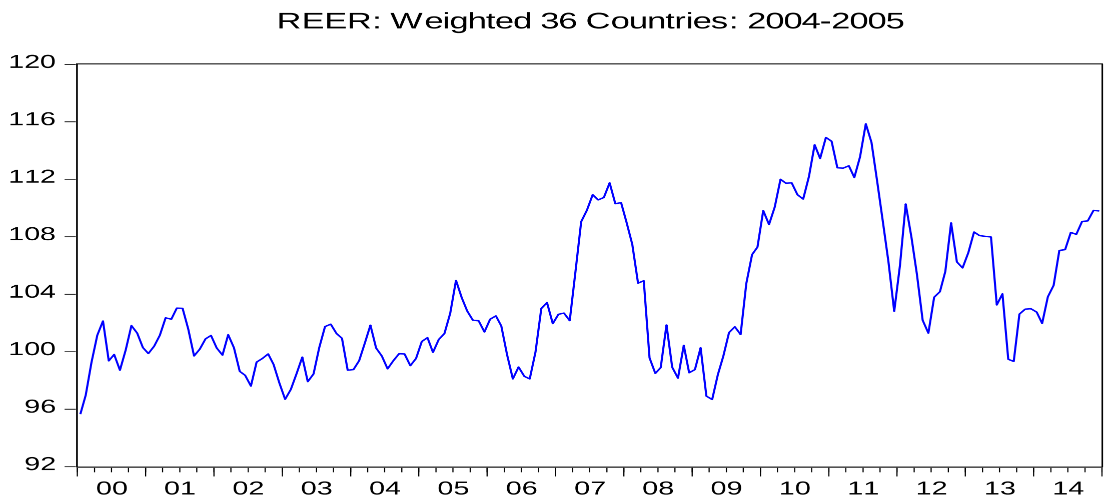


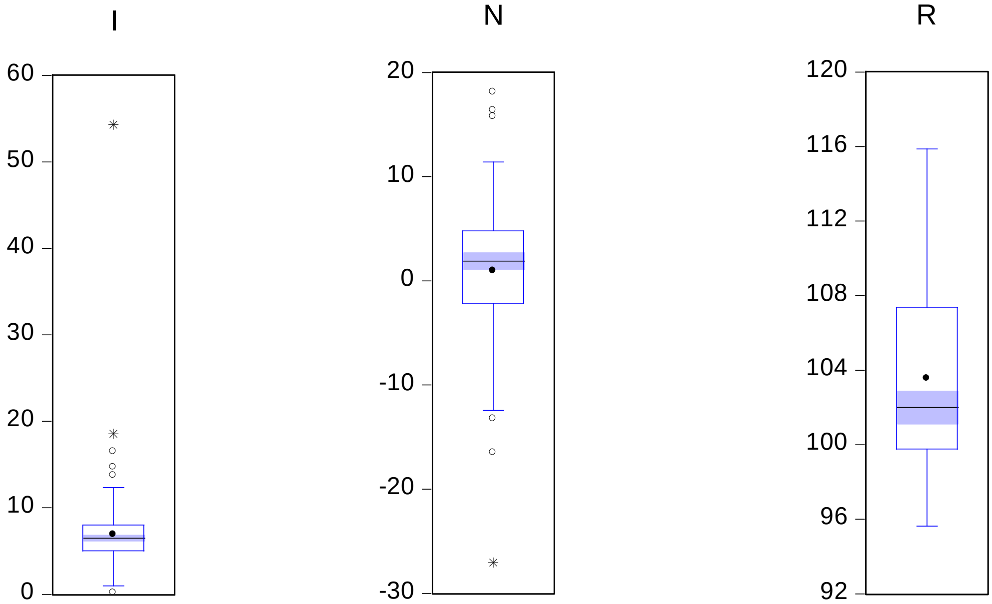
Figure 1(c): Plot of real effective exchange rate



[2] We have not presented the results of ADF and PP unit root tests to save space, however, it can be obtained from the author upon request.

The plots of Figure 1(a) – (c) indicate the movement of all the three series over the periods. In our study, we preferred monthly data over weekly or daily data for a number of reasons. Firstly, monthly data contain less noise and can therefore better capture the interactions between interest rates and stock prices. Secondly, monthly data have smaller biases due to nonsynchronous trading of some individual stocks. Thirdly, the results in terms of smoothness and distinction among the different time horizons produced by wavelet analysis on monthly data are much harder to achieve with higher frequency data. Consequently, to find similar results to those obtained with monthly data, a very large number of decomposition levels are required when using weekly or daily data.

Figure 2: Plots of series data of Interest Rate, Stock Prices and Exchange rates



We examine the dynamic linkage between interest rate, stock prices and exchange rate through wavelet analysis. We apply the maximal overlap discrete wavelet transform to the monthly returns for the three series using the Daubechies (D) wavelet filter of length $L = 4$, that is D(4), based on four non-zero coefficients Daubechies (1992), with periodic boundary conditions. Since monthly data are used, the scale 1 represents the highest frequency and is associated with a time horizon of 2 to 4 months. In turn, scales 2 to 7 correspond to 4-8, 8-16, 16-32, 32-64, 64-128 and 128-256 monthly periods, respectively. So, overall we have performed the analysis which is useful for both short-term and long-term investors.

Figure 3: Wavelet variance plots of interest rate, stock prices and exchange rate

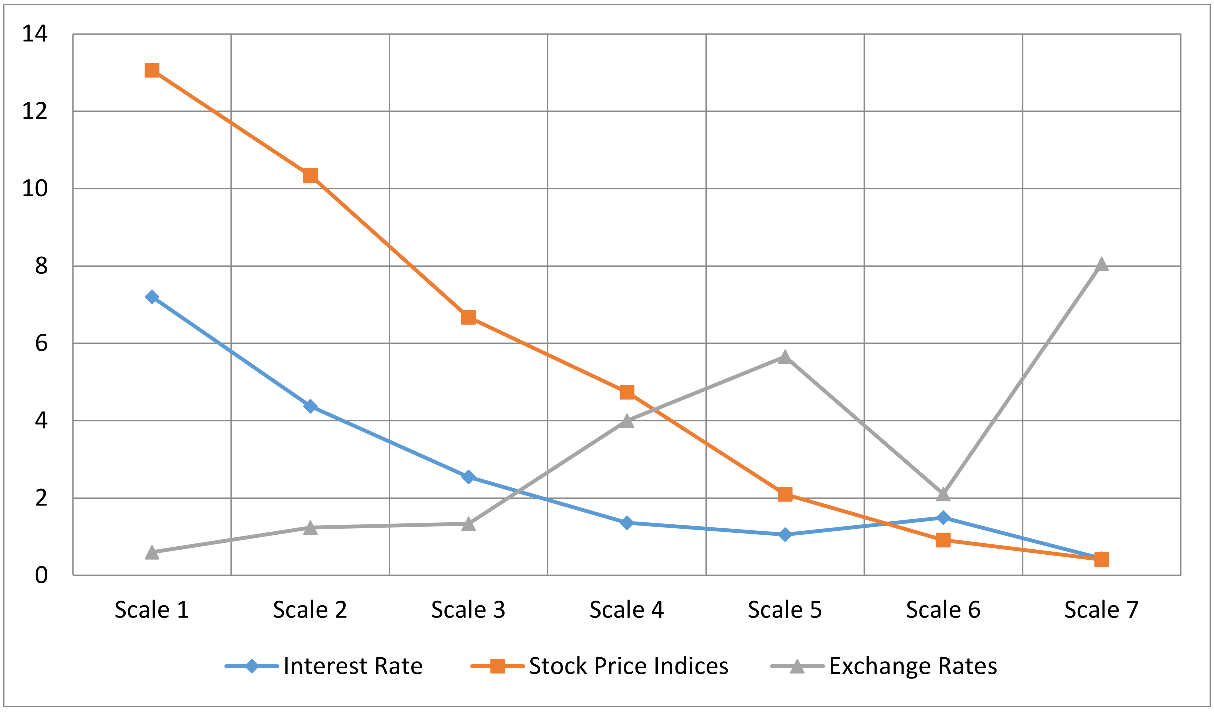
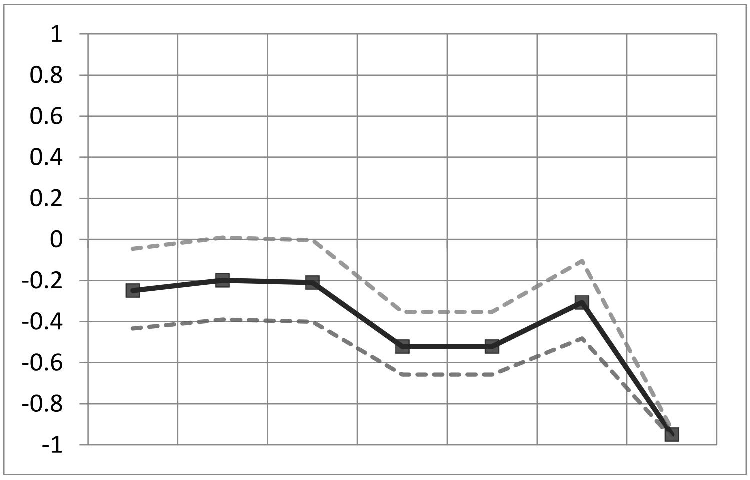
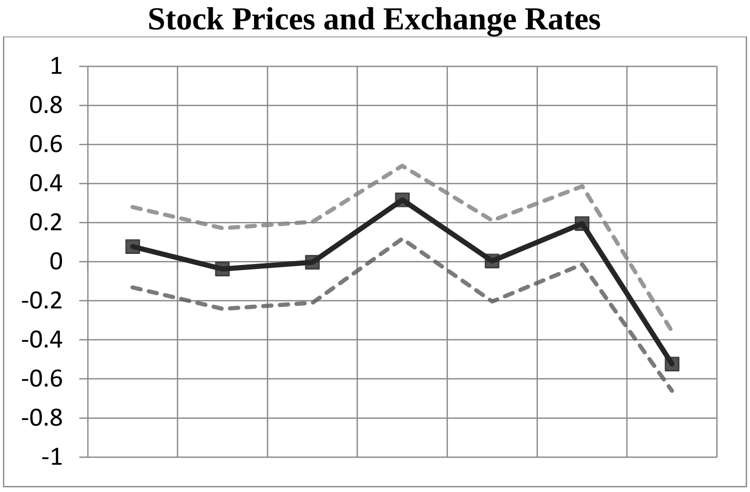


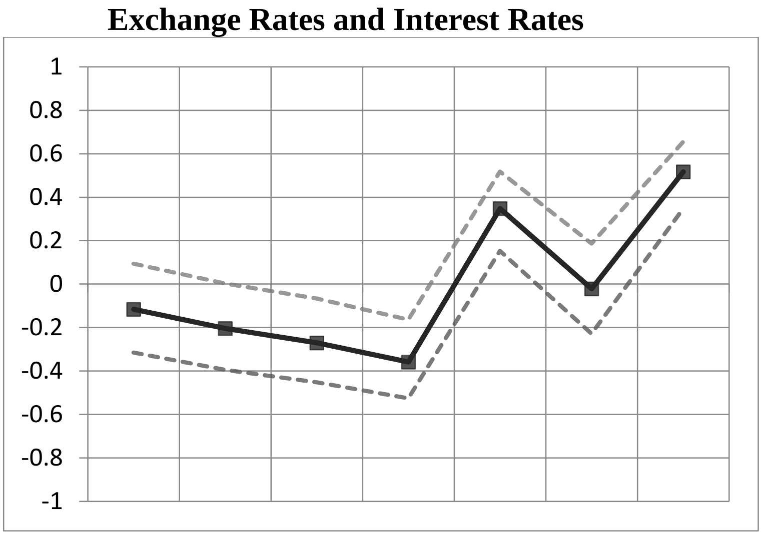
Fig. 3 illustrates the Wavelet variance of the three variables over time scales up to scale 7 for the whole sample. Two things are noteworthy from this figure. First, there is an approximate linear relationship with negative slope between the wavelet variance and the scale in case of interest rate and stock prices, suggesting that the wavelet variances of these two variables decline as the wavelet scale increases. This greater stability in the long run seems to indicate that investors with short-term horizons face higher risks than investors with longer investment horizons. Second, the Wavelet variances of stock returns are higher than those of call money rates over all time scales except the initial. Our finding is consistent with that of Kim and In (2007) for the G7 countries, confirming that the stock market are more volatile than the public debt market regardless of the investment horizon. We can also observe that the wavelet variance of exchange rate is not consistent over time scales. It had an increasing trend with a sudden fall at level 6.

Figure 4: Wavelet Correlation plots between the series of Interest rate, Stock Prices and Exchange rates

Interest Rates and Stock Prices







In our study, we have evaluated wavelet correlation between the pair-wise variables to estimate the relation between them at different scales. All these results have been presented graphically in the Figure 4. In the plots, the dashed lines indicate the 95% confidence intervals of the corresponding wavelet correlation, which are represented by solid black line with values emphasized by square boxes at different scales. The signs of wavelet correlation in case of Interest rate and stock prices are negative in all the scales, implying stock prices are hampered with the increase of Interest rates. This is in accordance to the prior research of several countries and also consistent with known fact of inverse relationship between Interest rates and stock prices.

In the case of stock prices and exchange rates, the wavelet correlation is not significantly different from zero almost at all the scales and there seems to be not much effect on one another. While in the case of exchange rates and interest rates, we can observe a Wavelet correlation bearing a negative value and also taking a decreasing trend at lower scales indicating inverse relationship, while the same inverse relation isn't observed at the higher scales. One of the main purposes of this paper is to establish lead/lag relationship between the three variables interest rates, stock prices and exchange rates over various time scales using the wavelet analysis. For this purpose we have plotted the cross-correlation curves for the three variables at different scales (Figure 5, 6 and 7) and also tested them for Granger Causality, presented in the Table 2 below. As we can observe from Table 2 that the pair-wise causality do exists among all the three variables mostly at higher scales (D4, D5, D6 and D7). The results indicate a bi-directional Granger causality between stock price and interest rate at higher scales, but found no causality at lower scales. While examining the causality between real exchange rate and interest rate, this study found a unidirectional causal relationship from interest rate to exchange rate, but the reverse is not true. Finally, we also notice a bi-directional causality between real exchange rate and stock prices at higher scales.

Table 2: Multi scale Granger causality analysis

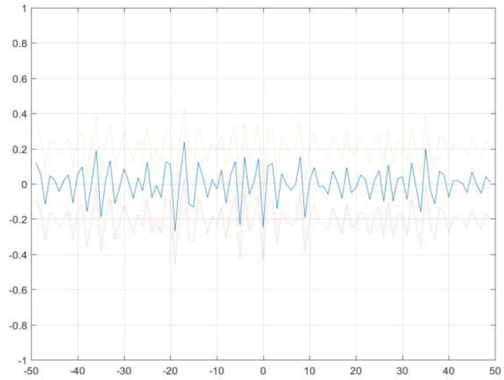
	S	D1	D2	D3	D4	D5	D6	D7
SP -> IR	0.212 (0.808)	0.568 (0.567)	0.724 (0.486)	1.704 (0.185)	5.015*** (0.008)	2.345* (0.099)	16.43*** (0.00)	14.36*** (0.000)
IR -> SP	1.275 (0.282)	0.500 (0.607)	0.897 (0.410)	4.019** (0.020)	3.806** (0.024)	4.363** (0.014)	4.20** (0.016)	16.24*** (0.000)
FX -> IR	0.881 (0.416)	0.590 (0.555)	0.143 (0.866)	0.610 (0.544)	1.654 (0.194)	2.317 (0.102)	1.08 (0.342)	3.76** (0.025)
IR -> FX	2.39* (0.094)	0.712 (0.492)	0.190 (0.826)	0.753 (0.472)	6.730*** (0.002)	48.37*** (0.00)	4.95*** (0.008)	11.27*** (0.000)
FX-> SP	0.114 (0.892)	0.267 (0.766)	2.634* (0.075)	2.040 (0.133)	7.548*** (0.001)	2.202 (0.114)	0.998 (0.370)	8.13*** (0.000)
SP-> FX	0.766 (0.466)	0.608 (0.545)	0.044 (0.956)	1.214 (0.299)	2.316 (0.102)	2.916* (0.057)	4.75*** (0.010)	36.10*** (0.000)

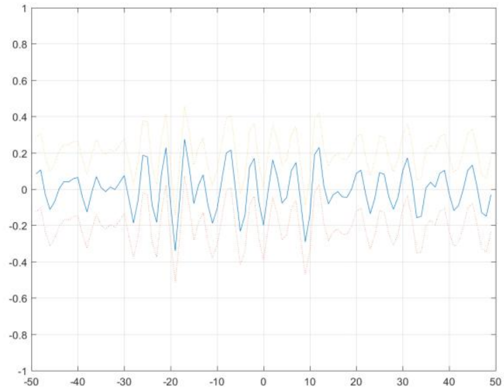
***, **, * indicate 1%, 5%, and 10% level of significance, respectively.

After discussing the multiscale causality among stock price, exchange rate and interest rate, this study further presents the Wavelet cross-correlation plots between interest rate, stock price and exchange rate at time t-λ and t+λ up to 50 month lags, with the corresponding approximate confidence intervals, against time leads and lags for all scales.

Figure 5: Wavelet cross-correlation plots between interest rate and stock price

Level 1 **Level 2**





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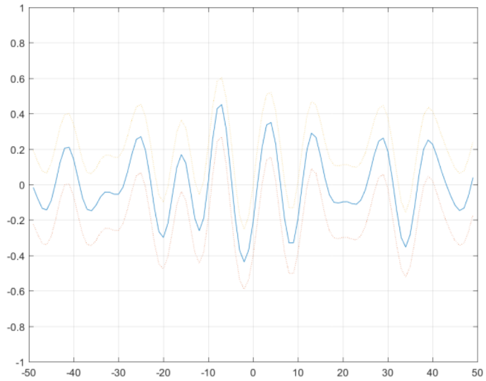
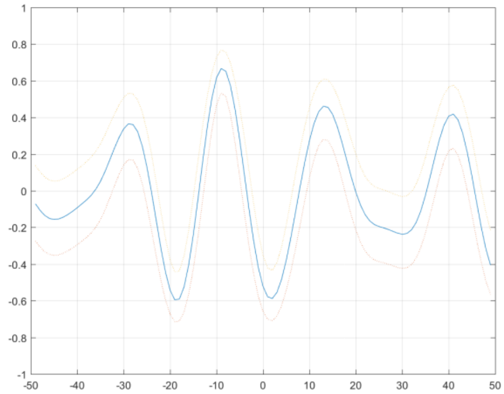
Level 4





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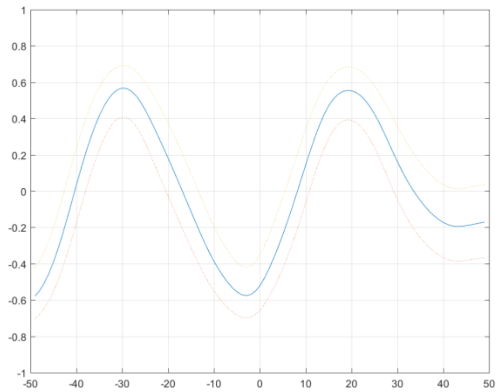

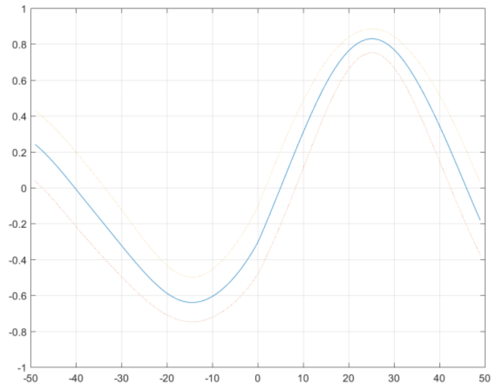

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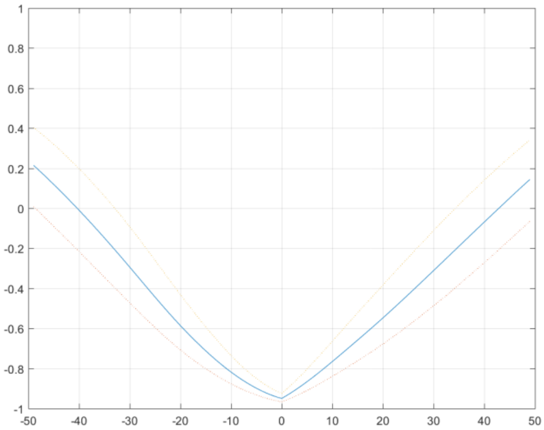
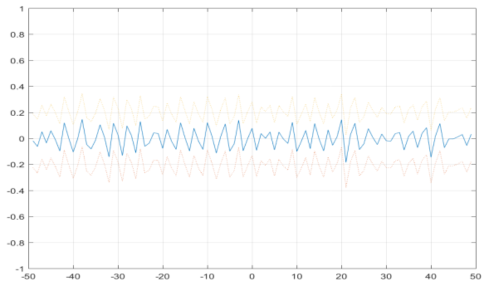


Figure 6: Wavelet cross-correlation plots between stock price and exchange rate

Level 1



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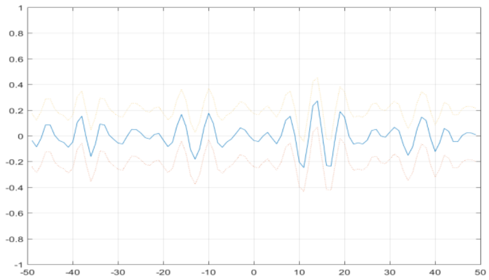

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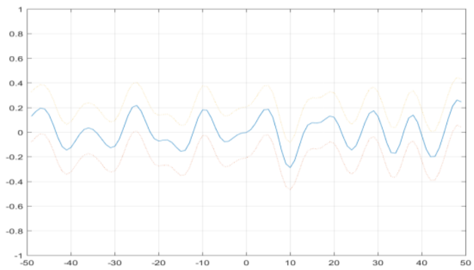

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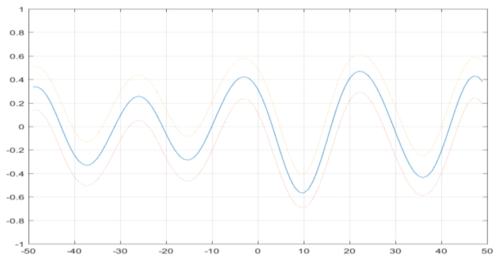
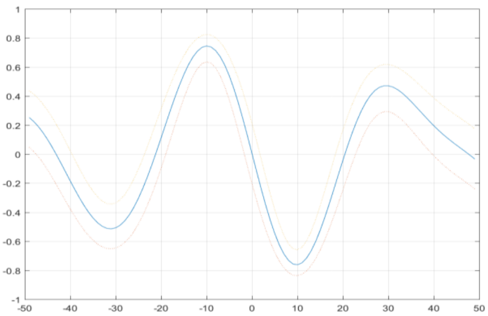


Level 5



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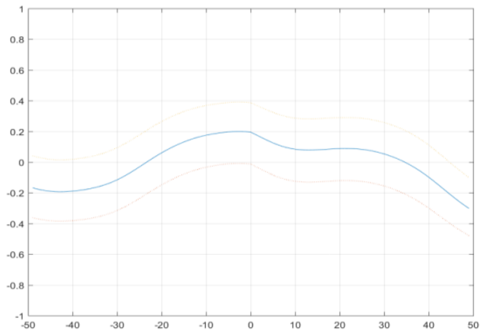


Level 7

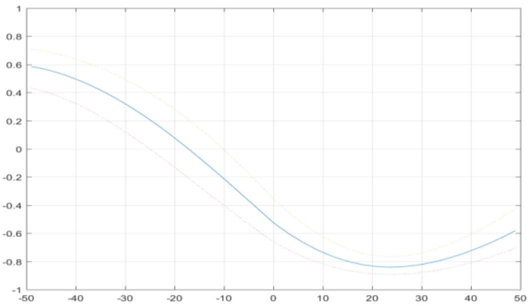
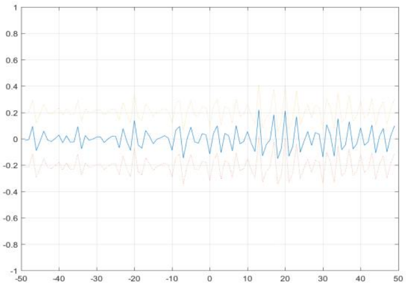


Figure 7: Wavelet cross-correlation plots between exchange rate and interest rate

Level 1



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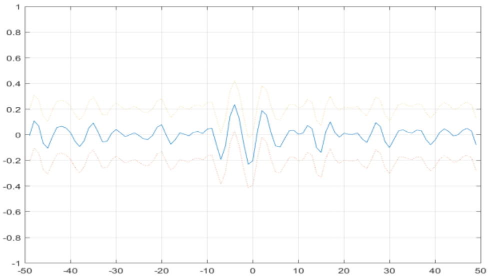
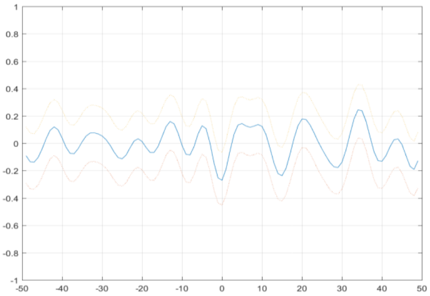


Level 3



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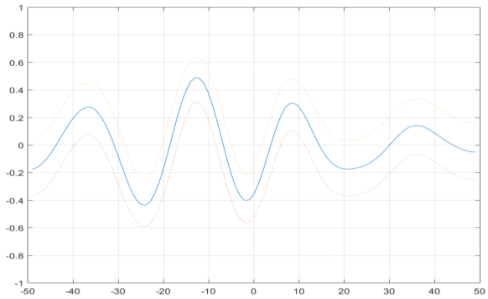

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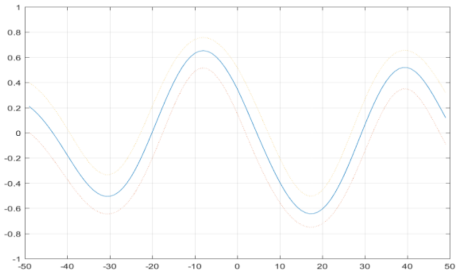

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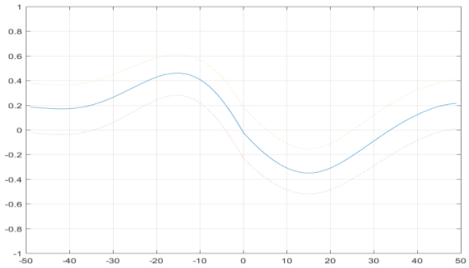

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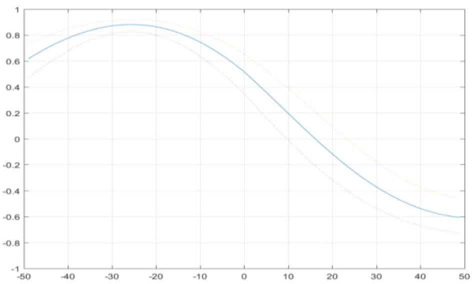

The figures 5-7 illustrate the Wavelet cross-correlation results, which indicate that the values of all the relations are not significantly different from zero at lower scales at both leads and lags. According to Fig-5, the dynamic Wavelet cross-correlation between interest rate and stock prices are negative at higher scales, which validate the theory. The theory states that an increase in the interest rates would put pressure on the company's ability to arrange more funds by issuing stocks and it reduces the profit, which in turn reduce the stock returns. Similarly, we also notice a negative Wavelet cross correlation between stock price and exchange rate for the higher scales. This result is not surprising. The increase in stock returns attracts more Foreign Institutional Investors (FIIs) to invest in the Indian stock market. The rises in stock return increase the demand for Indian rupees in the foreign exchange market, and hence, appreciation of Indian rupee against foreign currencies put downward pressure on REER. Finally, we noticed a positive relationship between interest rate and exchange rate, especially in the lags. The reason lies behind the fact that in many emerging markets with infamous history of crowding out effect because of budget deficits, which plays an important role in investment. If the interest rates increase for any reason, it is generally perceived as an upcoming problem in the country thus increase the real exchange rate.

4. Conclusions

There is abundant literature which examines the pair-wise linkage between stock price, exchange rate and interest rate by using plethora of techniques. The aim of this paper was to investigate dynamic linkage between these three variables for India using maximum overlap discrete wavelet transform (MODWT) which is very much appropriate when the variables are in discrete in nature. We use monthly data on stock return, exchange rate and interest rate from January 2000 to December 2014. Our major findings indicate that the empirical relationship between these variables is not significant at lower scales. As we go on higher scales, there is a clear linkage between them and three markets are associated with each other. Moreover, the direction and type of the relationship depends on the frequency bands and finally with the help of Granger causality tests we established a lead/lag relationship between stock price, exchange rate and interest rate. Our results further revealed a negative relationship between interest rate and stock price in higher scales, which is opposite to the findings of Andries et al. (2014).

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An Examination of Pricing Anomalies for Australian Stocks

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ABSTRACT

The Capital Asset Pricing Model (CAPM) beta is a widely used single factor for pricing risky assets, while other pricing factors are considered anomalies of the model. This paper examines the firm size and BV/MV stock pricing anomalies for the Australian stocks for the period January 2000 through December 2017. Utilising all stocks within the S&P/ASX 300 index, this paper calculates the SMB and HML factors by constructing specialised indices based on firm size and BV/MV attributes. The returns on small and small value stocks are significantly higher than the returns on large and large growth stocks and the small and small value indices outperform all other indices. Further, the SMB and HML coefficients are significant and able to explain most of the return co-variations, which are unexplainable by the CAPM beta. The findings confirm the presence of firm size and BV/MV effects for the Australian stock market with an original set of SMB and HML factors over an extended study period that has not being researched before. Thus, findings of this research add new knowledge in the area of asset pricing anomalies for Australian stock market.

Keywords: Pricing anomalies, firm size effects, book value to market value effects, CAPM and Fama French three-factor model.

1.0 Introduction

The Capital Asset Pricing Model (CAPM), since its discovery by Sharpe (1964) and Lintner (1965), has been widely used in pricing risky assets. It became a cornerstone method of assessing stock market risk and has been taught to all finance graduates in universities and colleges. The CAPM assumes that investors hold diversified investment portfolios and ought only to be compensated for beta risk, the alpha risk supposedly eliminated by the process of diversification. Thus, stocks market betas are considered to exclusively explain ex-post stock returns. However, subsequent studies by Basu (1977), Banz (1981) and Reinganum (1982), Jegadeesh (1990) and others, find evidence of higher returns for stocks, beyond that supported by their market betas.

The higher returns were attributed to risk premiums related to weaker firms with smaller market capitalization. ot raThis was particularly prevalent for stocks of smaller firms (size effect) and firms with high book value than their market value (value stocks). It was discovered that the additional return premiums, beyond that explained by stocks market betas, were risk premiums attributed to smaller firm size and arelated to is assumed as size and value risk premium, beyond market risk premium measured by stocks market betas.

Following this finding of anomaly in the CAPM, literature on finding what more explains stock returns started to develop. Fama and French (FF) (1992, 93, 96) extend the single factor CAPM with two additional variables, SMB and HML, and after performing robust tests on various sample sets, find evidence to conclude that their three-factor model captures most of the average-return anomalies of the CAPM. Their three-factor model includes the CAPM market beta, (SMB) for firm size risk and (HML) for value risk premium. Carhart (1997) extends the three factor model into a four factor model by including a momentum factor (WML), which presumably compensates for momentum strategy, that is, buying winners and selling losers.

Overtime the literature on asset pricing anomalies has grown considerably and numerous studies attempt to explain returns on stocks beyond stocks market beta with additional variables such as firm size, BV/MV, momentum, seasonality, earnings/price, cash-flow/price, percentage change in dividends, percentage change in BV/MV and liquidity factor. See for example DeBondt and Thaler (1985); Lakonishok, Shleifer, and Vishny (1994), Jegadeesh and Titman (1993); Chan, Hamao, and Lakonishok (1991); Rouwenhorst (1998); Griffin, Ji, and Martin (2003); Asness, Moskowitz and Pedersen (2009); Chui, Titman and Wei (2010) and Fama and French (2012) and others. However, most of these studies are on the USA market and out of sample evidence, including Australian market, is still sparse and inconclusive particularly in showing the consistency and persistency of the non-beta factors in explaining ex-post return variation on stocks.

Motivation and Contribution

The study aims to provide additional out of sample evidence to the US findings on size and BV/MV effects, using Australian data. It is motivated particularly by the limiting and somewhat contradictory Australian findings on stock market anomalies. For example, Halliwell et al. (1999) find FF (1993) model not improving the CAPM results for Australian stocks, while Gaunt (2004) find FF (1993) a more efficient model in explaining the share market returns in Australia. Faff (2001, 2004) further add to the debate, using daily data, and confirm significant presence of BV/MV risk factors for Australian stocks. However, Faff (2004) find the presence of size risk factors negative. In contrast Gharghori et al. (2007) find size effect significantly positive in Australia.

Gaunt (2004) and Brailsford et al. (2012) are the two latest studies that examine size and BV/MV effects in Australian stocks. Both note the shortcomings of previous Australian studies for missing accounting data for determining HML factors, inconsistency in portfolio formation to FF methodology and insufficient sample size with a bias towards large stocks. Utilising AGSM-CRIF database Gaunt (2004: p33) arranges a sample ccomprising "6,814 companies and Brailsford et al. (2012:p13) a sample consisting of "23,098 companies. Both studies confirm the presence of size and value premiums in Australian stocks.

This study adds to the literature as follows: First, it extends the study period of most previous Australian studies. The coverage of the previous studies by Halliwell et al. (1999), Faff (2004) and Gaunt (2004) end at 2000. Brailsford et al. (2012) study period ends at 2006. This study spans from January 2000 through April 2013 with an observation of 160 monthly returns over a 13-year period. This study period includes global financial crisis when the market risk increased significantly and it is interesting to find out how this additional risk impacts upon size and BV/MV factors. If with the increased market risk, size and value risk premiums increases as well, an interesting connection with systematic and un-systematic risk could be established for further research.

Second, it obtains and matches returns, prices, market capitalisation and accounting data for all stocks listed within the ASX 300 index and forms portfolios on size and BV/MV factors following FF (1993/96/2012) portfolio sorting methods. This study is perhaps the first to incorporate the improvements made in the area of portfolio sorting in FF (2012) from FF (1993/96). This study constructs diversified portfolios mimicking size and BV/MV risks for (left-hand side) LHS assets and SMB and HML factors for right hand side (RHS) explanatory variables the for regression model, which is also is an improvement from several previous Australian studies.

As such this study makes significant improvement over prior Australian studies which suffer from reliably estimating the HML factors due to unavailability of the accounting data on depreciation and book values. Most previous Australian studies use value and growth styled portfolios for estimating the HML factors. These portfolios are not diversified with a bias to a particular investment style strategy. FF (2012) highlight the importance of forming diversified portfolio as the LHS assets in the regression for their three factor model to fully capture size and value premiums. According to FF their model will fail if portfolios are poorly constructed (FF; 2012; p458).

Third, this study uses a sample set which on the one hand provides about 80% coverage of the Australian stock market, and on the other, avoids inclusion of thinly traded less important tiny stocks. With the All Ordinaries 500 index representing the Australian stock market, an Australian sample size of 6,814 and 23,098 stocks, Gaunt (2004) and Brailsford et al. (2012) respectively, ought to comprise unduly large number of less important, highly volatile, less liquid tiny stocks. FF (1993) specifically use NYSE median as size breakpoints to avoid undue weight on smaller and less liquid AMEX and Nasdaq stocks. For this reason, the sample selected in this study is considered consistent with FF (1993) sample selection method and a more meaningful representation of the Australian market than a larger sample with undue weight on less important tiny stocks.

It is worth noting that AMEX and Nasdaq stocks not included in FF (1993) sample are significantly bigger than most Australian stocks. So if FF considers the inclusion these big enough stocks by Australian standards inappropriate for analyzing size and BV/MV effects, then an Australian sample including a large number of tiny volatile stocks ought to produce unreliable findings about size and BV/MV effects in Australian stock returns. Thinly traded volatile returns would have extreme jumps either side of the mean return, which would bias the true mean towards extreme positive as well extreme negative. Such a behavior of particularly the returns on extreme small stock portfolio will distort the finding of size effect in stock returns. Since determination of size effect is an important aspect of this study, any distortion that construes the reliability in the results needs to be avoided.

The balance of the paper is organised as follows: Section 2 describes the data, portfolio construction and the testing variables. Section 3 presents summary statistics for returns. Sections 4 and 5 test the asset pricing regression models and discusses the results. Section 6 provides a summary and conclusion of the study.

2.0 Data and Variables

Stock returns, market capitalisation and accounting data are primarily from Data Stream. The sample period is from 1st January 2000 through 31st March 2013 and it includes all 300 stocks listed within the S&P/ASX 300 index. The whole of Australian share market is represented by the All Ordinaries index, which incorporates the largest 500 shares by market capitalisation traded on the Australian Securities Exchange (ASX). The other Australian index constituents include ASX 20, 50, 100, 200 and 300 indices.

The ASX 300 index includes the large cap, mid cap and small cap components of the Australian S&P/ASX index family. The 300 index, by the value of the market capitalisation and volume traded, represents about 80% of trading on ASX. These shares are the investment benchmark for the major investment portfolios, have a high level of liquidity and traded regularly. The problem of thinly traded penny shares is avoided, and the sample set is considered to be a good representative of the Australian Share Market.

Following the methodology convention of Fama French (1993) and Fama French (2012), starting January 2000, firms are sorted each month into small, medium and large size categories based on their average monthly market capitalisation. The size breaks are delineated at percentile breaks of 33% and 66%. That is, firms with market values below 33-percentile value are classified as small, those above 66-percentile as large and those in between as medium (or neutral as in Fama French; 1993).

The percentile breaks are calculated by taking the averages of all the firms within the index over each 12-month period. This allowed about 100 stocks in each size category and also allowed stocks to move in and out of a size category based on the changes in their market capitalisations. This sorting produces three size based portfolios, namely small, medium and large. Since these stocks are from the All Ordinaries index family, they are identified as small ordinaries (SOrds), medium ordinaries (MOrds) and large ordinaries (LOrds) respectively.

Next, all firms within the ASX 300 index are sorted, independently, into two BV/MV groups. Each month, the monthly book values are divided by the monthly market capitalisation to calculate the equivalent monthly BV/MV ratios. At the book-to-market ratio of one (1.00), the book value is exactly equal to the market value, and the stocks are considered to be trading at equilibrium price, with equal book and market value. Ideally, BV/MV ratio of one (1) was chosen as the breakpoint to divide the stock universe into value and growth categories. The two portfolios are identified as value ordinaries (VOrds) and growth ordinaries (GOrds).

The stocks with lower book value than market value are considered to be trading at a premium price reflecting a character of growth stocks. Investors buy these stocks at a high price-to-earnings ratio (low yield) in anticipation of future growth in capital values. Whereas the stocks with higher book value than market value are considered to be trading at a discount price reflecting a character of value stocks. Investors buy these stocks at low-price-earnings ratio (high yield) to take advantage of high returns or value premium. Typically, value investors are considered as yield investors.

Finally, within each size group, that is, small, medium and big, stocks are sorted into value and growth categories. This final sort produces another six portfolios, namely small value ordinaries (SVOrds), small growth ordinaries (SGOrds), medium value ordinaries (MVOrds), medium growth ordinaries (MGOrds), large value ordinaries (LVOrds) and large growth ordinaries (LGOrds). The construction of portfolios are depicted in Figure 1.

Figure 1
Portfolios Sorted by Size and BV/MV Ratios: January 2000-April 2013, 160 months. The eleven portfolios constructed are as follows: Small Ordinaries (SOrds), Medium Ordinaries (MOrds), Large Ordinaries (LOrds), Value Ordinaries (VOrds), Growth Ordinaries (GOrds), Small Value Ordinaries (SVOrds), Small growth Ordinaries (SGOrds), Medium Value Ordinaries (MVOrds), Medium Growth Ordinaries (MGOrds), Large Value Ordinaries (LVOrds) and Large Growth Ordinaries (LGOrds).

S&P/ASX 300	ASX 300					
Sorted into 3 Size Portfolios	SOrds		MOrds		LOrds	
Sorted by BV/MV Ratios	VOrds			GOrds		
Sorted by BV/MV Ratios within 3 Size Portfolios	SVOrds	SGOrds	MVOrds	MGOrds	LVOrds	LGOrds

Following the categorisation, monthly rates of return for each stock within each portfolio are calculated as follows:

$$R_T = [(P_T - P_{T-1}) + D_T] / P_{T-1} \quad (1)$$

Where: R_T is the return at period (T), P_T is the price at time (T), P_{T-1} is price at period ($T-1$), and D_T is dividend at period (T).

The monthly individual returns are weighted by their respective market capitalisation and summed to calculate the monthly value-weighted returns of each portfolio. A value of 1000 was assigned as the base value for all the portfolios as at January 2000 and following monthly index values are calculated through April 2013 as follows:

$$[(1+R_T) * IV_{T-1})] \quad (2)$$

Where R_T is the monthly return at time $_T$, IV_{T-1} is the index vale at time $_{T-1}$.

The eleven portfolios produced by size and BV/MV sorting are used as the LHS assets in the asset pricing regression. Fama French (1993) form 25 portfolios to use as LHS assets in their analysis. Given the small number stocks in our sample, producing 25 portfolios will result in very few stocks in each portfolio.

The explanatory variables in the asset pricing regression are the size factor SMB (small minus big) and the BV/MV factor HML (high book value minus low book value). The SMB factor is the average of the returns on SVOrds and SGOrds minus the average returns on LVOrds and LGOrds. The value-growth factor is constructed for small and large stocks and then averaged to produce HML. For example, HML_S = SVOrds - SGOrds and HML_L = LVOrds – LGOrds, and HML is the equal weighted average of HML_s and HML_L (Fama French, 2012).

3.0 Analyses and Results

160 monthly observations are analyzed over a 13-year period from January 2000 through April 2013. The monthly risk premiums (returns in excess of 90 Day Bank Bill rates) of the eleven portfolios sorted on size and BV/MV factors, together with the monthly risk premiums on the All Ordinaries and 10-year bonds are subjected to various analyses in order to examine the size and BV/MV effects for Australian stocks. The risk premiums or excess returns are inclusive of cash dividends and appreciations in values (total risk premium). The words risk premiums and excess returns are used interchangeably in this study.

Firstly, summary statistics on returns are presented to describe the data in terms of average returns, standard deviation, skewness and kurtosis. Coefficients of variation are calculated to make relative comparison on risk adjusted basis. The Jarque-Bera statistics is presented to describe the return distribution. Then the CAPM is utilized to examine the ex-post return predictability by the market security line. The Fama French three-factor model is used to examine the sensitivity of the stocks monthly risk premiums to the market risk premium, size and BV/MV premiums. The All Ordinaries index is used as the market index.

The dependent variables are the monthly risk premiums on the eleven portfolios formed on size and BV/MV factors. The explanatory variables in the regressions are: (i) $\beta_i[RM(t) - RF(t)]$-coefficients on market risk premium, (ii) $s_i SMB(t)$ -coefficients on size premium and (iii) $h_i HML(t)$ -coefficients on value premium. The beta coefficients measure the assets sensitivity on market risk premium. The coefficients on SMB measure the assets sensitivity to the returns on small cap stocks minus the returns on big cap stocks. The coefficients on HML measure the assets sensitivity to the returns on stocks with high book to market minus low book to market. As small cap stocks outperform big cap stocks and stocks with high book to market outperform stocks with low book to market, the SMB and HML returns supposedly positive.

3.1 Summary Statistics

Table 1 presents the summary statistics. The mean returns in column 1, Panel 1 and Panel 2 show that small stocks outperform big stocks by (1.26/.99) and value outperform growth by (1.35/.90). The risk/return ratios are lower in both cases, (1.86/3.29) and (2.05/3.17) respectively, which suggest that small and value stocks, outperform big and growth stocks on risk adjusted basis as well. When value premium is combined with the size premium within each size group, the extreme small portfolio, SVOrds, outperforms all other portfolios on risk adjusted basis, and noticeably value premium increases for small stocks, especially for the extreme small value portfolio, SVOrds, from extreme large value, LVOrds, (Panel 3 Table 1). This finding of increasing value premium in size pattern supports the latest similar findings by

FF (2012) in the international stocks. The increasing of value premium in size portfolios from big to small is also apparent in the results of several Australian studies.

Table 1
Summary Statistics for Size and Book-to-Market Value sorted portfolios. Table 1 presents the mean monthly returns, standard deviation, coefficient of variation, skewness, kurtosis and jarque-Bera statistics for the 3 portfolios sorted on size, two on BV/MV factors and 6 sorted two ways on BV/MV factors within ach 3 size groups. Also presented are the same for the ASX 300 and 10-year bond indices. 160 monthly observations are analyzed over a 13-year period from January 2000 through April 2013.
* denote significance at the 5% levels.

Portfolios	Mean	Standard Deviation	Risk/Return Ratio	Skewness	Kurtosis	Jarque-Bera
	Panel 1: Portfolios by Size: Small, Medium and Large					
SOrds	1.25%	2.33%	1.86	0.55*	4.98*	25.91*
MOrds	1.11%	2.72%	2.46	0.01	3.21	0.22
LOrds	0.98%	3.26%	3.31	0.24	2.98	1.16
	Panel 2: Portfolios by BV/MV Ratio					
VOrds	1.35%	2.78%	2.05	-0.71	2.63	0.79
GOrds	0.90%	2.84%	3.17	0.39*	3.39	3.85
	Panel 3: Portfolios by Size and BV/MV Ratio					
SVOrds	1.69%	3.29%	1.95	0.35*	3.97*	7.23*
MVOrds	1.31%	3.06%	2.33	-0.28	3.17	1.70
LVOrds	1.39%	3.43%	2.46	-0.28	2.71	2.02
SGOrds	0.40%	2.61%	6.53	0.21	3.48	1.98
MGOrds	0.92%	2.72%	2.95	0.35*	3.43	3.48
LGOrds	0.89%	3.32%	3.72	0.42*	3.24	3.74
	Panel 4: Stock and Bond Portfolios					
All Ords	0.93%	3.76%	4.05	-0.31	2.93	1.97
Bond	0.65%	1.53%	2.35	-0.43	4.39*	13.35*

The small growth stocks, SGOrds, have the lowest mean return and highest risk, and the large growth stocks, LGOrds, outperform the small growth stocks, SGOrds; whereas, small value stocks, SVOrds, outperform large value stocks, LVOrds (Panel 3, Table 1). Two important issues are worth noting about this finding. First, the lower returns of small growth stocks than large growth stocks suggest a reveal size effect for growth stocks. Second, it suggests that it is the value premium in the small stocks that increases their returns over large stocks. FF (2012) also finds a reversal size effect in growth stocks (FF 2012; p461). Most previous studies also find higher value premium than size premium, which is an indication what is specifically stated in this study that it is the value premium in small stocks for their higher performance than large stocks. The specifics of this finding need to further researched

SOrds, GOrds, SVOrds, MGOrds and LGOrds portfolios display excessive levels of skewness relative to a normal distribution. SOrds, SVOrds and bond portfolios also display excessive levels of kurtosis as well. The combined effect of skewness and kurtosis is measured by the Jarque Bera statistics. Based on the Jarque Bera tests, the null hypothesis that the return distributions are normal is not rejected, except for SOrds, SVOrds and bond portfolios.

SOrds and SVOrds are the only two portfolios with excessive levels of both skewness and kurtosis, and this combined effect has led to non-normal distributions (Table 1). The skewed finding in the distribution of returns is an indication of biased higher returns than normal distribution, which further confirms higher returns to small and low book value (value) stocks. This finding compliments the earlier coefficient of variation result. The return characteristics of neutral (medium) growth and medium value portfolios are shown to be within the middle range. This is consistent as per their neutral position towards size and value tilt. The ALL Ordinaries and large ordinaries, with a combination of large growth portfolios are shown to have performed mostly poorly. This is due to the lower performance of large growth stocks, which dominates these portfolios.

3.2 The CAPM Analysis

The ex-post model of the CAPM can be expressed as follows:

$$R_I - R_F = \beta_I (R_M - R_F) + \varepsilon_I \qquad (3)$$

$Where: \mathrm{R_I} = return$ on the index, $\mathrm{R_F}$ = risk free rate, performance, $\beta_\mathrm{I} = beta$ of the index, $\mathrm{R_M}$ = return on the market index, ε = ramdom error term

The time series regression takes the form of equation 4

$$R_I - R_F = \alpha + \beta_I (R_M - R_F) + \varepsilon_I \qquad (4)$$

The alpha and random error term are assumed to be insignificant in the CAPM equation (3).

$Where: \mathrm{R_I} = return$ on the index, $\mathrm{R_F}$ = risk free rate, α = Jensen's alpha as the measure of performance, $\beta_\mathrm{I} = beta$ of the index, $\mathrm{R_M}$ = return on the market index, ε = error term

However, in the regression analyses the alpha is usually estimated to test the reliability of the beta as the sole risk estimator. The null hypothesis is alpha = 0. The CAPM results are shown in Table Three below.

Table 2

The realised annual mean returns and excess returns, the CAPM estimated annual mean returns, excess returns left out by the CAPM and the beta coefficients with t-stats are reported in this table. The LHS assets are the monthly risk premiums of eleven portfolios sorted on size and BV/MV factors. The RHS variables are the single factor CAPM market betas. The study period spans from January 2000 through April 2013. The All Ordinaries index is used as the market index. 2-tailed test statistics are used to determine the significance of the coefficients; the significant coefficients are marked by astricts. * denote significance at the 5% levels.

Nos	Indices	Beta	t-stats	Actual Annual Mean Return	Annual Mean Risk Premium	CAPM Annual Risk Premium	Excess of CAPM
1	SOrds	0.38	(3.13)*	13.30%	9.80%	2.09%	7.71%
2	MOrds	0.76	(6.00)*	11.32%	7.82%	4.25%	3.57%
3	LOrds	0.90	(5.85)*	9.81%	6.31%	4.99%	1.32%
4	VOrds	0.75	(6.78)*	14.52%	11.02%	4.17%	6.86%
5	GOrds	0.86	(5.60)*	8.62%	5.12%	4.78%	0.34%
6	SVOrds	0.32	(1.84)	20.38%	16.88%	1.78%	15.10%
7	MVOrds	0.83	(5.73)*	14.00%	10.50%	4.60%	5.90%
8	LVOrds	0.81	(6.04)*	15.04%	11.54%	4.53%	7.01%
9	SGOrds	0.34	(2.36)	7.07%	3.57%	1.87%	1.70%
10	MGOrds	0.73	(5.71)*	8.94%	5.44%	4.09%	1.35%
11	LGOrds	0.97	(5.09)*	8.56%	5.06%	5.39%	-0.33%
12	Bond	0.20	(2.50)*	5.62%	2.12%	1.09%	1.04%
13	Market Index	1.00		9.07%	5.57%	5.57%	0.00%
	Risk Free	0.00		3.50%			

Table 2 shows the actual annual mean returns, actual annual excess mean returns, annual returns as per the CAPM prediction and beta coefficients for the portfolios sorted on firm size and BV/MV factors. The All Ordinaries index is used as the market index. The coefficients and the CAPM returns are estimated by regressing monthly excess returns of the individual portfolios against monthly excess returns of the market index. The beta coefficients compare the co-variability of the risk premiums on the portfolios sorted by size and BV/MV factors against the risk premiums on the market index.

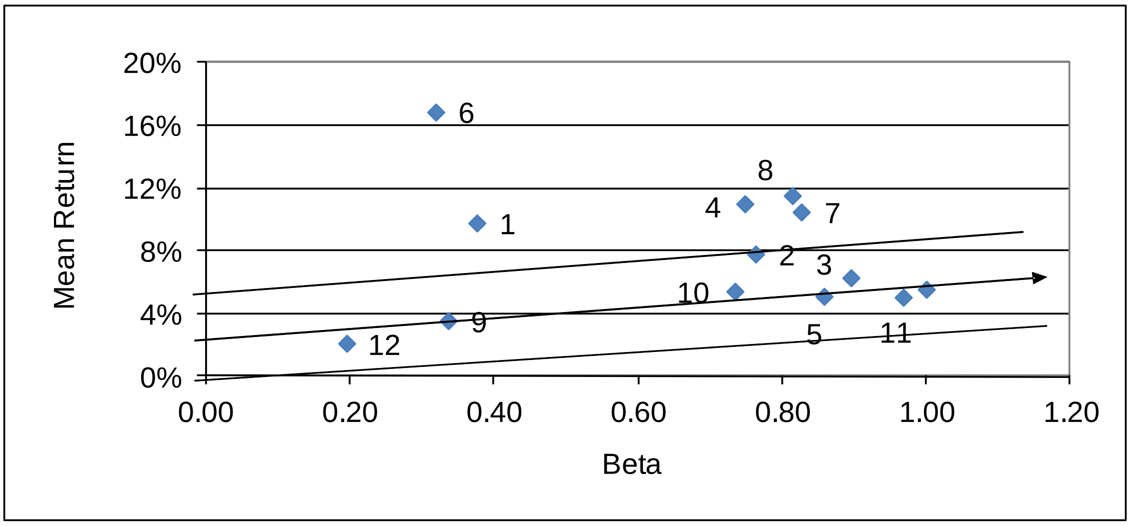
The results show that risk premiums on all portfolios are positive. This suggests, as expected, that investors are risk averse and only take extra risk for extra return. The testable implication of the CAPM, the null the $(R_M\text{-}R_F) > 0$ is not rejected. The beta coefficients for all portfolios except for small value and small growth portfolios are significant at 5% significance level. This indicates that the market factor is significant in explaining risk premiums on the portfolios. The null hypothesis that beta = 0 is not rejected. However, the alternative hypothesis, in this case, that alpha is = 0 also cannot be rejected at 5% level for SVOrds, SGOrds. This indicates that betas are not able to fully explain the risk premiums on small value and growth stocks

The betas for small and value portfolios are generally low and also lower for value portfolios than growth portfolios (Table 3). From our finding of higher returns on small and value portfolios over large and growth, the opposite is needed for the CAPM to explain size and value premiums in stock returns. This failure of the CAPM to explain size and value premiums in stock returns is in support of the original findings by FF (1993) which led them to developing the three-factor model. It is also consistent with the similar findings of several previous studies including the Australian studies by Faff (2004), Gaunt (2004) and Brailsford et al. (2012). FF (2012) also finds similar results for several international stock markets.

Due the lower market betas for small and value portfolios, the CPAM estimated risk premiums are significantly lower than the realised risk premiums on these portfolios. For example, the CAPM leaves out as much as 7.71%, 6.86% and 15.10%, 5.90% and 7.01% per annum on SOrds, VOrds, SVOrds, MVOrds and LVOrds respectively. The misspecification of CAPM is the largest for the small value portfolio which has the lowest market beta. The alpha or idiosyncratic risk, not shown here, are significant for these portfolios.

The positioning of the portfolios in relation to the CAPM security market line is depicted in figure 2. The dotted lines along the security market line indicate the significance of alpha values at 5% level. The alphas of the portfolios outside the dotted lines are considered to be positive and significantly away from zero in the rejection region of the alphas. Alphas for SOrds (1), VOrds (4), SVOrds (6), MVOrds (7) and LVOrds (8) respectively, clearly are outside the alpha ≠ zero region. These are mostly value portfolios across the three size groups, with SVOrds portfolio labelled as number 6 being the most significant outlier. This is the extreme small and value portfolio. The betas for these portfolios are lowest with the alphas or idiosyncratic risk significant (figure 2).

Figure 2
This figure depicts the position of the size and BV/MV sorted portfolios in relation to the CAPM market Line. A plus /minus 5% significance band is provided around the CAPM market line to capture variable in error on the regression model. The alphas outside this region are considered significantly away from zero with an interpretation that the null hypothesis, alpha ≠ zero, rejected. The market line is extended from the risk free (RF) rate of 3.5% through the beta of 1 for the market index. The All Ordinaries index is used as the market index. The study period is from January 2000 through April 2013.



From these results it could be concluded that the single index market model is an inappropriate model for capturing the returns on particularly small and value stocks. This finding is in correspondence with the earlier findings and a further confirmation of the presence higher risk in stocks returns beyond that could be fully explained by the systematic risk through the market betas of the stocks. The left out risk beyond market beta are described as idiosyncratic risk or residual risk. How the extended three factor model captures this additional risk is analysed next.

3. The Fama French Three-Factor Model

The Fama French Three-factor model is basically an extension of the CAPM including two additional variables, SMB and HML. The ex-ante form of the model can be expressed as follows:

$$E(R_I)t - RF(t) = \beta_I[(E(RM)t - RF(t)] + s_I E(SML)t + h_I E(HML)t + \varepsilon(t)_i \quad (5)$$

Where: $E(R_M) - R_F$, $\beta_1, E(SML)$, $E(HML), \varepsilon_1$ *are expected returns on the market, size factor in stocks and BV/MV factor in stocks;* β_I, s_I, h_I *are the slopes in the time series regression for each factor loading respectively.*

The time series regression takes this form,

Where: Ri(t) is the return on asset i for month t, RF(t) is the risk free rate, RM(t) is the market

$$R_I(t) - RF(t) = \alpha + \beta_I[RM(t) - RF(t)] + s_I(SML)(t) + h_I(HML)(t) + \varepsilon_I(t) \quad (6)$$

return, SMB(t) is the difference between returns on diversified portfolios of small stocks and big stocks and HML(t) is the difference between returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks.

As shown in **Table 2 and Figure 2**, CAPM leaves significant variation in stock returns unexplained. In table 3 the FF three-factor model, which in addition to the market factor (beta coefficient), includes slope coefficients on SML (small minus large) and HML (High minus Low) factors, in order to capture the residual co variations in the excess returns. The spreads on SML are the difference in returns between small and large indices. The spreads on HML are the difference in returns between stocks with high book value and low book value. The positive spreads on SML would indicate small stocks outperforming large, and the positive spreads on HML would indicate value outperforming growth.

The time series regression results in **Table 3** show that all alpha values are generally lower than the CAPM alphas. None are significant at the 5% level. The market betas for SOrds, SVOrds and SGOrds that were extremely low (statistically not distinguishable from zero) by the CAPM estimates, have improved in the 3-factor model (Panel 3, Table 1). The test statistics suggest that most betas are in the range of two to four standard deviations away from zero. This finding is consistent with the findings of improvements in beta estimates by the FF model for small stocks (Fama and French, 1996). Similar findings are also confirmed by Gaunt (2004) and Faff (2001, 2004) for Australian stocks.

SOrds, SVOrds and SGOrds have positive and significant loading on the SMB slope coefficients, which indicate presence of small firm premium in the returns for these portfolios. The SMB coefficients are negative and significant for large value and growth stocks (Panels 2&3, table 3). The negative slopes, particularly for LOrds, LVOrds and LGOrds, indicate lack of a size premium. The slopes on SMLB for medium size based indices should be zero. The insignificant slopes on SMB for MOrds, MVOrds and MGOrds support this statement. Overall, the regression results for SMB support the size premium hypothesis for Australian stocks and are consistent with the findings of the stock market literature (see for example Banz, 1981 and Fama and French 1993, 1996, 2012, Gaunt (2004), Brailsford et al. (2012) and others).

Table 3

Reported in this table are the regression results of the Fama French three factor model. The model estimated is that shown equation 6; where: Ri(t) is the return on asset i for month t, RF(t) is the risk free rate, RM(t) is the market return, SMB(t) is the difference between returns on diversified portfolios of small stocks and big stocks and HML(t) is the difference between returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The *t*-statistic for the regression coefficients uses HAC standard errors. The adjusted *R2* are calculated for each equation in the system. The *D*-statistics, which test for spurious in the regression model are also reported. The All Ordinaries index is used as the market index. The study period is from January 2000 through April 2013, with 160 monthly observations analysed. * denotes significance at the 5% level.

Dependent Variable	Alpha (t-stat)	Beta (t-stat)	SMB (t-stat)	HML (t-stat)	Adjusted R-Squared	Standard Errors	Durbin Watson
Panel1 - Indices by Size: Small, Medium and Large							
SOrds	0.004	0.833	0.290	0.229	0.820	0.020	1.979
	(1.23)	(4.49)*	(4.55)*	(2.16)*			
MOrds	0.006	0.630	-0.275	-0.053	0.633	0.023	2.130
	(1.98)	(4.94)*	(-3.85)*	(-0.45)			
LOrds	0.004	0.450	-0.710	0.229	0.626	0.020	1.979
	(1.12)	(4.49)*	(-11.13)*	(2.16)*			
Panel 2 - Indices by BV/MV Ratio							
VOrds	0.004	0.732	-0.409	0.553	0.523	0.019	2.080
	(1.88)	(5.45)*	(-6.65)*	(5.42)*			
GOrds	0.005	0.228	-0.508	-0.100	0.521	0.020	2.004
	(1.68)	(4.46)*	(-8.08)*	(-0.96)			
Panel 3 - Indices by Size and BV/MV Ratio							
SVOrds	0.005	0.920	0.327	0.865	0.800	0.025	1.977
	(1.88)	(2.93)*	(4.08)*	(6.49)*			
MVOrds	0.006	0.970	-0.311	0.200	0.750	0.026	2.253
	(1.47)	(4.48)*	(-3.87)*	(1.47)			
LVOrds	0.003	0.623	-0.630	0.811	0.601	0.022	1.962
	(1.60)	(4.65)*	(-9.06)*	(7.03)*			
SGOrds	0.004	0.863	0.236	-0.787	0.431	0.021	1.845
	(1.65)	(4.29)*	(3.48)*	(-7.05)*			
MGOrds	0.006	0.876	-0.174	-0.344	0.580	0.023	2.215
	(1.72)	(5.29)*	(-2.47)*	(-2.89)*			
LGOrds	0.005	0.760	-0.676	0.007	0.555	0.022	2.003
	(1.23)	(3.68)*	(-9.56)*	(0.06)			

VOrds, SVOrds and LVOrds have significant positive slopes on HML. Significant positive slopes on high BV/MV (value indices) indicate a value premium in the returns of these portfolios. Negative or insignificant slope coefficients indicate lack of the same premium. This should be case for growth indices and results indeed confirm this intuition. Similar to the findings for SMB, the finding for HML is also consistent with the stock market literature and supports the hypothesis of small and value stocks outperforming large and growth for stocks.

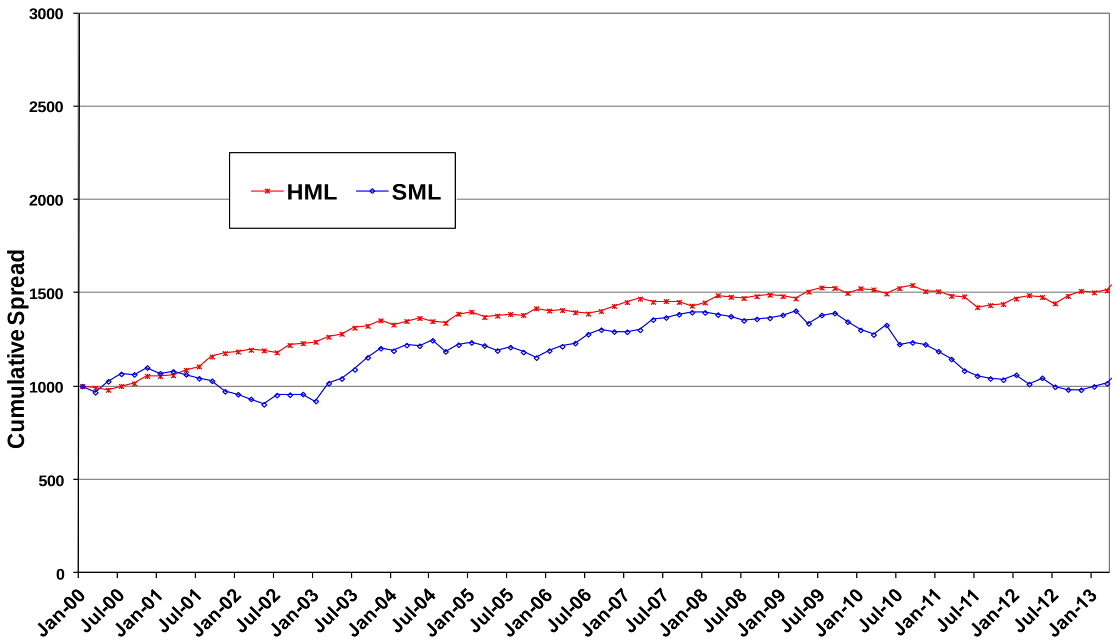
The overall regression results from the FF model seem to support the findings by Chan and Chen (1991) and Fama and French (1995, 1996). That is, the size effect is mainly driven by marginal firms in distress. These are usually small firms with depressed earnings and future growth, and thus the market drives the market values of these firms below their book values (high BV to low MV, value firms). Therefore, similar to small firms, value firms tend to have high returns and positive slopes on SMB and HML factor loadings. The higher returns on small and value firms are supposed to compensate investors for high risk due to depressed earnings and future growth (i.e., higher capitalisation rate implies high return due to low expected future growth).

Conversely, strong (usually large) and growth firms are shown to have negative slopes on SMB and HML factor loadings. The market values of these firms are usually higher than their book values in anticipation of high future growth and the capitalisation rates are low, implying higher expected returns from the future growth. Therefore, investors accept initial low returns by paying a high price, in anticipation of low risk and high growth in the future expected values of these firms.

The cumulative monthly spreads on SMB and HML over the 13-year study period is graphical depicted in **Figure 3**. The results show that over the 13-year period, the value premium accumulated by 51% [(1,512 - 1,000)/1,000]; that is almost 4% per year (51%/13 years). The small firm premium has been more volatile than value premium. It has been negative over 2001 through 2003, increasing to 1,403.97 (1403.97-1,000)/1,000 = 40% in March 2009 and then decreasing gradually again to the level of 1,014.49 in March 2013 (14.49%).

The finding of size effect being negative from 2001 through 2003 and then becoming significantly positive from 2007 through 2011, explains the negative finding of size effect by Faff 2004 and the positive finding of size effect Gharghori et al. (2007). These results confirm the time variant nature of firm size effect as also found by Avarov and Chordia (2006) and Lewellen and Nagel (2006). No Australian study thus far has examined the time variation effect in SMB and HML on stock returns.

Figure 3
The cumulative spreads on SMB and HML are graphical depicted in Figure 3. SMB is the difference between returns on diversified portfolios of small stocks and big stocks and HML is the difference between returns on diversified portfolios of high book-to-market (value) stocks and low book-to-market (growth) stocks. The study period is from January 2000 through April 2013, with 160 monthly observations analysed.



The finding of time variant effect in SMB also adds to debate of Annin and Falaschetti (1999) and Gustafson and Miller (1999). Annin et al found evidence to suggest that small capitalisation shares underperformed large capitalisation shares between 1990-1998. Gustafson and Miller (1999) provided an explanation to Annin et al's contrary finding by showing evidence that the size effect has a tendency to move in cycles. The movement in SMM spread in this study, to an extent, exhibits a cyclical pattern as well. The spread is thinner during 2000 through 2001, becomes negative during 2001 through 2003, which widens over 2004 through 2010 and then becomes thinner again after 2011 through 2013.

Whereas, the general pattern of the value spread is upward and rising (see figure 3). The existence of strong and persistent value premium shows in the regression results as well with the loading on HML increasing as average book-to-market ratios increase, leading to a strong positive and significant factor loading for the value portfolios. This result is robust evidence that HML has a significant explanatory power in explaining variations in returns on Australian stocks. These results are consistent with international studies on the three-factor model (Bagella, Becchetti & Carpentieri, 2000; Davis, Fama & French, 2000; Fama & French, 1993, 1996, 1998, 2012; Guant; 2004; Brailsford et al. (2012) and others).

4.0 Conclusion

The finding by Banz (1981) and Ibbotson, Kaplan and Peterson (1997) that the CAPM is misspecified in estimating risk premiums on small stocks, because it estimates low betas for small firms, is extended in this study. The similar earlier in Australian studies by Faff (2004), Gaunt (2004) and Brailsford et al. (2012) is also improved. This study further finds that market betas for small firms are low relative to their realised risk premiums, and the CAPM is unable to estimate approximately 5% of the realised annual risk premiums. Furthermore, the study finds evidence that the market betas on small firms are improved by almost 10% in the FF three-factor model, and the improved betas reduce the CAPM unexplained risk premiums by about 2% per annum. Additionally, the SML and HML factors mimicking size premiums and value premiums respectively, further reduce the unexplained CAPM risk premiums by 3%, and thus the FF three-factor model is able to capture almost all the realised risk premiums on small and value Australian stocks.

Brailsford et al. (2011) sample set mainly includes stocks in ASX 300, while Brailsford et al. (2011) hand pick stocks from AGSM data base and extend sample size significantly by including smaller stocks. They also claim to improve the data sorting method. However, the results of the two studies, particular evidence of value premium is not significantly different. They also show evidence of negative size, similar to the findings of earlier studies. Interestingly, the findings of this study on both size and value premium are not significantly different from previous studies either.

Therefore, criticisms of later Australian studies of the earlier studies are questionable to an extent. Although the later studies expand sample sizes, extend study periods and improve upon portfolio construction methods, they mostly provide rigour and robustness to the analyses and reconfirm most of the earlier findings, as opposed to serious refuting any particular finding.

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Commodity Futures Returns and Policy Uncertainty

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ABSTRACT

This paper investigates whether economic policy uncertainty is predictable using three sets of commodity futures market variables as predictors: the equal-weighted average of futures excess returns, the excess returns on a portfolio of going long in backwardated commodities, and the excess returns on a portfolio of going short in contango commodities. We find significant evidence of predictability in both in-sample and out-of-sample tests. Combination forecasts also reveal strong evidence of predictability. Our findings remain unchanged following a number of robustness tests.

Keywords: *Commodity Markets; Policy Uncertainty; Predictability; Backwardation; Contango.*

I. INTRODUCTION

Commodity futures prices have been traditionally viewed as indicators of future states of the economy. It follows from the theory of storage (Kaldor, 1939; Working, 1949) that futures prices reflect markets expectations about future demand and supply for commodities. Hou and Szymanowska (2015) argue that commodity future prices are highly correlated with consumption, since they represent 40% of personal consumption expenditures, with food commodities accounting for 15%, energy commodities accounting for 4%, and other commodities accounting for 21%. Moreover, commodities such as oil, copper, and soybeans are treated as barometers of the global economy (Hu and Xiong, 2013). Further, Gospodinov and Ng (2013) show that the convenience yield of commodity futures prices predicts inflation of the Unites States and G7 economies.

In this paper, we examine whether commodity futures market variables predict changes in the economic policy uncertainty (EPU) for the United States and for 14 additional countries,[3] which include other G7 economies and the BRIC countries. We use the index of policy uncertainty constructed by Baker *et al.* (2015). This index is constructed using three sub-components: a news measure of policy-related economic uncertainty, federal tax code expirations, and economic forecaster disagreement. We consider three sets of predictors: (i) the equal-weighted average of futures excess returns of all the commodities in the sample (CMKT), (ii) excess returns on a portfolio that goes long in the 25% most backwardated commodities (CBCK), and (iii) excess returns on a portfolio that goes short in the 25% most contango commodities (CCON). The monthly returns on a portfolio of backwardated and contango commodities are constructed by sorting the commodities based on roll yield, which is the logarithmic price difference between the nearest and second nearest futures contracts. Thus, a positive roll yield indicates a downward-sloping term structure, while a negative roll yield indicates an upward-sloping term structure.

The motivation for using commodity futures market backwardation and contango portfolio returns as predictors follows from the theory of storage of commodities. Accordingly, the downward-sloping term structure of commodity futures prices indicates a fall in inventories relative to demand, the benefits from holding physical commodity increase, and an increase in futures prices is expected (Fama and French, 1988; Ng and Pirrong, 1994). The reverse is true for the upward-sloping term structure of commodity futures prices. It signals a large supply relative to demand and a forthcoming drop in futures prices. Gorton *et al*. (2013) test these hypotheses and find that the basis is an inverse function of inventory levels. Thus, the degree of backwardation and contango of all commodities conveys the fundamental demand and supply conditions and investor beliefs about how these will change in the markets (Brooks *et al*., 2016).

Our empirical plan is based on four specific steps. First, we examine in-sample evidence of predictability for changes in the EPU of the United States by employing Westerlund and Narayan's (2012, 2015) methodology, which accounts for the persistency, endogeneity and heteroskedasticity of data. We find significant evidence of predictability, in that all three predictors predict changes in EPU at six-, 12-, and 24-month horizons. We ascertain the robustness of our results in a number of ways. First, we exclude crude oil from the sample of commodities and re-run the analysis. Our results may very well be driven by crude oil. Second, we add five macroeconomic risk variables to our regression model. It may be that the predictability we find is merely the result of the relation between commodity returns and

[3] Our choice of countries is dictated by the availability of EPU index data.

macroeconomic variables. Our main conclusion regarding the statistical significance of predictability at 6-, 12-, and 24-month horizons remains unchanged with all three predictors.

Our second approach involves testing in-sample predictability for the remaining 14 countries in our sample. Here, we augment our regression model with five macroeconomic variables. We find predictability to be strongest for the 24-month horizon. All three predictors predict at least 36% of the countries (five countries) at the 24-month horizon. The variable CMKT turns out to be the most popular predictor. Further, all three predictors predict a minimum of three countries at the 12-month horizon. The variation in in-sample predictability for different countries is consistent with the results of Cespedes and Velasco (2012), who show that the macro response of commodity booms and busts vary for countries, depending on the policy and structural features of the economy.

We also conduct a number of additional tests with the Unites States data for which we have EPU data from January 1985 to June 2015. First, we test whether the in-sample predictability holds for two sub-periods: the pre-financialization period (January 1985–December 2000) and the post-financialization period (January 2001–June 2015). Boons *et al*. (2014) argue that a structural break occurred following the passage of the Commodity Futures Modernization Act in December 2000. We find strong evidence of predictability post-financialization; nonetheless, our results regarding predictability at longer horizons hold in both sub-samples. Second, we test whether any particular commodity sector is driving the predictability. We find industrial sector returns to be the strongest predictor, followed by the returns of grains and oilseeds and livestock. However, we do not find evidence of the returns for foodstuffs and metals predicting changes in EPU at any of the horizons. Third, we examine the source of predictability by testing whether any particular category of EPU is more predictable. We find that predictability is concentrated around monetary policy uncertainty and fiscal policy uncertainty, while trade policy uncertainty is relatively unpredictable.

As a final step, we undertake out-of-sample forecasting analysis where we compare the forecasts from our predictive regression model with historical average forecasts. We also compute combination forecasts (CFs) that are the averages of forecasts from the all three predictive regression models. From this analysis, we find that CMKT is the most popular out-of-sample predictor, which we also discover from in-sample tests. The change in EPU for two countries is strongly predictable both in and out of sample. Further, our evidence of in-sample predictability at the long horizon of 24 months holds in out-of-sample tests as well. Thus, the out-of-sample tests largely corroborate in-sample evidence of predictability.

Our findings contribute to several strands of literature. First, we contribute to the literature that uses commodity market variables as predictors. For instance, Hong and Yogo (2012) find that the open interest of commodity futures prices predicts bond returns and movements in the one-month Treasury bill rate. Many studies find oil prices to have a strong effect on stock returns (Narayan and Sharma, 2011). Other recent studies find that commodity market futures returns explain the cross section of equity returns (Boons *et al*., 2014; Brooks *et al*., 2016). We show that commodity market variables are also useful in predicting EPU, even after controlling for other macroeconomic variables. Our findings also hold in out-of-sample tests.

In addition, a related strand of literature documents commodity futures backwardation or contango cycles as leading indicators of future economic activity (Bakshi *et al*., 2015; Fernandez-Perez *et al*., 2015). Bakshi *et al*. (2015) find that commodity term structure portfolios predict the gross domestic product (GDP) growth rate. Fernandez-Perez *et al*. (2015)

show that the commodity backwardation and contango portfolio returns predict long-run changes in investment opportunities and the business cycle. Our finding of strong evidence of predictability at the 24-month horizon using backwardated and contango portfolio returns adds to this literature.

Finally, our study contributes to the broader literature on forecasting macroeconomic variables. This literature uses a number of variables and methodologies to forecast macroeconomic variables, such as output, inflation, measures of real activity, and industrial production. For instance, Stock and Watson (2002) use a dynamic factor model to forecast eight macroeconomic variables, including industrial production and the Consumer Price Index. Stock and Watson (2003) document the role of asset prices in forecasting output and inflation. Further, Gospodinov and Ng (2013) find that the first two principal components extracted from the panel of convenience yields predict inflation. We show that EPU is predictable. Our study provides the first empirical evidence on this. We not only focus on the United States but also provide evidence for 14 other countries included in our sample.

The balance of the paper is organized as follows. Section II discusses the theoretical and empirical motivation for the link between commodities and economic policy. Section III presents the data, an empirical framework to test the null hypothesis of no predictability, and preliminary analyses. Our main findings from in-sample predictability tests and out-of-sample tests are discussed in Sections IV and V. The final section provides concluding remarks.

II. LITERATURE REVIEW

In this section, we provide theoretical and empirical evidence on the link between commodity futures market and the macroeconomic performance that has motivated us to take up this research question.

A. Theoretical Literature

There are a number of channels, such as fiscal policy and monetary policy, through which shocks to commodity prices affect the economy. Cespedes and Velasco (2014) evaluate the behavior of fiscal policy variables in 32 countries for which commodity-linked revenues play a major role in the economy. Using commodity boom and bust episodes, they show the presence of procyclical fiscal balances during the 1970s and 1980s, while the fiscal policy stance was countercyclical during the commodity boom that occurred before the 2008 global financial crisis. Cody and Mills (1991) investigate whether the information in commodity prices is useful in formulating monetary policies. They find that commodity prices are an indicator of future states of the economy and using these prices in formulating monetary policies improves economic performance by lowering the magnitude and variability of the average rate of inflation.

Further, using an open-economy model with nominal rigidities and financial frictions, Cespedes and Velasco (2012) show that fluctuations in commodity prices are often associated with macroeconomic volatility. They evaluate the macro response of a group of 59 countries to large commodity price shocks. They find a significant impact of commodity price shocks on output and investment dynamics. The impact of commodity price shocks on investment is larger for economies with less developed financial markets. In addition, the authors show that the macro response of commodity booms and busts vary for countries depending on the policy and structural features of the economy.

Shousha (2016) investigates the effects of commodity price shocks on real activity for a group of 10 advanced and emerging commodity exporting economies using two methods: a theoretical three-sector open economy model with financial frictions estimated using Bayesian methods and a panel vector autoregressive model. The author's results show that commodity price shocks are the major cause of fluctuations in the business cycle and the effect of commodity price shocks on real activity, credit, and country interest rates tends to be stronger for emerging economies. Change in country interest rates and working capital costs are the two main channels through which commodity price shocks affect both advanced and emerging economies.

B. Empirical Literature

A number of studies have shown the predictive ability of commodity futures market variables. For instance, Fernandez-Perez *et al*. (2015) show that commodity backwardation and contango portfolio returns predict long-run changes in investment opportunities and the business cycle. Their empirical evidence suggests that commodity market portfolio returns contain information beyond that of traditional predictors such as the dividend yield, the default spread, or the term spread. They also find that the backwardation and contango portfolios predict the real GDP growth of the G7 economies. Gospodinov and Ng (2013) use the convenience yields of 23 commodity futures prices and show that the first two principal components extracted from the panel of convenience yields have economically and statistically significant predictive power in predicting the inflation of the United States and G7 countries. The results are robust to the inclusion of unemployment gap and oil prices. The predictive power remains unchanged in out-of-sample forecasts as well. Hong and Yogo (2012) show that the open interest of commodity futures prices predicts bond returns and movements in the one-month Treasury bill rate, even after controlling for other known predictors.

The main message from the theoretical and empirical literature is that there is a strong relation between the commodity futures market variables and macroeconomic activity. This motivates our research question: Are commodity futures market variables useful in predicting the EPU?

III. DATA AND METHODOLOGY

A. Data

We use two sources of data. Our first dataset is the monthly data on the EPU index constructed by Baker *et al*. (2015). These data are downloaded from the Federal Reserve Economic Data website and are available for the United States, Canada, France, Japan, South Korea, Brazil, Germany, Russia, China, the United Kingdom, Italy, Australia, Spain, India, and the Netherlands. The sample period of the data for the United States and Canada is from January 1985 to June 2015. The sample sizes for the remaining countries vary, dictated by data availability, and are reported in Table I.

INSERT TABLE I

Our second dataset consists of the monthly futures prices of 27 commodities extracted from the Commodity Research Bureau database. These include four energy commodities (WTI crude oil, heating oil, natural gas, and RBOB gasoline), four foodstuffs (cocoa, orange juice, coffee, and sugar), eight grains and oilseeds (soybean oil, corn, oats, canola, wheat, soybean meal, soybeans, rough rice), two industrials (cotton and lumber), four livestock and meats (feeder cattle, live cattle, lean hogs, and pork bellies), and five metals (gold, copper, silver, palladium, and platinum). The sample period for the data is from January 1985 to June 2015. Our choices of commodities and sample periods are dictated by data availability. As is standard in the literature (Gorton *et al*., 2013), futures returns are computed using the settlement prices of the nearest and second nearest futures contracts. We roll over to the next contract on the last day of the month before the expiry month. We consider three commodity futures market variables as predictors[4] of EPU: (i) commodity futures excess returns (CMKT), (ii) excess returns on a portfolio going long in the 25% most backwardated commodities, and (iii) excess returns on a portfolio going short in the 25% most contango commodities (CCON). The variable CMKT is defined as the equal-weighted average of the futures excess returns of all the commodities in the sample. To compute CBCK and CCON, we first compute the roll yields for each commodity, which are the differences in the log prices of the first and second nearby futures contracts. We then sort the commodities futures contracts by the previous month's roll yield. Following Brooks *et al*. (2016), we take long positions in the nearest contracts of the 25% of commodities with the highest roll yields and short positions in the nearest contracts of the 25% of commodities with the lowest roll yields. The variables CBCK and CCON are the excess returns on the portfolios of long and short positions, respectively.

B. Estimation Approach

Our estimation approach is inspired by recent studies in the return predictability literature (Westerlund and Narayan, 2012, 2015) that address the three major issues—persistency, heteroskedasticity, and endogeneity—prevalent in our dataset. Following Westerlund and Narayan (2012, 2015), we employ the feasible quasi-generalized least squares (FQGLS) based estimator for in-sample predictability tests. Our time series predictive regression model to predict changes in EPU takes the following form:

$$y_{t+h} = \theta + \beta^{adj} x_t + \gamma(x_{t+h} - \rho_0 x_{t+h-1}) + \eta_{t+h} \qquad (1)$$

where y_{t+h} is the change in EPU at time $t+h$ and x_t is the predictor variable. In our case, y_{t+h} is the change in EPU for the United States and 14 other countries, while x_t is one of the three predictors (CMKT, CBCK, and CCON). The error term is characterized by a zero mean and variance σ^2. The term $\beta^{adj} = \beta - \gamma(\rho - \rho_0)$ can be interpreted as the limit of the bias-adjusted ordinary least squares estimator of Lewellen (2004). Westerlund and Narayan (2012) assume that $\rho = 1 + \frac{c}{T}$, where $c \leq 0$ is a drift parameter that measures the degree of persistency in x_t. The FQGLS estimator for testing the null hypothesis of no predictability captures the autoregressive conditional heteroskedasticity (ARCH) structure in the errors by weighting all the data by $1/\sigma_{\eta_t}$. The FQGLS-based *t*-statistic for testing $\beta = 0$ takes the following form:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \pi_{t+h}^2 x_{t+h-1}^d y_{t+h}^d}{\sqrt{\sum_{t=q_m+2}^{T} \pi_{t+h}^2 \left(x_{t+h-1}^d\right)^2}} \qquad (2)$$

where $\pi_{t+h} = 1/\sigma_{\eta_{t+h}}$ is the FQGLS weight and $x_t^d = x_t - \sum_{s=2}^{T} x_s/T$, with a similar definition for y_t^d, where T is the sample size and optimal lag length $q = \max\{q_x, q_{y,x}\}$ is selected using the Schwarz Bayesian criterion.

[4] Our choice of predictors is motivated by the recent literature that uses commodity market variables in predicting equity returns (Brooks *et al*., 2016; Fernandez-Perez *et al*., 2016)

C. Out-of-Sample Forecast Evaluation Measure

Following previous studies (Gospodinov and Ng, 2013; Narayan and Bannigidadmath, 2015; Bannigidadmath and Narayan, 2016), we use a recursive out-of-sample forecasting exercise. We estimate the predictive regression model for the in-sample period, t_0 to $t - h$, and generate h-period-ahead forecasts for $h = 3$, 6, 12, and 24 months. We then re-estimate the model over the period t_0 to $t + 1 - h$ and forecast the change in EPU for the next h periods. This process is repeated until $T - h$ observations. This forecasting exercise allows us to use the information available till $T - h$ observations, so that our forecasts resemble real-time forecasts. We use 50% of the full sample of data as the out-of-sample period. The out-of-sample estimation covers the period April 2000 to June 2015. We compare the out-of-sample forecasts with the historical mean model. The forecasting performance is evaluated by the well-known Campbell–Thompson (2008) out-of-sample R^2 (OR^2). This measure is given by $OR^2 = 1 - (MSFE_M/MSFE_H)$, where $MSFE_M$ and $MSFE_H$ are the mean squared forecast errors for the benchmark predictive regression model and the historical mean model, respectively. We also compute the *p*-value corresponding to Clark and West's (2007) $MSFE$-adjusted test statistic, which examines the null hypothesis that $OR^2 \leq 0$ against the alternative hypothesis $OR^2 > 0$.

D. Preliminary Statistical Features of the Data

Our main objective in this section is to understand the persistency, heteroskedasticity, and endogeneity of our data that motivate the application of the FQGLS estimator for in-sample predictability tests. Before we begin, however, we look at the mean and standard deviation of the predictors and dependent variables reported in Table II. The average commodity futures excess return (CMKT) is 3.26% per annum, with a standard deviation of 3.41%. Taking a long position in 25% of the most backwardated commodities yields a return of 8.95% per annum. The mean and standard deviations of changes in EPU indicate that the policy uncertainty of four countries—China, Russia, Brazil, and the Netherlands—are most volatile, while the policy uncertainty of the United States is the least volatile.

INSERT TABLE II

In Table II, we also report the results of persistency and heteroskedasticity tests. The first-order autoregressive coefficient (ρ) reported in the fourth column of the table suggests that predictors are not persistent. This result is quite expected. In turn, the first-order autoregressive coefficients for changes in the EPU of the United States and the United Kingdom are close to one, indicating persistency in these series. The autocorrelations associated with the squared variables are statistically significant for two (CMKT and CCON) of the three predictors, while, for the changes in EPU, the autocorrelations are statistically significant for South Korea, Russia, and India. The autocorrelations associated with the squared variable indicate the presence of ARCH effects. We also formally test for ARCH effects by filtering each series and running an autoregressive model with 12 lags. The *p*-value of the Lagrange multiplier test to examine the null hypothesis of no ARCH in the filtered series is reported in the last two columns of Table II. Strong presence of ARCH is seen in the predictor variables CMKT and CCON. For the changes in EPU, the null hypothesis of no ARCH is rejected for South Korea.

As a final test in the preliminary analysis, we search for evidence of endogeneity in the predictive regression model. The results are reported in Table III. We report the coefficient γ from Equation (3) and the *p*-value testing the null hypothesis that γ is statistically different from zero:

$$\varepsilon_{y,t} = \gamma\varepsilon_{x,t} + \eta_t \quad (3)$$

where $\varepsilon_{y,t}$ and $\varepsilon_{x,t}$ are the error terms from a predictive regression model and an AR(1) model of predictors, respectively. The statistical significance of γ indicates that the predictor variable is endogenous. For the changes in EPU of the United States, Canada, South Korea, Australia, and Spain, the predictors CMKT and CBCK are endogenous. Evidence of endogeneity also exists for the predictor CCON, where γ is significantly different from zero for France and Australia.

INSERT TABLE III

Our conclusion from the preliminary analysis is that persistency is not a serious concern; however, heteroskedasticity and endogeneity in the predictive regression model have to be addressed in our empirical framework. Our choice of the FQGLS-based estimator addresses these concerns.

IV. IN-SAMPLE PREDICTABILITY TESTS

In this section, we discuss the in-sample predictability tests for the United States followed by in-sample predictability tests for the remaining 14 countries. In the subsequent sub-sections, we conduct a number of additional tests for the United States, for which we have long data series spanning from January 1985 to June 2015.

A. In-Sample Predictability Test Results for the United States

In this section, we examine in-sample evidence of predictability for changes in EPU of the United States. The results from Equation (1) with $h = 3$, 6, 12, and 24 are reported in Panel A of Table IV. We find that CMKT (CBCK) predicts changes in EPU at all four horizons at the 1% (5%) significance level. With CCON as a predictor, the null hypothesis of no predictability is rejected at longer horizons of six, 12, and 24 months at the 1% level. The coefficients of CMKT and CBCK are positive, suggesting that these variables positively predict changes in EPU. The coefficients of CCON are negative, indicating that excess returns on a portfolio going short in contango commodities negatively predict changes in EPU. The R^2 statistics across all three predictors increase with increases in horizons and range from 0.71% for CCON at $h = 3$ to 6.01% for CMKT at $h = 24$. These results clearly suggest that all three predictors from the commodity futures market predict changes in US policy uncertainty.

INSERT TABLE IV

A number of studies have investigated the oil price–economic growth nexus (e.g., Hamilton, 2011; Narayan *et al.*, 2014). They show the importance of changes in oil price for macroeconomic variables such as inflation and economic output. It is therefore reasonable to question whether the in-sample predictability is driven by crude oil. To answer this question, we construct the predictors by excluding crude oil from the sample of commodities. This means we end up using 25 commodities in computing the CMKT, CBCK, and CCON predictors. The in-sample predictability results excluding crude oil from the sample are reported in Panel B of Table IV. Our main results remain unchanged. We find that all three predictors predict changes in EPU at all four horizons. The sign and statistical significance of the coefficients and the R^2 statistics of the regression model are robust to the exclusion of crude oil.

To check the robustness of our results, we augment our predictive regression model with five macroeconomic risk variables. These variables are growth in industrial production, changes in expected inflation, changes in unexpected inflation, the default spread, and the term spread. Following Brooks *et al*. (2016), we estimate expected inflation as the three-month moving average of the inflation rate. The unexpected inflation rate is then computed as the difference between the observed and expected inflation rates. The default term spread is the difference between Moody's Baa corporate bond yield and the 10-year long-term government bond yield; the term spread is the difference between the 10-year long-term government bond yield and the three-month Treasury bill rate.[5] The in-sample predictability results from the regression model augmented by five macroeconomic variables are reported in Panel C of Table IV. The predictors CMKT and CBCK predict changes in EPU at all four horizons, while CCON predicts changes in EPU at six-, 12-, and 24-month horizons. The R^2 statistics are significantly higher at longer horizons. Across the three regression models, the R^2 statistic, on average, is 46.41% when $h = 24$. This compares to an R^2 statistic of 4.71% when $h = 3$. The average R^2 statistics are 11.97% and 23.88% at the six- and 12-month horizons, respectively. In un-tabulated results, we find that the coefficients of the default spread and the term spread are mostly statistically significant across all models for all four horizons. The coefficients of the changes in expected and unexpected inflation are mostly significant at the 12- and 24-month horizons. The industrial production growth rate is statistically significant at the 12-month (six-month) horizon when CMKT (CBCK and CCON) is used as the predictor. Overall, our main results regarding the sign and statistical significance of predictor coefficients hold, irrespective of the inclusion of macroeconomic variables.

B. In-Sample Predictability Tests Results for Other Countries

In this section, we examine whether the in-sample predictability of changes in EPU by commodity market variables also holds for other countries for which EPU data are available. Table V reports the in-sample predictability results obtained from the predictive regression models augmented by five macroeconomic variables.[6] We find significant evidence of in-sample predictability for other countries. These results can be summarized as follows:

- The variable CMKT is the most popular predictor. It predicts changes in EPU for six out of 14 countries at the six- and 24-month horizons, followed by the predictability of changes in EPU for five countries at the three- and 12-month horizons, respectively.
- The variable CBCK predicts changes in EPU for five countries at the three- and 24-month horizons. This is followed by the predictability of changes in EPU for four and two countries at 12- and six-month horizons, respectively.
- The variable CCON predicts changes in EPU for five countries at the 24-month horizon and for three countries at the three-, six-, and 12-month horizons.
- The in-sample predictability across all three predictors is strongest at the 24-month horizon. As is the case for the United States, the R^2 statistics increase with increases in horizon for all countries except Russia.
- The predictability of changes in EPU is strongest for Canada, in that all three predictors predict changes in EPU at the 12- and 24-month horizon. At the three- and six-month horizons, two predictors predict changes in EPU for Canada. This is followed by Australia, where all three predictors predict changes in EPU at the three- and 24-month horizons.

[5] The industrial production series, Moody's Baa corporate bond yields, 10-year long-term government bond yields, and three-month Treasury bill rates are downloaded from the Federal Reserve Economic Data website.
[6] For some countries, we observe that including macroeconomic variables in the predictive regression model diminishes the predictive ability of the commodity market variables. We therefore report the regression model that accounts for macroeconomic variables. It is not uncommon to include US macroeconomic variables as proxies for their international counterparts due to the relevance of the US economy globally (e.g., Brooks *et al*., 2016).

- For four countries (Germany, South Korea, Spain, and India), two of the three predictors predict changes in EPU at two of the four horizons. For two countries (Italy and the Netherlands), one of the three predictors predicts changes in EPU for three out of four horizons.
- For Japan, Brazil, Russia, and China, the evidence of predictability is observed at one of the four horizons, while there is no evidence of predictability for the EPU of the United Kingdom and France.

INSERT TABLE V

C. Sub-Sample Analysis for the United States

We test whether the in-sample predictability results obtained over the full sample period also hold for the two sub-samples: the pre-financialization period (January 1985–December 2000) and the post-financialization period (January 2001–June 2015). We do this for the United States, for which we have EPU index data from January 1985 to June 2015. The results are reported in Table VI. The key findings can be summarized as follows:

- During the pre-financialization period, the predictability is mainly concentrated at longer horizons (six, 12, and 24 months). All three predictors predict changes in EPU when $h = 12$, while CMKT and CCON predict changes in EPU at horizons of six and 24 months. There is no evidence of predictability at the three-month horizon.
- The predictability at all horizons is stronger during the post-financialization period. All the predictors predict changes in EPU at the six-, 12-, and 24-month horizons, while CMKT and CBCK predict changes in EPU at the three-month horizon. The in-sample predictability at the shorter horizon of three months is concentrated in the post-financialization period.

Overall, our results regarding predictability at longer horizons hold in both the sub-samples. The evidence of strong predictability during the post-financialization period is consistent with the findings of Brooks *et al*. (2016), who find statistically significant commodity risk premium for the second sub-sample.

INSERT TABLE VI

D. In-Sample Predictability Tests with Commodity Sector Returns as Predictors

Lastly, we seek to answer whether there are any particular commodity sectors that are driving the in-sample predictability. To do so, we use the equal-weighted average of futures excess returns of all commodities in a sector as the predictor of change in EPU. The results with six commodity sector returns (energy, food stuffs, grains and oilseeds, industrials, livestock, and metals) as predictors are reported in Table VII. The regression model is also augmented by five macroeconomic risk variables discussed above. We observe that the returns of only two sectors (industrials and livestock) predict changes in EPU at $h = 3$. When $h = 6$, the null hypothesis of no predictability is rejected for grains and oilseeds and the industrials. Four sector returns (energy, grains and oilseeds, industrials, livestock and meats) predict changes in EPU at the 12-month horizon, while three sector returns (grains and oilseeds, industrials, livestock) predict changes in EPU at the 24-month horizon. This result indicates that predictability by sector returns is strongest for $h = 12$, followed by $h = 24$. The industrial sector return is the strongest predictor, in that it predicts the changes in EPU for all four horizons. This is followed by the returns of grains and oilseeds and livestock, which predict changes in EPU for three horizons. The energy sector returns predict changes in EPU only at the 12-month horizon. We find no evidence of foodstuffs and metals returns predicting changes in EPU at any of the horizons.

INSERT TABLE VII

E. In-Sample Predictability Tests for EPU Categories of the United States

We further investigate the predictability results for three of the major EPU categories: monetary policy uncertainty, fiscal policy uncertainty, and trade policy uncertainty. This enables us to identify the source of predictability to some extent. The results are reported in Table VIII. Predictability is strongest at the 24-month horizon. All three predictors predict changes in monetary policy uncertainty at the horizon of 24 months. Further, all three predictors predict changes in fiscal policy uncertainty at $h = 12$ and $h = 24$. Consistent with our earlier results, CCON positively predicts changes in monetary policy and fiscal policy uncertainty, while CMKT and CBCK negatively predict changes in monetary policy and trade policy uncertainty. The predictability for changes in trade policy uncertainty is relatively weak. Only one predictor (CCON) positively predicts changes in trade policy uncertainty at the 24-month horizon.

INSERT TABLE VIII

There are three main messages from our in-sample predictability results. First, the signs of the coefficients for all countries are consistent, in that CMKT and CBCK positively predict changes in EPU, while CCON negatively predicts changes in EPU. This result indicates that a rise (decline) in commodity prices leads to an increase (decrease) in the EPU index. Second, the statistical significance of coefficients indicates that CMKT is the most popular predictor, predicting changes in the EPU of 50% (eight out of 16) of the countries at the six- and 24-month horizons and 44% (37%) of the countries at the three-month (12-month) horizon. The variable CBCK is the second most popular predictor, followed by CCON. Both these predictors predict changes in EPU for at least seven countries at the horizon of 24 months and for a minimum of three countries at the three-, six-, and 12-month horizons. The evidence of strong in-sample predictability at the 24-month horizon is consistent with the literature that uses commodity market variables as predictors (Gospodinov and Ng, 2013; Fernandez-Perez *et al*., 2016). Our final message is that notable differences exist in predictability across countries. For instance, the in-sample predictability for changes in EPU of the United States, Canada, and Australia is the strongest, while the United Kingdom and France exhibit no evidence of in-sample predictability. This variation in in-sample predictability for different countries is consistent with the results of Cespedes and Velasco (2012), who show that the macro response of commodity booms and busts vary for countries, depending on the policy and structural features of the economy.

The additional in-sample tests with US data reveal that predictability at the short horizon of three months is concentrated in the post-financialization period, while predictability at the horizons of six, 12, and 24 months is evident during both the pre- and post-financialization periods. Further, we find that the industrial sector return is the strongest predictor of change in EPU, followed by the returns of grains and oilseeds and of livestock. There is no evidence that foodstuffs and metals returns predict changes in EPU at any of the horizons. Lastly, examining the predictability for three categories of EPU reveals strong evidence of predictability for monetary policy uncertainty and fiscal policy uncertainty at the horizons of 12 and 24 months.

V. OUT-OF-SAMPLE PREDICTABILITY TESTS

In this section, we examine the out-of-sample predictability of EPU for the United States and 15 other countries included in our sample. We also compute mean CFs—the average of the forecasts of changes in EPU obtained from the three predictive regression models—and examine their performance against the historical mean model.

A. Out-of-Sample Predictability Test Results for the United States

Table IX presents the out-of-sample predictability results for the United States. A positive OR^2 statistic indicates that the predictive regression model outperforms the historical average model. The *p*-value testing the null hypothesis $OR^2 \leq 0$ against the alternative hypothesis $OR^2 > 0$ is reported under the column $MSFEA$. The evidence of out-of-sample predictability at longer horizons (12 and 24 months) is very strong. Two predictors (CMKT and CCON) predict changes in EPU at both 12- and 24-month horizons. The variable CMKT is the most popular out-of-sample predictor, predicting changes in EPU at horizons of six, 12, and 24 months. There is no evidence that the CBCK-based predictive regression model beats the historical average model. The CFs reported in the last row yield statistically significant and economically sizable OR^2 values of 2.08% and 1.06% at horizons of 24 and six months, respectively. The out-of-sample forecasts for the United States match reasonably well with the in-sample forecasts, the exception being a lack of out-of-sample evidence for the predictor CBCK.

INSERT TABLE IX

B. Out-of-Sample Predictability Test Results for Other Countries

We now consider the predictability of changes in EPU for other countries reported in Table X. Panels A to C report the predictability results with CMKT, CBCK, and CCON as predictors, respectively. The performance of the CF model against the historical average model is reported in Panel D. Our key findings from this table are summarized as follows:

- The variable CMKT the most popular out-of-sample predictor. For six countries (Canada, Brazil, China, Australia, Spain, and the Netherlands), the CMKT-based predictive regression model outperforms the historical average model at the horizon of 24 months. Further, it predicts changes in EPU for five (two) countries at the horizon of 12 (six) months. There is no evidence that CMKT predicts changes in EPU at the horizon of three months. The CMKT-based predictive regression model yields relatively high and statistically significant OR^2 statistics that range between 0.29% and 7.55%.
- The variable CBCK turns out to be the weakest predictor. It predicts the changes in EPU for four countries (Canada at three- and 12-month horizons; Brazil at six-, 12-, and 24-month horizons; the Netherlands at the three-month horizon; and Spain at the six-month horizon). This is the only predictor that reveals out-of-sample predictability at the three-month horizon. In turn, CCON predicts changes in EPU for four countries at the 24-month horizon, for three countries at the 12-month horizon, and for two countries at the six-month horizon.
- Out-of-sample predictability is strongest for the 24- and 12-month horizons. This is followed by evidence of out-of-sample predictability at the horizon of six months. The CF model also reveals strong evidence of predictability at the 24-month horizon. The CF model beats the historical average model for four countries at the 24-month horizon and for three countries at the 12- and six-month horizons. The OR^2 statistics from the CF model are statistically significant and economically sizable, ranging from 1.71% for Spain to 6.22% for Brazil.
- The changes in the EPU of two countries (Brazil and Canada) are the most predictable. All three predictors reveal evidence of out-of-sample predictability for at least two of the four horizons. For Brazil, evidence of out-of-sample predictability is statistically

significant at the six-, 12-, and 24-month horizons. For Canada, all three predictors beat historical average forecasts at 12- and six-month horizons, respectively. These are also the countries that are predictable using the CF model.

- The changes in EPU of four countries (Australia, China, Italy, and Spain) show limited evidence of out-of-sample predictability, having only two predictors supporting predictability for at least one of the four horizons. Nonetheless, the CFs improve the forecasting performance for three countries, China, Italy, and Spain. For the Netherlands, only one predictor beats the historical average model at the three- and 24-month horizons.
- Seven countries (France, Japan, South Korea, Germany, Russia, the United Kingdom, and India) have the weakest evidence of predictability. The OR^2 statistics for these countries are statistically insignificant at all horizons.

INSERT TABLE X

There are three key findings arising from the in-sample and out-of-sample analyses. First, CMKT turns out to be the most popular predictor in both in-sample and out-of-sample tests, while CBCK, the second most popular predictor, turns out to be the weakest predictor out of sample. Second, changes in the EPU of two countries (United States and Canada) are the most predictable both in sample and out of sample. The strong evidence of predictability for changes in the EPU of Australia in sample transpire to limited evidence out of sample, while the reverse is true for changes in the EPU of Brazil. There is no evidence that any of the predictors predict changes in the EPU of Japan and Russia in both in-sample and out-of-sample tests. For five countries (France, South Korea, Germany, the United Kingdom, and India), there is no evidence of predictability out of sample. Our final point is that the strong evidence of in-sample predictability at the long horizon of 24 months holds in out-of-sample tests as well. The CF model also reveals strong evidence of predictability at the 24-month horizon. Therefore, the out-of-sample evidence largely corroborates the in-sample evidence.

VI. CONCLUSION

We undertake an extensive analysis to determine whether changes in EPU are predictable. We do this for the United States and as many as 14 other countries, which include other G7 countries and the BRIC countries. We consider three set of commodity futures market variables as predictors: the equal weighted average of futures excess returns, the excess return on a portfolio going long in 25% of the most backwardated commodities, and the excess return on a portfolio going short in 25% of the most contango commodities. Our analysis unveils a number of new findings. First, the signs of the coefficients for all countries are consistent, in that the equal-weighted averages of futures returns and returns on a portfolio of backwardated commodities positively predict changes in EPU, while returns on a portfolio of contango commodities negatively predict changes in EPU. Second, an equal-weighted average of futures returns is the most popular predictor. It predicts changes in EPU for 50% (eight out of 16) of the countries at the six- and 24-month horizons and for at least 37% of the countries at the three- and 12-month horizons. Third, the evidence of predictability is strong at longer horizons. Our findings are robust to the exclusion of crude oil from the sample and to the inclusion of macroeconomic variables in the regression. The out-of-sample forecast results broadly corroborate the in-sample evidence of predictability. In addition, CFs reveal evidence of predictability at longer horizons.

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Table I: Sample period of economic policy uncertainty index

This table reports the sample period of monthly economic policy uncertainty index data. We use 15 countries in our analysis. The sample period of economic policy uncertainty data varies by country and is dictated by data availability.

Country/Region	Code	Start date	End date
United States	US	1985:01	2015:06
Canada	CAN	1985:01	2015:06
France	FRA	1987:01	2015:06
Japan	JAP	1988:06	2015:06
South Korea	SK	1990:01	2015:06
Brazil	BRL	1991:01	2015:06
Germany	GER	1993:01	2015:06
Russia	RUS	1994:01	2015:06
China	CHN	1995:01	2015:06
United Kingdom	UK	1997:01	2015:06
Italy	ITA	1997:01	2015:06
Australia	AUS	1998:01	2015:06
Spain	SPA	2001:01	2015:06
India	IND	2003:01	2015:06
Netherlands	NET	2003:03	2015:06

Table II: Descriptive statistics

This table reports the selective descriptive statistics for the three predictor variables (CMKT, CBCK, and CCON), and for the changes in economic policy uncertainty of 15 countries. ρ refers to the autoregressive coefficient; AR (p) refers to the autocorrelation in the squared variable at lag p; and ARCH (q) refers to a Lagrange multiplier test of the zero slope restriction in an ARCH regression of order q.

	Mean	SD	ρ	AR(4)	AR(8)	ARCH(4)	ARCH(8)
CMKT	0.2717	3.4053	0.0107	0.0000	0.0000	0.0000	0.0000
CBCK	0.7460	4.8304	0.1175	0.1400	0.1140	0.2297	0.2017
CCON	0.0529	4.1601	-0.0069	0.0000	0.0000	0.0001	0.0001
US	1.2155	16.9705	0.8409	0.9180	0.9960	0.9761	0.9974
CAN	5.3728	35.8612	0.7851	0.8670	0.9670	0.1389	0.3845
FRA	9.3439	50.5162	0.7894	0.8140	0.5520	0.1412	0.2865
JAP	5.0428	32.2624	0.5806	0.4530	0.7130	0.6322	0.3602
SK	8.2787	50.0153	0.7226	0.0000	0.0000	0.0004	0.0000
BRL	15.4565	71.1121	0.5441	0.9080	0.2130	0.6335	0.0386
GER	8.6920	46.5928	0.6113	0.8270	0.9330	0.5936	0.6833
RUS	20.6645	80.0027	0.6285	0.0000	0.0020	0.2040	0.4519
CHN	18.8297	81.5665	0.6643	0.8840	0.9940	0.8206	0.9808
UK	5.2127	32.5913	0.8900	0.5620	0.0990	0.4004	0.7874
ITA	5.2891	35.2303	0.6086	0.9650	0.9940	0.3183	0.7606
AUS	7.5628	43.4658	0.7316	0.5220	0.7280	0.8077	0.7560
SPA	10.4236	56.5118	0.6509	0.9920	1.0000	0.9220	0.9815
IND	7.8865	43.5908	0.7209	0.0000	0.0000	0.6362	0.3434
NET	17.6012	71.3764	0.4113	0.9780	0.9990	0.7582	0.9781

Table III: Endogeneity tests

This table reports the endogeneity test results. We report the coefficient (γ) and the corresponding p-value from Equation (3). The predictor variable is deemed endogenous if γ is statistically different from zero.

Countries	CMKT	CBCK	CCON
US	-0.6962 (0.0074)	-0.5346 (0.0038)	0.2968 (0.1644)
CAN	-1.1588 (0.0354)	-1.1885 (0.0023)	0.4804 (0.2865)
FRA	0.5138 (0.5210)	-0.2667 (0.6475)	-1.2269 (0.0614)
JAP	-0.6786 (0.1963)	-0.4989 (0.1954)	0.6417 (0.1417)
SK	-1.5370 (0.0662)	-1.4131 (0.0212)	0.5075 (0.4669)
BRL	-1.4109 (0.2383)	-0.2236 (0.7999)	0.7188 (0.4701)
GER	-1.1619 (0.1434)	-0.3022 (0.6056)	0.4717 (0.4769)
RUS	-0.8497 (0.5376)	-0.3660 (0.7192)	0.3167 (0.7853)
CHN	-0.2234 (0.8747)	-1.3821 (0.1854)	-1.0245 (0.3977)
UK	-0.9723 (0.0886)	-0.6225 (0.1456)	0.1524 (0.7572)
ITA	-0.1469 (0.8120)	-0.7561 (0.1018)	0.4281 (0.4184)
AUS	-2.1706 (0.0046)	-1.4741 (0.0115)	1.4047 (0.0337)
SPA	-1.4458 (0.0713)	-2.0025 (0.0140)	0.9401 (0.3210)
IND	-0.8161 (0.3322)	-0.8530 (0.2033)	-0.2462 (0.7556)
NET	0.1495 (0.9143)	-1.1037 (0.3294)	-1.1971 (0.3552)

Table IV: In-sample predictability results for changes in EPU of the United States

This table reports the in-sample predictability test results for changes in economic policy uncertainty of the United States. We use three predictors, namely, equal-weighted commodity futures excess returns (CMKT), excess return on a portfolio going long in 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in 25% most contango commodities (CCON). We employ the Westerlund and Narayan (2012, 2015) FQGLS-based t-statistic for testing $\beta = 0$. The estimation covers the sample period January 1985–June 2015. Panel A reports the results on the null hypothesis of no predictability with predictors computed using all the 27 commodities in the sample. Panel B reports the predictability test results with predictors computed by excluding crude oil. Panel C reports the results for the predictive regression model augmented by five macroeconomic variables (industrial production growth rate, default spread, term spread, changes in expected and unexpected inflation). The coefficient on beta, its t-statistic, and R^2 are reported in each panel.

	$h=3$			$h=6$			$h=12$			$h=24$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
Panel A: All commodities												
CMKT	-0.2284	-3.1301	0.0268	-0.2609	-3.5774	0.0352	-0.3004	-4.1310	0.0464	-0.3414	-4.6480	0.0601
CBCK	-0.1667	-2.3869	0.0156	-0.1604	-2.2926	0.0160	-0.2065	-2.9428	0.0241	-0.2000	-2.6862	0.0209
CCON	0.1203	1.6060	0.0071	0.2153	2.8811	0.0233	0.2698	3.6146	0.0360	0.3507	4.6440	0.0598
Panel B: All commodities except WTI crude oil												
CMKT	-0.2115	-2.8723	0.0230	-0.2555	-3.4720	0.0336	-0.2961	-4.0343	0.0443	-0.3358	-4.5520	0.0579
CBCK	-0.1353	-1.9034	0.0100	-0.1572	-2.2130	0.0148	-0.1783	-2.4946	0.0175	-0.2002	-2.7160	0.0214
CCON	0.1547	2.0729	0.0119	0.2706	3.6547	0.0368	0.3009	4.0629	0.0451	0.3326	4.4161	0.0544
Panel C: Model augmented by macroeconomic variables												
CMKT	-0.2020	-2.4195	0.0537	-0.2408	-2.9871	0.1263	-0.2635	-3.5066	0.2451	-0.2874	-4.4627	0.4713
CBCK	-0.1403	-1.8268	0.0472	-0.1786	-2.4130	0.1192	-0.2074	-2.9866	0.2381	-0.2185	-3.5464	0.4601
CCON	0.0739	0.9544	0.0405	0.1433	1.9137	0.1135	0.1836	2.6240	0.2331	0.2202	3.6269	0.4609

Table V: In-sample predictability results for changes in EPU of other countries

This table reports the in-sample predictability test results for changes in economic policy uncertainty of the countries listed in the first column. We use three predictors, namely, commodity futures excess returns (CMKT), excess return on a portfolio going long in the 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in the 25% most contango commodities (CCON). We employ the Westerlund and Narayan (2012, 2015) FQGLS-based t-statistic for testing $\beta = 0$. The predictive regression model is augmented by five macroeconomic variables (industrial production growth rate, default spread, term spread, changes in expected and unexpected inflation). The sample period of estimation varies by country and is reported in Table I.

	$h = 3$			$h = 6$			$h = 12$			$h = 24$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
Panel A: CMKT												
CAN	-0.2458	-3.0200	0.0986	-0.2147	-2.6957	0.1502	-0.3854	-5.1214	0.2436	-0.3299	-4.6313	0.3527
FRA	-0.0965	-1.1044	0.0253	-0.0598	-0.6878	0.0500	-0.0550	-0.6455	0.0986	-0.0864	-1.0961	0.2689
JAP	-0.0478	-0.5283	0.0286	0.0602	0.6725	0.0459	-0.0807	-0.9223	0.1055	-0.1257	-1.4089	0.0832
SK	-0.0940	-1.0213	0.0219	-0.1710	-1.8730	0.0521	-0.3069	-3.4658	0.1347	-0.1573	-1.7253	0.1245
BRL	-0.1356	-1.4355	0.0288	-0.0685	-0.7192	0.0255	-0.1301	-1.3618	0.0429	-0.2067	-2.1958	0.0863
GER	-0.2066	-2.1440	0.0312	-0.2907	-3.0603	0.0843	-0.0973	-1.0365	0.0859	-0.2448	-2.7873	0.2486
RUS	-0.2956	-3.0924	0.0855	-0.0573	-0.5857	0.0423	-0.0918	-0.9159	0.0220	-0.0019	-0.0192	0.0222
CHN	-0.1267	-1.2720	0.0382	-0.0087	-0.0878	0.0421	-0.1945	-2.0657	0.1505	-0.0893	-0.9319	0.1380
UK	-0.1136	-1.1356	0.0679	-0.0563	-0.5679	0.0852	-0.1134	-1.2156	0.2006	-0.0451	-0.5846	0.5011
ITA	-0.1183	-1.1874	0.0636	-0.2037	-2.1403	0.1617	-0.1608	-1.7547	0.2286	-0.0138	-0.1609	0.3821
AUS	-0.3085	-3.0413	0.0616	-0.1657	-1.6149	0.0553	-0.1534	-1.5537	0.1777	-0.2533	-3.6893	0.6106
SPA	-0.1823	-1.5656	0.0374	-0.1854	-1.6867	0.0325	0.0504	0.4612	0.0783	-0.1604	-1.6210	0.2757
IND	-0.0489	-0.4306	0.0299	-0.2182	-1.6251	0.0523	-0.2094	-1.9517	0.1751	-0.2037	-2.4185	0.5367
NET	-0.3748	-3.4698	0.1427	-0.1754	-1.7026	0.2302	-0.0620	-0.7112	0.4620	0.0482	0.4617	0.2881
Panel B: CBCK												
CAN	-0.1610	-2.1434	0.0858	-0.0915	-1.2475	0.1372	-0.2145	-3.0339	0.2108	-0.2219	-3.2391	0.3323
FRA	0.0071	0.0856	0.0221	-0.0305	-0.3722	0.0489	-0.0502	-0.6131	0.0997	0.0246	0.3242	0.2659
JAP	-0.0659	-0.7671	0.0298	0.0260	0.3031	0.0449	-0.0883	-1.0538	0.1077	-0.2384	-2.7966	0.1025
SK	-0.1057	-1.1922	0.0243	-0.1168	-1.3288	0.0471	-0.2062	-2.4016	0.1160	-0.1996	-2.2935	0.1331
BRL	-0.0530	-0.5798	0.0235	-0.0310	-0.3370	0.0209	-0.0691	-0.7496	0.0351	-0.1473	-1.6190	0.0714
GER	-0.1279	-1.3760	0.0212	-0.2350	-2.5631	0.0746	-0.0755	-0.8346	0.0844	-0.1740	-2.0266	0.2282

Continued Overleaf

Table V: Continued

	$h=3$			$h=6$			$h=12$			$h=24$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
Panel B continued: CBCK												
RUS	-0.2524	-1.6331	0.0840	-0.0369	-0.3892	0.0416	-0.0696	-0.7215	0.0255	-0.0282	-0.2892	0.0207
CHN	-0.1086	-1.1326	0.0427	-0.0114	-0.1188	0.0432	-0.1263	-1.3827	0.1405	-0.0592	-0.6324	0.1387
UK	-0.0775	-0.7881	0.0593	-0.0295	-0.3002	0.0841	-0.0191	-0.2031	0.1827	-0.0078	-0.1024	0.4949
ITA	-0.1749	-1.8029	0.0718	-0.1446	-1.5085	0.1311	-0.1609	-1.7572	0.2240	0.0081	0.0961	0.3771
AUS	-0.2345	-2.3054	0.0491	-0.1628	-1.6028	0.0553	-0.0943	-0.9671	0.1715	-0.2479	-3.5523	0.6101
SPA	-0.2193	-1.9352	0.0607	-0.1948	-1.6876	0.0280	0.0811	0.6984	0.0767	-0.1500	-1.4258	0.2755
IND	0.0193	0.1568	0.0211	-0.1100	-0.8877	0.0319	-0.2278	-1.9403	0.1710	-0.1304	-1.3692	0.5203
NET	-0.3771	-3.2030	0.1295	-0.1548	-1.3986	0.2425	-0.0913	-0.9703	0.4744	0.0344	0.2957	0.2881
Panel C: CCON												
CAN	0.0647	0.8540	0.0793	0.1364	1.8475	0.1408	0.2539	3.5861	0.2155	0.1651	2.4264	0.3227
FRA	0.0090	0.1104	0.0217	0.0268	0.3308	0.0535	0.0339	0.4252	0.1021	0.0289	0.3910	0.2650
JAP	-0.0058	-0.0681	0.0273	-0.1022	-1.2190	0.0474	0.0984	1.2050	0.1073	0.1272	1.5239	0.0843
SK	0.0003	0.0038	0.0175	0.0813	0.9353	0.0416	0.2072	2.4659	0.1095	0.1093	1.2925	0.1176
BRL	0.0770	0.8776	0.0254	0.0635	1.7192	0.0196	0.1239	1.4097	0.0401	0.1708	1.9570	0.0752
GER	0.1323	1.4720	0.0241	0.1881	2.1128	0.0686	0.0443	0.5002	0.0842	0.1483	1.7652	0.2337
RUS	0.2879	3.2064	0.0878	0.0799	0.8596	0.0438	0.0061	0.0642	0.0190	-0.1307	-1.3707	0.0339
CHN	-0.0557	-0.5885	0.0318	-0.0245	-0.2589	0.0371	0.0924	1.0281	0.1434	-0.0256	-0.2808	0.1337
UK	0.0538	0.5661	0.0595	-0.0102	-0.1089	0.0844	0.0653	0.7253	0.1692	0.0406	0.5452	0.4955
ITA	-0.0187	-0.1977	0.0583	0.1051	1.1614	0.1548	0.1079	1.2391	0.2243	-0.0926	-1.1327	0.3862
AUS	0.1672	1.7092	0.0299	0.0092	0.0943	0.0437	0.0641	0.6720	0.1671	0.1583	2.3264	0.5897
SPA	0.0715	0.6569	0.0238	0.0951	0.8646	0.0194	-0.1252	-1.1625	0.0843	-0.0027	-0.0259	0.2640
IND	-0.0837	-0.7136	0.0260	0.0057	0.0473	0.0268	0.0204	0.1802	0.1448	0.2646	3.1123	0.5440
NET	0.2501	2.1647	0.0972	0.0360	0.3302	0.2112	0.1470	1.6566	0.4765	0.0204	0.1918	0.2891

Table VI: In-sample predictability results for two sub-samples for the United States

This table reports the in-sample predictability test results for changes in economic policy uncertainty of the United States for two sub-samples: the pre-financialization period (January 1985–December 2000) and the post-financialization period (January 2001–June 2015). We use three predictors, namely, commodity futures excess returns (CMKT), excess return on a portfolio going long in the 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in the 25% most contango commodities (CCON). We employ the Westerlund and Narayan (2012, 2015) FQGLS-based *t*-statistic for testing $\beta = 0$.

	Panel A: Pre-financialization period					
	$h = 3$			$h = 6$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
CMKT	-0.0562	-0.5233	0.0049	-0.2023	-1.8709	0.0189
CBCK	0.0374	0.3897	0.0026	-0.0854	-0.8874	0.0070
CCON	0.0949	0.8997	0.0061	0.1819	1.7112	0.0171
	$h = 12$			$h = 24$		
CMKT	-0.0562	-0.5233	0.0049	-0.2023	-1.8709	0.0189
CBCK	0.0374	0.3897	0.0026	-0.0854	-0.8874	0.0070
CCON	0.0949	0.8997	0.0061	0.1819	1.7112	0.0171
	Panel B: Post-financialization period					
	$h = 3$			$h = 6$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
CMKT	-0.3251	-3.1736	0.0559	-0.2937	-2.8550	0.0471
CBCK	-0.3373	-3.3493	0.0620	-0.2238	-2.1855	0.0291
CCON	0.1332	1.2338	0.0093	0.2325	2.1803	0.0320
	$h = 12$			$h = 24$		
CMKT	-0.2885	-2.7915	0.0440	-0.3821	-3.7584	0.0767
CBCK	-0.1817	-1.7594	0.0190	-0.2449	-2.3867	0.0325
CCON	0.2926	2.7509	0.0428	0.4178	4.0175	0.0867

Table VII: In-sample predictability using commodity sector returns as predictors

This table reports the in-sample predictability test results for changes in economic policy uncertainty of the United States using commodity sector returns as predictors. We use six commodity sector returns as predictors, namely, energy, food stuffs, grains and oil seeds, industrials, livestock and meats, and metals. Sector returns are computed as the equal-weighted average of futures returns of all commodities in a sector. We employ the Westerlund and Narayan (2012, 2015) FQGLS-based *t*-statistic for testing $\beta = 0$. The estimation covers the sample period January 1985–June 2015. We report the coefficient on beta, its *t*-statistic and R^2.

	$h = 3$			$h = 6$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
Energy	-0.1235	-1.4328	0.0493	-0.1020	-1.2212	0.1098
Food stuffs	0.0130	0.1698	0.0386	0.0304	0.4079	0.1055
Grains and oilseeds	-0.0947	-1.2352	0.0422	-0.2215	-3.0214	0.1269
Industrials	-0.2145	-2.6753	0.0579	-0.1761	-2.2718	0.1182
Livestock and meats	-0.1264	-1.6784	0.0475	-0.0567	-0.7752	0.1088
Metals	-0.0735	-0.9388	0.0431	-0.0692	-0.9107	0.1067
	$h = 12$			$h = 24$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
Energy	-0.1514	-1.9351	0.2263	-0.1029	-1.4316	0.4431
Foodstuffs	-0.0391	-0.5578	0.2202	-0.0369	-0.5951	0.4404
Grains and oilseeds	-0.1196	-1.7210	0.2244	-0.2264	-3.8753	0.4639
Industrials	-0.2581	-3.5943	0.2461	-0.1927	-3.1084	0.4554
Livestock and meats	-0.2123	-3.0827	0.2388	-0.1416	-2.3130	0.4484
Metals	-0.1010	-1.4217	0.2228	-0.0983	-1.5944	0.4443

Table VIII: In-sample predictability results for three categories of EPU for the United States

This table reports the in-sample predictability test results for the three categories of EPU, namely, the monetary policy uncertainty (MPU), the fiscal policy uncertainty (FPU), and the trade policy uncertainty (TPU). Here, our dependent variables in predictive regression model are the changes in MPU, FPU, and TPU of the Unites States, respectively. We use the same predictors, namely, commodity futures excess returns (CMKT), excess return on a portfolio going long in the 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in the 25% most contango commodities (CCON). We employ the Westerlund and Narayan (2012, 2015) FQGLS-based t-statistic for testing $\beta = 0$. The estimation covers the sample period January 1985–June 2015.

	$h = 3$			$h = 6$			$h = 12$			$h = 24$		
	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2	β	t_{FQGLS}	R^2
						CMKT						
MPU	-0.0283	-0.3833	0.0022	-0.0710	-0.9580	0.0026	-0.0433	-0.5822	0.0039	-0.3094	-4.1881	0.0493
FPU	0.0011	0.0148	0.0012	-0.0709	-0.9563	0.0027	-0.2655	-3.6320	0.0364	-0.2700	-3.6326	0.0375
TPU	0.0568	0.7680	0.0017	0.0253	0.3414	0.0016	0.0739	0.9955	0.0062	-0.0163	-0.2159	0.0016
						CBCK						
MPU	0.0267	0.3799	0.0054	-0.0391	-0.5552	0.0009	-0.0282	-0.3967	0.0015	-0.1795	-2.4069	0.0171
FPU	0.0164	0.2336	0.0031	-0.0190	-0.2692	0.0003	-0.1768	-2.5128	0.0190	-0.1835	-2.4611	0.0176
TPU	0.1014	1.4451	0.0058	0.0888	1.2647	0.0098	0.1396	1.5781	0.0136	0.0436	0.5797	0.0011
						CCON						
MPU	0.0050	0.0665	0.0008	0.0197	0.2607	0.0007	-0.0044	-0.0576	0.0020	0.2637	3.4466	0.0350
FPU	-0.0136	-0.1808	0.0002	0.0823	1.0900	0.0034	0.2280	3.0379	0.0257	0.2388	3.1091	0.0278
TPU	-0.1162	-1.5505	0.0067	-0.0512	-0.6782	0.0013	-0.0244	-0.3210	0.0047	-0.1341	-1.7309	0.0099

Table IX: Out-of-sample predictability results for the United States

	$h = 3$		$h = 6$		$h = 12$		$h = 24$	
	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$
CMKT	0.5014	0.1174	0.7090	0.0737	1.0106	0.0947	2.4757	0.0638
CBCK	0.1287	0.2786	0.7321	0.1106	-0.7517	0.3548	0.6794	0.1801
CCON	-0.4302	0.3752	0.5770	0.1219	1.5842	0.0714	1.7533	0.0390
CF	0.3346	0.1880	1.0622	0.0739	1.5050	0.1122	2.0804	0.0653

Notes: This table reports the out-of-sample predictability results for the United States. The out-of-sample forecasts of the traditional predictive regression model are compared against the historical mean model for April 2000–June 2015 out-of-sample period. h-step ahead out-of-sample forecasts are generated recursively using three predictors, namely, equal-weighted commodity futures excess returns (CMKT), excess return on a portfolio going long in the 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in the 25% most contango commodities (CCON). We also compute the forecast performance of combination forecasts (CF) which is the mean of forecasts from three individual predictive regression models. We report two forecast evaluation metrics, namely, Campbell-Thompson (2008) out-of-sample R^2 (OR^2) and *p*-value corresponding to Clark-West (2007) $MSFE$–adjusted statistic.

Table X: Out-of-sample predictability results for other countries

This table reports the out-of-sample forecast performance of predictive regression model against the historical mean model for the countries mentioned in the first column. The out-of-sample period is 50% of the full sample data. h-step ahead out-of-sample forecasts are generated recursively using three predictors, namely, commodity futures excess returns (CMKT), excess return on a portfolio going long in the 25% most backwardated commodities (CBCK), and excess return on a portfolio going short in the 25% most contango commodities (CCON). We also compute the forecast performance of combination forecasts (CFs) reported in Panel D. We compute two forecast evaluation metrics, namely, Campbell-Thompson (2008) out-of-sample R^2 (OR^2) and the Clark-West (2007) $MSFE$–adjusted statistic.

	$h = 3$		$h = 6$		$h = 12$		$h = 24$	
	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$
				Panel A: CMKT				
CAN	-0.2396	0.1528	-0.4620	0.2799	6.8432	0.0132	3.6471	0.0187
FRA	-1.5124	0.9200	0.6613	0.1195	-1.1536	0.6156	-1.8554	0.8860
JAP	-0.0694	0.3748	-0.8596	0.8691	-1.8171	0.4446	-1.0362	0.2420
SK	-2.0396	0.7223	-2.1482	0.8124	1.4812	0.0785	-1.1356	0.8298
BRL	-2.2645	0.7729	3.6516	0.0027	2.9323	0.0686	2.3650	0.0006
GER	-0.4652	0.2329	0.2070	0.1792	-5.4818	0.6250	1.4297	0.1298
RUS	-3.7922	0.3784	-0.4156	0.3656	-1.7215	0.8688	-5.6512	0.7200
CHN	-4.2700	0.5644	-0.3124	0.7450	0.2988	0.0310	3.1925	0.0659
UK	-4.3399	0.9600	-1.6171	0.8232	-11.0442	0.7391	-0.4662	0.5117
ITA	-4.2548	0.5596	3.2095	0.0385	-2.5987	0.2930	-0.6694	0.2772
AUS	-0.9044	0.3375	-1.4278	0.4565	-8.6326	0.5260	3.3735	0.0990
SPA	-0.3560	0.1833	-0.1385	0.0832	3.0819	0.0962	7.5519	0.0075
IND	-5.6623	0.9830	-1.2005	0.6752	-3.0854	0.7386	-3.4012	0.7089
NET	1.7391	0.1700	-11.3559	0.3899	-25.9213	0.4459	1.8827	0.0797
				Panel B: CBCK				
CAN	0.9967	0.0335	-0.4544	0.6301	1.6732	0.0662	1.2449	0.1074
FRA	-1.5638	0.8324	0.5379	0.1766	-1.3534	0.9487	-1.5191	0.8220
JAP	0.5579	0.1545	-0.2491	0.7857	-0.5923	0.7052	-0.9701	0.1249
SK	-2.1789	0.7393	-2.6116	0.9636	-1.8315	0.8533	-3.6677	0.8693
BRL	-2.7989	0.8586	2.1680	0.0087	1.1171	0.0728	2.9918	0.0089
GER	-0.1263	0.3672	0.1359	0.2522	-0.7380	0.8632	0.4636	0.2030
RUS	-1.3404	0.5117	0.2036	0.2549	-1.2082	0.6044	-3.2281	0.8852
CHN	-0.3464	0.9153	-0.5541	0.9207	0.9756	0.1319	0.9811	0.1567
UK	-2.2654	0.7897	-0.7946	0.7917	-0.2078	0.3442	0.0646	0.3988
ITA	1.8108	0.0675	0.5995	0.1996	-0.4689	0.4218	0.1424	0.3255
AUS	0.1261	0.3087	0.3819	0.2315	-1.1843	0.6007	0.9984	0.1995
SPA	-4.0276	0.8996	2.8728	0.0675	-8.1086	0.8175	-1.4585	0.7653
IND	-3.3908	0.9762	-2.8129	0.9380	-0.5114	0.5242	-2.6312	0.7739
NET	3.6794	0.0439	-3.7639	0.2287	-20.8548	0.5132	-0.0127	0.3887

Continued Overleaf

Table X: Continued

	$h = 3$		$h = 6$		$h = 12$		$h = 24$	
	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$	OR^2	$MSFEA$
Panel C: CCON								
CAN	-4.6894	0.9826	-1.0907	0.5490	1.9246	0.0639	0.2810	0.0052
FRA	-1.0763	0.9801	0.6145	0.1144	-1.0222	0.3928	-0.2984	0.6482
JAP	-0.7715	0.8393	-0.8187	0.9690	-0.2308	0.2293	0.4155	0.1896
SK	-1.0433	0.9546	-0.0820	0.3091	1.2854	0.1115	0.0685	0.3401
BRL	-2.0056	0.9198	0.9377	0.0772	2.6479	0.0730	3.9052	0.0067
GER	-0.7498	0.2719	0.9413	0.1423	-2.3821	0.4170	-1.5494	0.6484
RUS	-0.7389	0.2951	-0.9024	0.8921	-0.6740	0.5819	0.1316	0.1686
CHN	-1.1745	0.7913	-0.1075	0.7007	0.9436	0.0150	-1.0496	0.6644
UK	-1.5648	0.9576	-0.7763	0.6495	-5.2035	0.6914	-0.8762	0.6013
ITA	-1.9084	0.7042	2.2478	0.0404	-0.2153	0.2439	0.4225	0.2676
AUS	-0.0839	0.2963	-0.6046	0.5702	-0.9060	0.3546	0.9233	0.0759
SPA	-0.3475	0.2299	-1.3671	0.1715	1.4823	0.1502	2.9216	0.0341
IND	-5.7306	0.9333	-2.1195	0.8845	-1.4281	0.4516	-8.3354	0.7005
NET	-3.3140	0.4116	-21.0123	0.9039	-35.2400	0.1840	-1.4384	0.4537
Panel D: CF								
CAN	-0.9066	0.5783	-0.4131	0.4193	4.3987	0.0244	1.9836	0.0397
FRA	-1.2763	0.9407	1.0309	0.1121	-0.8937	0.6222	-1.0835	0.8624
JAP	0.0372	0.3396	-0.5982	0.9418	-0.4546	0.3850	0.6300	0.1605
SK	-1.5497	0.7910	-1.4482	0.8563	0.9999	0.1420	-1.3665	0.8430
BRL	-2.1472	0.8637	2.6907	0.0036	2.4791	0.0620	6.2153	0.0012
GER	0.1491	0.2267	0.9165	0.1482	-1.9801	0.5591	0.2926	0.2900
RUS	-1.1070	0.3683	-0.0921	0.4156	-1.0126	0.7308	-2.3133	0.4935
CHN	-1.2440	0.6626	-0.3076	0.8362	2.1049	0.0315	2.5140	0.0912
UK	-2.6194	0.9397	-0.9137	0.8330	-4.3540	0.7178	-0.2381	0.5290
ITA	-0.8819	0.3998	3.2953	0.0399	0.0035	0.2884	0.4257	0.2431
AUS	0.0929	0.3043	-0.2662	0.3950	-2.4974	0.4850	2.7188	0.1013
SPA	0.0581	0.2813	1.7052	0.0934	0.0896	0.3571	5.1817	0.0078
IND	-4.6687	0.9793	-1.9255	0.9071	-1.3363	0.6058	-3.7608	0.7709
NET	1.7461	0.1575	-9.7350	0.5537	-20.7495	0.3256	0.5903	0.1827

Output Impacts of the Interaction between Foreign Direct Investment and Domestic Credit: Case Study of Pacific Island Countries

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ABSTRACT

In this paper we examine the link among foreign direct investment (FDI), domestic credit expansion, and economic growth for six Pacific Island countries. Using data over 1982-2011, we relate the interaction between domestic credit to private sector and FDI and its impacts on output. With employment of cointegration analyses and the generalized methods of moments estimator, our empirical analyses show that FDI and domestic credit to private sector serve as substitutes to promote output in Fiji, Papua New Guinea and Tonga; they are complementary in enhancing output in Samoa, Solomon Islands and Vanuatu.

Key words: foreign direct investment, domestic credit, output, Pacific Island countries

1. Introduction

It is argued that foreign direct investment and level of financial development are among the most important variables the empirical economic literature suggests as being highly correlated with economic growth across countries. There are several studies (such as Odhiambo, 2008; Wolde-Rufael, 2009; Minea and Villieu, 2010; Hsueh et al., 2013; Uddin et al., 2013; Uddin, et al., 2014; Narayan and Narayan, 2013; Mishra and Narayan, 2015) that examine the impact of financial sector on economic growth and find that finance sector expansion has a positive effect on economic growth. Similarly, many studies (such as Tekin, 2012; Fedderke and Romm, 2006; Herzer et al., 2008; Azman-Saini et al., 2010; Ahmed, 2012; Feeny et al., 2014; Iamsiraroj and Ulubasoglu, 2015) examine FDIs impact on economic growth and generally find positive effect of FDI on economic growth.

More recently, some studies examine the interaction between FDI and financial sector development and its interactive effect on economic growth. However, these studies suggest two widely different views regarding the nature of interactive effect on economic growth. Some studies (such as Anwar and Cooray, 2012; Alfaro et al., 2003; Hermes and Lensink, 2003; Choong et al., 2004; Durman, 2004; Choong et al., 2005; Alfaro et al., 2009; Lee and Chang, 2009; Choong et al., 2010; Suliman and Elian, 2014) suggest that financial sector development and FDI play a complementary role in promoting economic growth and therefore interactive effect is positively related with economic growth. In contrast, studies such as Rebelo and Vegh (1995), Gourinchas et al. (2001), Tornell and Westermann (2002), Mendoza and Terrones (2008), Reis (2013), Converse (2014), Benigno and Fornaro (2014) and Benigno, Converse and Fornaro (2015); Rajan and Zingales (2001) and Hsu et al. (2014) suggest that FDI and domestic credit play a substitution role in promoting economic growth, hence the interactive effect is likely to be negative. Particularly, in economies with limited investment opportunities and small market, inflow of foreign direct investment is likely to displace domestic investment and direct domestic credit to less productive activities such as consumption and hence it retard returns of domestic credit lending.

While a number of studies examined effects of domestic credit, FDI and their interactive effect on output in developed and developing countries, there is none that examined the interactive effect in Pacific Island countries (PICs). Therefore, this paper examines these relationships in six PICs using time series analyses. We believe that impacts of foreign direct investment, domestic credit and their interactive effect on economic performance in PICs cannot be assumed to be the same as those for other countries. PICs, which are characterized by their smallness, remoteness, limited economic structure, lacks of investment opportunities and markets, are increasingly becoming difficult for doing business (AusAid, 2008; World Bank, 2011). Limited investment opportunities can lead to excessive competition between excessive FDI and domestic credit; thereby divert domestic credit to less productive activities and consequently reduce their effectiveness on output. On the other hand, PICs are also significantly different from each other in terms of their level of economic development (Narayan et al., 2013). This may suggest that FDI and domestic credit’s interactive effect on output may also vary within Pacific Island countries, depending on the level of financial development and absorption capacity of each country. Therefore, in order to improve our understanding of output effects of FDI, domestic credit and their interaction in PICs, it is essential to perform studies on individual countries.
Rest of the paper is organized as follows: Section 2 surveys relevant literature; Section 3 presents the model and data; Section 4 describes methodologies and empirical findings; and Section 5 concludes.

2. Literature Review

Domestic credit and foreign direct investment are two important alternative sources of finance of capital investment funds to finance investment opportunities in the host countries. Therefore, impacts of foreign direct investment and domestic credit on economic growth have been extensively investigated in the finance and growth literatures; different lines of thoughts and empirical evidence have been postulated.

One line of studies evaluates impact of domestic credit on economic growth while excluding FDI in the model. These studies generally believe that domestic credit is supply-leading, in the sense that it fosters economic growth by acting as productive input (Schumpeter, 1934; McKinnon, 1973; Shaw, 1973; Galbis, 1977; Fry, 1978; Goldsmith, 1969; Greenwood and Jovanovic, 1990; Thakor, 1996; Hicks, 1969).

A second line of studies examines impact of FDI without considering the influence of domestic credit's impact on economic growth. These studies argue that FDI provides important source of external finance, promote productivity gains, technology transfer, introduction of new processes, skill transfer, and better market network (Amsden, 2011; Algaro et al., 2004; Farla et al, 2014; Crespo and Fontoura, 2007; Gui-Diby, 2014).

More recently, a few studies have looked at growth effect of interaction between FDI and financial sector development; however, they fail to produce conclusive view. There are two alternative views for understanding the interactive relationship between credit expansions (quality of financial intermediation) and FDI benefits. First view proposed by Alfaro et al. (2003) contends that well developed financial system promotes impact of FDI in the host economy. According to this view an economy is consisted of two sectors, namely foreign production sector and domestic production sector. A continuum of agents indexed by their availability can either choose to work for foreign firms or alternative establish and work for their own firms subject to setup cost. Efficient financial markets are characterized by ease of access to credit for businesses and household. Such system allows more entrepreneurs to take advantage of benefits from FDI and magnifies the effect of FDI. Similarly, Hermes and Lensink (2003) and Choong et al. (2004) argue that, since financial system promotes efficient allocation of resources and enhances absorption capacity with respect to FDI inflows, economies with well-developed financial system will be able to reap greater and positive benefit from FDI. Alfaro et al. (2009) further suggest that countries with weaker financial sector lack absorption capacity to benefit from advantages of FDI. Empirically, Durman (2004) finds that deeper financial system promoted impact of FDI on growth in a sample of 80 countries over the period 1979-1998. Choong et al. (2005) find that financial sector played a key role in enhancing impact of FDI in case of Malaysia over the period 1970-2001. Lee and Chang (2009) observe that financial development positively enhanced impact of FDI on economic growth in a sample of 37 countries over the period 1970-2002. Choong et al. (2010) observe positive influence of financial sector development on impact of FDI in a sample of 16 low income countries over the period 1988-2006. More recently, Suliman and Elian (2014) argue that financial sector development effectively contributes to resource allocation to higher return investment and thus it facilitates greater exploitation of FDI resources; they find that well-functioning financial sector substantially enhanced FDI's impact in Jordon over the period 1980-2009.

On the contrary, another school of thoughts argue that, foreign capital inflow to non-financial sector of the host country can crowd out the benefits of domestic credit expansion especially in economies with limited investment opportunities. According to this view, domestic credit and FDI compete for limited investment opportunities; therefore, it is possible that a large portion of productive activities in such economies are financed by foreign capital and thus domestic financial intermediaries are forced to provide credit to less productive activities – largely to finance household activities. See, for instance, Rebelo and Vegh (1995), Gourinchas et al. (2001), Tornell and Westermann (2002), Mendoza and Terrones (2008), Reis (2013), Converse (2014), and Benigno and Fornaro (2014). McMillan and Rodrik (2011) further argue that shift in domestic credit from productive to less productive activities is detrimental to economic growth. Empirically, Benigno, Converse and Fornaro (2015) observe that capital inflows contributed to resource shift from productive to less productive sector which diminished economic performance in a sample of 70 countries over a 35-year period. Accordingly, Rioja and Valev (2004) suggest that once an economy reaches a significant high level of financial development, FDI needs to be gradually reduced since domestic investment is sufficient to sustain economic growth.

In the context of Pacific Island countries, small Pacific Island economies relied heavily on FDI to finance their investment following their independence. FDI provided major sources of funding for infrastructure and business development in these countries. FDI continues to provide substitute for domestic bank credit to non-financial firms as foreign capital cost is lower than domestic bank lending; however, since these economies are faced with limited absorption capacity, FDI and domestic credit compete to finance limited productive activities. Nonetheless, substitution effect from FDI does not mean a decline in domestic credit. Financial development and liberalization cause substantial flows of domestic credit into the banking system, which lowers financial constraints faced by domestic firms. Coincidently, domestic banks are forced to diversify increasing volume of credit to households. Based on the above survey, we hypothesize that magnitude of FDI impact on domestic output is reduced with simultaneous increase in FDI and domestic credit expansion.

3. The Model and Data

In Pacific Island countries, FDI played an important role in promoting economic growth in early decades when these countries lacked capital, modern technology and advanced management. In the financial market, FDI provided financial source to supplement insufficient credit in these economies. However, when domestic credit developed to certain level, FDI may start to crowd out domestic credit in small island economies given these small economies' limited absorption capacity. Such interaction may lead to FDI's non-linear impacts on output.

The empirical model to assess FDI's economic growth, with incorporation of FDI's crowding-out domestic credit effect, in Pacific Island countries takes the following time series structure:

$$Y_t = \beta_0 + \beta_1 I_t + \beta_2 F_t + \beta_3 C_t + \beta_4 F_t C_t + \sum \gamma_j D_{j,t} + \varepsilon_t \qquad (1)$$

where new notations

Y_{it} = natural logarithm of real GDP per capita (US$);
I_{it} = natural logarithm of investment per capita (US$);
C_{it} = domestic credit to private sector (% of GDP);
F_{it} = foreign direct investment (% of GDP);
$F_{it}C_{it}$ = interaction between FDI ratio and domestic credit ratio; and
$D_{j,t}$ = a vector of dummy variables to capture effects of structural breaks.

According to the World Bank, FDI is not necessarily included in gross fixed capital formation. Therefore using I_{it} and F_{it} simultaneously in the above model doesn't impose multicollinearity problem is estimation, which is confirmed by the coefficient of correlation between the two variable as small as -0.034.

Explanatory variables in Equation (1) and their expected roles in Pacific Island countries' economic development are described as follows:

1) Investment per capita ('I_{it}')
Investment per capita (in natural logarithm) is used to measure increment in physical capital input. Investment is positively associated with long-run output. Data on investment and the dependent variable real GDP per capita are obtained from United Nations National Accounts Main Aggregates database.

2) FDI ('F_{it}')
FDI should promote output since it supplements domestic credit and brings to recipient countries advanced technology and management. However, FDI's positive impact may be complicated by its effect of crowding out domestic credit. Nonetheless, FDI itself should remain positive contribution to recipient countries' output and output growth if such crowding-out is controlled for. Data on FDI are obtained from International Debt Statistics (2014).

3) Domestic credit to private sector ('C_{it}')
Domestic credit is measured by domestic credit to private sector as percent of GDP. As a measure of financial deepening, domestic credit is an efficient fund source to domestic investment, and therefore should be positively associated with output. However, domestic credit to private sector's impact is complicated by competition from foreign capital. Data on domestic credit to private sector are obtained from World Bank's Global Financial Development database.

4) Interaction between FDI and domestic credit ('$F_{it}C_{it}$')
We hypothesize that FDI and domestic credit compete in small economies if they grow beyond individual countries' absorption capacity. If this holds, simultaneous increases in FDI and domestic credit beyond certain levels would lead to inefficient use of financial sources and therefore hinder economic development.
If the above hypothesis holds, this interaction term will enable us to identify turning points of FDI's marginal effect on output. Furthermore, different PICs might have different turning points given their heterogeneity. For this, we further consider interacting $F_{it}C_{it}$ with country-specific but time-invariant country dummy variables. These turning points in turn serve as benchmarks under which FDI supplements domestic credit and beyond which FDI crowds out domestic credit in respective countries.

Note that since this interactive term captures effects of the two variables moving in same directions, it is not necessary to separate trend component from cyclical component for each factor.

5) Structural breaks ('$D_{j,t}$')
Political instability such as military coups may impose structural breaks to small states such as Fiji and Papua New Guinea. These structural breaks can be addressed by using dummy variables. In addition, cyclones and typhoons are major natural disasters in the South Pacific region, bringing devastating damages to the small island economies in the region. Information on occurrence of natural disasters and their damages to lives and economies is obtained from Centre for Research on the Epidemiology of Disasters (CRED). Dummy variables are generated based on the affected population-to-total

population ratio. A dummy variable is generated to have value 1 for years where the ratio is more than 10 percent, and value 0 otherwise. These dummy variables are time and country variant; and they expect to have negative effects on economic development in the South Pacific region.

The above model is estimated using time-series data for six Pacific Island countries (Fiji, Papua New Guinea, Samoa, Solomon Islands, Tonga and Vanuatu) over 1982-2011. Choice of sample countries is based on available data on foreign direct investment over the past three decades. Table 1 summarizes statistics of variables.

Table 1: Relevant Key Indicators of Six PICs

Country	Year	GDP per capita (US$)	FDI (%)	Domestic credit (%)	Investment (%)
Fiji	1982-1990	2577.7	2.44	26.80	17.67
	1991-2000	3099.8	2.52	35.74	15.18
	2001-2010	3561.6	6.89	68.82	16.47
	2011-2012	3554.5	8.94	74.56	15.76
Papua New Guinea	1982-1990	716.9	4.13	24.41	14.93
	1991-2000	857.8	3.41	18.07	12.41
	2001-2010	831.3	1.40	19.90	17.94
	2011-2012	1057.5	-1.40	30.38	30.29
Samoa	1982-1990	1530.7	0.78	14.23	27.10
	1991-2000	1631.7	2.49	23.64	18.45
	2001-2010	2333.7	1.87	39.12	10.71
	2011-2012	2439.0	2.85	47.27	9.00
Solomon Islands	1982-1990	933.2	2.75	20.09	20.52
	1991-2000	1075.9	4.02	13.08	10.40
	2001-2010	934.5	5.48	23.83	12.91
	2011-2012	1187.0	9.31	23.13	14.77
Tonga	1982-1990	1934.6	0.08	28.56	20.26
	1991-2000	2204.0	0.71	36.04	19.32
	2001-2010	2543.9	1.03	46.38	23.48
	2011-2012	2671.0	3.96	31.88	31.58
Vanuatu	1982-1990	1780.0	5.65	32.46	19.31
	1991-2000	1963.1	10.17	35.37	20.85
	2001-2010	1970.0	5.74	45.90	28.45
	2011-2012	2103.0	6.03	67.93	29.34

Source: Authors' calculation based on data from various sources as stated in Table 2.

4. Methodologies and Findings

In this section two issues in time series regression analysis are addressed: (1) Regression results are non-spurious. This requires cointegression of variables that are integrated of order one. (2) Endogeneity of regressors, should be addressed by using instrumental variables estimators.

Analytical results are reported along with description of methodologies which are used to obtain unbiased, consistent and efficient regression results.

4.1. Integration and Cointegration Tests

Integration and cointegration tests are necessary in order to avoid risk of obtaining spurious regression results. Unit root test allowing for the presence of up to two structural breaks, described by Clemente, Montanes and Reyes (1998), is used to test the null hypothesis that a time series contains unit root. Integration tests for variables at level and in first differences are based on tests with maximum 2 lags. Since all test statistics for integration tests of variables at level are greater than critical statistics at the 5 percent significance level, the null hypothesis of non-stationary time series is not rejected for all variables at level. Integration tests for variables in first differences reject the null hypothesis of non-stationarity at the 5 percent significance level, since all test statistics are smaller than critical values at the 5 percent significance level. These conclude that all quantitative variables are integrated of order 1, with the presence of up to two structural breaks. Optional breakpoints are hypothesized and tested in the Clemente, Montanes and Reyes (1998) unit root tests. A *p*-value of less than 0.05 is taken as the evidence to reject the null hypothesis that a year is not a structural break at the 5 percent significance level. Dummy variables, which are included in the final regression model for each country, are decided based on unit root test of estimated errors obtained in ordinary least squares estimation.

The same unit root test is further used to test estimated errors from each ordinary least squares regression $\hat{\varepsilon}_t$. Since observed test statistics are respectively smaller than the 5 percent critical values in the Clemente, Montanes and Reyes (1998) unit root tests (see Table 2), respective combinations of quantitative variables in Equations (1) produce stationary error terms in all time-series regressions. This suggests that estimation of Equation (1) would yield non-spurious regression results for each country under study.

Table 2. Clemente, Montanes and Reyes (1998) Unit Root Test Results

Variable	Optimal breakpoint 1 (*p*-value)	Optimal breakpoint 2 (*p*-value)	Observed *t*-stat (H_0: *rho* – 1 = 0)	5% critical value
Fiji				
Y_t	1990 (0.000)	2000 (0.000)	-4.520	-5.490
I_t	1986 (0.123)	1999 (0.000)	-4.478	-5.490
C_t	1988 (0.000)	2003 (0.000)	-5.292	-5.490
F_t	1990 (0.917)	2003 (0.000)	-4.724	-5.490
ΔY_t	1988 (0.051)	2006 (0.145)	-6.485	-5.490
ΔI_t	1988 (0.065)	2007 (0.600)	-8.233	-5.490
ΔC_t	2000 (0.009)	2007 (0.020)	-6.604	-5.490
ΔF_t	2001 (0.428)	2007 (0.339)	-8.235	-5.490
$\hat{\varepsilon}_t$	1986 (0.091)	2001 (0.000)	-6.917	-5.490

Table 2 (continued)

Variable	Optimal breakpoint 1 (*p*-value)	Optimal breakpoint 2 (*p*-value)	Observed *t*-stat (H_0: *rho* – 1 = 0)	5% critical value
Papua New Guinea				
Y_t	1994(0.014)	1996 (0.428)	-3.865	-5.490
I_t	1997 (0.005)	2009 (0.000)	-4.760	-5.490
C_t	1993 (0.000)	2008 (0.000)	-4.260	-5.490
F_t	1990 (0.066)	2005 (0.004)	-4.682	-5.490
ΔY_t	1991 (0.053)	1995 (0.118)	-6.256	-5.490
ΔI_t	1998 (0.520)	2008 (0.058)	-5.941	-5.490
ΔC_t	1992 (0.688)	2001 (0.014)	-5.919	-5.490
ΔF_t	1993 (0.996)	1997 (0.957)	-9.142	-5.490
$\hat{\varepsilon}_t$	1993 (0.068)	2000 (0.071)	-6.337	-5.490

Table 2 (continued)

Variable	Optimal breakpoint 1 (*p*-value)	Optimal breakpoint 2 (*p*-value)	Observed *t*-stat (H_0: *rho* – 1 = 0)	5% critical value
Samoa				
Y_t	1997 (0.000)	2002 (0.000)	-4.976	-5.490
I_t	1986 (0.550)	1994 (0.000)	-2.523	-5.490
C_t	1987 (0.000)	2002 (0.000)	-3.413	-5.490
F_t	1995 (0.895)	2006 (0.283)	-4.220	-5.490
ΔY_t	1992 (0.004)	2005 (0.015)	-6.252	-5.490
ΔI_t	1995 (0.864)	2001 (0.823)	-5.762	-5.490
ΔC_t	1988 (0.563)	1992 (0.621)	-8.040	-5.490
ΔF_t	1995 (0.894)	2006 (0.754)	-6.563	-5.490
$\hat{\varepsilon}_t$	1994 (0.061)	2001 (0.030)	-5.815	-5.490

Table 2 (continued)

Variable	Optimal breakpoint 1 (*p*-value)	Optimal breakpoint 2 (*p*-value)	Observed *t*-stat (H_0: *rho* – 1 = 0)	5% critical value
Solomon Islands				
Y_t	2002 (0.033)	2006 (0.001)	-3.145	-5.490
I_t	1986 (0.001)	2006 (0.008)	-3.512	-5.490
C_t	1989 (0.000)	2002 (0.000)	-4.194	-5.490

F_t	2000 (0.039)	2005 (0.000)	-3.905	-5.490
ΔY_t	1997 (0.005)	2002 (0.000)	-5.666	-5.490
ΔI_t	2000 (0.797)	2003 (0.588)	-7.314	-5.490
ΔC_t	1988 (0.549)	1993 (0.128)	-5.552	-5.490
ΔF_t	1995 (0.924)	2003 (0.630)	-7.159	-5.490
$\hat{\varepsilon}_t$	1986 (0.061)	1997 (0.075)	-7.218	-5.490

Table 2 (continued)

Variable	Optimal breakpoint 1 (p-value)	Optimal breakpoint 2 (p-value)	Observed t-stat (H_0: $rho - 1 = 0$)	5% critical value
Tonga				
Y_t	1993 (0.000)	2000 (0.000)	-5.090	-5.490
I_t	1991 (0.237)	1997 (0.002)	-2.408	-5.490
C_t	1994 (0.000)	2002 (0.087)	-3.706	-5.490
F_t	1991 (0.163)	2003 (0.042)	-4.541	-5.490
ΔY_t	1988 (0.064)	2005 (0.391)	-6.647	-5.490
ΔI_t	1991 (0.151)	1994 (0.260)	-6.132	-5.490
ΔC_t	1989 (0.348)	2005 (0.050)	-7.322	-5.490
ΔF_t	2003 (0.607)	2009 (0.410)	-9.967	-5.490
$\hat{\varepsilon}_t$	1995 (0.000)	2002 (0.603)	-5.865	-5.490

Table 2 (continued)

Variable	Optimal breakpoint 1 (p-value)	Optimal breakpoint 2 (p-value)	Observed t-stat (H_0: $rho - 1 = 0$)	5% critical value
Vanuatu				
Y_t	1990 (0.001)	2007 (0.023)	-4.994	-5.490
I_t	1987 (0.010)	2005 (0.000)	-5.162	-5.490
C_t	1989 (0.089)	2005 (0.000)	-3.862	-5.490
F_t	1988 (0.000)	1997 (0.000)	-5.199	-5.490
ΔY_t	1989 (0.180)	2004 (0.572)	-6.409	-5.490
ΔI_t	2001 (0.684)	2004 (0.856)	-6.479	-5.490
ΔC_t	2001 (0.191)	2007 (0.015)	-6.917	-5.490
ΔF_t	1984 (0.476)	1992 (0.267)	-6.381	-5.490
$\hat{\varepsilon}_t$	1986 (0.001)	2003 (0.000)	-7.024	-5.490

4.2. The Two-step GMM Estimator

An important concern in empirical analyses is endogeneity, as most regressors can be endogenous. Ignorance of addressing endogeneity problem would lead to biased and inconsistent regression results. As a solution, instrumental variables estimators should be adopted. The current study adopts the two-step GMM estimator. This estimator provides estimates which are efficient for arbitrary and statistics robust to heteroscedasticity. Furthermore, the Hansen test and Davidson-MacKinnon tests are employed to test for overidentification restriction and endogeneity respectively. While weak instruments are unable to address endogeneity, too many instruments 'can overfit endogenous variables, failing to expunge their endogenous components and biasing coefficient estimates' (Roodman 2009, p.135). Therefore, special care should be paid to choosing instruments in the experimental process by observing changes in Hansen test statistics and estimated coefficients, upon changing the set of instrumented variables. In this paper we use the second and third lags of instrumented variables as excluded instrumental variables.

The two-step GMM estimates of Equation (1) are summarized in Table 3. Since *p*-values from Hansen J test are all greater than 0.25, a benchmark value suggested by Roodman (2009), the null hypothesis of overidentification of parameters is not rejected in individual regressions. Similarly, since *p*-values from Davidson-MacKinnon tests are all less than 0.05, the null hypothesis that instrumented variables are expogeneity is rejected at the 5 per cent significance level. These suggest the two-step GMM estimates are consistent and efficient.

4.3. Regression Findings

In the two-step GMM estimation of Equation (1), instrumented variables are decided based on observing changes in Davidson-MacKinnon test statistics upon changes in assumed endogenous variables; they vary across regressions for different countries. While exogenous explanatory variables are used as included instruments, the second and third lags of these instrumented are used as excluded instruments. Regression results are summarized in Table 3.

Investment's positive impact on output is consistently evidenced across the regressions, with magnitudes varying from 0.115 for Tonga to 0.445 for Vanuatu. Domestic credit to private sector is found to significantly enhance output in countries under study, except for Solomon Islands and Vanuatu. While FDI significantly and positively contributes to economic development in Fiji, Papua New Guinea and Tonga, it hinders economies of Samoa, Solomon Islands and Vanuatu.

With regards to the variable of interest, the interaction term has a significant and positive impact on output in Samoa, Solomon Islands and Vanuatu. This, together with FDI's performance in these countries, suggests that FDI's negative impacts in these three countries are mitigated with the development of domestic financial sector in these countries. In other words, FDI and domestic credit are complementary to each other in promoting economic development of host countries.

On the other hand, the interaction term is found to have negative impacts on output in Fiji, Papua New Guinea and Tonga where both domestic credit and FDI have positive output impacts. This suggests that excessive competition between FDI and domestic credit reduces individual efficiency of the two fund sources in small island economies. This finding is consistent with the fact that increase in FDI to trading sector in countries like Fiji has diverted a significant portion of domestic credit to non-productive activities such as purchase of residential properties, cars and other household items; and that excessive credit flow in these economies has amplified domestic prices as reflected in massive increases in rental and house prices in PICs.

Table 3: FDI's Impacts on Economic Output

Dependent variable: Natural logarithm of real per capita GDP, Y_{it}

Explanatory variable	(i) Fiji	(ii) Papua New Guinea	(iii) Samoa	(iv) Solomon Islands	(v) Tonga	(vi) Vanuatu
	Coeff. (z-stat)	Coeff. (z-stat)	Coeff. (z-stat)	Coeff. (z-stat)	Coeff. (z-stat)	Coeff. (z-stat)
Investment, I_t	.368 (2.46) ***	.233 (2.66) ***	.283 (1.80) *	.164 (2.85) ***	.115 (2.06) **	.445 (1.97) **
Domestic credit, C_t	.006 (3.12) ***	.0003 (1.59) *	.018 (3.73) ***	-.042 (-5.76) ***	.010 (7.35) ***	-.045 (-1.67) *
FDI, F_t	.010 (1.92) **	.048 (3.08) ***	-.149 (-4.43) ***	-.051 (-2.88) ***	.074 (2.65) ***	-.229 (-1.66) *
F_tC_t	-.0003 (-1.85) *	-.002 (-2.06) **	.004 (3.68) ***	.003 (3.91) ***	-.001 (-1.70) *	.006 (1.77) *
Dummy $D_{1,t}$	-.041 (-1.92) **					
Dummy $D_{2,t}$			-.082 (-1.97) **	-.004 (-1.10)	-.005 (-2.01) **	-.075 (-1.65) *
Constant	5.518 (6.19) ***	5.567 (14.79) ***	5.440 (4.25) ***	6.808 (28.40) ***	6.604 (21.61) ***	6.571 (9.77) ***
Centered R^2	0.7523	0.7234	0.8701	0.6827	0.8579	0.6461
Root MSE	.06652	.08023	.07131	.08942	.04136	.04659
# instrumented	I_t and C_t	I_t, C_t and F_t	I_t and C_t	I_t and C_t	I_t and C_t	C_t
Hansen J χ^2 (p-value)	2.412 (0.6605)	1.501 (0.6820)	0.747 (0.6883)	3.460 (0.4840)	3.235 (0.5192)	0.090 (0.7643)
Davidson-MacKinnon F (p-value)	7.545 (0.0230)	6.347 (0.0959)	8.599 (0.0136)	10.100 (0.0064)	4.655 (0.0976)	6.338 (0.0118)

Note:
(1) *, **, *** represent significance at the 10%, 5% and 1% level respectively.
(2) $D_{2,t}$ refers to disaster dummy variables as described in Section 3.
(3) In column (i), $D_{1,t}$ refers to structural break in 2001 as found in Table 2.

5. Conclusion

This study investigated output impacts of the interaction between foreign direct investment and domestic credit to private sector in Fiji, Papua New Guinea, Samoa, Solomon Islands, Tonga and Vanuatu over 1982-2011. The generalized method of moments estimator was employed to time-series regression analyses. It was strongly evidenced that FDI and domestic credit were complementary in enhancing labour productivity in Samoa, Solomon Islands and Vanuatu; while they were substitutional in enhancing labour productivity in Fiji, Papua New Guinea and Tonga.

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Is Stock Return predictability Time-varying?

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ABSTRACT

Using historical data (January 1927 to December 2014), this paper shows that stock return predictability is time-varying based on some of the well-known predictors in the literature. Our analysis reveals that these time-varying patterns of the predictability are concentrated around the 1974 oil price shock and the 1987 market crash. We also examine the determinants of time-varying predictability and we show both expected and unexpected shocks (emanating from financial variables) explain return predictability.

Keywords: *Heteroskedasticity; Time-varying Predictability; Predictive Regression*

I. Introduction

Historically, predictability of stock returns has been a popular topic in asset pricing. While the early literature finds that stock returns are predictable (Fama and French, 1989; Ferson and Harvey, 1991), the more recent studies find mixed results (Goyal and Welch, 2008). Among influential studies, Campbell and Thompson (2008) argue that many predictive regressions beat the historical average returns when some restrictions are amount on the signs of the coefficients and forecast returns. They employ theoretical restrictions on valuation models and illustrate that those models beat the historical average return forecasts in out-of-sample tests. Moreover, Rapach et al (2010) combine individual forecasts to obtain superior out-of-sample forecasts.

Lack of consensus on predictability has motivated research on new econometric models testing for stock return predictability. \ (see, Stambaugh (1999), Lanne (2002), Lewellen (2004), Campbell and Yogo (2006), Ferrira and Santa-Clara (2011), Kostakis et al. (2015), Phillips and Magdalions (2009), Westerlund and Narayan (2012, 2015)).

The branch of literature related to our study is those that search for evidence of time-variation within predictability relationships. These studies (e.g., Chen (2009); Park (2010); Timmermann (2008); Kim et al. (2011); Paye and Timmermann (2006); Lettau and van Nieuwerburgh (2008); and Kasparis et al. (2015)). Paye and Timmermann (2006), for instance, examine breaks in the coefficients of the predictive equation, while Lettau and van Nieuwerburgh (2008) consider the presence of shifts in the predictor variable.

Using panel data techniques, Hjalmarsson (2010) employs a recursive regression approach to provide evidence in favor of time-varying predictability, especially arising from interest rate variables. Notably, Henkel et al. (2011) argue that the equity predictability based on valuation ratios and macroeconomic variables is identified in recessions and turbulence. Their main point is that return predictability is found only during economic contractions and not in expansions in the case G7 countries. This evidence is supported by Guiodlin et al. (2013), who argue that stock return predictability by dividend yield is time-varying , which is linked to the business cycle employing a monthly data for US sector portfolios with 5-year rolling fixed window predictive regressions. There is a vast literature on US stock data but international markets have got low attention comparatively. In line with international stock market evidence, a recent paper on time-varying predictability, Bannigidadmath et. al (2015) discuss the sectoral return predictability for India.

Overall, the above literature leans towards the view that returns predictability may exist over certain time periods but with different views of what determines such time periods. Not only the concept of time-varying predictability is researched for stocks and aggregate market level, but also in other different disciplines, this has become a growing concern. This phenomenon extends to energy market using a time-varying parameter model with generalized autoregressive conditional heterockedastic for four countries of Gulf Cooperation Council crude-oil markets, Arouri et. al. (2010) examine the dynamic behaviour of crude-oil prices and find evidence of short-term predictability in oil-price changes over time.

Our paper belongs to the second strand of studies and contribute to the time-variation in predictability literature in several ways. Thus, in regards to the lack of consistent evidence of return predictability, we argue that predictability is time-varying and hence there are some phases of predictability. Empirically, we consider a sample comprised of monthly observations on US CRSP value weighted excess index returns for the period of 1927:01-2014:12. This corresponds to the mostly used sample period in previous studies and as a consequence, our results can be comparable with the existing results in the literature and allow us to see clearly the time-varying nature of the variables. Our analysis of time-varying mean and variance proceeds with fourteen predictors - the dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR) have been previously used to forecast either stock returns or excess returns.

In this paper we contribute to the stock return predictability literature by investigating whether financial variables predict the CRSP value weighted index. Our empirical investigation is based on two specific approaches. First, we contribute further insights for the stock return predictability literature by employing an In-sample analysis utilizing a time series predictive regression model recently proposed by Westerlund and Narayan (2012; 2014) with a feasible generalized least squares (FGLS) procedure that accounts for persistency, endogeneity and heteroskedasticity in a unifying framework. Secondly, we extend the FGLS based predictive regression model to a time-varying model and test for predictability over time individually for each predictor variable. We then get the time-varying estimates as the dependent variable and regress them on expected and unexpected financial variable shocks coming from the predictors to examine the determinants of the predictability over time.

Our time-varying predictability approach contributes empirically into US stock return predictability in a number of ways. Though, there has been some studies on time-varying predictability such as Guidolin et.al (2013), their approach is predictive regression model with Newy-west t-statistics and do not account for econometric issues related to return heteroskedasticity. In addition to that Kim et. al (2011) measure the time-varying return predictability by automatic variance ratio test, automatic portmanteau test and some generalized spectral test respectively. In line with research Henkel et.al (2011), they consider regime-switching vector autoregression (RSVAR) model to predict aggregate returns on G7 countries. Bannigidadmath and Narayan (2015) examine stock return predictability using similar FGLS model in time-varying perspective yet, the main difference in that of their paper is they examine sectoral return predictability of India whereas in our case we make use of this model to predict US aggregate stock returns. The second difference is, we further extend the analysis by using both recursively expanding window and 20-year rolling window to get the time-varying estimates from the FGLS model as for the robustness and compare the results. Thirdly, we concentrate mainly on the in-sample predictability for US data.

Therefore, this is the first study to the best of our knowledge applying FGLS method proposed by Westerlund and Narayan (2012; 2014) onto US market in the phenomenon of time-varying concept. Second key contribution is in view of looking for the determinants of predictability. Therefore, our study also connects to the literature by investigating the determinants of the predictability. Bannigidadmath and Narayan (2015) examine the determinants of the time-varying predictability of India sectoral data and find both expected and unexpected shocks from the financial ratios explain these sectorial return predictability. Following their consensus, we examine the determinants of time-varying predictability for CRSP value weighted excess index returns. This is the first paper which applies expected and unexpected shocks from financial variables to determine the determinants for US data. There has been some attempt to identify the determinants of the predictability on US sector portfolios data by Guidolin et. al (2013) and they examine the industrial production and recessions. Nevertheless, they find the time-variation is linked to the business cycle and predictability is greater in recessionary periods.

Third contribution is this paper brings new evidence on US data by identifying predictability time periods from 1927 to 2014. As argued in the literature, the predictability is not a consistent phenomenon and some of the predictor variables show predictability evidence 50% of the months of the data when initial 20 years were treated as In-sample data book to market ratio, dividend pay out ratio, default yield spread, long-term bond return, long term yield, net-equity expansion and stock variance are among them. And some variables show weak predictability like dividend to price ratio, dividend yield, earnings to price and treasury bill rate the predictive ability.

Fourth contribution of the paper is that predictors considered here show a time-varying nature of predictability and some of the most prominent time-varying predictability phases are concentrated around the market crashes 1974 Oil price shock and 1987 crash. Meanwhile it becomes apparent that the predictability of returns from fundamentals such as DY is time-varying and the phases of predictability have been mainly displayed during both Oil shock 1974 and 1987. DP shows predictive ability mainly post World War II. Among the macroeconomic variables, a substantial time-varying return predictability pattern is evident by LTR during two crashes 1974 and 1987.

The rest of the paper is organized as follows. Section 2 details the motivation of this research and meanwhile, Section 3 reports the predictive regression framework methodology and the data description. Section 4 provides the preliminary data analysis of the empirical dataset with some graphical representation of each of variable under topics of persistency, endogeneity and heteroskedasticity. Finally, Section 5 concludes.

II. Time-varying Predictability Motivation

Following the literature, though the predictability of stock returns has been evidenced empirically till recent past, for a more than a decade poor predictability of stock returns has also been a major topic. Therefore, it is fascinating to know whether the key underlying factors for this debate are due to any time-variations within predictability relationships. Early predictability studies[7] have employed samples which included the turbulent 1970s and also the recession of the early 1980s. But, some recent work by Goyal and Welch (2008), the sample covers till early of 21st century including the “Great Moderation” period from mid 1980s. Henkel et al. (2011) argue as the equity predictability using various valuation ratios and macroeconomic variables is identified in recessions and turbulence, the empirical evidence will be dependent on such studies where those conditions are apparent.

A growing body of empirical evidence documents instabilities and nonlinearities in the time-series properties of the popular predictors as well as the stock returns. Instability in the economic models would reflect the changes to monetary policy or tax policy, large macroeconomic shocks such as oil price etc. Recently Kim et. al. (2011) examine the degree of return predictability of U.S. stock market returns on monthly Dow Jones Industrial Average Index and find return predictability varies over time and mostly influenced by changing market conditions. In attempting to reconcile the return predictability while addressing the structural changes in predictors, Lettau and Nieuwerburgh (2008) explore financial ratios. Apart from the structural breaks in the predictive regressions, it also has been found the presence of the structural breaks in the price indices as well[8]. Furthermore, Narayan and Smyth (2007) identify the structural breaks in the trend of the price indices for stock markets in G7 countries. The

[7] Rozeff (1984) , Shiller (1981) and Fama (1981,1984)
[8] Viceira (1997), Pastor and Stambaugh (2001) investigates the structural breaks in the equity premium based on the estimating method Bayesian framework

asymmetric impact of shocks to predictors may have implications regarding the stock return predictability and we argue one cause of the predictability over time could be due to source of uncertainty known as model instability in the sense of random changes or structural breaks[9]. The evidence incorporating structural instability by breaks suggest that the predictive ability of the financial variables may vary over time.

Though, the predictability of return literature is mostly considered in a linear framework, evidence in favour of non-linear dynamics in the stock returns and various predictors exclusively valuation ratios has grown substantially in recent years. Typically, standard linear tests reveal that valuation ratios are unit root processes or there is no mean reversion[10]. For instance, Coakley and Fuertes (2006) documents the asymmetries in the time evolution of valuation ratios employing a non-linear two-regime model and further Mcmillan and Wohar (2010), examines forecasting ability of the dividend to price ratio for international stock market returns of G7 countries using present value model approach including both linear and non-linear frameworks. In response to poor out of sample forecastability of valuation ratios, Wu and Hu (2011) revisits the annual US data from 1872 to 2007 on S&P 500 Index returns and predictor price to dividend ratio in a perspective of time varying nature. They employ non-linear exponential smooth transition (ESTAR) model with time varying mean approach and find evidence in support of the time-varying mean and non-linear dynamics of price to dividend ratio. Therefore, they reconcile the controversy on return predictability by successfully applying non-linear regression model with time-varying mean framework.

In addition to the fact that the financial variables behave non-linearly, stock price indices or returns to show non-linearity (see Narayan (2006) and Lanne et. al (2013)). These evidences suggest that non-linear behaviour of predictors and returns may be another reason to have time varying patterns of predictability literature. In attempt to identifying any time-varying nature, Guidolin, McMillan and Wohar (2013) argue that return predictability is time-varying and it is linked to the business-cycle by employing monthly data for US sector portfolios.

In our study both mean and variance predictability in the nature of time-varying is examined. In the perspective time-varying approach, apart from the time-varying mean, a growing number of studies have provided evidence of time-varying volatility[11]. A recent paper on time-varying predictability, Bannigidadmath et. al (2015) discuss the sectoral return predictability for India and they examine the determinants of the time-varying predictability and find both expected and unexpected shocks from the financial ratios explain these sectoral return predictability.

A. Data and Methodology

Our data set comprises monthly data January 1927 to December 2014 are considered to predict monthly stock market. For this study, the data are obtained from Amith Goyal's web page (http;//www.hec.unil.ch/agoyal/). The dependent variable is always CRSP-value weighted index returns including dividends in excess of the risk free rate. There are fourteen predictors to test for the predictive ability including the dividend-price ratio (DP), dividend yield (DY),

[9] Instability of the stock returns model has been examined by Pesaran and Timmwemann (1995), Bossaerts and Hillion (1999), Lettau and Ludvigson (2001), Paye and Timmermann (2006), Coakley and Fuertes (2006) Rapach and Wohar (2006), Ang and Bekaert (2007), Lettau and Van Nieuwerburgh (2008), Goyal and Welch (2008) and Pettenuzzo and Timmermann (2011)

[10] Lim and Brooks (2011) survey both linear and non-linear predictability in stock returns in the empirical finance literature.

[11] The predictability in the second moments of returns see example Bollerslev (1986) and French et. al (1987). Marquering and Verbeek (2004) explore the predictability of both mean and volatility and See Stock and Watson (2003, 2007) model the time variation in volatility with a stochastic volatility model.

dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). For a description of the variables refer to Appendix A.

We use predictive regression frameworks proposed by Westerlund and Narayan (2012). For the robustness, we compare results of in-sample predictive regressions by Westerlund and Narayan (2012) with Lewellen (2004) model. Lewellen (2004) addresses the problems of biasedness and persistency using OLS method yet do not account for other issues. In contrast, predictive regression model proposed by Westerlund and Narayan (2012) can handle the issues of endogeneity, persistency and specifically heteroskedasticity of both the returns and predictors using the Generalized Least Squares (GLS) estimation method.
Thus by Westerlund and Narayan (2012, 2014), the key model is the predictive regression model in which stock returns are regressed on each lagged predictor. The null hypothesis is to test for no predictability and is $H_0: \beta = 0$.

$$r_t = \alpha + \beta\, x_{t-1} + \varepsilon_t \tag{1}$$

$$x_t = \phi + \rho\, x_{t-1} + \mu_t \tag{2}$$

r_t is the return on CRSP value weighted stock index in excess of the risk-free rate from time $\mathrm{t}-1$ to t., x_t is a predictor and ε_t is the disturbance term. In the empirical part of the paper we consider fourteen predictor variables including valuation ratios which are supposed to be highly persistent. Therefore, assuming that ε_t is correlated with μ_t.

$$\varepsilon_t = \gamma\mu_t + \eta_t \tag{3}$$

where ε_t and η_t are iid and symmetric with mean zero and $\gamma = \mathrm{cov}(\varepsilon, \mu)/var(\mu)$. Lewellen (2004) assumes $\rho \approx 1$, and defines the bias-adjusted estimator with OLS estimating method as

$$\hat{\beta}_{adj}^{Lew} = \hat{\beta} - \gamma(\hat{\rho} - \rho) \tag{4}$$

Where $\hat{\beta}_{adj}^{Lew}$ represents the β coefficient by Lewellen model with OLS method of estimation.
In improving the predictive regression framework, Westerlund and Narayan (2012, 2014) test the alternative hypothesis, assuming β is local-to-zero as $T \rightarrow \infty$,

$$\beta = \frac{b}{T} \tag{5}$$

Where b is constant and not depending on T. Similarly, assuming most of the predictors persistent,

$$\rho = 1 + \frac{c}{T} \tag{6}$$

Where the parameter $c \leq 0$ measures the degree of persistency inx_t.

$$\hat{\beta}_{adj}^{WN} = \hat{\beta} - \gamma(\rho - 1) \tag{7}$$

$\hat{\beta}_{adj}^{WN}$ denotes the β coefficient produce by Westerlund and Narayan (2012) model with GLS estimation method.
Suppose the variances of $\varepsilon_t$and η_t are denoted by σ_ε^2 and σ_η^2.
In order to model for the heteroskedasticity, autoregressive conditional heteroskedasticity (ARCH) is assumed for the variance equation of η_t

$$var(\eta_t|I_{t-1}) = \sigma_{\eta t}^2 = \lambda_0 + \sum_{j=1}^{q} \lambda_j\, \eta_{t-j}^2 \tag{8}$$

Where I_t is the information available at time t. To have σ_η^2 positive, assume $\lambda_0 > 0, \lambda_1, \cdots, \lambda_q \geq 0$ and $\sum_{j=1}^{q} \lambda_j < 1$.
Similarly, $var(\varepsilon_t|I_{t-1}) = \sigma_{\varepsilon t}^2$ can be treated in an ARCH way. Now, the conditional variance of ε_t is written as

$$var(\varepsilon_t|I_{t-1}) = \sigma_{\varepsilon t}^2 = \gamma^2\sigma_{\mu t}^2 + \sigma_{\eta t}^2 \tag{9}$$

B. IS (In-Sample) Method

To assess whether the predictability is time-varying, we estimate the predictive regression model, with the in-sample (IS) and expanding (recursive) window method by dedicating the first twenty years of data in-sample. Thus, we first estimate the Westerlund and Narayan (2012) model, over the time period February1927 to January 1947 and obtain the parameter estimates. The first β coefficients are generated for this period. Similarly, at the second step, expand the sample by one period forward to March 1927 to February 1947 and re-estimate the model and obtain the respective β coefficient and the corresponding sub-sampling and asymptotic confidence interval are noted. Therefore, the final IS estimate is the full sample β coefficient and the relevant confidence intervals. To test for the robustness, above mentioned IS data analysis is done with expanding window using Lewellen (2004) model. The next section details the empirical findings of this study with the above mentioned two types of models.

III. Preliminary Data Analysis

Firstly, the preliminary analysis is conducted for all the dependent and predictor variables and are tabulated in the Table I along with commonly used descriptive statistics. Among the predictors, DFR is most volatile, followed by LTR. By skewness measure, it is observed that most of the predictors are skewed and further, kurtosis measure is larger than the threshold value three except for DP and DY. This implies that most of the distributions are flat tailed. Null of Normal distribution is tested by Jarque-Bera test and p-value column indicates that all the variables reject the hypothesis of normal distribution at 1% significance level. In order to test for autocorrelations, we estimate the autocorrelations at different lags for the squared variables and results are shown in last five columns. It could be seen that autocorrelations are high and slowly declining in almost all the variables. We consider this as evidence of ARCH. We haven't reported the p-values of these coefficients, nevertheless all the autocorrelations are significant at 5% level of significance

Looking at the stochastic properties of the fourteen predictors and returns series over the period of full sample January 1927 to December 2014 in Table II, it is clear that the most of the series are highly persistent, as judged by a first-order sample correlation coefficients, ρ of above 0.90 except for EXCRSP_VW, DFR, INFL, LTR and SVAR. The ADF shows a unit root test implemented on the fourteen predictors and returns with a time trend. The column Lag contains the order of the lag augmentation chosen by the method BIC with maximum lags eight. Most of the variables reject the unit root null exceptions follow by variables LTY and TBL. We can conclude that the majority of the variables are stationary including returns. Nevertheless, many of the estimates of ρ are very close to one and hence, most of the predictors exhibit unit-root like behaviour, which confirms that our local-to-unity model for ρ seems appropriate. Last four columns show the results for testing null of no ARCH using Lagrange Multiplier test. At ARCH with six lags, all the variables reject the hypothesis of no ARCH at 10% significance level. At twelve lags, except for the variable INFL, the rest of the variable reject no ARCH at 5% level of significance.

In Table III, columns two to four report the results from Wald test for the null of no ARCH effect in the estimated variance equation of η_t, the number of lags used as determined by BIC and corresponding p-values. Similarly, the columns from five to seven are the results for the variance equation ε_t.It can be concluded that the null of no ARCH is rejected for both error terms in all the regressions which confirms the evidence of ARCH in Table 3. In addition, columns eight and nine represent estimated coefficients of error correlations $\rho_{\varepsilon\epsilon}$ and $\rho_{\varepsilon e}$. $\rho_{\varepsilon\epsilon}$ measures the extent of endogeneity and $\rho_{\varepsilon e}$ measures the combined effect of both endogeneity and the ARCH. If the is no endogeneity then the estimated correlations coefficients should be close to zero. The Table 3 indicates most of the correlations are deviated from zero threshold and the least correlation is reported by the variable TMS. The highest correlation is reported by DP and is followed by BM and EP respectively. Furthermore, formally testing the endogeneity, with estimation method OLS and testing the null $\gamma = 0$ are reported in the table. The corresponding t-statistic and p-values are reported in the last two columns of the table. Null of $\gamma = 0$ is rejected by majority of the variables at 5% level of significance except for INFL, NTIS and TMS.

A. Time-Varying Endogeneity

The Figure I plots p-values of the endogeneity for some of the predictors which show time-varying nature. The predictors which are not drawn the graphs EP, DP, BM, DFY, NTIS, SVAR, LTR indicate rejection of null hypothesis through out of the sample period from 1947 to 2014 and indication of endogenous variables. Meanwhile the rest of the predictors illustrates either mix or no endogeneity time periods. Among the graphs, INFL shows p-values always greater than 10% significance level confirming no endogeneity for the selected sample data. The predictor DE indicates endogeneity starting from late 2008 until end of the sample period. Observing LTR, except for the years from 1955 to 1975, the rest of the time, an endogeneity is presented. Variable TMS does not show endogeneity except for few months in the year 1980.

B. Time-Varying Persistency

The figure II plots the persistency results of monthly predictors and the dependent variable CRSP value Weighted returns. Specifically, using expanding window method, by allowing first 20 years of data for IS and gradually increasing (expanding) the data series by one observation at a time, we compute the persistency. Likewise, at the end of sample we have 886 observations of persistency results starting from January 1947 to December 2014.

C. Time-Varying Heteroskedasticity

To test for the heteroskedasticity of the variables, each variable is run with a regression of AR(12) model and the resulting residuals are run on an ARCH (12) model. Only the variable INFL shows no heteroskedasticity as it's shown by the Figure III, none of the p-values are significant. Variables DE and SVAR show mixed results. We can notice a time-varying pattern of the p-values and they are tending to be small at the end of the sample period. Predictors DE and SVAR show heteroskedasticity, particularly when reached to the end of the sample period. The rest of the variables indicate null hypothesis of No ARCH is rejected throughout show heteroskedasticity. Therefore, as we have already assumed, one of the econometric issues considered to be heteroskedasticity and is an inherited in some of the predictors.

IV. In-sample Predictability

In-sample predictability by each predictor variable is depicted in Table IV. According to the Westerlund and Narayan (2012) FGLS sub-sampling method, we find the predictors, book to market, dividend pay out ratio (DE), default yield spread (DFR), long term return (LTR), long term yield (LTY) , net equity expansion (NTIS) and stock variance (SVAR) have time-varying predictive ability consisting more than 50% of the sample period after taking first 20 years as In-sample. Moreover, INFL, and TMS indicate predictability throughout the sample-period as therefore, we don't take this as time-varying. One of the key features is that the predictors DP and DY show very weak or no time-varying predictive ability during the sample period nevertheless, DY is one main predictor that has been identified to predict stock returns in the literature.

A. Financial ratios as predictors: Book to market ratio (BM), Dividend-price ratio (DP), Dividend yield (DY) Dividend pay-out ratio (DE) and Earnings to price (EP)

Book to market ratio (BM) is one key variable that researchers paid much attention in searching for the ability to predict stock returns. Some of the studies, Kothari and Shankan(1997) Welch and Goyal (2008) and Ferreira & Santa-Clara (2011) successfully identified the predictive ability of BM ratio on returns. Table IV indicates, when we test at the 5% level of significance, there are about 96% of the months of the total out-of-sample show the predictive ability of the variable BM. We can conclude that there is time-varying pattern of the BM variable on CRSP excess returns and this time variation is mainly coming from the years 1947 to 1998's in which includes the Oil shock in 1974.Another main phase is from November 2000 to December 2014 which includes global recession

Referring to Table IV, a time varying pattern is discovered for DP and according to both Lewellen (2004) and Westerlund and Narayan (2012) models The predictor DP shows very weak predictive ability of about 1% of the months from the entire sample period. These results confirm, recent studies by Campbell and Thomson (2008) and Ferreira & Santa-Clara (2011) find no apparent predictability by DP.

Among the fundamentals that investigated for the predictive ability, DY is known to be the most popular predictor for the stock returns. Table IV shows statistically significant phases of predictability accumulated to 9% of the sample period which is very weak predictability comparatively . We can notice the bulk of the predictability is evident during 1955 to 1950.

For variable DE, about 96% of the out-of-sample period show predictive ability except the time period march 1998 to October 2010. Predictability phases include both 1974 Oil shock and 1987 market crash. EP ratio is another key variable that quite a number of studies which identify EP as a good predictor for example Campbell and Shiller (1988), Lettau and Nieuwerburgh (2008) are among them. Nevertheless, according to Table IV, we don't get results in favour of EP as only about 37% of the out-of-sample period are significant at the 5% level, hence we treat overall it is as weak significance. This is in line with Kim et. al (2011) whom do not get any results in favour of EP predicting stock returns with a multiple regression model while controlling for the market crashes, crisis and bubbles.

B Macroeconomic and other variables as predictors: Inflation (INFL), Long-term bond yield (LTY), Term spread (TMS), T-bill rate (TBL), Net-equity expansion (NTIS), Default yield spread (DFY), Default return spread (DFR) and Stock variance (SVAR)

In Table IV, the predictor INFL provides significance throughout the out-of-sample period at the 5% s level indicating no-time variation. In the literature, those who find predictability are Kim et. al.(2011) whom examine the predictive ability using time-varying perspective at daily frequency and Rapach et. al. (2005) investigate the data at monthly frequency, specifically the predictive regression model including the lagged returns as a control variable with the inflation. LTY is another variable of our interest of investigating in predicting stock returns. Table IV presents 55.5% statistically significant phases from the out-of-sample and thus an indication of time-varying pattern. which exclusively includes the 1987 market crash. Thus the evidence of predictability is considerable Rapach et. al (2005), Shrimph (2010) and Kim et. al. (2011) are successful in finding predictability by LTY. Except for Rapach et.al (2005), other two studies examine the predictability while incorporating time-variation of it. Rapach et al (2005) use the lagged returns as a control variable in addition to the predictor in the predictive model. Table IV indicates that the LTR provides time varying nature on predicting stock returns and it is about 76% of the months in the sample. The predictability is significant in the early years of out-of-sample, from the year 1947 to till the end of 1990 and after the predictability vanishes. We find evidence of time varying predictability of LTR specifically at times of market crashes in 1974 due to Oil price and 1987.

Further, variable TMS, indicates 100% of the months with significance as highly predictable . This is inconsistent with the literature, no evidence is concluded by authors Schrimph (2010) who uses time-varying perspective and Ferreira and Santa-Clara (2011) with some-of-the parts method. When TBL is considered, Table IV illustrates a time-varying predictability at about 46% of the sample are statistically significant at the 5% significance level. The phases of predictability start at around 1947 to until the end of sample 1984 excluding some months in between. We can conclude that T-bill indicates a some-what time variation in the predictability and meanwhile the predictable time pockets include the 1974 Oil shock. Evidence of predictability of TBL is documented by Rapach et. al (2005), Boudoukh et. al (2008) and Campbell & Thompson (2008) are among those who found successfully that T-bill predicts stock returns. Torous et al. (2004), Goyal and Welch (2008) and Ferreira & Santa-Clara (2011) are unable to get results in favour of significance.

NTIS is in support of time-varying predictability nature as it consists 58% of the out-of-sample period significant at 5% significance level. The predictability is mainly coming from 1976 onwards until 2013. DFY is another predictor which shows 65% of the out-of-sample months being predictable in time-varying manner. It shows one steady predictable phase from September 1970 to December 2014 and is evident of the Oil shock in 1974 and including market crash in 1987. Comparatively, DFR has high predictive power, indicating of 100% significant out-of-sample months from the sample. Therefore, we conclude that the predictability of DFR is not time varying. Finally, predictor SVAR with 80% of the significant months show, time-varying pattern. The predictability starts in the first phase from 1947 to 1982 which includes 1974 Oil shock. The last phase extendd from 1995 to 2014 until the end of the sample period.

V. Determinants of the predictability

Since we have found that the return predictability is time-varying, now we are moving further to identify if so the reasons behind this predictability. This section unfolds the determinants of the time-varying nature. Two approaches are used to get the time-varying estimates of t-statistics. They are namely expanding window approach and 20 year fixed rolling window method. For expanding window method we allocate first 20 years observations as in-sample and then by expanding by one month FGLS t-statistics are computed. Similarly, we get the FGLS t-statistics using 20 year fixed rolling window approach. Our objective here is to find the determinants for the time-varying predictability. Our consensus is that expected and unexpected shocks from the financial variables determine the time-variation. Therefore we run multiple regression model where t-statistics are being the dependent variables. Apart from the expected and unexpected shocks in the right hand side variables, we introduce the dummy variables for the periods of predictive ability by that respective variable.

A. Expanding Window Approach

By the predictive regression model (1) we have identified the predictability phases and are shown in Table V using the expanding window approach. We use those predictability phases as indicators of dummy variables in this section. Predictability phases are obtained by running model (1) with expanding window method. The first twenty years of data are used to get the In-sample coefficients. We run the following time-series regression model for each predictor variable and we compute expected and unexpected financial predictor risks by using a multiple regression with dummy variables representing the predictability phases which are in the Table IV. We have avoided the predictability phases if it contains less than twelve consecutive months. Thus, only any phases with more than twelve months is introduced by a dummy variable in the model. Therefore, we have different number of dummy variables in the multiple regression model depending on the number of predictability phases.

$$X_t = \alpha_0 + \alpha_1 X_{t-1} + \beta_i D_{it} + \epsilon_t \tag{10}$$

Where X_t represents predictor variable and can be any of the fourteen predictors. For example BM, TBL etc. D_i represents the dummy variables, $\beta_i's$ are the coefficients of the dummy variables and i represents the number of dummy variables. By Table IV, the maximum predictability phases are coming from variable DY which is 6 and it is represented with six dummies in this multiple regression model along with a lagged DY. We estimate these regressions; one for each predictor variable using the ordinary least squares estimator, where the standard errors have been corrected for heteroskedasticity and autocorrelation using eight lags. In this way we test for the slope coefficients to be statistically significant zero.

By model (10) we interpret the fitted values as the level of expected financial risk $E^{Risk}$and the residual from the model as our measure of unexpected financial risk UE^{Risk}. To test the hypothesis that financial risk expected and unexpected risks determine time-varying predictability we run the following two time series regression models and estimate using OLS. The standard errors have been corrected for heteroskedasticity and autocorrelation using eight lags.

$$Pred_t = \alpha_0 + \alpha_{1i} D_{it} + \varepsilon_t \tag{11}$$

$$Pred_t = \alpha_0 + \alpha_{1i} D_{it} + \alpha_2 E_t^{Risk} + \alpha_3 UE_t^{Risk} + \varepsilon_t \tag{12}$$

The time-varying predictability variable, $Pred_t$ is nothing but t-statistics computed using the predictive regression model in (1). By expanding window approach with initial sample of twenty years of data, we extract the t-statistics recursively expanding the data by one month. These t-statistics allow us as the dependent variable in the models (11) and (12). Thus we consider above two regressions: first the expanding t-statistic is regressed on the predictability phases identified in Table V. Second the same regression in (11) is augmented with the expected and unexpected risks (model 12)

Our hypothesis is that not only is the predictability coefficient linked to the expected and unexpected risks but that the nature of that linkage will vary with the identified predictability phases in Table IV. The Table V depicts the regression model results of each predictor variable after controlling for the predictable phases which are mentioned in Table IV by running the WN model using expanding window. There are thirteen lagged predictor coefficients significant at 5% significance level except for the variable LTR. Most of the coefficients are very close to 1 apart from the variables DFR, INFL, NTIS and LTR. Due to persistency in the regressors, the standard errors have been corrected for heteroskedasticity and autocorrelation using eight lags. The dummy variable D_2 is significant in both variables BM and EP. Further, two dummy variables D_2 and D_4 of TBL are significant at 1% and 5% levels of significance. Also the dummy D_1 is highly significant of the predictor LTR.

Table VI presents the results for the model (11), by taking the t-statistics as the dependent variable from the FGLS model by Westerlund and Narayan (2012,2014) and the independent variables are the predictive time phases from the Table IV for each predictor. Most of the time phases are significant to these models except for few occasions which indicate mix results LTY, NTIS and TBL with insignificant dummy variables.

In order to identify the determinants of the time-varying predictability, we focus on the expected and unexpected financial risks. Table VII shows the regression model (12) for expected and unexpected risks for each predictor variable while accounting for the predictive time phases as dummy variables. EP and LTR illustrate both significant expected and unexpected risks whereas BM and DE show only unexpected risks are significant. Further, TBL show only expected risk is a significant to the model. There is no evidence that expected and unexpected risks explain predictability in the rest of the variables.

B. Robustness check: Rolling window approach

To assess whether predictability is time-varying, we estimate WN (2012) model using rolling fixed regressions. We set the initial 50% of the sample as for the In-sample data and estimate the model. That is we estimate the model over the time period from February 1927 to January 1971 and obtain the parameter estimates. We then roll the sample one period forward to March 1927 to February 1971 and re-estimate the model, obtaining the parameter values. This continues through the full sample period and though this forego 50% of the sample data, it gives us 528 t-statistic values for each of the variable in. Having obtained the rolling t-statistics, we then wish to consider whether their movement is related to expect and unexpected risks. The rolling t-statistics are used as the dependent variable $Pred_t$ in the model (12).

The regression results from the model (10) are indicated in Table VIII. The results are similar to that of Table V, from the expanding window method. The lagged predictor is always significant except for LTR. Rolling window method finds no significant predictive phases by predictors DE,DDP,INFL and TBL. Nevertheless predictors BM, DY, EP , NTIS and LTY indicate only some of the time periods are significant to the model whereas SVAR is the only predictor which has all the significant time phases. As similar to expanding window method, we now turn to the next step, the expected and unexpected risks are taken from the model (10), expected risks are the fitted values from the model and unexpected risks are the residuals from the model (10). These expected and unexpected risks are used in model (12) with the dummy variables to test the hypothesis of time-varying predictability is linked to the risks and predictive phases.

Regression results from the models (11) are reported in Tables IX , by taking rolling window t-statistics as the dependent variable and the independent variables are predictive phases by Rolling window approach. For LTR, there is one predictive period and is not significant and apart from that BM, DE, DP, DY, LTY, NTIS and SVAR show all the dummy variables which represent predictive phases are significant at different levels of significant. We discover mixed predictive phases by the predictors, TBL, INFL and EP. In order to find the determinants of the time-varying phenomenon, Table X presents the results of estimating the model (12) for each variable, based on the rolling window t-statistics as dependent variable and predictive phases, expected and unexpected risks as the independent variables. Here we can see the both risks are significant pertaining to the variables BM, DP and DFY. And LTR, LTY and TBL show expected risks are significant whereas EP shows only unexpected risk is significant. The rest of the variables do not indicate any of the determinants is affected to the model. Comparing expanding window and rolling window models for the determinants, rolling window method shows more significant results.

VI. Conclusion

Predictability of stock returns has been a popular topic with its vital implications to portfolio allocation, asset pricing, and stock market efficiency. The main finding of the paper is that some predictors considered here show a time varying nature of predictability and some of the predictability phases are concentrated around the market crashes in 1974 and 1987. Meanwhile it becomes apparent that the predictability of returns from fundamentals such as book-to-market (BM) and dividend pay out ratio (DE) are time varying and the bulk of predictability display during Oil shock 1974 and 1987 crash. Among the other predictors, DFY, LTR, LTY,NTIS and SVAR are other significant variables and adhere to time-varying notion throughout the sample data in hand. Weak evidence of time varying predictability is observed in very popular predictor variable DP which is about 1% of the out-of-sample are statistically significant. Moreover, DY, TBL and EP also show weak evidence of time varying nature. We also reveal both expected and unexpected predictor risks are found to be the determinants of the time varying predictability when the phases of predictability are controlled for.

Appendix A

A Definition of predictors

Dividend-price ratio (DP): Difference between the log of dividends (12-month moving sums of dividends paid on S&P500) and the log of prices (S&P500 Index price).
Dividend yield (DY): Difference between the log of dividends (12-month moving sums of dividends paid on S&P500) and the log of lagged prices (S&P500 Index price).
Dividend payout ratio (DE): Difference between the log of dividends (12-month moving sums of dividends paid on S&P500) and the log of earnings (12-month moving sums of earnings on S&P500).
Earnings to price (EP): Difference between the log of earnings (12-month moving sums of earnings on S&P500) and the log of prices (S&P500 Index price).
Book to market ratio (BM): Ratio of book value to market value for the Dow Jones Industrial Average.
Inflation (INFL): Growth in the consumer price index with a one month lag.
Long-term bond yield (LTY): Long term government bond yield.
Long-term bond return (LTR): Long term government bond return.
Term spread (TMS): Difference between the long term government bond yield and the T-bill.
T-bill rate (TBL): Three-month Treasury bill rate.
Net-equity expansion (NTIS): Ratio of 12-month moving sums of net issues by NYSE-listed stocks to NYSE market capitalization.
Default yield spread (DFY): Difference between BAA-and BAA rated corporate bond yields.
Default return spread (DFR): Difference between long-term corporate bond and long term bond returns.
Stock variance (SVAR): Sum of squared daily market returns on the S&P500

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Figure I: Endogeneity

The figure illustrates the associated p-values for the model (3) , $\varepsilon_t = \gamma\mu_t + \eta_t$ estimate the endogeneity test of the null hypothesis that $\gamma = 0$. The horizontal line shows the 10% significance level and whenever the lines fall below shows the presence of endogeneity. The excess returns are calculated by return on CRSP value weighted index in excess of the three-month Treasury bill rate. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR).

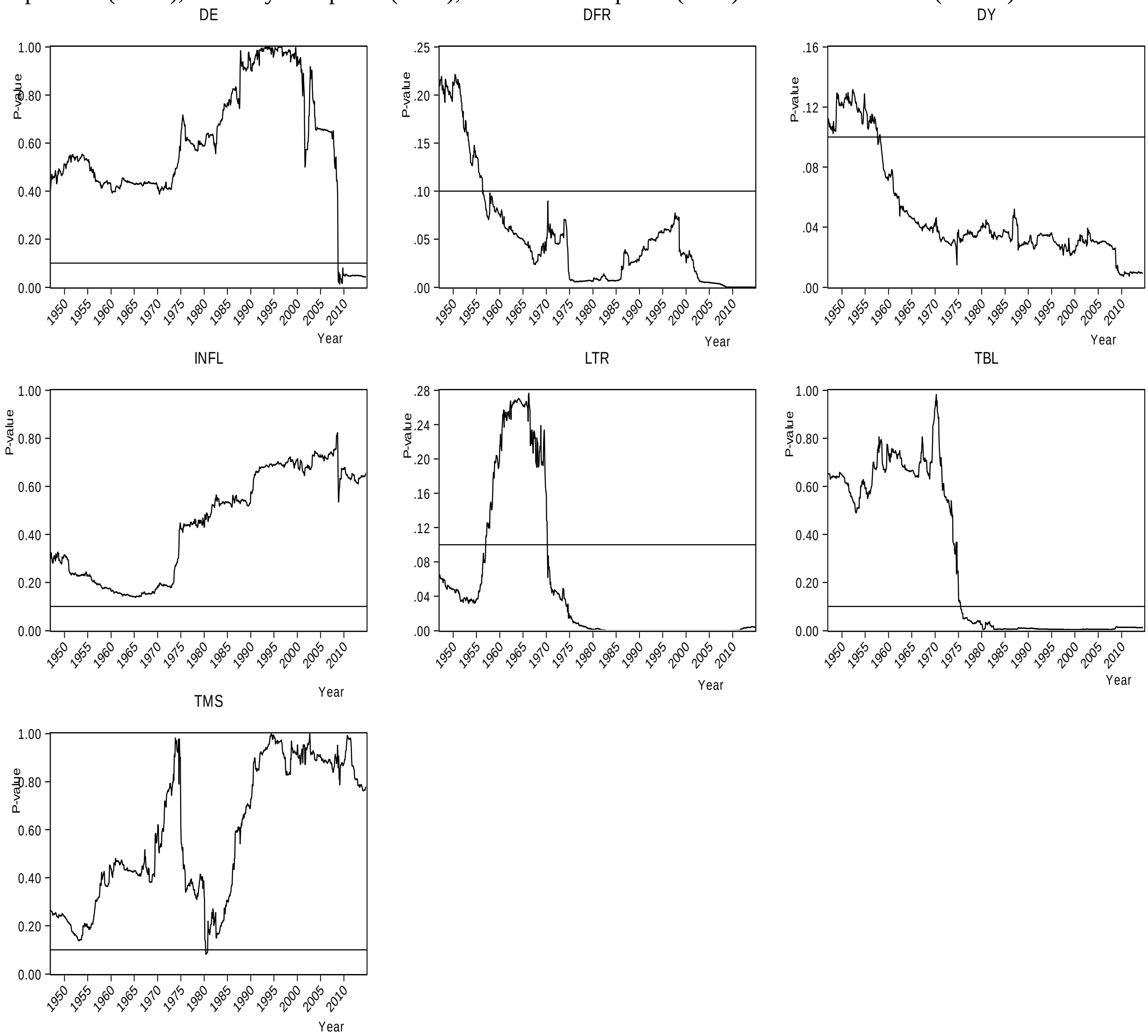

Figure II: **Time-varying Persistency**.

The figure depicts AR(1) coefficients against time period years. Typical AR(1) model is used to get the coefficients for each predictor as well as the return series CRSP value weighted including dividends individually. The excess returns are calculated by return on CRSP value weighted index in excess of the three-month Treasury bill rate. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR)

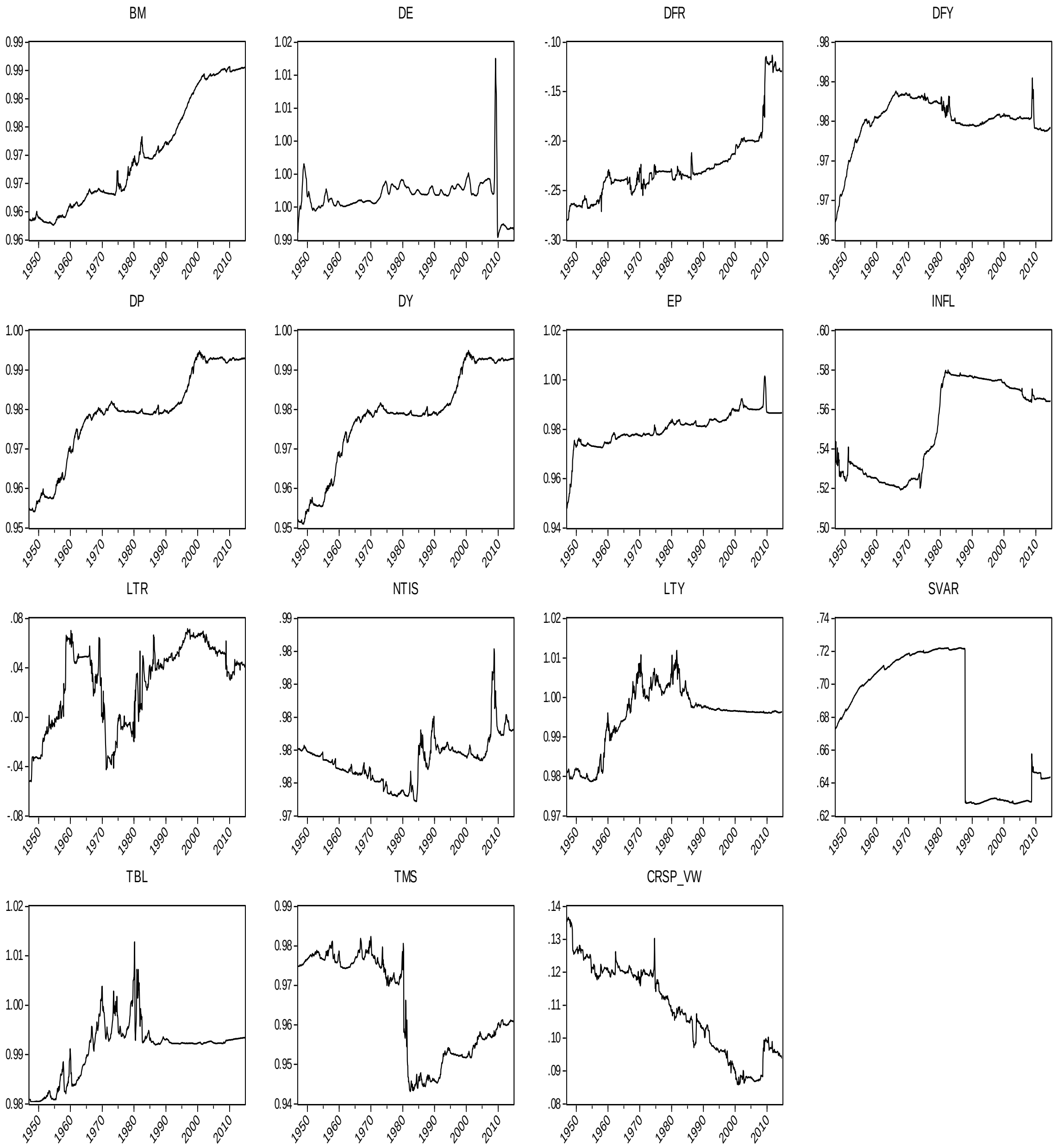

Figure 3: Heteroskedasticity.

The null of no heteroskedasticity is tested for each predictor variable with AR(12) model and residuals are tested with ARCH(12) model. The figure displays P-values against time.

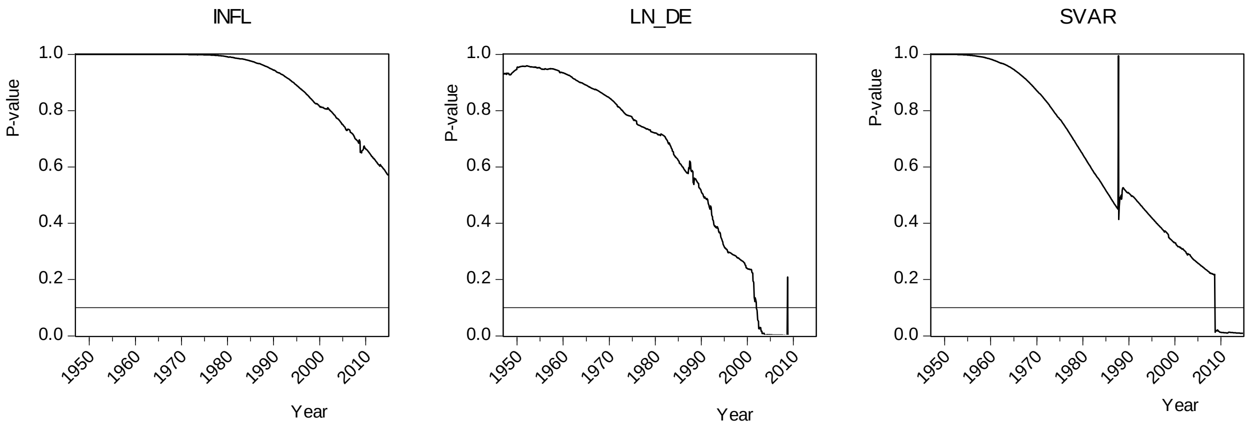

Table I: Summary Statistics, Monthly CRSP excess returns and predictors 1927:01 to 2014:12

The table reports summary statistics for monthly CRSP value weighted excess returns and fourteen predictors. The excess returns are calculated by return on CRSP value weighted index in excess of the three-month Treasury bill rate. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). The summary statistics contain mean (Mean), Coefficient of variation (CV), skewness (Skew.), kurtosis (Kurt.), J–B refers to the empirical statistic of the Jacque–Bera test for normality and the resulting p-Values are also reported. AR (1) up to AR (36) are the autocorrelation coefficients of the first order autoregressive model at lag 1, 6, 12, 24 and 36 respectively.

Variable	Mean	CV	Skew.	Kurt.	J-B	p-Value	AR(1)	AR(6)	AR(12)	AR(24)	AR(36)
CRSP_VW	0.007	8.479	0.411	12.584	4067.541	0	0.300	0.116	0.128	0.052	0.016
BM	0.578	0.460	0.739	4.474	191.473	0	0.959	0.799	0.606	0.436	0.326
DE	-0.631	-0.529	1.469	8.733	1824.487	0	0.990	0.850	0.742	0.546	0.453
DFR	0.000	48.712	-0.352	10.824	2712.685	0	0.246	0.219	0.082	-0.004	0.005
DFY	0.011	0.621	2.436	11.488	4210.957	0	0.938	0.749	0.544	0.300	0.203
DP	-3.356	-0.137	-0.292	2.787	16.978	0	0.993	0.951	0.897	0.817	0.769
DY	-3.351	-0.136	-0.321	2.771	20.462	0	0.993	0.952	0.899	0.822	0.774
EP	-2.725	-0.153	-0.686	5.833	435.656	0	0.984	0.806	0.617	0.468	0.398
INFL	0.002	2.042	1.146	18.907	11353.740	0	0.218	0.043	0.038	0.034	0.039
LTR	0.005	4.990	0.591	7.783	1067.114	0	0.286	0.118	0.093	0.041	0.039
LTY	0.052	0.536	1.049	3.526	205.527	0	0.993	0.960	0.917	0.848	0.794
NTIS	0.018	1.379	1.755	11.904	4027.137	0	0.969	0.773	0.486	0.166	0.073
SVAR	0.003	1.983	5.526	41.674	71117.440	0	0.369	0.151	0.121	0.109	0.061
TBL	0.035	0.885	1.045	4.228	258.078	0	0.977	0.858	0.782	0.614	0.501
TMS	0.017	0.773	-0.267	3.089	12.880	0	0.950	0.776	0.596	0.253	0.024

Table II:Unit root and Heteroskedasticity results for the full sample

ρ refers to the autoregressive coefficient in Equation (2) $x_t = \phi + \rho\, x_{t-1} + \mu_t$, A standard augmented Dickey-Fuller (ADF) test, which examines the null hypothesis of a unit root and its p-Values are reported. The column Lag contains the order of the lag augmentation chosen by the method BIC with maximum lags eight. ARCH (q) refers to a Lagrange multiplier test of the zero slope restriction and ARCH regression of order q, and the p-value of the test is reported. The excess returns are calculated by return on CRSP value weighted index in excess of the three-month Treasury bill rate. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR)

Variable	ρ	ADF	p-Value	Lag	ARCH(6)	p-Value	ARCH(12)	p-Value
CRSP_VW	0.094	-29.515	0.00	0	20.915	0.00	22.698	0.00
BM	0.985	-3.921	0.01	8	81.711	0.00	57.841	0.00
DE	0.991	-5.412	0.00	7	14.318	0.00	23.512	0.00
DFR	-0.129	-36.902	0.00	0	34.597	0.00	19.303	0.00
DFY	0.975	-3.635	0.03	3	36.385	0.00	47.892	0.00
DP	0.991	-3.417	0.05	1	19.636	0.00	19.967	0.00
DY	0.991	-3.434	0.05	1	19.021	0.00	18.471	0.00
EP	0.986	-4.226	0.00	2	7.183	0.00	18.956	0.00
INFL	0.565	-6.411	0.00	6	1.859	0.08	0.874	0.57
LTR	0.042	-31.276	0.00	0	21.378	0.00	11.877	0.00
LTY	0.996	-0.946	0.95	0	43.204	0.00	24.867	0.00
NTIS	0.979	-5.168	0.00	5	15.871	0.00	19.064	0.00
SVAR	0.643	-6.615	0.00	0	4.907	0.00	2.193	0.01
TBL	0.992	-1.926	0.64	8	98.570	0.00	47.023	0.00
TMS	0.960	-5.302	0.00	1	32.232	0.00	27.366	0.00

Table III: Wald and Endogeneity tests

Wald test for ARCH effects of individual variable and also when used as a predictor are noted in columns 3 and 6. Correlations of regressor and regressend errors and Endogeneity gamma values, s-statistics and corresponding p-values are recorded in the last three columns. The excess returns are calculated by return on CRSP value weighted index in excess of the three-month Treasury bill rate. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR).

	Returns			Predictor			Correlations		Endogeneity		
Variable	Lag	Wald	*p*-value	Lag	Wald	*p*-value	$\rho_{\varepsilon\epsilon}$	$\rho_{\varepsilon e}$	gamma	t-statistic	p-value
BM	1	34.309	0.00	3	564.842	0.00	-0.834	-0.542	-1.011	-49.126	0.00
DE	3	158.076	0.00	2	261.319	0.00	-0.062	-0.050	-0.077	-2.007	0.04
DP	4	987.568	0.00	3	125.734	0.00	-0.977	-0.860	-0.962	-147.402	0.00
DFR	3	143.352	0.00	3	187.945	0.00	0.146	0.135	0.601	4.805	0.00
DFY	3	69.489	0.00	4	311.935	0.00	-0.269	-0.118	-9.508	-9.062	0.00
DY	3	156.400	0.00	3	122.536	0.00	-0.079	-0.022	-0.078	-2.584	0.01
EP	1	373.529	0.00	3	96.248	0.00	-0.765	-0.718	-0.622	-38.525	0.00
INFL	3	162.169	0.00	1	8.132	0.00	0.014	-0.026	0.182	0.446	0.66
LTR	3	157.898	0.00	3	128.657	0.00	0.089	0.094	0.201	2.884	0.00
LTY	3	156.656	0.00	3	261.745	0.00	-0.110	-0.131	-2.485	-3.595	0.00
NTIS	3	166.083	0.00	1	28.419	0.00	-0.030	-0.073	-0.328	-0.971	0.33
SVAR	3	157.208	0.00	1	58.095	0.00	-0.237	-0.295	-2.959	-7.909	0.00
TBL	3	172.845	0.00	2	162.285	0.00	-0.077	-0.103	-1.143	-2.503	0.01
TMS	3	158.273	0.00	2	53.320	0.00	0.009	0.019	0.133	0.285	0.78

Table IV:Phases of Predictability

In-sample predictive ability periods using the predictive regression frameworks from Lewellen (2004) and Westerlund and Narayan (2012) are reported in the table. The results are based on the following regression models, $r_{t+1} = \alpha + \beta\, x_t + \varepsilon_{t+1}$, and $x_t = \phi + \rho\, x_{t-1} + \mu_{t.}$ $r_{t+1}$is the return on CRSP value weighted index in excess of the risk-free rate from time t to t+1. The returns are regressed on each lagged predictor, $x_{t.}$ and ε_{t+1} is the disturbance term. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). Column one is the list of predictor variables and from column two and three are results of the Lewellen model. Columns four to seven show the time phases for Westerlund and Narayan (2012) model. The percentages of significant confidence intervals at 95% confidence level are reported in brackets in columns 2, 4, and 6 respectively and when the percentage is over 50% or more regarded as time varying predictability, and thus is indicated by "Y". "N" represents less than 50% of significance and 100% significance.

Predictors	Lewellen (2004)		Westerlund and Narayan (2012) FGLS			
			Asymptotic Confidence Intervals Results		Sub-sampling Confidence Intervals Results	
	Time varying (Y/N) [% of Months]	Time phases of predictability by 95% CI	Time varying (Y/N) [% of Months]	Time phases of predictability	Time varying (Y/N) [% of Months]	Time phases of predictability
BM	N [100%]	1947M01-2014M12	**Y [97.91%]**	1947M01-1998M12 2000M09-2014M12	**Y [96.45%]**	*1947M01-1998M02* *2000M11-2014M12*
DE	N [25.70%]	1951M12-1953M07 1971M07-2014M12	**Y [99.02%]**	1947M01-1970M09 1971M07-2014M12	**Y [98.65%]**	*1947M01-1955M05* *1956M08-2014M12*
DFR	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12
DFY	N [100%]	1947M01-2014M12	**Y [93.023%]**	1947M01-1971M05 1972M01-1973M03 1974M05-2008M12 2009M02-2010M12 2012M08-2013M01	**Y[65.116%]**	*1970M09-2014M12*
DP	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12	N [0.861%]	1957M06-1957M09

DY	N[5.875%]	1947M01-1950M03	**Y[99.116%]**	1947M01-2009M01 2009M04-2014M12	N [9.302%]	1948M11-1949M07 1948M03-1949M04 1955M09-1960M05
EP	N [100%]	1947M01-2014M12	**N[99.876%]**	2001M09-2003M05 2008M09-2009M09	N [36.957%]	*1949M01-1950M09* 1974M07-1974M10 1975M12-1976M01 1976M08-1977M01 *1977M04-1979M06* *1979M09-1980M08* *1983M01-1990M09* *1990M12-1993M08* 1994M01-1994M10 1994M12-1995M03 1995M09-1996M03 *1996M05-2002M03*
INFL	N [27.906%]	1951M01-1969M12	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12
LTR	**Y [52.141%]**	1947M01-1955M12 1982M10-2008M10	**Y [65.483]**	1947M01-1990M04 2001M11-2003M04 2008M11-2014M12	**Y [75.764%]**	*1947M01-1990M09* 1990M12-1991M05 1991M08-1991M11
LTY	**Y [80.048%]**	1953M04-1955M05 1956M10-1957M05 1957M07-1958M11 1960M02-1960M12 1962M05-1963M03	**Y [92.044%]**	1947M01-1951M07 1954M12-1956M09 1957M08-1971M01 1973M02-2014M12	**Y [55.446%]**	1947M01-1960M01 1961M01-1961M12 1966M05-1966M12 *1970M12-1973M11* *1981M01-1987M01*

		1966M06-1968M09 1969M01-2014M14				*1987M10-1997M01* *2009M06-2011M12*
NTIS	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12	**Y [58.629%]**	1973M02-1973M11 1976M01-2008M09 2010M04-2013M04
SVAR	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12	**Y [88.127%]**	*1947M01-1982M06* *1988M04-1992M05* *1995M05-2014M12*
TBL	**Y [66.829%]**	1969M07-2014M12	**Y [89.586%]**	1950M08-1960M03 1960M12-1962M03 1966M05-2014M12	N [46.144]	*1947M01-1966M02* *1968M04-1969M05* *1973M06-1979M05* *1981M03-1982M11* *1983M05-1984M12*
TMS	**Y [60.097%]**	1973M11-2009M01 2009M05-2014M12	N [100%]	1947M01-2014M12	N [100%]	1947M01-2014M12

Table V

The table shows the results by the regression (10) $X_t = \alpha_0 + \alpha_1 X_{t-1} + \beta_i D_{it} + \epsilon_t$ The dummy variables D_1 to D_6 represent the predictability phases in Table 4 and they are obtained by expanding window method. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Predictor Variable	α_1	D_1	D_2	D_3	D_4	D_5	D_6
BM	**0.983***** (89.485)	-0.001 (-0.190)	-0.004 (-0.852)				
DE	**0.987***** (52.555)	-0.007 (-0.916)	-0.006 (-0.510)				
DP	**0.993***** (211.653)						
DFR	**-0.128**** (-2.240)						
DFY	**0.975***** (81.673)	0.000 (-0.283)					
DY	**0.993***** (258.671)	-0.005 (-0.541)	-0.003 (-0.197)				
EP	**0.975***** (63.688)	0.016 (1.390)	0.024*** (3.048)	0.009 (0.687)	-0.001 (-0.075)	**-0.023*** (-1.696)	**-0.027*** (-1.904)
INFL	**0.565***** (10.549)						
LTR	0.040 (1.085)	-0.002 (-1.261)					
LTY	**1.003***** (253.296)	0.000 (0.867)	0.000 (0.274)	-0.001 (-1.394)	0.000 (-1.516)	**-0.001**** (-2.379)	
NTIS	**0.974***** (58.621)	**-0.001*** (-1.696)	**-0.002*** (-1.928)				
SVAR	**0.612***** (6.085)	**-0.001**** (-2.397)	**-0.001**** (-2.219)	-0.001 (-1.048)			
TBL	**0.998***** (181.213)	0.000 (1.246)	**0.001**** (2.498)	0.001 (0.892)	**-0.003***** (-3.431)	0.000 (0.105)	
TMS	**0.961***** (95.239)						

Table VI

This table reports the coefficients of $\alpha_{1\,i}$ (D_i, dummies depending on the predictive phases) , α_2 from the model: $Pred_t = \alpha_0 + \alpha_{1i}D_{it} + \varepsilon_t$ (where i can be 1, 6). $Pred_t$s are t-statistics computed by equation (1) with each predictor at a time. The variables from which the predictive phases are identified including dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Variable	D_1	D_2	D_3	D_4	D_5	D_6
BM	**1.747***** (4.276)	**0.746**** (2.094)				
DE	**0.526***** (4.496)	**3.013***** (3.176)				
DP						
DFR						
DFY	**1.517***** (3.788)					
DY	**-0.984*** (-1.884)	**-1.427***** (-2.800)				
EP	**-0.859***** (-2.753)	**-0.607*** (-1.938)	**-0.576*** (-1.876)	**-0.728**** (-2.218)	**-0.751**** (-2.431)	**-1.106***** (-3.389)
INFL						
LTR	**1.081***** (3.224)					
LTY	**1.427***** (4.343)	**1.317***** (5.607)	**-0.950***** (-3.955)	**-1.158***** (-4.555)	-0.067 (-0.296)	
NTIS	**-0.904***** (-2.627)	0.013 (0.044)				
SVAR	**-41.642**** (-2.060)	**-99.861***** (-4.371)	**-59.660***** (-2.879)			
TBL	**2.729***** (7.410)	**1.862***** (7.793)	-0.186 (-0.556)	**-0.950***** (-3.592)	**-1.018***** (-4.253)	
TMS						

Table VII:Determinants of time-varying predictability: Expanding (Recursive) window

This table reports the coefficients of $\alpha_{1\,i}$ (D_i, dummies depending on the predictive phases), α_2 (E) and α_3 (UE) from the model: $Pred_t = \alpha_0 + \alpha_{1i}D_{it} + \alpha_2 E_t + \alpha_3 UE_t + \varepsilon_t$ (where i can be 1,…, 6). The risks are calculated by the financial variables including dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Variable	D_1	D_2	D_3	D_4	D_5	D_6	E	UE
BM	**1.310*** (1.695)	0.566 (1.565)	–	–	–	–	0.791 (0.791)	**1.928***** (2.755)
DE	**0.640***** (4.782)	**3.020***** (3.998)	–	–	–	–	-1.123 (-0.798)	**-2.043**** (-2.542)
DP	–	–	–	–	–	–	-0.326 (-0.553)	0.431 (0.440)
DFR	**-**	**-**	-	–	–	–	0.710 (0.136)	0.005 (0.006)
DFY	**1.589***** (4.595)	–	–	–	–	–	-16.266 (-0.743)	2.392 (0.198)
DY	-0.474 (-0.730)	**-1.237***** (-2.826)	–	–	–	–	-0.860 (-0.971)	0.688 (0.530)
EP	**-0.251*** (-1.911)	-0.159 (-1.096)	-0.038 (-0.290)	**-0.628**** (-2.403)	**-1.000***** (-3.191)	**-1.512***** (-3.424)	**-0.723***** (-3.269)	**-0.682*** (-1.869)
INFL	–	–	–	–	–	–	-26.392 (-0.219)	-8.019 (-0.187)
LTR	**1.022***** (5.553)	–	–	–	–	–	**-30.209**** (2.464)	**-1.367***** (-2.677)

LTY	**1.436*** (3.554)	**1.315*** (5.225)	**-0.967** (-2.116)	**-1.164*** (-3.863)	-0.061 (-0.232)		0.304 (0.048)	4.452 (0.904)
NTIS	-0.908 (-2.759)	0.006 (0.025)	–	–	–	–	-0.319 (-0.095)	4.148 (1.481)
SVAR	**-41.642** (-2.046)	**-99.861*** (-4.354)	**-59.660*** (-2.812)	–	–	–	-117.927 (-0.053)	99.455 (0.215)
TBL	**2.513*** (8.794)	**2.004*** (10.160)	0.051 (0.204)	-0.126 (-0.327)	**-0.506*** (-1.941)		**-10.316*** (-2.839)	-4.423 (-0.916)
TMS	–	–	–	–	–	–	48.435 (1.373)	26.335 (1.335)

Table VIII: Rolling Window

This table reports the results of the regression model $X_t = \alpha_0 + \alpha_1 X_{t-1} + \beta_i D_{it} + \epsilon_t$ Where X_t is predictor variable and D_i represent dummies for the predictive phases. The predictors include dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Predictor as dependent Variable	α_1	D1	D2	D3	D4	D5
BM	**0.982*** (91.41)	0.006 (0.984)	**-0.009** (-2.233)			
DE	**0.988*** (51.457)	-0.005 (-0.593)	-0.014 (-0.407)			
DP	**1.000*** (1612.978)	0.010 (1.174)	-0.0003 (-0.663)	-0.006 (-1.340)		
DFR	**-0.129** (-2.240)					
DFY	**0.975*** (81.934)					
DY	**0.990*** (188.242)	-0.003 (-0.683)	**-0.026*** (-2.767)			
EP	0.987*** (108.388)	**-0.018** (-2.551)	-0.006 (-0.839)	-0.008 (-0.756)	0.002 (0.148)	
INFL	**0.555*** (10.032)	0.001 (1.428)	-0.000 (-0.194)	-0.000 (-1.273)		
LTR	0.041 (1.411)	-0.001 (-1.131)				
LTY	**0.990*** (208.865)	0.000 (1.299)	**-0.000*** (-1.711)			
NTIS	**0.979*** (56.077)	**0.001*** (1.921)	**-0.001** (-2.364)	**0.001*** (1.734)	**-0.001*** (-3.071)	0.000 (0.257)
SVAR	**0.641*** (6.578)	**-0.001*** (-2.819)	**-0.001*** (-2.720)			
TBL	**0.983*** (128.477)	0.001 (0.933)	0.001 (1.535)	-0.000 (-1.730)		
TMS	**0.960*** (95.239)					

Table IX: Rolling Window

This table reports the results from the model: $Pred_t = \alpha_0 + \alpha_i D_{it} + \varepsilon_t$ (where i can be 1,…, 5). The dummy variables D_1 to 5 represent the predictability phases The predictors are dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Variable	D_1	D_2	D_3	D_4	D5
BM	**4.897***** (9.979)	**-1.838***** (-5.987)			
DE	**5.785***** (22.363)	**3.075***** (7.681)			
DP	**1.351**** (2.368)	**2.910***** (4.646)	**2.107***** (4.646)		
DFR					
DFY					
DY	**2.762***** (4.696)	**-2.688***** (-7.841)			
EP	**-2.175***** (-5.371)	1.913*** (4.695)	**-2.295***** (-5.428)	**0.829**** (2.031)	
INFL	**3.396***** (7.303)	-0.641 (-1.403)	**1.454***** (4.244)		
LTR	0.839 (0.187)				
LTY	**-2.569***** (-4.845)	**1.7643***** (3.477)			
NTIS	**-1.127***** (-6.392)	**-1.408***** (-9.027)			
SVAR	**-1.690***** (-9.471)	**-2.189***** (-11.056)			
TBL	**-0.734**** (-2.538)	**-2.174**** (-2.330)	1.782 (0.524)		
TMS					

Table X:Determinants of time-varying predictability-Rolling window approach

This table reports the coefficients of $\alpha_{1\,i}$ (D, dummies depending on the predictive phases) , α_2 (E) and α_3 (UE) from the model: $Pred_t = \alpha_0 + \alpha_{1i}D_{it} + \alpha_2 E_t + \alpha_3 UE_t + \varepsilon_t$ (where i can be 1,…, 5). The risks are calculated by the financial variables including dividend-price ratio (DP), dividend yield (DY), dividend pay-out ratio (DE), earnings to price (EP), book to market ratio (BM), inflation (INFL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), T-bill rate (TBL), net-equity expansion (NTIS), default yield spread (DFY), default return spread (DFR) and stock variance (SVAR). "***", "**" and "*" indicate s significance at 1%, 5% and 10% significance level respectively.

Variable	D_1	D_2	D_3	D_4	D5	E	UE
BM	**4.595***** (9.401)	**-1.479***** (-3.253)				**1.108*** (1.718)	**2.039**** (2.170)
DE	**4.342***** (3.469)	1.621 (1.131)				0.357 (0.489)	-6.261 (-1.422)
DP	0.207 (0.567)	**1.696***** (4.413)	**1.327***** (6.070)			**1.944***** (3.752))	**1.742**** (2.198)
DFR						-6.090 (-0.443)	0.433 (0.167)
DFY						-80.472 (-1.475)	-70.308 (-1.465)
DY	**2.034*** (6.841)	**-1.450***** (-5.341)				**1.772***** (5.127)	**1.577**** (2.047)
EP	**-2.237***** (-7.023)	**1.886***** (5.401)	**-2.231***** (-4.108)	**0.859*** (1.817)		0.113 (0.299)	**-1.024**** (-2.113)
INFL	**3.413***** (6.659)	-0.649 (-1.236)	**1.438***** (3.723)			-8.095 (-0.323)	2.339 (0.331)
LTR	0.890 (1.351)					**23.073*** (1.724)	0.728 (1.298)
LTY	**-1.786***** (-4.538)	**1.070**** (1.972)				**-27.593***** (-4.116)	11.654 (1.353)
NTIS	**-1.828***** (-6.383)	**-1.395***** (-5.994)	**-1.258***** (-5.144)	**0.706***** (3.267)	**2.766***** (12.991)	-0.469 (-0.074)	14.404 (1.262)
SVAR	**-1.690***** (-8.771)	**-2.189***** (-10.722)				-0.008 (-0.001)	-2.156 (-0.295)
TBL	-0.002 (-0.007)	**-1.314**** (-1.999)	0.999 (0.481)			**-23.496***** (-3.510)	1.997 (0.302)
TMS						-6.382 (-0.258)	-5.714 (-0.471)

Can Investors Gain from Investing in Certain Sectors?

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ABSTRACT

In this paper, we analyse investor behaviour on the NYSE. We show that average returns from dynamic trading strategies, regardless of the different portfolio constraints, out-perform passive trading strategies in all sectors. In addition, the performance of dynamic strategies is much more impressive in some sectors than in others. We also undertake a profitability and safety analysis based on a portfolio of high-performing sectors and show that at higher levels of expected returns, a rise in profitability comes at the expense of less safety. Our results, on the whole, reveal that investors can gain substantially by investing in certain sectors.

Key words: *Mean-variance; Profitability; Dynamic Trading Strategies; Portfolio; Sectors.*

1. INTRODUCTION

Can investors gain by investing in certain sectors within a market? This is the question we answer in this paper. We, thus, contribute to the vast literature that studies various trading rules and investment strategies that investors could possibly employ to profit from different markets. However, to the best of our knowledge, the literature has not yet analysed whether choosing some sectors over others within a market could be relatively more profitable using a multivariate predictive regression model and an optimal portfolio choice model.

Our work is closely related to the voluminous literature on return predictability. That literature has considered a wide range of macroeconomic predictors (see Campbell, 1987; Rapach and Wohar, 2006), and financial ratio predictors (see Fama and French, 1988; Kothari and Shanken 1997; Welch and Goyal, 2008; Campbell and Thompson, 2008; Rapach *et al*., 2010). Given these two approaches to return predictability, our paper belongs to the second strand of the literature which considers financial ratios as predictors of returns. One issue here is that the literature has not considered whether investing in certain sectors of the market will be relatively more profitable. A feature of this literature is that there is greater focus on profitability at the market level and not at the sector level, and where the focus is on the sector level the story revolves around a bivariate predictive regression and forecasting model (see, *inter alia*, Westerlund and Narayan, 2015; Narayan and Bannigidadmath, 2015 and the references cited therein). Thus, we have no knowledge yet on whether investors in certain sectors of the market will gain more if they choose a particular sector over another within a market based on using not one predictor but many predictors of returns simultaneously. In other words, the extant literature has, thus far, assumed that firms and indeed sectors making up the market are homogeneous, so that the investor utility obtained for the market applies to all investors (regardless of the sector in which they invest). This literature has also assumed a bivariate predictive regression model implying that it is one predictor (financial ratio) that matters to returns and not multiple predictors, all modelled together. This is clearly not the case; another branch of the financial economics literature has demonstrated that firms are heterogeneous. For an analysis of heterogeneity of sectors on the New York Stock Exchange (NYSE), see Hirshleifer *et al*. (2009) and Narayan and Sharma (2011). An added advantage of a sectoral approach to trading rules is that one can form portfolios based on the most profitable sectors, and identify risk-return relationships that have economic significance for investors. Moreover, a recent study by Bannigidadmath and Narayan (2016) shows that multiple financial ratio shocks actually determine time-varying predictability. This study therefore ends up questioning the bivariate predictive regression models adopted by the literature. Given our sectoral and multivariate predictive regression approach, we explore the optimal capital allocation for a mean-variance investor under different investment scenarios. This provides additional insights into possible asset allocation decisions when investors face different investment scenarios and when investors actually track not one predictor of returns but multiple predictors. This type of portfolio analysis has not previously been undertaken and could provide valuable information for investors. This constitutes our main contribution to the literature on asset pricing.

To address the research gaps identified above, our approach is as follows. We first estimate, using monthly data over the period August 1995 to August 2010, an excess return predictive regression model for each of the 11 sectors representing firms listed on the NYSE. We use three predictors, namely, the book-to-market ratio, cash-flow-to-price ratio, and dividend yield, and generate forecasts using a GARCH (1,1) model. Our in-sample period is from August 1995 to June 2002, resulting in an out-of-sample forecasting period of July 2002 to August 2010. We find that dividend yield is the most popular predictor of excess returns across all sectors, followed by the book-to-market ratio and then the cash-flow-to-price ratio. We generate excess return forecasts for each firm in each of the 11 sectors. We then apply a number of trading rules to these return forecasts. Our main idea is to see how a mean-variance investor can gain by using excess return forecasts. In addition, we subject our trading rules to different portfolio constraints. Following Marquering and Verbeek (2004), we restrict the weights in risky assets to between zero and one; and following Campbell and Thompson (2008), we constrain the weights to between zero and 1.5. This approach allows us to identify investors who are willing to pay more to trade under a dynamic trading strategy. We find that mean returns from dynamic trading strategies out-perform those from the passive trading strategies in all sectors. In fact, in certain sectors - such as technology and hardware, electricity, household, financial, travel, and banking - mean returns are much higher compared to other sectors. Similar sectoral disparities are found in terms of investor utilities. Clearly, our analysis reveals that investors can gain substantially by investing in certain sectors. We take the analysis forward by performing a profitability and safety analysis on a normalized efficient frontier for a portfolio of best performing sectors, and find that at higher levels of expected returns, a rise in profitability comes at the expense of less safety. This provides a unit analysis for an individual risk-averse investor's desire to forego safety in order to achieve higher target returns. This also provides a practical guideline for a portfolio manager who can design investment allocation decisions based on a client's level of tolerance for risk.

We organise the rest of the paper as follows. In the next section, we discuss the data. In section 3, we explain our forecasting model and set out the trading rules guiding a mean-variance investor. In section 4, we discuss the results from the trading strategies. Section 5 presents a robustness test, while the penultimate section undertakes a portfolio selection analysis. In the final section, we provide some concluding remarks.

2. Data and Preliminary Observations

The objective of this section is two-fold. We first introduce the data followed by some preliminary discussions on the behaviour of the data series. In particular, we concentrate on some statistical features of the data by first checking the integrational property of the four data series, and conclude the section with a discussion of the summary statistics of the data. The knowledge on the degree of integration of the variables is crucial as the forecasting model assumes that all variables in the predictive regression model are stationary. Our analysis here checks whether the data series are stationary and, as a result, decides on the form in which the variables should be specified in the predictive regression model. Finally, the summary statistics of the data series are important to signal at the outset how the sectors are different from a statistical point of view.

2.1 Data source

In this paper, we have monthly time series data spanning the period September 1996 to August 2010. We have data for 1344 firms listed on the NYSE. For each firm, we have four data series: firm returns, book-to-market ratio, cash-flow-to-price ratio, and dividend yield. Given our objective of analysing different trading strategies at the sector level, we ensure that we have as many firms as possible with a sufficient number of time series observations for econometric estimation. We settle at 169 time series observations per firm, at which we maximise the number of firms for which consistent time series data on all four variables are available. Our data filtering process closely follows Chordia et al. (2001) and Chordia et al. (2011), and is based on the following criterion: (a) exclude all stocks that are priced at less than \$5; (b) exclude all stocks that are priced greater than \$500; and (c) exclude all stocks which had four consecutive days of missing values. Approaches (a) and (b) ensure that results are not influenced by unduly high and low priced stocks. All the data have been downloaded from the Centre for Research in Security Price (CRSP) database.

2.2 Preliminary features

We begin with a Dickey-Fuller (1979) unit root test that examines the null hypothesis of a unit root against the alternative of a stationary series. The test is applied to all four data series and results are reported separately for each of the 11 sectors and for the market (Table 1). We first consider dividend yield. For the market, the unit root null is not rejected, rendering dividend yield to be nonstationary. However, at the sector level, we find mixed results. The unit root null is rejected at the 5% level for energy and financial sectors, and at the 10% level for the utility sector; for the rest of the eight sectors, dividend yield turns out to be nonstationary.

For the cash-flow-to-price ratio variable, again there is mixed evidence of stationarity. For seven sectors - banking, electricity, financial, mining, real estate, travel and leisure, and utility - the unit root null is not rejected. By comparison, for the market, the null is rejected at the 1% level. The cash-flow-to-price ratio variable is also stationary for the energy sector (1% level), industrial and technology sectors (5% level), and household sector (10% level). For the book-to-market ratio, of all the predictor variables considered, overwhelming evidence of a unit root is found for the market, as well as for all sectors, at the 5% level. At the 10% level the unit root null is rejected only for the utility sector. Finally, market returns and all sector returns are strongly stationary; the null hypothesis is rejected at the 1% level.

The main implication of our results here is that variables which turned out to be nonstationary will enter the predictive regression model in the first difference form. When we take the first difference of the nonstationary variables for each of the sectors, we find the variables to be stationary (see Table 1).

INSERT TABLE 1

In Table 2, we present some commonly-reported descriptive statistics for stock returns and excess stock returns for the market and for the 11 sectors. Sector-based portfolios are simply equal- weighted returns. Apart from mean returns over the period August 1996 to August 2010, we also report the standard deviation, coefficient of variation, skewness, and kurtosis. The main idea behind reporting these descriptive statistics is to give credence to our proposal to consider trading strategies by sector. The descriptive statistics clearly portray that, based on different statistical measures, the sectors differ from the market, reflecting nothing but the heterogeneity of sectors. Consider mean returns as an example. Monthly market returns are around 0.33%. At least three sectors -energy, financial, and industrial - have mean returns that are double that of the market. Several sectors have returns one-and-a-half times that of the market. A similar picture emerges when we compare excess market returns with excess sectoral returns. While excess market return over the period was negative, apart from the electricity sector which has a negative excess return, the rest of the sectors have a positive excess return. The highest excess return is found for the energy, household, and industrial sectors. The coefficient of variation implies significant disparities in volatility by sector, and sectoral volatility also deviates substantially from market volatility at least in the case of excess returns.

INSERT TABLE 2

The message emerging from the descriptive statistics on returns is clear: that the sectors perform differently, both amongst sectors and in comparison to the market. This implies that sectors are heterogeneous. This is not a new finding. It merely reflects what is already known (see, for instance, Narayan and Sharma, 2011). However, it opens up the question: Can investors, by devising sector-based trading strategies, make economic gains?

3. Forecasting Model

The goal of this section is to propose an excess return predictive regression model that we later use to generate forecasts for excess returns to analyse sectoral investor profitability and utility from various trading rules. Our empirical model is motivated by our data set. Because we have monthly time series data, the possibility of heteroskedasticity in the residuals of the predictive regression model is high. Many studies have demonstrated this to be a feature of monthly stock return data (see, for instance, French *et al*., 1987). To control for heteroskedasticity, we propose a simple GARCH (1,1), where we let r_t be the excess return on an asset, and BM, DY, and CFP represent the book-to-market ratio, dividend yield, and cash-flow-to-price ratio, respectively. Our choice of these three predictor variables is motivated by data availability on a consistent basis (that is, without missing observations), and the extant literature. A large volume of studies has shown that BM predicts either returns or excess returns. For time series studies, see Lettau and Nieuwerburgh 2008; Kothari and Shanken, 1997; Lewellen, 2004; Pontiff and Schall, 1998), and for evidence based on cross-sectional studies, see Desai *et al*. (2004) and Pincus *et al*. (2007). The choice of BM is further motivated by the seminal work of Fama and French (1992), who suggest that BM has the ability to explain cross-sectional variation in stock returns. According to asset pricing theory, BM serves as a proxy for a risk factor in returns. It is consistent with the intertemporal model of Merton (1973) and Breed (1979), who suggest that the market return does not completely capture relevant risks emanating from an economy. Given this, additional factors are required to explain expected returns. If BM is cross-sectionally correlated with factor loading, then the premium on BM simply reflects a compensation for the risk. The predictive content of DY has a theoretical appealing. The intuition behind the choice of DY is simple. When the stock prices are relatively high, it is common to expect the future returns to be lower and vice versa. However, the extent of return predictability associated with the dividend yield remains inconclusive.

The relationship between cash flow and returns is well explained by Sloan (1996), whose main argument is based on the fact that investors tend to underrate cash flows when forming future earnings expectations. Cash flow is also perceived as a measure of change in the permanent component of stock prices (Cohen *et al*., 2002). In related empirical work, Vuolteenaho (2002) and Cohen *et al*. (2002) show that cash flow has a positive effect on returns. Similarly, several studies (Avramov and Chordia, 2006; Lewellen, 2004; and Kothari and Shanken, 1997) have shown that DY predicts returns. It follows that in a multivariate predictive regression framework, and in light of our research question on hand, the choice of BM, DY, and CFP has an empirical appeal.

We use a GARCH-based predictive regression model, similar to the one used by Marquering and Verbeek (2004). Moreover, in a recent study on return predictability, Westerlund and Narayan (2012) show that a predictive regression model that accounts for heteroskedasticity performs best. The GARCH (1,1) predictive regression model has the following form:

$$r_t = \alpha_0 + \alpha_1 BM_{t-1} + \alpha_2 DY_{t-1} + \alpha_3 CFP_{t-1} + \varepsilon_t \quad (1)$$

$$h_t = \nu + \nu_1 \varepsilon_{t-1}^2 + \nu_2 h_{t-1}^2 \quad (2)$$

We define the conditional variance of return as:

$h_t \equiv \mathrm{Var}(r_t|\Omega_{t-1}) = E\left[\left(r_t - \alpha_1 BM_{t-1} - \alpha_2 DY_{t-1} - \alpha_3 CFP_{t-1}\right)^2 \middle| \Omega_{t-1}\right]$, where Ω_{t-1} denotes the set of all information available at time $t-1$.

It is common to apply a range of diagnostic tests to examine the forecasting performance of the model. Recent studies (Rapach *et al*., 2010; Welch and Goyal, 2008; Westerlund and Narayan, 2012) have compared a predictive regression model with a historical average-based forecasting model. The objective is to see how well a predictive regression model, based on some financial ratio predictors, performs relative to an historical average model for forecasting. In this section, to give credence to our proposed forecasting model, we conduct three out-of-sample forecasting evaluation tests, namely, the Theil U statistic, the Diebold and Mariano (DM) statistic (1995), and the Campbell and Thompson (2008) out-of-sample R^2 statistic. The Theil U statistic is defined as the ratio of the square roots of the mean-squared forecasting errors of the predictive regression model relative to the historical average. The DM test examines the null hypothesis that the mean-squared forecasting error of the predictive regression model is equal to that of the historical average model. Finally, the Campbell and Thompson (2008) out-of-sample R^2 test takes the following form:

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(r_t - \widehat{r_t})^2}{\sum_{t=1}^{T}(r_t - \overline{r_t})^2} \qquad (3)$$

where $\hat{r}$ is the fitted value from the predictive regression estimated through period $t-1$, and $\bar{r}$ is the historical average return estimated through period $t-1$. If the out-of-sample R^2 is positive, the predictive regression has a lower average mean-squared prediction error than the historical average return.

Following the literature which has demonstrated that the forecasting performance of the model can be influenced by the choice of the out-of-sample period (see Welch and Goyal, 2008), we consider three out-of-sample periods. We consider a short out-of-sample period where the in-sample is set at 65% of the sample; a long out-of-sample period, where the in-sample is set at 30%, and a medium out-of-sample period, where the in-sample is set at 50%. We notice, however, that with long and short out-of-sample periods, given our relatively small data set spanning 169 observations, there are not enough observations for either in-sample or out-of-sample estimates. We, therefore, prefer a medium out-of-sample period which gives us around 85 observations for in-sample estimates and around 85 observations for out-of-sample estimates on which to base our forecasting evaluations. This approach is similar to Rapach and Wohar (2006) and Westerlund and Narayan (2012).

The results are reported in Table 3. The first half of the table summarises the results on the rejection of the null of no predictability for each of the three predictors. The results are presented by sector. The second half of the table reports the out-of-sample forecasting evaluation statistics. For only two sectors—utilities and real estate—we find that the null of no predictability is rejected for all three predictors. This implies that all three predictors, BM, DY, and CFP, predict returns for utilities and real estate sectors. We notice that DY is the most common predictor of returns—the null is rejected for six out of 11 sectors. By comparison, BM only predicts returns in four of the 11 sectors. Thus, in general, we can conclude that while on the basis of the DY predictor there is greater evidence of return predictability, evidence of predictability based on the BM and CFP predictors is relatively weak. Our results, generally speaking, are in agreement with the literature. The popularity of DY as a predictor of returns is consistent with the findings of Avramov and Chordia (2006), Lewellen (2004), and Kothari and Shanken (1997). The evidence on CFP is consistent with the findings of Hirshleifer *et al*. (2009), who find that cash flow predicts returns but the predictability is sector-specific. Finally, we find relatively limited evidence of predictability when we use BM; this finding seems to be inconsistent with the literature. However, one limitation of this literature, as highlighted by Narayan and Sharma (2011), is that it treats sectors as homogenous. In other words, the bulk of the literature has examined predictability at the market level and not at the sector level. Thus, sectoral heterogeneity—an observation also made by Hirshleifer *et al*. (2009)—has not been explored, at least in a time series framework, when it comes to predictability of returns based on BM, CFP, and DY.

We now turn to the forecasting evaluation of the predictive regression model and compare it with an historical average based model. The out-of-sample forecasting evaluation is more encouraging as it generally favours the predictive regression model over the historical average model. Based on the Theil U statistic, the financial ratio based predictive regression model is superior to the historical average as the test statistics turn out to be less than one in eight out of 11 sectors. In eight sectors, the DM test statistic rejects the null hypothesis of equal predictive power, favouring the predictive regression model, as the sign turns out to be negative. Finally, the Campbell and Thompson out-of-sample R^2 is greater than zero in nine of the 11 sectors, demonstrating the superior performance of our proposed predictive regression model compared with the historical average based forecasts.

INSERT TABLE 3

There is an important message here. The return predictability literature that uses financial ratios as predictors has generally found greater evidence of in-sample predictability and extremely weak evidence of out-of-sample predictability. Our results on predictability at the sector-level are different from the literature in two ways. First, we do not find weak evidence of in-sample predictability. At best, we obtain reasonable evidence that financial ratios predict excess returns at the sector level. Second, and perhaps most significantly, we discover that there is greater evidence of out-of-sample predictability compared to in-sample predictability.

4. Performance of Trading Strategies

4.1 Evidence from conventional measures

We report the mean returns and the standard deviation (in columns 2 and 3, respectively), and the Sharpe Ratio (SR, column 4) in Table 4. In Table 5, we report the Jensen’s alpha and its t-statistic (in columns 2 and 3, respectively), and the Treynor-Mazuy (TM) t-statistic (in the final column). We consider three passive trading strategies: (a) invest 100% in the sector (strategy 1); (b) invest 50% in the sector and 50% in the risk-free asset (strategy 2); and (c) invest 100% in the risk-free asset (strategy 3). In addition, we consider two dynamic trading strategies, which we set as follows: (1) devise a trading strategy that optimises a portfolio based on predicted excess returns using book-to-market ratio, cash-flow-to-price ratio, and dividend yield as predictors (strategy 4—where the portfolio weight in risky asset is set to be between 0 and 1); and (2) devise a trading strategy (strategy 5) where the portfolio weight in risky asset is set to be between 0 and 1.5, which is motivated by Campbell and Thompson (2008). They argue that it is imperative to impose realistic portfolio weights, which prevent ‘the investor from shorting stocks or taking more than 50% leverage …” (p. 1525). In other words, if forecasts for excess returns are good, investors may borrow up to 50% of their investment value and invest in risky assets.

INSERT TABLES 4 and 5

We begin by considering the trading rule performance of the NYSE before we consider the specific sectors. We find that investing 100% in the market will provide a monthly average return of 0.11% with a standard deviation of 1.3%, while investing 100% in a risk-free asset (US 3-month Treasury bill rate) will deliver a return of 0.25% with a standard deviation of

0.22%. A 50:50 investment strategy, shared equally between risk-free and risky assets, produces a return of around 0.18%. By comparison, a 50:50 investment strategy leads to the highest return for firms in the technology and hardware sector (2.39%), followed by firms in the household sector (0.60%), and firms in the banking sector (0.56%). The sector with the lowest return is mining.

Next, we consider returns from our two dynamic trading strategies by sector. We immediately notice substantial disparities in the performance of sectors. Some sectors experience significantly higher returns from trading strategy 4. For example, mean returns in the technology and hardware sectors are around 4.7%, followed by returns in the electricity sector (1.5%), finance sector (1.2%), and banking, travel and household sectors (around 1.1%) based on the predicted excess return model. The sectors with relatively small returns are mining, industrial, utilities, real estate, and energy, where returns are less than 1%.

By comparison, with trading strategy 5, we find that the mean returns and standard deviations are relatively high across all sectors. For example, the sector with the highest return from this strategy is technology and hardware (6.9%), followed by electricity (2%); returns are between 1 to 1.5% for banking, financial, household, and travel and leisure; and returns for the remaining four sectors are less than 1%. By comparison, for the market the return from strategy 5 is 0.5% with a standard deviation of 0.8%.

Given the clear sector-driven results, reflecting merely the heterogeneity of the sectors with respect to different trading strategies, we now consider whether investing based on particular portfolios out-performs investing in sectors. To achieve this, we first use the simple SR, defined as the mean excess return on the portfolio (managed) relative to the standard deviation of the portfolio return.

All SR results are reported in Table 4 and are organised by sector so that we can compare the attractiveness of portfolio investments by sector. In the case of the banking sector, for example, we find the SR from passive strategies is 0.18 or 0.19, while the SR for the two dynamic portfolios is 0.70 and 0.74, respectively. For the rest of the sectors, we notice a similar attractiveness for dynamic trading strategies over passive strategies. This suggests that for a given level of risk, reward for dynamic portfolios is higher than passive portfolios. One other feature of the results is that in seven of the 11 sectors, the dynamic portfolio with weights between 0-1 has the highest SR, while for the rest of the four sectors the portfolio with weights between 0-1.5 has the highest SR. When we compare this performance of the sector-based dynamic trading strategies with that of the market (NYSE), we find that eight sectors have a higher SR compared to the market. Moreover, at the sectoral level, we notice the variance in SR ranges from 0.3 in the case of energy to 0.9 in the case of finance. The sectoral analysis, thus, compared to the market, proffers an important message: the sector-based dynamic trading strategies provide returns (and risks) that are heterogeneous. The implication is clear, investors can profit by carefully choosing the sector(s) in which they invest.

The second implication of our analysis of the trading strategies is that both dynamic trading strategies outperform passive trading strategies. This implies that investors would clearly profit by considering dynamic trading strategies of the type considered here. This is not to imply that our trading strategies are the best and that one should stick by them. Of course, there is no limit to the number of trading strategies that one could consider, and it is not too difficult to extend and make innovations to the trading strategies considered here. Our sole aim here is to demonstrate the relevance of dynamic trading strategies over passive trading strategies, and show that the performance of such dynamic strategies is associated with different risk-return options for investors if they were to invest in the different sectors of the market. Our analysis, thus, provides a solution for an investor who is considering investing in a market but is unsure of the sector in which he/she should invest. Our trading rules analysis by sector provides such an investor with various risk-return options based on which, from a mean-variance investor perspective, an optimal investment decision can be made.

In light of commonly-acknowledged limitations of the SR, such as the fact that it does not appropriately account for time-varying volatility, it is imperative to consider other popular tests for gauging the performance of portfolios. Therefore, we consider two other widely-used tests, namely, the Jensen's Performance Index (commonly known as Jensen's alpha) and the Treynor-Mazuy (TM) test statistic. Jensen's alpha is used to determine the abnormal return of a security or portfolio over the theoretically expected return, which are essentially the predicted returns, such as those based on Equation (1). The test for Jensen's alpha is simple and amounts to regressing the excess market returns on excess portfolio returns using OLS. The intercept term in such a regression specification is known as Jensen's alpha. A positive alpha merely signals to an investor that he/she can reasonably invest some part of his/her wealth in this portfolio. As easy as it seems, an OLS regression to obtain Jensen's alpha is problematic in the presence of market timing, however. The problem is that beta tends to vary over time in the presence of market timing, rendering an OLS estimate of alpha to be biased. To obviate such a bias, Treynor and Mazuy (1966) proposed a simple correction in the form of the following regression model:

$$r_t = \alpha + \theta r_{m,t} + \rho\left[r_{m,t}\right]^2 + \omega_t \qquad (4)$$

Here, r_t is the excess return for a sector; $r_{m,t}$ is the excess market return, which we take to be the NYSE; and $\omega_t \sim (0, \sigma^2)$ is the conventional error term. Evidence of successful market timing comes from a positive ρ coefficient.

We begin with the results from Jensen's alpha. As in previous assessments, we discover significant disparities depending on the sector. Consider the following, for example. First, abnormal returns based on strategy 4, are between 0 and 1% in nine sectors, and over 1% in two sectors (finance and technology). Second, based on strategy 5, abnormal returns in finance and banking sectors are over 1%, while, for the rest of the sectors, abnormal returns are less than 1%. Third, we notice substantial within-sector disparity in abnormal returns between the two dynamic strategies: in most sectors, abnormal returns from strategy 5 are higher than those from strategy 4. What differs, however, is the magnitude of the abnormal returns, which reflects nothing but sectoral heterogeneity which investors can exploit.

Finally, we now consider the TM test statistic for evidence of successful market timing by sector for our two dynamic trading strategies. For the market, the TM test statistics are statistically insignificant, implying no successful market timing. However, when we consider evidence at the sector-level, we find successful market timing for the trading strategies in the travel, technology, and household sectors.

So far, in analysing the profitability of dynamic trading strategies, we have assumed no transaction costs. This is an extremely strong assumption given that transaction costs are an integral part of trading and, as a result, should be explicitly accounted for. In what follows, we attempt to analyse the profitability of the dynamic trading strategies in the presence of transaction costs. As is common in this literature (see, for instance, Marquering and Verbeek 2004), we consider two levels of transaction costs: medium (0.5%) and high (1%). The results on mean returns, standard deviation, and the three trading evaluation techniques (Sharpe Ratio, Jensen's alpha, and TM) are reported in Tables 5 and 6 for each of the 11 sectors, and for the market as a whole. We find that as the transaction cost rises, compared to a situation of no transaction costs, the mean returns decline for all sectors from the dynamic strategies, regardless of the restrictions on the portfolio weights, accompanied by a decline in the strategy's standard deviation. Based on evidence from the Sharpe Ratios, we notice that regardless of the transaction costs, all sector-based dynamic trading strategies outperform their benchmark passive strategies. Across all sectors, we notice that Jensen's alpha declines monotonically but remains positive and statistically significant regardless of the level of transaction costs. Finally, the Treynor-Mazuy test confirms the lack of market timing ability for the majority of the sectors and, generally, market timing is independent of transaction costs.

INSERT TABLE 6

4.2 Evidence from a utility-based measure

The conventional approaches to evaluating trading rules suffer from some well-known and documented issues. In the case of time-varying volatility, for instance, the Sharpe ratio overestimates risk; biases in Jensen's alpha are a strong characteristic when exposed to time-varying portfolio weights; and, in a strict sense, as Marquering and Verbeek (2004) argue, the TM test is really a test of market timing not of economic value.

Our approach is similar to Campbell and Thompson (2008), Rapach *et al*. (2010), and Westerlund and Narayan (2012), where realised utility gains are computed for a mean-variance investor on a real time basis. A mean-variance investor has the following utility function:

$$E_t\{r_{t+1}\} - \frac{1}{2}\gamma Var_t\{r_{t+1}\} \tag{5}$$

Such that for a given portfolio weight of π_{t+1} for the risky asset, the utility simply becomes:

$$r_{f,t+1} + \pi_{t+1}E_t\{r_{t+1}\} - \frac{1}{2}\gamma\pi_{t+1}^2 + Var_t\{r_{t+1}\} \tag{6}$$

Where r_{t+1} is the return on the sector, $r_{f,t+1}$ is the risk-free rate of return, Var_t is the rolling variance of the risky asset, γ is the risk aversion factor, and π_{t+1} is the investor's portfolio weight in period t+1, computed as follows:

$$\pi_{t+1}^* = \frac{E_t\{r_{t+1}\} - r_{f,t+1}}{\gamma Var_t\{r_{t+1}\}} \tag{7}$$

Apart from restricting the portfolio weight to between 0 and 1, we also, following Campbell and Thompson (2008), constrain the portfolio weight on stocks to lie between 0% and 150% each month.

The average utility level, ex post, becomes:

$$\hat{U} = \frac{1}{T}\sum_{t=0}^{T-1}\left[r_{t+1} - \frac{1}{2}\gamma\pi_{t+1}^2 Var_t\right] \tag{8}$$

The average utility is computed for the dynamic portfolio as well as the passive portfolio. This allows us to compare the utilities from the two types of portfolios. We are, as a result, able to obtain the maximum fee an investor is willing to pay for holding the dynamic portfolio over a passive one.

The results on average utilities for the three passive and the two active trading strategies for three different levels of risk aversion ($\gamma = 3, 6, 12$) are reported in Table 7. The results are organised by sector, giving us the flexibility of comparing the investor preference for dynamic versus passive strategies by sector. Let us begin with the market by considering an investor with no transaction cost and with $\gamma = 6$, who invests 100% of his wealth in a risky asset. Such an investor has an ex post utility of 0.05% per month. The same investor, who follows strategy 4, has an ex post utility of 2.28% and, from strategy 5, has an ex post utility of 0.48%. It follows that the investor is better off following a dynamic trading strategy relative to the passive strategy as he/she is willing to pay more per month to hold the dynamic strategy. More specifically, the economic values of the two dynamic strategies—relative to the 100% risky asset (passive) strategy—are 2.2% and 0.4%, respectively. The corresponding gains in economic value for the two dynamic strategies over a passive strategy that invests 50% in a risky asset and 50% in a risk-free asset are 2.1% and 0.4% per month, respectively.

INSERT TABLE 7

Are there larger economic gains to be made from dynamic portfolios if investors take the preference for investing in certain sectors? The results suggest that investors do gain substantially more from dynamic trading strategies if they carefully choose the sectors for investment. Consider again an investor $\gamma = 6$ who invests 100% of his wealth in a risky asset, against a dynamic trading strategy where the portfolio weight is set to between 0-1.5 (strategy 5). We notice that the economic gain for investors in the technology and hardware sector is about 2.7% (strategy 5), which declines to about 0.578% per month for strategy 4. This performance is followed by investors in the electricity and travel sectors, where the economic gain from the dynamic portfolio is around 2% per month. Some four sectors have gains from dynamic portfolios (relative to a 100% passive portfolio) in the range of 1-1.6% per month, while the remaining four sectors have gains of less than 1% per month.

When we consider an investor $\gamma = 6$ with dynamic trading strategies, relative to a combination of risky and risk-free assets (that is, 50% in risky and 50% in risk-free assets), we generally notice that in all sectors economic gains, while still favouring the two dynamic strategies, have declined, albeit slightly. However, the ranking (importance) of sectors does not change. We still find that investors in the technology and hardware, banking, electricity, financial, travel and leisure, and household sectors experience relatively higher economic gains from dynamic trading strategies compared to passive trading strategies.

One aspect of trading we have ignored so far, which has implications for the economic gains, is transaction costs. We now re-estimate all economic gains for the market and for all the 11 sectors, and report the results in Table 8. The transaction costs are at the 0.1% (small), 0.5% (medium) and 1% (high) levels. For simplicity and to conserve space, we only compare the dynamic portfolios with only one passive strategy—one that invests 50% in a risky asset and 50% in a risk-free asset. The results from alternative passive strategies are broadly similar and detailed results are available from the corresponding author upon request.

INSERT TABLE 8

The following features of the economic gains in the presence of transaction costs stand out and deserve a mention. First, we notice that economic gains from dynamic strategies are greater than those from passive trading strategies, implying investor preference for holding dynamic strategies rather than static strategies. Second, as expected, we notice that in the presence of transaction costs, economic gains from dynamic portfolios are less than in the absence of transaction costs. Third, sectoral prominence in terms of economic gains stands out. There are sectors, such as technology and hardware, household, electricity, financial, travel and leisure, and banking, which if investors choose to invest in them, are likely to deliver higher economic gains compared to investments in other sectors.

5. Robustness Test

In considering the relevance of dynamic trading strategies by sector and the economic significance of dynamic strategies, we are concerned about the robustness of the results. Thus, we proceed to address the issue of robustness by considering different levels of transaction costs and risk aversion.

Let us begin by considering returns from our two dynamic trading strategies by sector in the presence of medium and high transaction costs (Table 6). Our first observation is that mean returns from both dynamic trading strategies, as expected, are lower with a higher transaction cost. For example, in the real estate sector, the mean returns from strategy 4 fall from 0.70% (medium transaction cost) to 0.62% (high transaction cost). The decline in returns is accompanied by an even larger decline in risk—the standard deviation declines from around 2% to 1.8%. Our second observation is that regardless of the level of transaction costs, sectoral heterogeneity is the same as previously observed under no transaction costs; that is, the best performing sectors are still the electricity and technology and hardware sectors, followed by travel, finance, banking and household sectors.

INSERT TABLE 6

We also notice that the introduction of transaction costs does not change the ranking of the sectoral performance. For example, the sector with the highest return is still technology and hardware. Thus, our results on sectoral performance from dynamic trading strategies are robust to different magnitudes of transaction costs.

In Table 7, where we compute average realised utilities without transaction costs, so far we have constrained the risk aversion factor to six, which is considered to be medium risk. The natural question is: Do the results hold in the case of low and high risk aversion factors? To answer this question, in Table 7, we also report the results for risk aversion factors of three and 12. We find that regardless of the level of risk aversion, the two dynamic trading strategies out-perform the three passive trading strategies. For example, if we take the financial sector as an example, the investor utility (when $\gamma = 3$) from strategy 4 is 1.2%, and from strategy 5 it is 1.6%, whereas, the utility from a passive strategy that invests 50% in a risky asset and 50% in a risk-free asset is only around 0.3%. When $\gamma = 12$, the familiar dominant performance of the two dynamic portfolios is noticed. Most sectors experience a similar sort of dominating performance from the two dynamic strategies regardless of the level of risk aversion. Thus, our results in favour of dynamic trading strategies and sectoral heterogeneity hold regardless of the risk aversion factors.

6. Optimal Portfolio Selection

The goal of this section is to undertake a sectoral-based portfolio selection analysis. Based on the results from the previous section, we choose the top six sectors (banking, electricity, financial, household, technology, and travel and leisure), which have the highest positive expected return over the sample period. We draw on the Markowitz (1959) mean-variance framework, which allows us to find the efficient frontier of a portfolio consisting of n securities. The solution can be obtained by using the following objective function:

$$\min \sigma^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j s_{ij} = W^T SW \tag{9}$$

$$\text{Subject to } \sum_{i=1}^{n} w_i \bar{r}_i = W^T \bar{R} = \mu \quad (10)$$
$$\sum_{i=1}^{n} w_i = 1 \quad (11)$$

Where:
(a) μ is the expected rate of return of the portfolio;
(b) σ^2 is the variance of portfolio returns;
(c) $\bar{r_i}$ is the mean rate of return on security i, and $\bar{R} = (\bar{r}_1, \bar{r}_2, \dots, \bar{r}_n)^T$;
(d) $w_i$is the portfolio weight of security i, and $W = (w_1, w_1, \dots, w_n)^T$;
(e) $s_{ij}$is the covariance of returns of the two securities i and j; and
(f) $S = {S_{ij}}_{n\times n}$ is the covariance matrix of n securities.

We solve the above problem using the Lagrange Multiplier approach under five scenarios:

- Scenario 1: The allocation of investment funds across sectors is subject to no borrowing and short-selling, which amounts to minimising (10) subject to $1 \geq w_i \geq 0$ and $\sum w_i = 1$.
- Scenario 2: The allocation of investment funds across all sectors is subject to limited borrowing and short-selling, which amounts to minimising (10) subject to $1.5 \geq w_i \geq -0.5$ and $\sum w_i = 1$.
- Scenario 3: The allocation of investment funds across all sectors is subject to no borrowing and short-selling $(1 \geq w_i \geq 0)$ but including a minimum return requirement, which amounts to setting $\mu \geq r_*$, where r_* is the average of the returns of the six sectors (0.64%).
- Scenario 4: The allocation of investment funds across sectors is subject to limited borrowing and short-selling $(1.5 \geq w_i > -0.5)$ but including a minimum return requirement, which amounts to setting $\mu \geq r^*$, where r^* is the average of the six sectors return (0.64%).
- Scenario 5: The portfolio weight is set to be equal across sectors.

The results on the optimum asset allocation and their respective risk and return under each of the scenarios are presented in Table 9. The results are organised as follows. The top six sectors that comprise our portfolio are represented in column 1. In columns 2 to 6, the portfolio weights under each of the five scenarios are presented. In row eight, we report the expected return on the portfolio for each of the scenarios, and the standard deviation of expected returns appears in row nine.

INSERT TABLE 9

The first message emerging from our portfolio analysis is that while with no short-selling and no restrictions on the minimum required return, expected returns are higher than a case where limited short-selling is allowed, the higher returns come with an additional risk of around 0.03%. Interestingly, when a minimum return requirement equivalent to the minimum mean sectoral return (0.64%) is imposed with and without short-selling and borrowing restriction, while expected returns are the same, the risk from a strategy without short-selling is about 0.12% higher (on an annual basis) than a strategy with limited short-selling. In other words, portfolio allocations perform sub-optimally when no short-selling is allowed. A limited amount of short-selling and borrowing leads to a reduction in risk.

It follows that the main implication here is that if investment allocations are performed sub-optimally then investors incur greater uncertainty from their portfolios. Thus, allowing limited short-selling is imperative for investors to minimise the risk.

The second message from our results is that investment allocations when no short-selling is allowed are dominated by electricity and financial sectors, with weights of close to 43%. By comparison, when a minimum expected return requirement is imposed, the corresponding weights for these sectors are 35% and 45%, respectively. The portfolio weights of electricity and financial sectors are most dominant regardless of whether or not a minimum expected return requirement is imposed. When the strategy allows for short-selling, long-term investment allocations (under scenarios 2 and 4) are dominated, yet again, by the electricity and financial sectors. We also discover that short-selling activities are mainly concentrated in the banking, household, and technology sectors.

Finally, we compare the expected returns and risks of investors from the four investment strategies with a naïve investor who simply allocates an equal weight to each of the sectors. The results appear in the last column of Table 9. We find that while the expected returns for the naïve investor are amongst the lowest compared to all four strategies, so is the risk. The message is that if the sole objective of an investor is to minimise risk, this can simply be achieved through an equal weighting of investment among the six sectors.

It can be argued that one limitation of our portfolio analysis so far is that we have assumed that all investments are in risky assets. In other words, we do not allow the investor to choose between a risky and a risk-free asset. To introduce risk-free assets in our analysis, we consider two specific scenarios. Under the first scenario, we restrict borrowing and short-selling and impose a minimum target return requirement (i.e., average sectoral returns) as before. The results from this scenario, in terms of allocation of funds between risky and risk-free assets, are reported in column 2 of Table 10. We notice that the portfolio manager is likely to invest around 40% of total portfolio funds in a risk-free asset. Amongst risky assets, around 10% of investments are likely to go into each of the sectors. Under the second scenario, we allow for limited short-selling ($w_i \leq 1.5$) and a minimum target return requirement as before. We notice that with limited short-selling, where short-selling activities are concentrated in the banking and travel and leisure sectors, a portfolio manager is likely to allocate around 32.8% of funds into a risk-free asset. Amongst risky assets, the most attractive sectors under limited short-selling are household (38%), followed by financial (28%), and electricity (13%). We notice that by allowing limited short-selling, the portfolio manager is able to reduce risk from 2.43% to 2.26%, and improve expected returns from 0.54% to 0.60%. The implication emerging from this analysis is that investing in a combination of risky and risk-free assets with limited short-selling provides an avenue for investors to further reduce portfolio risk.

INSERT TABLE 10

To conclude this analysis, we compare results from portfolio allocation without allowing an investor to invest in risk-free assets (Table 9), with one that allows an investor to choose between risky and risk-free assets (Table 10). We notice that when the investor has access to this choice, expected returns from the portfolio are relatively low, by about 6.3%; however, the reduction in risk is relatively more substantial, at about 0.302%.

Next, we attempt to derive an efficient frontier for mean-variance investors from the best identified sectors. Essentially, we use predicted price information over the period June 2002 to August 2010 to derive the efficient frontier. The efficient frontier is plotted in Figure 1 and takes a standard bullet shape. The frontier displays the expected returns and standard deviations of some critical points (A, E, and F) on the efficient frontier. In Table 11, we present the target expected return (E), its standard deviation (s) and variance (V) for the 19 portfolio combinations. The target monthly expected return ranges from 0.46% to 0.82%. The efficient portfolios on the E-F arc at an expected return of 0.62% have a standard deviation of around 2.87%, which almost doubles when expected return increases to 0.8%. We also compute a measure of the sensitivity of standard deviation to changes in return expectations, and report it in the fifth column $e(s, E)$. This elasticity measure explains how sensitive or vulnerable investors are when taking up additional risks every time the expected return increases by 1%. At an expected return of 0.62%, the elasticity is around 0.09 (portfolio point at 9 in column one), suggesting that a 1% rise in expected portfolio return will lead to a 0.09% increase in risk. For a moderately higher portfolio with a monthly expected return of 0.70%, a 1% increase in expectation will lead to around 14% increase in risk.

INSERT FIGURE 1

What do our results imply? They imply that investors have on hand a wide range of risk-return options to consider in selecting their optimum portfolios. This choice is obviously dependent on how risk averse an investor is. Surprisingly, the extant literature has not considered how an individual investor, or a portfolio manager, can identify the optimum point on the efficient frontier, based on his risk aversion behaviour that corresponds to the trade-off between safety and profitability. We do so here. Based on the work of Enrique and David (2004), we also normalise the expected returns and variances for portfolios using the following ratios:

$$P = \frac{E - \dot{E}}{\dot{E} - \ddot{E}} \tag{12}$$

$$S = \frac{V - \dot{V}}{\dot{V} - \ddot{V}} \tag{13}$$

Where P notes the profitability index and S denotes the safety index. Here, $\dot{E}$ and $\ddot{E}$ denote the smallest and largest expected return among the efficient portfolios, respectively, while $\dot{V}$ and $\ddot{V}$ denote the smallest and largest variance amongst the set of efficient portfolios, respectively. Both indices range from zero to one. The main purpose of these indices is that they provide investor information about the decrease (or increase) in safety from an increase (or decrease) in profitability. Essentially, this exercise provides insights on an investor's preference between safety and profitability. Our results suggest that at a 0.62% expected return, the elasticity is -0.16, implying that a rise in profitability of about 1% is offset by a fall in safety by about 0.16%. At the extreme end, when expected return is 0.82%, a 1% rise in profitability is offset by a fall in safety by about 13%. Generally, we notice that at higher levels of expected returns, a rise in profitability comes at the expense of less safety. Our analysis shows that investors have different preferences for profitability and safety. This information can be utilised by a portfolio manager in designing investment allocations.

In Figure 2, we plot the normalised efficient frontier, which displays the safety and profitability indices. It should be kept in mind that while the set of efficient portfolio points (the E to F arc in Figure 1) satisfy the mean-variance objective function, the normalised efficient frontier offers an additional avenue for investor information, particularly when the question is: What percentage of safety an investor is willing to forgo if he/she wants to increase profitability by 10%? The solution to this problem naturally arises from the intersection of the profitability and safety indices in Figure 2, which takes place at the point at which investor utility is maximised, that is, at the 14th efficient portfolio. At this point, monthly return is expected to be 0.72% with a standard deviation of 3.92%.

INSERT FIGURE 2

In our final analysis, we take the view that it is imperative to use investor utility to choose the most efficient portfolio. Thus, for a mean-variance investor, we use the utility function of individual investors to compute utility at different levels of risk aversion. None of the previous studies addresses the issue of how an investor will make choices between profitability and safety while optimizing utility. Here, our objective is to link an investor's portfolio optimization with his optimum level of utility, profitability and safety at various levels of risk aversion. The results are reported in Table 12. In the last two columns of Table 12, we also report the corresponding profitability and safety indices corresponding to risk aversion factors for each of the 19 portfolios on the efficient frontier. We find that an investor (with the least risk aversion, A=1) will maximise utility at 0.65%, with 0.89 level of profitability. This suggests that for investors with a maximum level of risk-tolerance, safety will be at the reduced level of 0.43. In this case, utility is maximised at portfolio code 17. An investor with a moderate risk aversion factor (A=6) will maximise utility at 0.38%, at which profitability will be 0.526 and safety will be 0.930. Thus, utility is maximised at portfolio code 10. An investor highly sensitive to risk (A=12) will maximize utility 0.125%, with a profitability of index of 0.47 and a safety index of 0.96. The main implication of our analysis here is that investors with the least risk-aversion will obtain higher utility by taking a higher level of risky investment. In comparison, investors with least-tolerance for risk will obtain higher utility by undertaking lower risk investment with a greater safety requirement.

INSERT TABLE 12

7. Concluding Remarks

This paper addresses the question: Can investors benefit by carefully investing in selected sectors within a market? We perform an extensive sectoral portfolio analysis of various investment strategies for 1344 stocks listed on the NYSE, using monthly data for the period August 1995 to August 2010. Using a mean-variance framework, we discover a number of new findings that suggest if investors carefully choose the sectors in which they want to invest, significant economic gains are possible.

Our main findings are as follows. First, we find that dynamic strategies, regardless of constraints on portfolio weights, out-perform passive trading strategies. We discover that returns from dynamic trading strategies in certain sectors, such as technology and hardware, electricity, household, financial, travel, and banking, are relatively high compared to investments in other sectors. We find that these findings are robust to different levels of transaction costs.

Second, when we compute investor utilities, we find that regardless of transaction costs and the level of risk aversion, investors have a preference for investments in certain sectors. These, unsurprisingly, are the same sectors that dominated returns from the dynamic trading strategies.

Third, we form a portfolio of top-performing sectors and estimate the portfolio efficient frontier. Our profitability and safety analysis reveals that at higher levels of expected returns, a rise in profitability comes at the expense of less safety.

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Table 1: Unit root tests by sector

In this table, we report the Dickey-Fuller (DF) unit root test for variables relating to the market and sector. The DF test examines the null hypothesis of a unit root against the alternative of a stationary series. The optimal lag length in the DF model, used to control for serial correlation, is chosen using the Schwarz Information Criterion. Our approach is that we begin with a maximum of eight lags and then apply the SIC to obtain the optimal lag length. The test statistics are reported together with the probability value, which is used to examine the null hypothesis.

Market	statistic	prob.	Banking_stat	prob.	Elect_stat	Prob
Ret	-8.33	0.00	-11.60	0.00	-8.31	0.00
log DY	-1.66	0.45	-1.64	0.46	-2.14	0.23
CFP	-10.03	0.00	-2.40	0.14	-1.75	0.40
log BM	-2.03	0.27	0.61	0.99	-2.18	0.22
dlog DY	-8.07	0.00	-11.42	0.00	-7.87	0.00
d CFP	-7.55	0.00	-12.37	0.00	-8.40	0.00
d log BM	-8.23	0.00	-11.32	0.00	-7.89	0.00
Energy	**statistic**	**prob.**	**Financial_stat.**	**prob.**	**HH_stat.**	**Prob**
Ret	-8.31	0.00	-9.30	0.00	-7.29	0.00
log DY	-3.32	0.02	-3.02	0.04	-2.03	0.27
CFP	-10.04	0.00	-1.63	0.46	-2.65	0.09
log BM	-1.81	0.37	-1.71	0.42	-1.96	0.30
dlog DY	-11.46	0.00	-9.17	0.00	-7.15	0.00
dCFP	-7.55	0.00	-7.61	0.00	-6.63	0.00
dlog BM	-9.38	0.00	-8.98	0.00	-7.38	0.00
Industrial	**statistic**	**prob.**	**Mining_stat.**	**prob.**	**RE_stat.**	**prob.**
Ret	-9.33	0.00	-11.64	0.00	-7.31	0.00
log DY	-1.94	0.31	-1.61	0.47	-1.34	0.61
log CFP	-2.91	0.05	-1.71	0.42	-1.24	0.65
log BM	-2.02	0.28	-1.52	0.52	-0.67	0.85
dlog DY	-10.44	0.00	-10.36	0.00	-7.27	0.00
dlog CFP	-8.68	0.00	-8.53	0.00	-6.50	0.00
dlog BM	-8.61	0.00	-11.45	0.00	-8.82	0.00
Tech.	**statistic**	**prob.**	**Travel_stat.**	**prob.**	**Utility_stat.**	**prob.**
Ret	-8.68	0.00	-7.22	0.00	-9.20	0.00
log DY	-2.13	0.24	-2.46	0.13	-2.72	0.08
log CFP	-3.08	0.03	-1.90	0.33	-0.50	0.89
log BM	-1.64	0.46	-1.90	0.33	-2.77	0.07
dlog DY	-8.64	0.00	-10.93	0.00	-8.69	0.00
dlog CFP	-11.32	0.00	-8.43	0.00	-10.02	0.00
dlog BM	-7.70	0.00	-7.39	0.00	-8.47	0.00

Table 2: Descriptive statistics of returns and excess returns for the market and sectors

In this table, we represent some commonly reported descriptive statistics of the stock returns and excess stock returns both for the market as well as for each of the sectors. In particular, we report mean returns, standard deviation, coefficient of variation, skewness, and kurtosis.

	Stock returns					Excess stock returns				
	Mean (%)	SD (%)	CV	Ske.	Kurt.	Mean (%)	SD (%)	CV	Ske.	Kurt.
Banking	0.38	6.80	18.03	-0.91	2.62	0.01	6.79	969.71	-0.89	2.52
Electricity	0.34	4.50	13.16	-0.53	0.65	-0.03	4.49	160.29	-0.54	0.57
Energy	0.85	7.52	8.80	-0.18	0.44	0.48	7.51	15.53	-0.19	0.41
Financial	0.60	5.20	8.64	-0.56	2.49	0.23	5.18	22.32	-0.54	2.36
Household (HH)	0.78	6.64	8.54	-0.13	0.77	0.41	6.66	16.32	-0.10	0.81
Industrial	0.75	8.42	11.27	-0.55	2.49	0.38	8.43	22.30	-0.47	2.43
Mining	0.55	11.25	20.35	0.11	2.66	0.18	11.29	61.71	0.11	2.61
Real Estate (RE)	0.43	5.85	13.59	-1.09	5.43	0.06	5.87	96.16	-1.00	5.20
(Tech.)	0.54	9.43	17.36	-0.27	1.50	0.17	9.43	54.51	-0.28	1.51
Travel	0.59	7.54	12.84	0.47	4.13	0.22	7.56	34.83	0.52	4.24
Utilities	0.44	3.75	8.54	-0.33	0.47	0.07	3.75	54.39	-0.34	0.42
Market	0.33	4.02	12.11	-0.75	1.31	-0.04	4.03	106.05	-0.69	1.19

Table 3: Forecasting results

In this table, we report two sets of results. The first half of the table summarises the results on return predictability based on the three predictors: DY, BM, and CFP. More specifically, we answer the question: Is the null of no predictability rejected? The results are summarised by sector, and the final row reports the corresponding results for the market. In the second half of the table we undertake an out-of-sample forecasting evaluation, drawing on three test statistics: the Theil *U* statistics, the DM statistic, and the out-of-sample R^2 in decimal. * (**) *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Is the null of no predictability rejected?			Forecasting evaluation		
	DY	BM	CF	Theil *U*	DM	R^2
Banking	Yes	No	No	0.95	-6.52*	0.0904
Electricity	No	Yes	No	0.99	-7.82*	0.0055
Energy	Yes	No	No	0.95	-2.17**	0.0281
Financial	Yes	No	Yes	0.99	-1.78***	0.0113
Household	Yes	No	No	0.98	-2.17**	0.1485
Industrial	No	No	No	1.00	-1.36	-0.0181
Mining	No	No	No	0.99	0.82	-0.0093
Real Estate	Yes	Yes	Yes	1.00	-1.36	0.0113
Tech	No	No	Yes	0.99	-2.17**	0.1485
Travel	No	Yes	No	1.02	-2.16**	0.0281
Utilities	Yes	Yes	Yes	0.99	-1.784*	0.0113
Market	No	No	No	0.99	-2.32 **	0.0919

Table 4: Sectoral performance from passive and dynamic trading strategies without transaction costs

In this table, we report the mean (%), standard deviation (%) and the Sharpe Ratio (SR) for the passive and dynamic trading strategies with no transaction costs. The SR is calculated as the average excess return of the strategy divided by the sample standard deviation. The passive strategies are comprised of three different strategies: (1) 100% investment in the sectors; (2) 50% investment in the sectors and 50% in risk-free assets; and (3) 100% investment in risk-free assets. The last two strategies are dynamic, where the optimal portfolio is based on predicted excess returns. Optimal μ (0-1) allows for no borrowing, and optimal μ (0-1.5) accounts for limited borrowing.

	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Panel A: Banking				Panel B: Electricity		
100% Market	0.857	3.198	0.188	-0.059	3.974	-0.080
50% Market	0.557	1.643	0.182	0.101	1.999	-0.080
0% Market	0.257	0.220			0.220	
Optimal μ (0-1)	1.098	1.133	0.740	1.471	1.572	0.769
Optimal μ (0-1.5)	1.404	1.625	0.704	2.038	2.362	0.753
Panel C: Energy	Mean	Std. Dev.	SR	Panel D: Finance	Std. Dev.	SR
100% Market	0.097	1.190	-0.135	0.303	2.986	0.015
50% Market	0.177	0.621	-0.129	0.280	1.558	0.015
0% Market	0.257	0.220		0.257	0.220	
Optimal μ (0-1)	0.419	0.520	0.305	1.213	1.035	0.920
Optimal μ (0-1.5)	0.441	0.609	0.297	1.625	1.481	0.922
Panel E: Household	Mean	Std. Dev.	SR	Panel F: Industrial	Std. Dev.	SR
100% Market	0.945	2.141	0.320	-0.019	1.714	-0.161
50% Market	0.603	1.066	0.321	0.119	0.892	-0.155
0% Market	0.260	0.220		0.257	0.220	
Optimal μ (0-1)	1.115	1.412	0.606	0.407	0.560	0.263
Optimal μ (0-1.5)	1.205	1.533	0.616	0.407	0.560	0.263
Panel G: Mining	Mean	Std. Dev.	SR	Panel H: RE	Std. Dev.	SR
100% Market	-1.336	1.050	-1.518	-0.195	3.061	-0.148
50% Market	-0.539	0.553	-1.440	0.031	1.543	-0.146
0% Market	0.257	0.220		0.257	0.220	
Optimal μ (0-1)	0.265	0.224	0.023	0.719	1.994	0.230
Optimal μ (0-1.5)	0.265	0.224	0.023	0.893	2.947	0.215
Panel I: Tech	Mean	Std. Dev.	SR	Panel J: Travel	Std. Dev.	SR
100% Market	4.515	6.981	0.610	-0.249	4.405	-0.115
50% Market	2.386	3.416	0.623	0.004	2.206	-0.115
0% Market	0.257	0.220		0.257	0.220	
Optimal μ (0-1)	4.739	6.002	0.746	1.151	2.439	0.365
Optimal μ (0-1.5)	6.946	9.093	0.735	1.316	2.875	0.368
Panel K: Utility	Mean	Std. Dev.	SR	Panel L: Market	Std. Dev.	SR
100% Market	0.642	0.520	0.739	0.106	1.336	-0.113
50% Market	0.449	0.325	0.592	0.182	0.688	-0.110
0% Market	0.257	0.220		0.257	0.220	
Optimal μ (0-1)	0.628	0.475	0.774	2.911	9.219	0.288
Optimal μ (0-1.5)	0.734	0.639	0.741	0.493	0.828	0.284

Table 5: Jensen's Alpha and TM statistic

Jensen's Alpha is derived from the OLS estimate of the intercept in the regression of excess return of the strategy for each sector on the excess return of the market. The column next to this contains the corresponding test statistics. The Treynor- Mazuy (TM) test statistic is the t-value of the squared return coefficient in a regression of the excess returns on a constant, the excess returns, and the squared excess return of the S&P 500 index. These statistics are derived for the dynamic strategies with no, medium (0.5%), and high (1%) transaction costs. Optimal μ (0-1) allows for no borrowing, and optimal μ (0-1.5) accounts for limited borrowing.

	No			Medium			High		
	J-alpha	t-stat.	TM	J-alpha	t-stat.	TM	J-alpha	t-stat.	TM
Panel A: Banking									
Optimal μ (0-1)	0.90	0.61	-1.04	0.82	6.33	-0.95	0.74	6.31	-0.16
Optimal μ (0-1.5)	1.23	6.38	-0.94	1.11	5.91	-0.86	1.02	5.91	-1.61
Panel B: Electricity									
Optimal μ (0-1)	0.16	2.64	-0.63	0.16	2.46	-0.65	0.17	2.37	-0.69
Optimal μ (0-1.5)	0.16	2.64	-0.63	0.16	2.46	-0.65	0.17	2.37	-0.69
Panel C: Energy									
Optimal μ (0-1)	0.18	2.95	-0.62	0.15	2.76	-0.58	0.12	2.41	0.11
Optimal μ (0-1.5)	0.20	2.76	-0.47	0.16	2.61	-0.44	0.13	2.33	0.01
Panel D: Finance									
Optimal μ (0-1)	1.11	11.14	-3.34	0.98	10.30	-3.17	0.86	9.36	-2.81
Optimal μ (0-1.5)	1.59	10.47	-3.20	1.41	9.69	-3.01	1.24	8.87	-2.69
Panel E: Household									
Optimal μ (0-1)	0.57	4.01	4.27	0.50	3.57	4.54	0.54	3.57	2.36
Optimal μ (0-1.5)	0.67	4.18	3.74				0.63	3.67	1.93
Panel F: Industrial									
Optimal μ (0-1)	0.16	2.69	-0.63	0.16	2.45	-0.65	0.17	2.37	-0.66
Optimal μ (0-1.5)	0.16	2.69	-0.63	0.16	2.45	-0.65	0.17	2.37	-0.66
Panel G: Mining									
Optimal μ (0-1)	0.01	1.61	-0.72	0.01	1.64	-0.74	0.00	1.32	-0.63
Optimal μ (0-1.5)	0.01	1.61	-0.72	0.01	1.64	-0.74	0.73	5.27	2.28
Panel H: Real Estate									
Optimal μ (0-1)	0.51	2.16	-0.48	0.49	2.01	-0.44	0.38	1.80	-0.22
Optimal μ (0-1.5)	0.69	1.83	-0.46	0.69	1.83	-0.46	0.55	1.71	-0.27
Panel I: Tech									
Optimal μ (0-1)	1.48	6.35	4.12	1.46	6.52	6.00	0.02	6.84	1.40
Optimal μ (0-1.5)	0.89	6.30	5.26	0.82	5.94	4.47	0.73	5.27	2.28
Panel J: Travel									
Optimal μ (0-1)	0.57	1.96	2.42	0.57	1.86	2.47	0.80	2.60	0.46
Optimal μ (0-1.5)	0.76	2.15	1.90	0.76	2.06	1.97	1.00	2.74	0.12
Panel K: Utility									
Optimal μ (0-1)	0.38	7.44	-0.40	0.26	6.06	-0.44	0.14	4.95	0.59
Optimal μ (0-1.5)	0.49	6.74	-0.57	0.33	5.63	-0.60	0.16	4.64	0.20
Panel L: Market									
Optimal μ (0-1)	2.67	2.70	-0.66	2.72	2.72	-0.62	2.77	2.50	-0.72
Optimal μ (0-1.5)	0.24	2.89	-1.16	0.21	2.71	-1.14	0.19	2.55	-0.85

Table 6: Trading performance in the presence of transaction costs

This table only reports the trading performances of the dynamic strategies with medium (0.5%) and high (1%) transaction costs. It reports the mean (%), standard deviation (%) and the Sharpe Ratio. Optimal μ (0-1) allows for no borrowing, and optimal μ (0-1.5) accounts for limited borrowing.

	Medium			High		
Panel A: Banking	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	1.02	1.11	0.69	0.92	1.01	0.65
Optimal μ (0-1.5)	1.30	1.58	0.66	1.15	1.45	0.61
Panel B: Electricity	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	1.42	1.54	0.75	1.25	1.42	0.70
Optimal μ (0-1.5)	1.96	2.31	0.74	1.70	2.12	0.68
Panel C: Energy	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	0.40	0.48	0.28	0.38	0.44	0.27
Optimal μ (0-1.5)	0.41	0.54	0.28	0.39	0.49	0.27
Panel D: Finance	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	1.10	1.00	0.85	1.00	0.96	0.77
Optimal μ (0-1.5)	1.47	1.42	0.85	1.32	1.36	0.78
Panel E: Household	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	1.05	1.38	0.57	0.96	1.24	0.57
Optimal μ (0-1.5)	1.12	1.48	0.58	1.04	1.39	0.56
Panel F: Industrial	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	0.40	0.58	0.24	0.41	0.64	0.23
Optimal μ (0-1.5)	0.40	0.58	0.24	0.41	0.64	0.23
Panel G: Mining	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	0.27	0.22	0.02	0.26	0.22	0.01
Optimal μ (0-1.5)	0.27	0.22	0.02	0.26	0.22	0.01
Panel H: Real Estate	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	0.70	2.03	0.22	0.62	1.79	0.20
Optimal μ (0-1.5)	0.87	3.00	0.20	0.77	2.65	0.19
Panel I: Tech	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	4.74	6.00	0.75	4.55	5.91	0.73
Optimal μ (0-1.5)	6.95	9.09	0.74	6.65	8.95	0.71
Panel J: Travel	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	1.18	2.57	0.36	1.13	2.46	0.35
Optimal μ (0-1.5)	1.35	3.03	0.36	1.30	2.94	0.35
Panel K: Utility	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	0.51	0.52	0.61	0.41	0.32	0.45
Optimal μ (0-1.5)	0.57	0.52	0.60	0.43	0.37	0.45
Panel L: Market	Mean	Std. Dev.	SR	Mean	Std. Dev.	SR
Optimal μ	2.96	9.31	0.29	3.02	10.29	0.27
Optimal μ (0-1.5)	0.47	0.80	0.27	0.45	0.76	0.25

Table 7: Average realised utilities (without transaction costs)

In this table, we report the average realised utilities associated with the passive and dynamic strategies with zero transaction costs. The average utilities are reported according to the risk aversion factor, γ, which is presumed to take the values of 3, 6, or 12. Optimal μ (0-1) allows for no borrowing, and optimal μ (0-1.5) accounts for limited borrowing.

	γ =3	γ=6	γ=12	γ=3	γ=6	γ=12
	Banking			Electricity		
100% Market	0.23	0.13	-0.08	-0.31	-0.57	-1.07
50% Market	0.29	0.29	0.27	0.09	0.07	0.04
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	1.08	1.06	1.03	1.36	1.25	1.03
Optimal μ (0-1.5)	1.37	1.34	1.28	1.81	1.59	1.14
	Energy			Financial		
100% Market	0.08	0.05	0.01	0.25	0.20	0.09
50% Market	0.18	0.17	0.17	0.28	0.27	0.27
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	0.42	0.42	0.41	1.21	1.20	1.19
Optimal μ (0-1.5)	0.44	0.44	0.43	1.62	1.61	1.59
	Household			Industrial		
100% Market	0.88	0.81	0.67	-0.06	-0.10	-0.19
50% Market	0.60	0.59	0.59	0.12	0.11	0.11
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	1.10	1.08	1.05	0.41	0.40	0.40
Optimal μ (0-1.5)	1.19	1.17	1.13	0.41	0.40	0.40
	Mining			RE		
100% Market	-1.35	-1.37	-1.40	-0.33	-0.47	-0.75
50% Market	-0.54	-0.54	-0.54	0.02	0.01	0.00
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	0.27	0.27	0.27	0.69	0.65	0.58
Optimal μ (0-1.5)	0.27	0.27	0.27	0.83	0.77	0.64
	Tech.			Travel		
100% Market	4.42	4.33	4.15	-0.53	-0.80	-1.35
50% Market	2.38	2.38	2.36	-0.01	-0.03	-0.07
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	4.98	4.91	4.77	1.11	1.06	0.97
Optimal μ (0-1.5)	7.26	7.10	6.78	1.26	1.20	1.08
	Utilities			Market		
100% Market	0.64	0.64	0.63	0.08	0.05	0.00
50% Market	0.45	0.45	0.45	0.18	0.18	0.18
0% Market	0.26	0.26	0.26	0.26	0.26	0.26
Optimal μ (0-1)	0.63	0.63	0.62	2.60	2.29	1.66
Optimal μ (0-1.5)	0.73	0.73	0.73	0.49	0.48	0.47

Table 8: Average realised utilities with transaction costs

Here, we report the average realised utilities with low (0.1%), medium (0.5%), or high (1%) transaction cost. Optimal μ (0-1) allows for no borrowing, and optimal μ (0-1.5) accounts for limited borrowing.

		0.10%	0.50%	1%		0.10%	0.50%	1%
Banking	50% Market	0.285	0.285	0.285	Electric.	0.069	0.069	0.069
	Optimal μ (0-1)	1.046	0.989	0.886		1.239	1.199	1.053
	Optimal μ (0-1.5)	1.319	1.242	1.100		1.573	1.517	1.314
Energy	50% Market	0.174	0.174	0.174	Finance	0.274	0.274	0.274
	Optimal μ (0-1)	0.446	0.393	0.376		1.173	1.092	0.989
	Optimal μ (0-1.5)	0.479	0.407	0.388		1.573	1.448	1.307
HH	50% Market	0.594	0.594	0.594	Industr.	0.114	0.114	0.114
	Optimal μ (0-1)	1.094	1.018	0.934		0.410	0.394	0.400
	Optimal μ (0-1.5)	1.183	1.085	1.009		0.410	0.394	0.400
Mining	50% Market	-0.541	-0.541	-0.541	RE	0.014	0.014	0.014
	Optimal μ (0-1)	0.267	0.265	0.263		0.609	0.630	0.576
	Optimal μ (0-1.5)	0.267	0.265	0.263		0.717	0.743	0.676
Tech.	50% Market	2.375	2.375	2.375	Travel	-0.030	-0.030	-0.030
	Optimal μ (0-1)	4.891	4.611	4.416		1.067	1.071	1.033
	Optimal μ (0-1.5)	7.066	6.660	6.364		1.208	1.215	1.173
Utility	50% Market	0.449	0.449	0.449	Market	0.178	0.178	0.178
	Optimal μ (0-1)	0.637	0.512	0.405		2.291	2.330	2.308
	Optimal μ (0-1.5)	0.755	0.567	0.424		0.476	0.456	0.434

Table 9: Portfolio asset allocation across top six sectors under four different conditions

This table reports optimum asset allocation across six sectors, and the corresponding portfolio risk and return under four different scenarios, including a condition where it is assumed that the investor is naïve. The changes in standard deviation suggest an incremental benefit from switching from investment with short-selling restriction, to investment allocation with limited short-selling. Finally, X represents investment weight and S1 to S4 represent the different trading strategies.

Capital allocation	X, S1	X, S2	X, S3	X, S4	X, Naive
Banking	0.045	0.054	0.010	-0.015	0.167
Electricity	0.435	0.452	0.354	0.390	0.167
Financial	0.425	0.424	0.446	0.446	0.167
Household	0.010	-0.018	0.148	0.147	0.167
Technology	0.010	-0.004	0.010	-0.042	0.167
Travel & Leisure	0.075	0.092	0.033	0.073	0.167
Expected return	0.614	0.610	0.639	0.639	0.610
Standard deviation (SD)	2.894	2.861	2.957	2.947	2.860
Changes in SD		-0.033		-0.0103	

Table 10: Capital allocation between risky and risk-free assets

This table reports optimum asset allocation between risky assets (6 sectors) and risk-free assets. We also report corresponding portfolio risk and return under two different scenarios. The changes in standard deviation suggest an incremental benefit from switching from investment with short-selling restriction, to investment allocation with limited short-selling. Finally, X represents the investment weight and S1 and S2 represent the two strategies.

Sectors	X,S1	X,S2
Banking	0.100	-0.051
Electricity	0.100	0.128
Financial	0.100	0.278
Household	0.100	0.378
Technology hardware	0.100	0.047
Travel & Leisure	0.100	-0.108
Risk-free asset	0.400	0.328
Total portfolio weight	1.000	1.00
Expected portfolio return	0.535	0.601
Standard deviation (SD)	2.427	2.264

Table 11: Portfolios on efficient frontier and their critical parameters

In this table, we present the parameters of the efficient frontiers; namely, the expected return (E), portfolio standard deviation (s) and variance (V), portfolio return elasticity, profitability index (P), safety index (S), and the elasticity of profitability to safety (e(P,S).

Portfolio code	s	V	E	e(s,E)	P	S	e(P,S)
1	4.62	21.34	0.46	0.00	0.00	0.87	0.00
2	4.25	18.06	0.48	-18.52	0.11	0.91	0.00
3	3.90	15.24	0.50	-17.28	0.16	0.95	0.04
4	3.59	12.90	0.52	-15.61	0.21	0.98	0.06
5	3.32	11.03	0.54	-13.55	0.26	0.99	0.05
6	3.10	9.63	0.56	-10.92	0.32	1.00	0.03
7	2.95	8.69	0.58	-7.69	0.37	1.00	-0.01
8	2.87	8.23	0.60	-3.96	0.42	0.98	-0.08
9	2.87	8.24	0.62	0.09	0.47	0.96	-0.16
10	2.95	8.72	0.64	4.13	0.53	0.93	-0.27
11	3.11	9.68	0.66	7.84	0.58	0.89	-0.40
12	3.33	11.10	0.68	11.04	0.63	0.84	-0.58
13	3.60	12.99	0.70	13.64	0.68	0.78	-0.80
14	3.92	15.35	0.72	15.71	0.74	0.71	-1.10
15	4.26	18.19	0.74	17.32	0.79	0.62	-1.48
16	4.64	21.49	0.76	18.57	0.84	0.53	-2.02
17	5.03	25.27	0.78	19.54	0.89	0.43	-2.80
18	5.63	31.68	0.80	30.11	0.95	0.32	-4.04
19	7.83	61.26	0.82	109.91	1.00	0.00	-12.75

Table12: Linkage between investors' utility, profitability and safety

In this table, we present the linkage between the level of investor utility with different levels of risk-aversion, and the trade-off between profitability (P) and safety (S). "A" is the risk aversion coefficient. The optimum expected utility is observed for the least risk-averse, moderately risk averse, and higher level of risk averse investor.

Portfolio code	E(U) A=1	E(U) A=3	E(U) A=6	E(U) A=9	E(U) A=12	Profitability	Safety
1	0.353	0.140	-0.180	-0.500	-0.821	0.000	0.869
2	0.390	0.209	-0.062	-0.333	-0.604	0.105	0.915
3	0.424	0.271	0.043	-0.186	-0.414	0.158	0.951
4	0.455	0.326	0.133	-0.061	-0.254	0.211	0.977
5	0.485	0.375	0.209	0.044	-0.122	0.263	0.993
6	0.512	0.416	0.271	0.127	-0.018	0.316	1.000
7	0.537	0.450	0.319	0.189	0.058	0.368	0.997
8	0.559	0.476	0.353	0.229	0.106	0.421	0.984
9	0.579	0.496	0.373	0.249	0.125	0.474	0.962
10	0.596	0.509	0.378	0.247	0.117	0.526	0.930
11	0.612	0.515	0.370	0.225	0.079	0.579	0.888
12	0.625	0.514	0.347	0.181	0.014	0.632	0.837
13	0.635	0.505	0.310	0.115	-0.079	0.684	0.776
14	0.643	0.490	0.259	0.029	-0.201	0.737	0.705
15	0.649	0.467	0.194	-0.078	-0.351	0.789	0.625
16	0.653	0.438	0.115	-0.207	-0.529	0.842	0.534
17	0.654	0.401	0.022	-0.357	-0.736	0.895	0.434
18	0.642	0.325	-0.150	-0.626	-1.101	0.947	0.325
19	0.514	-0.099	-1.018	-1.937	-2.856	1.000	0.000

Figure 1: Mean-standard deviation efficient frontier based on 19 portfolio codes

In this figure, we plot the efficient frontier. It takes a standard bullet shape. The frontier displays the expected returns and standard deviations of some critical points (A, E, and F) on the efficient frontier. The vertical axis contains the expected returns, while the horizontal axis contains the standard deviation of the expected returns.

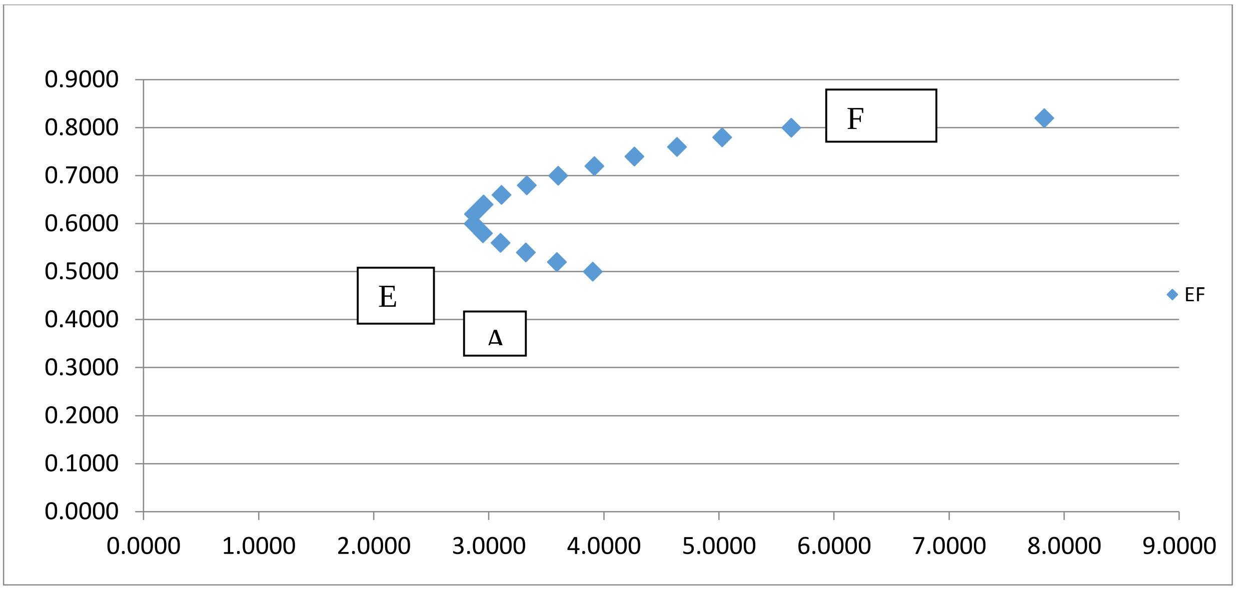
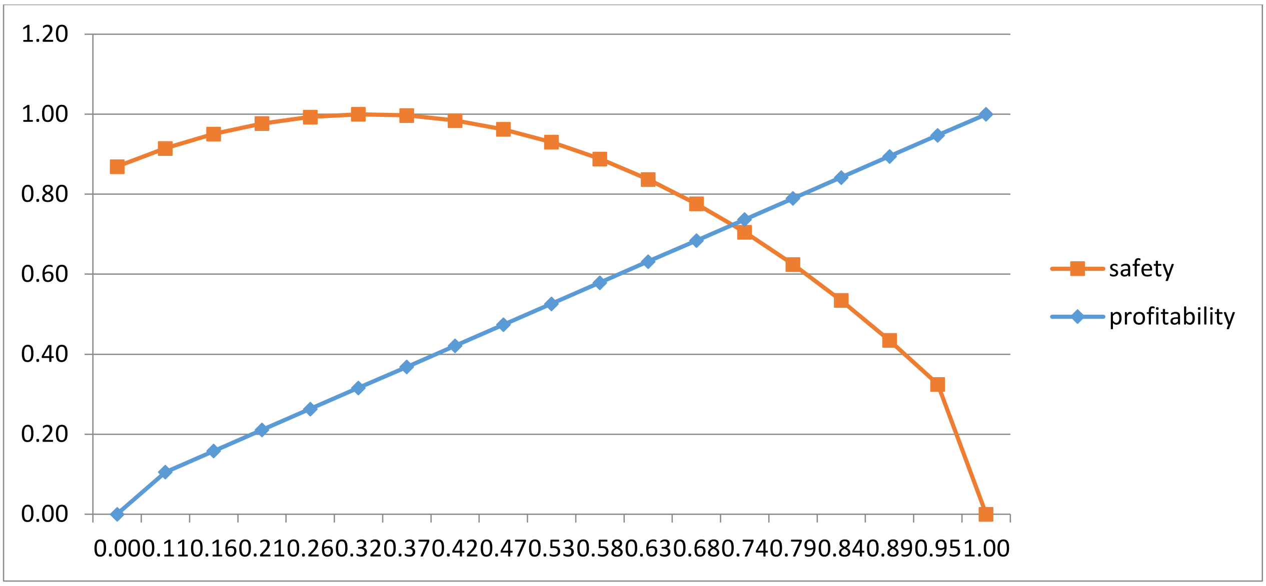


Figure 2: Normalised efficient frontier

In this figure we plot the trade-off between profitability (P) and safety index (S). The intersection point between profitability and safety is the optimum portfolio combination (14th portoflio code) at which investors maximise utility.



Exchange Rate, Cross Elasticities between Exports and Imports and Current Account Sustainability: The Spanish Case.

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ABSTRACT

This paper presents an analytical reformulation of the traditional approach to the current account sustainability from the perspective that in very open economies the independence of GDP and exchange rates cannot be postulated, and therefore the Marshall -Lerner condition could not be maintained. We use a macroeconomic model of dynamic stochastic general equilibrium (DGSE) , to simulate the impacts of variations of the exchange rate , cross elasticity export-import or tax rate on consumption, would have on the Spanish economy and specifically on its current account sustainability.

Key words: Marshall-Lerner condition, Current Account Sustainabilaty, Macroeconomic model of dynamic stochastic general equilibrium, Cross elasticities export- import.

JEL classification: F41, F44, F30, F11

1.-Introduction

The economic globalization process that has been characteristic of the evolution of the world´s economic system in the last few decades has been analysed in depth from a financial perspective , but studies of its implications for the real economy and particularly the foreign sector of national economies , have not been as plentiful. Traditionally, economic theory has analyzed the foreign sector in relation to compliance with the Marshall-Lerner condition, according to which " for a currency devaluation to have a positive impact on trade balance , the sum of price elasticity of exports and imports(in absolute value) must be greater than 1". This condition implicitly assumes that the GPD is independent from the exchange rate. In a globalised economy in which trade has heavily increased, there are many countries in which the ratio between the trade balance and the GPD is very high, so this assumption is not sustained. Loose monetary policies implemented by some countries as a way of competitive devaluation of theirs currency trying to boost its economies and its exports in particular, at the expense of the rest of the world. Imports and Exports remove the restriction that consumption, investment and firm´s sales are limited by domestic demand. A monetary expansion is in the long term a beggar thyself policy only if the Marshall-Lerner condition does not hold.

Whether or not a current account deficit is sustainable has important implications for policy. If the current account deficits of a nation are sustainable, then implies that the government should have no incentive to default on its international debt. International capital flows allow the domestic economy to borrow from abroad and to hold foreign assets (1). An open economy ought to be able to attain a higher level of welfare than a closed economy.

In this work we can distinguish two kinds of goals. On the one hand, reformulate the theoretical analysis on the sustainability of the current account, from the perspective that in very open economies the independence of GDP and exchange rates cannot be postulated, and therefore the Marshall -Lerner condition could not be maintained.

On the other hand , a second purpose is the use of a macroeconomic model of dynamic stochastic general equilibrium (DGSE) , to simulate the impacts of variations of the exchange rate , cross elasticity export-import or tax rate on consumption, would have on the Spanish economy and specifically on its current account sustainability.

The economic literature includes numerous theoretical and empirical studies of the impact of exchange rate variations on the balance of trade, the maintain of the Marshall-Lerner condition and the current account sustainability.

Cucuru Stephania(2008) analysed the sustainability of the large and persistent U.S. current account deficits and opens up questions about potential inconsistencies in the international accounts. Cuñado, Juncal et al.(2008)examine whether or not the current account deficits for the OECD countries can be characterized by a unit root process with regime switching. The econometric methodology allows them to distinguish periods that are associated with unsustainable outcomes from those in which the intertemporal national long-run budget constraint (LRBC) holds. Holmes, Mark J et al (2011) conduct an investigation into the sustainability of the Indian current account using data for 1950 onwards. A necessary condition for current account sustainability is that exports and imports are cointegrated.and they use pararametric tests for cointegration . By employing these procedures recursively, two distinct regimes are identified characterized by whether or not imports and exports are cointegrated.

The regime of noncointegration runs until the late 1990s and the second regime of cointegration is present after that. This latter regime coincides with the liberalization of the Indian economy. Matesanz and Fugarolas (2009), using multivariate cointagration tests and error -correcting models to obtain the determinants of the Argentinean balance of payments, find no empirical support for maintaining the Marshall-Lerner condition or existence of the J-curve in the short term.

Chen, Shyh-Wei(2011) examines whether or not the current account deficits for the OECD countries can be characterized by a unit root process with regime switching. The econometric methodology allows him to distinguish periods that are associated with unsustainable outcomes from those in which the intertemporal national long-run budget constraint (LRBC) holds. Among the main results, it is found that it is very likely that the LRBC will not hold for the Australia, the Czech Republic, Finland, Hungary, New Zealand, Portugal, or Spain, thus signifying a red signal that the current account deficits observed during the period were probably not on a sustainable path. Welfens (2011) considers the impact of FDI inflows and FDI outflows and shows that the presence of (cumulated) FDI requires higher import elasticities in absolute terms than stated in the standard Marshall-Lerner condition. Sastre, L. (2012) presents an analytical reformulation of the Marshall-Lerner condition under the assumption that the independence of the GPD from the exchange rate cannot be postulated in open economies in which the foreign trade flow/GDP ratio is high.

2.-Current Account Sustainability

The National income identity would be:

$Y_T = C_T + I_T + G_T + X_T - tcr_T * M_T$ (1)

Where C_T ,I_T , G_T , denotes consumption, inversion, and public spending; X_T, M_T and tcr exports, imports and exchange rate, all variables are expressed in real prices.

$X_T - tcr_T * M_T$ (2) Is net trade

If we express as B_T the net holding of foreign assets and assuming zero inflation and perfect mobility of the capital, then the rates of return would be equal to the real interest rates, then

$X_T - tcr_T * M_T + r * B_{T-1} = \Delta B_T$ (3)

Where $r * B_T$ denotes payments on net foreign capital holdings and ΔB_{T+1} the net foreign asset position. The left hand side of the equation is the current account position and the right hand side of the equation the capital account.

Dividing de two members of the equation by Y, we will have

$$\frac{B_T}{Y_T} = (1+r)\frac{B_{T-1}}{Y_T} + \frac{X_T - tcr * M_T}{Y_T}$$

$$\frac{B_T}{Y_T} = (1+r)\frac{Y_{T-1}}{Y_T}\frac{B_{T-1}}{Y_{T-1}} + \frac{X_T - tcr * M_T}{Y_T}$$

$$\frac{B_T}{Y_T} = \frac{1+r}{1+g}\frac{B_{T-1}}{Y_T} + \frac{X_T - tcr * M_T}{Y_T}$$

Due to $\frac{1+r}{1+g} \cong 1 + r - g$

$$\frac{B_T}{Y_T} = (1+r-g)\frac{B_{T-1}}{Y_{T-1}} + \frac{X_T - tcr * M_T}{Y_T}$$

$$\frac{B_T}{Y_T} - \frac{B_{T-1}}{Y_{T-1}} = (r-g)\frac{B_{T-1}}{Y_{T-1}} + \frac{X_T - tcr * M_T}{Y_T}$$

The analysis of the solution depend on $(r-g) \leq 0 \;\; or \;\; \geq 0$
If r <g; the interest rate lower than the growth rate; the current account do not depend only of the Balance of Trade to the sustainability of the current account
If r>g the interest rate is higher than the growth rate; to analyze the sustainability of the current account it would be necessary determine if the futures deficits and surplus are enough to pay the net debt in the case that the country be in debt or if it is in creditor analyze if the futures deficits and surpluses are enough to run down the initial creditor.
Considering (3), the long run equilibrium net stock of foreign assets when the initial net asset holding is given, must satisfy.

$$X_T - tcr_T * M_T + r * B_T = B_{T+1} - B_T$$
$$B_T * (1+r) = B_{T+1} + Q_T * M_T - X_T$$

$$B_T = \frac{B_{T+1} + tcrM_T - X_T}{1+r}$$

If Q_T , X_T and M_T are constant. In the steady state net foreign asset holding satisfy

$$B_T = \frac{tcrM_T - X_T}{r}$$
$$X_T - tcrM_T + rB_T = 0$$

Provided the transversality condition

$$\sum_{S=1}^{\infty} \frac{B_{T+S}}{(1+r)^S} = \sum_{S=1}^{\infty} \frac{X_{T+S} - tcrM_{T+S}}{(1+r)^S} = 0$$

The implication is that the trade deficit is larger than this, and then the current account is unsustainable.

3.-Intertemporal approach to the current account

We have to distinguish the current account sustainability from the intertemporal approach to the current account. In a dynamic general equilibrium model we must take account of the optimality of consumption and savings decisions by combining the BOP with a simple intertemporal model of consumption (see Obtsfeld and Rogoff 1995)
If we definite de domestic savings S_T as $S_T = Y_T - I_T - G_T = C_T + X_T - tcrM_T$

$$B_T = -\frac{X_T - tcrM_T}{r}$$

$$B_T = -\frac{X_T - tcrM_T}{r} - \sum_{S=1}^{\infty} \frac{X_{T+S} - tcrM_{T+S}}{(1+r)^S}$$
$$B_T = -\sum_{S=0}^{\infty} \frac{X_{T+S} - tcrM_{T+S}}{(1+r)^{S+1}} = -\sum_{S=0}^{\infty} \frac{S_{T+S} - C_{T+S}}{(1+r)^{S+1}}$$

Deriving consumption from the life cycle theory (see Wickens 2011)

$$C_T = \frac{r}{1+r} W_T$$

Where wealth in the open economy is

$$W_T = \sum_{S=0}^{\infty} \frac{S_{T+S}}{(1+r)^S} + B_T$$

$$C_T = \frac{r}{1+r}\left[\sum_{S=0}^{\infty} \frac{S_{T+S}}{(1+r)^S} + B_T\right]$$

Being current account

$$CA_T = S_T + rB_T - C_T$$

Substituting C_T in the current account would have

$$CA_T = -\sum_{S=0}^{\infty} \frac{S_T - S_{T+S}}{(1+r)^S} = -\sum_{S=0}^{\infty} \frac{X_T - tcrM_T + C_T - [X_{T+S} - tcrM_{T+S} + C_{T+S}]}{(1+r)^S}$$
$$= \sum_{S=0}^{\infty} \frac{tcr[M_T - M_{T+S}] - [X_T - X_{T+S}] + C_{T+S} - C_T}{(1+r)^S}$$

Thus, to be sustainable, a current- account deficit must be offset by the present value of changes in current and future domestics savings.

4.-Exchange rates and current account sustainability

The question for net foreign assets and the current account to be stable and the net position remain unchanged to a set interest rate is how the increase in imports and exports occurs.

Since,

$$B_T = -\sum_{S=0}^{\infty} \frac{X_{T+S} - tcrM_{T+S}}{(1+r)^{S+1}}$$

And

$$CA_T = \sum_{S=0}^{\infty} \frac{tcr[M_T - M_{T+S}] - [X_T - X_{T+S}]}{(1+r)^S} + \sum_{S=0}^{\infty} \frac{C_{T+S} - C_T}{(1+r)^S}$$

The export and import demand for small open economies would be respectively (see Sastre L. 2011)

$$X = \varphi(G^f, M, tcr)$$

Where $\partial G^f/\partial tcr = 0$; $\partial X/\partial tcr \neq 0$; $\partial X/\partial M \neq 0$

$$M = \varphi(G, X, tcr)$$

Where $\partial G/\partial tcr = 0$; $\partial M/\partial tcr \neq 0$; $\partial M/\partial X \neq 0$

G is the quantity of goods produced in the country (non-marketable); G^f is the quantity of non marketable goods produced abroad and tcr is the real effective exchange rate or the ratio between foreign and domestic prices.

The Balance of trade (BC) would be:

$$BC = X - M = \varphi(G^f, M, tcr) - tcr\varphi(G, X, tcr)$$

And then

$$\frac{dBC}{dtcr} = M\left[\in_{X,tcr}\left(1 + \in_{M,X}\right) + \in_{M,tcr}\left(1 + \in_{X,M}\right) - 1\right] = 0 \quad (1)$$

Where $\in_{X,tcr}$ = elasticity exports –exchange rate

$\in_{M,X}$ = cross elasticity between imports and exports

$\in_{M,tcr}$ = elasticity import- exchange rate

$\in_{X,M}$ = cross elasticity between exports and imports

We can consider the followings four propositions from (1)

Proposition 1

If $\in_{M,X} = 0$ and $\in_{X,M} = 0$; it characterizes an economy that depends little on other countries, with zero correlation between exports and imports. Then we would have $\frac{dBC}{dtcr} > 0$ when $\in_{X,tcr} + \in_{M,tcr} > 1$

In this case, The Marshall-Lerner condition is maintained and this, to be sustainable, a current –account deficit could be offset by a devaluation of the currency to restore the current account deficit and no necessarily be compensated for by the present value of changes and current and futures domestic savings .

Proposition 2

If $\in_{M,X} \neq 0$ and $\in_{X,M} = 0$; those conditions characterize an economy in wich de demand for imports depend on exports but exports do not depend on imports. In this case $\frac{dBC}{dtcr} > 0$ When $\left[\in_{X,tcr} \left(1 + \in_{M,X}\right) + \in_{M,tcr}\right] > 1$

This condition would correspond to economies in which many industries import raw materials or intermediate products and then export the final products (see Krugman 1995). In this case an exchange rate devaluation may not restore the balance, it will depend on the cross elasticity between import and exports.

If $\in_{M,X} < 0$; $\left[\in_{X,tcr} + \in_{M,tcr}\right] > 1 + \left(\in_{M,X} * \in_{X,tcr}\right)$

Thus , to be sustainable, a current deficit may be offset by the present value of changes in current and futures domestic savings.

If $\in_{M,X} > 0$; $\left[\in_{X,tcr} + \in_{M,tcr} + \in_{M,X} * \in_{X,tcr}\right] > 1$

An exchange rate devaluation may assure the sustainability of the current account

Proposition 3

If $\in_{M,X} = 0$ and $\in_{X,M} \neq 0$, this would represent an economy in which exports depend on imports , but imports would no depend on exports . Then $\frac{dBC}{dtcr} > 0$ and $\left[\in_{X,tcr} + \in_{M,tcr} \left(1 + \in_{X,M}\right)\right] > 1$

This condition would correspond to the economies of countries used by multinational corporations as logistic bases for their products . The theory depends on "slicing up the production process" (see Krugman 1995) . Multinational corporations do not react to unexpected changes in the demand for their products in the countries in which they operate by varying their production costs , but by re-allocating their international stocks (see Sastre 2011).

If $\in_{X,M} < 0$; $\left[\in_{X,tcr} + \in_{M,tcr}\right] > 1 + \left(\in_{X,M} * \in_{X,tcr}\right)$

Thus , to be sustainable, a current deficit may be offset by the present value of changes in current and futures domestic savings.

If $\in_{X,M} > 0$; $\left[\in_{X,tcr} + \in_{M,tcr} + \in_{X,M} * \in_{X,tcr}\right] > 1$

An exchange rate devaluation may assure the sustainability of the current account

Proposition 4

If $\in_{M,X} \neq 0$ and $\in_{X,M} \neq 0$, these would apply to an economy in which import demand depends on export demand and vice versa. In this case, $\frac{dBC}{dtcr} > 0$ and Eq (4) would be without changes:

$$\left[\in_{X,tcr} \left(1 + \in_{M,X}\right) + \in_{M,tcr} \left(1 + \in_{X,M}\right)\right] > 1$$

In these economies, the empirical problem of estimating export and import flow determinants should be considered from de perspective of their simultaneity Sastre(2005).

If $\left[\in_{X,tcr}\in_{M,X}+\in_{M,tcr}*\in_{X,M}\right] > 0$

Exchange rate devaluation may assure the sustainability of the current account

If $\left[\in_{X,tcr}\in_{M,X}+\in_{M,tcr}*\in_{X,M}\right] < 0$

Thus, to be sustainable, a current deficit may be offset by the present value of changes in current and futures domestic savings.

5.-Current Account sustainability: The Spanish case

Spain joined the euro zone with an asymmetrical inflation relative to the average of the countries that integrate it. The countries that make up the euro zone are transferred to the European Central Bank the monetary policy and share a common currency so nominal exchange and nominal interest rates are exogenous variables to the model; this does not mean that real change and real interest rates are exogenous variables, since prices are not homogeneous and in fact differ significantly among the countries of the euro zone.

The entry of Spain in the euro zone, with higher inflation than the whole of the countries, meant that the real rate of interest in Spain was less than the rest of the countries that integrate it and at the same time the exchange rate, measured by the price differential, reflected a continued deterioration in real terms of the trade with the rest of the euro zone. This situation resulted in a growth of domestic demand in Spain higher than the average of the euro zone countries, accompanied by deterioration in the trade balance with an increase of the external financing needs.

In this section, it is developed a real three sector model of a small open economy[12]. The country produces a traded good using capital K and labor L. Since the time horizon is large , the model abstracts from money and all nominal rigidities . The main modeling innovation is the introduction of the foreign sector with the possibility that the Marshall-Lerner condition be not sustained , to analyze the current account and debt sustainability.

We lay out the model in stages, starting with the specification of

Households

In the economy, there will be a large number of consumers, with identical preferences, represented by the following utility function.

$$\varphi(C_t\,, 1-L_t\,) = \alpha \ln C_t + (1-\alpha)\ln(1-L_t)$$

C_t represents private consumption, leisure is defined as 1-L. The percentage $\alpha(0<\alpha<1)$ indicates the proportion of consumption on total income.

The overall consumption index takes the following form

$$C_t = \left[n^{1/p}(C_t^h)^{\frac{p-1}{p}} + (1-n)^{\frac{1}{p}}(C_t^f)^{\frac{p-1}{p}}\right]^{\frac{p}{p-1}}$$

Where C_t^h and C_t^f are index of domestic and foreign goods and p>0 measures the elasticity of substitution between domestic and foreign goods.

P_t^h and P_t^f are respectively the price indexes corresponding to domestic and foreign consumption baskets C_t^h and C_t^f and P_t (defined below) is the consumer price index.

$$P_t = \left[n(P_t^h)^{1-p} + (1-n)(P_t^f)^{1-p}\right]^{\frac{1}{1-p}}$$

[12] The model is based in Torres ,J.L.(2008) , Buriel et al (2010) and Tervala,J(2012)

Where tc is the nominal exchange rate then the purchasing power parity(PPP) holds : $P_t = tc_t * P_t^f$
Where P_t^f is the foreign consumer price index
Since tc is equal for all countries of the euro zone share currency, would have the prices P_t and P_t^f would be the variables that would set competitiveness between the countries of the region and therefore the flows of exports and imports.
The problem of the households is maximizing their utility.
Max $U_t = \sum_{t=0}^{\infty} B^t(\alpha \ln C_t + (1-\alpha)\ln(1-L_t))$
Subject to the budgetary restriction of a representative consumer

$$B_t + PC_t = (1+R_t)B_{t-1} + \left(1-\tau_t^l\right)W_t L_t + (1-\tau_t^\pi)\pi_t + G_t$$

B_t denotes bonds (that pay one unit of domestic currency in period t+1 held at the beginning of period t; R_t is the nominal interest rate on bonds between t-1; w is the nominal wage paid to the household in a competitive labour market , and π denotes the household´s share of the nominal profits of domestic firms (All domestic household own an equal share of all domestic firms; B consumers discount factor ; G_t transfers from de Government to householdss; and τ_t^c , τ_t^l , τ_t^π tax rates to consumption, wages and nominal profits of domestic firms.

Firms

All markets are perfectly competitive. Its goal will be to maximize benefits assuming given prices of capital and labor. The problem for firms will consist of maximizing the benefits period to period.
Max $\pi_t = A_t K_t^\alpha L_t^{1-\alpha} - R_t K_t - W_t L_t$
The capital stock is defined as $K_{t+1} = (1-\delta)K_t + I_t$
Where K_t stock of private capital; K_0 initial capital stock and I_t private inversion.

The Government

The role of the Government is to earn income through taxes to fund transfers to families. The budget constraint will be:
$(\tau_t^c)C_t + \left(\tau_t^l\right)W_t L_t + (\tau_t^\pi)(\pi_t) = G_t$

The Foreign Sector

In relation to the Spanish economy, to study the long –run equilibrium relation between volume of imports and its determinants in one relation and the volume of exports and its determinants in another relation, we assume that the import and export demand equations take the following forms (see Sastre L. 2005).

$$X_t = Y_t^{\in_y} * it_t^{\in_{it}} * M_t^{\in_{x,m}}$$

The imports function expressed in national production units, would be:

$$M_t = I_t^{\in_I} * pr_t^{\in_{pr}} * X_t^{\in_{m,x}}$$

Where X is the volume of exports of goods and services; M is the volume of imports of goods and services; Y is the GPD of the OECD countries ; it and pr are the export and import price competitiveness indicators respectively; and finally , $\in_y$, $\in_{it}$, $\in_I$, $\in_{pr}$, $\in_{x,m}$, $\in_{m,x}$ are respectively elasticity's export- income of the OCDE, export- competitiveness ,import- investment , cross elasticity´s export-import and import-export
The balance of trade (BC) would be:

BC= $X_t - M_t = Y_t^{\epsilon_y} * it_t^{\epsilon_{it}} * M_t^{\epsilon_{x,m}}$ - $I_t^{\epsilon_I} * pr_t^{\epsilon_{pr}} * X_t^{\epsilon_{m,x}}$
Conditions of sustainability of external debt and the current account balance

$$B_T = -\sum_{S=0}^{\infty} \frac{X_{T+S} - tcM_{T+S}}{(1+r)^{S+1}}$$

$$CA_T = \sum_{S=0}^{\infty} \frac{tc[M_T - M_{T+S}] - [X_T - X_{T+S}]}{(1+r)^S} + \sum_{S=0}^{\infty} \frac{C_{T+S} - C_T}{(1+r)^S}$$

Finally the economy must comply with the following condition of feasibility
$Y_T = C_T + I_T + G_T + X_T - tc_T * M_T$ (1)

Stochastic simulation

Since we will calibrate the model, we need to assign values to the parameters. We calibrate parameters are as shown in the following table:

Table 1

Parameter	Definition	Value
α	technological parameter	0.35
β	Discount factor	0.97
γ	Parameter preferences	0.450
τ_t^c	Consumption tax	0.116
τ_t^l	Tax on labor income	0.348
τ_t^π	Tax on capital income	0.225
ϵ_y	Export Elasticity OECD DGP	1.20
ϵ_{it}	Elasticity Export – competitiveness	-1.80
$\epsilon_{x,m}$	Cross elasticity export-import	0.64
ϵ_I	Elasticity Import- Investment	0.84
ϵ_{pr}	sticity - competitive imports	-0.35
$\epsilon_{m,x}$	Cross elasticity import -export	0.51

The values of the parameters α , β , γ , are taken from the literature. The relevant tax rates τ_t^c, τ_t^l , τ_t^πcorrespond to estimated effective average rates for the Spanish economy, Boscá et al (2008) . The different elasticities of export and import flows , $\in_y$, $\in_{it}$, $\in_{x,m}$, $\in_I$, $\in_{pr}$,$\in_{m,x}$, have been estimated for the Spanish economy Sastre L (2012) .

Stochastic simulation

In this simulation, we assume that the type of real effective exchange with countries outside the euro zone or the real exchange rate only considering the price differential for trade with the euro zone, still an Autoregressive process of the first order, such that:

$$\log tc_t = (1-\rho_{tc})\log \overline{tc} + \rho_{tc}\log tc_{t-1} + \varepsilon_t^{tc} \quad ; \quad \varepsilon_t^{tc} \sim (0, \sigma_{tc}^2)$$

In this case we suppose that ρ_{tc} = 0.95, σ_{tc}=0.01 and $\overline{tc}$=1 .

From the computation of the model, we can calculate the deviations of the variables with respect to its steady-state value, allowing you to graphically represent the so-called impulse-response functions.

The figure 1 shows the effects of the shock along forty periods . In the first place we observe an increase in the level of production, the investment ,the hours worked and the interest rate. Consumption, Stock of Capital and wages decreases.

Regarding the Foreign Sector, Fig 2 shows : The Export increase and as consequence of the increase of the level of production and the induced effect of the export on the import : the import increase too.

The External Debt is reduced and the Current Account improves until reach its staid state. In Spain, a devaluation of the exchange rate improves the Current Account: The Marshall-Lerner is maintained .

Fig . 1

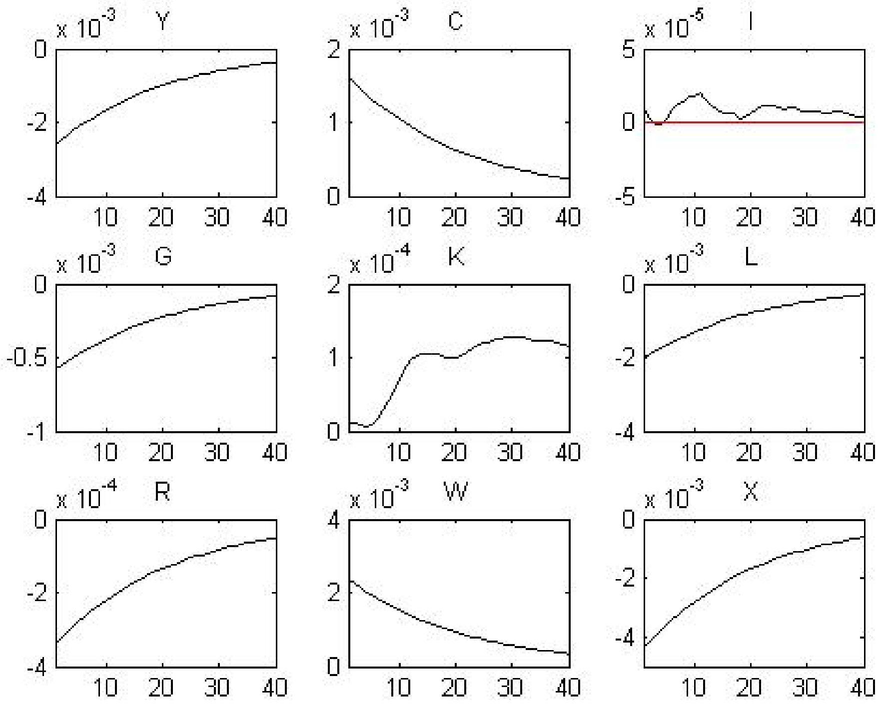
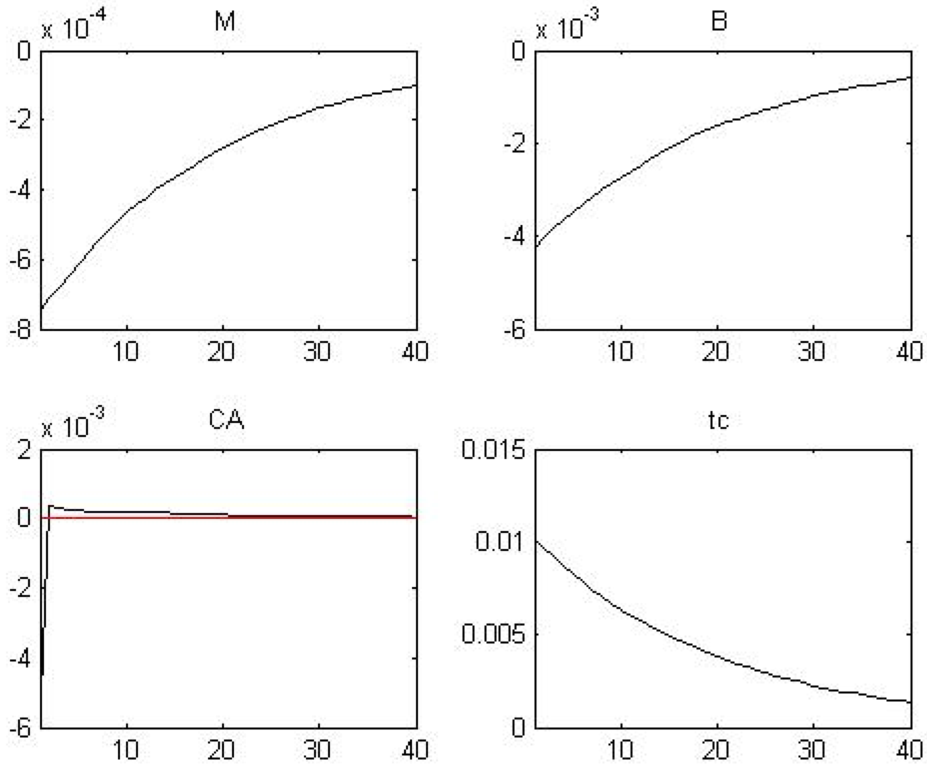


Fig 2



Deterministic simulation

In this case we consider a permanent devaluation of the nominal five percent to replacement rate in relation to countries outside the framework of the euro area , similar to a devaluation of domestic prices relative to countries within the euro zone simulation.
In Figure 3, the effects of devaluation in terms of production, consumption , hours worked and external debt is. Production increases so after instant to stabilize. The consumption decreases significantly to grow slowly after reaching the new steady state .
In the external sector , Fig 4 : exports grow and imports grow too as an effect induced by these , as well as by the production increase. The external debt and current account balance improved, the Marshall- Lerner condition is maintained.

Fig 3

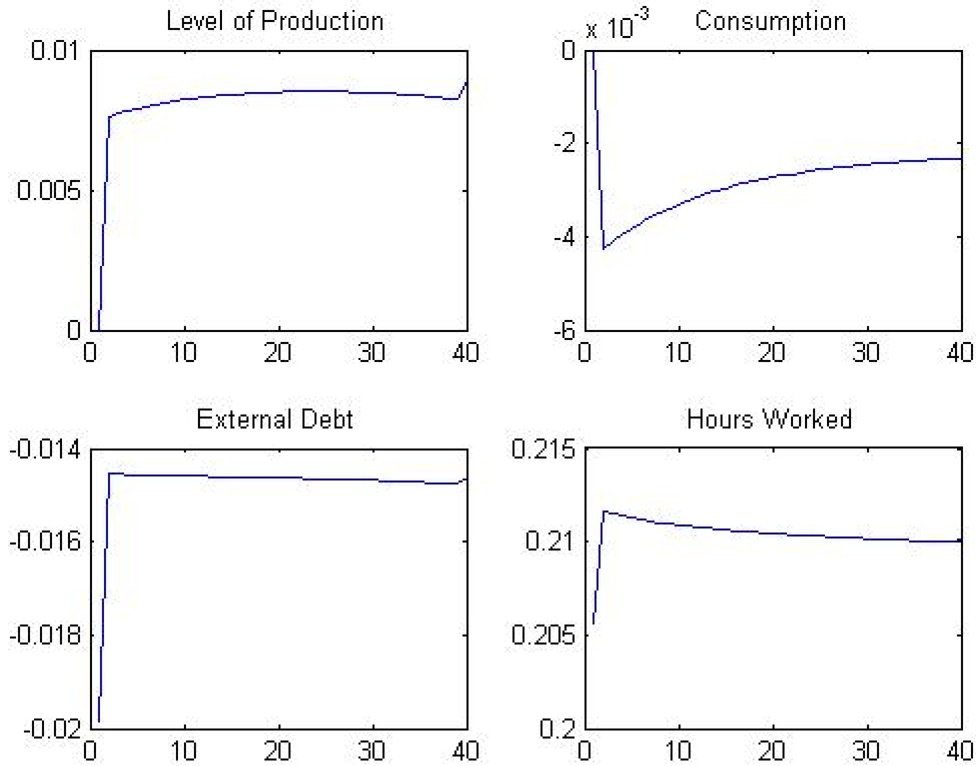
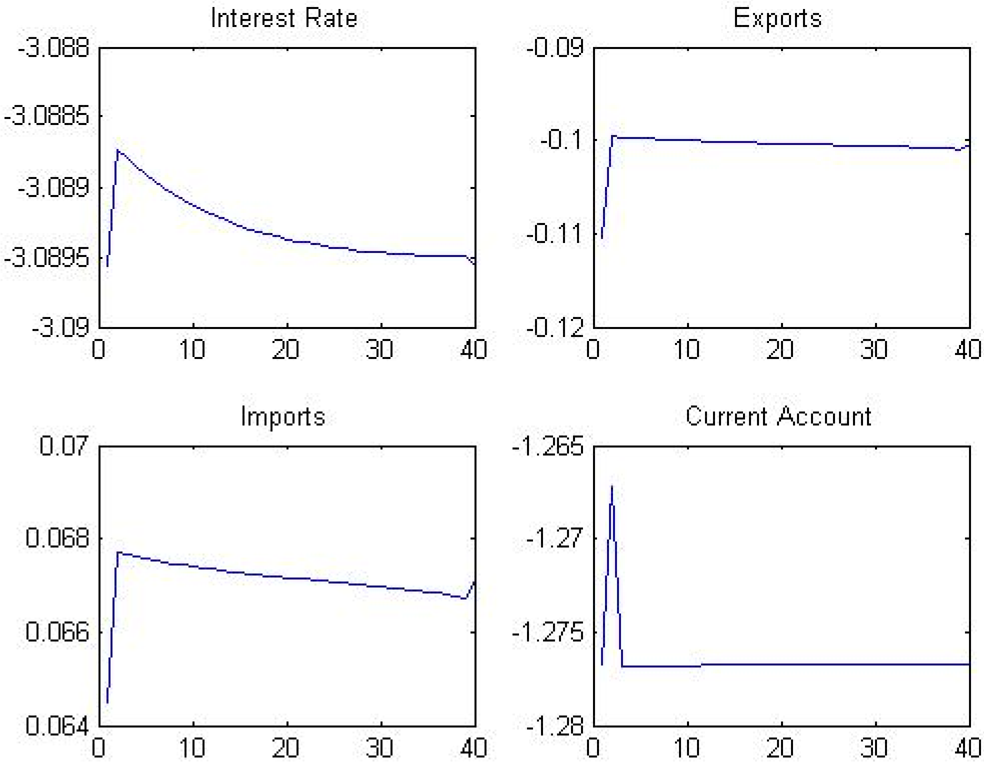

Level of Production
Consumption
x 10-3
External Debt
Hours Worked

Fig 4


Interest Rate
Exports
Imports
Current Account

Cross-elasticity export-import simulation

In this case we consider a reduction in the cross-elasticity export-import, i.e. the quantity of imports for a given volume of exports. With this simulation check that a reduction of this structural parameter would cause a similar effect than a devaluation of the exchange rate . That is, increased production, decreased consumption and improved external debt and current account. See Fig 5 and 6

Fig 5

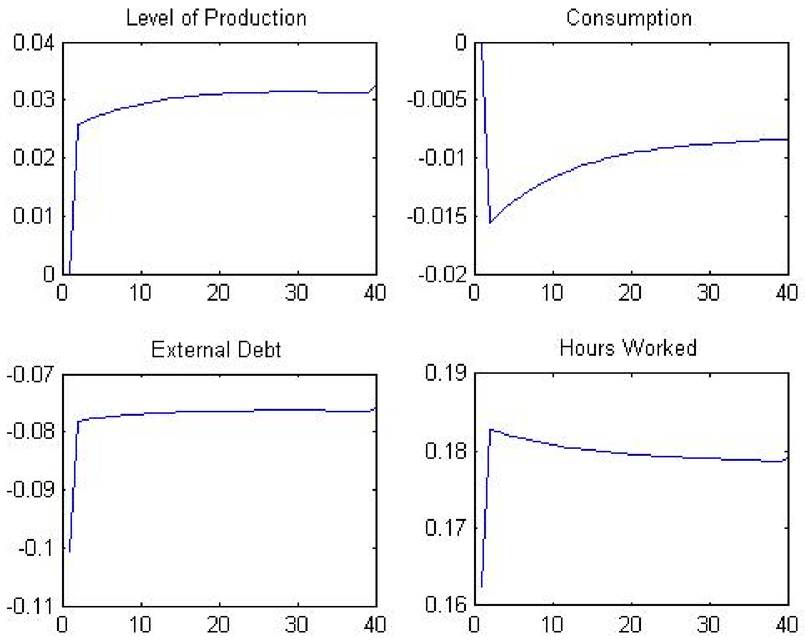
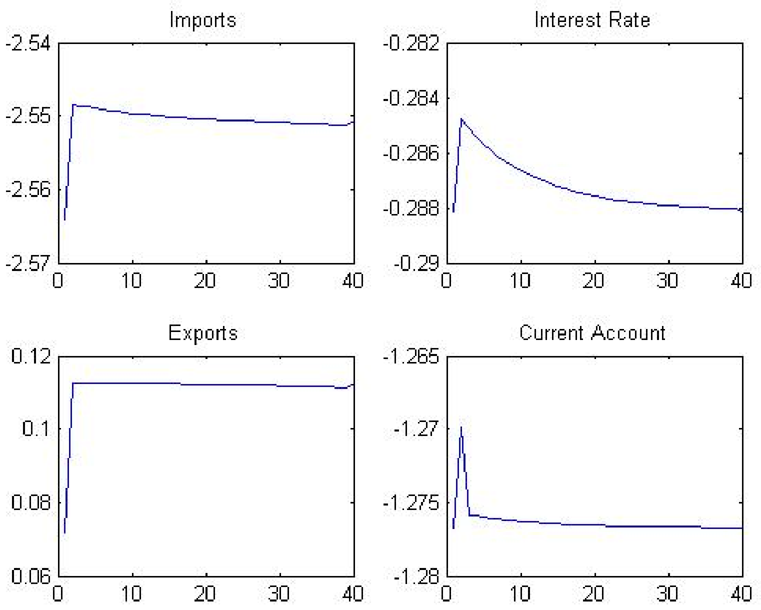


Fig 6



Consumption tax simulation

Figures 7 and 8, shows the impact of increased consumption taxation on the external sector of the economy : Decrease consumption , wages and worked hours. This result is a consequence of the existence of an intertemporal effect of work for leisure. The tax increase reduces the purchasing power of wages which at first is offset by an increase in hours worked but quickly reduced significantly.

The external debt and current account balance improved as a result of the decline in domestic consumption.

Fig 7

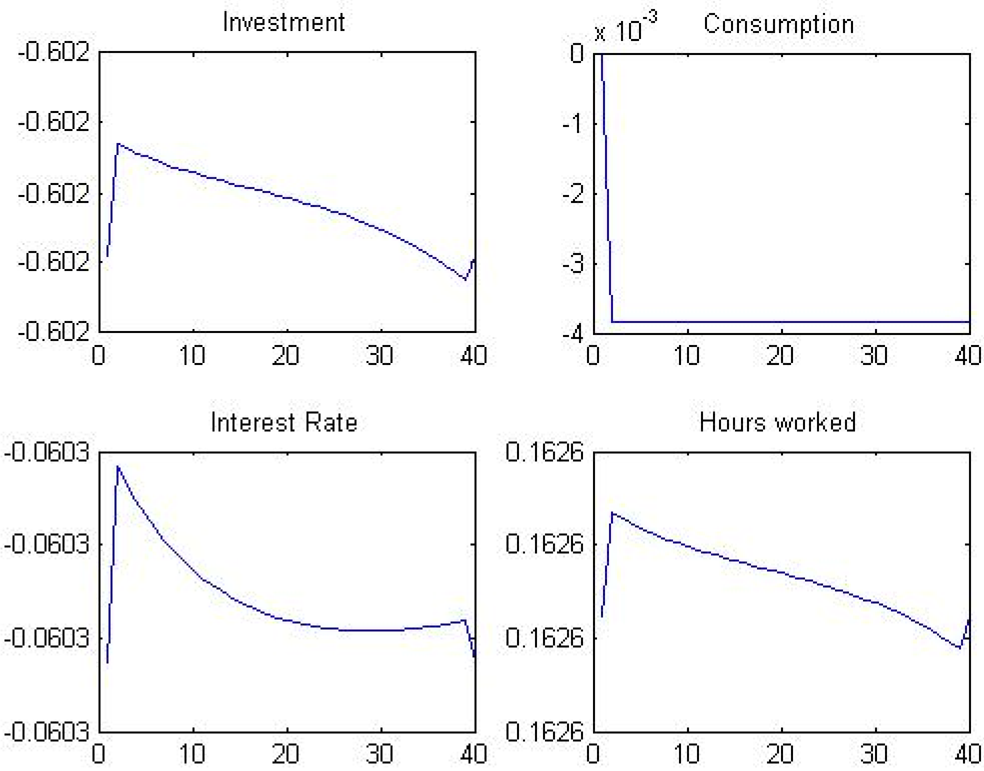
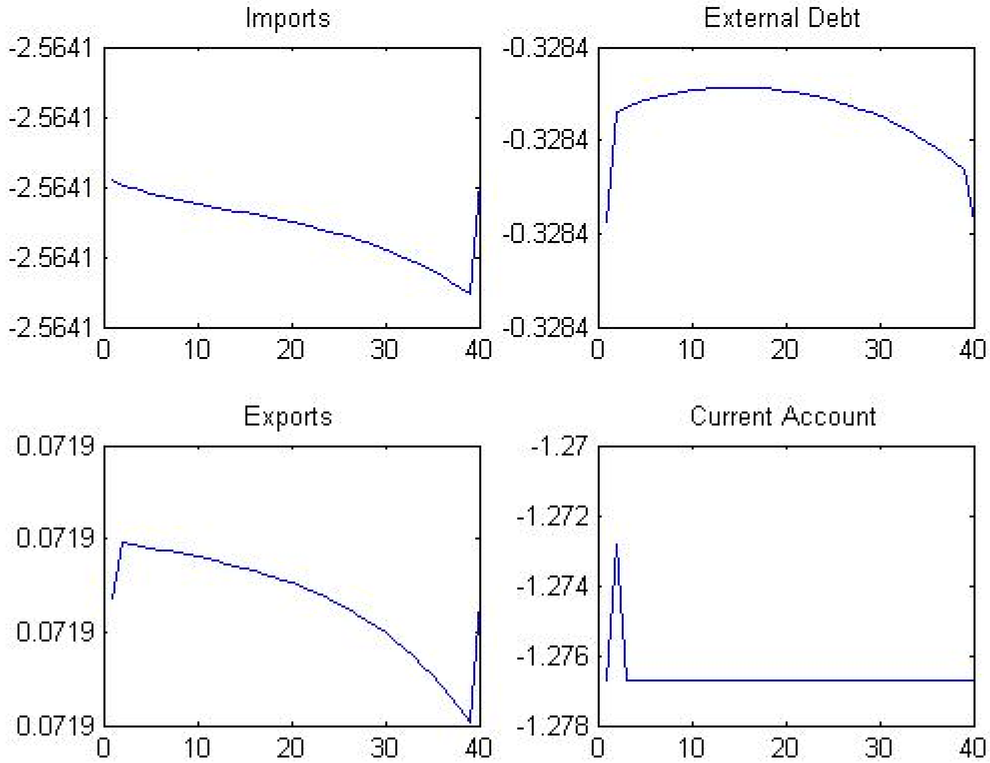


Fig 8



Conclusions

In this paper, a reformulation of the theoretical analysis of the sustainability of the current account balance is presented from the perspective that the Marshall-Lerner condition is not necessarily satisfied. We present four different propositions to the traditional approach to the Marshall-Lerner condition regarding the positive impact of currency devaluation on the balance of trade. Those propositions have theoretical implications in the sustainability of the current account and the external debt. We have also distinguished between the sustainability of the current account and the intertemporal approach to the sustainability of the current account.

To study the sustainability of external debt and current account of the Spanish economy, we used a stochastic dynamic macroeconomic model (DSGE). We have simulated the impact of variations of the exchange rate, the cross elasticity between exports and imports and consumption taxation in a set of macroeconomics variables including the fulfill of the Marshall-Lerner condition in the Spanish economy. The simulation results indicate that a devaluation of the exchange rate or an increase in consumption taxation would improve the sustainability of the external debt and the current account balance and a decrease in cross-elasticity exports-imports would be similar to a devaluation of the exchange rate effect. In the Spanish economy ,the Marshall-Lerner condition is accomplished.

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Reaction of the credit default swap market to the release of periodic financial reports

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ABSTRACT

This paper studies the reaction of the credit default swap (CDS) market to the release of periodic financial reports. The results support the value relevance of accounting information for the CDS market. In panel data regression models, size- and sector-based analysis indicates that particular sectors (namely, financial, energy, health care, and utilities) and some size groups are more responsive to release of financial reports. This finding confirms a delayed reaction of the CDS market to the information content of these regulated financial reports. The implication is that the CDS market is characterized by the limited attention phenomenon.

Keywords: CDS Market; Financial Reports; Panel Data Regression; Delayed Reaction.

1. Introduction

In this paper, we examine the reaction of the credit default swap (CDS) market following release of periodic financial reports. Three features of the literature motivate our study. First, one branch of the CDS literature addresses the importance of accounting variables in CDS pricing and incorporates this information as determinants of CDS spread. Dasa, Hanounab, and Sarin (2009), for instance, illustrate that accounting-based variables explain approximately two-thirds of CDS spread variation. More importantly, these authors find that accounting-based variables are relevant to CDS spread changes even without the inclusion of firm-specific and market-based variables. Batta (2011) also provides evidence for the role of accounting information in the CDS market, although he claims that the influence of this information occurs mainly through stock and bond markets. Correia, Richardson, and Tuna (2012) confirm that accounting information, in conjunction with market-based information, plays an instrumental role in explaining cross-sectional variation of CDS spread.

In addition to studies that focus on the role of accounting information in CDS pricing, other studies (see, for instance, Greatrex, 2008; Zhang and Zhang, 2013) examine the response of the CDS market to release of segregated accounting information, such as earnings announcements and earnings surprises. The key outcome from these studies is that this type of financial disclosure is value-relevant for the CDS market.

Thus, these studies point out the key role of accounting information in influencing the CDS market. Based on this evidence, our hypothesis is that the CDS market reacts to the release of periodic financial reports because these reports contain company-level information.

The second feature of the literature relates to the content of financial reports. Periodic financial reports play a critical role in diminishing information asymmetry and the agency problem between a firm's managers and its shareholders or debtholders.[13] Moreover, according to signaling and agency theories, managers have incentives to voluntarily disclose information to benefit the firm; see, for example, Dainelli, Bini, and Giunta (2013), Morris (1987), and Watson, Shrives, and Marston (2002).

According to the US Securities Exchange Act of 1934, companies that hold more than $10 million in assets or have more than 500 shareholders are mandated to file financial reports annually and quarterly with the US Securities and Exchange Commission (SEC). These reports are known as "Form 10-K" (annual) and "Form 10-Q," (quarterly).[14] These reports include more than simply accounting information. Various sections, for instance, contain detailed and comprehensive information about the firm. In specific sections of these reports, managers must provide explanations for the performance and condition of the firm. These sections include "Risk Factors," "Defaults upon Senior Securities," "Management's Discussion and Analysis of Financial Condition and Results of Operations (MD&A)," and "Quantitative and Qualitative Disclosures about Market Risk."

13 See Healy and Palepu (2001) for a discussion on corporate disclosure, information asymmetry and agency problem.
14 The SEC created the EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system in 1984. Firms were then obligated to file their reports through this system from 1997.

It follows that these sections of those reports contain valuable information for credit market participants to evaluate counterparty risk as well as default risk of the firm. For example, in the MD&A section of a 2005 quarterly financial report of the Ford Motor Company, managers pointed to a downgrade in the firm's credit rating and its consequences on the credit market: [15]

As a result of S&P downgrading the long-term credit rating for Ford and Ford Credit to BB+ (non-investment grade) on May 5, 2005, we anticipate increased borrowing costs. We also anticipate that Ford credit will experience restricted access to unsecured debt markets, which would cause its outstanding unsecured commercial paper and unsecured term debt balance to decline.

Another example relates to the annual report of Baker Hughes Incorporated for the fiscal year ending December 31, 2009.[16] The "Risk Factor" section of this report contains appropriate information about the credit market:

Failure to complete the merger with BJ Services could negatively affect our stock price and our future business and financial results. If the merger is not completed, our ongoing business may be adversely affected and will be subject to several risks, including the following: We will incur substantial transaction and merger-related costs as well as assume additional debt from BJ Services in connection with the merger and our stockholders will be diluted by the merger. We will assume approximately $500 million of long-term debt from BJ Services.

There is a broad literature in finance on textual analysis and measuring qualitative information. The findings of this strand of literature show that negative and positive words in corporate periodic reports, newspaper articles, and investor message boards can affect financial markets (see, for instance, Loughran and McDonald, 2011; Tetlock, Saar-Tsechansky, and Macskassy, 2008). Therefore, besides accounting-based information, we expect the narrative content of other parts of obligatory periodic reports to contain information valuable to the CDS market. We focus on entire reports rather than their segments. To the best of our knowledge, this study is the first attempt to investigate the reaction of the CDS market to release of periodic financial reports. Our main purpose is to determine whether regulatory financial reports are value-relevant for the CDS market.

The third feature of the literature that motivates our research relates to the close relationship between the CDS and equity markets. According to the *option pricing theory* of Merton (1974), equity markets are theoretically related to credit markets. In this model, a firm's debt is treated like a short position on a credit put option accompanied by riskless debt. In a similar vein, equity is viewed as a call option on the value of firms, with a strike value equal to the book value of firm liabilities. Several studies in the CDS literature empirically investigate the theoretical link between CDS and equity markets in the context of price discovery, co-movement, and contagion or spillover effects (see, for example, Forte and Lovreta, 2009; Longstaff, Mithal, and Neis, 2005; Narayan, Sharma, and Thuraisamy, 2014; Norden and Weber, 2004).

With respect to the close association between the CDS market and the stock market, numerous studies examine the reaction of the stock market surrounding release of financial reports. For

15 Downloaded from https://www.sec.gov/Archives/edgar/data/37996/000003799605000158/e051005body.txt.
16 Available at https://www.sec.gov/Archives/edgar/data/808362/000095012909000672/h65827e10vk.htm.

example, Asthana and Balsam (2002) specifically examine the impact on stock price of accounting information released electronically on the EDGAR system. These authors report that the stock market reacts positively to disclosures contained in quarterly and annual reports. In addition, Balsam, Bartov, and Marquardt (2002) generate evidence associated with the information content of annual reports by studying the reaction of the stock market to announced accruals. They document a negative relationship between unexpected discretionary accruals and cumulative abnormal stock returns around 10-Q filings. Griffin (2003) builds on earlier studies to assess the value relevance for stock market investors of quarterly and annual reports surrounding filing day. This author illustrates that the market responds to SEC filings on the filing day and one or two days thereafter. Likewise, Asthana, Balsam, and Sankaraguruswamy (2004) present evidence about the informativeness of SEC filings via the EDGAR system. Their results indicate that the volume of small trades increases two days before and ending two days after 10-K is filed with the SEC. Li and Ramesh (2009) also examine the economic significance of stock market reaction to annual and interim periodic SEC filings. These authors find that the market reacts notably when periodic reports contain earnings information.

Taking into account the close relation between stock and CDS markets and the importance of financial reports for stock markets, we expect that the CDS market will respond to the release of periodic financial reports as well. Thus, our main research question is to investigate whether periodic financial reports are value-relevant for the CDS market.

We follow the following approaches to address our research question. We adopt a panel data regression model and include two indicator variables to determine the effect of periodic financial reports on the CDS market.[17] With a panel data setup, our analysis is based on a unique data set covering the period 2004–2015. More specifically, we construct 28 panels sorted by sector, size, leverage level, credit rating, and economic situation (pre- 2007 global financial crisis (GFC), during the GFC, and post-GFC) to examine whether the CDS spreads of 196 US firms change after release of quarterly and annual financial reports. We evaluate the behavior of the CDS market from 1 day up to 10 days after release of reports.

We generate four main findings. First, we show that periodic financial reports contain valuable information for the CDS market. More specifically, the results show that the indicator variables, which signify the effect of periodic reports on the CDS market, are statistically significant. Second, we find that the reaction of the CDS market to release of reports is delayed, because our indicator variables are not significant on filing dates and the day after filing. Third, we demonstrate that the behavior of the CDS market to the release of financial reports differs across sectors, size groups, and portfolios constructed based on leverage levels, credit ratings, and economic conditions. Fourth, our results reveal that there is a distinction in the response of the CDS market between the releases of annual versus quarterly financial reports. This finding points to the possibility of "window dressing" in the preparation of annual financial reports to impress debt holders or lenders.[18]

17 Regarding the sensitivity of the event study methodology to the choice of market return, estimation periods, and other factors, we believe that using the panel data regression method provides more reliable results. Moreover, this model helps address the issue of heteroscedasticity better than the event study methodology. Therefore, we adopt panel data regression as our main approach.

18 Window dressing denotes actions taken or not taken preceding the release of financial statements with the purpose of improving the appearance of reports, for example, to postpone cash payments after issuing reports to make the book amount of cash temporarily positive.

Our approach and findings contribute to several strands of the literature. First, we add to studies that show that accounting information contributes to CDS pricing (see, for example, Batta, 2011; Das, Hanouna, and Sarin, 2009; Demirovic and Thomas, 2007; Demirovic, Tucker, and Guermat, 2015). Financial reports have not been considered by the literature, despite their information richness. Our viewpoint in this research is more comprehensive than considering only accounting information. We investigate the behavior of the CDS market with respect to release of mandatory reports. Our findings on the reaction of the CDS market after release of mandatory reports contribute to the literature on content analysis and qualitative measurement in understanding market behavior.

Second, this study contributes to the strand of literature (see, for example, Greatrex, 2009; Zhang and Zhang, 2013) that focuses on the reaction of the CDS market after release of public information. Specifically, we contribute to a related body of literature (see, for instance, Callen, Livnat, and Segal, 2009; Finnerty, Miller, and Chen, 2013; Hull, Predescu, and White, 2004; Jenkins, Kimbrough, and Wang, 2016; Norden and Weber, 2004) that shows that credit rating and earnings announcements both influence CDS spreads. We demonstrate that release of periodic reports affects the market even after controlling for release of this public information.

Third, our results add to studies that examine the efficiency of the CDS market. Several studies investigate this issue in regard to release of public information and reach mixed results. Some studies indicate that the CDS market is efficient (see, for instance, Hull et al., 2004; Norden and Weber, 2004; Zhang, 2009; Zhang and Zhang, 2013), while others show that the CDS market is inefficient (see, Batta, 2011; Greatrex, 2008). Jenkins et al. (2016) take a neutral position and suggest that the CDS market is efficient in normal conditions, but acts inefficiently in unstable situations. Our findings point toward inefficiency of the CDS market, because we document that the reaction of the CDS market to release of financial reports is statistically significant on subsequent days. However, we show that the CDS market behaves less inefficiently during GFC because, in such periods, the market incorporates new information faster compared to non-GFC periods.

Fourth, our finding showing a delayed response from the CDS market after release of financial reports indicates the existence of the *limited attention phenomenon* in this market. The *limited attention theory* originates from the work of Kahneman (1973). Hirshleifer and Teoh (2003, p. 5) state that “[l]imited attention is a necessary consequence of the vast amount of information available in the environment, and of limits to information-processing power.” The outcome of investors with limited attention is inefficiency in markets, because such investors may fail to update their beliefs quickly and effectively. This finding is important for regulators’ efforts to redesign the structure of financial reporting and to push firms toward providing more transparent information with less required cognitive effort by investors.

Finally, our study adds to the accounting literature that investigates the consequences of financial disclosure (see, inter alia, Bonsall and Miller, 2017; Botosan, 2000; Healy and Palepu, 2001; Sengupta, 1998). These studies find that accounting disclosure affects the cost of equity capital, bond ratings, and cost of bonds. We complement these studies by showing that corporate disclosure impacts the CDS market as well.

This paper proceeds as follows. Section 2 reviews existing studies and develops our hypotheses. In Section 3, we discuss data, variables, and methodology. Section **Error! Reference source not found.** sets forth the results, while the robustness of the results is investigated in Section **Error! Reference source not found.**. We discuss our findings in Section 0. Finally, in Section 7, we set forth concluding remarks.

2. Literature review and hypothesis development

2.1. Literature related to the role of accounting information in credit markets

Studies on the role of financial disclosure in credit markets can be divided into two groups. One group attempts to incorporate accounting information for pricing the CDS. The starting point of these studies is marked by numerous empirical models that utilize financial ratios to predict financial distress (see, inter alia, Altman, 1968; Beaver, 1966; Ohlson, 1980). Demirovic and Thomas (2007) investigate the relevance of accounting information for credit markets by considering credit rating as a proxy for credit risk.

More importantly, Das et al. (2009) are among the first to study the relevance of accounting information in the CDS market. These authors follow the Moody's private debt manual and construct 10 variables representing liquidity, sales growth, capital structure, size, trading activity, and profitability. Their results show that accounting-based models are comparable with market-based models and have a complementary role in CDS pricing. Batta (2011) provides more detail on the role of accounting information in CDS pricing. This author documents a decline in explanatory power of accounting information in explaining CDS variation when additional information, such as bond price, credit rating, and stock return, is included in the regression model. Accordingly, Batta claims that the role of this information in CDS pricing through related markets, such as stock and bond markets, is more significant than the direct role.

Correia et al. (2012) utilize market variables and accounting information, such as total assets, net income, and total liabilities, to construct variables to forecast corporate default. Using CDS and bond spreads as alternative variables for default risk, these authors provide evidence on the usefulness of accounting information in explaining credit spread.

More recently, Demirovic et al. (2015) assess the usefulness of accounting information for bond spreads. Adopting a panel data regression with fixed (firm/time) effect, these authors show that adding accounting variables improves the explanatory power of the market-based model. They confirm that a Merton-based measure of distance to default does not incorporate all credit-relevant information and that accounting data holds incremental information in conjunction with that information.

The second category of literature focuses on disclosure of separated accounting information. The aim of these studies is to investigate the reaction of the CDS market centered on the event day, and to test the informational efficiency of this market. For example, Greatrex (2009) and Callen et al. (2009) analyze the reaction of the CDS market to earnings announcements. Greatrex (2009) adopts event study methodology based on data from 2001 to 2006 and finds that the impact of earnings announcement on the CDS market is statistically and economically significant. This author claims that the market is inefficient based on this finding. Likewise, Callen et al. (2009) observe a negative relation between CDS spread and earnings for reference entities with low credit rating and short tenor over the period 2002–2005. These authors also provide evidence showing inefficiency in the market.

Shivakumar, Urcan, Vasvari, and Zhang (2011) evaluate change in CDS price in response to release of management earnings forecasts and find that the market reacts significantly to

forecast news even more strongly than actual earnings. These authors also document that this reaction is more severe during GFC.
Further, Zhang and Zhang (2013) examine the response of the CDS market in the US through an event study around earnings news during the period 2001–2005. These authors show an increase in CDS spread for negative announcements one month prior to the events and reveal that this reaction is stronger for speculative-grade firms. In contrast to previous studies, they show market efficiency.

All the papers mentioned above in this section provide evidence toward the value relevancy and incremental role of financial disclosure for the CDS market. The main research gap is that the reaction of the CDS market after release of periodic financial reports is unknown.

2.2. Hypothesis development

According to the studies mentioned in the preceding subsection, we know that accounting information is value-relevant for the CDS market and contains incremental information for this market. Moreover, financial reports play a critical role in risk assessment of reference entities or counterparties and are useful for both sides of CDS contracts. CDS sellers may employ this information to determine whether counterparties are financially stable. On the other hand, CDS buyers can utilize financial reports to assess the default risk of reference entities and CDS sellers simultaneously, known as double risk. Moreover, we know that, in addition to the financial data detailed in periodic financial reports, specific sections of periodic financial reports, namely, “Risk Factors,” “MD&A” and “Quantitative and Qualitative Disclosures about Market Risk,” may hold credit-relevant information for the CDS market. All of these sections provide evidence about the value relevance of periodic financial reports for the CDS market. In this way, we construct our first hypothesis. We cannot predict the sign of the reactions because the sign is related to the content of the reports, and our main concern is to distinguish whether the CDS market reacts to the release of periodic financial reports.

> Hypothesis 1: The CDS market reacts to release of quarterly and annual reports.

Annual and quarterly financial reports have some differences. Annual reports are more comprehensive in comparison to quarterly reports and are more detailed. Knutson (1992) states that annual reports are recognized as one of the most essential reports for analysts. Moreover, in contrast to quarterly reports, annual reports are audited documents. Consequently, quarterly reports may be perceived as less reliable than annual reports, and investors pay more attention to the release of annual reports to update their beliefs. On the other hand, annual reports are summaries of previous quarterly information, and may be considered less interesting to investors who have already analyzed previous quarterly information. Therefore, the CDS market may react differently to the release of 10-Qs and 10-Ks. Hence, our second hypothesis is as follows:

> Hypothesis 2: The CDS market reacts differently to the release of quarterly versus annual financial reports.

Several theoretical studies (see, inter alia, Epstein and Schneider, 2008; Lang, 1991; Veronesi, 1999) claim that market reaction to release of information depends upon information uncertainty. Applying this argument to the CDS market, we predict that release of financial reports is probably more informative during GFC with greater information uncertainty. Moreover, Shivakumar et al. (2011) show that CDS reaction to some accounting information was stronger during GFC. As a result, motivated by these findings, this study provides results for CDS market behavior toward the release of accounting information during GFC and non-GFC periods. Therefore, our third hypothesis is as follows:

> Hypothesis 3: The US CDS market reacts differently in GFC and non-GFC situations in regard to the release of periodic financial reports.

Numerous studies examine corporate disclosure practices in several countries and attempt to relate the extent of financial disclosure to firm characteristics, such as size, industry, and profits (see, inter alia, Ahmed and Courtis, 1999; Cooke, 1989; Cooke, 1992). The findings from these studies suggest that there are systematic differences in corporate financial reporting by corporate characteristic. Large firms are much more in the public eye and these firms are followed by more analysts (Lang and Lundholm, 1993) compared to small firms. Large firms are under pressure from investors, their agents, and other users to engage in acceptable levels of disclosure. Moreover, Firth (1979) suggests that information propagation is a costly exercise and such expenses are likely more affordable for large firms. Meek, Roberts, and Gray (1995) find that large firms generally disclose more information than small firms due to lower information production costs, or lower costs of competitive disadvantage associated with their disclosures. Furthermore, agency theory suggests that large firms have higher agency costs, therefore, the probability of disclosing more information is higher for these types of firm.[19]

These findings imply that large firms provide more information to the public in comparison to small and medium-size firms. There are, therefore, size effects and we hypothesize that there is a greater reaction by the CDS market for large firms compared to small- and medium-size firms.

Apart from firm size-based reactions to release of periodic financial reports, there is also evidence suggesting heterogeneity of industries from financial exposure (see, for example, Cooke, 1992; Stanga, 1976). Demirovic and Thomas (2007), for instance, demonstrate that the incremental informativeness of accounting information differs not only by firm size but also by industry. Meek et al. (1995) solidifies this message by highlighting that proprietary costs, such as competitive disadvantage and political costs, vary across industries. Competitive disadvantage and political costs, it is argued, may change the incentive of firms to disclose financial information. For example, because of the nature of financial firms' activities, they are likely to be more sensitive to disclosure than other firms. Furthermore, Choi and Hiramatsu (1987) discuss how accounting in certain industries is highly regulated. The utility and financial industries are known to be highly regulated. A priori, we expect a significant response from the utility and financial sectors after release of periodic financial reports compared to other sectors. Accordingly, our next hypothesis is as follows:

> Hypothesis 4: Reactions of the CDS market to release of financial reports vary across sectors and size groups.

[19] Moreover, a survey by Buzby (1974) confirms that many items of information that financial analysts believe to be important are not being adequately disclosed by small and medium firms.

3. Research design

3.1. Variable selection

Several studies in the CDS literature attempt to find the determinants of CDS spread based on reduced-form and structural variables. Galil, Shapir, Amiram, and Ben-Zion (2014) propose a parsimonious model to explain CDS spread changes; three of our control variables are based on the findings of this study. Galil et al. (2014) consider several groups of variables as contributing factors for CDS spread, and finally specify three variables that outperform the other considered variables in explaining CDS spread variation. Based on availability of data, we include three of these variables in our model, namely, stock return, change in stock return volatility, and change in spot rate (5-year treasury constant maturity rate). Moreover, we control for the effect of earnings announcements and credit ratings. The list of included variables is presented in **Error! Reference source not found.**, and a discussion of the selected variables follows below.

INSERT TABLE 1

3.1.1. Stock return (SR)

Merton (1974) argues that the increase in a firm's market value of equity decreases the probability of default. In this study, we use stock return as an indicator of firm value, because an increase in firm return can decrease the CDS spread, theoretically. Numerous studies empirically confirm this reverse relationship (see, inter alia, Aunon-Nerin, Cossin, and Hricko, 2002; Blanco, Brennan, and Marsh, 2005; Galil et al., 2014); thus, we expect a negative sign for this variable in our results as well.

3.1.2. Stock return volatility (ΔVOL)

Based on option pricing theory, firm debt is considered a short position of a put option on the firm's assets accompanied by a risk-free loan. Therefore, higher uncertainty on the market value of firm assets increases the probability of default, and consequently an increase in the CDS spread is expected. Prior research provides empirical results on a positive relationship between equity volatility and CDS spread (see, inter alia, Abid and Naifar, 2006; Aunon-Nerin et al., 2002; Blanco et al., 2005; Ericsson, Jacobs, and Oviedo-Helfenberger, 2004). To calculate volatility, we use a methodology similar to Galil et al. (2014), Campbell and Taksler (2002), and Jan Ericsson, Jacobs, and Oviedo (2009), and compute the annualized variance of each stock's return based on its preceding 250 trading days. We predict a positive relation between this variable and change in CDS return.

3.1.3. Changes in spot rate ($\Delta Spot$)

We follow Galil et al. (2014) and include a variable that measures change in spot rate to control for macroeconomic factors. They mention that higher spot rates can increase the reinvestment rate, and this causes a surge in future value of cash flows. Consequently, the probability of default is reduced and a reduction in CDS spread is expected. Consistent with 5-year tenor CDS contracts, we add the variable for 5-year maturity spot rate to our model. We predict a negative association between change in spot rate and CDS return.

3.1.4. Effect of earnings announcement (ER)

Many studies confirm that earnings announcements contain information relevant to the stock market. Along this line, some studies in the CDS literature empirically show that earnings announcements convey information for the CDS market as well (see, inter alia, Callen et al., 2009; Greatrex, 2009; Jenkins et al., 2016; Zhang and Zhang, 2013). Therefore, we control for the effect of earnings announcement by considering an indicator variable, and we expect this variable to be significant in our model. We cannot predict the expected sign because the earnings news may contain good news or bad news for investors based on dispersion in analyst earnings forecasts.

3.1.5. Effect of credit rating announcement (*CR*)
Hull et al. (2004) and Norden and Weber (2004) are among the first studies to examine the reaction of the CDS market to credit rating announcements. These authors show that credit ratings contain information relevant to the CDS market. Moreover, Aunon-Nerin et al. (2002) investigate the determinants of CDS spread and verify that credit rating is the single most important source of information on credit risk. Further, Micu, Remolona, and Wooldridge (2006) note that credit rating announcements hold relevant pricing information for the CDS market. As a result, we control for this effect in our model via an indicator variable, and we predict this variable to be strongly significant in our results. The sign of this variable is not clear and depends on the downgrading or upgrading in credit rating, which can be negative or positive.[20]

3.1.6. Variables related to periodic financial reports (*QR*, *AR*)
The focus throughout this study is to examine the reaction of the CDS market after release of periodic financial reports. We add two indicator variables to recognize the effect of quarterly reports and annual reports for the CDS market. We predict these variables to be significant, but the expected signs are not clear because the direction of change in the CDS spread depends on the content of reports.

3.2. Data
We obtain the release dates of annual and quarterly reports from the DataStream Professional database. Note that, in addition to the date of a periodic report's filing, we also consider the dates of amended report releases, because the contents of these reports may contain useful information for market participants as well.

The data related to CDS spread for modified structuring type (MR)[21] are extracted from Bloomberg, and the S&P 500 Index constituents are from DataStream. Data are daily for the period May 7, 2004 to April 30, 2015. We focus on the CDS price with 5-year tenor because it

20 We do not differentiate between downgrade and upgrade events, since credit rating announcement is not our main interest.
21 There are four restructuring clauses in CDS contracts that define the credit events that trigger settlement. These are key elements of the price of CDS, and a contract with a broader range of credit events has a higher CDS spread.
Variations include: 1) Complete Restructuring (CR) (a.k.a. full restructuring, FR): Any restructuring event qualifies as a credit event and any bond of maturity up to 30 years is deliverable. This was the standard for IG and HY trades but was replaced by MR in 2001. 2) Modified Restructuring (MR): Restructuring agreements count as a credit event, but the deliverable obligation against the contract has to be limited to those with a maturity of 30 months or less after the termination date of the CDS contract or the reference obligation that is restructured (regardless of maturity); generally used for IG trades in the US. This doc-clause started in 2001. 3) Modified-Modified (MM): In 2003, market participants in Europe found the 30-month limit on deliverable bonds to be too restrictive, so MM was introduced with a maturity limit of 60 months for restructured obligations and 30 months for all other obligations. This is used mostly in Europe. 4) No Restructuring (XR) (a.k.a. NR): All restructuring events are excluded as trigger events. This is prevalent in the high yield market. (https://www.markit.com/news/Credit%20Indices%20Primer.pdf)

is the most liquid type in the market.[22] Of the 500 constituents of the S&P 500 Index, only 196 stocks with corresponding CDS spread have sufficient time series data. As a result, we exclude the remaining stocks and our final data set consists of 196 firms. This sample has 505,037 observations. Moreover, the corresponding equity prices for available CDS data, dates of announcement for earnings, and credit ratings are acquired from DataStream, Bloomberg, and Compustat, respectively. A list of data sources is presented in **Error! Reference source not found.**.

INSERT TABLE 2

After obtaining the required data, we winsorize them at 1% and 99% to remove the effect of outliers. Following this, we divide our data sample into sectors based on the Global Industry Classification Standard (GICS). In addition, we split our sample into three size groups based on firm market capitalization. Specifically, our approach is to sort the data by the contemporaneous daily market capitalization and then consider two breakpoints to create three equal groups (low, medium, and large) of rims. Our sample covers approximately 53% of the US market. Moreover, the sector-based panels indicate that the consumer staples, financial, and industrial sectors comprise more than 50% of our data sample.

Our initial data set contains 2,375, 6,312, and 6,311 observations for release dates of annual reports, quarterly reports, and earnings announcements, respectively. In 47 annual reports, and 2,044 quarterly reports, filing of reports and earnings disclosures occurred concurrently. According to the literature, the CDS market reacts to earnings announcements on the release day. Therefore, regarding controlling for contamination, we remove these coincident dates from our sample. In addition to earnings announcements, we consider the effect of coincident credit rating announcements. For this purpose, we eliminate 497 (280 for quarterly and 217 for annual reports) concurrent releases of periodic reports and announcements of earnings or credit ratings. The number of observations for each type of event in our data sample is provided in **Error! Reference source not found.**.

INSERT TABLE 3

3.3. Methodology

Although the effects of periodic financial reports have been studied in the stock market literature, the present study is quite new to the CDS literature. The methodology used in the stock market literature is mostly the event study, but as Peterson (1989) argues, application of this methodology to debt securities has some obstacles due to inadequate quoted price data, infrequent trading, and the influence of the term structure. Moreover, there are many variations in the application of this methodology (Peterson, 1989), which impacts the results. For instance, the event study methodology is highly sensitive to the techniques used to estimate expected return or the choice of significance test (Armitage, 1995). In the CDS market, there is not an aggregate index for the whole market.[23] Therefore, the few studies that use an event study methodology in the CDS literature mostly create a credit-based index from their data samples

22 We employ the same data set used by Narayan, Sharma & Thuraisamy (NST, 2014). However, we update this data set to cover the April 30, 2015 period. The NST data set contains 212 firms; after updating, we were forced to remove 16 firms because they did not have sufficient data series.

23 There are two main indices in the CDS market, one is CDX, which contains North American and emerging market companies and the other is the iTraxx indexes, which contain companies from the rest of the world. CDX and iTraxx indices are of different types and there is not an aggregate index that represents the whole market.

and consider this as the market index. We believe that this constructed sample-based index does not indicate the market return, and the results obtained via this methodology may not be reliable. Furthermore, heteroscedasticity is a significant problem in the event study literature (Froot, 1989). Therefore, as an alternative methodology, we use a panel data regression model to determine the response of the CDS market to release of financial information.

We use heteroscedasticity-consistent standard errors and a fixed effect estimator to generate more reliable results.[24] Our regression model for evaluating the response of the CDS market to release of financial reports is as follows:

$$\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5\, SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta\, Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T} \quad (1)$$

In this regression model, $QR_{i,t}$ and $AR_{i,t}$ ($ER_{i,t}$ and $CR_{i,t}$) are dummy variables that take value 1 when quarterly reports and annual reports (earnings and credit rating announcements) are released and zero otherwise. $SR_{i,t}$ is daily stock return, $\Delta Vol_{i,t}$ is the variance of stock return, and $\Delta\, Spot_{i,t}$ shows the change in 5-year treasury rate.

We study the response of the CDS market over a 10-day period following the filing of periodic compulsory financial reports.[25] This approach is inspired by Griffin (2003), who evaluates the value relevance of quarterly and annual financial reports for stock market investors surrounding the filing date and measures investor response by unsigned excess stock returns 10 days around the filing date. Moreover, You and Zhang (2009) and You and Zhang (2011) conduct their analysis over a 21-day period centered on the filing date. In view of this, we run the panel regression model from t+1 to t+10.

3.4. Descriptive statistics

The descriptive statistics of control variables are presented in **Error! Reference source not found.**. We also provide summary statistics for the average change in CDS return for different categories of firm size, sectors, and economic conditions in The third feature of the data relates to average change in CDS return across different size groups and sectors. **Error! Reference source not found.** through

To provide more detailed findings, we continue our investigation based on the various panels of firms by size and sector. **Error! Reference source not found.** displays results of the CDS market's reaction to the release of financial reports based on size. Note that the release of quarterly reports is more value-relevant for small and large firms. Moreover, the level of significance decreases for large firms compared to small firms. The results show that annual reports contain information sufficient to move CDS of large firms. The coefficients of *AR* are mostly negative, and the response to annual reports is faster in comparison to quarterly reports for large firms. This evidence is in conformity with the findings of the preceding table and confirms the faster adjustment to information contained in annual reports by the CDS market compared to quarterly reports.

INSERT TABLE 11

24 We initially include time fixed effects as well; however, since the change in daily CDS price is infrequent, we consider only the fixed effects estimator.

25 We did a preliminary analysis for the time period (-10, 0) to investigate the reaction of the CDS market to the release of periodic reports before the release of reports. Our analysis shows no response from the CDS market over this (-10, 0) window. Therefore, we limit our analysis to the post-release of periodic financial reports period.

provide details about CDS return after the release of quarterly and annual reports across sectors and size groups of firms. The evidence here implies at least four findings: (1) the majority of sectors respond negatively after release of annual reports, while these reactions are mostly positive after release of quarterly reports; (2) there is variation in magnitude and sign of the change in CDS return across sectors: for example, the CDS changes after release of annual reports are larger and negative for financial, energy, health care, info tech, and industrial sectors compared to the other sectors; (3) the size-based tables indicate that CDS return after release of quarterly reports is positive for small and large firms but negative for medium-size firms; and (4) the CDS change after release of annual reports is negative for medium and large firms and positive for small firms.

INSERT TABLES 5-9

The fourth feature of the data derives from **Error! Reference source not found.**. This table illustrates that CDS change after release of reports is different during the pre-GFC, GFC, and post-GFC periods. Moreover, it provides support for the changing behavior of the market after release of quarterly versus annual reports.

These features of the data help to determine whether release of financial reports is value-relevant for the CDS market and, if it is, how exactly the reaction of the market differs between the two types of report. Moreover, it provides support for H3 and H4 described in Section 2, about the heterogeneity of CDS response after release of reports across size, sector, and economic factors.

4. Empirical results

4.1. Empirical analysis

Empirical results based on the panel data regression models are shown in **Error! Reference source not found.**. The results illustrating stock return, change in volatility, and change in spot rate are strongly significant for all considered days. As explained in Section 3, the signs of these variables are consistent with expectations, and they are statistically significant. Stock return and change in spot rate have negative relations with CDS spread, and change in volatility is positively related to CDS spread variation. In addition, as the literature documents, we confirm that earnings announcement and credit announcement are value-relevant for the CDS market. More importantly, the results indicate that the CDS market responds to the information content of financial reports. The response of CDS through **Error! Reference source not found.**. The descriptive statistics reveal several interesting features of the data. The first feature is that the signs of CDS spread change, stock return, and volatility are consistent with the literature. According to **Error! Reference source not found.**, the mean CDS spread is negative, while the corresponding signs for stock return and change in volatility are positive and negative, respectively.

INSERT TABLE 4

The second feature of the data is that, as Table 5 reveals, the average CDS return during t+2 to t+10 for periodic financial reports differs in sign and magnitude compared to the duration without the release of the periodic financial reports. Moreover, note that the standard deviation of average return is higher after the release of reports, from t+2 to t+10. Therefore, this implies that there is not an immediate response from the CDS market after the release of reports.

The third feature of the data relates to average change in CDS return across different size groups and sectors. **Error! Reference source not found.** through

To provide more detailed findings, we continue our investigation based on the various panels of firms by size and sector. **Error! Reference source not found.** displays results of the CDS market's reaction to the release of financial reports based on size. Note that the release of quarterly reports is more value-relevant for small and large firms. Moreover, the level of significance decreases for large firms compared to small firms. The results show that annual reports contain information sufficient to move CDS of large firms. The coefficients of *AR* are mostly negative, and the response to annual reports is faster in comparison to quarterly reports for large firms. This evidence is in conformity with the findings of the preceding table and confirms the faster adjustment to information contained in annual reports by the CDS market compared to quarterly reports.

INSERT TABLE 11

provide details about CDS return after the release of quarterly and annual reports across sectors and size groups of firms. The evidence here implies at least four findings: (1) the majority of sectors respond negatively after release of annual reports, while these reactions are mostly positive after release of quarterly reports; (2) there is variation in magnitude and sign of the change in CDS return across sectors: for example, the CDS changes after release of annual reports are larger and negative for financial, energy, health care, info tech, and industrial sectors compared to the other sectors; (3) the size-based tables indicate that CDS return after release of quarterly reports is positive for small and large firms but negative for medium-size firms; and (4) the CDS change after release of annual reports is negative for medium and large firms and positive for small firms.

INSERT TABLES 5-9

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These features of the data help to determine whether release of financial reports is value-relevant for the CDS market and, if it is, how exactly the reaction of the market differs between the two types of report. Moreover, it provides support for H3 and H4 described in Section 2, about the heterogeneity of CDS response after release of reports across size, sector, and economic factors.

5. Empirical results

5.1. Empirical analysis

Empirical results based on the panel data regression models are shown in **Error! Reference source not found.**. The results illustrating stock return, change in volatility, and change in spot rate are strongly significant for all considered days. As explained in Section 3, the signs of these variables are consistent with expectations, and they are statistically significant. Stock return and change in spot rate have negative relations with CDS spread, and change in volatility is positively related to CDS spread variation. In addition, as the literature documents, we confirm that earnings announcement and credit announcement are value-relevant for the CDS market. More importantly, the results indicate that the CDS market responds to the information content of financial reports. The response of CDSto issuance of quarterly reports occurs after two days. In the same vein, the results show that the reaction of this market to release of annual reports occurs with delay as well. Moreover, our analysis demonstrates that the speed of CDS market adjustment to release of information is greater for annual reports relative to quarterly reports, because the coefficients of dummy variables related to 10-Q reports are statistically significant from t+2 to t+10, while the corresponding coefficients for 10-K reports are statistically significant only at t+2 and t+3.

INSERT TABLE 10

To provide more detailed findings, we continue our investigation based on the various panels of firms by size and sector. **Error! Reference source not found.** displays results of the CDS market's reaction to the release of financial reports based on size. Note that the release of quarterly reports is more value-relevant for small and large firms. Moreover, the level of significance decreases for large firms compared to small firms. The results show that annual reports contain information sufficient to move CDS of large firms. The coefficients of *AR* are mostly negative, and the response to annual reports is faster in comparison to quarterly reports for large firms. This evidence is in conformity with the findings of the preceding table and confirms the faster adjustment to information contained in annual reports by the CDS market compared to quarterly reports.

INSERT TABLE 11

Moreover, the results of sector-based analysis presented in**Error! Reference source not found.** indicate that SEC filings are not value-relevant for all sectors. The most responsive sector to release of quarterly reports is financial firms, followed by the healthcare, energy, telecom, and utility sectors. Other sectors, namely, info tech, materials, and consumer staples, react to release of reports, but not as consistently as the former sectors. The sector response to annual reports is not as significant as the response to quarterly reports. The energy sector reacts faster, that is, one day after release date, while the financial, healthcare, and materials sectors respond on the second day, and firms in the utility sector react only after five days. Although the telecom sector reacts to release of quarterly reports, we document no response from this sector to release of annual reports.
Regarding testing the efficiency of the CDS market, our results support the hypothesis of inefficiency because we observe movements in price for several days after release of financial information.

INSERT TABLE 12

5.2. Does reaction of the CDS market differ by economic situation?
This study provides results for CDS market behavior in various economic situations. We categorize the data into three subsample periods based on GFC. According to the Federal Reserve Bank of St. Louis, the GFC began on February 27, 2007. Therefore, the pre-GFC period in our data set is from May 7, 2004 to February 26, 2007. The second subsample, which we refer to as the GFC period, is from February 27, 2007 to December 31, 2010, and the post-GFC period is from January 1, 2011 to April 20, 2015. The statistical results presented in **Error! Reference source not found.** show that the mean of CDS prices in the GFC period is higher relative to the pre-GFC period (53.8 vs 135.9 bps); it then decreases to 112 bps in the post-GFC era.

INSERT TABLE 13

Results related to the reaction of the CDS market in different economic situations are reported in **Error! Reference source not found.**. We summarize our main findings below.

First, the response of the CDS market to release of quarterly reports during the GFC period is faster relative to non-GFC periods (in t+1 for the GFC period vs t+2 and t+3 for the pre-GFC and post-GFC periods, respectively), which implies that the CDS market during the GFC period incorporates new information more quickly. Second, the sector-based analysis shows that the financial, energy, health care, telecommunication, and utility sectors are more responsive to release of financial reports. Third, the results from the size-based analysis indicate that reaction of the CDS market to release of periodic accounting information is higher for the post-GFC period.[26] Finally, the CDS market is inefficient during the non-GFC period but acts less inefficiently during the GFC period.

INSERT TABLE 14

6.Robustness check (Additional analysis)

6.1. Leverage-based analysis

Leverage is a widely used determinant of credit spread (see, for example, Collin-Dufresne et al., 2001; J Ericsson et al., 2004; Galil et al., 2014). The descriptive statistics confirm the leverage-based heterogeneity with respect to CDS spread.[27] Therefore, we split our data set into 10 different levels of the leverage ratio.[28] We provide further evidence regarding the reaction of the CDS market to release of financial reports based on the different levels of leverage. The results in **Error! Reference source not found.** confirm the value relevance of periodic financial reports for the CDS market and indicate that financial reports contain information more relevant to firms with higher leverage ratios. Consistent with previous results, this shows that the CDS market reacts more to quarterly reports in comparison to annual reports. Moreover, the results illustrate that the reaction is mostly with delay.

INSERT TABLE 15

6.2. Credit rating–based analysis

We categorize our data sample based on long-term S&P credit rating. If the S&P credit rating of a firm is BBB- or higher, it is classified as investment grade (IG), and if it is rated BB or lower, it is perceived as speculative grade or high yield (HY). Information contained in **Error! Reference source not found.** reveals that more than half (55%) of our sample of firms is HY and the rest belong to the IG group. As expected, the mean of CDS for speculative groups is significantly higher (almost 7.5 times) than the mean CDS price for IG firms, because the quality of credit rating of IG firms is better than HY firms. We run the regression model for

26 To save space, we do not report the results of size-based and sector-based analysis for different economic situations. The detailed tables are available from the authors.

27 In order to save space, we do not report this descriptive statistic.

28 We follow Galil et al. (2014) and define the leverage ratio as book value of debt (sum of long-term debt and current debt) divided by the sum of book value of debt and equity value (number of outstanding shares multiplied by the share price). We obtain quarterly data for long-term debt and current debt in liabilities as representative of short-term debt. Then, we follow previous studies (see, for example, Collin-Dufresne, Goldstein and Martin, 2001; Ericsson, Jacobs and Oviedo, 2009; Galil et al., 2014) and use linear interpolation to estimate the daily data for components of debt value. Daily data for equity value are extracted from DataStream.

each group separately. The results presented in **Error! Reference source not found.** demonstrate that financial reports are value-relevant for both IG and HY firms, but it seems that IG firms are more responsive to annual reports, and HY firms react more to quarterly reports. It also confirms that the reaction of the CDS market to this information is not immediate, which constitutes evidence for the inefficiency of this market.

INSERT TABLES 16-17

6.3. Reaction of the CDS market with different tenors

To further analyze the response of the CDS market after release of financial reports, we repeat our analysis for CDS with different time maturities, namely, 1, 2, 3, 4, 7, and 10 years. We extract the related data from DataStream, which are available from December 14, 2007 to April 30, 2015. **Error! Reference source not found.** provides details on the mean, median, and standard deviation (SD) of CDS spread for various time tenors. CDS contracts with longer maturities have higher CDS prices in comparison to short-tenor CDS contracts. The results presented in **Error! Reference source not found.** indicate that, consistent with the CDS market with 5-year tenor (the most liquid type), CDS markets with short and long maturities also react to the release of compulsory periodic financial reports, and these reactions are mostly with delay.29 According to **Error! Reference source not found.**, we find that the CDS market reacts faster to release of annual reports in comparison to release of quarterly reports.

INSERT TABLES 18-19

7. Discussion of results

As mentioned in Sections 4 and 5 above, we investigate the reaction of the CDS market over a 10-day period following compulsory periodic SEC filings. The outcomes of the analysis are described as follows.

7.1. The CDS market reacts to release of periodic financial reports

The coefficients of dummy variables related to the effect of a financial report's release on CDS spread are statistically significant. This clarifies that the CDS market reacts to release of financial information and confirms that periodic financial reports hold information relevant for the CDS market. Unlike previous studies that consider restricted accounting information, such as total assets, net income, and total liabilities, we examine financial reports beyond accounting ratios and consider the effect of the release of these detailed reports as a whole. As mentioned above (see Section1), some sections of SEC mandatory reports, such as "Risk Factors," "Defaults upon Senior Securities," "Management's Discussion and Analysis of Financial Condition and Results of Operations," and "Quantitative and Qualitative Disclosures about Market Risk" may contain valuable information for CDS market participants.

7.2. Reaction of the CDS market to release of periodic financial reports occurs with delay

The response of the CDS market with 5-year tenor to release of annual reports is strongly significant on the second and third days after filings, and it shows no significant reaction on other days. In contrast to annual reports, the reaction of the CDS market to quarterly reports is persistent in our analysis, but only from t+2, and the magnitudes of the corresponding coefficients increase in later days. These findings show that the reaction of the CDS market to

29 The results for size-based and sector-based analysis for the CDS market with different time maturities are available upon request.

release of financial reports is not quick, and the response of this market is with some days' delay. This evidence is explained as follows. First, we know that the stock market has a dominant role over the CDS market in price discovery (see, inter alia, Forte and Peña, 2009; Narayan et al., 2014; Norden and Weber, 2009). Moreover, previous studies regarding the response of the stock market to SEC filings show that the stock market reacts mostly to the release of accounting information on the day of filing or one or two days after the SEC filing date (see, for example, Griffin, 2003; You and Zhang, 2009). Therefore, the reaction of the CDS market is expected to occur after the response of the stock market, at least one day after the event day. Another important explanation for this finding has roots in the *limited attention theory*, originating from the work of Kahneman (1973). Hirshleifer and Teoh (2003, p. 5) state, "Limited attention is a necessary consequence of the vast amount of information available in the environment, and of limits to information-processing power."

The results shown in **Error! Reference source not found.**, 11, and 12 indicate that the magnitude of the coefficients related to impacts of periodic reports increase in the following days and are persistent over our study period. You and Zhang (2011) claim that when price drift is due to cognitive bias or risk, the magnitude of drift does not decrease over time. Thus, we can surmise that the behavior of the CDS market toward release of this information can be explained by cognitive limitation of investors, or the limited attention phenomenon. To provide support for the existence of limited attention phenomenon in CDS market, we do additional analysis to check its existence. Some studies show that the stock market reaction is weaker on days with more SEC filings (see, Hirshleifer et al., 2009) or at times when investors are distracted by other events such as weekend holidays or religious holidays (see, for instance, DellaVigna and Pollet, 2009; Pantzalis and Ucar, 2014).

Motivated by the study of DellaVigna and Pollet (2009), we investigate the reaction of CDS market when the release day is Friday vs the release of reports on the other weekdays. If inattention influences CDS price, we should observe less immediate response and more drift for Friday announcements. The results are provided on **Error! Reference source not found.**. The reaction of CDS market when the release of reports is on Fridays is not statistically significant until t+9 which is weakly significant at 10%. In contrast, when quarterly reports release on other days (non-Fridays), it is statistically from t+2. This situation also exists for the reaction of market after the disclosure of annual reports. The response of CDS market is significant at the 10% level at t+4 when annual reports become public on Friday while it is strongly significant at t+2 for other weekday releases. These findings support explanations of post-financial reports release drift based on underreaction to information caused by limited attention.

INSERT TABLE 20

7.3. Reaction of the CDS market to release of periodic financial reports varies for firms from different sectors, sizes, leverage levels, and credit ratings

Results of size-based and sector-based analysis offer more detailed evidence of the reaction of the CDS market to the information content of financial reports. The results of the sector-based analysis show that some sectors such as financial, utility, energy, and healthcare are more responsive to information disclosure. It seems that periodic accounting reports are more value-relevant for the financial sector in comparison to the other sectors. One reason for this finding is that the financial sector is the main participant in the CDS market. Further, as discussed in Section 1, financial reports can provide opportunities for credit investors to evaluate counterparty risk as well as default risk for the reference entities. Moreover, we know that accounting in certain industries is heavily regulated (Choi and Hiramatsu, 1987, p. 34). The utility and financial sectors are known to be highly regulated; therefore, the content of released reports should be adequate.

Furthermore, according to the descriptive statistics, we find that small firms have high levels of CDS price and high volatility. We also know that the utility sector encompasses the lowest proportion of market capitalization. Therefore, this implies that the utility sector is categorized as risky.

Moreover, results of size-based analysis show that firms in large groups are more responsive to annual financial information release. This is consistent with our expectation due to the higher level of released information by large firms, since such firms are under pressure by investors and other users to provide information. Moreover, this is consistent with the Hirshleifer, Lim, and Teoh (2009), who find that announcements by large firms have a weaker distraction effect than those of small firms; also, Basu (1997) documents that the stock market underreacts more to announcements by smaller firms. Moreover, comparison of the reaction of the CDS market toward quarterly and annual reports across different size groups reveals that large firms incorporate the received information from annual reports faster than quarterly reports. This situation is opposite for small firms, and we observe a stronger reaction to quarterly reports than annual reports. We conclude that for large firms, annual reports are more important than quarterly reports, and vice versa for small and medium firms.

Moreover, we decompose the firms placed in larger size clusters and find that approximately half the firms in these categories are classed as financial or healthcare sector firms. Moreover, a larger fraction of firms in size group 1 belongs to the utility sector, which has the lowest market capitalization and high CDS price volatility.

Our analysis based on firm leverage shows that high-leverage firms are more responsive to release of financial reports, and the reactions of this type of firm are significantly more frequent in comparison to firms with lower levels of leverage.

In summary, we find that the size groups and sectors that respond to release of financial reports have at least one of the following characteristics: high mean of log CDS price, high volatility of log of CDS price, high leverage, or low/high market capitalization.

In addition, credit rating–based analysis demonstrates that periodic financial reports are value-relevant for both HY and IG firms, but it seems that investors pay more attention to quarterly reports for HY firms and to annual reports for IG firms. This finding is consistent with expectations because in contrast to the HY firms, IG firms have mostly stable situations, and their financial positions do not change significantly in each financial quarter; thus, their annual reports might be more interesting as opposed to quarterly reports.

7.4. Reaction of the CDS market to quarterly and annual financial reports differs

The information contained in quarterly and annual reports has various characteristics. Both report types are lengthy and complex. Hirshleifer (2001) discusses that investors pay less attention to information that requires greater cognitive effort to understand. Our findings support this claim; the CDS market absorbs the information contained in annual reports faster because, in contrast to the quarterly reports dummy variable, the dummy variables related to annual reports are significant mainly two days following report release. This finding is robust in our analysis for CDS with different tenors. Moreover, it seems that the CDS market underreacts to the information content of quarterly reports more than annual reports, because the coefficients of related variables are strongly significant for most days of our investigated window. These findings are consistent with You and Zhang (2009), who observe that investors in the equity market underreact to the content of periodic reports. These authors argue that disclosure of this kind of financial information is quite challenging for investors to digest, and subsequent evidence of price drift is observed.

Our results indicate that the level of drift in investor reaction to release of quarterly reports is higher relative to annual reports. This finding is consistent with Brav and Heaton (2002), who claim that when uncertainty about the information structure is high among investors, a pattern of underreaction is plausible, as a result of rational learning and failure to incorporate information completely. This evidence is also compatible with several features of the reports. Quarterly reports are released three times per year, and this type of report is not audited; thus, uncertainty is higher compared to the content of officially audited annual reports. Consequently, it is expected that investors underestimate the significance of the information content of quarterly reports and do not absorb the information content fully.

Moreover, Ahmed, Billings, Morton, and Stanford-Harris (2002) mention that most qualitative information, such as risk disclosure, which is more value-relevant for the CDS market, in quarterly reports is repetition from previous annual reports, possibly increasing the ignorance of investors toward the importance of quarterly reports.

Another explanation stems from the activity of speculators in the CDS market. Dissemination of information can provide an incentive for market participants, especially speculators, to trade in markets. Norden and Radoeva (2013) argue that when uncertainty is higher, the probability of speculation is higher. Since uncertainty about the content of quarterly reports is higher compared to annual reports, speculative activity is more probable, which can lead to more drift in the reaction of the CDS market.

7.5. Reactions of the CDS market to release of annual reports versus quarterly reports are in opposite directions

Apart from the statistical significance of our results, the signs of the coefficients on the reaction of the CDS market to release of quarterly and annual reports differ. Our results indicate that the coefficient of the dummy variable for quarterly reports is mostly positive, which implies that after release of quarterly reports, credit risk increases due to information content. The reverse situation exists for annual reports. Based on the results obtained from our full sample (shown in **Error! Reference source not found.**), the coefficients related to annual reports are negative. The size-based panels also confirm this negative relationship. Moreover, the sector-based analysis shows that, except for utility and consumer staples, other sectors (energy, financial, health care, and materials sectors) react negatively to release of annual reports. This shows that annual reports in most cases contain positive news for CDS, and we observe a decline in CDS spread after release of annual reports. This observation can be perceived as evidence of "window dressing" actions to improve the appearance of a firm's financial reports to impress shareholders or lenders.

These findings are important as a matter of economic significance. The periodic payments that buyers of CDS contracts pay to sellers depend on the CDS spread, which is proportional to the underlying notional value, so a higher CDS spread incurs higher cost for a buyer. As mentioned above, the coefficient related to quarterly reports is positive, and the magnitudes of the coefficient have an increasing function. Therefore, the days after release of quarterly reports for a particular firm are considered profitable situations for sellers of CDS contracts, yielding them greater profit by receiving a higher amount from buyers. In contrast, it would not be the right time for buyers to enter CDS contracts for firms that recently released their quarterly reports.

In contrast, regarding the positive coefficient on the effect of annual reports on CDS spread, if hedgers and speculators intend to buy a CDS contract for a specific reference entity, the day after release of the annual report is a good opportunity to do so; in this way, they will pay a lower amount as CDS premium to CDS providers.

8. Concluding remarks

We examine how the release of compulsory quarterly and annual financial reports influences CDS markets. The recent body of literature on the role of accounting information in CDS pricing motivates this study. Using daily data for various panels of sector and size, we identify that the contents of these reports are value-relevant to the CDS market even after controlling prior announcements for earnings and credit ratings. We find that some sectors (specifically, financial, energy, health care, and utility) and large firms are more responsive to release of financial information.

Another important finding is that the reaction of the CDS market to release of financial information is sluggish and delayed, which implies that investors in this market, similar to the stock market, have limited attention and processing power. This observation supports the notion of inefficiency in the CDS market. Moreover, the results illustrate that the reaction of the CDS market to release of quarterly and annual reports is dissimilar. CDS return usually increases after filings of quarterly reports, and decreases after disclosure of annual reports. These findings provide evidence of "window dressing" actions to improve the appearance of a firm's financial reports to impress shareholders, credit holders, or credit providers.

Moreover, we investigate whether the reaction of the CDS market varies during GFC and non-GFC periods. We find that the response of this market toward the release of financial information is faster in a GFC period relative to a non-GFC period. We implement additional analysis to confirm our results; that is, we construct panels based on credit rating, leverage ratio, and CDS with different tenors. The results confirm the robustness of our findings.

Our study contributes mainly to the strand of literature that investigates the behavior of CDS markets in response to public information. We demonstrate that the limited attention phenomenon is present in the CDS markets, and our results provide additional evidence in favor of inefficiency in the CDS markets. The outcomes from this study can benefit regulators, investors, and corporate managers. Investors, particularly speculators, hedgers, and arbitragers, can benefit from the findings of this study to construct portfolios of CDS contracts in regard to the distinctions among different size groups and sectors. They can also adopt profitable strategies around release of periodic financial reports. Corporate managers can become better informed as to what extent the information content of their periodic releases can affect the credit risk of their firms. Finally, regulators can redesign the structure of reports with the aim of facilitating an efficient market by compelling firms to release more transparent information requiring less cognitive effort.

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Table 1: Definition of variables

In this table, we list the name and description of all variables that we consider in our model. In third column we provide the description for each of variable and in the fourth column we show how to create the variables. The expected sign for each variable is provided in the last column.

Variable		Description	Variable Measurement	Expected Sign (Significant: Yes or No?)
Spread variable	$\Delta CDS_{i,t+T}$	Change in CDS spread for 196 firms of S&P 500 index	$\Delta\, CDS_{i,t+T} = \log(CDS_{i,t+T} / CDS_{i,t}) * 100$	
Firm-specific variables	$SR_{i,t}$	Daily stock return	$SR_{i,t} = \log(SR_{i,t} / SR_{i,t-1}) * 100$	- (yes)
	$\Delta Vol_{i,t}$	Equal-weighted 250 days variance of individual stock return	$Vol_{i,t} = STD[SR_{i,t} - \text{market (S\&P index) return}_{i,t}]$	+ (yes)
Market factors	$\Delta Spot_{i,t}$	Change in 5-year Treasury bill rate	$\Delta Spot_{i,t} = Spot_{i,t} - Spot_{i,t-1}$	- (yes)
Dummy variable for controlling the effect of prior earnings announcement	EA_{it}	1 if credit rating of firm i was announced in the day t, and 0 otherwise		? (yes)
Dummy variable for controlling the effect of prior credit announcement	CR_{it}	1 if quarterly earnings of firm *i* was announced in the day t, and 0 otherwise		? (yes)
Dummy variable for the impact of annual financial reports	AR_{it}	1 if annual financial reports of firm *i* release on day t, and 0 otherwise		? (yes)
Dummy variable for the impact of quarterly financial reports	QR_{it}	1 if quarterly financial reports of firm *i* release on day t, and 0 otherwise		? (yes)

Table 2: Data sources

This table provides the list of required data and the corresponded databases that used to obtain data.

Data Type	Used Databases
CDS price	DataStream-Bloomberg
Equity price	DataStream
SEC filing dates	DataStream Professional
Earnings announcement dates	Bloomberg
5-year treasury rate	Federal Reserve Economic Data (FRED)
Historical monthly S&P long-term corporate issuer-level debt rating and credit rating announcement date	Compustat
Quarterly financial data	Compustat

Table 3: Number of observations for each type of event

This table provides the details about the number of events for each type of exposure in our data set. To control for contamination, we remove the events that the releases of accounting information and announcements of earnings or credit ratings occurred on the same day. The third column shows the number of concurrent events. The final number of events in our data after removing the outliers is written on the last column.

Type of Exposure	Initial Number of Events in Data Sample	Number of Concurrent Release Dates (Financial Reports with Earnings Announcement or Credit Announcement)	Number of Observations after Removing the Concurrent Dates	Number of Observations after Removing Concurrent Dates and Outliers in the Final Sample
Quarterly reports	6,312	2,044	4,268	3,625
Annual reports	2,375	47	2,328	1,892
Earnings announcements	6,311	2,091	4,220	3,620
Monthly credit rating announcements	26,820	497	26,323	15,660

Table 4: Descriptive statistics

This table reports the mean, median and standard deviation (SD) for daily change in volatility, daily change in spot rate (5-year treasury rate) and daily stock return in Panel A. We calculate the volatility of stock return based on the previous 250 trading days. We compute the stock return by $\text{Stock Return}_{i,t} = \log(\text{Stock Price}_{i,t} / \text{Stock Price}_{i,t-1}) * 100$. Similarly, Panel B reports the detailed statistics for dependent variables (*Daily CDS Return*). We compute the daily CDS return according to this formula: $\Delta\text{CDS}_{i,t+T} = \log(\text{CDS}_{i,t+T} / \text{CDS}_{i,t}) * 100$ for t+1 to t+10.

Panel A: Control variables			
Day	Mean	Median	SD
SR (daily)	$1.64*10^{-2}$	0	$6.73*10^{-1}$
Δ Vol (daily)	$-7.29 *10^{-5}$	0	$2.56*10^{-3}$
Δ Spot (daily)	$-2.77*10^{-4}$	0	$5.2*10^{-2}$
Panel B: Dependent variable - *Daily CDS Return* (bps)			
Day	Mean	Median	SD
t+1	-0.044	0	2.244
t+2	-0.073	0	3.432
t+3	-0.11	0	4.443
t+4	-0.129	0	5.347
t+5	-0.146	0	6.133
t+6	-0.17	0	6.878
t+7	-0.186	0	7.569
t+8	-0.211	-0.012	8.194
t+9	-0.231	-0.022	8.795
t+10	-0.252	-0.037	9.369

Table 5: Average of change in CDS return on event days and normal days

This table provides details (the number of observations (N), mean, standard deviation (SD)) about the change of CDS returns during 10 days after release of quarterly and annual reports. The first three columns are related to the change in CDS return during 10 days in normal days without financial exposure and the rest of tables signify the behavior of market after release of periodic financial reports.

	Normal Durations			After Release of Quarterly Reports			After Release of Annual Reports		
Days	N	Mean	SD	N	Mean	SD	N	Mean	SD
t+1	511,716	-0.03	3.73	3,625	-0.02	3.92	1,892	-0.14	3.09
t+2	511,531	-0.04	5.08	3,621	0.08	5.38	1,892	-0.22	6.05
t+3	511,344	-0.06	6.17	3,618	0.13	6.46	1,891	-0.17	6.48
t+4	511,154	-0.07	7.17	3,617	0.34	7.23	1,891	-0.15	7.77
t+5	510,972	-0.07	8.07	3,611	0.42	8.18	1,890	0.05	8.7
t+6	510,781	-0.08	8.91	3,609	0.69	8.91	1,890	0.26	11.3
t+7	510,592	-0.08	9.73	3,606	0.89	9.8	1,890	0.19	9.80
t+8	510,401	-0.1	10.43	3,605	1.09	10.53	1,890	0.05	9.91
t+9	510,209	-0.11	11.11	3,605	1.35	11.33	1,889	0.11	10.65
t+10	510,018	-0.12	11.78	3,605	1.35	11.61	1,889	0.17	11.45

Table 6: Average of change in CDS return after release of periodic financial report by size

We split data into three groups based on the firm's market capitalization. This table provides details (mean, standard deviation (SD) and average in number of observations about the change in CDS return after release of quarterly (Panel A) and annual reports (Panel B) for size group.

Day	Small		Medium		Large	
	Mean	SD	Mean	SD	Mean	SD
	Panel A: After Release of Quarterly Report					
t+1	-0.001	4.728	-0.151	3.446	0.101	3.468
t+2	0.206	6.281	-0.195	4.966	0.240	4.787
t+3	0.355	7.193	-0.189	6.104	0.254	6.021
t+4	0.619	8.086	-0.009	6.848	0.427	6.706
t+5	0.788	9.008	0.012	7.976	0.492	7.472
t+6	1.080	9.853	0.222	8.712	0.792	8.066
t+7	1.384	10.864	0.410	9.621	0.889	8.818
t+8	1.530	11.399	0.688	10.534	1.077	9.581
t+9	1.723	12.330	0.948	11.236	1.409	10.346
t+10	1.787	12.695	0.974	11.408	1.308	10.662
No. Obs	1181		1247		1197	
	Panel B: After Release of Annual Report					
t+1	0.004	3.631	-0.067	2.532	-0.351	2.991
t+2	0.140	5.755	-0.078	5.360	-0.721	6.911
t+3	0.248	6.267	-0.176	5.885	-0.585	7.209
t+4	0.284	8.118	-0.021	6.753	-0.726	8.311
t+5	0.369	8.961	0.150	8.120	-0.361	8.968
t+6	0.944	14.403	0.372	8.979	-0.539	9.601
t+7	0.522	10.241	0.610	9.171	-0.571	9.912
t+8	0.288	10.568	0.541	8.957	-0.669	10.097
t+9	0.284	11.153	0.649	9.939	-0.606	10.772
t+10	0.255	11.834	0.705	10.970	-0.442	11.521
No. Obs	640		621		631	

Table 7: Average of change in CDS return after release of annual reports by sectors

This table provides descriptive statistics (mean, standard deviation (SD) and average in number of observations (N)) for the change in CDS return after release of annual reports by different sectors. We divide our data into 10 sectors based on the GICS.

Sectors	Consumer Discretionary		Consumer Staple		Energy		Financial		Health Care	
Days	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
t+1	0.03	2.61	0.37	4.86	-0.32	2.29	-0.32	2.29	-0.4	2.44
t+2	0.03	4.77	0.48	6.13	-0.41	3.29	-0.41	3.29	-1.18	11.23
t+3	0.38	6.07	0.99	6.85	-0.64	3.95	-0.64	3.95	-1.16	11.61
t+4	0.65	8.11	1.27	7.32	-0.71	4.63	-0.71	4.63	-1.34	12.53
t+5	0.89	9.44	1.06	8.04	-0.5	5.84	-0.5	5.84	-1.06	12.34
t+6	0.85	9.99	0.94	9.2	-0.79	7.68	-0.79	7.68	-0.98	13.32
t+7	0.85	9.68	0.87	9.17	-0.71	7.6	-0.71	7.6	-1.06	13.54
t+8	0.38	8.99	0.96	9.8	-0.93	7.59	-0.93	7.59	-1.3	14.01
t+9	0.17	9.56	1.01	10.4	-0.85	7.88	-0.85	7.88	-1.12	14.71
t+10	0.03	10.56	0.86	10.7	-0.7	8.58	-0.7	8.58	-0.82	15.04
N	350		220		152		152		172	
Sectors	Industrial		Info Tech		Material		Telecom		Utilities	
Days	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
t+1	-0.29	3.38	-0.38	2.69	-0.18	3.19	0.11	2.09	0	2.67
t+2	0.02	7.11	0.01	4.34	-0.5	4.46	0.92	5.6	-0.02	4.15
t+3	-0.17	6.59	-0.56	5.41	-0.66	4.79	0.63	6.08	-0.09	4.46
t+4	-0.76	7.84	-1.14	5.83	-0.18	7.04	-0.02	9.99	0.14	5.3
t+5	-0.73	8.53	-1.04	6.39	0.15	8.81	0.55	10.85	0.42	6.07
t+6	0.66	18.74	-1.38	7.35	0.13	9.69	1.52	6.7	0.77	7.41
t+7	-0.36	9.85	-0.83	7.79	0.49	10.31	0.79	11.42	1.08	7.78
t+8	-0.55	9.53	-1.34	8.15	0.27	10.51	1.15	10.8	1.22	8.4
t+9	-0.23	10.64	-1.48	8.58	0.58	11.18	0.79	11.42	0.76	9.41
t+10	-0.12	12.1	-1.95	9.26	1.17	12.71	1.63	11.87	0.61	9.98
N	264		89		140		29		188	

Table 8: Average of change in CDS return after release of quarterly reports by sectors

This table provides descriptive statistics (mean, standard deviation (SD) and average in number of observations (N)) for change in CDS return after release of quarterly reports by different sectors. We divide our data into 10 sectors based on the GICS.

Sectors	Consumer Discretionary		Consumer Staple		Energy		Financial		Health Care	
Days	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
t+1	-0.01	3.46	0.19	3.92	0.18	2.96	-0.2	6.12	0.01	4.05
t+2	0.14	4.47	-0.18	5.02	0.09	4.83	0.37	7.83	0.44	5.66
t+3	0.13	5.35	0.15	5.92	0.21	6.14	0.73	8.39	0.74	6.92
t+4	0.21	6.39	0.33	6.42	0.79	6.84	1.12	9.08	1.15	7.87
t+5	0.15	7.09	0.09	6.59	1.19	8.47	1.67	10.11	1.5	8.46
t+6	0.19	7.75	0.35	7.52	1.6	9.37	1.92	10.83	1.71	8.98
t+7	0.25	8.59	0.38	8.97	2.02	9.76	2.41	12.14	1.74	9.32
t+8	0.35	9.13	0.31	9.04	2.54	10.49	2.42	13.07	1.96	9.79
t+9	0.52	9.77	0.42	9.7	3.01	11.03	3.17	14.56	1.89	10.19
t+10	0.38	10.28	0.31	9.95	2.96	11.35	3.04	14.36	2.1	10.73
N	548		441		362		508		348	
Sectors	Industrial		Info Tech		Material		Telecom		Utilities	
Days	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
t+1	-0.13	3.46	-0.27	2.9	-0.19	3.09	0.16	2.67	0.09	3.02
t+2	-0.29	4.41	0.21	6.95	-0.5	5.33	0.41	3.39	0.28	3.88
t+3	-0.55	6.08	-0.31	8.88	-0.53	6.14	0.86	4.94	0.16	4.9
t+4	-0.37	7.07	-0.73	8.93	-0.63	6.59	0.99	6.42	0.26	5.93
t+5	-0.49	7.82	-1.45	11.28	-0.97	7.59	1.17	6.76	0.64	6.86
t+6	-0.34	8.63	-0.85	11.21	-0.29	8.93	1.29	8.01	0.98	7.63
t+7	-0.29	9.47	-0.89	11.61	0.13	10.66	1	8.39	1.38	8.31
t+8	-0.14	10.43	-0.16	12.42	0.38	12.47	1.12	8.66	1.84	8.93
t+9	0.17	11.36	-0.46	13.82	0.33	12.63	1.85	8.97	2.11	9.35
t+10	0.11	11.93	-0.19	13.09	0.64	14.09	1.7	9.61	2.25	9.28
N	566		169		201		63		407	

Table 9: Average of change in CDS return after release of periodic financial reports in different economic situations

This tables provides information about the mean, standard deviation (SD) and average in number of observation (N) for change in CDS return after release of periodic reports in three economic situations. We divide the data sample into three various durations based on the 2007 global financial crisis (GFC). According to the Federal Reserve Bank of St. Louis' the start of crisis was on 27 February 2007. Therefore, the pre-GFC period in our data set is from 05/07/2004 to 26/02/2007. The second sub sample, which we call GFC duration, is from 27/02/2007 until 31/12/2010 and the post-GFC span is from the 01/01/2011 up to 30/4/2015. Panel A, provides details about the change in CDS return after release of quarterly reports during three economic situations. Similarly, Panel B illustrates this information after release of annual reports.

Days	Panel A: After Release of Quarterly Reports						Panel B: After Release of Annual Reports					
	Pre-GFC		GFC		Post-GFC		Pre-GFC		GFC		Post-GFC	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
t+1	-0.05	4.26	0.03	3.88	-0.04	3.71	-0.11	3.99	-0.1	3.89	-0.17	1.73
t+2	-0.18	5.47	0.35	6.09	0	4.56	0.26	5.27	0.07	7.72	-0.64	5.27
t+3	-0.06	6.35	0.31	7.66	0.1	5.2	0.42	6.63	0.28	8.01	-0.74	5.26
t+4	0.15	6.94	0.62	8.47	0.21	6.1	0.79	8.79	0.34	9.28	-0.94	5.95
t+5	0.09	7.86	0.76	9.68	0.33	6.74	1.47	10.4	0.69	10.51	-1.07	5.98
t+6	0.25	8.69	1.14	10.28	0.56	7.57	1.66	11.29	1.49	16.37	-1.2	6.5
t+7	0.36	9.6	1.55	11.53	0.62	8.02	1.85	11.3	1.18	12.25	-1.27	6.61
t+8	0.31	10.02	2.06	12.58	0.71	8.54	1.97	11.04	0.69	12.55	-1.34	6.88
t+9	0.27	10.3	2.63	13.93	0.88	8.95	1.87	12.32	1	13.42	-1.35	7.07
t+10	-0.18	10.12	2.83	14.21	0.98	9.52	1.95	13.67	1.22	14.27	-1.39	7.41
N	911		1292		1414		475		521		895	

Table 10: Result of panel regression model for the full sample

This table reports the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5\, SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta\, Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and $\Delta\, Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators. *, **, and *** denote results are significant at 1%, 5% and 10%, respectively. The last two columns report the number of observation and R^2 of the regression.

Day	β_0	*QA*	*AR*	*EA*	*CR*	*SR*	ΔVOL	ΔSpot	No of Obs.	R^2
t+1	-0.002***	0.013	-0.066	-0.013	-0.097***	-0.420***	4.313***	-2.207***	505,037	0.021
	(-2.57)	(0.34)	(-1.39)	(-0.32)	(-5.8)	(-30.66)	(2.96)	(-27.41)		
t+2	-0.019***	0.104*	-0.306***	0.019	-0.215***	-0.652***	10.003***	-3.977***	504,850	0.023
	(13.61)	(1.72)	(-4.03)	(0.34)	(-8.58)	(-33.33)	(4.2)	(-31.09)		
t+3	-0.012***	0.217**	-0.197**	0.034	-0.416***	-0.779***	13.201***	-5.28***	504,662	0.021
	(-5.92)	(2.51)	(-1.97)	(0.43)	(-13.54)	(-34.41)	(4.08)	(-35.17)		
t+4	0.065***	0.325***	-0.186	0.154	-0.599***	-0.876***	14.674***	-6.287***	504,473	0.019
	(25.73)	(2.95)	(-1.59)	(1.54)	(-17.81)	(-34.04)	(3.45)	(-34.49)		
t+5	0.102***	0.368***	-0.070	0.310***	-0.775***	-0.928***	18.741***	-7.262***	504,285	0.018
	(34.67)	(2.69)	(-0.52)	(2.66)	(-19.75)	(-35.14)	(3.83)	(-35.67)		
t+6	0.115***	0.615***	-0.110	0.474***	-0.918***	-0.987***	21.865***	-7.544***	504,097	0.016
	(34.01)	(4.04)	(-0.74)	(3.32)	(-21.08)	(-35.37)	(3.95)	(-33.76)		
t+7	0.115***	0.758***	0.110	0.630***	-0.980***	-0.995***	27.512***	-7.544***	503,909	0.014
	(28.54)	(4.24)	(0.73)	(3.95)	(-21.28)	(-34.79)	(4.38)	(-31.65)		
t+8	0.144***	0.895***	0.078	0.803***	-1.033***	-1.025***	34.383***	-8.024***	503,721	0.013
	(34.85)	(4.88)	(0.5)	(4.62)	(-20.49)	(-34.23)	(5.02)	(-31.13)		
t+9	0.117***	1.175***	0.155	0.989***	-0.950***	-1.072***	40.055***	-7.438***	503,533	0.012
	(26.66)	(5.86)	(0.89)	(5.4)	(-17.92)	(-34.65)	(5.27)	(-26.99)		
t+10	0.077***	1.202***	0.182	1.211***	-0.901***	-1.071***	42.51***	-7.492***	503,345	0.011
	(17.02)	(5.80)	(0.93)	(6.12)	(-16.86)	(-34.42)	(5.23)	(-26.7)		

Table 11: The reaction of the CDS markt to release of periodic financial reports by size

This table presents the reaction of the CDS market to the release of quarterly and annual financial reports based on the three size groups (small, medium and large) by firm's market capitalization. We provide the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} . low + \beta_2 . AR_{i,t} . low + \beta_3 . ER_{i,t} . low + \beta_4 . CR_{i,t} . low + \beta_5\ SR_{i,t} . low + \beta_6 . \Delta Vol_{i,t} . low + \beta_7 . \Delta\ Spot_{i,t} . low + \beta_8 . QR_{i,t} . mid + \beta_9 . AR_{i,t} . mid + \beta_{10} . ER_{i,t} . mid + \beta_{11} . CR_{i,t} . mid + \beta_{12}\ SR_{i,t} . mid + \beta_{13} \Delta Vol_{i,t} . mid + \beta_{14} \Delta\ Spot_{i,t} . mid + \beta_{15} . QR_{i,t} . high + \beta_{16} . AR_{i,t} . high + \beta_{17} . ER_{i,t} . high + \beta_{18} . CR_{i,t} . high + \beta_{19} . SR_{i,t} . high + \beta_{20.} \Delta Vol_{i,t} . high + \beta_{21} . \Delta\ Spot_{i,t} . high + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and$\Delta\ Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators.

	Small Size		Medium Size		Big Size		
Day	*QR*	*AR*	*QR*	*AR*	*QR*	*AR*	R^2
t+1	0.03	-0.018	-0.268*	-0.046	-0.150	-0.304**	0.18
	(0.28)	(-0.12)	(-1.78)	(-0.31)	(-1.40)	(-2.05)	
t+2	0.255*	0.099	-0.456**	-0.049	-0.307**	-0.659***	0.19
	(1.73)	(0.49)	(-2.23)	(-0.24)	(-2.10)	(-3.28)	
t+3	0.411**	0.197	-0.464*	-0.130	-0.342*	-0.500**	0.21
	(2.30)	(0.81)	(-1.82)	(-0.53)	(-1.92)	(-2.05)	
t+4	0.677***	0.214	-0.456	0.023	-0.515**	-0.644**	0.20
	(3.25)	(0.76)	(-1.58)	(0.08)	(-2.49)	(-2.27)	
t+5	0.837***	0.275	-0.502	0.188	-0.585**	-0.282	0.17
	(3.57)	(0.87)	(-1.54)	(0.59)	(-2.51)	(-0.88)	
t+6	1.128***	0.843**	-0.600*	0.417	0.891***	-0.454	0.14
	(4.36)	(2.40)	(-1.67)	(1.17)	(-3.46)	(-1.29)	
t+7	1.441***	0.430	-0.503	0.661*	-0.986***	-0.483	0.12
	(5.09)	(1.12)	(-1.28)	(1.70)	(-3.5)	(-1.25)	
t+8	1.618***	0.212	-0.408	0.617	-1.197***	-0.560	0.10
	(5.33)	(0.52)	(-0.97)	(1.48)	(-3.96)	(-1.35)	
t+9	1.822***	0.216	-0.483	0.746*	-1.548***	-0.480	0.08
	(5.63)	(0.49)	(-1.07)	(1.68)	(-4.80)	(-1.29)	
t+10	1.904***	0.201	-0.357	0.822*	-1.463***	-0.299	0.07
	(5.55)	(0.43)	(-0.75)	(1.75)	(-4.28)	(-0.64)	

Table 12: The reaction of the CDS market to release of periodic financial reports by sector

This table presents the reaction of the CDS market to release of quarterly and annual financial reports based on the 10 different sectors. We provide the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5 SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and $\Delta Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators. For save the space we report the R^2 and number of observation only for the first regression model in t+1 on the last two rows. The number of observations decrease for later days. *, **, and *** denote results are significant at 1%, 5% and 10%, respectively.

Panel A: Reaction of the CDS Market to Release of Quarterly Reports by Sector

Day	Con. Discretionary	Con. Staple	Energy	Financial	Healthcare	Industrial	InfoTech	Material	Telecom	Utility
t+1	-0.09	0.07	0.12	0.09	-0.03	-0.07	-0.021	-0.10	-0.04	0.13
	(-1.59)	(0.59)	(1.00)	(1.11)	(-0.25)	(-0.65)	(-0.11)	(-0.69)	(-0.24)	(1.18)
t+2	0.02	0.03	0.20	0.40**	0.02	-0.13	-0.18	-0.08	0.35	0.38**
	(0.17)	(0.14)	(1.03)	(2.42)	(0.15)	(-0.8)	(-0.98)	(-0.37)	(0.88)	(2.2)
t+3	0.08	0.45**	0.44*	0.67***	0.41*	-0.27	-0.36	-0.65***	1.17***	0.39
	(0.36)	(2.15)	(1.84)	(3.34)	(1.89)	(-1.11)	(-1.16)	(-2.58)	(2.8)	(1.6)
t+4	0.03	0.38*	0.59*	1.00***	0.80**	-0.30	-0.61	-0.32	1.30***	0.59**
	(0.09)	(1.67)	(1.85)	(3.68)	(2.49)	(-1.03)	(-1.25)	(-1.19)	(2.74)	(1.99)
t+5	0.23	0.16	0.99**	1.32***	0.84**	-0.41	-1.01*	-0.65	1.35***	0.62*
	(0.65)	(0.45)	(2.36)	(4.28)	(2.56)	(-1.24)	(-1.84)	(-1.46)	(3.23)	(1.82)
t+6	0.14	0.35	1.41***	1.50***	1.14***	-0.13	-0.89	-0.35	1.55***	1.27***
	(0.35)	(0.83)	(3.32)	(4.52)	(2.82)	(-0.41)	(-1.51)	(-0.63)	(2.71)	(2.9)
t+7	0.20	0.18	1.86***	1.96***	1.35***	-0.09	-0.82	-0.00	0.24	1.41***
	(0.48)	(0.39)	(3.22)	(5.11)	(3.23)	(-0.25)	(-1.31)	(0.00)	(0.65)	(2.6)
t+8	0.07	0.26	2.19***	1.98***	1.69***	0.10	-0.45	0.02	0.42	1.69***
	(0.13)	(0.57)	(3.61)	(4.65)	(3.56)	(0.25)	(-0.68)	(0.03)	(1.03)	(3.88)
t+9	2.08	0.30	2.74***	2.65***	1.71***	0.21	-0.46	0.41	1.23**	2.08***
	(5.00)	(0.66)	(4.33)	(6.17)	(2.95)	(0.48)	(-0.6)	(0.60)	(2.11)	(5.00)

t+10	022	0.23	2.57***	2.51***	1.94***	0.27	-0.32	0.42	1.57	2.36***
	(0.37)	(0.52)	(4.48)	(5.8)	(3.23)	(0.6)	(-0.35)	(0.46)	(1.49)	(5.14)

Panel B: Reaction of the CDS Market to Release of Annual Reports by Sector

Day	Con. Discretionary	Con. Staple	Energy	Financial	Healthcare	Industrial	InfoTech	Material	Telecom	Utility
t+1	0.14	-0.02	-0.42***	-0.14	-0.19	-0.01	-0.04	-0.27*	-0.12	0.06
	(1.30)	(-0.17)	(-3.02)	(-1.21)	(-1.39)	(-0.06)	(-0.18)	(-1.67)	(0.21)	(0.49)
t+2	-0.08	-0.19	-0.57**	-0.73***	-0.43*	-0.10	0.01	-0.56**	-0.06	-0.16
	(-0.45)	(-0.89)	(-2.49)	(-4.12)	(-1.79)	(-0.46)	(0.02)	(-2.22)	(-0.22)	(-0.68)
t+3	0.36	0.46*	-0.82***	-0.49**	-0.32	-0.34	-0.51	-0.64*	-0.37	-0.19
	(1.35)	(1.83)	(-2.59)	(-2.2)	(-1.42)	(-1.35)	(-1.02)	(-1.71)	(-1.32)	(-0.69)
t+4	0.19	0.73**	-0.78*	-0.54*	-0.38*	-0.43	-0.80	-0.51	0.41	0.06
	(0.66)	(2.13)	(-1.77)	(-1.69)	(-1.67)	(-1.54)	(-1.38)	(-1.6)	(0.47)	(0.21)
t+5	0.25	0.60*	-0.61	-0.33	-0.19	-0.52	-0.78	-0.33	1.85	0.36
	(0.76)	(1.76)	(-1.12)	(-0.86)	(-0.85)	(-1.46)	(-1.41)	(-0.89)	(0.95)	(1.17)
t+6	0.32	0.28	-1.44***	-0.26	-0.01	-0.53	-1.07	-0.36	1.33	0.82**
	(1.00)	(0.64)	(-3.42)	(-0.62)	(-0.02)	(-1.34)	(-1.35)	(-0.63)	(0.82)	(2.09)
t+7	0.27	0.72*	-0.92	-0.21	-0.08	-0.13	-0.50	-0.26	2.19	1.19***
	(0.7)	(1.780	(-1.46)	(-0.51)	(-0.26)	(-0.42)	(-0.69)	(-0.76)	(1.31)	(3.51)
t+8	0.02	0.97***	-1.17**	0.11	-0.21	-0.15	-0.98	-0.48*	2.57	1.26***
	(0.04)	(2.61)	(-2.2)	(0.26)	(-0.58)	(-0.47)	(-1.16)	(-1.86)	(1.43)	(3.74)
t+9	1.23	0.73	-1.12*	0.64	0.15	-0.09	-1.10	-0.23	2.17	1.23***
	(2.62)	(1.6)	(-1.95)	(1.21)	(0.41)	(-0.27)	(-1.19)	(-0.82)	(0.93)	(2.62)
t+10	-0.19	0.80	-0.93	0.60	0.49	-0.03	-1.55	-0.05	3.07	0.99*
	(-0.4)	(1.51)	(-1.43)	(1.11)	(1.15)	(-0.07)	(-1.27)	(-0.15)	(1.18)	(1.74)
No of O**s.	92904	57973	41776	79280	44620	70363	23268	39164	7977	48212
R^2	0.029	0.009	0.02	0.033	0.011	0.017	0.026	0.03	0.022	0.015

Table 13: CDS price based on the three different economic situations

This table reports the descriptive statistics for CDS price in basis points (bps) during pre-GFC, GFC and post-GFC periods. Columns 2, 3 and 4 represent the mean, the standard deviation (SD) and median of CDS price.

	CDS Price (bps)		
Economic Condition	Mean	SD	Median
Pre-GFC period	53.8	76.7	31.5
GFC period	135.9	225.4	72.6
Post-GFC period	111.9	122.3	71.5

Table 14: Reaction of the CDS market in different economic situations

This table represents the reaction of the CDS market to release of quarterly and annual financial reports during different economic situations. We provide the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5 \, SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta \, Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover, $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and $\Delta \, Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators. *, **, and *** denote results are significant at 1%, 5% and 10%.

Duration	Pre-GFC		GFC		Post-GFC	
Day	*QR*	*AR*	*QR*	*AR*	*QR*	*AR*
t+1	0.11	0.03	-0.11*	-0.06	0.05	-0.10**
	(1.17)	(0.24)	(-1.75)	(-0.58)	(1.11)	(-2.18)
t+2	0.09	0.12	0.08	-0.54***	0.12*	-0.36***
	(0.73)	(0.69)	(0.66)	(-3.23)	(1.65)	(-4.7)
t+3	0.37**	0.51**	0.05	-0.34	0.24**	-0.44***
	(2.23)	(2.14)	(0.3)	(-1.53)	(2.42)	(-4.43)
t+4	0.50**	0.78***	0.13	-0.28	0.34***	-0.56***
	(2.53)	(2.76)	(0.64)	(-1.1)	(2.98)	(-4.79)
t+5	0.40*	1.16***	0.04	-0.06	0.59***	-0.64***
	(1.92)	(3.48)	(0.14)	(-0.19)	(4.15)	(-4.58)
t+6	0.58**	1.12***	0.32	-0.12	0.83***	-0.65***
	(2.42)	(3.39)	(1.77)	(-0.34)	(5.17)	(-4.32)
t+7	0.78***	1.87***	0.50	0.08	0.90***	-0.68***
	(3.21)	(4.75)	(1.51)	(0.25)	(4.97)	(-4.3)
t+8	0.84***	2.24***	0.68**	-0.33	1.04***	-0.68***
	(3.29)	(5.3)	(2.09)	(-0.92)	(5.8)	(-3.93)
t+9	0.78***	2.34***	1.18***	-0.12	1.33***	-0.67***
	(2.77)	(5.09)	(3.36)	(-0.3)	(6.74)	(-3.81)
t+10	0.56*	2.38***	1.33***	-0.07	1.40***	-0.65***
	(1.89)	(4.72)	(3.64)	(-0.16)	(6.81)	(-3.31)

Table 15: Reaction of the CDS market to release of periodic financial reports by leverage

This table presents the reaction of the CDS market to release of quarterly and annual financial reports based on the 10 different leverage groups (Lev1 to Lev10). We provide the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5\ SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta\ Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and $\Delta\ Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators. ***, ** and * denote results are significant at 1%, 5% and 10%, respectively. The leverage ratio is calculated by book value of debt divided by summation of book value of debt and equity value. We estimate daily book value of debt by using linear interpolation between monthly data.

Panel A: Reaction of the CDS Market to Release of Quarterly Reports

Day	Lev1 (Low)	Lev2	Lev3	Lev4	Lev5	Lev6	Lev7	Lev8	Lev9	Lev10 (High)
t+1	-0.31	0.01	0.01	-0.43	0.41**	0.09	-0.21*	0.10	0.09	0.38**
	(-1.46)	(0.05)	(0.8)	(-1.08)	(2.22)	(0.59)	(-1.82)	(0.6)	(0.72)	(2.09)
t+2	-0.32**	0.03	-0.04	-0.03	0.39*	0.18	-0.07	0.24	0.22	0.56**
	(-2.49)	(0.13)	(-0.25)	(-0.2)	(1.77)	(0.84)	(-0.6)	(1.38)	(1.25)	(2.19)
t+3	-0.49***	0.04	0.02	-0.07	0.66**	0.29	0.20	0.46**	0.25	0.81***
	(-2.59)	(0.14)	(0.1)	(-0.24)	(2.32)	(1.14)	(1.17)	(2.17)	(1.02)	(2.63)
t+4	-0.40	-0.04	-0.14	0.16	0.76**	0.10	0.27	0.93***	-0.58	1.08**
	(-1.6)	(-0.12)	(-0.46)	(0.41)	(2.29)	(0.3)	(1.22)	(3.49)	(-1.39)	(2.49)
t+5	-0.54*	-0.28	-0.21	0.06	0.67*	0.39	0.66**	1.11***	0.27	1.27***
	(-1.77)	(-0.71)	(-0.58)	(0.13)	(1.72)	(0.95)	(2.18)	(3.4)	(0.84)	(2.58)
t+6	-0.53	-0.26	0.17	0.15	1.31***	0.64	0.97***	1.27***	0.73**	1.48**
	(-1.38)	(-0.61)	(0.38)	(0.33)	(3.01)	(1.35)	(2.75)	(3.23)	(2.00)	(2.54)
t+7	-0.38	-0.29	0.33	0.36	1.25**	0.87*	0.98**	1.52***	1.15***	1.74***
	(-0.96)	(-0.72)	(0.7)	(0.78)	(2.27)	(1.76)	(2.430	(3.28)	(2.6)	(2.88)
t+8	-0.62	0.19	0.58	0.24	1.28**	0.60	1.26***	1.70***	1.51***	1.87***
	(-1.45)	(0.43)	(1.21)	(0.5)	(2.47)	(1.12)	(3.09)	(3.69)	(2.98)	(3.3)
t+9	-0.26	0.24	0.87*	0.79	1.27**	0.67	1.52***	1.85***	2.25***	2.16***
	(-0.46)	(0.49)	(1.67)	(1.34)	(2.2)	(1.23)	(3.22)	(3.94)	(3.95)	(3.56)

t+10	-0.05	-0.05	0.71	0.70	1.58**	0.70	1.84***	1.98***	2.32***	2.10***
	(-0.1)	(-0.1)	(1.34)	(1.06)	(2.48)	(1.2)	(3.41)	(3.7)	(3.86)	(3.57)

Panel B: Reaction of the CDS Market to Release of Annual Reports

Day	Lev1 (Low)	Lev2	Lev3	Lev4	Lev5	Lev6	Lev7	Lev8	Lev9	Lev10 (High)
t+1	-0.23	-0.15	-0.22	0.18	0.12	-0.04	0.03	0.37	-0.55***	-0.33
	(-0.87)	(-0.7)	(-1.26)	(-1.06)	(0.76)	(-0.21)	(0.11)	(0.76)	(-3.02)	(-1.41)
t+2	-0.01	-0.39	-0.35	-0.55**	0.28	-0.40*	-0.01	-0.25	-0.77***	-0.69***
	(-0.07)	(-1.61)	(-1.24)	(-2.36)	(1.39)	(-1.78)	(-0.05)	(-0.95)	(-3.05)	(-2.89)
t+3	0.15	-0.18	-0.28	-0.43	0.52*	-0.36	0.07	-0.33	-0.56**	-0.52*
	(0.4)	(-0.52)	(-0.86)	(-1.25)	(1.7)	(-1.22)	(0.21)	(-1.13)	(-2.04)	(-1.77)
t+4	0.17	-0.50	-0.40	-0.43	0.65*	0.06	0.27	-0.22	-0.58	-0.82**
	(0.45)	(-1.44)	(-1.05)	(-1.16)	(1.73)	(0.2)	(0.71)	(-0.61)	(-1.39)	(-2.08)
t+5	0.35	-0.43	-0.50	-0.20	0.95**	-0.20	0.37	0.01	-0.29	-0.72
	(0.71)	(-1.11)	(-1.22)	(-0.47)	(2.08)	(-0.52)	(0.91)	(0.02)	(-0.6)	(-1.6)
t+6	-0.08	-0.40	-0.95**	-0.06	1.32***	-0.38	0.63	-0.26	-0.12	-0.60
	(-0.18)	(-0.91)	(-2.15)	(-0.13)	(2.65)	(-0.85)	(1.32)	(-0.5)	(-0.22)	(-1.04)
t+7	0.15	-0.33	-0.47	-0.10	1.55***	-0.03	0.75	0.05	-0.05	-0.23
	(0.3)	(-0.72)	(-0.89)	(-0.19)	(2.63)	(0.08)	(1.33)	(0.07)	(-0.08)	(-0.44)
t+8	-0.37	-0.45	-0.09	-0.03	1.71***	-0.18	0.67	0.15	0.15	-0.46
	(-0.69)	(-0.84)	(-0.16)	(-0.06)	(2.92)	(-0.36)	(1.16)	(0.22)	(0.25)	(-0.8)
t+9	-0.39	-0.56	0.00	-0.28	1.73***	-0.04	0.88	0.51	0.28	-0.08
	(-0.76)	(-1.06)	(0.00)	(-0.47)	(2.65)	(-0.08)	(1.38)	(0.64)	(0.41)	(-0.12)
t+10	-0.31	-0.64	0.23	-0.26	1.57**	0.05	0.78	0.76	0.24	-0.20
	(-0.55)	(-1.1)	(0.41)	(-0.4)	(2.26)	(0.09)	(1.14)	(0.88)	(0.37)	(-0.26)

Table 16: Credit rating breakdowns

This table provides information about the credit rating of our observations. We obtain monthly credit rating from Compustat and then convert it to daily frequency. We consider the daily credit rating of each observation based on its previous rating announcement and then divide data into two categories. If the credit rating of firm by Standard & Poor is "BBB-" it is classified as investment grade (IG) and if it is rated "BB" or lower it is known as speculative-grade or high-yield (HY) firms. Based on this classification majority of our observations are categorized as HY firms (55%). The average of CDS price for speculative-grade category is almost 7.5 times higher than the average of CDS price for IG group.

S&P Credit Rating		N	Percent	Mean of CDS Price (bps)	Median of CDS Price (bps)
IG	AA	38,151	7.55	40.71	29.11
	A	80,639	15.95	42.90	31.67
	A+	34,846	6.89	61.53	45.07
	A-	73,833	14.61	73.29	47.61
Total (average)		227469	45%	(54.61)	
HY	BB	265,628	52.55	124.05	80.79
	B+	5,630	1.11	407.94	349.50
	B	5,000	0.99	555.11	407.57
	B-	960	0.19	582.72	463.30
	CC	755	0.15	1474.02	1446.49
Total (average)		277973	55%	(417.45)	

Table 17: Reaction of the CDS market to the release of periodic financial reports based on the credit rating

This table shows the reaction of the CDS market to release of periodic financial reports. We divide our data into two groups: investment grade (if credit rating is BBB or higher by Standard & Poor's) and speculative grade (if credit rating is BB+ or lower). Panel A illustrates the reaction of speculative grade and, Panel B is related to reactions of investment grade groups to the release of periodic financial reports. We provide the results of the panel regression model from t+1 up to t+10 after filing date of periodic financial reports. Our regression model is: $\Delta CDS_{i,t+T} = \beta_0 + \beta_1 . QR_{i,t} + \beta_2 . AR_{i,t} + \beta_3 . ER_{i,t} + \beta_4 . CR_{i,t} + \beta_5 \, SR_{i,t} + \beta_6 \Delta Vol_{i,t} + \beta_7 \Delta \, Spot_{i,t} + \alpha_i + \varepsilon_{i,t+T}$. $QR_{i,t}$ and $AR_{i,t}$ are indicator variables for the release of quarterly report and annual reports. Moreover $ER_{i,t}$ and $CR_{i,t}$ are indicator variables for controlling the effect of prior earnings announcement and credit ratings. The other control variables are stock return, change in volatility of stock return and change in 5-year treasury rate, which are represented by $SR_{i,t}$, $\Delta Vol_{i,t}$ and Δ $Spot_{i,t}$, respectively. We use robust standard error and fixed effect estimators. ***, ** and * denote results are significant at 1%, 5% and 10%, respectively. The last column of each panel reports the R^2 of regression.

Credit type	Panel A: Speculative grade			Panel B: Investment grade		
Day	*QR*	*AR*	R^2	*QR*	*AR*	R^2
t+1	0.07	0.07	0.0259	-0.05	-0.24*	0.017
	(1.45)	(1.14)		(-0.81)	(-3.21)	
t+2	0.14*	-0.12	0.0279	0.06	-0.55***	0.0193
	(1.75)	(-1.15)		(0.67)	(-5.12)	
t+3	0.22**	-0.02	0.0256	0.21	-0.42***	0.0173
	(2.06)	(-0.15)		(1.58)	(-2.9)	
t+4	0.38***	0.04	0.0232	0.25	-0.47***	0.0163
	(2.76)	(0.24)		(1.51)	(-2.71)	
t+5	0.59***	0.18	0.0209	0.10	-0.38*	0.0154
	(3.47)	(0.97)		(0.49)	(-1.88)	
t+6	0.83***	0.14	0.0192	0.35	-0.43*	0.0139
	(4.28)	(0.71)		(1.59)	(-1.89)	
t+7	1.04***	0.45**	0.0167	-0.42*	-0.32	0.0122
	(4.46)	(2.2)		(1.67)	(-1.49)	
t+8	1.14***	0.39*	0.0157	0.60**	-0.31	0.0117
	(4.53)	(1.75)		(2.41)	(-1.45)	
t+9	1.37***	0.35	0.0147	0.93***	-0.10	0.0107
	(5.06)	(1.43)		(3.32)	(-0.38)	
t+10	1.42***	0..29	0.0133	0.93***	0.04	0.01
	(5.11)	(1.09)		(3.29)	(0.13)	

Table 18: Descriptive statistics for log (CDS) for different maturity

This table provides descriptive statistics, namely, mean, median and standard deviation (SD) for log CDS price in basis points (bps) with various time maturities (1-, 2-, 3-, 4-, 7- and 10-year tenors).

	Log CDS price (bps)		
CDS Type	Mean	Median	SD
1- year	3.37	3.23	1.17
2-year	3.73	3.61	0.99
3-year	4.03	3.91	0.81
4-year	4.26	4.15	0.83
7-year	4.62	4.53	0.70
10-year	4.65	4.50	0.77

Hedging in Energy Market by a Dynamic Statistical Learning Model

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ABSTRACT

The recent price volatility in the energy market highlights the importance of hedging and the need of its incorporation into an investor's set of trading strategies. Our study proposes a statistical learning model for hedging commodity price risk associated with the holding of energy financial product. From a technical perspective, the proposed model utilizes a nonparametric approach for multivariate surface mapping in order to estimate the optimal hedge ratio given the observed price movement and other factors. This learning model is then compared with the more conventional time series approach based on GARCH model. In our empirical analysis, the two models are applied to hedge against price risk inherent to crude oil contracts traded in the commodity exchanges. Diagnostic statistics are computed and out-of-sample performances are evaluated. In addition to the base models, our study examines the impact of incorporating the coefficient of absolute risk aversion and the transaction costs to the statistical learning and time series approaches. We find that the proposed statistical learning approach outperforms the time series approach as well as the un-hedged portfolio with the absence transaction costs. With transaction costs, the nonparametric learning approach is better than the others if the hedger is risk averse. On the other hand, our empirical results indicate that explicit consideration of risk aversion does not alter the relative hedging performances of models and that the performance gaps among the models become more pronounced.

Keywords: Financial market, crude oil and energy sector, commodity hedging, statistical learning, VEC-GARCH, kernel regression.

INTRODUCTION

Financial and commodity trading often involves a certain level of risk. Thus, it is not uncommon for institutional and individual investors to hedge against potential risk, such as undesirable / unfavorable price movements. Consequently, academic researchers and practitioners have developed numerous approaches to estimate the hedge ratios. Hedge ratio estimation of futures is important for investors and plays an important role when we estimate hedging effectiveness. Studies after studies have found that time-varying hedge ratios (THRs) lead to more risk reduction than traditional constant hedge ratios. This paper comparatively evaluates the use of nonparametric statistical learning and parametric times-series models to the observed time series of cash and futures in hedging. We apply the two approaches to obtain the THRs. Hence, the primary purpose of the paper is to assess the hedging effectiveness through out-of-sample testing. Also, our study attempts to answer the question of whether transaction costs alter the relative performances of hedging schemes driven by statistical learning and time series approaches. Moreover, the empirical experiment investigates if the incorporation of coefficient of absolute risk aversion to the approaches affects our conclusions or not.

LITERATURE REVIEW

The applied economics literature has focused on the use of statistical models of observed time series of cash and futures prices in hedging. Early development of the type of optimal hedging is found in Johnson (1960), Peck (1975), and Kahl (1983), among others. This kind of hedgers considers not only risk but also returns. It makes progress to think of return of hedging-portfolio. In early stage, scholars hypothesize that hedgers only care risk, an assumption which lacks reasonable and supportive argument. Scholars, like Johnson, Peck, and Kahl, consider an agent with a non-tradable position in a cash commodity, who plans to buy or sell some number of commodity futures contracts that will maximize her utility. The notion traditionally involves choosing a level of hedging that would minimize the variance of changes in the hedger's portfolio value by making static estimates of the variances of changes in the cash and futures prices and the covariance between those changes. This kind of estimation is still inadequate and out-of date. Because it infers that hedge rations are constant, not time varying (i.e. dynamic). Since the price of financial asset varies from minute to minute, we must adopt more advanced technologies to estimate optimal hedge ratios. In this paper, we propose a time-varying hedging scheme guided by a statistical learning approach based on kernel regression. Its efficacy is compared to a more conventional time varying hedging method based on the parametric GARCH model. Both approaches are adapted to the traded crude oil contracts to estimate THRs.

Recently, the model of autoregressive conditional heteroskedastic (ARCH) [Engle (1982)] and generalized ARCH (GARCH) [Bollerslev (1986)] have been used to estimate time-varying hedge ratios (THRs). The time-varying joint distribution of cash and future price changes has been examined for hedging financial instruments [Cecchetti, Cumby and Figlewski (1988)]. Bivariate GARCH (BGARCH) models also have been used to estimate THRs in commodity futures [Baillie and Myers (1991); Myers (1991)], in foreign exchange futures [Kroner and Sultan (1991)], in interest rate futures [Gagnon and Lypny (1995)], and in stock index futures [Park and Switzer (1995)]. These more recent studies suggest that conventional hedging procedures can produce misleading results. It worth noting that the use of differenced data will lose information about the long-run relationship between two time series[Engle and Granger(1987)].To improve the appearance of things , we should consider error correction term into our model .Ghosh (1993) tests to determine whether the spot and futures price series are co-integrated and estimated the relevant error correction model. He found that the hedge ratio thus obtained was significantly better than the traditional regression approach. Kroner and Sultan (1993) use a bivariate ECM using GARCH error structure and find that their hedge ratio model provides more effective hedging. Chou, Denis and Lee (1996) apply ECM to Nikkei index and find that ECM gets more effective hedge ratio.

The nonparametric learning models we use in this paper are kernel function, and its extension, kernel regression. Kernel function has been applied in many researches. Lien and Tse (2000, 2001) consider a futures hedge strategy that minimizes the lower partial moments (LPM).They use two statistical methods to estimate the optimal hedge ratios, and one of them is kernel function. Stanton and Whitelaw (1995) develop a new strategy for dynamically hedging mortgage-backed securities. They also use kernel function to estimate the time-varying hedge ratios. Chen and Leung (2005) compare multivariate kernel function with Black-Scholes (adapted to account for skew) and the GARCH option pricing models.

MODELS AND METHODOLOGIES

Hedging Commodity Price Risk Using Time Series Approach

Typically, this type of hedging considers an agent with a non-tradable position in a cash commodity, who plans to buy or sell some of commodity futures contracts that will maximize her utility. We find a time-varying hedge ratio, b_t, which is the ratio of the size of the futures market position to the size of the cash market position. Then we apply the following equation to account for the change in the hedger's portfolio value over the discrete interval from time *t-1* to time *t*:

$$P_t - P_{t-1} = (L_t - L_{t-1}) - b_{t-1}(F_t - F_{t-1}) \qquad (1)$$

where P_t , L_t , and F_t represent portfolio value, the local cash price of the commodity held by the hedger, and the futures price, respectively, in period *t*. There is one more thing we have to note when the hedger may not be able to deliver her commodity against the futures contract at par value locally, or she may be holding a different grade of the commodity than that specified in the futures contract. We therefore distinguish between a local cash price of an arbitrary commodity, and the price at the specified futures delivery location of the specified commodity. We refer to the former as a local cash price L_t as above, and to the latter as the spot price S_t. In order to simplify the condition, we assume that the condition $L_t = S_t$ holds throughout the paper. In most situations, maximizing a mean-variance function is usually the hedger's objective. This is equivalent to maximizing constant relative risk aversion utility when end-of-period terminal wealth is normally distributed. Furthermore, under such circumstances the mean-variance objective is the expected certainty equivalent income. The hedger's objective can thus be represented by the following expression:

$$\underset{b_{t-1}}{Max}\left(E\langle \Delta P_t \mid \Omega_{t-1}\rangle - \frac{\lambda_U}{2} Var\langle \Delta P_t \mid \Omega_{t-1}\rangle\right) \qquad (2)$$

where $E()$ is the conditional expectation operator, ΔP_t is the change in portfolio value from t-1 to t, Ω_{t-1} is the information available as of t-1, λ_U is the coefficient of absolute risk aversion, and *var*() is the conditional variance operator .We can check if the CEI will be significantly different when λ_U changes. In this paper, we let λ_U take on the values of 0, 2, 4, and 10 for the sake of comparison. Risk-minimizing objective is a special case of Equation (2) when $\lambda_U=\infty$. Note that, given Equation (1), the conditional variance term in Equation (2) can be expanded to:

$$Var\langle \Delta L_t | \Omega_{t-1} \rangle + b_{t-1}^2 Var\langle \Delta F_t | \Omega_{t-1} \rangle - 2b_{t-1} Cov\langle \Delta L_t, \Delta F_t | \Omega_{t-1} \rangle \qquad (3)$$

where cov() is the conditional variance operator. The objective-maximizing hedge ratio is then given by following equation:

$$b_{t-1} = \frac{-\lambda_U^{-1} E\langle \Delta F_t | \Omega_{t-1} \rangle + Cov\langle \Delta L_t, \Delta F_t | \Omega_{t-1} \rangle}{Var\langle \Delta F_t | \Omega_{t-1} \rangle} \qquad (4)$$

The second-order condition for this problem is the negative of the risk aversion coefficient multiplied by the conditional variance of changes in the futures price, and we are thus guaranteed a global maximum for a risk-averse hedger. We have the minimum-variance hedge ratio when the first term in the numerator is zero, and it means that $\lambda_U=\infty$.When $\infty > \lambda_U > 0$, the optimal hedge ratio contains the minimum-variance component, and a speculative component. This implies that an investor / trader should take into account of adverse effects of risk as well as speculative motive. On the other hand, a hedger should predict the price of the futures to make avoid loss in or make profit from the portfolio. For example, an anticipated increase in the futures price will compel our hedger to increase the size of the futures position.

Given the above condition, we can now consider CEI with transaction costs. It is practical to combine CEI with transaction costs. It is because there are expenses incurred when investors buy futures for hedging. Further, financial assets' prices changes as time goes by, and so do THRs. Hence, investors or hedgers can get better hedging effectiveness if they change their futures positions according to THRs. Nevertheless, it may not be wise to change futures positions every time THRs change. By doing so, it may incur excessive transaction costs .Investors should make transactions for rebalancing their portfolios when the benefits offset or exceed the costs. In other words, when the increased expected utility from rebalancing is great enough to offset the transaction costs expected to be incurred. This notion is summarized in Equation (5). Assume that y is the transaction cost of one futures contract. Observing from the futures market, the range of y is from 8~10 U.S dollars. Retail Investors have higher costs, 10 U.S dollars, while institutional investors only have 8 U.S dollars, and we decide to have y=10 U.S dollars to be costs of each futures contract in the paper. A mean-variance expected utility-maximizing investor will rebalance at time t if and only if the following equation is satisfied (Kroner and Sultan (1993)):

$$CEI\ (b_{rebalanced}) - 100 * y * b_{rebalanced} > CEI\ (b_{unrebalanced}) - 100 * y * b_{unrebalanced} \qquad (5)$$

where $b_{rebalanced}$ is the newest rebalancing hedge ratio, and $b_{unrebalanced}$ is the hedge ratio before rebalancing. Now we can decompose the time-varying hedge ratio, *b*, into two parts. The conditional expected futures price change and conditional variance and covariance forecasts. The time-varying hedge ratio in Equation (4) requires the time-series modeler to provide the two kind of information.

Recent academic hedging research advocates obtaining the first piece of information using a vector error correction (VEC) model. This is an appropriate modeling technique in the event that each of the two price series is found to be non-stationary process, but a linear combination of the two is found to be stationary one (Engle and Granger, 1987). This linear combination is interpreted as representing a long-run equilibrium between the two levels series. The VEC model (VECM) is essentially a vector auto-regression model in which a deviation from the long-run equilibrium (the "error") in one time period is subject to some degree of correction in the following time period. A basic representation of a VEC for two variables is as follow:

$$\Delta y_t = \pi_0 + \sum_{i=1}^{r} \pi_i \Delta y_{t-i} + \alpha\beta y_{t-1} + \varepsilon_t \tag{6}$$

where y_t is the 2×1 vector of observations at time t, π_0 is a 2×1 parameter vector, each π_i is a 2×2 coefficient matrix, β is the co-integrating vector characterizing the long-run equilibrium, α is a 2×1 coefficient vector, and ε_t is a vector of innovations. The inner term βy_{t-1} is the deviation from the long-run equilibrium, and α characterizes the rate at which each of the two variables responds to this deviation. Equation (6) can then be used to generate forecasts of futures price changes – $E(\Delta F_t | \Omega_{t-1})$.

The other pieces of information that are required to calculate the THRs in equation (4) are the conditional variances and covariance-cov $(\Delta L_t, \Delta F_t | \Omega_{t-1})$ and var$(\Delta F_t | \Omega_{t-1})$.The two terms can be forecast using multivariate versions of the auto-regressive conditional heteroskedasticity (ARCH) model of Engle (1982) or the generalized ARCH (GARCH) model of Bollerslev (1986). A GARCH error structure implies that the conditional second moment of the innovation vector of a model follows an autoregressive, moving average process – it is a function of past innovation vectors and past second moments. Here we employ a multivariate GARCH (1, 1) model with the diagonal vech parameterization of Bollerslev, Engle, and Wooldridge (1988). The conditional distribution of the error from Equation (6) is then given by:

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \tag{7}$$

$$Vech(H_t) = \varpi + A\,vech(\varepsilon_{t-1}\varepsilon_{t-1}^{\Gamma}) + \beta\,vech(H_{t-1}) \tag{8}$$

were vech() is the column stacking operator that stacks the lower triangular portion of a symmetric matrix, ***W*** is a 3×1 vector of constants, and ***A*** and ***B*** are a diagonal 3× 3 coefficient matrices. We show the diagonal vech parameterization of Bollerslev, Engle, and Wooldridge (1988) equation again.

$$\begin{bmatrix} H_{11t} \\ H_{12t} \\ H_{22t} \end{bmatrix} = \begin{bmatrix} W_{01} \\ W_{02} \\ W_{03} \end{bmatrix} + \begin{bmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \times \begin{bmatrix} \varepsilon_{11.t-1}^2 \\ \varepsilon_{1,t-1,}\varepsilon_{2,t-1} \\ \varepsilon_{22,t-1}^2 \end{bmatrix} + \begin{bmatrix} B_{11} & 0 & 0 \\ 0 & B_{22} & 0 \\ 0 & 0 & B_{33} \end{bmatrix} \begin{bmatrix} H_{11,t-1} \\ H_{12,t-1} \\ H_{22,t-1} \end{bmatrix}$$

or

$H_{11t}=W_{01}+A_{11}*\varepsilon^2_{1,t-1}+B_{11}*H_{11,t-1}$ (variance of spot)
$H_{12t}=W_{02}+A_{22}*\varepsilon_{1,t-1}\varepsilon_{2,t-1}+B_{22}*H_{12,t-1}$ (covariance between cash and futures)
$H_{22t}=W_{03}+A_{33}*\varepsilon^2_{2,t-1}+B_{33}*H_{22,t-1}$ (variance of futures)

where h_{11},h_{22} are the conditional variance of the errors(ε_{1t},ε_{2t}) from the mean equations, which in this application is the bivariate VAR model (with error correction term) and h_{12} represent the conditional covariance between spot and futures.

Equations (7) and (8) can be used to form forecasts of the variance of futures price changes and the covariance between futures and cash price changes. The VEC-GARCH model described by Equations (6) to (8) provides a way to estimate THRs and thus to assess the hedging effectiveness of both statistical learning and time series approaches in the out-of-sample period.

Hedging Commodity Price Risk Using Multivariate Statistical Learning Approach

In the last section, we described the parametric VEC-GARCH model, to estimate THRs. Now, we introduce another approach, the nonparametric kernel regression, to estimate THRs. Multivariate statistical learning method is capable of performing a nonlinear projection and functional mapping in N-th dimensional space**.** Contrasting to parametric linear models, the nonparametric counterparts rely on the data itself to dictate the structure of the response function. Under normal circumstances, a nonparametric model does not require the pre-specification of functional forms prior to estimation. Hence, this model may be superior to traditional parametric models in generating an unknown conditional mean in the absence of knowledge regarding the functional forms for the conditional mean. The nonparametric model is also useful when the unknown distribution describing the process of interest is nonlinear. Interested readers should refer to Chen and Leung (2005), and Casdagli and Eubank (1992) for more detail exposition of the methodology.

The multivariate statistical learning approach proposed in the paper is the generalized kernel estimator of an unknown density function $f(x)$, which is expressed by the equation:

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad (9)$$

where x is a p-dimensional vector, n is the number of observations, $K()$ represents the kernel function, and $\boldsymbol{H}$ is a bandwidth or smoothing parameter matrix. $\boldsymbol{X}$ is differenced from all the other X_i rows of the data set with each of these differences scaled by $\boldsymbol{H}$ and as-signed a probability mass via K. $\boldsymbol{X}$ is a given arbitrary row or vector. One can think of a kernel estimate in terms of a standardized distance between a point and each data point which is then converted into a probability based on this distance. Points close to the data get larger probability than points farther away. The multivariate nonparametric estimation contains two parts. One is kernel function $K()$ and the other is the bandwidth $\boldsymbol{H}$. One popular class of kernel functions is the symmetric beta family which includes the normal density, the Epanechnikov (1969) kernel, and the bi-weight kernel as special cases. Our paper employs the product Epanechnikov kernel for the kernel function $K()$. The Epanechnikov kernel is optimal based on the calculus solution of minimizing the integrated mean square error of the kernel estimator. The multivariate Epanechnikov kernel is given by the formula:

$$K(z) = \prod_{j=1}^{p} k(z_j) \qquad (10)$$

for z = ($z_1, z_2, \ldots\ldots\ldots, z_p$) and

$$k(z_j) = \begin{cases} \frac{3}{4\sqrt{5}}(1 - \frac{1}{5}z_j^2) & if\ z_j^2 < 5.0 \\ 0 & otherwise \end{cases} \qquad (11)$$

According to Scott (1992) and Hardle (1990, 1991), the choice of bandwidth is more crucial than the choice of kernel function for successful estimation of the proper response. We have mentioned that, given the value of *x*, data closer to it get more probability than those far from it. Hence, we can roughly view that if data are not very meaningful in the estimation of the dependent variable if they are too far away from the vicinity of *x*. This is due to the very limited information they have on the dependent variable. The function of bandwidth is to discriminate between the short distance and the long distance to the observed *x*. If data do not locate in the range of *x*'s anticipated state space, then it is not effective too. Based on Scott's conclusion, the asymptotically optimal bandwidth performs generally well for independent multivariate normal distribution. The expression of the asymptotically optimal bandwidth is:

$$H=diag(\Omega^{-0.5}*n^{(-1/(p+4))}) \qquad (12)$$

where $\Omega^{-0.5}$ is the variance-covariance matrix of covariate *x*, ***n*** is the number of observations, and ***p*** is the number of variables.

Let *f*(*y*, *x*) denote the joint density of a set of random variables of interest (*Y*, ***X***), where *Y* is a scalar random variable, ***X*** is a *p*-dimensional vector of inputs (explanatory factors) and let (y_i, x_i) be a realization of (*Y*, ***X***). The density of ***Y*** conditional on (*X* = *x*) will be denoted by *g*(*x*) = *f*(*y*, *x*) / $f_1(x)$ where $f_1(x)$ denotes the marginal density of ***X***. The conditional mean of *Y* with respect to a vector ***X*** of explanatory factors is defined as:

$$E(Y|X=x) = \int y \frac{f(y, x_{1,\ldots\ldots,} x_p)}{f_1(y, x_1, \ldots, x_p)} dy = \int y \frac{f(y,x)}{f_1(x)} dy = \int y g(x) dy \qquad (13)$$

Substituting the appropriate kernel estimators and simplifying the terms yield the following estimator:

$$Y_i^* = m(X) = E(Y|X=x) = \frac{\sum_{i=1}^{n} K(H^{-1}(x - x_i))Y_i}{\sum_{i=1}^{n} K(H^{-1}(x - x_i))} \qquad (14)$$

where ***H*** denotes the appropriate bandwidth parameter matrix for the covariate vector ***x***.

We use the multivariate statistical learning model to estimate the time-varying hedge ratio (THR). In equation (4), we can see the hedge ratio is consisted of three variables, E($\Delta F_t | \Omega_{t-1}$), cov($\Delta L_t, \Delta F_t | \Omega_{t-1}$) ,and var($\Delta F_t | \Omega_{t-1}$).So our explanatory variables ***X*** are E($\Delta F_t | \Omega_{t-1}$),cov($\Delta L_t, \Delta F_t | \Omega_{t-1}$),and var($\Delta F_t | \Omega_{t-1}$) in the out-of-sample sub-period. In order to get the out-of-sample hedge ratio (Y_i*), we put the in-sample data E(ΔF$_t$|Ω_{t-1}), cov(ΔL$_t$,ΔF$_t$|Ω_{t-1}), and var(ΔF$_t$|Ω_{t-1}) as x_i 's in Equation(15),and then apply the estimated model to the out-of-sample $\boldsymbol{X}$ .The purpose that we put the out-of-sample forecast cov(ΔL$_t$,ΔF$_t$|Ω_{t-1}),and var(ΔF$_t$|Ω_{t-1}),and E(ΔF$_t$|Ω_{t-1}) into $\boldsymbol{X}$ is to see whether or not the $\boldsymbol{X}$ has any information about Y_i* (the out-sample hedge ratios). In the next step, we estimate the optimal in-sample hedge ratio $\boldsymbol{b_{t-1}}^*$, which makes CEI maximized. Finally, we put the in-sample $\boldsymbol{b_{t-1}}^*$ into Y_i. After the above process, we get the objective out-of sample hedge ratios (Y_i*). By applying the Equation (2), we can determine the hedging effectiveness of the two approaches.

We can show the nonparametric kernel regression used for the estimation of THR in a rather straightforward equation:

$$Y_i^*(E, C, V) = \frac{\sum_{i=1}^{n} k\left(\frac{E-E_i}{h_E}\right) * k\left(\frac{C-C_i}{h_C}\right) * k\left(\frac{V-V_i}{h_V}\right) * Yi}{\sum_{i=1}^{n} k\left(\frac{E-E_i}{h_E}\right) * k\left(\frac{C-C_i}{h_C}\right) * k\left(\frac{V-V_i}{h_V}\right)} \qquad (15)$$

where E is E(ΔF$_t$|Ω_{t-1}), C is cov(ΔL$_t$,ΔF$_t$|Ω_{t-1}), and V is var(ΔF$_t$|Ω_{t-1}). h_E, h_C ,and h_V are the respective bandwidths for the three variables; K is the kernel function; Y_i is the in-sample hedge ratios; Y_i* is the final estimated out-of-sample hedge ratios.

DATA AND DIAGNOSTIC STATISTICS

Data Description

Our dataset, provided by the CRB Database, is based on end-of-the-week observations of the New York Mercantile Exchange (NYMEX) crude oil futures contracts, and their associated spot prices. The futures and spot price data are observed over the period from January 1995 through June 2014. We split each data series into two sub-periods. The first time period, from January 1995 through December 2007, is used for in-sample parameter estimation. Out-of-sample hedging effectiveness is evaluated over the second time period, from January 2008 through June 2014. It should be noted that there is one NYMEX crude oil futures delivery in each month. Hence, the price data for individual futures contracts are patched to construct a rolling nearby futures series (*NEAR*), which are then used to estimate the parameters in the in-sample sub-period and to evaluation hedging effectiveness during the out-of-sample sub-period. Cash position is 100,000 barrels. One futures contract contains 1,000 barrels.

Summary Statistics

In order to have a better understanding of the data, basic descriptive statistics for the time series (both cash and futures) are computed and various diagnostic tests on autocorrelation, normality, heteroskedasticity, and stationarity are performed. The results are tabulated in Table 1 with respect to the in-sample and out-of-sample sub-periods.

Generally speaking, results from Table 1 suggest that the data series do not conform to normal distribution, are skewed, and have excessive kurtosis. It is a common feature that financial assets follow an asymmetric fat-tail distribution. The Ljung-Box Q(12) statistic tests for autocorrelation is significant. Statistics from Q^2 (12) along with ARCH (6) indicate that heteroskedasticity condition exists.

Table1: Summary statistics for cash and futures series during the in-sample and out-of-sample sub-periods

	Cash (in-sample)	Cash (out-of-sample)	Futures (in-sample)	Futures (out-of-sample)
Mean	34.190	89.010	35.285	90.138
Stdev	19.004	18.961	20.662	17.365
Skewness (sk=0)	1.149 [0.000]	-0.485 [0.028]	0.982 [0.000]	-0.369 [0.036]
Kurtosis (ku=0)	0.382 [0.003]	0.888 [0.001]	0.563 [0.002]	0.934 [0.004]
J-B	94.702 [0.000]	12.724 [0.003]	102.870 [0.000]	13.750 [0.001]
ARCH(6)	635.454 [0.000]	246.804 [0.000]	628.613 [0.000]	237.922 [0.000]
Q(12)	5824.831 [0.000]	2680.906 [0.000]	5789.636 [0.000]	2605.135 [0.000]
Q^2(12)	3257.835 [0.000]	1539.086 [0.000]	3291.257 [0.000]	1323.882 [0.000]
	Cashdiff (in-sample)	Cashdiff (out-of-sample)	Futuresdiff (in-sample)	Futuresdiff (out-of-sample)
Skewness (sk=0)	-0.893 [0.000]	-0.259 [0.000]	-1.106 [0.001]	-0.583 [0.006]
Kurtosis (ku=0)	2.432 [0.000]	2.032 [0.000]	1.352 [0.000]	1.125 [0.000]
J-B	231.566 [0.000]	23.621 [0.000]	305.386 [0.000]	30.267 [0.000]

* Q(12) and Q^2(12) are the Ljung-Box (1978) Q statistics on the first 12 lags of the sample autocorrelation function of the raw series and of the squared series; these statistics are distributed as $\chi^2(24)$.
* ARCH(6) is the Engle (1982) test for ARCH effects; the statistic is distributed as $\chi^2(6)$.
* J-B is the Jarque-Bera (1980) test for normality; the statistic is distributed as $\chi^2(2)$.
* the number in the parenthesis is p-value.

Now we have to analyze the in-sample time series data. Augmented Dickey-Fuller (ADF) tests for unit roots are applied to the series over the in-sample estimation period. We utilize an ADF function with no time-trend but an intercept. The optimal lag length (*K*) was chosen according to Schwarz (1978) information criterion. The results in Table 2 indicate that the t-tests for cash and futures do not reject the null hypothesis, implying that cash and futures series are non-stationary. Given this, we test the first-difference of the series and find that the differenced series are both stationary (difference-stationary process). It follows that the first-order differenced cash and futures are used for subsequent estimations. In order to know whether or not there is any co-integration relationship between S and NEAR, the Engle-Granger (1987) test is conducted. Regressing S on NEAR and a constant results in the following potential co-integration relation as displayed in Equation (17). ADF is run again and used to verify whether or not ECT, the residual term, represents a stationary series. If that is the case then S and NEAR exhibit a co-integrated relationship.

$$\text{ECT}=\text{Cash}+0.075-1.535\times\text{Futures} \qquad (16)$$

From the last term in Table 2, we indicate that ECT series strongly rejects the null hypothesis of a unit root, and we can trust that S and NEAR have co-integration relation.

Table 2: Results from Augmented Dickey-Fuller Tests on Price Data [a]

Series	Lag length (k)	t-statistics
Cash	0	-2.162
Cashdiff	0	-20.035
Futures	1	-3.120
Futuresdiff	2	-12.613
ECT	0	-18.985

[a] Tests for the presence of unit roots, using an intercept but no time trend. The critical value –3.43 (1%) is given in Fuller (1976). The optimal lag length (*K*) was chosen using the Schwarz (1978) information criterion.

Parameter Estimation and Parameter Inference

Before employing the multivariate GARCH (1, 1) model to estimate parameter, univariate GARCH (1, 1) is applied to see if the two first-difference series are appropriate or not. The specification of the GARCH model as well as the estimation results are shown in Table3.

Table3: Parameter estimates and residual diagnostics for the univariate GARCH(1,1) model:

$$X_t = u + \varepsilon_t$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t^2\right)$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

Series	Cashdiff	Futuresdiff
μ	-0.013 (0.017)	0.016 (0.018)
ω	0.062 (0.005)	0.095 (0.003)
α	0.127 (0.007)	0.146 (0.026)
β	0.673 (0.016)	0.572 (0.017)

Log-likelihood	-167.161	-135.813
m^3	-0.565	-0.380
m^4	3.037	2.315
Q(12)	13.868 (0.421)	11.473 (0.368)
Q^2(12)	6.226 (0.903)	4.835 (0.657)

The numbers in parenthesis beside the parameter estimates are asymptotic standard errors. m^3 and m^4 are the sample skewness and sample kurtosis, respectively, of the standardized residuals. $Q(12)$ and $Q^2(12)$ denote Ljung-Box test statistics for 12^{th}-order autocorrelation in the standardized and squared standardized residuals, respectively, with the numbers in parenthesis being the associated *p*-values.

Further, as reported in Table 3, Q (12), which denotes the Ljung-Box(1978) test statistics for 12*th*-order autocorrelation in the standardized residuals, suggests no autocorrelation phenomenon while Q^2(12), which denotes the Ljung-Box test statistics for squared standardized residuals, finds that ARCH effects do not exist. Hence, the univariate GARCH (1, 1) specification is confirmed and fits the data well. Under the assumption of normality, we use VECM-multivariate GARCH (1, 1) model to analyze our data further. Results from the analysis based on Schwarz (1978) information criterion, only the ECT term in the mean equation is required and neither constants nor autogressive terms are needed.

Given the findings, we generate parameter estimates with respect to the multivariate GARCH (1, 1) model. The results are reported in Table 4 below. It can be seen that all parameters are significant at the 5% significance level. The coefficients α_1 (negative, adjust downward) and α_2 (positive, adjust upward) can be interpreted as proxies for the speed of adjustment parameters. The larger of them is, the greater response of s_t or f_t to the previous period's deviation from long-run equilibrium. α_1 is significant, it means that the error correction term is useful in the conditional mean equation to increase the mean equation's predictive ability, and also useful to increase the variance equation's predictive ability (Lee, 1994). All A_{ij} coefficients are significant, indicating that the ARCH effect exists. Likewise, all B_{ij} coefficients are also significant, pointing to the existence of the GARCH effect. Diagnostics on the standardized residuals from the multivariate GARCH (1, 1) models, presented in the bottom panel of Table 4, suggesting that the models are well-specified.

Table 4: Parameter estimates and residual diagnostics for the multivariate GARCH (1,1) model:

$$\Delta yt = \alpha ECTt-1+\varepsilon t\,;\,\Delta yt = (CASHDIFF, FUTURESDIFF)^{T}$$
$$\varepsilon t \mid \Omega_{t-1} \sim N(0, Ht)$$
$$Vech(Ht) = \varpi + A\ vech(\varepsilon_{t-1}\varepsilon^{T}_{t-1}) + B\ vech(Ht-1)$$

	Coeff (Std Error)	Significance
α_1	-0.972 (0.031)	0.007
α_2	0.261 (0.067)	0.013
W_{11}	0.052 (0.00012)	0.002
W_{12}	0.067 (0.00009)	0.000
W_{22}	0.054 (0.00003)	0.001
A_{11}	0.167 (0.00017)	0.000
A_{22}	0.230 (0.00006)	0.000
A_{33}	0.138 (0.0001)	0.000
B_{11}	0.842 (0.0002)	0.000
B_{22}	0.721 (0.00005)	0.000
B_{33}	0.823 (0.0002)	0.000
Log-likelihood	584.967	
CASHDIFF equation		
m^3	-0.361	(0.016)
m^4	3.602	(0.002)
Q(12)	17.035	(0.327)
$Q^2(12)$	10.823	(1.256)
FUTURESDIFF equation		
m^3	-0.248	(0.024)
m^4	3.185	(0.003)
Q(12)	18.542	(0.201)
$Q^2(12)$	9.665	(1.135)

The numbers in parenthesis beside the parameter estimates are asymptotic standard errors. m^3 and m^4 are the sample skewness and sample kurtosis, respectively, of the standardized residuals. $Q(12)$ and $Q^2(12)$ denote Ljung-Box test statistics for 12th-order autocorrelation in the standardized and squared standardized residuals, respectively, with the numbers in parenthesis being the associated p-values.

RESULTS AND DISCUSSION

A primary purpose of our empirical analysis is to compare the hedging effectiveness of the proposed multivariate statistical learning approach and the more conventional parametric time series approach. To achieve this goal, we create two commodity portfolios made up of cash and futures positions. These portfolios are then guided by the two hedging approaches separately over the experimental investment / trading horizon. Technically, each portfolio is re-balanced dynamically by the time-varying THR estimated by Epanechnikov kernel regression or VEC-GARCH model. This simulation mimics the fact that, as new innovation is exposed in the financial market, cash and futures price reactions will cause the time-varying hedge ratio change to respond to the new information. In order to truly observe the effectiveness on commodity hedging, an un-hedged portfolio is also added to the analysis for benchmark comparison. For the current study, we adopt CEI as a common evaluation criterion for the hedging effectiveness of all portfolios as described earlier in the paper. In other words, the CEI measure will quantify the relative efficacy of the underlying statistical approaches during crude oil trading period (i.e., the out-of-sample testing sub-period).

To provide a more comprehensive examination of the approaches and possibly to yield additional insights on how externalities influence hedging performance, we incorporate two control factors into our empirical investigation. The first one is hedger's transaction costs. The second one is hedger's risk aversion level, which is represented by the coefficient of absolute risk aversion, λ_U, in Equation (2). When λ_U is equal to 0, an investor is, essentially, fearless and completely risk neutral. When the parameter is equal to 2, an investor is risk averse and his utility decreases one unit for each unit of increase in variance (i.e., proportionally). However, when lambda is greater than 2, an investor is highly risk averse and his utility decreases more than one unit for each unit of increase in the variance (i.e., exponentially). Past literature such as Gagnon, Lypny, and McCurdy (1998) and Haigh and Holt (2000) simply set λ_U equal to 2 in their experimental analyses. Our paper explores the impact of risk aversion level on hedging through the use of a spectrum of values of λ_U = 0, 2, 4, and 10.

Hedging effectiveness (CEI) of the un-hedged portfolio along with the hedged portfolios guided by the two statistical approaches over the out-of-sample sub-period are displayed in Tables 5 and 6. Table 5 reports the scenario of no transaction costs whereas Table 6 shows the case with transaction costs. The tables also show the empirical results when different degrees of hedger's risk aversion (λ_U = 0, 2, 4, 10) are considered.

Table 5: Out-of-sample hedging effectiveness (without transaction costs)

$\boldsymbol{\lambda_U}$	0	2	4	10
Average CEI				
Un-hedged	-1.75E+03	-1.35E+09	-2.16E+09	-5.72E+09
Hedged by VEC-GARCH	-3.74E+02	-1.97E+08	-2.68E+08	-7.05E+08
Hedged by kernel regression	**-3.62E+02**	**-1.80E+08**	**-2.47E+08**	**-6.36E+08**

*The best performer in each category is highlighted.

With the absence of transaction costs, it can be observed in Table 5 that the hedging performance is the best when Epanechnikov kernel regression is used to guide the oil commodity portfolio position. Its average CEI is larger than the hedged portfolio driven by VEC-GARCH time series approach which, in turn, is superior to the un-hedged portfolio. This rank is true across different hedger's risk aversion level (λ_U = 0, 2, 4, 10). Also, the value of CEI becomes smaller when a hedger tends to be more and more risk averse. Besides, the performance gaps among kernel regression, VEC-GARCH and un-hedged portfolios become more pronounced as risk aversion increases.

Table 6 shows the corresponding results when transaction costs are incorporated into the hedging decision. The findings generally conform to those in Table 5 with a major exception – the un-hedged portfolio performs the best when λ_U = 0 (i.e., risk neutral), although it is quite close to the results of kernel regression. Essentially, the portfolio guided by multivariate kernel regression performs the best when transaction costs and risk aversion exist. Also, the performance gaps among the three portfolios become more pronounced as λ_U becomes larger. However, a comparison between Tables 5 and 6 indicates that these gaps are much wider when transaction costs are considered in decision making. To further explore the reason behind these observations, we collect the numbers of re-balances occurred during the out-of-sample sub-period. They are tabulated inside the parentheses in Table 6. It can be seen that VEC-GARCH initiates much more re-balances than kernel regression, pointing to the possibility of over-trading or excessive overall transaction costs.

Table 6: Out-of-sample hedging effectiveness (with transaction costs)

$\boldsymbol{\lambda_U}$	0	2	4	10
Average CEI				
Un-hedged	**-4.254E+02**	-1.607E+09	-4.613E+09	-3.836E+09
Hedged by VEC-GARCH	-4.79E+02 (189)	-1.592E+08 (154)	-3.54E+08 (152)	-6.798E+08 (149)
Hedged by kernel regression	-4.61E+02 (128)	**-1.165E+08** (70)	**-2.684E+08** (69)	**-5.035E+08** (69)

*The best performer in each category is highlighted.
*Y is the cost of each contract = 10 U.S dollars.
*Numbers in the parenthesis are rebalancing times.
*CEI ($b_{rebalanced}$)-100*y* $b_{rebalanced}$ >CEI ($b_{unrebalanced}$)-100*y* $b_{unrebalanced}$

CONCLUSIONS

Determining a good approach to estimate accurate THRs is a key aim for every rational trader / hedger. Essentially, we pick up the approach which maximizes the CEI. In this paper, we analyze the relative hedging effectiveness of nonparametric statistical learning and parametric time series approaches. The analysis is subject to with and without transaction costs and different coefficient of absolute risk aversion (λ_U). It is obvious that different $\boldsymbol{\lambda_U}$ have little effect on our result. It is found that kernel regression learning is the best strategy for hedging with the absence of transaction costs. With transaction costs, it is also the best when the hedger is risk averse. Moreover, performance gaps among nonparametric kernel regression, parametric VEC-GARCH and un-hedged portfolios become more pronounced as risk aversion increases. Crude oil is a pearly resource and is pretty hard to be replaced given its pervasive role in the global energy sector. Many factors can influence its price. Further studies should point to development of models capturing academic theories and industrial practices.

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Intraday Effects of the Currency Market

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ABSTRACT

We investigate intraday patterns in the currency market. We use hourly exchange rates of the six most liquid currencies (i.e. the Australian Dollar, British Pound, Canadian Dollar, Euro, Japanese Yen, and Swiss-Franc) vis-à-vis the United States Dollar over the period 2004-2014. We show that the bilateral exchange rates of these currencies exhibit a strong presence of time-of-the-day effects. Specifically, we uncover three new intraday effects previously unknown in the literature, namely, local markets post-opening effect, major markets activities effect, and markets overlapping times effect. We also show that currencies' behaviour induced by these intraday effects has implications for investors.

JEL classification: C58; F31; G15
Keywords: Foreign Exchange; Intraday Effects; High Frequency; Trading Strategy

I. Introduction

In this paper, based on an empirical model consisting of hourly currency returns of the six most traded currencies against the United States Dollar (USD) over the period from 2004 to 2014, we examine high frequency effects in the currency market. Our main objectives are twofold. First, we examine whether particular patterns (in currency returns) exist around specific times of the day. Second, we explore the implications of these possible patterns for currency market traders. While our first objective is statistical while the second objective is to explore the economic meaning of the statistical results. Our specific approaches are the following. We first investigate the behaviour of each currency within local and foreign trading hours. In addition to the entire trading session-based analysis, we also test whether the first two to six hours of trading sessions are characterised by different features. This helps us to determine the extent to which these tendencies are related to the opening times of the local/foreign markets and to check whether these possible tendencies persist during the entire local/foreign trading sessions. We then examine the impact of the opening, closing, and trading hours of the major global markets (i.e., Asia, Europe, Pacific, and North America) on the behaviour of currency returns. The role of opening, closing and trading hours on currency returns is unknown. What is also unknown is how the overlapping trading times between major markets impact the intraday behaviour of currency returns. We investigate this. The global financial crisis (GFC) had repercussions for the currency market. Yet, what is unknown is how the intraday effects evolved in the currency market during and following the financial crisis. We, therefore, examine the intraday effects in the currency market during the GFC and the post-GFC period. Finally, we test the implications of our statistical results by proposing trading strategies. The idea is to see if the statistical evidence on the behaviour of the currency markets has any economic meaning for currency market investors.

There are several features of the extant literature that motivate our study. First, there are conflicting views and a lack of conclusive/robust empirical evidence regarding the presence of intraday anomalies with respect to currency returns. For instance, while Ranaldo (2009) argues that currencies tend to appreciate during foreign trading hours, Breedon and Ranaldo (2013) find no significant pattern during foreign trading hours. Second, the literature is outdated, as the earliest study covers data up to 2007.[30] Therefore, there is a lack of recent evidence on intraday effects with respect to currency returns. More specifically, there is no evidence on the intraday patterns in the currency market during the GFC or the post-GFC era that would show whether these high frequency calendar anomalies persistent during and after the financial crisis. Finally, the economic significance of these calendar effects has been ignored by previous studies, and the literature fails to show the implications of these high frequency effects for currency market participants. Our study is therefore motivated by these research gaps and presents the first comprehensive empirical evidence on intraday effects in the currency market using a sample period which includes the pre-GFC, GFC, and post-GFC periods.

These inspirations contribute three new findings on currency market behaviour, which were previously unknown. First, we find that all currencies (except the JPY) tend to depreciate but only during the post-opening hours of the local market, and they all tend to appreciate during the entire foreign (international market opening hours) trading sessions. Second, we find that among all the major global markets, the opening hours of the Asia-Pacific markets

[30] Breedon and Ranaldo (2013)

have the most significant effects on currency returns and cause all currencies to depreciate. In addition, we notice that currencies (except the GBP) tend to appreciate within the overlapping trading times between the Asian and European markets while they tend to depreciate within the overlapping trading time between the North American and Pacific markets. Furthermore, we find that the currencies mostly follow similar patterns even during the financial crisis (except for the CHF, which shows different patterns during the post-GFC era). Third, we estimate the economic significance of the intraday effects in the currency market by using a simple trading strategy. We conclude that our findings regarding the intraday effects in the currency market can be used to implement trading strategies that can generate significant profits for investors. More specifically, we find that our trading strategy offers profits of at most 18% per annum to investors.

Our findings complement the literature in three ways. First, our paper joins a small group of studies on high frequency currency effects. In this literature, Cornett, Schwarz, and Szakmary (1995) study the time-of-the-day effects in the currency futures market by looking at the intraday patterns of the Deutsche Mark, British Pound, Swiss Franc, Japanese Yen, and Canadian Dollar, all against the USD, during US trading hours for the period from 1977 to 1991. They find a significant tendency for all the foreign currencies (except the Canadian Dollar) to appreciate only within the first hour and the last two hours of the US market trading time. Ranaldo (2009) studies the time-of-the-day effects in the currency spot market by using the same currencies as Cornett et al. (1995) for the period from 1993 to 2005. He finds a significant tendency for the currencies to appreciate (depreciate) during foreign (local) trading hours. In addition, Breedon and Ranaldo (2013) study these patterns for six cross currencies and find that the currencies tend to depreciate only during local trading hours; they find no significant pattern during foreign trading hours. We add to this literature several new insights, principally that: (a) all currencies in our sample (except the JPY) tend to depreciate but only during the post-opening hours of the local market, and they all tend to appreciate during the entire foreign trading sessions; (b) among all the major global markets, the opening hours of the Asia-Pacific markets have the most significant effects on currency returns and cause all currencies to depreciate; and (c) currencies (except the GBP) tend to appreciate within the overlapping trading times between the Asian and European markets while they tend to depreciate within the overlapping trading time between the North American and Pacific markets.

Second, our study while focusing on high frequency effects on the currency market complements the corresponding literature on low frequency effects on the currency market returns (see, for example, McFarland, Pettit, and Sung, 1982; McCulloch, 1986; Aydoğan and Booth, 2003; Ke, Chiang, and Liao, 2007) and on currency return volatilities (see, for instance, Taylor, 1987, Dacorogna, Muller, Nagler, Olsen, and Pictet, 1993; Berument, Coskun, and Sahin, 2007). These studies generally show that the currency market can be characterised by week-of-the-month (WOM), weekend, and the day-of-the-week (DOW) effects. We show that intraday currency returns are influenced by a range of other intraday anomalies.

Third, our findings connect with the high frequency currency market studies alluded to above from an economic significance point of view. None of these studies, for instance, show how investors can make use of the high frequency currency effects in devising successful trading strategies. We do, and, as a result, have a clear economic significance contribution to this literature. In other words, our paper contains both a statistical as well as an economic story.

The rest of this paper is organised as follows. In Section II, we discuss our hypotheses and key motivations. Section III describes the estimation approach. The data, empirical findings, and additional tests are presented in Section IV, where we propose a new trading strategy to demonstrate the economic significance of our findings. In the final section, we provide concluding remarks.

II. Hypothesis Development

In this study, we contribute to the exchange rate literature by investigating the following three hypotheses:

Hypothesis 1 (H1): Currencies tend to depreciate/appreciate within local/foreign trading hours.

Cornett et al. (1995), Ranaldo (2009) and Breedon and Ranaldo (2013), as far as we are aware, are the only studies in the literature that investigate currencies' behaviour during local and foreign trading times. Based on these studies, it is expected that currencies depreciate/appreciate during local/foreign trading hours because market participants tend to be net purchasers of foreign currencies during the trading hours of their own market and vice versa. Cornett et al. (1995) find that foreign currencies tend to appreciate only within the first hour and the last two hours of the US market trading time. Moreover, Ranaldo (2009) studies the same currencies as Cornett et al. (1995) during the period from 1993 to 2005 and finds a significant tendency for the currencies to appreciate (depreciate) during foreign (local) trading hours. In addition, Breedon and Ranaldo (2013) study these patterns for six cross currencies and find that the currencies tend to depreciate only during local trading hours; they find no significant pattern during foreign trading hours. Therefore, there are conflicting views in the literature and a lack of conclusive empirical evidence regarding time-of-the-day effects with respect to currency returns. Moreover, this strand of the literature focuses on statistical analysis and provides no practical implications. Thus, we investigate these effects from a different perspective; that is, we provide evidence on the possible beneficial implications for the participants of the currency market.

Hypothesis 2 (H2): The opening, closing, and trading hours of the major global markets affect the behaviour of currency returns.

According to the transaction hypothesis (Cornett et al., 1995), firms in all countries around the world prefer to conduct foreign exchange transactions during their local trading hours, which lead to excess demand for US dollar in those regions and excess demand for foreign currencies in the US. This affects the intraday movements in exchange rates. Consequently, it is expected that the US dollar will appreciate during periods when the US market is closed and other markets are actively trading. This motivates our second hypothesis that intraday patterns can be explained by the activities (i.e., opening, closing, and trading hours) of the major global markets. This hypothesis allows us to uncover whether these patterns (i.e., opening, closing, and trading hours) can be taken as evidence of the presence of time-of-the-day effects in the currency market.

Hypothesis 3 (H3): The overlapping trading times between the major markets affect the behaviour of currency returns.

Harvey and Huang (1991) note distinctive features of the currency market which may cause different intraday patterns than those documented for other markets, such as the equity market. In particular, they argue that availability of electronic trading during the overlapping business hours of different markets has resulted in high volume of transactions (demand for currencies) within these specific times of the day. This inspires us to explore a new factor, namely, the overlapping trading times between the major markets, which can potentially affect the intraday patterns of exchange rate returns. Therefore, we hypothesize that the overlapping trading times between the major global markets influence the behaviour of currency returns.

III. Estimation Approach

To examine the intraday effects with respect to currency returns, we first calculate the returns of the selected currencies against the USD by using the mid-quote[31] price at the beginning and end of each hour: $\mathrm{EP_t} = (\mathrm{P_t^{OB}} + \mathrm{P_t^{OA}} + \mathrm{P_t^{CB}} + \mathrm{P_t^{CA}})/4$, where $\mathrm{EP_t}$ is the estimated mid-quote price at time t and $\mathrm{P_t^{OB}}, \mathrm{P_t^{OA}}, \mathrm{P_t^{CB}}$, and $\mathrm{P_t^{CA}}$ are the prices at the opening bid, opening ask, closing bid, and closing ask, respectively. Consequently, the return is: $\mathrm{R_t} = \mathrm{Log}(\mathrm{EP_t}/\mathrm{EP_{t-1}}) \times 100$, where $\mathrm{EP_t}$ is the foreign currency value of the USD at time t and $\mathrm{R_t}$ denotes the hourly currency returns. Then, to ensure that our proposed hypothesis tests are free of heteroscedasticity, we consider GARCH (1,1) model with a *t*-distribution[32], which can be written in a general form as:

$$\mathrm{R_t} = \sum_{i=1}^{24} \alpha_i \mathrm{H_i} + \sum_{j=1}^{n} \beta_j \mathrm{R_{t-j}} + \varepsilon_t \qquad (1)$$
$$\sigma_t^2 = \omega + \theta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2$$

where $\mathrm{H_i}$ is a dummy variable for the $\mathrm{i^{th}}$ interval of a day (e.g., $\mathrm{H_{08:00}}$ =1 if observation *i* falls at 08:00 AM and zero otherwise), α and β are the parameters to be estimated, and ε_t represents the error term. The lagged values of the returns ($\sum_{j=1}^{n} \beta_i \mathrm{R_{t-j}}$) are included in the model to control for autocorrelation, n is chosen according to the Schwarz information criterion, σ_t^2 is the conditional variance of the error term, ω is the constant term, and λ and θ are parameters.

IV. Data and Empirical Findings

A. Data and preliminary results

We test our hypotheses based on hourly returns of the six[33] most traded currencies (Australian Dollar (AUD), British Pound (GBP), Canadian Dollar (CAD), Euro (EUR), Japanese Yen (JPY), and Swiss Franc (CHF)) against the USD.[34] According to the Bank of International Settlements (BIS) Triennial Survey for 2013, in the spot market, 87% of transactions are based on the USD, followed by the EUR (33.4%), JPY (23%), GBP

[31] Following the literature (e.g. Melvin and Yin, 2000; Bauwens, Omrane, and Giot, 2005; Cabrera, Wang, and Yang, 2009) we use mid-price in computing the returns.
[32] We estimate the model assuming that the residuals follow a conditional Student's t-distribution.
[33] We find the Chinese Yuan is an interesting currency to consider in this study because of its important role in both the Asian and global markets. However, China has a hybrid fix and a floating exchange rate regime that is controlled by the government, which makes it unsuitable for studying intraday effects.
[34] All six exchange rates are quoted in terms of the foreign currency per the USD.

(11.8%), AUD (8.6%), CHF (5.2%), and CAD (4.6%). Overall, these currencies are involved in approximately 87%[35] of the total transactions of the currency market (BIS Triennial Survey, 2013).

The data are sourced from Thomson Reuters Tick History and cover the period from 1 January 2004 (12:00 AM – GMT) to 1 January 2014 (11:00 PM – GMT).[36] Excluding weekends, we have a total of 62,640 observations per currency.[37] As far as we are aware, this is one of the largest high-frequency samples that has ever been considered to examine intraday effects with respect to currency returns in the foreign exchange literature.[38] A longer time-series of data allows us to capture the dynamic evolution of currency behaviour. It also allows us to test the robustness of a proposed hypothesis. A plot of the data is provided in Figure I, and a summary of the data appears in Table I. Several interesting features of currency returns are reflected in Figure I. For example, some currencies (the EUR and GBP) are relatively stable, whereas others are extremely volatile (the AUD). The significant impact of the GFC can be observed for all currencies as they all experience strong patterns of volatility clustering during the GFC period.

INSERT FIGURE I

Selected descriptive statistics of the currency returns are reported in Table I. We report the mean (annualised) exchange rate returns, standard deviation, skewness, and kurtosis of each currency. We also compute the Jarque-Bera statistic to test whether the returns are normally distributed, the augmented Dickey Fuller (1979, ADF) *t*-statistic to test whether the return series are stationary, autocorrelation statistics to check whether the return residuals are serially correlated, and the ARCH-LM *F*-statistic to test for heteroscedasticity.

INSERT TABLE I

The key message emanating from the data can be summarized as follows. First, over the sample period (i.e., 2004 to 2014), we notice that 4 of the 6 currencies appreciated (negative mean) against the USD; the exceptions are the GBP and JPY. The largest annualised appreciation is experienced by the Swiss Franc (4.43%), followed by the AUD (1.56%) and CAD (1.37%). The most volatile currency, based on the standard deviation of the exchange rate returns, turns out to be the AUD while the EUR and GBP are relatively less volatile compared to the other currencies. For 4 of the 6 currencies, the skewness is negative, suggesting that the chances of further appreciation for these currencies are high. By contrast, for the remaining two currencies (the AUD and GBP), skewness is positive, implying that the chance of further depreciation is high. The large kurtosis statistics, for all

[35] Each transaction involves two currencies, therefore, percentages for all currencies should add up to 200%.
[36] Trading hours are one of the unique characteristics of the currency market, which enable practitioners to perform their exchanges at any time of the working day with less restrictions compared to other markets and regardless of their geographic location. However, most of the transactions take place within working hours of each market. Therefore, in this study our main focus is on the intraday patterns of the currency returns during the trading hours of these markets as well as their interaction with trading hours of other markets.
[37] In some cases, we have missing exchange rate data at the hourly frequency. Our approach here is to use linear interpolation technique to deal with missing values.
[38] This large data sample allows: (1) a more historical perspective; and (2) to capture more events in the exchange rate market. With (1) and (2), we have a relatively more precise and dynamic analysis.

currencies, are indicative of fat tails — a feature of high frequency exchange rate returns (see Westerfield, 1977).

Second, the null hypothesis of normality based on the Jarque-Bera test is rejected at the 1% level of significance for all variables, which confirms that none of the returns are normally distributed. The results of the ADF (stationarity) test, which examines the null hypothesis of a unit root against the alternative of stationarity. The test is implemented for a model with an intercept but no trend and confirm that the return series are stationary. Additionally, autocorrelation values are computed by taking the square of the exchange rate return variable and testing the null hypothesis of "no autocorrelation" at various lag lengths. The results reported here are based on a lag length of 10, and they confirm that residuals are characterized by serial correlation. Finally, we examine the presence of heteroscedasticity by running an autoregressive model of exchange rate returns with 30 lags. We then extract the residuals from this model and test the null hypothesis that there is "no ARCH" based on the LM test. We report the p-values associated with the F-statistics. The results reveal that the null hypothesis of 'no ARCH' is easily rejected at the 1% level of significance, which confirms the existence the heteroscedasticity in all the currency returns.

In summary, we observe that each of the selected currencies shows unique statistical characteristics (some depreciate, some appreciate, some have negative and some have positive skewness), which provides us with an opportunity to examine intraday effects for currencies with different characteristics. Moreover, the preliminary results strongly suggest the existence of autocorrelation and heteroscedasticity in the data, justifying our approach of using a GARCH-type model to test the intraday patterns of the currency returns.

Before testing our hypotheses, we first run our intraday GARCH-type regression model (Eq. 1) on each currency. The results (coefficients of hourly dummy variables), presented in Figure II, suggest that all six currencies follow a similar intraday pattern. This can be considered as evidence of the presence of TOD effects in the currency market. Therefore, in the following sections we will investigate in more detail the existence of these effects and the factors that affect the intraday patterns in the currency market.

INSERT FIGURE II

B. Hypothesis 1: Currencies behave differently during local and foreign trading hours

Based on earlier studies (Cornett et al., 1995 and Breedon and Ranaldo, 2013), theoretically, it is expected that currencies depreciate/appreciate during local/foreign trading hours because market participants tend to be net purchasers of foreign currencies during the trading hours of their own market and vice versa. Therefore, in this section, we test our first hypothesis, which examines whether currencies tend to depreciate/appreciate within the local/foreign trading hours during our study period (2004 - 2014). The results are reported in Table II. Panel A reports the results of the local trading sessions while Panel B contains the results of the foreign trading sessions. Here, we investigate currency behaviour within the entire local/foreign trading sessions and during the first two to six trading hours of the local and foreign markets which has not been investigated previously.[39]

[39] We use cumulative dummies to capture the trends in the currencies' behaviour, and we stop at the first six hours because our focus at this point is on the post-opening hours of the local (foreign) trading markets. In the sections that follow, we will investigate the remaining hours from different perspectives.

This investigation is important because, first, it shows the extent to which currency returns are related to the opening times of the local/foreign markets and, second, it allows us test whether any observed behaviour of returns is consistent during the entire local/foreign trading sessions.

INSERT TABLE II

Based on previous studies[40], we expect the currencies to depreciate during the local trading sessions. However, the results for the entire local trading sessions (panel A – first row) show that, on average, only European currencies (i.e., CHF, EUR, and GBP) depreciate within the local trading sessions.[41] Similarly, the results for the entire foreign trading sessions (panel B – first row) show that, on average, all the currencies except the JPY appreciate within the non-local (foreign) trading hours. Therefore, we apply an additional test – that is post-opening effect test (Panel A and B, 2 to 6 post opening hours) – to examine the currencies' behaviour within the post-opening hours (first two to six trading hours) of the local/foreign markets.

As Panel A shows, despite the currencies showing different behaviours within the entire local trading sessions, currencies (except the JPY) tend to depreciate within the first two to six post-opening hours of the local market. This result indicates that the currencies tend to depreciate within the opening hours of the local market, not during the entire trading session. On the other hand, the results in Panel B show that all the currencies except the CAD and JPY appreciate not only during the entire foreign trading sessions but also within the first two to six post-opening hours of the foreign markets. This result confirms the tendency of the currencies to appreciate during foreign trading sessions.

In summary, two main features of the results are observed. First, our results suggest that all the currencies (except the JPY) tend to depreciate only during the post-opening hours of the local markets. Second, all the currencies tend to appreciate during the entire foreign trading sessions, and these results are robust across the first two to six opening hours of the foreign markets for all the currencies (except for the CAD). The implication is that this information can be useful in devising trading strategies—something that we study in detail in Section F.

In sum, although our findings in this section provide some insights into the impact of the post-opening period of local and foreign markets, these effects cannot entirely explain the similar patterns observed in Figure II. Therefore, in the sections that follow, we will investigate these intraday patterns from different points of view by investigating potential common factors in the currency market.

C. Hypothesis 2: Major global markets' opening, closing and trading hours affect the currency market

In this section, we test our second hypothesis, which suggests that the opening, closing, and trading hours of the major global markets (i.e., Asia – 00:00-08:00 GMT, Europe 07:00-16:00 GMT, North America 13:00-22:00 GMT, and Pacific 22:00-06:00 GMT) affect the

[40] Cornett et al. (1995), Ranaldo (2009), and Breedon and Ranaldo (2013).

[41] In this study, we use the foreign currency value according to the USD. Therefore, the negative/positive sign of the return indicates the appreciation/depreciation of the currency.

behaviour of currency returns.[42] More specifically, we examine whether the intraday trends of the currencies observed in the previous section are also related to the activities of the major global markets. The results are reported in Table III. Panel A reports the impact of the opening (first three hours of trading) and closing times (last three hours of trading) of the major global markets on the currency returns while Panel B shows the impact of the entire trading session of each major market on the currency returns.

The first result that we notice is that all the currencies experience depreciation within the first three hours of trading on the Asia and Pacific markets.[43] The second observation that we make is that during the first three hours of trading on the North American markets, European currencies show significant appreciation, with annualised means of approximately 11% (CHF), 9% (EUR), and 5% (GBP), while the CAD depreciates significantly by approximately 11%. These results are consistent with our previous findings (Table II) that the currencies tend to depreciate within the opening hours of the local markets. In addition, we notice that the currencies mostly tend to appreciate before the closing time of the European and North American markets with the exception of the JPY.

In Panel B, we present the results for the entire trading sessions of the major markets (i.e., Asia-Pacific[44], Europe, and North America). We find that the European currencies (CHF, EUR, and GBP) depreciate during the trading sessions of the geographically related major markets and appreciate during the trading sessions of the North American markets. On the other hand, consistent with our previous findings in Section B, we notice that the JPY experiences significant appreciation during the trading sessions of the Asia-Pacific markets, while it depreciates significantly during the trading sessions of the European and North American markets.[45]

INSERT TABLE III

In summary, the main finding of this section is that among all the major global markets, the opening hours of the Asia and Pacific markets have the most significant effect on currency returns (where all currencies depreciate) regardless of the geographical locations of the corresponding market. Although our findings in this section confirm the impact of the major markets' activities (opening, closing and trading hours) on the behaviour of currency returns, they cannot entirely explain the reasons underlying these intraday patterns in the foreign exchange market. Therefore, in the next section we test our third hypothesis to examine the impact of the overlapping trading times of the markets on the behaviour of currency returns.

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[42] We define these major markets as all those countries whose trading hours (considering daylight saving time) fall into these time spans (e.g., Asia covers most of east Asian countries, such as Japan, China, Hong Kong, Korea, Singapore; Europe covers most of the European countries; North America covers the US and Canada; and Pacific covers Australia and New Zealand).

[43] We stop at three post-opening/pre-closing hours of the markets because our focus at this stage is on the opening/closing hours of the major global markets and because we want to avoid interactions with other effects, such as overlapping trading hours between the major markets.

[44] In Table III, Panel (B), we merge the sessions in the Asia and Pacific markets (Asia-Pacific) because of their close trading sessions (Asia – 00:00-08:00 GMT and Pacific 22:00-06:00 GMT).

[45] Hardouvelis (1984), Hakkio and Pearce (1985), Ito and Roley (1987), and Cai, Cheung, Lee, and Melvin (2001) examine announcement effects as the main driving force behind the calendar anomalies of the JPY-USD exchange rate.

D. Hypothesis 3: Overlapping trading times in the currency market

In this section, we test our final hypothesis, which investigates the impact of the overlapping trading times between the major markets on the behaviour of the currency returns. In Table IV, Panel A, we report the results with respect to the overlapping trading times between the Asian and European markets (AS-EU), between the European and North American markets (EU-US), and between the North American and Pacific markets (US-PA). The results suggest that all the currencies (except the GBP) tend to appreciate within the overlapping trading time between the Asian and European markets, while they tend to depreciate within the overlapping trading times between the North American and Pacific Markets.[46]

In Panel B, we exclude the overlapping times and report the currency behaviour during the non-overlapping hours of each major market (i.e., Asia-Pacific, Europe, and North America). We find that all the currencies except the JPY tend to appreciate during the non-overlapping hours of the North America trading session.

INSERT TABLE IV

To conclude, in this section, we verify that three major factors significantly affect the intraday patterns in the currency market: local and foreign trading hours, trading hours of the major global markets, and overlapping trading times between these major global markets.

E. Additional tests

The conflicting views in the literature, as explained in Section I, regarding the intraday patterns of currency returns motivate us to perform an additional test to determine whether the use of different sample periods (as used in previous studies[47]) can explain the inconclusive findings in the literature. Therefore, in this section, we divide our sample into three subsamples (i.e., pre-GFC, GFC, and post-GFC) to compare the intraday effects in the currency market within these three time periods and to determine whether our findings are robust to different sample periods.[48]

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[46] Harvey and Huang (1991) and Cai et al. (2001) study the impact of overlapping trading times on currency volatility. They suggest that macroeconomic announcements (especially US announcements) and the liquidity caused by simultaneous operation of the major markets are the main factors that cause the abnormal exchange rate behaviour.

[47] Cornett et al. (1995), Ranaldo (2009), and Breedon and Ranaldo (2013).

[48] We also conduct additional tests (using different data frequencies) to check the robustness of our findings in the previous sections regarding the intraday patterns in the currency market. We test the intraday effects of the currency returns based on 2-hourly and 3-hourly data frequencies. Here, apart from testing the robustness of our findings, we also seek to gain a better understanding of the currency market by using our findings in the previous three sections (i.e., Sections B, C, and D) to explain the intraday patterns of the currency returns. Consistent with our previous results, we find no significant pattern for the CAD; however, we notice similar patterns among the European currencies. Additionally, we find that all the currencies tend to appreciate around the opening hours of the European markets (06:00-09:00), while they all tend to depreciate around the closing hours of the US market (18:00-21:00). Furthermore, we verify our previous findings regarding the appreciation/depreciation of the currencies around the opening hours of the local/foreign markets. Finally, we highlight the role of overlapping trading times with respect to the intraday effects on the currency returns, which needs to be considered in designing trading strategies. For instance, around the opening hours of the US market, all the currencies are expected to depreciate against the USD; however, we observe that the European currencies depreciate, which is related to the overlapping between the closing time of the European markets and the opening time of the US market. On the other hand, at the closing time of the US market, when there is no overlap, all the currencies tend to depreciate as

There are many possible criteria for identifying the GFC's timeline. Melvin and Taylor (2009) suggest the early summer (July and August) of 2007 as the beginning of the crisis period in equity and currency markets. In addition, Frankel and Saravelos (2012) study different crisis measures; such as, percentage change in nominal currency, equity market returns, and real gross domestic product. Based on their indicators, they declare the second quarter of 2009 as the start of the recovering period (the end of financial crisis).[49] Therefore, in this study, we define our three subsample periods (i.e., pre-GFC, GFC, and post-GFC) as follows: the pre-GFC sample period covers the period from 1 January 2004 to 30 June 2007; the GFC sample period covers the period from 1 July 2007 to 31 May 2009; and the post-GFC sample period covers the period from 1 June 2009 to 1 January 2014. Table V reports the impact of the global financial crisis on the intraday effects on the currency returns. Here, we show the impact of the GFC on the behaviour of the currencies within the local and foreign trading sessions. We find that in almost all cases (97%), currencies follow similar intraday patterns (within the local and foreign trading sessions) even during the financial crisis. As a result, we conclude that, first, the GFC did not impact the intraday behaviour of the currencies and second, our previous findings on the intraday patterns of the currency market are robust and insensitive to different sample periods (i.e., before, during, and after the GFC).

INSERT TABLE V

F. Economic significance

In this section, based on our previous findings in Section IV, we propose a simple buy-and-sell (SBS) trading strategy to examine whether our findings have any economic significance for investors. More precisely, we test whether the intraday patterns observed in this study can be used in trading strategies to provide economically meaningful profits for investors.

Based on our hypotheses, we create buy and sell signals to check the profitability of our trading strategy during the study period (i.e., 01/1/2004–01/1/2014). The results from testing our first hypothesis suggest that all the currencies (except the JPY) tend to depreciate only during the post-opening hours of the local market and that they all tend to appreciate during the foreign trading sessions. Therefore, according to the findings in Table II, our first condition (H1) is to go long[50] whenever we have a depreciation of the local currency against USD[51] during the first six opening hours of each market and to go short during the remaining hours (e.g., we buy the AUD from 23:00 to 04:00[52] GMT, and we sell it during the remaining hours).

The results from testing our second hypothesis suggest that the opening hours of the Asia and Pacific markets have the most significant effects on the currency returns and cause

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expected. Appendix A reports the results of 2-hourly and 3-hourly models on the intraday effects in the currency market.

[49] This is consistent with what the National Bureau of Economic Research (NBER) reported in September 2010 (http://www.nber.org/cycles/sept2010.html), determining that the recession ended and a recovery began in June 2009.

[50] Except the JPY, for which we go long.

[51] In this study, as mentioned earlier, all the currencies are quoted vis-à-vis the USD, such that an increase (decrease) in the rate reflects a depreciation (appreciation) of the local currency against the USD.

[52] We do not include the 6th opening hour (05:00) since according to our results in Table II, there is no significant positive effect at this time. We follow a similar procedure for all three constraints of our trading strategy.

depreciation in all the currencies. Therefore, our second constraint (H2) is to go long during the opening hours of the Asia and Pacific markets (i.e., 22:00-03:00 GMT) and to keep previous positions (buy/sell) during the remaining hours.

Finally, the results from testing our third hypothesis suggest that all the currencies (except the GBP) tend to appreciate within the overlapping trading time between the Asian and European markets, while they tend to depreciate within the overlapping trading time between the North American and Pacific markets. Therefore, our last condition (H3) is to go long during the overlapping trading time between the North American and Pacific markets (i.e., 21:00-23:00 GMT) and to go short during the overlapping trading time between the Asian and European markets (i.e., 06:00-09:00 GMT) for all the currencies except the GBP, for which we go long.[53]

Following Szakmary and Mathur (1997), we allow a transaction cost of ten basis points (0.1%) each time a new position (i.e., long or short) is established. Thus, the adjusted returns, or profits (P_t), are computed as follows:

$$P_t = Long_t r_t + (Long_t - 1) r_t - 0.001 |Long_t - Long_{t-1}| \qquad (2)$$

The first two terms on the right-hand side of the equation represent the raw returns, when an investor takes either a long or a short position in the market. The final term in the equation accounts for the transaction costs (0.1%) that are incurred whenever a new position is taken in the market.

Table VI reports the annualised net profit from our proposed SBS trading strategy for each of the six currencies with respect to each of the three hypotheses tested earlier. In the first step (H1), where we apply our first constraint – that is, to go long during the post-opening hours of the local markets (whenever we have a depreciation of the local currency against USD) and to go short during the remaining hours, the JPY shows the highest annualised profit of 11.6% followed by the CHF (9.9%) and EUR (9.2%). The CAD and GBP show the lowest annualised profit of 4.6% and 6.7%, respectively. In the second step (H1-2), we add a new constraint – that is, to go long during the opening hours of the Asia and Pacific markets and to keep previous positions (buy/sell) during the remaining hours. Here, the EUR (18%) and EUR (17.8%) show the highest profit, while, the CAD (10.3%) again shows the lowest profit. Adding the second constraint has the highest impact on the GBP: annualised profits increase by 168% compared with the first constraint. The currencies that gain are CAD (125%) and EUR (96%), while the JPY (15%) shows the lowest increase in profit. In the final step (H1-3), we add our last constraint – that is, to go long during the overlapping trading time between the North American and Pacific markets and to go short during the overlapping trading time between the Asian and European markets and to keep the previous positions (buy/sell) during the remaining hours. At this stage, the JPY (26%) and AUD (18%) show the highest increase in the annualised profit. Adding our third condition slightly reduces profits on CAD. The reason is that the third effect (overlapping trading times) is less significant for the CAD (i.e., the effect is significant only at the 10% level) than for the other currencies (where the effects are significant at the 1% level).

INSERT TABLE VI

[53] We skip the conditions where we have insignificant effects, such as the EUR during the AS-EU overlapping times or the CHF during the US-PA overlapping times (Table IV).

Overall, we find that our trading strategy offers profits of at most 18% per annum to investors and that adding our constraints significantly improve the performance of our trading strategy. Hence, we conclude that our findings regarding the intraday patterns in the currency market can be used in trading strategies to generate significant profits for investors.

V. Concluding Remarks

In this study, we provide evidence on the presence of the intraday effects in the foreign exchange market. Our empirical exercise is based on the hourly returns of the six most liquid currencies (i.e., the Australian Dollar, British Pound, Canadian Dollar, Euro, Japanese Yen, and Swiss Franc) measured against the USD over the period from 2004 to 2014. We discover three new time-of-the-day effects in the currency market: (a) currencies tend to depreciate during the post-opening hours of the local market (i.e., the local market post-opening effect); (b) currency returns are significantly affected during the opening and closing times of the major global markets (i.e., the major markets activities effect); and (c) the overlapping trading times between major markets have a significant effect on the behaviour of currencies (i.e., the markets overlapping times effect).

We also check whether these effects are consistent in different sample periods (i.e., pre-GFC, GFC, and post-GFC). We find that the currencies follow similar patterns even during the financial crisis, suggesting that our findings are insensitive to different sample periods. Finally, we show that these intraday effects can be used in trading strategies to generate significant profits for investors. We propose a simple buy-and-sell trading strategy that exploits the time-of-the-day effects on currency returns. We show that intraday trading based on time-of-the-day effects is profitable; the British Pound, Australian Dollar, and Japanese Yen are the most profitable currencies, followed by the Euro and Swiss Franc. The Canadian dollar, by comparison, is the least profitable.

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Figure I: A plot of spot returns

This figure plots the hourly spot returns of the six currencies vis-à-vis the USD (i.e., AUD, CAD, CHF, EUR, GBP, and JPY) covering the period from 1 January 2004 (12:00 AM – GMT) to 1 January 2014 (11:00 PM – GMT), excluding the weekends, with a total of 62,640 observations per currency.

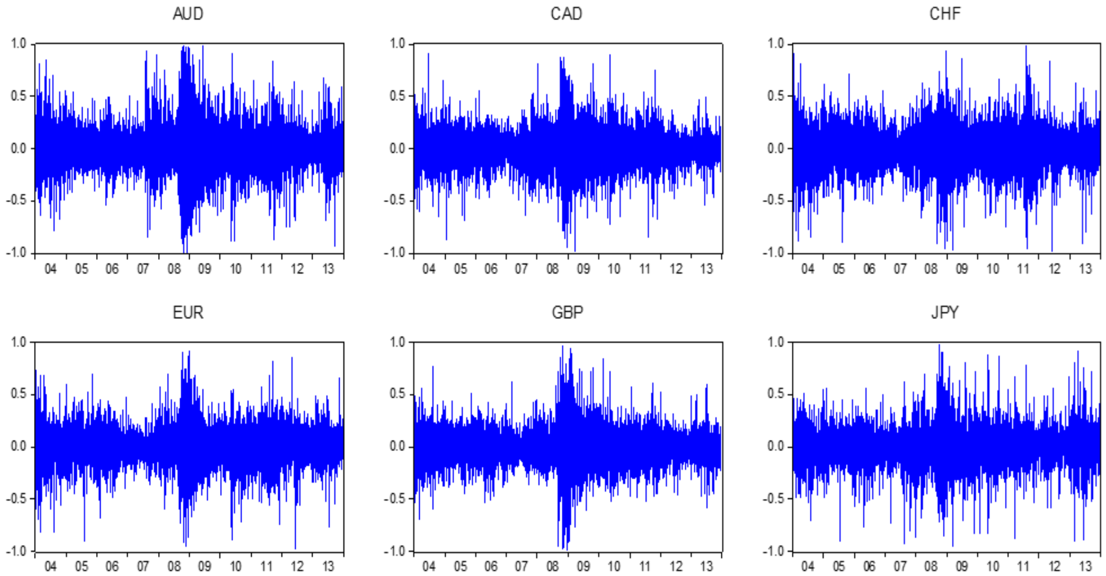

Figure II. A plot of intraday patterns

This figure plots the hourly intraday patterns of the returns (y - axis) of the six currencies (i.e., AUD, CAD, CHF, EUR, GBP, and JPY) covering the time (x - axis) from 00:00-23:00 (GMT).

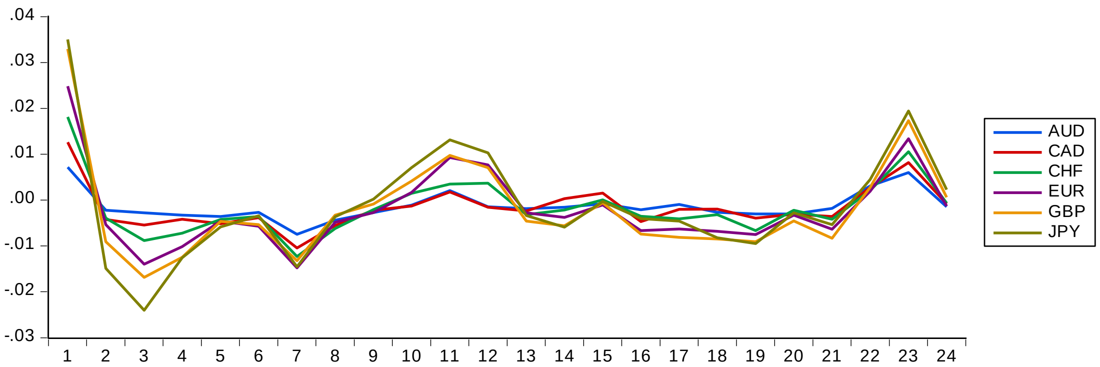

Table I: Descriptive statistics of the returns

This table reports selected descriptive statistics, namely, annualised mean on exchange rate returns, its standard deviation, skewness, and kurtosis followed by the outcomes of the normality (Jarque Bera), stationarity (ADF), autocorrelation, and heteroskedasticity tests. The evaluation period covers the hourly data from 1 January 2004 to 1 January 2014.

	AUD	CAD	CHF	EUR	GBP	JPY
Annualised Mean	-1.560	-1.373	-4.430	-0.624	0.686	0.187
Standard Dev.	0.124	0.096	0.099	0.093	0.092	0.097
Skewness	0.181	-0.020	-0.138	-0.005	0.090	-0.095
Kurtosis	10.187	11.431	11.169	11.424	12.942	11.694
Normality	<.001	<.001	<.001	<.001	<.001	<.001
Stationarity	-88.714	-77.895	-76.967	-78.684	-77.349	-85.962
Autocorrelation	<.001	<.001	<.001	<.001	<.001	<.001
Heteroskedasticity	<.001	<.001	<.001	<.001	<.001	<.001

Table II: Currencies' tendency within local and foreign trading hours (GMT)

This table reports the tendency for appreciation/depreciation within local and foreign trading hours of the selected currencies, namely, The Australian Dollars (AUD), the Canadian Dollars (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), and the Japanese Yen (JPY). First row in Panel A/Panel B, shows currency behaviour within the local/foreign markets' trading sessions. We use dummy variables for local and foreign trading hours considering the daylight saving times. For instance, for AUD local trading time, we have (1) if an interval falls anywhere between 10:00 PM and 06:00 AM (GMT) and zero otherwise. The remaining rows show currency behaviour within the first 2-6 trading hours (post opening–PO) of the local and foreign markets. *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	AUD (23:00 - 06:00)	CAD (13:00 - 21:00)	CHF (07:00 - 16:00)	EUR (07:00 - 16:00)	GBP (07:00 - 16:00)	JPY (00:00 - 06:00)
Panel A: Local trading sessions and post-opening						
Local	-0.149***	-0.046	0.123***	0.174***	0.056*	-0.163***
	(0.00)	(0.29)	(0.00)	(0.00)	(0.10)	(0.00)
2 Hrs PO	0.610***	0.253***	-0.154*	0.091	0.177***	-0.285***
	(0.00)	(0.00)	(0.07)	(0.13)	(0.00)	(0.00)
3 Hrs PO	0.311***	0.097*	-0.202***	0.085*	0.207***	-0.523***
	(0.00)	(0.08)	(0.00)	(0.10)	(0.00)	(0.00)
4 Hrs PO	0.193***	0.031	0.140***	0.254***	0.179***	-0.424***
	(0.00)	(0.59)	(0.00)	(0.00)	(0.00)	(0.00)
5 Hrs PO	0.112*	0.056	0.241***	0.317***	0.132***	-0.399***
	(0.09)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
6 Hrs PO	0.052	0.028	0.224***	0.295***	0.076*	-0.319***
	(0.42)	(0.57)	(0.00)	(0.00)	(0.08)	(0.00)
Panel B: Foreign trading sessions and post-opening						
Foreign	-0.124***	-0.045*	-0.124***	-0.094***	-0.069***	0.156***
	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
2 Hrs PO	-0.320***	0.219*	-0.223***	-0.267***	-0.202**	-0.176***
	(0.00)	(0.08)	(0.01)	(0.00)	(0.05)	(0.01)
3 Hrs PO	-0.310***	0.205**	-0.203***	-0.189***	-0.208***	-0.115**
	(0.00)	(0.04)	(0.00)	(0.00)	(0.01)	(0.04)
4 Hrs PO	-0.215***	0.297***	-0.174***	-0.162***	-0.205***	-0.027
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.60)
5 Hrs PO	-0.163***	0.215***	-0.178***	-0.181***	-0.225***	0.046
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.34)
6 Hrs PO	-0.147***	0.132***	-0.155***	-0.139***	-0.176***	0.096**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)

Table III: Major global markets' activities and the currency behaviour

This table reports the impacts of major global markets' activities on the behaviour of the selected currencies. Panel A (sorted by time, from 00:00 GMT – Asian markets opening time to 22:00 GMT – Pacific markets opening time) shows the behaviour of the currencies within the first three hours (OP) and the last three hours (CL) of major markets (i.e., Asia – 00:00-08:00 GMT, Europe 07:00-16:00 GMT, North America 13:00-22:00 GMT, and Pacific 22:00-06:00 GMT). While Panel B compares the impact of the whole trading session of each major market (i.e., Asia-Pacific, Europe, and North America). *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	AUD	CAD	CHF	EUR	GBP	JPY
Panel A: Opening (1 to 3) and closing (3 to 1) hours of the major global markets						
Asia-OP						
1-Hour	0.718***	0.546***	0.547***	0.672***	0.814***	0.206***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2-Hours	0.367***	0.202***	0.329***	0.334***	0.171***	-0.301***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3-Hours	0.156**	0.024	0.072	0.010	-0.006	-0.542***
	(0.04)	(0.68)	(0.23)	(0.85)	(0.90)	(0.00)
Pacific-CL						
3-Hours	-0.129	-0.033	-0.018	-0.077	0.033	-0.040
	(0.13)	(0.57)	(0.77)	(0.16)	(0.52)	(0.53)
2-Hours	-0.155	-0.096	0.020	-0.046	0.066	-0.021
	(0.13)	(0.16)	(0.72)	(0.48)	(0.26)	(0.78)
1-Hour	-0.265**	-0.116	0.024	-0.215***	0.037	0.194**
	(0.05)	(0.19)	(0.88)	(0.00)	(0.75)	(0.05)
Asia-CL						
3-Hours	-0.373***	-0.164***	-0.051	-0.097**	0.063	-0.135**
	(0.00)	(0.00)	(0.38)	(0.05)	(0.18)	(0.02)
2-Hours	-0.477***	-0.172***	-0.031	-0.005	0.104**	-0.200***
	(0.00)	(0.00)	(0.64)	(0.94)	(0.05)	(0.00)
1-Hour	-0.436***	-0.117	-0.067	0.139*	0.156**	-0.038
	(0.00)	(0.14)	(0.49)	(0.07)	(0.02)	(0.67)
Europe-OP						
1-Hour	-0.436***	-0.117	-0.067	0.139*	0.156**	-0.038
	(0.00)	(0.14)	(0.49)	(0.07)	(0.02)	(0.67)
2-Hours	-0.245***	0.007	-0.100	0.082	0.123**	-0.039
	(0.00)	(0.91)	(0.14)	(0.18)	(0.02)	(0.57)
3-Hours	-0.162**	0.005	-0.036	0.073	0.032	0.057
	(0.03)	(0.92)	(0.55)	(0.16)	(0.51)	(0.34)
N. America-OP						
1-Hour	-0.157	0.187**	-0.247***	-0.159*	-0.182**	-0.031
	(0.19)	(0.05)	(0.01)	(0.08)	(0.03)	(0.74)
2-Hours	0.001	0.253***	-0.135*	-0.098	0.075	-0.058
	(0.98)	(0.00)	(0.08)	(0.15)	(0.26)	(0.43)
3-Hours	-0.044	0.069	-0.157***	-0.177***	-0.121**	0.064
	(0.56)	(0.28)	(0.01)	(0.00)	(0.04)	(0.30)
Europe-CL						
3-Hours	-0.042	0.078	-0.139**	-0.151***	0.013	0.055
	(0.58)	(0.22)	(0.03)	(0.01)	(0.82)	(0.38)
2-Hours	-0.037	0.005	-0.150*	-0.177***	0.020	0.117
	(0.68)	(0.95)	(0.06)	(0.01)	(0.77)	(0.12)
1-Hour	-0.212*	-0.257**	0.117	-0.313***	-0.079	0.340***
	(0.08)	(0.02)	(0.33)	(0.00)	(0.44)	(0.00)
N. America-CL						
3-Hours	-0.150*	-0.065	-0.144**	-0.125**	-0.212***	0.104
	(0.08)	(0.33)	(0.04)	(0.04)	(0.00)	(0.13)
2-Hours	-0.117	-0.058	-0.120	-0.136*	-0.231***	0.181**
	(0.27)	(0.46)	(0.15)	(0.07)	(0.00)	(0.02)

1-Hour	0.308**	-0.033	-0.064	-0.017	0.084	0.170
	(0.04)	(0.76)	(0.75)	(0.87)	(0.55)	(0.13)
Pacific-OP						
1-Hour	0.602***	0.215**	0.237	0.285***	0.391***	0.211**
	(0.00)	(0.04)	(0.28)	(0.00)	(0.01)	(0.04)
2-Hours	0.384***	0.192***	0.149*	0.188***	0.275***	0.130*
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.09)
3-Hours	0.543***	0.354***	0.263***	0.367***	0.386***	0.139**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Panel B: Complete trading sessions of the major global markets						
Asia-Pacific	-0.024	-0.012	0.031	0.004	0.104***	-0.248***
	(0.65)	(0.76)	(0.46)	(0.91)	(0.00)	(0.00)
Europe	-0.029	0.026	0.123***	0.174***	0.056*	0.144***
	(0.59)	(0.51)	(0.00)	(0.00)	(0.10)	(0.00)
N. America	0.005	-0.005	-0.175***	-0.167***	-0.132***	0.129***
	(0.93)	(0.91)	(0.00)	(0.00)	(0.00)	(0.00)

Table IV: The impact of overlapping trading times on the exchange rates

This table reports the impact of the overlapping trading times on the behaviour of the currency returns. Panel A shows the overlapping trading time between: Asian and European markets (AS - EU) from 06:00 to 09:00 (GMT); European and US markets (EU - US) from 13:00 to 16:00 (GMT); North American and Pacific markets (US - PA) from 21:00 to 23:00 (GMT). Panel B shows currency behaviour during the non-overlapping times in trading sessions of each major global market (i.e., Asia-Pacific, Europe, and North America). Last row in each panel, shows the overall tendencies of these currencies during the overlapping and non-overlapping times. *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	AUD	CAD	CHF	EUR	GBP	JPY
Panel A: Overlaps						
AS-EU	-0.340***	-0.093*	-0.100*	-0.010	0.116***	-0.093*
	(0.00)	(0.07)	(0.08)	(0.85)	(0.01)	(0.10)
EU-US	0.002	0.084	-0.139**	-0.131**	0.055	0.052
	(0.98)	(0.19)	(0.04)	(0.02)	(0.34)	(0.41)
US-PA	0.608***	0.145*	0.042	0.204***	0.242***	0.129*
	(0.00)	(0.07)	(0.61)	(0.00)	(0.00)	(0.10)
Overall	0.066	0.036	-0.045	0.055	0.159***	0.027
	(0.24)	(0.38)	(0.30)	(0.15)	(0.00)	(0.53)
Panel B: Non-Overlaps						
Asia-Pacific	-0.056	-0.068	0.013	-0.092**	-0.144***	-0.319***
	(0.41)	(0.16)	(0.80)	(0.04)	(0.00)	(0.00)
Europe	0.040	-0.034	0.331***	0.289***	-0.082*	0.237***
	(0.60)	(0.54)	(0.00)	(0.00)	(0.10)	(0.00)
North America	-0.135*	-0.076	-0.126**	-0.177***	-0.272***	0.120**
	(0.07)	(0.20)	(0.04)	(0.00)	(0.00)	(0.03)
Overall	-0.059	-0.064*	0.025	-0.050	-0.176***	-0.046
	(0.28)	(0.10)	(0.55)	(0.19)	(0.00)	(0.27)

Table V: GFC and currencies tendency within the local and foreign trading sessions

This table reports the impact of GFC on the behaviour of the currencies within the local and foreign trading session of the selected currencies. The results are reported under four sample groups, namely, the full sample (1 January 2004 to 1 January 2014), the pre-GFC sample (1 January 2004 to 30 June 2007), the GFC sample (1 July 2007 to 31 May 2009), and the post-GFC sample (1 June 2009 – 1 January 2014). *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	Full Sample (Jan 2004 - Jan 2014)	Pre-GFC (Jan 2004 - Jul 2007)	GFC (Jul 2007 - Jun 2009)	Post-GFC (Jun 2009 - Jan 2014)
Panel A: Local Trading Sessions				
AUD	-0.149***	-0.159**	-0.360**	-0.095
	(0.00)	(0.03)	(0.02)	(0.19)
CAD	-0.046	-0.114*	0.096	-0.033
	(0.29)	(0.06)	(0.49)	(0.53)
CHF	0.123***	0.304***	0.121	-0.158***
	(0.00)	(0.00)	(0.20)	(0.00)
EUR	0.174***	0.164***	-0.030	0.035
	(0.00)	(0.00)	(0.70)	(0.44)
GBP	0.056*	0.026	0.015	0.049
	(0.10)	(0.56)	(0.85)	(0.25)
JPY	-0.163***	-0.215***	-0.459***	-0.432***
	(0.00)	(0.01)	(0.00)	(0.00)
Panel B: Foreign Trading Sessions				
AUD	-0.124***	-0.090*	-0.254***	-0.105**
	(0.00)	(0.06)	(0.01)	(0.02)
CAD	-0.045*	0.034	-0.102	-0.079***
	(0.07)	(0.43)	(0.26)	(0.01)
CHF	-0.124***	-0.069*	-0.084	0.074
	(0.00)	(0.09)	(0.26)	(0.22)
EUR	-0.094***	-0.0088***	-0.154**	-0.077**
	(0.00)	(0.01)	(0.02)	(0.03)
GBP	-0.069***	-0.124**	0.029	-0.025
	(0.00)	(0.03)	(0.81)	(0.69)
JPY	0.156***	0.131***	0.157**	0.155***
	(0.00)	(0.00)	(0.04)	(0.00)

Table VI: Annualised net profits of the SBS trading strategy

This table reports the annualised net profits (%) of the Simple Buy-and-Sell (SBS) trading strategy based on the conditions of our three hypotheses (H1, H2, and H3) for each of the selected currencies. *t*-statistics, which examines the null hypothesis that profits are zero, are presented in parentheses.

BSB Profit	AUD	CAD	CHF	EUR	GBP	JPY
H1	8.93	4.59	9.86	9.19	6.65	11.55
	(2.89)	(1.92)	(3.98)	(3.96)	(2.91)	(4.77)
H1-2	13.94	10.34	15.66	17.97	17.80	13.27
	(4.51)	(4.33)	(6.33)	(7.74)	(7.80)	(5.48)
H1-3	16.40	9.82	15.66	18.57	18.31	16.68
	(5.31)	(4.08)	(6.33)	(8.00)	(8.02)	(6.89)

APPENDIX A

Table I: Intraday Effects of Currency Returns (2-Hourly Model)

This table reports the Intraday Effects of Currency Returns using a 2-hourly model. *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	AUD	CAD	CHF	EUR	GBP	JPY
00:00-02:00	0.247***	0.158***	0.289***	0.251***	0.089*	-0.193***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)
02:00-04:00	-0.302***	-0.177***	-0.286***	-0.404***	-0.285***	-0.351***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
04:00-06:00	-0.311***	-0.142**	0.010	-0.116*	-0.034	0.040
	(0.00)	(0.02)	(0.88)	(0.06)	(0.54)	(0.58)
06:00-08:00	-0.597***	-0.214***	-0.070	-0.078	0.023	-0.089
	(0.00)	(0.00)	(0.26)	(0.15)	(0.65)	(0.17)
08:00-10:00	-0.189**	0.015	-0.023	-0.029	-0.112**	0.199***
	(0.03)	(0.80)	(0.74)	(0.64)	(0.05)	(0.00)
10:00-12:00	0.028	-0.018	0.514***	0.488***	0.074	0.335***
	(0.76)	(0.78)	(0.00)	(0.00)	(0.26)	(0.00)
12:00-14:00	-0.170**	0.058	-0.028	-0.052	-0.055	0.050
	(0.04)	(0.38)	(0.70)	(0.41)	(0.38)	(0.46)
14:00-16:00	-0.148*	-0.039	-0.144*	-0.222***	-0.042	0.184***
	(0.08)	(0.61)	(0.06)	(0.00)	(0.52)	(0.01)
16:00-18:00	-0.185**	-0.013	-0.216***	-0.300***	-0.198***	0.182**
	(0.05)	(0.87)	(0.01)	(0.00)	(0.00)	(0.02)
18:00-20:00	-0.300***	-0.052	-0.112	-0.104	-0.156**	0.074
	(0.00)	(0.51)	(0.16)	(0.15)	(0.02)	(0.34)
20:00-22:00	0.068	-0.094	-0.083	-0.109	-0.157***	0.233***
	(0.052)	(0.21)	(0.30)	(0.13)	(0.01)	(0.00)
22:00-00:00	0.230**	0.144	0.081	0.116*	0.175***	0.192***
	(0.02)	(0.05)	(0.28)	(0.08)	(0.00)	(0.00)

Table II: Intraday Effects of Currency Returns (3-Hourly Model)

This table reports the Intraday Effects of Currency Returns using a 3-hourly model. *, **, *** Denotes statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively and p-values are in parentheses. All coefficients are multiplied by 100.

	AUD	CAD	CHF	EUR	GBP	JPY
00:00-03:00	0.054	0.008	0.057	-0.032	-0.069	-0.389***
	(0.45)	(0.89)	(0.29)	(0.51)	(0.12)	(0.00)
03:00-06:00	-0.315***	-0.125**	-0.073	-0.181***	-0.101**	0.020
	(0.00)	(0.02)	(0.21)	(0.00)	(0.03)	(0.74)
06:00-09:00	-0.494***	-0.139***	-0.093*	-0.075*	0.014	-0.028
	(0.00)	(0.00)	(0.07)	(0.10)	(0.74)	(0.59)
09:00-12:00	-0.015	-0.021	0.377***	0.334***	-0.015	0.320***
	(0.83)	(0.69)	(0.00)	(0.00)	(0.77)	(0.00)
12:00-15:00	-0.142**	0.112**	-0.062	-0.070	0.009	0.042
	(0.04)	(0.04)	(0.30)	(0.18)	(0.87)	(0.45)
15:00-18:00	-0.194***	-0.082	-0.198***	-0.304***	-0.198***	0.225***
	(0.01)	(0.22)	(0.00)	(0.00)	(0.00)	(0.00)
18:00-21:00	-0.258***	-0.098*	-0.121*	-0.146***	-0.221***	0.154***
	(0.00)	(0.10)	(0.06)	(0.01)	(0.00)	(0.01)
21:00-00:00	0.258***	0.097	0.044	0.056	0.116**	0.187***
	(0.00)	(0.14)	(0.48)	(0.18)	(0.02)	(0.00)

Predicting Exchange Rate Returns

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ABSTRACT

We test whether forward premiums predict spot exchange rate returns for 25 developed and developing countries. We apply a recently developed time series predictability test that allows us to model not only persistency and endogeneity of the forward premium but also the heteroskedasticity of the variables. We discover return predictability for 11 countries and, in seven of the countries, forward premium positively predicts returns. Using a simple trading strategy, we show that investors can make more profits from a forward premium model compared to a random walk model. We also find that sign matters for profitability; countries where forward premium negatively predicts exchange rate returns, profits are mostly positive compared to when the sign is positive.

Keywords: *Exchange Rate; Forward Premium; Heteroskedasticity; Persistency; Endogeneity; Predictability.*

1. Introduction

Meese and Rogoff's (1983a,b) finding that standard empirical exchange rate models could not out-perform a simple random walk model has instigated a rich body of literature on exchange rate predictability over the last three decades. One strand of this literature, commonly referred to as the unbiased efficiency hypothesis, examines whether forward rate premium is the optimal unbiased predictor of future spot exchange rate changes. Empirical evidence, dating back to works of the 1980s, suggests that the forward rate is not a predictor of the future spot exchange rate. In other words, the forward premium is found not to be an optimal predictor of the rate of depreciation; see, for instance, Hansen and Hodrick (1980), Frankel (1980), Bilson (1981), and Hsieh (1993).[54]

Moreover, later studies that found predictability claimed that forward premium negatively predicted exchange rate changes (see Froot and Thaler, 1990). The negative predictability has not been ignored though. Several theoretical explanations for this empirical departure from the unbiased efficiency hypothesis have been proposed, and an excellent survey on this can be found in Taylor (1995). First Fama (1984) and then Hodrick and Srivastava (1986) contended that the negative slope coefficient is likely to be due to the existence of a time varying risk premium. The work of Froot and Frankel (1989) exposed the role of expectation errors to the negative slope. And, Chakraborty and Evans (2008) explain the negative slope coefficient based on perpetual learning. Finally, while Cornell (1989) claimed that measurement errors in the data were responsible, these claims were quickly squashed by Bekaert and Hodrick (1993), who demonstrated that measurement errors were not that important. Bansal (1997) showed that a particular term structure model can account for the puzzling empirical evidence. Finally, some studies argue that the negative sign can be a result of the carry trade strategy (see Brunnermeier *et al*., 2009; and Menkhoff *et al*., 2012).

The debate has, thus, raged on why the forward premium negatively predicts the rate of depreciation. The answer to this question has direct implications for economic models, such as the capital asset pricing model (CAPM) (see Mark, 1988) and the consumption and money-based general equilibrium models (see Bansal *et al*., 1995; Backus *et al*., 1993; Bekaert, 1996). However, purely from an investor's point of view, the fact that exchange rate is predictable points to opportunities for making profits. Initially, there was concern that since the forward premium negatively affects future exchange rate changes, effectively an exchange rate appreciation, the forward premium is unlikely to contain useful information for investors (see Cumby and Obstfeld, 1984). This view was challenged and overturned by Clarida and Taylor (1997), who argued that the failure of the forward rate to predict the future spot rate did not necessarily imply that forward rates did not contain valuable information for forecasting future spot exchange rate.[55] More specifically, they note (p. 354): "… while the forward premium (the difference between the forward rate and the current spot rate) typically explains only a tiny fraction of subsequent exchange rate movements (as measured by the R^2) and the estimated slope coefficient is typically of the opposite sign to that suggested by the risk-neutral efficient

[54] In a recent study, Corte et al. (2016) show that currency volatility risk premia predicts exchange rate returns. Byrne et al. (2016) use time-varying exchange rate predictability models and find that such models beat the random walk model in the majority cases. These results are supported by the work of Ince et al. (2016) which undertakes extensive out-of-sample analysis of exchange rate predictability. Moreover, using nonlinear panel data models of exchange rate Lopez-Suarez and Rodriguez-Lopez (2011) also find strong out-of-sample evidence of exchange rate predictability.

[55] These findings were supported by Clarida *et al*. (2003) and Nucci (2003), and for an excellent analysis of the exchange rate issues, in particular on why exchange rate predictability may not hold, see Rossi (2013).

markets hypothesis (RNEMH), the estimated slope coefficient is nevertheless often statistically significantly different from zero … This suggests that there is important information in the term structure, which can be extracted”. And, rather fittingly, Clarida and Taylor (1997, p. 361) write that: “Further empirical work might be addressed toward establishing the robustness of these conclusions”.

Over a decade later, Corte *et al*. (2009) attempted to provide further evidence on the economic significance of forward premiums and, in so doing, provide the most recent update on the existing gap in the literature (p. 3497): “… little attention has been given to the question of whether the statistical rejection of the Uncovered Interest Parity and the forward bias resulting from the negative estimate of β offers economic value to an international investor facing FX [foreign exchange] risk”. From Clarida and Taylor (1997) to Corte *et al*. (2009), the message remains clear: additional empirical work is needed to establish the economic significance of forward premiums. We take a position in this literature and undertake an extensive investigation of the economic significance of forward premiums.

Our objective is to test for exchange rate predictability using the forward premium as the predictor variable. We use historical daily time series data for no fewer than 25 countries. In this regard, our paper is similar to the work of Corte *et al*. (2009). However, there are things we do differently from Corte *et al*. (2009). First, we use relatively high frequency data (daily data) and consider 25 currencies, while Corte *et al*. (2009) use monthly data and consider only three currencies. This is a significant step because Corte *et al*. (2009, p. 3523) request such an analysis by writing: “ … our motivation for investigating predictability at the one-month horizon is founded on the prevailing view in this literature that exchange rates are not predictable at short horizons. It is clear, therefore, that one possible direction in extending the analysis of this paper is to study the predictability … for higher frequencies and longer horizons. We leave this for future research”. We discover evidence of exchange rate predictability for no fewer than 11 countries out of a possible 25. Moreover, where evidence of predictability is found for developing countries, the results suggest that the slope coefficient is positive, consistent with theory.

Second, we utilise time series predictability tests that account not only for the persistency and endogeneity of the predictor variable, but also heteroskedasticity in the variables. While Corte *et al*. (2009) pay attention to heteroskedasticity by applying a GARCH model, issues of endogeneity and persistency are left for future research, and we address these issues. Our empirical analysis shows that persistency and endogeneity of the predictor variable and heteroskedasticity of the variables are strong features of the daily data set. Therefore, modelling these three salient features of the data in a coherent manner in predictive regression models is imperative to demonstrate the robustness of the results.

Third, our treatment of predictability is different not only in terms of the large number of countries and currencies we consider, but also due to the fact that we use a range of forward premiums reflecting different maturities. In particular, we use the 30-day, 90-day, 180-day, and 360-day forward premiums. This ensures that we are able to check the robustness of the results. Our findings reveal that for the 11 countries where predictability is found, they are found regardless of the forward premium maturity date used. Interestingly, of the 11 countries, seven countries had a positive sign on the forward premium but only two of these countries had statistically significant profits. By comparison, there were four countries with a negative sign on the forward premium and in three of these countries there were statistically significant profits. These results suggest that a negatively signed forward premium offers investors relative more profits than when the sign is positive.

Finally, we utilise not only statistical measures of the out-of-sample predictability but also a trading-based approach to testing for predictability. Here, we apply the excess predictability test developed by Anatolyen and Gerko (2005), which examines the null hypothesis of no mean predictability in out-of-sample profits obtained from a simple trading strategy sufficient to generate buy and sell signals. We generate profits from a simple trading strategy that takes a long position when predicted returns are greater than zero, and a short position when predicted returns are less than or equal to zero. The predicted returns are obtained from both the forward premium model and the random walk model, allowing us to test for the mean of no predictability in predicted returns. From this exercise, we discover strong evidence that for nine out of the 11 countries the null hypothesis of no mean predictability is rejected, suggesting that profits generated from the forward premium model are superior to those generated from the random walk model.

2. Empirical framework and econometric approach

2.1 Empirical framework—A motivation

There is a history, dating back to the 1980s, reflected in a number of surveys of the literature (see Hodrick, 1987; Engle, 1996; Taylor, 1995) that the simple, risk-neutral efficient markets hypothesis (RNEMH) fails to hold in empirical applications. There are two fundamental interest parity conditions, namely, the Covered Interest Parity condition (CIP) and the Uncovered Interest Parity (UIP) condition, which bind the relationship between spot and forward exchange rates. The CIP states that the interest rate differential between domestic and foreign securities of the same type is simply equal to the relevant forward exchange rate premium. Several studies have documented strong empirical support for the CIP (see, *inter alia*, Taylor 1989, 1995). The UIP, on the other hand, states that the expected rate of nominal exchange rate depreciation is simply equal to the difference in nominal interest rates across countries on the same financial assets. As Isard (1993) makes it clear, financial assets are in relevant currencies and share common characteristics, such as those relating to maturity and risk. Clarida and Taylor (1997) show that the empirical framework, whereby the future changes in spot exchange rate are regressed on the one period lagged forward premium, can be arrived at by combining the CIP and the UIP together with the rational expectations assumption. It follows that the predictive regression model has the following form:

$$ER_t = \alpha + \beta FP_{t-1} + \varepsilon_t \qquad (1)$$

where ER is the percentage change in the spot exchange rate, computed as $(S_{t+1} - S_t)/S_t$. With each spot price there is a forward price, denoted ERP. Therefore, we compute the forward premium (FP) as $(ERP_t - S_t)/S_t$.

Our approach is that we use time series predictive regression models that: (a) account for biasness in the predictive slope, induced by persistence and endogeneity of the predictor variable, as shown initially by Stambaugh (1999) and then Lewellen (2004); and (b) account for not only persistency and endogeneity but also heteroskedasticity of the predictor and the error driving the returns, such as those proposed by Westerlund and Narayan (2012, 2014). As we will show, persistency, endogeneity, and heteroskedasticity are all features of our data set. Thus, our approach of accommodating these salient features of the data represent an improvement in the econometric estimation of the predictive regression model over existing studies in this literature.

2.2 Econometric Approach

The goal of this section is to outline our empirical approach to estimating the exchange rate predictive regression model. In this regard, we follow Narayan and Westerlund (2012) and begin with the following representation of Equation (1):

$$ER_t = \alpha + \beta FP_{t-1} + \epsilon_t \tag{2}$$

$$FP_t = \mu(1-\rho) + \rho FP_{t-1} + \varepsilon_t \tag{3}$$

This framework allows us to model the persistency and endogeneity of the predictor variable and any ARCH effects in the model.

The null hypothesis of no predictability is $H_0: \beta = 0$. It is reasonable to assume, at least for a start, that, γ, the correlation between ϵ_t and ε_t is statistically significant. We, therefore, have the following relationship between the error terms:

$$\epsilon_t = \gamma \varepsilon_t + \eta_t \tag{4}$$

where ε_t and η_t are iid and symmetric with mean zero, and finite fourth-order moments. The variances of ε_t and η_t are denoted by σ_ε^2 and σ_η^2, respectively.

When predictors are highly persistent and their innovations correlated with return innovations—a case commonly found in the stock return predictability literature—the result is a small-sample bias in the conventional ordinary least squares estimator (see Stambaugh, 1999). For this reason, we ignore OLS estimator at the outset. While corrections to obviate the bias have been proposed, most famously by Lewellen (2004), the one issue that remains unaccounted for in these studies is heteroskedasticity. In a recent proposal on return predictability, Westerlund and Narayan (WN, 2012, 2014)[56] develop a feasible generalised least squares (FGLS) test that not only accounts for the rather traditionally recognised issues of persistency and endogeneity of the predictor variables, but also the heteroskedasticity properties of the returns errors and predictor variable. Heteroskedasticity in returns (and, indeed, in financial data), particularly in high frequency data, is nothing but a stylised fact and extracting it is just a matter of application. We will demonstrate this later.

The FGLS estimator of β proposed by Westerlund and Narayan (2012, 2014) is based on an augmented version of Equation (1), and has the following form:

$$ER_t = \alpha - \gamma\mu(1-\rho) + \beta^{adj} FP_{t-1} + \gamma \Delta FP_t + \epsilon_t \tag{5}$$

where $\beta^{adj} = \beta - \gamma(\rho - 1)$ can be interpreted as the limit of the bias-adjusted OLS estimator of Lewellen (2004). Westerlund and Narayan (2014) assume that $\rho = 1 + \frac{c}{T}$, where $c \le 0$ is a drift parameter that measures the degree of persistency in the forward premium. The implication is that if $c = 0$, then forward premium has an exact unit root, whereas, if $c < 0$

[56] A note on our choice of the WN estimator is in order. We, for instance, do not use predictability methods suggested by Amihud et al. (2009, 2010) simply because our aim is not to test for the null hypothesis of no predictability using multiple predictors. We have a single predictor model. The WN test is based on a single-predictor model. Importantly, given the features of our data set, the WN model controls not only for persistent and endogenous predictor variable, it also accounts for model heteroscedasticity. There are other predictability models, such as Kim (2014); however, the limitation of his model is that it does not control for heteroscedasticity.

then the forward premium is locally stationary in the sense that ρ approaches one from below as T increases.

Westerlund and Narayan (2012) argue that there is at least one empirical regularity—heteroskedasticity—that is not formally captured in predictive regression models. They propose modelling heteroskedasticity by using the following variance equation for η_t:

$$var(\eta_t|I_{t-1}) = \sigma_{\eta t}^2 = \lambda_0 + \sum_{j=1}^{q} \lambda_j \eta_{t-j}^2 \tag{6}$$

where I_t is the information available at time t. In order to ensure that σ_η^2 is positive, Westerlund and Narayan (2012) assume that $\lambda_0 > 0$, $\lambda_1, \dots, \lambda_q \geq 0$ and $\sum_{j=1}^{q} \lambda_j < 1$. They then also apply a simple ARCH model assumption to $var(\varepsilon_t|I_{t-1}) = \sigma_{\varepsilon t}^2$. Because in Lewellen $\rho = 0.9999$, any information contained in the ARCH structure of the errors is unexploited. The GLS estimator captures the ARCH structure by weighting (ω) all the data by $1/\sigma_{\eta t}$.

Importantly, Westerlund and Narayan (2014)[57] show that the FGLS-based test that exploits the information contained in the ARCH is more powerful than the OLS-based test that ignored ARCH. They show that the conditional variance of ϵ_t is:

$$var(\epsilon_t|I_{t-1}) = \sigma_{\epsilon t}^2 = \gamma^2 \sigma_{\varepsilon t}^2 + \sigma_{\eta t}^2 \tag{7}$$

and the GLS *t*-statistic is of the form:

$$t_{GLS} = \frac{\hat{\beta}_{GLS}}{1/\sqrt{\sum_{t=2}^{T} \omega_t^2 \left(FP_{t-1}^d\right)^2}} \tag{8}$$

Here, ω_t is the GLS weight, $\hat{\beta}_{GLS}$ is the GLS estimator of β from Equation (2), and $FP_t^d = FP_t - \sum_{s=2}^{T} FP_s/T$, where T is the sample size.

3. Empirical findings

This section has three objectives. First, we provide a preliminary analysis of the data set, focusing on the salient features of the predictor variables, such as persistency and endogeneity, and any ARCH effects in the model, which have implications for testing the null hypothesis of no predictability. Second, we test for exchange rate return predictability using the in-sample GLS test proposed by Westerlund and Narayan (2012, 2014). Third, we undertake an extensive out-of-sample predictability analysis. Here, we focus on both statistical and economic measures.

3.1 Data and preliminary analysis

We have time series daily data for 25 developed and developing countries. These countries are listed in column 1 of Table 1. We have 12 developing countries (Argentina, Chile, Kenya, South Korea, Mexico, Malaysia, Peru, Pakistan, Poland, Russia, Singapore, and Taiwan), 9 developed countries (Australia, Canada, Spain, Ireland, Israel, Iceland, Sweden, Japan, and the

[57] We used Gauss software to estimate the predictability model. The code implemented for the FGLS test is available upon request.

UK), and four emerging countries (China, India, Brazil, and South Africa)[58]. It also important to note that in the case of Argentina, China, Spain, and Ireland, their exchange rates have had a crawling peg[59] whereas other currencies in our analysis have a floating exchange rate regimes. The daily sample period for each country is different and is conditional on data availability. This is reported in column 2 of Table 1. In parentheses in column 2, we also report the number of data points (observations) per country. It is easy to see the variance in sample size from this data. There are over 5,000 observations for Australia, Ireland, and Japan and for another seven countries, we have over 4,000 daily observations. On the whole, we have good time series data for a predictability test. All data (spot and forward rates) are downloaded from BLOOMBERG. They are the closing price of direct quotes reported at the U.S trading time.

INSERT TABLE 1

Next, we examine some key features of the data. For this purpose, we focus on exchange rate returns and only one (the 30-day forward rate) of the five forward rates. Results for the other forward rates are the same so, to conserve space, we do not repeat them. Detailed results are, however, available upon request. We begin with the mean and standard deviation of the spot exchange rate change and the 30-day forward premium. These results are reported in columns 3 and 4 of Table 1. A positive sign on the mean of exchange rate implies an appreciation of the local currency vis-à-vis the US dollar. Over the sample period considered, 13 currencies had appreciated against the US dollar while the other 16 had depreciated. The largest appreciation was experienced by Iceland, followed by South Africa and Brazil, while the largest depreciation was experienced by Israel. With respect to the 30-day forward premium, we notice that in eight countries it was negative while in the remaining 21 countries the forward premium was positive. Argentina and Russia had the most volatile forward premiums, whereas Canada had the least volatile forward premium. Overall, these simple descriptive statistics imply that we have a very diverse set of countries in our sample. Therefore, a time series analysis of exchange rate predictability is appropriate.

We turn now to three issues that matter directly for predictability tests and, indeed, for the choice of the particular type of time series predictive regression model. First, let us consider the issue of persistency. We refer now to Table 2, column 4. Here we have reported the conventional Dickey and Fuller (1979) test, which examines the null hypothesis of a unit root. A rejection of the null implies zero or little persistency—a condition on which most predictive regression models are estimated—while the acceptance of the null would suggest otherwise, rendering slope biasness in predictive regression models. As is typical in this test, we allow for lags of the dependent variable to control for any serial correlation. Our approach is simple and proceeds as follows. We choose a maximum of eight lags and then apply the Schwarz

[58] We also have data for four other countries, namely, Denmark Egypt, Oman, and Tunisia, but we do not consider them in our paper because they have had a fixed exchange rate regime during the sample period under consideration.

[59] Argentina had de factor crawling band around the US dollar over the period February 2003 to June 2009 and from July 2009 to June 2011, it had de facto crawling peg to the US dollar; China also had a crawling peg arrangement with the US dollar (IMF has classified this as soft pegs or intermediate regimes); Ireland had a de facto peg to DM over the period November 1996 to 01 January 1999, and later it joined the Euro currency union. Finally, in the case of Spain, they had a de facto peg to DM over the period 1994 to 1999 and later it joined the Euro currency union.

Information Criterion to arrive at the optimal lag lengths. The optimal lag lengths are reported in square brackets beside the test statistics used to test the null hypothesis in column 4. The probability value is reported in parenthesis. The results are reported for exchange rate returns and the 30-day forward premium. Reading the results suggests that while the null hypothesis of a unit root is comfortably rejected at the 1% level for the exchange rate returns, the same cannot be said for forward premiums. For 13 countries, the null is not rejected. These countries are Australia, Spain, the UK, Ireland, Israel, Japan, Kenya, Peru, Poland, Russia, Sweden, Singapore, and South Africa. Even for the 13 countries for which the null is rejected, the autoregressive (AR) coefficient from an AR(1) model suggests that the coefficient is extremely high and very close to one; the exceptions are Malaysia and South Korea, where the coefficient is around 0.5 (see column 3). By comparison, we note that the AR coefficients from the returns are close to zero (see column 2). The key implication here is that the usual suspect that the predictor variable is persistent in predictive regression models is confirmed to be true in our data set.

INSERT TABLE 2

Next, we explore whether the predictor variable is endogenous. As explained earlier, endogeneity can be tested by regressing the error term from the predictive regression model on the error term from the predictor variable, as depicted in Equation (3). The results from this regression model are reported in column 5 of Table 2. We report the coefficient on γ, its *t*-statistic, and the probability value. We find that for 13 out of the 25 countries, γ is statistically significant at the 5% level or better. These countries are Australia, Argentina, China, Spain, the UK, India, Japan, South Korea, Malaysia, Peru, Pakistan, Singapore and Taiwan. The implication here is that for these countries there is clear evidence that the forward premium is endogenous. Hence, while endogeneity of the forward premium is not an issue for all countries in our sample, it does matter for a sizeable number of countries. Therefore, like persistency, the issue of endogeneity needs to be accounted for in predictive regression models.

This now takes us to the final issue of relevance to predictive regression models—that being the heteroskedasticity of the returns and forward premium. To investigate the presence or otherwise of heteroskedasticity, we begin with an analysis of autocorrelation. Specifically, we estimate autocorrelations of squared returns and forward premiums at lags of six and 36. These results are reported in Table 3. For returns, we notice that for seven countries there is no evidence of autocorrelations; the autocorrelations are small and statistically insignificant, in that the p-values are greater than 0.1. However, for the remaining 22 countries strong evidence of autocorrelations are found at both short and long lags. This evidence is also confirmed by the Ljung-Box portmanteau test results, not reported here. By comparison, in monthly data, the evidence of ARCH is extremely weak, as demonstrated in the work of Baillie and Bollerslev (2000), and our results for daily spot returns seem consistent with those reported in Baillie and Bollerslev (1989). When we consider autocorrelations in the forward premium, for all 25 countries the null hypothesis of no autocorrelation is rejected strongly, suggesting that daily forward premiums are extremely heteroskedastic. Since the presence of heteroskedasticity is the main issue considered in this paper from an econometric modelling point of view, we consider it imperative to conduct some additional tests on it. We, therefore, run an autoregressive model with 30 lags for returns and forward premiums, and do a formal test of the null hypothesis on ‘no ARCH’ in the residuals of each variable. The results from this exercise are reported in Table 4. We find much stronger evidence of ARCH. The null hypothesis is rejected for all countries, regardless of lags considered, in the case of forward premiums, while in the case of exchange rate returns the null is rejected for most countries. The only country for which the null is not rejected is China.

INSERT TABLES 3 AND 4

As a final check on heteroskedasticity, we report the Wald test for the null of no ARCH effect in the estimated variance equations for η_t and ε_t and its *p*-value, and the number of lags used. These results are reported in Table 5. The lags are chosen using the Bayesian Information Criteria. Corroborating the previously reported evidence of ARCH, we find that the null of no ARCH is comfortably rejected for both error terms in all regressions for returns. For forward premiums, the null is not rejected for two countries, namely, China and Malaysia.

INSERT TABLE 5

This then completes our preliminary analysis. We conclude that, for most countries, not only are persistency and endogeneity of the predictor variable an issue, but so is heteroskedasticity. The only test that we are aware of that specifically models heteroskedasticity of variables in a predictive regression framework is Westerlund and Narayan's (2012, 2014), who propose a GLS-based test to examine the null hypothesis of no predictability. In fact, Westerlund and Narayan (2012) show that, in the presence of heteroskedasticity, the Westerlund and Narayan (2012, 2014) GLS-based test out-performs the Lewellen (2004) and the OLS estimators.

3.2 In-sample predictability

The results from the GLS-based predictability test are reported in Table 6. We find relatively good evidence of predictability. We find that the null hypothesis that forward premiums do not predict changes in spot exchange rate is rejected for 11 out of 25 countries. The null is rejected at the 1% level for Argentina, China, India, South Korea, Malaysia, Russia and Taiwan; at the 5% level for Spain and Ireland; and was much weaker, at the 10% level for Australia and Singapore. When we consider forward premiums at different dates of maturity, the results on predictability hold.

INSERT TABLE 6

In addition, we find that for seven out of the 11 countries for which the null is rejected, forward premiums predict exchange rate returns positively. These seven countries are Argentina, China, India, South Korea, Malaysia, Russia and Taiwan. There are two features of the results that need to be refreshed. First, the countries for which the null is rejected are either emerging or developing countries. Second, the focus of the extant literature has been almost exclusively on the developed countries. Therefore, when we break away from this tradition and consider forward premium predictors for a range of different emerging and developing countries, where evidence of predictability exists, the evidence is in support of the theory that forward premiums positively predict exchange rate changes. On the whole, our results are consistent with those obtained by Bansal and Dahlquist (BH, 2000), one of the very few studies based on developing/emerging countries. However, the BH study is based on pooled regressions performed on different groups of countries while ours is a time series analysis. BH, for a sample of low income, high income, and emerging market countries, find a positive slope coefficient, while for a pooled regression based on a sample of developed countries they find a negative slope coefficient.

3.3 Out-of-sample analysis

3.3.1 Statistical measures

In this section, we consider some of the commonly used metrics, namely, the out-of-sample R^2, which we denote as OOS_R^2, the Theil U statistic, and the forecast encompassing statistic proposed by Clark and McCracken (2001), which we denote as ENC-NEW. These tests are used as measures of the out-of-sample forecasting performance of our forward premium model relative to a random walk (RW) model, which is typically used in the return predictability literature as a benchmark model. Following Welch and Goyal (2008) and Westerlund and Narayan (2012), we choose 50% of the sample period for each country and then use the estimates from this period to forecast exchange rate returns recursively for the rest of the 50% of the sample. Therefore, our out-of-sample period is 50% of the sample.[60]
The OOS_R^2 is similar to that proposed by Campbell and Thompson (2008):

$$OOS_{R^2} = 1 - \frac{MSE_{model}}{MSE_{RW}} \tag{9}$$

where MSE_{model} is the mean square error of the out-of-sample predictions from our proposed model, while MSE_{RW} is the mean squared error from the RW model. When $OOS_{R^2} > 0$, our proposed predictive regression model predicts returns better than the RW model, and vice versa. By comparison, the Theil U statistic is defined as the ratio of the square roots of the mean-squared forecasting errors of the predictive regression model relative to the RW model. If the Theil $U < 1$, our proposed predictive regression model outperforms the historical average.

Finally, the Clark and McCracken (2001) ENC-NEW is as follows:

$$\text{ENC} - \text{NEW} = \frac{(T-T_0)^{-1}\sum_{t=T_0}^{T}\hat{\mu}_{0,t+1}(\hat{\mu}_{0,t+1}-\hat{\mu}_{1,t+1})}{(T-T_0)^{-1}\sum_{t=T_0}^{T}\hat{\mu}_{1,t+1}^2}$$

(10)

where t_0 to T_0 denotes in-sample period and we forecast the returns for the period $T_0 + 1$. Here T_0 is the number of in-sample observations. The ENC-NEW test statistic examines whether restricted model forecasts encompass the unrestricted model forecasts. In other words, it examines whether the forward premium returns provide no useful information for predicting spot exchange return relative to a RW model of spot returns.

The results are reported in Table 7. The total number of observations in the out-of-sample analysis for each country is reported in column 2. The ratio of the Theil U statistic is reported in column 3. We find that the ratio is less than 1 for China, Spain, Ireland, Malaysia, Russia, Singapore and Taiwan. This suggests that the proposed predictive regression model outperforms the RW model for those seven countries. This result is corroborated by the OOS_R^2, which is positive for those seven countries and negative for the other four countries. Clark and McCracken ENC-NEW statistic, meanwhile, suggests a positive sign and is statistically significant for all countries, favouring the predictive regression model.

INSERT TABLE 7

[60] For an excellent out-of-sample evaluation of spot and forward rates can be found in Chiang (1988).

3.3.2 Trading strategy based profits

From an economic point of view, when it comes to forecasting, an investor's concern is always about how much better off he/she is from paying attention to the forecasts from the predictive regression model, where the predictor variable is forward premium as opposed to simply using a random walk model to generate forecasts of exchange rate changes. In other words, this is a question of the economic significance of forward premium as a predictor of changes in exchange rate. The intuition is simple. If by following forecasts from the forward premium predictive regression model an investor can make more profits compared to a random walk model, then one can claim that the forward premium model is relatively better than a random walk model. Before we begin to consider profits from the two models, it is imperative to highlight a relevant issue from the literature on the economic significance of predictor variables, particularly in predicting stock returns. First, typically in this literature, on the assumption of a mean-variance investor, investor utility or certainty equivalent return has been computed. This framework requires an investor to obtain portfolio weights, the sum of which equates to unity, that are then assigned to risky and risk-free assets. Typically, in this literature, excess returns rather than returns are predicted. In our model of predictability, we have changes in exchange rates and a risk-free asset is not part of the model at the outset. While this can be introduced, it is not the point of the paper. We specifically test a hypothesis for which limited success has been documented. Therefore, rather than taking issue with investor utility, we focus on investor profits. In this regard, it is not uncommon in the exchange rate literature to test for profitability of exchange rates (see LeBaron, 1999; Dueker and Neely, 2007). In fact, there is considerable literature on this, and our motivation is, indeed, derived from this literature.

Our exchange rate trading strategy is as follows. We generate trading signals on the basis of exchange rate forecasts from a random walk model (RWM) and from the forward premium model (FPM). Based on these trading signals, we undertake buy and sell decisions. Our trading strategy can be summarised as follows: an investor takes a long position whenever $\widehat{ER}_{t+1} > 0$ and a short position whenever $\widehat{ER}_{t+1} \leq 0$, where $\widehat{ER}_{t+1}$ is the predicted exchange rate. This trading strategy is motivated by the work of Anatolyen and Gerko (2005), who use the same exchange rate trading strategy to extract buy and sell signals. We follow Szakmary and Mathur (1997) and compute profits (π) as follows:

$$\pi_t = Long_t * ER_t + (Long_t - 1) * ER_t - |Long_t - Long_{t-1}| * 0.001 \qquad (11)$$

where $Long_t = 1$ whenever there is a buy signal, and $Long_t = 0$ whenever there is a sell signal. Whenever a new position is established, a 0.1% transaction cost is allowed for, as shown by the last term on the right-hand side of the equation.

The main reason we follow Anatolyen and Gerko (2005) is because it allows us to use their proposed trading strategy to test for mean predictability, which is based on profits obtained from the out-of-sample trading strategy. They propose an excess profitability (EP) test, which can be computed as follows:

$$EP = \frac{\pi_{FP} - \pi_{RW}}{\sqrt{var_{FP} - var_{RW}}} \qquad (12)$$

Here, π_{FP} and π_{RW} are the average profits (returns) based on the forward premium and random walk models, respectively; and var_{FP} and var_{RW} are the variances of π_{FP} and π_{RW}, respectively. The EP test has a standard normal distribution under the null hypothesis of no mean predictability. Anatolyen and Gerko (2005) show that the variance can be computed as follows:

$$var(\pi_{FP} - \pi_{RW}) = 4\frac{T-1}{T^2} p_{\widehat{ER}}(1 - p_{\widehat{ER}}) var(ER_t) \tag{13}$$

Here, T is the sample size (out-of-sample), $p_{\widehat{ER}}$ is the probability that the return forecast has a non-negative sign, and $var(ER_t)$ represents the variance of the actual exchange rate return series.

Our results are summarised in Table 8. Columns 2 and 3 report profits and standard deviation, respectively, from the benchmark random walk model, while the corresponding results from the forward premium based model are reported in columns 4 and 5. In the final column, we report the EP test statistic. Regarding profits from our simple trading strategy, we observe the following. First, the forward premium based forecasts lead to either profit maximisation or loss minimisation compared to profits from a random walk model. In other words, profits from the random walk model are negative for all countries, while five countries have positive returns when using forecasts drawn from the forward premium model, and, where returns are negative, they are smaller than the negative returns from the random walk model. These results suggest that investors in all 11 countries are better off by devising buy and sell signals from the forward premium predictive regression model. Equally interestingly we discover that when the forward premium negatively predicts exchange rate returns, there is greater evidence of profitability compared to when it positively predicts returns. For example, out of the seven countries for which the forward premium positively predicts exchange rate returns in only two countries (Russia and Taiwan) profits are positive. By comparison, in four countries the forward premium negatively predicts returns and in three of these countries (Australia, Spain, and Ireland) profits are positive.

Second, previously we reported that based on the statistical measures of out-of-sample performance, the Theil U and the OOS_R^2 favoured the forward premium model over the random walk model for seven countries. From the trading strategy-based profits, we notice that for four of these seven countries (Spain, Ireland, Russia and Taiwan) returns are positive.

Finally, we consider the excess predictability (EP) test results reported in the last column of Table 8. Two results are worth highlighting here. First, for nine of the 11 countries, the null of no mean predictability is rejected, suggesting that the forward premium model generates better out-of-sample forecasting performance based on our trading strategy. It follows that a trading strategy based out-of-sample forecasting performance provides greater evidence in support of a forward premium model over a random walk model. Second, of the seven countries for which purely statistical measures had suggested that a forward premium based model is superior to a random walk model, the EP test corroborates this finding, except for Malaysia, where the null is not rejected at any of the conventional levels of significance.

INSERT TABLE 8

3.3.3. Robustness test

So far our empirical analysis is based on a sample period that includes the global financial crisis. It is possible that our results reported in previous sections could be affected by the global financial crisis. To check whether or not this is the case, we re-estimate all results over the pre-crisis period; that is, we include data only up to 9/14/2008. In the process, some countries (Kenya, the UK, Malaysia, and Russia) to begin with had either limited data over the pre-crisis period (insufficient for time series estimation) or had only data over the crisis period. We only report here the results on predictability (see Table 9); the rest of the results, such as those relating to persistency, endogeneity, and heteroskedasticity, are not reported here simply because they are similar to the ones reported for the entire sample size. The main features of the data remain the same. Reading the results from the predictability test, we find that the null is rejected for seven countries: for India at the 10% level; for Chile and Spain at the 5% level; and, for China, Ireland, Pakistan, and Taiwan at the 1% level. Consistent with previous results, forward premium positively predicts exchange rate returns for all five developing countries and negatively for the two developed countries. Like before, sign matters for profitability. Of the six countries for which forward premium negatively predicted returns, two had positive profits while of the six countries where predictability appeared with a positive sign, for only Pakistan profits were positive.

INSERT TABLE 9

In Table 10 we report the out-of-sample predictability results. Based on the Theil U statistic, except for India and Ireland, Theil $U < 1$ suggesting that the forward premium based predictive regression model outperforms the RW model for the remaining five countries. The OOS_R^2 and the ENC-NEW provide relatively stronger evidence in favour of the forward premium model over the RW model.

INSERT TABLE 10

Finally, we estimate profits from our simple strategy as before for the seven countries and report the results together with the standard deviation of profits and the excess profitability test in Table 11. As with previous results, we find that the forward premium based forecasts lead to either profit maximisation or loss minimisation compared to profits from a random walk model. In other words, profits from the random walk model are negative for all countries, while four countries have positive returns when using forecasts drawn from the forward premium model, and, where returns are negative, they are smaller than the negative returns from the random walk model. The results of the excess profitability test suggest that the null of no mean predictability is rejected for all seven countries. This means that the forward premium model generates better out-of-sample forecasting performance based on our trading strategy.

On the whole, from our empirical analysis over the pre-global financial crisis period, we conclude that the results are unchanged. The main findings, that forward premium positively predicts exchange rate returns for developing countries and that the forward premium based model consistently beats the random walk model in out-of-sample evaluations, hold.

INSERT TABLE 11

4. Concluding remarks

In this paper we undertake an extensive test of spot exchange rate return predictability by using the forward premium as the predictor variable. We have a data set covering 25 developed and developing countries, we use daily historical time series data, and we apply a recently proposed

GLS-based test for return predictability that accounts for all three salient features of the data—namely, persistency, endogeneity, and heteroskedasticity. These features of the data have been shown to have a spurious effect on predictability if left unattended. Our findings are different from the literature. We find that forward premiums predict exchange rate returns for as many as 11 countries. Unlike the literature, we discover that for seven countries (Argentina, China, India, South Korea, Malaysia, Russia and Taiwan) forward premiums predict returns positively. Using a range of out-of-sample predictability tests, we find that for as many as seven countries there is strong evidence of out-of-sample predictability.

We also devise a simple trading strategy where buy and sell signals are generated using predicted and actual exchange rates. The profits are generated from a random walk model and from the forward premium-based model. We find that for all 11 counties where forward premiums predict returns, regardless of the sign of predictability, profits from the forward premium model are greater than those from the random walk model. Interestingly, we discover that when the forward premium negatively predicts exchange rate returns there is a greater evidence of profitability compared to when the sign is positive. Out of the seven countries where the sign on predictability is positive in only two countries (Russia and Taiwan) profits are positive. By comparison, in four countries the sign is negative but profits are positive in three of these countries (Australia, Spain, and Ireland). Finally, when we apply a trading-based test for out-of-sample predictability, we discover even stronger evidence of predictability for as many as nine of the 11 countries.

There are three implications of our findings. First, our results support the Clarida and Taylor (1997) finding that, regardless of the sign of predictability, there is information content in forward premiums that investors can potentially utilise to make profits. Second, the often powerful performance of the random walk model over fundamentals-based exchange rate models does not hold in our empirical analysis. Where we discover statistical evidence that forward premium predicts exchange rate returns, we also find that this predictability translates into relatively higher profits compared to a random walk model. Finally, we show that when the sign on predictability is negative—inconsistent with theory—profitability is greater compared to when the sign is positive.

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Table 1: Descriptive statistics

This table reports the sample size of historical time series daily data for each country (column 2) and the mean and standard deviation of spot exchange rate returns (column 3) and the 30-day forward premium (column 4).

		ER-Returns		FP-30-day	
Countries	Sample Size	Mean	Standard Deviation	Mean	Standard Deviation
Australia (AUS)	16/08/1996-30/06/2011	0.00008	0.0070	-0.0016	0.0015
Argentina (ARS)	13/10/2005-30/06/2011	0.0002	0.0017	0.0098	0.0194
Brazil (BRL)	11/06/2002-30/06/2011	-0.0001	0.0097	0.0082	0.0059
Canada (CAD)	14/02/2007-30/06/2011	-0.0001	0.0067	0.0001	0.0005
Chile (CLP)	13/10/2005-30/06/2011	-0.00005	0.0058	0.0008	0.0018
China (CNY)	09/03/1999-30/06/2011	-0.00005	0.0006	-0.0012	0.0031
Spain (ESP)	20/07/1998-30/06/2011	-0.00004	0.0056	0.0002	0.0011
UK (FP-90-day)	08/09/1999-30/06/2011	0.00001	0.005	-0.0026	0.003
Ireland (IEP)	14/07/1997-30/06/2011	0.00005	0.0056	0.00005	0.0009
Israel (ILS)	10/02/2006-30/06/2011	-0.0002	0.0052	0.0002	0.0008
India (INR)	09/03/1999-30/06/2011	0.00002	0.0027	0.0038	0.0038
Iceland (ISK)	16/08/2004-30/06/2011	0.0003	0.0111	0.0059	0.0019
Japan (JPY)	03/01/1997-30/06/2011	-0.00005	0.006	-0.0027	0.0017
Kenya (KES)	23/04/2009-30/06/2011	0.0002	0.0036	0.0025	0.0020
S. Korea (KRW)	09/03/1999-30/06/2011	-0.00001	0.0061	0.0007	0.0039
Mexico (MXN)	18/11/2002-30/06/2011	0.00006	0.0059	0.0039	0.0018
Malaysia (MYR)	05/08/2008-30/06/2011	-0.00007	0.0038	0.0011	0.0031
Peru (PEN)	13/10/2005-30/06/2011	-0.00009	0.0029	0.0002	0.0025
Pakistan (PKR)	03/11/2004-30/06/2011	0.0002	0.0026	0.0052	0.0031
Poland (PLN)	18/06/2004-30/06/2011	-0.00009	0.0088	0.0015	0.0016
Russia (RUB)	04/09/2008-30/06/2011	0.0001	0.006	0.0087	0.0126
Sweden (SEK)	14/02/2007-30/06/2011	-0.00002	0.0083	0.0002	0.0010
Singapore (SGD)	01/02/1999-30/06/2011	-0.00007	0.0026	-0.0011	0.0011
Taiwan (TWD)	11/12/1998-30/06/2011	-0.00002	0.0022	-0.0012	0.0029
S. Africa (ZAR)	18/06/2004-30/06/2011	0.00007	0.0099	0.0049	0.0019

Table 2: ADF and endogeneity test results

This table reports a number of preliminary tests of the data. In columns 2 and 3, we report the autoregressive coefficient of the spot exchange rate return and the forward premium, respectively. These coefficients are used to judge the degree of persistency. The ADF test, which examines the null hypothesis of no unit root, is reported in column 3. The null hypothesis of a unit root is tested for both variables. The optimal lag length, chosen using the Schwarz Information Criterion, is reported in the square brackets. The optimal lag length is selected by starting with a maximum of eight lags. The p-values, used to test the unit root null, are reported in parentheses. The last column reports the endogeneity test results. This test is based on regressing the error term from the predictive regression model on the error term from the predictor variable; the coefficient, t-statistics, and p-value are reported.

Countries			ADF-test results		Endogeneity		
	ER(-1)	FP1(-1)	ER-returns	FP-30-day	gamma	t-stat	p-value
Australia	-0.0497	0.9982	-77.4280[0] (0.0001)*	-1.1856[7] (0.6830)	2.009	2.02	0.043
Argentina	0.1242	0.9884	-40.3469[0] (0.0000)*	-3.9639[8] (0.0016)*	0.097	7.769	0
Brazil	-0.0026	0.9533	-42.6940[1] (0.0000)*	-4.4419[4] (0.0003)*	-0.016	-0.172	0.863
Canada	-0.0360	0.9806	-41.3818[0] (0.0000)*	-3.0887[8] (0.0276)**	-0.154	-0.091	0.928
Chile	0.1150	0.9745	-40.6524[0] (0.0000)*	-2.9729[2] (0.0377)**	0.14	0.449	0.654
China	-0.0309	0.9766	-69.1369[0] (0.0001)*	-5.3473[3] (0.0000)*	0.077	5.58	0
Spain	-0.0130	0.9979	-69.6363[0] (0.0000)*	-1.2497[8] (0.6549)	-2.498	-2.12	0.034
UK (FP-90-day)	0.0226	0.9989	-64.2131[0] (0.0001)*	-1.6899[8] (0.4364)	-1.284	-2.317	0.02
Ireland	-0.0147	0.9935	-72.4528[0] (0.0001)*	-1.6739[6] (0.4446)	-0.493	-0.655	0.513
Israel	0.0797	0.9889	-40.8825[0] (0.0000)*	-1.8024[3] (0.3797)	1.126	1.193	0.233
India	0.0109	0.8438	-66.2861[0] (0.0000)*	-9.6597[6] (0.0000)*	0.232	11.762	0
Iceland	-0.0469	0.9496	-22.1523[5] (0.0000)*	-4.2887[3] (0.0005)*	0.199	0.564	0.573
Japan	-0.0086	0.9958	-73.3449[0] (0.0001)*	-1.2413[7] (0.6586)	-1.087	-2.226	0.026
Kenya	-0.0637	0.9908	-29.9893[0] (0.0000)*	-0.7863[1] (0.8219)	-0.229	-0.606	0.545
S. Korea	-0.0100	0.4387	-67.6908[0] (0.0001)*	-13.7242[8] (0.0000)*	0.584	23.886	0
Mexico	-0.0634	0.9906	-59.7353[0] (0.0001)*	-3.2758[7] (0.0161)**	0.676	1.572	0.116
Malaysia	-0.0480	0.5775	-34.0714[0] (0.0000)*	-12.979[1] (0.0000)*	0.573	13.262	0
Peru	0.0249	0.9855	-20.7440[3] (0.0000)*	-2.5732[4] (0.0988)	0.358	2.47	0.014
Pakistan	0.0183	0.9889	-28.8123[3] (0.0000)*	-3.4483[1] (0.0095)*	-0.031	-0.27	0.787
Poland	0.0340	0.9968	-48.9458[0] (0.0001)*	-1.5591[8] (0.5034)	-3.432	-2.568	0.01
Russia	0.1146	0.9673	-28.5475[0] (0.0000)*	-2.5867[8] (0.0960)	-0.089	-1.525	0.127
Sweden	-0.0054	0.9942	-40.1581[0]	-1.7793[7]	-1.202	-0.631	0.528

			(0.0000)	(0.3911)			
Singapore	-0.0267	0.9943	-69.1179[0] (0.0001)*	-2.3672[6] (0.1513)	-1.353	-3.86	0
Taiwan	0.0113	0.8770	-66.8769[0] (0.0001)*	-7.8536[8] (0.0000)*	0.273	11.82	0
S. Africa	-0.0257	0.9943	-51.9645[0] (0.0001)*	-1.6192[7] (0.4725)	1.274	1.356	0.175

Table 3: Autocorrelation results

In this table, we report results from a test of autocorrelation. We square both variables and test for autocorrelation at lags of six and 36. We report the resulting autocorrelation coefficient and its p-value used to test the null hypothesis of no autocorrelation.

Countries	ER-returns				Forward premium –30-day			
	6 lags		36 lags		6 lags		36 lags	
	AC	p-value	AC	p-value	AC	p-value	AC	p-value
Australia	0.031	0.0000	0.020	0.0000	0.993	0.0000	0.964	0.0000
Argentina	0.002	0.0000	0.036	0.0000	0.902	0.0000	0.466	0.0000
Brazil	0.034	0.0000	0.002	0.0000	0.898	0.0000	0.716	0.0000
Canada	0.065	0.032	0.001	0.001	0.925	0.0000	0.658	0.0000
Chile	0.015	0.0000	0.036	0.0000	0.929	0.0000	0.823	0.0000
China	0.021	0.0000	-0.008	0.0000	0.915	0.0000	0.743	0.0000
Spain	0.016	0.135	0.008	0.287	0.995	0.0000	0.977	0.0000
UK (FP-30-day)	-0.002	0.208	0.027	0.015	0.994	0.0000	0.961	0.0000
Ireland	0.015	0.162	0.013	0.461	0.985	0.0000	0.960	0.0000
Israel	0.024	0.001	-0.016	0.012	0.959	0.0000	0.826	0.0000
India	0.021	0.186	0.011	0.0000	0.615	0.0000	0.360	0.0000
Iceland	-0.082	0.0000	0.056	0.0000	0.881	0.0000	0.578	0.0000
Japan	-0.031	0.002	0.013	0.001	0.988	0.0000	0.960	0.0000
Kenya	0.056	0.091	0.019	0.689	0.918	0.0000	0.660	0.0000
S. Korea	-0.002	0.007	0.033	0.0000	0.214	0.0000	0.176	0.0000
Mexico	0.031	0.0000	0.027	0.0000	0.960	0.0000	0.853	0.0000
Malaysia	-0.006	0.764	0.006	0.837	0.131	0.0000	-0.001	0.0000
Peru	0.022	0.0000	0.040	0.0000	0.948	0.0000	0.814	0.0000
Pakistan	-0.033	0.0000	0.053	0.0000	0.946	0.0000	0.860	0.0000
Poland	-0.015	0.345	-0.039	0.0000	0.980	0.0000	0.923	0.0000
Russia	0.007	0.008	-0.014	0.0000	0.812	0.0000	0.627	0.0000
Sweden	0.051	0.038	-0.014	0.173	0.968	0.0000	0.833	0.0000
Singapore	0.014	0.173	0.017	0.240	0.975	0.0000	0.939	0.0000
Taiwan	0.024	0.082	0.02	0.0000	0.684	0.0000	0.435	0.0000
S. Africa	0.012	0.244	0.005	0.011	0.984	0.0000	0.943	0.0000

Table 4: Heteroskedasticity test results

In this table, we report results on heteroskedasticity of the exchange rate return and the forward premium variables. Essentially, we run an autoregressive model for each variable with 36 lags and test for the null hypothesis of 'no ARCH' in the residuals of the model. The null is tested at lags of six and 36. The LM test statistic is reported together with the p-value (in parentheses). * denotes statistical significance at the 1% level.

Countries	ER-returns		Forward Premium-30-day	
	ARCH (6)	ARCH (36)	ARCH (6)	ARCH (36)
Australia	151.7775 (0.0000)*	68.1019 (0.0000)*	2810.446 (0.0000)*	618.6345 (0.0000)*
Argentina	7.0632 (0.0000)*	17.8301 (0.0000)*	5542.078 (0.0000)*	1226.536 (0.0000)*
Brazil	99.5893 (0.0000)*	41.2227 (0.0000)*	630.8633 (0.0000)*	122.3500 (0.0000)*
Canada	29.5154 (0.0000)*	1.9114 (0.0000)*	421.4135 (0.0000)*	113.3722 (0.0000)*
Chile	29.4704 (0.0000)*	11.6100 (0.0000)*	62.3001 (0.0000)*	24.5214 (0.0000)*
China	0.1059 (0.9958)	0.0797 (1.0000)	1985.401 (0.0000)*	354.2245 (0.0000)
Spain	16.9445 (0.0000)*	17.5345 (0.0000)*	916.7611 (0.0000)*	188.0977 (0.0000)*
UK (FP-90-day)	41.3038 (0.0000)*	30.7739 (0.0000)*	2330.707 (0.0000)*	513.8964 (0.0000)*
Ireland	18.5289 (0.0000)*	18.0078 (0.0000)*	772.7704 (0.0000)*	196.9079 (0.0000)*
Israel	29.4529 (0.0000)*	8.7224 (0.0000)*	444.9113 (0.0000)*	82.6331 (0.0000)*
India	41.5054 (0.0000)*	19.4834 (0.0000)*	1618.272 (0.0000)*	310.3435 (0.0000)*
Iceland	328.7071 (0.0000)*	64.6809 (0.0000)*	1158.401 (0.0000)*	198.6252 (0.0000)*
Japan	37.7424 (0.0000)*	14.6735 (0.0000)*	580.8685 (0.0000)*	171.562 (0.0000)*
Kenya	5.6153 (0.0000)*	2.4681 (0.0000)*	284.5759 (0.0000)*	53.0305 (0.0000)*
S. Korea	43.3882 (0.0000)*	57.6269 (0.0000)*	340.0255 (0.0000)*	93.5108 (0.0000)*
Mexico	133.4806 (0.0000)*	45.9287 (0.0000)*	2435.658 (0.0000)*	476.4694 (0.0000)*
Malaysia	3.8722 (0.0008)*	5.3471 (0.0000)*	82.9264 (0.0000)*	15.2578 (0.0000)*
Peru	27.7443 (0.0000)*	9.2035 (0.0000)*	1211.931 (0.0000)*	219.6265 (0.0000)*
Pakistan	101.62 (0.0000)*	20.7136 (0.0000)*	2106.923 (0.0000)*	381.2816 (0.0000)*
Poland	80.8361 (0.0000)*	27.7971 (0.0000)*	2019.920 (0.0000)*	506.8488 (0.0000)*
Russia	5.0489 (0.0000)*	5.7087 (0.0000)*	520.1515 (0.0000)*	86.5256 (0.0000)*
Sweden	86.0705 (0.0000)*	10.7948 (0.0000)*	618.6772 (0.0000)*	165.5125 (0.0000)*
Singapore	17.8942 (0.0000)*	13.0405 (0.0000)*	1599.637 (0.0000)*	288.8336 (0.0000)*
Taiwan	8.8008 (0.0000)*	4.8919 (0.0000)*	737.4505 (0.0000)*	125.3323 (0.0000)*

S. Africa	13.6119 (0.0000)*	10.1284 (0.0000)*	737.8994 (0.0000)*	151.6750 (0.0000)*

Table 5: Wald test results

In this table, we report further tests for heteroskedasticity based on a Wald test. We report the Wald test for the null of no ARCH effect in the estimated variance equations for η_t and ε_t, its *p*-value, and the number of lags used. The results are reported for both exchange rate returns and the forward premium variables. Where *p*-values are less than 0.01, the null is rejected at the 1% level.

Countries	ER-Returns			Predictor-FP1		
	Wald	Lag	p-value	Wald	lag	p-value
Australia	909.01	5	0.0000	636.769	3	0.0000
Argentina	37.315	4	0.0000	445.552	4	0.0000
Brazil	452.085	4	0.0000	541.085	5	0.0000
Canada	97.071	2	0.0000	620.153	4	0.0000
Chile	122.156	3	0.0000	1261.124	4	0.0000
China	0.0000	0	-1.0000	465.63	5	0.0000
Spain	43.61	1	0.0000	2273.077	5	0.0000
UK (FP-90-day)	157.713	3	0.0000	916.746	1	0.0000
Ireland	48.119	1	0.0000	1010.158	5	0.0000
Israel	68.782	1	0.0000	255.282	2	0.0000
India	205.423	2	0.0000	500.008	5	0.0000
Iceland	1880.678	5	0.0000	298.859	3	0.0000
Japan	129.29	1	0.0000	1217.661	3	0.0000
Kenya	31.176	1	0.0000	54.531	1	0.0000
S. Korea	159.585	3	0.0000	1971.992	5	0.0000
Mexico	430.813	5	0.0000	1301.017	4	0.0000
Malaysia	0.0000	0	-1.0000	47.634	2	0.0000
Peru	172.068	4	0.0000	149.249	1	0.0000
Pakistan	602.149	4	0.0000	68.695	4	0.0000
Poland	197.193	1	0.0000	318.447	5	0.0000
Russia	21.077	1	0.0000	261.046	4	0.0000
Sweden	19.147	1	0.0000	333.47	4	0.0000
Singapore	65.408	3	0.0000	194.185	4	0.0000
Taiwan	34.687	1	0.0000	380.772	3	0.0000
S. Africa	29.195	1	0.0000	140.327	5	0.0000

Table 6: In-sample predictability test results

In this table, we report the results from the time series predictive regression model proposed by Westerlund and Narayan (2011, 2012). The regression model regresses the exchange rate returns on the one-period lagged forward premium variable. The null hypothesis is that the forward premium does not predict exchange rate returns. The predictor variable, forward premium, is proxied by 30-day, 90-day, 180-day, and 360-day premiums. For each country's predictive regression model we report the coefficient on the one-period lagged premium (predictor) variable and its *p*-value.

Countries	30-day		90-day		180-day		360-day	
	Coefficient	p-value	Coefficient	p-value	coefficient	p-value	coefficient	p-value
Argentina	0.006***	0.0000	0.003***	0.0000	0.002***	0.0000	0.001***	0.0000
Australia	-0.144*	0.094	-0.050*	0.084	-0.025*	0.096	-0.013*	0.084
Brazil	-0.039	0.234	-0.011	0.679	-0.008	0.559	0.000	0.833
Canada	0.234	0.868	0.103	0.759	0.060	0.575	0.033	0.420
Chile	0.013	0.558	0.007	0.484	0.003	0.416	0.002	0.298
China	0.021***	0.000	0.007***	0.000	0.003***	0.000	0.001***	0.000
Spain	-0.168**	0.040	-0.059**	0.033	-0.030**	0.043	-0.016**	0.045
UK	NA	NA	-0.005	0.959	-0.003	0.965	-0.003	0.858
Ireland	-0.220**	0.016	-0.078**	0.011	-0.038**	0.019	-0.020**	0.023
Israel	0.091	0.571	-0.003	0.980	-0.010	0.732	-0.011	0.494
India	0.048***	0.000	0.009**	0.021	0.001	0.269	0.001	0.266
Iceland	-0.102	0.927	0.028	0.430	0.009	0.561	0.012	0.356
Japan	-0.057	0.339	-0.019	0.351	-0.010	0.314	-0.006	0.240
Kenya	-0.057	0.485	-0.012	0.667	-0.004	0.815	-0.002	0.888
S. Korea	0.384***	0.000	0.110***	0.000	0.039***	0.000	0.015***	0.003
Mexico	-0.072	0.845	-0.023	0.947	-0.011	0.993	-0.004	0.841
Malaysia	0.318***	0.000	0.148***	0.000	0.078***	0.002	0.024	0.173
Peru	0.033	0.675	0.013	0.835	0.008	0.864	0.004	0.886
Pakistan	0.001	0.175	-0.002	0.196	-0.001	0.255	0.000	0.250
Poland	0.029	0.427	0.004	0.610	-0.001	0.807	-0.004	0.788
Russia	0.057 ***	0.000	0.023***	0.000	0.012***	0.002	0.007***	0.007
Sweden	0.197	0.285	0.060	0.371	0.035	0.340	0.017	0.416
Singapore	-0.078*	0.067	-0.026*	0.080	-0.013*	0.082	-0.007*	0.088
Taiwan	0.092***	0.000	0.026***	0.000	0.012***	0.000	0.005***	0.009
S. Africa	0.038	0.894	0.026	0.835	0.019	0.569	0.010	0.480

Table 7: Out-of-sample predictability

This table reports the out-of-sample predictability for each of the 11 countries. The out-of-sample size appears in column 2. We set the out-of-sample period equivalent to 50% of the sample size. In columns 3-5 we report three of the commonly-used metrics, namely, the Theil U statistic, the out-of-sample R^2, which we denote as OOS_R^2, and the forecast encompassing statistic proposed by Clark and McCracken (2001), which we denote as ENC-NEW. These tests are used as measures of the out-of-sample forecasting performance of our forward premium model relative to a random walk model, which is typically used in the return predictability literature as a benchmark model.

Countries	Sample size	Theil U	OOS_R^2	$ENC-NEW$
Australia	2715	1.0030	-0.0056	0.404
Argentina	1043	1.1567	-0.3366	3.438
China	2248	0.9912	0.0173	33.142
Spain	2364	0.9954	0.0087	1.787
Ireland	2550	0.9949	0.0095	0.916
India	2248	1.0003	-0.0004	2.441
South Korea	2248	1.0013	-0.0027	8.974
Malaysia	530	0.9990	0.0022	1.861
Russia	515	0.9954	0.0087	2.036
Singapore	2266	0.9991	0.0016	-5.494
Taiwan	2292	0.9931	0.0139	19.961

Table 8: Results on profits

In this table, we report profits from our simple trading strategy. We also report the excess profitability test which, essentially, examines the null hypothesis of no mean predictability of out-of-sample profits from the random walk model (RWM) and the forward premium model (FPM). We generate trading signals on the basis of exchange rate forecasts from a RWM and from the FPM. Based on these trading signals, we undertake buy and sell decisions. Our trading strategy is as follows: an investor takes a long position whenever $\widehat{ER}_{t+1} > 0$, and a short position whenever $\widehat{ER}_{t+1} \leq 0$, where $\widehat{ER}_{t+1}$ is the predicted exchange rate. This trading rule is applied to forecasts from the forward premium model and from a random walk model. The profits and standard deviation are reported. In the final column we report the excess profitability test based on the forecasts.
***denotes statistical significance at the 1% level.

Countries	Random Walk Model		Forward Premium Model		Excess Profitability Test
	Profits	Std. dev.	Profits	Std. dev.	
Australia	-0.003	0.0082	0.001400	0.0082	2.9155***
Argentina	-0.0013	0.0019	-0.00320	0.0018	-3.6565***
China	-0.0042	0.0011	-0.00013	0.00089	16.0835***
Spain	-0.00052	0.0055	0.000020	0.0055	5.1125***
Ireland	-0.00053	0.0055	0.000077	0.0054	5.9495***
India	-0.00033	0.00365	-0.00007	0.0036	3.9313***
South Korea	-0.00032	0.0077	-0.00045	0.0077	-0.9423
Malaysia	-0.00027	0.00387	-0.00019	0.0039	0.7237
Russia	-0.00035	0.00447	0.000143	0.00449	2.9058***
Singapore	-0.00045	0.00295	-0.000006	0.00292	7.5166***
Taiwan	-0.00051	0.00244	0.000089	0.00239	13.002***

Table 9: Robustness Test - In-sample predictability test results over the pre-crisis period

In this table, we report the results from the time series predictive regression model proposed by Westerlund and Narayan (2011, 2012). The regression model regresses the exchange rate returns on the one-period lagged forward premium variable. The null hypothesis is that the forward premium does not predict exchange rate returns. The predictor variable, forward premium, is proxied by 30-day premiums. For each country's predictive regression model we report the coefficient on the one-period lagged premium (predictor) variable and its *p*-value.

Countries	30-day		Countries	30-day	
	Coefficient	p-value		coefficient	p-value
Argentina	-0.012	0.104	S. Korea	-0.004	0.615
Australia	-0.113	0.111	Mexico	-0.044	0.367
Brazil	-0.036	0.165	Peru	0.042	0.824
Canada	0.5736	0.1204	Pakistan	0.093***	0.0000
Chile	0.345**	0.031	Poland	-0.030	0.968
China	0.0231***	0.0000	Sweden	0.2104	0.1450
Spain	-0.175**	0.018	Taiwan	0.068***	0.0000
Ireland	-0.219***	0.010	S. Africa	0.0283	0.8070
Israel	-0.030	0.906	Iceland	0.108	0.538
India	0.016*	0.075	Japan	-0.039	0.629

Table 10: Robustness test - Out-of-sample predictability results

This table reports the out-of-sample predictability for each of the seven countries. The out-of-sample size appears in column 2. We set the out-of-sample period equivalent to 50% of the sample size. In columns 3-5 we report three of the commonly-used metrics, namely, the Theil U statistic, the out-of-sample R^2, which we denote as OOS_R^2, and forecast encompassing statistic proposed by Clark and McCracken (2001), which we denote as ENC-NEW. These tests are used as measures of the out-of-sample forecasting performance of our forward premium model relative to a random walk model, which is typically used in the return predictability literature as a benchmark model.

Countries	Sample size	Theil U	OOS_R^2	$ENC-NEW$
Chile	534	0.9029	-0.0155	3.207
China	1739	0.9990	0.0000	30.614
India	1739	1.0021	0.0010	0.218
Ireland	2041	1.0155	0.0000	1.103
Pakistan	706	0.9469	0.0061	14.718
Spain	1855	0.9628	0.0008	2.712
Taiwan	1783	0.9482	0.0020	7.334

Table 11: Robustness test - Results on profits

In this table, we report profits and the standard deviation of profits from our simple trading strategy. We also report the excess profitability test which, essentially, examines the null hypothesis of no mean predictability of out-of-sample profits from the random walk model (RWM) and the forward premium model (FPM). We generate trading signals on the basis of exchange rate forecasts from a RWM and from the FPM. Based on these trading signals, we undertake buy and sell decisions. Our trading strategy is as follows: an investor takes a long position whenever $\widehat{ER}_{t+1} > 0$, and a short position whenever $\widehat{ER}_{t+1} \leq 0$, where $\widehat{ER}_{t+1}$ is the predicted exchange rate. This trading rule is applied to forecasts from the forward premium model and from a random walk model. In the final column we report the excess profitability test based on the forecasts. ***denotes statistical significance at the 1% level.

Countries	Random Walk Model		Forward Premium Model		Excess Profitability Test
	Profits	Std. dev.	Profits	Std. dev.	
Chile	-0.00067	0.0055	-0.00019	0.0055	2.4908***
China	-0.00037	0.00098	-0.00011	0.00081	14.2301***
India	-0.0003	0.00256	-0.00011	0.00253	3.8599***
Ireland	-0.00031	0.00479	0.000148	0.00479	4.7323***
Pakistan	-0.00044	0.00368	0.00027	0.00359	5.5342***
Spain	-0.00029	0.00472	0.000122	0.00469	4.0304***
Taiwan	-0.00052	0.00217	0.000026	0.00211	12.0627***