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Managing COP21 using a Stock and Oil Market Integration Index

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Abstract

COP21 implementation should lead to a decline in the future demand for fossil fuels. We construct a monthly integration index and then demonstrate that oil investors can offset adverse oil price risk by holding various global stock portfolios during the November 1994 to May 2017 period. The portfolios are formed from eight different combinations of developed and emerging stock markets. We show that measuring the degree of stock-oil market integration for these portfolios is critical to managing the time-varying degrees of integration that exist between oil and stock markets. Importantly, under normal market conditions, when markets are segmented, there is the opportunity for oil investors to diversify the additional energy price risk, caused by COP21, through the purchase of stocks. Even over the full sample period, we document risk adjusted positive benefits to investors from holding diversified oil-stock portfolios for the global stock market regions, except for the Far East.

Keywords: Commodities, COP21, Financial Market Integration, International Asset Pricing, Market Risk, WTI Oil, Risk of Climate Change, Systematic Risk.

1. Introduction

One key impact arising from COP21[1] is the expected ongoing decline in the future demand for fossil fuels such as coal, oil and gas. These outcomes also link with broader public policy concerns over the impacts of climate change, which The Institute for Sustainability Leadership (2015) stresses is basically unhedgeable. In this context, Jefferson (2015) highlights that the world in the 21st century faces tremendous energy challenges that mainly arise from the demand side due to increasing population growth. Thus, there is a strong need for a sustainable global energy policy.

In this paper, we construct a stock-oil integration index to show how oil investors can in fact diversify and then offset, or hedge, the demand related oil price risks that will arise from COP21. Central to these risk management strategies is the measurement of the statistical relationship between oil and financial assets. We show that investors that consider these relationships receive positive economic benefits since they can outperform naïve trading strategies. These findings add to an existing debate on the importance of better understanding the two-way impact of oil and stock market prices on one another, since they are also vital for regulatory and macroeconomic policy, both at a country and global level (Bernanke, 2016).

Financial assets may be combined with energy assets into portfolios along with developed and emerging country stock markets. Recent empirical studies on these portfolios have highlighted their time-varying correlation relationships, often with risk spill-overs between specific stock and energy markets. The focus of many of these studies tends to be on the impact of energy prices on developed country stock markets, which have historically been oil importers and those emerging markets, which tend to be oil exporters, such as those in the MENA region[2] (e.g. Mensi et al. 2013; Demirer et al. 2015; Tsai, 2015; Kyrtsou et al. 2016; Balcilar et al. 2017). However, rather than investigate the stock markets of specific countries, we investigate impacts on region wide and global portfolios.

In constructing the oil-stock integration index, this study builds upon existing portfolio theory applied to international financial markets (e.g. Solnik, 1977; Stulz, 1981). Importantly, theory shows that by holding uncorrelated assets in an international portfolio, from markets that may be isolated by geography, regulation or function, the risk of one stock market can be used to offset the risk of the other. Combining portfolios across industries and other markets with varying degrees of liquidity and market access, allows an investor to eventually form diversified portfolios that minimise risk and transactions costs, while maximising expected return.

Globalisation, the removal of capital controls and financial market regulatory convergence over the past two to three decades has tended to remove those barriers that once prevented investors undertaking various cross-border transactions. These changes have effectively expanded the range of possible investment opportunities available to investors beyond simply domestic ones. Consequently, in the spirit of many of these international studies, where the focus is on the inclusion of emerging stock markets, such as Bekaert and Harvey (1995, 1997, 2000), Gerard

[1] COP21 refers to the agreement from the 2015 United Nations Climate Change Conference in Paris. The key result was an agreement to set a goal of limiting global warming to less than 2 degrees Celsius (°C) compared to pre-industrial levels. The agreement calls for zero net anthropogenic greenhouse gas emissions to be reached during the second half of the 21st century.

[2] The Middle East and North Africa (MENA) countries include: Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Malta, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, West Bank and Gaza, and Yemen. Ethiopia and Sudan are sometimes included.

et al. (2003), Chi et al. (2006) and Jeon et al. (2006), we include emerging markets as well as various combinations of developed markets in our portfolio analysis.
Because of these changes, financial markets have become both more efficient and integrated. Integration measures the degree that price changes in one market affect all markets. An extensive recent literature (see for example, Sadorksy (2014), Khalfaoui et al. (2015), Mensi et al. (2015), Kyrtsou et al. (2016), Batten, Kinateder, Szilagyi and Wagner (2017, henceforth simply BKSW, 2017)) in fact shows that these relationships vary over time as local market, or idiosyncratic factors (such as a change in government), that may limit system-wide impacts, are overridden by global factors. As the recent Global Financial Crisis (GFC) of 2007-2008 has shown, some shocks affect all markets, irrespective of location, although the impacts measured in terms of scale and scope may differ[3].

We contribute to the far-ranging debate on the impacts of COP21 by showing how the impact of declining energy demand influences financial assets. Since these impacts can be measured, they can also subsequently be hedged, using existing derivative financial products, such as options and futures amongst others. Our approach follows an existing asset-pricing literature that determines the degree of integration between energy and key stock markets, measured as portfolios and then to use these statistical relationships to form stock-energy market portfolios under different conditions of integration and segmentation. Segmentation refers to the opposite state to integration, when the price effects in one asset market have no effect on the other.

But exactly how can investors do this? We begin by providing a clear understanding of the dynamic relationship between a key energy asset, West Texas Intermediate (WTI) and stock portfolios from various stock markets[4]. We show that under normal market conditions, when markets are segmented, there is the opportunity for oil investors to diversify the additional oil price risk, caused by COP21, through the purchase of stocks. From an energy policy perspective, it is worth noting that the reliance on imported oil by many countries as a key source of energy, can be very costly, not only just due to climate change induced reasons. For example, Brown and Huntington (2015) analyze the broad macroeconomic costs that arise from the U.S. reliance on imported oil[5].

Next, the temporal nature of these relationships is considered. Previous research by BKSW (2017), has already identified dynamic and time-varying integration between different stock markets, and stock and energy markets. When energy and stock markets are highly integrated there are few diversification benefits to investors. Importantly, during periods of financial market crisis, there is no benefit to investors as markets are highly integrated. Thus, investors need to move beyond simple purchases of stocks and energy assets, to a more active management of their portfolios. We show the cost-saving benefits of a naïve buy-and-hold strategy are easily out-performed by more active portfolio management, which considers the degree of integration between oil and stock markets.

The paper is set out as follows: next in the method section we discuss more fully the literature on financial market integration and how it can be incorporated into the COP21 framework. For brevity, this discussion is not exhaustive and key papers with a detailed literature are mentioned.

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[3] For example, Batten et al. (2017) and Mensi et al. (2017) and the references mentioned therein, amongst others.
[4] This paper does not consider other non-financial assets (e.g. such as housing), but these could also be considered. We thank a conference participant at the 2017 International Symposium on Environment and Energy Finance Issues, IPAG Business School, France for making this point.
[5] Note that while the U.S. is now a net exporter of oil it will likely remain an importer of mostly crude oil and export mostly petroleum products such as gasoline and diesel (EIA, 2017).

Then, in the third section, we introduce and describe the stock and oil market data used in the statistical analysis. The fourth section reports the key results from measuring the degree of integration between oil and various stock market portfolios. The use of a rolling estimation procedure allows the construction of a monthly oil-stock integration index that is reported in annual tables for the various portfolios[6]. The final section allows for concluding remarks.

2. Method

Typically, in econometric studies, investigation of the degree of integration between two financial assets, employs the cointegration framework of Johansen (1991) and Escribano and Granger (1998). This framework has practical limitations. For example, Arouri and Foulquier (2012) question its use due to instability in time series due to economic crisis. Pukthuanthong and Roll (2015) also show that alternatives, such as simple correlations, are a poor measure of market integration. In this paper, we follow the earlier work of BKSW (2017) and use an international asset pricing model that better reflects the time-varying nature of energy stock market integration. The use of a portfolio framework allows measurement of the degree of risk reduction through diversification and importantly allows for assessment of the temporal nature of the integration dynamics. The use of this method underpins our approach for the construction of an integration index that can be practically used by investors to deal with the implementation of COP21.

Originally, Solnik (1977) and Stulz (1981) proposed that in a fully integrated international financial market, in which purchasing power parity holds, the conditional international version of the ICAPM can be expressed as

$$E(R_{it}|\,\mathcal{F}_{t\text{-}1}) - R_{ft} = \delta_{m,t\text{-}1}\, cov(R_{it}, R_{mt}|\,\mathcal{F}_{t\text{-}1}), \tag{1}$$

where R_{it} is the return on asset i, R_{ft} is the risk-free rate, $R_{m,t}$ is the return on the world market portfolio, $\mathcal{F}_{t\text{-}1}$ is the information set available at time t-1 and $\delta_{m,t\text{-}1}$ is the price of world market risk. Energy prices tend to be highly correlated and so for simplicity we consider market risk as being represented by the oil price, which is represented in Equation (1) as m. From a practical point of view oil trades in international markets and has a common, international and arbitrageable price, which by convention is in U.S. dollars per barrel of oil. If our stock market portfolios i, are fully integrated with this oil market portfolio, then local market idiosyncratic risk is fully diversifiable and its associated price is zero.[7] We assume a single world price for oil risk, and so can determine the degree of market integration of each asset i, which is represented by various stock market indices. To estimate the level of overall stock market integration with an individual energy commodity (oil), we set up the regression equation

$$E(R_{it} - R_{ft}) = \varphi\, [\beta_i E(R_{mt} - R_{ft})] + \gamma_i + \varepsilon_{it}, \tag{2}$$

where R_{it}, R_{ft}, and R_{mt} are the monthly returns on the risky asset i, the risk-free asset and the oil portfolio, respectively; i represents the stock market portfolio investigated and t represents time, which is measured at an interval of one month; ε_{it} is the error-term; φ is the regression coefficient of $[\beta_i E(R_{mt} - R_{ft})]$ and γ_i are country-region specific effects. The risk free asset is the monthly return from holding a 1-year U.S. Treasury Bond, for one month, which is the return interval of R_{it}. We use the one year rate since over the sample period of our study some shorter term

[6] We suggest that monthly level tables will be made available on an external website.

[7] See Chi et al. (2006), Jeon et al. (2006), Arouri and Foulquier (2012), Arouri et al. (2012) among many others. As noted by Gerard et al. (2003), the price of market risk is the expected compensation that an investor would receive for taking on a unit of world covariance risk. However, given the likely situation of partial segmentation, then expected returns are a function of both global market risk and non-diversifiable local market risk.

Treasury securities had negative yields.

We follow BKSW (2017) and Model (2), as a two-step estimation methodology. First, we calculate β_i as an estimate of $cov(R_{it},R_{mt})/var(R_{mt})$, where the covariance/variance estimation period is the prior 24 months of returns of R_i and R_m. This approach is consistent with the asset pricing literature and allows an investor to hold a portfolio for two years (i.e. a long-term investor not a speculator, who might only hold a position for a short time period, such as one week). For example, Park and Lee (2011) use a rolling window of eighteen months of stock returns to capture time variation in the covariance structure of a portfolio. Second, based on an *a priori* computed β_i, we estimate the parameters of Model (2) by ordinary least squares for both the complete sample and for a five-year rolling period (i.e. 60-months).

In Model (2), the coefficient φ measures the level of energy market integration, where $\varphi = 0$ indicates no and $\varphi = 1$ full energy market integration. The parameter γ_i accounts for country-region specific effects, as in Chi et al. (2006). Note, if the markets investigated are efficient and highly integrated then γ_i should not be significantly different from zero and φ should be close to one. Autocorrelation is often a common feature of financial market returns and may be present in the excess stock returns of our sample. Due to the presence of autocorrelation in the excess returns ($R_{it} - R_{ft}$) of some of the portfolio assets under investigation, an appropriate autoregressive term was also applied as a robustness check to the regression results.

As in Batten et al. (2015, 2017), we use a restricted version of Equation (2) to establish the presence of a risk adjusted excess return for asset *i*. For this purpose, we restrict $\varphi = 1$. In the restricted case, Equation (2) becomes:

$$E(R_{it} - R_{ft}) - \beta_i\ E(R_{mt} - R_{ft}) = \gamma_i + \varepsilon_{it} \qquad (3)$$

The variable γ_i should equal zero if there is no excess return on a risk adjusted basis (i.e. there is no country-specific pricing error). Note, we do not impose a non-negativity constraint on the integration coefficient (as in Bekaert and Harvey (1995)), although we are mindful of the assumption that investor risk aversion must be positive.

3. Data

We measure oil prices in U.S. dollars from January 1990 to May 2017. There are three main types of oil actively traded in financial markets: Brent, West Texas Intermediate, and the Dubai Fateh. All are measured and traded in U.S. Dollars per Barrel. Monthly prices are sourced from the World Bank. These contracts are highly correlated (BKSW, 2017) and West Texas Intermediate is the most liquid of these contracts with 276.8 million contracts traded in 2016 on the New York Mercantile Exchange, compared with the Brent contract with 210.6 million trading on the ICE Futures Exchange[8].

The stock portfolios comprise the following:
- MSCI Emerging Markets
- MSCI MXWO (Developed Markets)
- MSCI ACWI (Emerging and Developed Markets)
- MSCI Europe
- MSCI G7 Countries (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States)

[8] Source: Futures Industry Association survey data: https://fia.org/

- MSCI Far East (Japan, Hong Kong and Singapore)
- MSCI North America (Canada and the United States)
- S&P 500 (United States only index)

According to the classification by Standard and Poor's (S&P), there are 22 developed countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, the U.K., and the U.S.), and 30 emerging countries (Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Romania, Russian Federation, Slovenia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela).

The MSCI Europe Index represents the performance of large and mid-cap equities across 15 developed countries in Europe (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the U.K.). The Index has a number of sub-Indexes which cover various sub-regions market segments/sizes, sectors and covers approximately 85% of the free float-adjusted market capitalization in each country[9]. The MSCI Far East Index captures large and mid-cap representation across three countries (Japan, Singapore and Hong Kong) and has 392 constituents. The index covers approximately 85% of the free float-adjusted market capitalization in each country. Finally, the monthly return on the 1-Year Treasury Constant Maturity Rate (percent and not seasonally adjusted) is sourced from the Board of Governors of the Federal Reserve System (U.S.) from the H.15 Selected Interest Rates and is used as the risk-free rate when calculating risk adjusted returns[10].

(Insert Table 1 about here)

Key descriptive statistics are reported in Table 1. The statistics are for the full sample period from January 1990 to May 2017. We report statistics for monthly closing prices, P_{it}, and corresponding returns are measured as the difference in the natural logarithm of intermonth prices ($R_{it} = lnP_{it} - lnP_{it-1}$). All risky asset returns (stock markets and oil) display negative skewness, which is a common finding especially for stock markets. In addition, we detect a positive excess kurtosis in all markets, whereas the highest (lowest) value is observed for the MSCI Emerging Markets (3.42) and MSCI Far East (1.16), respectively. Oil returns show higher volatility than stock markets. Nevertheless, oil returns have a positive mean in contrast to the MSCI Far East. Among stock markets the highest (lowest) volatility is documented for the MSCI Emerging Markets (0.0292) and S&P 500 (0.0181), respectively.

(Insert Table 2 about here)

It is also well known that many financial time series display autoregressive properties due to the presence of serial correlation in their return structure. Table 2 reports the results from the application of a first order autoregressive filter to the eight portfolio return series (column one). The coefficient reported in the second column is positive in all cases, but only significant, as noted by the *t-statistic* and its associated *p-value*, for the first three portfolios. This suggests that an additional robustness test should be undertaken for the estimation of the integration index that uses first order filtered returns in addition to the monthly returns. These results are reported later in the paper.

[9] Source: https://www.msci.com/market-cap-weighted-indexes
[10] http://www.federalreserve.gov/

(Insert Table 3 about here)

In addition to serial correlation, Pearson pairwise correlations for all the variables are reported to highlight the difficulty that many investors face when constructing diversified international stock portfolios. First, all pairwise stock portfolio correlations are positive and significant, with the highest correlations between developed country stock market portfolios (e.g. the correlation between the MXWO and the G7 countries is 0.9970), while the lowest correlations were between the Far East and the North American and S&P 500 indices (e.g. the correlation between the Far East and the S&P 500 was 0.5180). The stock portfolios to oil correlations were low but still positive for oil measured both as Brent and WTI, although the correlation between oil and the S&P 500 indices was -full sample- not significant for both WTI and Brent oil, and not significant for the North American and WTI oil. Brent and WTI are both highly positively correlated, which suggests they are effectively price substitutes (except for the North American portfolio case), while U.S. 1-year bond holding periods returns are negatively correlated to stock returns. This last finding is consistent with stocks and bond returns being portfolio substitutes (e.g. investors substitute stocks for bonds in their portfolios when bond yields rise and the reverse when bond yields fall).

(Insert Table 4 about here)

4. Results

Oil-Stock Portfolio Integration Index

The estimation of the integration index between various stock portfolios and the WTI oil price, was estimated from Equation (2) using monthly data. Table 4 reports the results of the full sample Ordinary Least Squares regression, while Tables 5 and 6 report the results from a 60-month (5-year) rolling estimation, with annual averages and standard deviations estimated using an Analysis of Variance (ANOVA) in Table 5 and tests for equal variance in Table 6.

Table 4 also reports three time variables to represent the period from January 1990 to the onset of the Asian Crisis in July 1997; August 1997 to October 2001, which includes the impact of September 11, 2001; November 2001 until September 2008, when Lehman defaulted on September 15, 2008. In each of the regressions the constant was not signficant. The integration coefficients were all significant and positive for all portfolios, with values ranging from 0.5490 for the Far East portfolio to 0.6632 for the North America (NA) portfolio. The Adjusted R^2 were all less than 10%.

The time variables were generally not signficant, with the exception of time period 2 for the Emerging Markets (EM) and Far East portfolios, where they were both negative and significant. In both cases the negative coefficients, would have reduced the level of integration, thereby offering investors the opportunity to hedge some of their stock market declines (due to the crisis periods) by holding oil assets. In addition to the time variables, the regressions for the EM, MXWO and ACWI portfolios were also restimated with AR(1) filtered returns to accomodate the autoregressive properties dsecribed in Table 2. In all three cases the integration coefficent was slightly reduced by including the AR(1) terms, although they all reamined significant.

(Insert Tables 5 and 6 about here)

Tables 5 and 6 report the annual average and standard deviation of the integration index between various stock portfolios and the WTI oil price, estimated from Equation (3) using monthly data.

There is only one year (2007) where we detect a negative index value for all markets. The reason is that the beginning of the GFC from August 2007 influenced all global stock markets, although oil market prices remained resilient against the negative stock market trend until July 2008. The markets with the highest (lowest) number of negative index values are Europe (11) and Far East (5), respectively. A possible reason why stock markets in the Far East show a positive integration coefficient is their economies are important locations for crude oil processing. Another interesting finding for the Far East it that during the GFC (year 2007 and 2008) the integration coefficient has the lowest standard deviation among all markets.

Asset Allocation Strategy

Finally, we determine if the information provided by the integration index φ_t can be used as part of an asset allocation strategy, where the investor reallocates their portfolio every month t. The final Table 7 reports the results for two different scenarios: Panel A consists of results for a passive strategy with 100% investment in a single market without considering the integration between stock markets and WTI oil. In contrast, Panel B represents the situation where x_t% is invested in a stock market and (1-x_t)% in WTI oil. The time-varying weight x_t is determined by the level of WTI-stock market integration, whereas the weight x_t is restricted to $0 \leq \varphi_t \leq 1$. The portfolio weights are updated monthly using the monthly integration index φ_t. The sample period is from November 1994 to May 2017 (271 months) and all results are based on excess returns estimated from Equation (3).

(Insert Table 7 about here)

We find that without considering information from the integration index all portfolios – except for the MSCI Far East – have a positive mean. Based on the Sharpe ratio (SR) we detect the best performance for the S&P 500 (SR = 0.0982) and the weakest one for the MSCI Far East (SR = -0.0009). The consideration of WTI-stock market integration offers some important benefits for investors. We detect for all markets an increase of the SR, where the greatest benefit is for the MSCI G7 countries (SR = 0.0427) and the lowest one is for the S&P 500 (SR = 0.0009). Furthermore, Panel B shows that the best asset allocation strategy is MSCI North America in combination with WTI (SR = 0.1084). However, there is no change for the weakest portfolio. The MSCI Far East combined with WTI yields now a positive but very low SR of 0.0065.

5. Conclusion

The paper shows that under normal market conditions stock and oil markets are segmented. This provides an opportunity for oil investors to diversify the additional energy price risk, caused by COP21, through the purchase of stocks. Generally, in the full sample, investors receive positive risk adjusted positive benefits from holding oil-stock portfolios. The exception is the Far East stock portfolio that comprises the Japanese, Hong Kong and Singapore stock markets, with the latter two countries being major financial centres, although they are also important locations for crude oil processing.

In conclusion, the use of the integration relation between oil and stock markets allows the hedging of energy price risk. Nonetheless, there is an important caveat, due to the unpredictable nature of the impacts that can arise from both demand and supply shocks. The recent technological developments that have enabled horizontal drilling and fracking also highlight potential challenges to price prediction. One key implication of these results in the importance of policymakers to monitor financial system impacts in the form of price stress testing that is currently undertaken in the banking sector, to better monitor the transition from a carbon-intensive to a low-carbon industry. These tests could be based upon the expected temperature increase, the subsequent amount of (carbon dioxide) CO^2 emissions, the degree of time-varying energy market integration, and the additional cost of being "green". Based on our findings we could say that the systemic risk induced by decarbonisation is expected to be higher in times of high energy market integration compared to periods of market segmentation.

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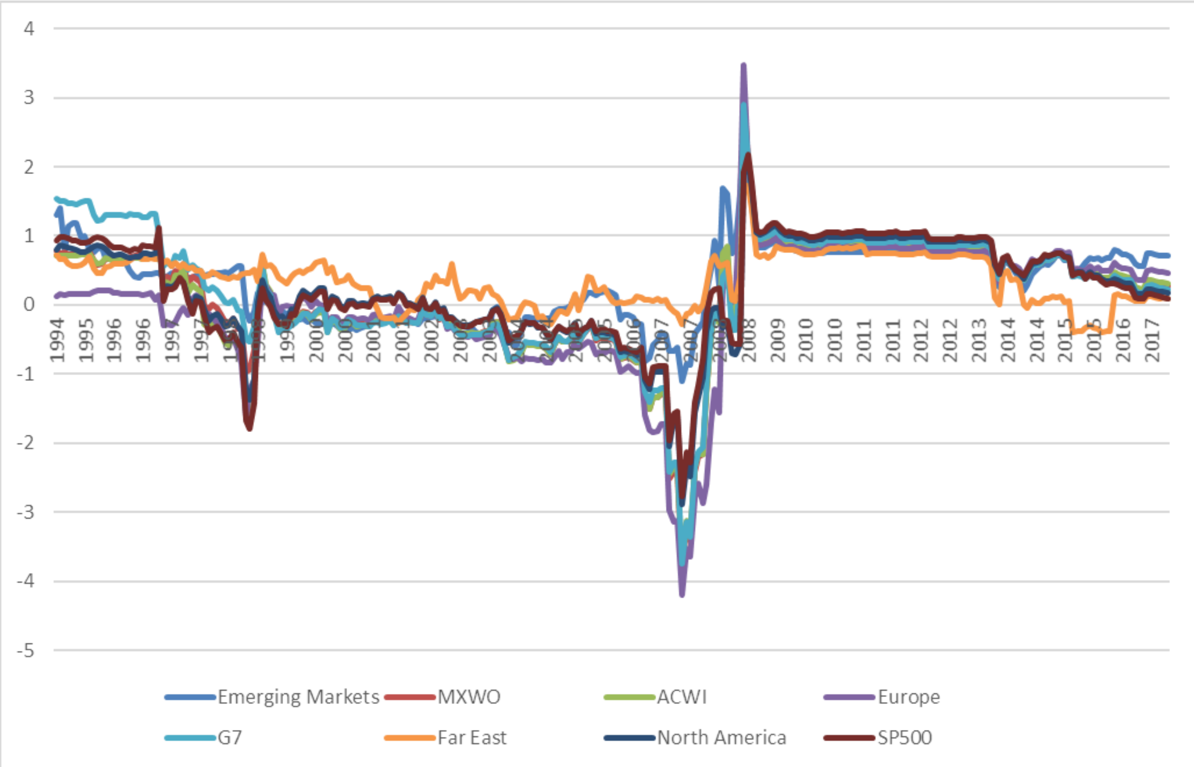
Figure 1: 5-Year Integration Index of Various Stock Market Portfolios to WTI-Oil



Notes: The Figure plots the monthly degree of integration between various stock portfolios and WTI-Oil estimated from November 1994 to May 2017. The Figure clearly shows one very important finding that all markets show an almost perfect level of integration (this is approx. 1) with WTI from 2008 - 2013. This period is exactly when the Fed performed "Quantitative Easing (QE)", which started on late November 2008 and ended when Bernanke announced on September 2013 a cut-back of the Fed's QE programme. As a result, QE lead to a near perfect and stable level of integration of all markets, regardless whether emerging or developed, or combinations thereof.

Table 1: Descriptive Statistics

Variable (Levels)	N	Mean	StDev	Minimum	Maximum	Skewness	Excess Kurtosis
EM	329	622.8000	302.7000	179.0000	1337.4000	0.3900	-1.2800
MXWO	329	1090.6000	387.1000	423.1000	1878.3000	0.0500	-1.0200
ACWI	329	268.7000	95.0800	104.2800	455.1700	0.0400	-1.0900
Europe	329	1183.4000	439.4000	447.0000	2235.4000	-0.0300	-0.8500
G7	329	965.1000	337.4000	384.3000	1691.1000	0.1000	-0.9500
Far East	329	2693.5000	502.6000	1472.5000	3892.3000	-0.2300	-0.7000
North America	329	1158.9000	527.4000	311.7000	2411.5000	0.2300	-0.6000
S&P 500	329	1123.0000	510.0000	304.0000	2384.2000	0.2900	-0.4700
WTI	329	46.7300	30.3100	11.2800	133.9300	0.7900	-0.6300
Brent	329	47.6600	33.9100	9.8200	132.7200	0.8700	-0.5700
1-Year U.S. Bond	329	3.1350	2.3940	0.1000	8.4000	0.1400	-1.3100
Variable (Returns)							
R_EM	329	0.0020	0.0292	-0.1505	0.0669	-1.0400	3.4200
R_MXWO	329	0.0016	0.0188	-0.0918	0.0450	-0.8400	2.0800
R_ACWI	329	0.0016	0.0192	-0.0964	0.0472	-0.8800	2.3500
R_Europe	329	0.0015	0.0219	-0.1041	0.0537	-0.8000	1.9700
R_G7	329	0.0015	0.0186	-0.0883	0.0439	-0.7900	1.8400
R_Far East	329	-0.0003	0.0246	-0.0898	0.0913	-0.1100	1.1600
R_North America	329	0.0025	0.0183	-0.0865	0.0445	-0.8200	2.0100
R_S&P 500	329	0.0025	0.0181	-0.0806	0.0459	-0.7800	1.8000
R_WTI	329	0.0010	0.0371	-0.1462	0.1638	-0.3100	2.0100
R_Brent	329	0.0011	0.0397	-0.1351	0.1993	-0.1700	2.4100
R_1-year U.S. Bond	329	0.0009	0.0021	-0.0037	0.0086	0.7600	0.8900

Notes: The Table reports the descriptive statistics (mean, standard deviation (StDev), minimum, Maximum, Skewness and excess kurtosis) of the key variables investigated in the study. The top panel reports levels, while the bottom panel reports returns. The Emerging Market (EM), Developed countries (MXWO), Developed and Emerging (ACWI), Europe, G7, Far East, and North America are all MSCI stock index portfolios. The MSCI index portfolios and the Standard & Poor's (S&P) 500 index are priced in U.S. dollars. West Texas Intermediate (WTI) and Brent are oil prices expressed in U.S. dollars. The 1-year U.S. Bond is the yield of a 1-year U.S. Treasury bond. The bottom panel reports the returns on these prices. The sample period is from January 1990 to May 2017.

Table 2: Stock Portfolio Autoregressive Properties

Variable (Returns)	AR(1) Coefficient	t-statistic	p-value
R_EM	0.1665	2.99	0.003
R_MXWO	0.0920	1.65	0.099
R_ACWI	0.0993	1.79	0.075
R_Europe	0.0915	1.64	0.101
R_G7	0.0858	1.54	0.124
refers East	0.0904	1.63	0.105
R_North America	0.0608	1.09	0.275
R_S&P 500	0.0528	0.95	0.343

Notes: The Table reports the first order autoregressive (AR(1)) properties of each index portfolio. Only the Emerging Markets (EM), MXWO and the combined ACWI portfolios had statistically significant AR(1) coefficients. This information is later used as a robustness test for construction of the integration index.

Table 3: Pearson Correlations of Variables

	R_EM	R_MXWO	R_ACWI	R_Europe	R_G7	rare East	R_North America	R_S&P 500	R_WTI	R_Brent
R_MXWO	0.7700									
p-value	0.0000									
R_ACWI	0.8050	0.9980								
p-value	0.0000	0.0000								
R_Europe	0.7230	0.9220	0.9230							
p-value	0.0000	0.0000	0.0000							
R_G7	0.7460	0.9970	0.9920	0.8980						
p-value	0.0000	0.0000	0.0000	0.0000						
R_Far East	0.5880	0.7560	0.7550	0.5990	0.7630					
p-value	0.0000	0.0000	0.0000	0.0000	0.0000					
R_North America	0.7170	0.9170	0.9140	0.8110	0.9210	0.5230				
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000				
R_S&P 500	0.7000	0.9130	0.9080	0.8060	0.9170	0.5180	0.9970			
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
R_WTI	0.1880	0.1460	0.1560	0.1750	0.1370	0.1220	0.0870	0.0670		
p-value	0.0010	0.0080	0.0040	0.0010	0.0130	0.0270	0.1140	0.2230		
R_Brent	0.2210	0.1630	0.1760	0.1920	0.1540	0.1440	0.1040	0.0850	0.9400	
p-value	0.0000	0.0030	0.0010	0.0000	0.0050	0.0090	0.0600	0.1230	0.0000	
R_1-year U.S. Bond	-0.1830	-0.1780	-0.1790	-0.1410	-0.1800	-0.1980	-0.1410	-0.1360	-0.1260	-0.1180
p-value	0.0010	0.0010	0.0010	0.0100	0.0010	0.0000	0.0110	0.0140	0.0220	0.0320

Notes: The table reports the pairwise Pearson correlations and associated p-values for the variable returns for the full sample period from January 1990 to May 2017. All correlations are positive and significant except for the returns on the 1-year U.S. bond, where the pairwise correlations are all negative and significant. This suggests that in the full sample, an increase (decrease) in the bond price resulted in a decrease (increase) in stocks. This is consistent with bonds and stocks been investment substitutes. The highest stock market correlations were between the developed country stock indices (e.g. MXWO: G7 was 0.9970), whereas the lowest were between the Far East and the U.S. S&P 500 index (0.5160). Brent and WTI were also highly correlated at 0.9400.

Table 4: Oil-Stock Integration Regressions

EM	Coefficient	SE	t-statistic	p-value		**MXWO**	Coefficient	SE	t-statistic	p-value		**ACWI**	Coefficient	SE	t-statistic	p-value
Constant	0.0002	0.0028	0.0800	0.9380		Constant	0.0015	0.0018	0.8600	0.3890		Constant	0.0013	0.0018	0.7100	0.4780
φ	0.5741	0.1357	4.2300	0.0000		φ	0.6057	0.1472	4.1100	0.0000		φ	0.6496	0.1457	4.4600	0.0000
T1	0.0035	0.0044	0.8000	0.4250		T1	0.0023	0.0028	0.8100	0.4180		T1	0.0013	0.0029	0.4500	0.6500
T2	-0.0084	0.0049	-1.7300	0.0850		T2	-0.0008	0.0031	-0.2700	0.7840		T2	-0.0028	0.0032	-0.8600	0.3880
T3	0.0060	0.0042	1.4300	0.1540		T3	0.0004	0.0026	0.1400	0.8900		T3	0.0003	0.0028	0.1100	0.9110
AR^2	0.0710					AR^2	0.0450					AR^2	0.0560			
Europe						**G7**						**Far East**				
Constant	-0.0001	0.0021	-0.0400	0.9700		Constant	0.0016	0.0018	0.9200	0.3590		Constant	0.0008	0.0023	0.3300	0.7400
φ	0.6298	0.1480	4.2600	0.0000		φ	0.6596	0.1548	4.2600	0.0000		φ	0.5490	0.1949	2.8200	0.0050
T1	0.0031	0.0033	0.9300	0.3530		T1	0.0008	0.0028	0.2700	0.7860		T1	-0.0008	0.0036	-0.2100	0.8340
T2	-0.0007	0.0037	-0.2000	0.8390		T2	-0.0025	0.0031	-0.8000	0.4250		T2	-0.0069	0.0039	-1.7600	0.0790
T3	0.0022	0.0032	0.6900	0.4920		T3	-0.0006	0.0027	-0.2200	0.8230		T3	0.0006	0.0034	0.1800	0.8560
AR^2	0.0500					AR^2	0.0490					AR^2	0.0260			
NA						**S&P500**										
Constant	0.0024	0.0018	1.3200	0.1860		Constant	0.0026	0.0018	1.4500	0.1490						
φ	0.6632	0.1594	4.1600	0.0000	φ	φ	0.6439	0.1694	3.8000	0.0000						
T1	0.0016	0.0028	0.5600	0.5790		T1	0.0014	0.0028	0.4900	0.6230						
T2	-0.0020	0.0031	-0.6400	0.5240		T2	-0.0021	0.0031	-0.6800	0.4970						
T3	-0.0016	0.0027	-0.5900	0.5580		T3	-0.0020	0.0027	-0.7600	0.4500						
AR^2	0.0490					AR^2	0.0400									

Notes: The Table reports the full sample period (January 1990 to May 2017) Ordinary Least Squares regression of Equation (2). φ is the integration coefficent, T1, T2 and T3 are dummy variables for the period from January 1990 to the onset of the Asian Crisis in July 1997; August 1997 to October 2001, which includes the impact of September 11, 2001; November 2001 until September 2008, when Lehman defaulted on September 15, 2008. AR^2 represents the Adjusted R-squared of the regression.

Table 5: Oil-Stock Portfolio Integration Index (Annual Average)

Level	N	EM	MXWO	ACWI	Europe	G7	Far East	NA	S&P 500
1995	12	0.9105	0.7023	0.6886	0.1774	1.3958	0.5693	0.8099	0.9361
1996	12	0.5047	0.7041	0.6870	0.1503	1.2793	0.6453	0.7408	0.8496
1997	12	0.4208	0.3380	0.2086	-0.1144	0.5428	0.5389	0.1365	0.0780
1998	12	0.3065	-0.3516	-0.6629	-0.6803	-0.0581	0.4266	-0.4701	-0.7232
1999	12	-0.0983	-0.0783	-0.0733	0.0715	-0.1097	0.4832	0.0294	-0.0614
2000	12	-0.3051	-0.2117	-0.2441	-0.1399	-0.2222	0.4548	0.0839	0.0452
2001	12	-0.2277	-0.2466	-0.2467	-0.1625	-0.2583	-0.0502	0.0793	0.0567
2002	12	-0.2238	-0.2117	-0.2012	-0.1805	-0.2112	0.2488	-0.0541	-0.0745
2003	12	-0.2909	-0.3946	-0.3905	-0.4502	-0.4129	0.1364	-0.2198	-0.2320
2004	12	-0.2787	-0.6472	-0.6610	-0.7874	-0.6240	-0.1329	-0.3865	-0.3733
2005	12	0.0778	-0.4549	-0.4398	-0.6443	-0.4368	0.1123	-0.3514	-0.3390
2006	12	-0.2407	-0.8723	-0.8608	-1.0831	-0.8234	0.0685	-0.7254	-0.6747
2007	12	-0.5951	-2.3795	-2.3253	-2.8443	-2.2847	-0.0541	-1.6548	-1.5243
2008	12	1.1869	0.5176	0.5437	0.1890	0.4388	0.7266	0.2107	0.3550
2009	12	0.8405	0.9473	0.9282	0.8711	0.9724	0.7615	1.0418	1.0890
2010	12	0.7586	0.8901	0.8679	0.8222	0.9113	0.7821	0.9693	1.0271
2011	12	0.7604	0.8987	0.8773	0.8342	0.9174	0.7671	0.9815	1.0444
2012	12	0.7449	0.8641	0.8465	0.7956	0.8838	0.7219	0.9485	1.0014
2013	12	0.6503	0.7682	0.7511	0.7003	0.7877	0.5874	0.8557	0.8976
2014	12	0.4874	0.5657	0.5562	0.5988	0.5557	0.1894	0.5797	0.6050
2015	12	0.6295	0.5422	0.5502	0.6211	0.5279	-0.1702	0.5652	0.5480
2016	12	0.6851	0.3370	0.3699	0.4861	0.3116	-0.0202	0.2907	0.2290
2017	5	0.7228	0.2958	0.3367	0.4799	0.2535	0.1031	0.1986	0.1188
Average		0.3657	0.1370	0.1175	-0.0062	0.2444	0.3580	0.2287	0.2432
F-Statistic		69.6600	59.3400	56.9000	42.7900	71.3300	36.1800	57.1400	59.2200
p-value		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The Table reports the average annual integration index between various stock portfolios and the WTI oil price, estimated from Equation (3) using monthly data. The *F-statistic* is a test of differences in annual averages and is significant for all portfolio combinations. The sample period is from January 1990 to May 2017. Only data from 1995 is reported since the earlier years of data was used for the index construction. 1994 consisted of only two months of data and so is not reported. Only five months of 2017 data was available at the time of estimation.

Table 6: Oil-Stock Portfolio Integration Index (Annual Standard Deviation)

Level	N	EM	MXWO	ACWI	Europe	G7	Far East	NA	S&P 500
1995	12	0.1814	0.0682	0.0474	0.0282	0.1124	0.0666	0.0399	0.0376
1996	12	0.0946	0.0539	0.0667	0.0244	0.0816	0.0394	0.0788	0.0865
1997	12	0.0191	0.1923	0.2650	0.1589	0.1687	0.0727	0.1786	0.2249
1998	12	0.2874	0.3292	0.4718	0.4406	0.2596	0.0461	0.4724	0.5675
1999	12	0.1068	0.2669	0.2852	0.1323	0.2821	0.1124	0.1877	0.1819
2000	12	0.0524	0.0940	0.0932	0.1150	0.1037	0.1323	0.1020	0.0925
2001	12	0.0657	0.0400	0.0528	0.0572	0.0432	0.1940	0.0563	0.0620
2002	12	0.0424	0.0903	0.0887	0.1294	0.0977	0.1977	0.0958	0.0943
2003	12	0.1428	0.0881	0.0919	0.0716	0.0857	0.1003	0.0950	0.0922
2004	12	0.1636	0.0871	0.0929	0.0291	0.0930	0.1112	0.0991	0.0953
2005	12	0.0999	0.0877	0.0907	0.0785	0.0844	0.1903	0.0600	0.0493
2006	12	0.3401	0.3407	0.3526	0.4246	0.3134	0.0417	0.2550	0.2448
2007	12	0.2513	0.8256	0.7910	0.7804	0.8249	0.1065	0.6537	0.6460
2008	12	0.7180	1.2201	1.2131	1.7620	1.1822	0.5839	1.0310	1.0104
2009	12	0.0536	0.0485	0.0493	0.0486	0.0501	0.0537	0.0572	0.0573
2010	12	0.0110	0.0263	0.0239	0.0320	0.0250	0.0429	0.0219	0.0257
2011	12	0.0070	0.0165	0.0138	0.0164	0.0181	0.0476	0.0136	0.0144
2012	12	0.0131	0.0332	0.0291	0.0369	0.0348	0.0237	0.0375	0.0495
2013	12	0.1708	0.1694	0.1687	0.1579	0.1701	0.2521	0.1656	0.1698
2014	12	0.1278	0.0895	0.0943	0.0808	0.0908	0.1945	0.1063	0.1019
2015	12	0.0762	0.1480	0.1390	0.1257	0.1479	0.2309	0.1430	0.1571
2016	12	0.0802	0.0819	0.0841	0.0795	0.0829	0.2214	0.0859	0.0917
2017	5	0.0149	0.0213	0.0205	0.0174	0.0232	0.0116	0.0248	0.0289
Average		0.1330	0.1848	0.1931	0.2019	0.1833	0.1296	0.1710	0.1761
Levene's Test		11.4200	9.4300	10.7700	12.5700	8.2800	4.5200	6.4900	7.6300
p-value		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The Table reports the standard deviation of the annual integration index between various stock portfolios and the WTI oil price estimated from Equation (3) using monthly data. Given non-normality in the underlying return series the Levene's-statistic is used to test equality of variance and is significant (unequal) for all portfolio combinations. The sample period is from January 1990 to May 2017. Only data from 1995 is reported since the earlier years of data was used for the index construction. 1994 consisted of only two months of data and so is not reported. Only five months of 2017 data was available at the time of estimation.

Table 7: Asset Allocation Strategy

	Panel A: Results without Integration			*Panel B: Results with Integration*			*Difference Panel B–A*		
Panel A: Results for individual Markets without Integration	Mean	SD	SR	Mean	SD	SR	Mean	SD	SR
MSCI Emerging Markets	0.000089	0.029987	0.0030	0.000981	0.030573	0.0321	0.000892	**0.000586**	0.0291
MSCI MXWO (Developed Markets)	0.001005	0.019376	0.0519	0.002549	0.028544	0.0893	0.001544	0.009168	0.0374
MSCI ACWI (Emerging and Developed Markets)	0.000930	0.019830	0.0469	0.002434	0.028624	0.0850	0.001504	0.008794	0.0381
MSCI Europe	0.000796	0.022683	0.0351	0.001880	0.029943	0.0628	0.001084	0.007260	0.0277
MSCI G7 Countries	0.001027	**0.018950**	0.0542	0.002740	**0.028268**	0.0969	**0.001713**	0.009318	**0.0427**
MSCI Far East	-0.000888	0.022271	-0.0009	0.000185	0.028639	0.0065	0.001073	0.006368	0.0074
MSCI North America	0.001865	0.019336	0.0968	**0.003084**	0.028433	**0.1084**	0.001219	0.009097	0.0116
S&P 500 (U.S. only)	**0.001871**	0.019059	**0.0982**	0.003074	0.028678	0.1072	0.001203	0.009619	0.0009
WTI Oil	0.000963	0.037137	0.0259	-	-	-	-	-	-

Notes: This Table reports the mean, the standard deviation (SD) and the Sharpe Ratio (SR) for different trading strategies with no transaction costs. The Sharpe Ratio is a measure for calculating risk-adjusted return, and is the average return earned in excess of the risk-free rate divided by the standard deviation of return on an investment. Panel A consists of results for a passive strategy with 100% investment in a single market without considering the integration between stock markets and WTI oil. Panel B represents the situation where x_t% is invested in a stock market and (1-x_t)% in WTI oil. The time-varying weight x_t is determined by the level of WTI-stock market integration, whereas the weight x_t is restricted to $0 \leq \varphi_t \leq 1$. The parameter φ_t is the time-varying level integration. Bold values mark the best value within each group, i.e. the highest mean, the lowest SD and highest SR. The sample period is from November 1994 to May 2017 (271 months) and all results are based on excess returns.

Oil Prices and Geopolitical Risk: A Frequency and Time-varying Analysis

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Abstract

This paper firstly investigates the frequency- and time-varying co-movement and causal relationship between oil prices (proxied by West Texas Intermediate, Brent, Dubai and Nigerian Forcados oil crude price) and international geopolitical risk based on wavelet analysis over the period 1985-2016. Overall, our results demonstrate significant dynamic co-movement and causality in the varying time-frequency domain. We find high degree of co-movement between international geopolitical risk and oil prices at high frequencies (short run) for the entire sample period, however, such correlation no longer exists at low frequencies (long run) for most of the time. Our results are also robust to controlling for global economic outlook. Our findings provide valuable implications for policy makers and oil market investors based on the information of geopolitical risk and its dynamic relationships with oil prices; in particular, most of oil-producing countries are located in sensitive geopolitical areas.

Keywords: Oil Price, Wavelet Coherence, Phase-Difference, Time-Frequency Domain, Geopolitical Risk.

1. Introduction

Understanding the fluctuation of crude oil prices is vital due to its close relationship with the macro economy and the performance of other markets.[11] Previous studies have studied the various determinants of oil prices (e.g., Benhmad, 2012; Mu and Ye, 2011; Tiwari et al., 2013; Wang and Sun, 2017). Among these factors, a critical one is geopolitical risk (Naccache, 2011; Speight, 2011; Noguera-Santaella, 2016), which also attracts considerable attention from both academic economists and policy makers. Political unrest and terrorist attacks, if not civil or international wars, are common phenomena that historically plagued many nations in the world. Major geopolitical events are often perceived to result in dramatic changes in the business cycle and in financial markets (Greenspan, 2002; Carney, 2016; Berkman et al., 2011). There is an increasing body of literature analyzing the nature of geopolitical risks, particularly conflicts, and their relation to economics (Skaperdas, 2008). Yet, up so far, the literature of oil prices and geopolitical risks are largely developed in a parallel fashion. The interaction between the two has not been addressed. This paper attempts to reduce this gap in literature.

As a threat to the market volatility, geopolitical risk is critical in explaining oil market behaviors. The reason is that it can alter investors' expectation on the market condition both in the short run and long run. On the one hand, as an immediate response, investors may anticipate a higher likelihood of supply disruption or sharp change in demand in the near future. This would lead to fluctuations in oil prices in the short run even though such changes do not eventually occur (Noguera-Santaella, 2016). On the other hand, geopolitical risks may have lasting effects on the stability of the contracting frameworks, business governance and market regulation, which all rely on political and socio-economic stability to be effective (Van der Linde et al., 2004). Accordingly, investors may be suspicious about oil market outcomes over a longer horizon due to uncertainty. Such pessimism may last in the long run unless geopolitical risks are reconciled by outside interventions.[12] In sum, information of geopolitical risks should be absorbed and reflected in oil prices.

Causation may also run from oil prices to geopolitical risks. Oil is commonly conjectured as a resource to trigger conflict (Caselli et al., 2015). Historical and political scientist have identified a potential role for oil riches in dozens of (often militarized) territory claim tensions, border disputes or even wars.[13] This relates to the phenomenon of "resource curse": natural resource abundance magnifies the risk of conflict. A large body of economic theoretical literature has identified multiple channels through which it occurs, which are nicely

[11] For the analyses between crude oil prices and macroeconomic performances, see Hamilton (1983), Mork (1989), Lee et al. (1995), Hamilton (1996), Hamilton (2003), Killian (2008), Elder and Serletis (2010), Aguiar-Conraria and Soares (2011), Rahman and Serletis (2011), Naccahe (2011), etc. For the relation between oil prices and other markets, previous researchers typically investigate this issue by looking into stock returns. For this strand of literature, see Jones and Kaul (1996), Lee et al. (2012), Asteriou and Bashmakova (2013), Gupta and Modise (2013), Cunado and Perez de Gracia (2014), Narayan and Gupta (2015), etc. Please refer to Ramos and Veiga (2011) for a more thorough survey.

[12] De Soysa, Gartzke and Lie (2011) demonstrate that oil-importing superpowers like the U.S. have the incentive to protect oil-rich countries such that major petrostates may be less likely to suffer from conflicts due to oil predation. If true, it implies that the long-term impact of geopolitical risks, at least that around major oil-producing arears, largely diminishes.

[13] Examples of militarized tensions involving territorial claims include areas in the South China Sea, the East China Sea and the border between Sudan and South Sudan, etc. Examples of border disputes include those between Nigeria and Cameroon (Bakassi peninsula), Ecuador and Peru (Cordillera del Condor), China and Vietnam (Paracel Islands), etc. Examples of wars include the Iran-Iraq war, Iraq's invasion of Kuwait and the Falklands War, etc. For references of these conflicts as well as others, please see Caselli et al. (2015).

summarized by Berman et al. (2017). Channels for large-scale conflicts under the context of geopolitical risks relevant for the current study may include: (1) presence of natural resources increases the prize to be seized through the capture of the territory or the state; (2) obtaining natural resources enhances rebellion feasibility by relaxing financing constraints of the set-up and sustainment of a rebel movement; (3) resource wealth makes rentier states rely on resource rents and not develop state capacity and institutions, making them less effective in counterinsurgency; (4) cheap labor is freed up if resource price spikes lead to the boost of capital-intensive resource extracting and therefore shrink labor-intensive sectors.[14] Resource price spikes, which increase resource wealth, would facilitate the above channels through which resource abundance raise conflict risk (e.g., Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman et al., 2017). In sum, variations in oil prices may affect geopolitical risks.

Perhaps one important reason for a lack of literature on the interaction between geopolitical risk and oil prices is the difficulty to find a reliable measure for geopolitical risk. We exploit a new data set to investigate this issue: the Geopolitical Risk Index (henceforth, GPR index), constructed by Caldara and Iacoviello (2017), which is the first data to measure geopolitical risk comprehensively and objectively. The authors define geopolitical risk as the risk associated with wars, terrorist acts and tensions between states that affect the normal course of domestic politics and international relations. The GPR index incorporates both pure geopolitical risks (e.g., military-related tension, nuclear tension, war and terrorist threats) and actual geopolitical events (as opposed to just risks, e.g., the beginning of a war, terrorist acts), therefore representing a comprehensive measure of geopolitical uncertainty. The quantitative index is available from 1985 to 2016, and is constructed by counting the occurrence of words regarding geopolitical tensions in leading international newspapers.[15] As for oil prices, we use the West Texas Intermediate (WTI) crude oil spot price for our benchmark analysis, which is commonly used in the previous literature. We also exploit the Brent, Dubai and Nigerian Forcados crude oil spot prices to check for robustness of our results.

We utilize a novel wavelet analysis technique to explore the relationship between the GPR index and each of the 4 crude oil prices.[16] Wavelet analysis expands the time series into a time-frequency space whereby researchers can visualize both time- and frequency-varying information of the series in a highly intuitive way.[17] In contrast, conventional time-domain methods (e.g, cointegration analysis and vector correction model), which leave out the frequency-domain, fail to capture useful and important information under the analysis of oil prices because the relations between oil and macroeconomic variables may vary at different frequencies (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Benhmad, 2012; Tiwari et al., 2013).[18] In our case, although it is reasonable to think that oil prices and geopolitical risk

[14] Other channels through which natural resource abundance facilitates smaller-scale conflicts or violence (not the focus of the current study) include: (1) exacerbated grievances due to frustrations from environmental degradation or banned access to lucrative mining jobs; and (2) changes in the size and composition of population in mining areas due to migration under mining booms. For a literature review of these channels, see Berman et al. (2017).
[15] Such methodology is pioneered by Saiz and Simonsohn (2013) and Baker et al. (2016).
[16] The methodology has been commonly applied in oil market analysis in previous literature (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Benhmad, 2012; Vacha and Barunik, 2012; Tiwari et al., 2013; Lee and Chang, 2015).
[17] Frequency in wavelet analysis implies the different relationships between variables at different time scales.
[18] For instance, Naccache (2011) demonstrates that oil prices may act like a supply shock at high and medium frequencies (in the short and medium run), therefore affecting industrial production, whereas industrial production affects oil prices at lower frequencies (in the longer run) through a demand effect.

are correlated at high frequencies, the co-movement at low frequencies is ambiguous since oil-importing superpowers have incentives to intervene and eventually reconcile geopolitical risks, particularly those around major oil-exporting regions. Thereby, wavelet analysis is superior in the sense that it allows us to catch the dynamic relationship between geopolitical risk and oil price across different time and frequencies for advanced investigation.

Such attractiveness of wavelet analysis sheds light on practical recommendations for energy commodity management. Oil markets are comprised of investors with different time horizons (Ellen and Zwinkels, 2010). Meanwhile, since most oil-producing countries are located in sensitive geopolitical areas, the geopolitical risk information is vital for business strategies in the oil markets. Decomposing data into time scales, wavelet analysis thus provides useful insight on the relative importance of geopolitical information for heterogenous agents with different time horizons and effective combinations of financial products of different maturity terms for risk diversification (Chang et al., 2015). The time- and frequency-varying features in causality can also significantly improve price prediction accuracy and decision-making process.

Our empirical works begin with tests for the GPR index and oil prices for unit roots and cointegration. After providing the presence of unit roots and cointegration relationships, we perform the wavelet coherency analysis to investigate the dynamic co-movement between crude oil prices and the GPR index across different time periods and frequencies, and the phase-difference technique to derive the time-varying causal relationship between the two. In this way, we can observe high-frequency (short-term) and low-frequency (long-term) relationships between the crude oil prices and the GPR index as well as possible structural breaks and time variations. For robustness check, we also apply the partial wavelet coherency and partial phase difference to account for the effects of global economic outlook (proxied by the GDP growth forecast of the world economy) on geopolitical risk and oil prices, aiming to reveal the true co-movement and causality between the two variables. Overall, for all 4 oil price indexes, we find high degree of co-movement between international geopolitical risk and oil prices at high frequencies (wavelet scale of less than 2 years), whereas the co-movement becomes weak at low frequencies. We identify a structural break in the relationship after 2010 where the two variables also comoves at low frequencies. As for the (partial) phase difference analyses, interestingly, we observe different patterns across different oil price indexes. Generally, geopolitical risk positively contributes to oil prices for WTI and Brent index. On the other hand, we mainly find that oil prices positively contribute to geopolitical risks for Dubai and Nigerian index.

Our findings provide important policy implications in several aspects. First, geopolitical risk information is particularly relevant for short-term oil market investors (e.g., arbitragers or speculators) with a horizon less than 2 years. Our results suggest that they should keep a close eye on geopolitical risk and exploit its variations to improve oil price forecast accuracy and make more effective investment decisions. Specifically, short-term investors in the WTI and Brent market should consider adding more assets of oil to gain profits when geopolitical risk rises. Second, policy makers, particularly those in major oil-importing countries, should be alerted about national energy security in front of increasing geopolitical risk and engage adequate efforts to prevent it from escalating to a serious level. Third, since oil prices all move in phase with geopolitical risk in all 4 major markets, there seems to be no room for hedging and risk diversification across different oil markets purely based on geopolitical risk. Fourth, based on evidence of positive effects of oil prices on geopolitical risks in the Dubai and

Nigerian market, we also emphasize the importance for policy makers to understand the channel through which oil price spikes leads to higher geopolitical risk. In sum, our results help investors and policy makers have a deeper understanding about oil price fluctuations and business strategies based on common and yet critical information: geopolitical risk, which is a perspective that has been largely unknown.[19]

To our best knowledge, the only study that specifically attempts to investigate geopolitical risks and oil prices is Noguera-Santaella (2016).[20] The author examines the effects on oil prices of 32 geopolitical events including revolutions, civil and international wars and conflicts. Our study improves in several aspects. First, rather than discrete dummy variables for limited actual conflicts, we take advantage of a better and more comprehensive measure of geopolitical risk which incorporates not only actual events such as terrorist activities and wars between states, but also the potential of adverse events such as inter-state tensions or disputes. This makes our study more relevant for usual decision-making for investors in oil market. Second, compared to the static analysis employed in Noguera-Santaella (2016), we investigate the dynamic relationship between geopolitical risk and oil prices in time- and frequency-domain, providing more precise investment strategy recommendations for oil market participants at different time horizons. Third, Noguera-Santaella (2016) only considers the effects of geopolitical events on oil prices, whereas we also consider the reverse causality. Fourth, the paper applies the ARMA and GARCH techniques, which may easily suffer from problems such as unit root and instability of variables. If true, this would invalidate the empirical results. Finally, the paper only uses the WTI oil prices, while we provide extra robustness checks by comparing 3 additional spot crude oil prices and observe different patterns in the relationship. Our study also relates to a considerable body of empirical literature documenting evidence that the oil abundance can result in conflicts.[21] Some of the studies take advantage of oil price spikes to examine the impact of a rise in oil revenue on the occurrence or intensity of conflicts. However, the vast majority of them focus only on civil conflicts or small-scale violence. As an exception, Caselli et al. (2015) analyzes the nexus between the location of oil fields and interstate wars. We extend the horizon to large-scale international geopolitical risk and link it to oil prices.

Our study contributes to the literature in several aspects. First, we firstly investigate the interaction between oil prices and the true geopolitical risk, proxied by a comprehensive index that covers not only breakouts of geopolitical events but also risks indicating higher likelihood of such adverse events either in the short run or long run. Second, we study the dynamic bidirectional causality between oil prices and geopolitical risk. Previous researches have only looked at single-direction causality running from one variable to the other. Third, by exploiting the wavelet technique, we extend previous time-domain analysis to frequency-domain analysis, which renders important market strategy recommendations for different investors in the oil market.

[19] Previous literature look into other perspectives in forming investment (e.g., hedging, risk diversification, etc.) strategies in the oil markets: exchange rates (Benhmad, 2012; Tiwari et al., 2013), other energy commodities (Vacha and Barunik, 2012), spot and future contracts (Chang and Lee, 2015), etc.
[20] Two other papers, Kollias et al. (2013) and Blomberg et al. (2009) look into the impact of terrorist acts, a narrower perspective of geopolitical risk, on oil prices.
[21] See De Soysa (2002), Fearon and Laitin (2003), Ross (2004, 2006), Fearon (2005), Humphreys (2005), Cotet and Tsui (2013), Dube and Vargas (2013), Lei and Michaels (2014) and Caselli et al. (2015) for oil abundance and civil conflicts.

The remainder of the paper proceeds as follows. Section 2 illustrates the empirical methodology applied in this study. Section 3 describes the data, discusses the empirical results and proposes some broad investment strategy recommendations. Section 4 concludes.

2. Methodology

Wavelet analysis is developed in mid-1980s as an alternative to the Fourier analysis, which is a common methodology to uncover relations at different frequencies. The major flaw of the Fourier analysis is that it discards time-localized information, making it difficult to distinguish transient relations or to identify structural breaks (Auiar-Conraria and Soares, 2011). In contrast, the wavelet transform decomposes a time series into some basis wavelets, which are stretched and translated versions of a given mother wavelet localized in both the time and frequency domains. In this way, the series expands into a time-frequency space through which researchers can view its oscillations in an intuitive manner. Moreover, wavelet analysis also works well for non-stationary or locally stationary series, while Fourier analysis is merely suitable for stationary series (Roueff and Sachs, 2011).

In this paper, we choose the continuous wavelet transform proposed by Aguiar-Conraria and Soares (2011) and Aguiar-Conraria et al. (2012) to decompose the concerned series into wavelets. For a given time series $x(t)$, the continuous wavelet transform, represented as $W_x(s,\tau)$, is expressed as:

$$W_x(s,\tau) = \int_{-\infty}^{+\infty} x(t)\psi_{s,\tau}^{\ *}(t)dt, \qquad (1)$$

where $\psi_{\tau,s}^{\ *}(t)$ is the complex conjugate of the basis wavelet function, $\psi_{\tau,s}(t)$, which comes from a given mother wavelet, $\psi(t)$, in the following fashion:

$$\psi\ (s,\tau) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}). \qquad (2)$$

s and τ are the scale and location parameters respectively, with the former controlling how the mother wavelet is stretched and the latter setting where the wavelet is centered.

A mother wavelet of the continuous wavelet transform must satisfy three conditions. First, its mean must equal zero such that it oscillates across positive and negative values, and thus locally nonzero. In other words,

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \qquad (3)$$

Second, its square must integrate to unity in order to make sure of a limit to an interval of time, that is,

$$\int_{-\infty}^{+\infty} \psi^2(t)dt = 1 \qquad (4)$$

Third and finally, it must meet the admissibility condition, which is:

$$0 \prec C_\varphi = \int_0^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega \prec +\infty\,, \qquad (5)$$

where $\hat{\psi}(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$. In this paper, we choose the Morlet wavelet, introduced by Grossman and Morlet (1984), as the applicable mother wavelet, which is the most commonly used and has the following form:

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-\omega_0^2/2}.$$

Following Grinsted et al., (2004), we set ω_0 to be 6, under the condition of which the Morlet wavelet reaches the optimal trade-off between time and frequency localization. Since Auiar-Conraria and Soares (2013) have shown that the Fourier frequency is equal to $\omega_0/2\pi s$, the wavelet scale is approximately the reciprocal of the Fourier frequency. This implies that a longer (shorter) wavelet scale corresponds to a lower (higher) frequency.

In wavelet theory, the wavelet power spectrum of one series *x(t)* (i.e., the auto-wavelet power spectrum) is defined as $|W_x(s,\tau)|^2$, which measures the localized variance of *x(t)* at each frequency. In the situation of bivariate case, the cross-wavelet power spectrum is the square of the absolute value of the cross-wavelet transform of the two series, written as:

$$\left|W_{xy}(s,\tau)\right|^2 = \left|W_x(s,\tau)\right|^2 \left|W_y^*(s,\tau)\right|^2 \qquad (6)$$

where the asterisk presents the complex conjugation and *x(t)* and *y(t)* are the two series. The cross-wavelet power spectrum serves as an estimate of the localized covariance between *x(t)* and *y(t)* for a specified frequency. The wavelet coherency, which can be regarded as the local correlation between these two series, is calculated based on the cross-wavelet and auto-wavelet spectrum in the following fashion (Torrence and Webster, 1999):

$$R_{xy}^2(s,\tau) = \frac{|S(s^{-1}W_{xy}(s,\tau))|^2}{S(s^{-1}|W_x(s,\tau)|^2)S(s^{-1}|W_y(s,\tau)|^2)} \qquad (7)$$

where *S* is the smoothing operator along with both time and scale. The wavelet coherency is then a value within the range of [0,1] in a time-frequency window. Particularly, a coherency of zero indicates no co-movement between the two series, and stronger coherency suggests stronger co-movement between the two series.

Given the fact that positive and negative co-movements cannot be distinguished from squared wavelet coherency, we then utilize wavelet phase difference to examine the positive and negative co-movements as well as lead-lag relationships between GPR index and oil prices. As suggested in Bloomfield et al., (2004), the phase difference which characterizes the phase relationship between *x(t)* and *y(t)* can be calculated as: $\phi_{xy} = \tan^{-1}\left(\frac{I\{S(s^{-1}W_{xy}(s,\tau))\}}{R\{S(s^{-1}W_{xy}(s,\tau))\}}\right)$, with

$\phi_{xy} \in [-\pi,\pi]$. (8)

Here *I* and *R* are the imaginary and real parts of the smoothed cross-wavelet transform. A zero value in the phase difference analysis results implies that the correspondent two series move together in the same direction, whereas a value of π or $-\pi$ indicates they move in opposite direction. Specifically, if $\phi_{xy} \in (0,\pi/2)$, the two series move in phase (positively co-move), and *x(t)* leads *y(t)*. If $\phi_{xy} \in (\frac{\pi}{2},\pi)$, the two series move out of phase (negatively co-move), and *y(t)* leads *x(t)*. If $\phi_{xy} \in \left(-\frac{\pi}{2},0\right)$, the two series move in phase and *y(t)* leads *x(t)*. If $\phi_{xy} \in$

$(-\frac{\pi}{2}, -\pi)$, the two series move out of phase and *x(t)* leads *y(t)*. Previous studies argue that wavelet phase difference dominates the conventional Granger causality test because it can detect causality in both time and frequency domains whereas the Granger test only assumes a single causal relationship for the whole sample and at each frequency (Grinsted et al., 2004; Tiwari et al., 2013).

Out of the concern that global economic outlook may exert considerable impact on both geopolitical risk and crude oil prices, we attempt to tease out the effects of global economic by using the GDP growth forecast of the world to reveal the true co-movement and causality between the series. We utilize partial coherency and partial phase difference to achieve as a tool. Following Aguiar-Conraria and Soares (2013), we define the square partial wavelet coherency between *x(t)* and *y(t)* with the series z*(t)* controlled for as follows:

$$R^2_{xy|z}(s,\tau) = \frac{|R_{xy}(s,\tau) - R_{xz}(s,\tau)R^*_{yz}(s,\tau)|^2}{(1-(R_{xy}(s,\tau))^2)(1-(R_{yz}(s,\tau))^2)} \tag{9}$$

where $R_{xz}(s,\tau)$ and $R_{yz}(s,\tau)$ represent the wavelet coherency between *x(t)* and *z(t)* and that between *y(t)* and *z(t)* respectively. We could then derive the partial phase difference as follows:

$$\phi_{xy|z} = \left(\frac{I(C_{xy|z}(s,\tau))}{R(C_{xy|z}(s,\tau))}\right) \tag{10}$$

where *I* and *R* are respectively the imaginary and real parts of the complex partial wavelet coherency, $C_{xy|z}(s,\tau)$, which is the complex type of $R_{xy|z}(s,\tau)$ before taking the absolute value.

3. Data and Empirical Results

In this section, we begin with the discussion of data employed in our study. Then we move on to talk about the empirical results and correspondent implications on investment strategy for oil market participants. Our empirical analysis consists of three steps. First, we test for the unit root for the GPR index, the crude oil prices and the world economic outlook data, and whether these variables are cointegrated. Second, we conduct a wavelet coherency analysis to observe the dynamic co-movement between the crude oil prices and the GPR index. Finally, we perform the phase difference technique to investigate the time-varying causal relationship between the two. In the second and third step, we also check for robustness our findings by applying partial wavelet coherency and partial phase difference to eliminate the effects of world economic outlook to uncover the real co-movement and causality between the crude oil prices and geopolitical risk.

3.1 Data Description

We take advantage of a novel data set to measure geopolitical risk: the GPR index, with higher value indicating higher risk. Constructed by Caldara and Iacoviello (2017), the data set is the first to evaluate geopolitical risk properly and comprehensively.[22] Following the methodology

[22] According to Caldara and Iacoviello (2017), the GPR index is advantageous to other available indexes of geopolitical risks which have inherent shortcomings in various aspects: (1) they are often qualitative and subjective; (2) they either stay rather constant over time, or are available only for a short period; (3) some

pioneered by Saiz and Simonsohn (2013) and Baker et al. (2016), the authors built the GPR index by reflecting automated text-search results of the electronic archives of 11 national and international newspapers: The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post. The index is calculated based on the number of articles that contained words regarding geopolitical tensions for each month (as a share of the total number of news articles).[23] The index is then normalized relative to the average in the 2000-2009 decade (roughly 350 articles per month). Put another way, a reading of 200, for instance, indicates that newspaper mentions of geopolitical risk in that month were twice as frequent as during the 2000s.

The GPR index incorporates not only pure geopolitical threats and tensions but also actual geopolitical events and activities. The search identifies articles with references to 6 groups of words. The first 4 groups are related to geopolitical threats and tensions. Specifically, Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of militarized tensions involving large regions of the world and a U.S. involvement. Group 2 includes words directly associated with nuclear tensions. Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively. Finally, as opposed to just risks, Groups 5 and 6 capture press coverage of actual adverse geopolitical events (e.g., terrorist acts or the beginning of a war) which can be reasonably expected to result in increases in geopolitical uncertainty. Please refer to Caldara and Iacoviello (2017) for more detailed explanations of the words in each category.

Since the outlook of world economy could influence oil prices (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Wang and Sun, 2017), we also check the robustness of our findings by accounting for the global economic outlook when performing the wavelet analysis between geopolitical risk and each of the 4 crude oil prices. We take advantage of the economic outlook data from the OECD Statistics. The OECD Economic Outlook data analyses the major economic trends over the coming 2 to 3 years. It provides in-depth coverage of the main economic issues and the policy measures required to foster growth in each member country as well as some non-member countries and the world. We choose the forecast of the GDP growth of the world to proxy the global economic outlook.

[Insert Figure 1 here]

Figure 1 reports the time series plots of the GPR index and the global economic outlook data. The GPR index ranges from around 50 to as high as over 200. We can see that it is characterized by several spikes which are associated with key geopolitical events that escalated tensions or conflicts. The first spike occurs during the Kuwait invasion and subsequent Gulf War in 1990-1991. The most significant rise in the GPR index happens during the 9/11 terrorist attack and stays high until the US-Iraq war ended. Afterward, the index rises in correspondence to major

measures, though quantitative, are constructed based on variables that are meant to respond to, rather than measure geopolitical risks (e.g., gold, the dollar index and other financial market indicators).

[23] With press coverage being exploited, the authors' methodology has the following potential flaw: the GPR index may correspond to or even be largely driven by changes in geopolitical-related risk aversion of the public or state-dependent bias in news coverage. The authors tackle this issue by comparing the GPR index and a news-based index of disasters (an instrument used in Jetter, 2017), which is exogenous to geopolitical risk and yet likely to attract large media attention (and diminish media coverage of geopolitical risk). If the two are (negatively) correlated, it implies that the GPR index can be driven by variations in media attention unrelated with geopolitical risk. They find the correlation between the two index is statistically insignificant, alleviating such a concern. The authors conclude that the actual risk and media perception of risk are highly correlated.

terrorist events in the E.U. such as the March 2004 Madrid bombing, the July 2005 London bombing. The last notable spike is associated with geopolitical tensions in Ukraine and Iraq as well as the rise of the terrorist group, ISIS (Islamic State of Iraq and Syria). As for the world economic outlook data, the forecast of the world GDP growth rate ranges from -1% to 5% in our data sample. The world economy grows steadily through the end of the 1990s and most of the 1990s and 2000s. The forecasted economic downtowns are manifested in a few troughs in the figure, which include the early 1990s recession, the 1997 Asia financial crisis, the early 2000s recession and the most dramatic one, the 2008 financial crisis.

[Insert Figure 2 here]

We obtain the spot crude oil prices (dollar/barrel) of the 4 origins (WTI, Brent, Dubai and Nigerian) from the BP Statistical Review of World Energy. The evolution of the 4 price time series is shown in Figure 2. At the first glance, we can tell that the 4 prices move closely together. The only notable difference is that the spike of the WTI oil price in 2010-2014 is not as large as those of Brent, Dubai and Nigerian oil. The oil price frequencies vary by different time domains. The crude oil prices oscillate around 20 dollars per barrel before 2000, but steadily turn upwards until 2007. The main reason may be contributed to the rapid economic growth of developing countries, such as China and India (Wang and Wu, 2013). However, we find that the structural break point exists in 2008, where the global financial crisis may account for the downward fall of oil prices (Chang and Berdiev, 2013; Lee and Hsieh, 2014). Afterward, we observe an upward trend that may be ascribed to the economic recovery of developed countries following the crisis and then a sharp fall that may be driven by the boom of shale gas/oil fracturing. The summary statistics of the variables is documented in Table 1.

[Insert Table 1 here]

3.2 Evidence from the Cointegration Test

Before we determine whether all series are cointegrated, we first examine the integrated order of all the variables by utilizing the unit-root tests. Specifically, we perform the Agumented Dicky-Fuller (ADF) unit root test (Dicky and Fuller, 1979) and the Phillips-Perron (PP) unit root test (Phillips and Perron, 1988). We first apply the tests to the levels of the series, and then to their first differences. The results are reported in Table 2. The second and the third columns show the ADF test results. The lag lengths (reported in parentheses) are chosen based on the Akaike information criterion (AIC). As documented in the second column where the tests are applied to the levels of series, the null hypothesis of a unit root cannot be rejected for any of the series. However, when we re-apply the test to the first differences, the null hypothesis is rejected at the 1% level for all series. Thereby, we find evidence that all variables are integrated of order one. The PP test results, documented in the last two columns, tell the same story. We set the bandwidths according to the Bartlett Kernel, which are reported in parenthesis. Again, we cannot statistically reject the null hypothesis of a unit root for any of the variables when applying the test to levels, whereas we are able to do so at 1% level when applying the test to first differences. Given that all the variables are found to be cointegrated of order one, we then test for the cointegrating relationship between them.

[Insert Tables 2 and 3 here]

We first use Johansen (1988) techniques to test for pairwise cointegration relations between 4 crude oil prices and the GPR index. The tests for the number of cointegrating vectors are based on maximum eigenvalue and trace eigenvalue statistics of the stochastic matrix in the multivariate framework. The results are shown in Table 3. One can see that both tests suggest the existence of one cointegrating vector: the null hypothesis of no cointegration for all equations can be rejected at 1% significance level, whereas the null of at most 1 cointegration vector cannot be statistically rejected. In Table 4, we provide the empirical results when we include global economic outlook data into each of the above pairwise cointegration tests. For both tests, the null of no cointegration is rejected in all equations at 1% significance level. However, we are not able to reject the existence of at most 1 cointegration relation or at most 2 cointegration relation at even 10% significance level. Hence, we find evidence that cointegration exist between oil prices, GPR index and world economic outlook.

[Insert Tables 4 and 5 here]

We further check for robustness by applying the Engle-Granger Cointegration test. We choose the lag order to be zero in accordance with automatic lags specification based on Akaike criterion. No matter which pairwise cointegration relationship (between a specific oil price and the GPR index) is investigated, and no matter whether the world economic outlook is included or not, the null hypothesis of no cointegration is rejected at least at 5% significance level. Therefore, we again confirm that the oil prices and the GPR index are cointegrated in the long run.

3.1 Empirical Results of the Wavelet Coherence and Phase Difference

Although traditional cointegration tests provide evidence of co-movement between oil prices and the GPR index, yet, as discussed earlier, we are dissatisfied with the fact that only one cointegration is discovered to proxy the co-movement in the historical interactive process of the two variables. Next, we resort to the wavelet analysis to investigate the dynamic interaction between oil prices and geopolitical risks in both frequency and time domains.

[Insert Figures 3 to 6 here]

Figure 3-6 illustrate the wavelet coherencies and phase-differences between the GPR index and each of the crude oil prices, respectively. In each figure, the left two graphs provide the results where the world economic outlook is not controlled for; instead, the right two graphs document results of the partial wavelet coherency and partial phase difference analysis as shown in equation (9) and (10), where the world economic outlook is controlled for. In each figure, the upper two graphs document the wavelet coherency results, while the lower two graphs document the phase difference results. In the wavelet coherency analysis graphs, the cone of influence is shown with a black line that looks like "region", indicating the contour is significant at the 5% significance level. The y-axis refers to the frequencies, which is converted to time units (years) for ease of interpretation; the x-axis refers to the time (1985-2016). The color of the graph indicates the strength of coherency at each frequency, ranging from blue (low coherency) to red (high coherency). For phase-difference analysis graphs, the (partial) phase difference between the two series is shown in the y-axis, while time is shown in the x-axis.

Since the WTI oil price is mostly commonly used oil price index, we start with the *WTI-GPR* pair for our wavelet analysis. From the wavelet coherency results, we observe very interesting results. Different from traditional cointegration tests, wavelet coherency analysis uncovers significant dynamic correlations between the WTI oil prices and the GPR index in the time-frequency domain. To be specific, first, one can easily find that almost all area corresponding to low frequencies is blue, implying that the degree of co-movement between the WTI oil prices and the geopolitical risk is weak for low frequencies in almost the entire sample period. The only exception is the period of 2010-2016. That is, the degree of long-run co-movement between the two variables is not significantly strong until 2010. One potential explanation of none existence of long-run correlation between geopolitical risk and oil prices could be that major oil-importing superpowers such as the U.S. have incentives to intervene any tensions or conflicts in oil-exporting regions to prevent uncertainty or disruption of oil production (De Soysa, Gartzke and Lie, 2011). Second, contrarily, for high frequencies, specifically fluctuations with duration less than 1.5 years, the WTI oil price and the GPR index exhibits a strong relationship for the entire sample period. The close short-term dependence and yet loose long-run correlations between the two series during majority of the time imply that geopolitical risk is an important factor to be taken into consideration for short-term investors (e.g., arbitragers and speculators) in the oil market, whereas it may be less relevant for long-term investors (e.g., oil producers and policy makers). However, since the co-movement varies over time, we can see that the dynamic pattern changes greatly after 2010 when the WTI oil prices move significantly more closely with geopolitical risks at low frequencies too. Thus, the geopolitical risk information may deserve more attention from long-term investors in the current decade and future.

Since the co-movement mostly exists in the short run, we perform the phase difference analysis in the high frequency. Specifically, we choose the 1-4 year frequency band. Our evidence shows that the causal relationship between the WTI oil price and geopolitical risk varies across different time periods. During 1985-2000 and 2010-2016, given that the phase difference lies in between $(0,\pi/2)$, we can tell that the two series move in phase (i.e., positively comove), with geopolitical risk leading the oil prices. This implies that an increase in the geopolitical risk leads to a rise in the WTI oil prices in the short run. During 2000-2010, the phase difference is marginally above $\pi/2$, providing some evidence that the GPR index and the WTI oil prices moves out of phase during this period, with the WTI oil price leading the GPR index. Since the evidence is rather weak, we argue that the short-run causality between the two variables mainly runs from the GPR index to the WTI oil prices and they move in phase, at least during our sample.

The outlook of world economy can significantly influence the oil prices (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Wang and Sun, 2017). This implies that the above results estimated by wavelet coherency and phase difference without removing the simultaneous effects of economic growth on oil prices may suffer from some inaccuracy. Accordingly, we further estimate the partial wavelet coherency and partial phase difference with world economic outlook, proxied by the overall GDP growth forecast of the global economy, as a control variable to reveal the true relationship between the oil prices and geopolitical risks. Figure 3.3 and 3.4 report the findings. For partial wavelet coherency analysis, we find stronger evidence of co-movement between the WTI oil prices and the GPR index for high frequencies (mostly in the frequency band smaller than 2 years) during the entire sample period. Moreover, for the most recent period of 2010-2016, the degree of correlation between the two variables are even higher for all frequencies including the lowest ones. This again presents evidence of a possible structural break in the relationship. As for the partial phase difference analysis, we observe dynamic lead-lag relationship that slightly differs from previous results. The partial phase difference lies between $(0, \pi/2)$ over even longer periods of the sample. The periods with partial phase difference marginally above $\pi/2$ shrinks to 2003-2008. This further confirms the finding that in most time the two series moves in phase and the geopolitical risk positively contributes to the WTI oil price. To check for the robustness of our findings, we perform the above analysis for interactions between geopolitical risk and other 3 oil prices (Brent, Dubai and Nigerian), the results of which are shown in Figure 4-6. We can see no matter whether the world economic outlook data is accounted for or not, the wavelet coherency analysis all provides very similar results as what we have interpreted in Figure 3. Accordingly, we demonstrate that our findings that the co-movement between geopolitical risk and oil prices mainly exist in the short run are robust to the choices of the oil price index utilized.

As for the (partial) phase difference analyses, we continue to look into the high frequency (the frequency band of 1-4 years). However, we observe different patterns across different oil price indexes. Although the GPR-Brent pair exhibits very similar pattern in the dynamic causality between geopolitical risk and oil prices as that shown in Figure 3, the *GPR-Dubai* and *GPR-Nigerian* pairs share a common pattern that varies substantially from the *GPR-WTI* and *GPR-Brent* pairs. For *GPR-Dubai* and *GPR-Nigerian* pairs (shown in Figure 5 and 6), instead of a relatively stable causality relationship in previous results, we find that the causality varies across different time periods. During 1985-1992, given that the phase difference lies in between $(0,\pi/2)$, we can tell that the two series move in phase with geopolitical risk leading the oil prices. During 1992-1995 and 2005-2010, we also observe positive co-movement between the two, though the causal link runs from the oil price to geopolitical risk. On the contrary, in the time window of 1995-2005 and 2010-2016, the two series move out of phase with geopolitical risk taking the lead.

We next turn to the partial phase difference analyses when world economic outlook is taken into account for the GPR-Dubai and GPR-Nigerian pairs. For both pairs, the partial phase difference lies between $(-\pi/2, 0)$ from the beginning of the sample till around 2008, suggesting that in most time the two series moves in phase and the WTI oil prices leads the GPR index. This is in line with the intuition that oil price spikes, which facilitates various channels through which “oil recourse curse” occur (as discussed in earlier section), increase likelihood of geopolitical tensions or even actual conflicts. Different from the findings when world economic outlook is not controlled for, the only period when the phase difference falls in the range of $(-\pi, -\pi/2)$ is 2008-2016, providing suggestive evidence that geopolitical risk negatively contributes to oil prices during the time window. We hold caution for such interpretation as the innovation of shale oil extraction made oil prices experience a significant decline after 2010. This could dominate the positive co-movement between geopolitical risk and oil prices. Thus, we choose to interpret our results as demonstrating a positive causality running from Dubai/Nigerian oil prices to geopolitical risks.

In sum, we find robust evidence that the co-movement and causality between the oil prices and geopolitical risk varies across frequencies and evolves over time. Interestingly, we also find that the dynamic relationship between the two also exhibits different patterns for different oil markets. Overall, we demonstrate the bi-directional causal relationship between the oil prices and the geopolitical risk indeed exists: in majority of the sample period, for the WTI and Brent index, the causality runs from geopolitical risk to oil prices, while for the Dubai and Nigerian index, the causality runs from the opposite direction. Additionally, we also observe structural breaks in the data and the causal relationship is dynamic across time, which are all missed in conventional time-domain cointegration tests. Our results are to some extent consistent with the Noguera-Santaella (2016)’s findings, and to some extent not: we both find that prior to 2000, geopolitical events positively affected oil prices; however, Noguera-Santaella (2016) fails to identify impacts of geopolitical events on oil prices afterwards, whereas we continue to observe significant causality between the two. This can be largely due to the distinct dataset and empirical methodology utilized in our paper.

Our findings provide critical information for not only participants in the oil market but also policy makers. First, we show that the oil prices and geopolitical risk correlate with each other mainly at higher frequencies (the $\leq$ 2-year frequency band). Moreover, our results demonstrate that for the WTI and Brent oil prices, an increase in geopolitical risk result in a rise in oil prices in the short run. This implies that investors with a short-term horizon should pay special attention to the information of geopolitical risks in order to allocate their assets more effectively. Market performance forecasts based on variations of geopolitical risk should focus on shorter time horizons so as to enhance the forecasting accuracy. In terms of investment strategy, short-term investors should consider purchasing more assets in front of an increase in geopolitical risk. For policy makers in major oil-importing countries, our results again highlight the importance of reconciling geopolitical tensions or conflicts for maintaining energy security. Second, for the Dubai and Nigerian market, we identify a structural break at 2010 after which the geopolitical risk and oil prices are also negatively correlated at low frequencies (i.e., long term). This implies that in the current decades and possibly in the future, investors with a long-term horizon in the two markets should consider reducing their assets or at least be cautious about purchasing extra assets, when geopolitical risk becomes more serious. This also implies room for hedging between long-term and short-term contracts in these two markets. However, we hold such recommendation with prudence as the significant oil price decline due to the shale extraction boom may have driven the results. Future studies could revisit this question when updated data with longer horizon is available. Third, our study provides evidence that (for the Dubai and Nigerian spot markets) fluctuations of oil prices could positively contribute to the geopolitical risks. We thus urge policy makers to focus on oil price variations as a trigger for geopolitical tension and conflicts.

4. Concluding Remarks

Although each has been studied thoroughly as a separate issue, the interaction between geopolitical risk and oil prices remains unaddressed in the previous literature. In this study, we attempt to investigate the dynamic relationship between oil prices and geopolitical risk in both time- and frequency- domains by utilizing a novel method: wavelet analysis. Its main advantage relative to traditional time-domain techniques is that time-domain techniques lose sight of the frequency domain, which may result in the failure to capture useful and important information. Previous researchers have found that the relations between oil prices and various macroeconomic variables may exist at different frequencies (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Benhmad, 2012; Tiwari et al., 2013).

We take advantage of a new data set to properly and comprehensively measure geopolitical risk, constructed by Caldara and Iacoviello (2017). The data is a normalized index based on the occurrence of words regarding geopolitical tensions and conflicts in leading international newspapers. The empirical results show that the correlation between geopolitical risk and oil prices is indeed time- and frequency-varying. Generally, we find that the two series have strong degree of co-movement in high frequencies (short-term fluctuations), whereas evidence of co-movement in low frequencies (long-term fluctuations) only exists during 2010-2016. Our results also manifest dynamic causality between the two series across time. Overall, geopolitical risk positively contributes to oil prices for WTI and Nigerian index, while oil prices positively contribute to geopolitical risks for Brent and Dubai index.

Overall, we hope our empirical results, based on multi-frequency analysis, can provide more useful information to investors and oil producers for investment strategies. Our findings of short-term co-movement between geopolitical risk and oil prices imply that investors with a short-term horizon should particularly exploit the geopolitical risk information to form better strategies. These findings are also helpful for policy makers to incorporate the dynamics of the causality relationships between oil prices and geopolitical risks in their policy-making process.

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Figure 1. Plots of the Economic Outlook and GPR.

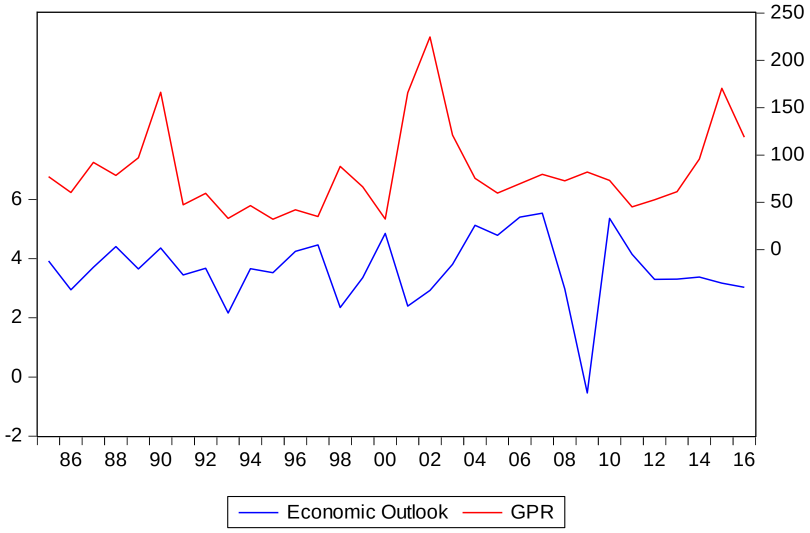


Figure 2. Plots of the Crude Oil Prices.

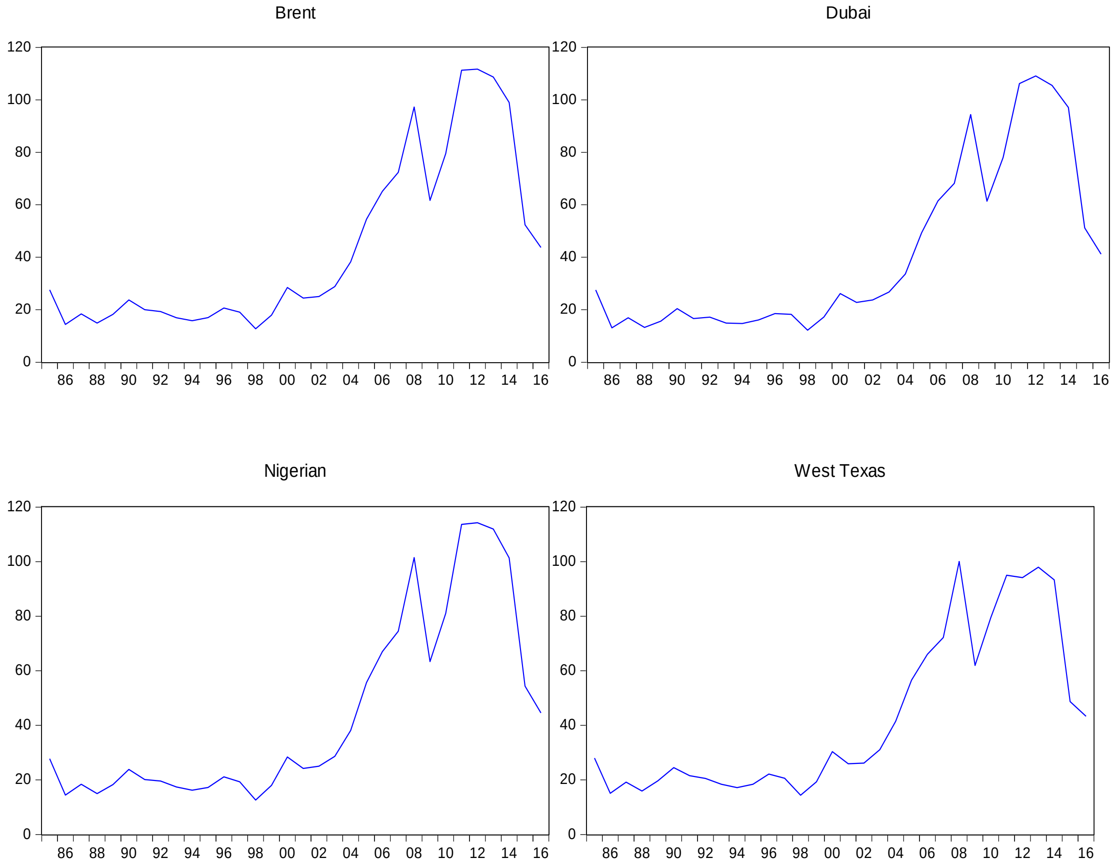
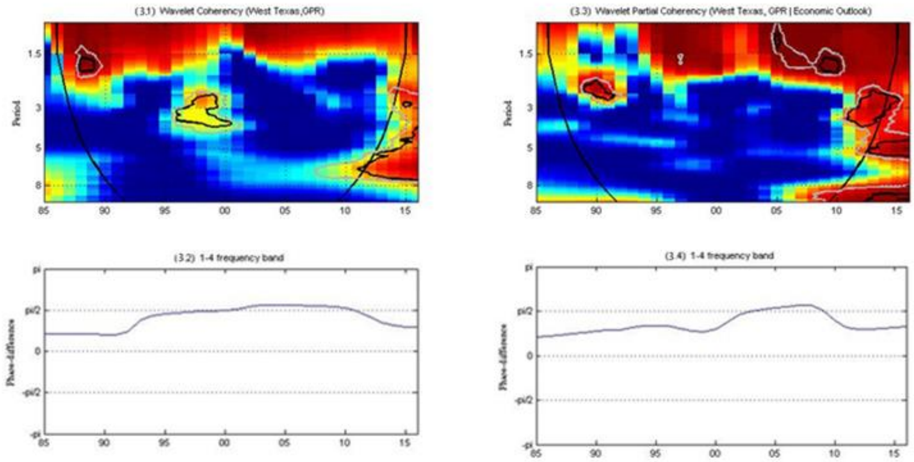
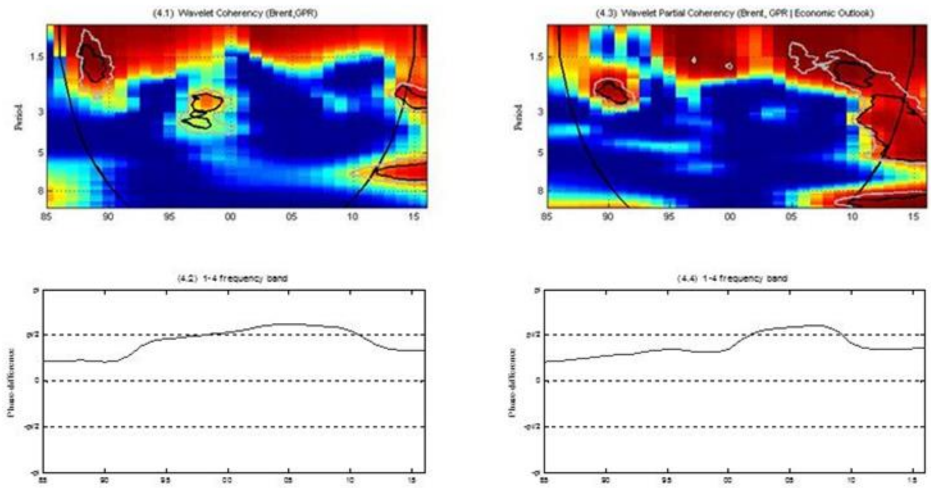


Figure 3. Wavelet Analysis: GPR Index vs. WTI Oil Prices



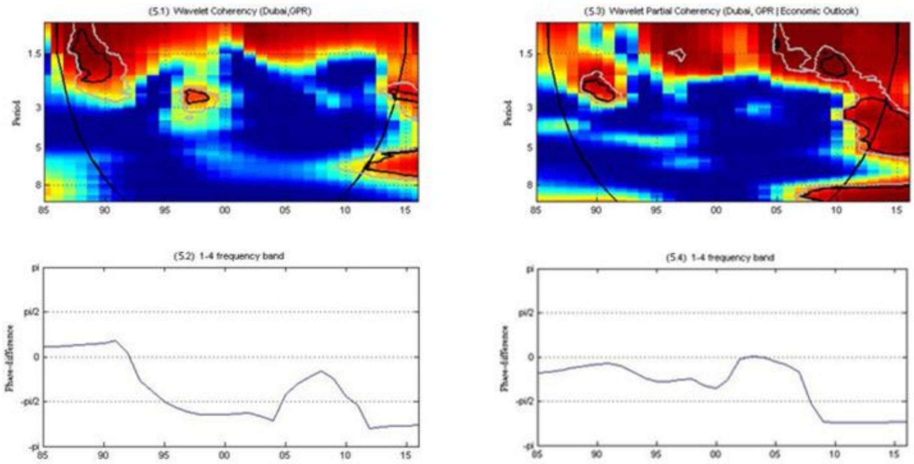
Note: the upper two graphs show the results of wavelet coherency analysis, while the bottom two graphs present the phase-difference correlations. The left two graphs document the results where the economic outlook is not controlled for. The right two graphs document the results where the economic outlook is controlled for.

Figure 4. Wavelet Analysis: GPR Index vs. Brent Oil Prices



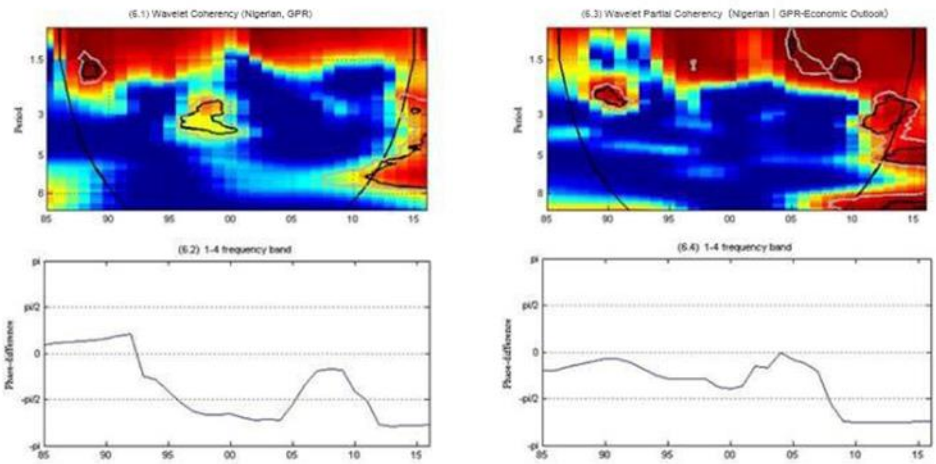
Note: the upper two graphs show the results of wavelet coherency analysis, while the bottom two graphs present the phase-difference correlations. The left two graphs document the results where the economic outlook is not controlled for. The right two graphs document the results where the economic outlook is controlled for.

Figure 5. Wavelet Analysis: GPR Index vs. Dubai Oil Prices



Note: the upper two graphs show the results of wavelet coherency analysis, while the bottom two graphs present the phase-difference correlations. The left two graphs document the results where the economic outlook is not controlled for. The right two graphs document the results where the economic outlook is controlled for.

Figure 6. Wavelet Analysis: GPR Index vs. Nigerian Oil Prices



Note: the upper two graphs show the results of wavelet coherency analysis, while the bottom two graphs present the phase-difference correlations. The left two graphs document the results where the economic outlook is not controlled for. The right two graphs document the results where the economic outlook is controlled for.

Table 1. Data Descriptive

Variable	N	Mean	S.D	Min	Max	Median
Brent	32	43.10	32.80	12.72	111.7	26.29
Dubai	32	40.90	32.23	12.21	109.1	24.97
Nigerian	32	43.97	33.86	12.62	114.2	26.40
West Texas	32	42.46	29.31	14.39	100.1	27.07
GPR	32	81.96	45.48	32.12	224.8	72.97
Economic Outlook	32	3.650	1.170	-0.540	5.540	3.660

Table 2. Unit Root Tests.

Variable	ADF		PP	
	Level	First difference	Level	First difference
Brent	-1.782 (0)	-4.934 (0)***	-2.050 (3)	-4.935(3) ***
Dubai	-1.765 (0)	-4.903 (0)***	-2.060 (3)	-4.912(3) ***
Nigerian	-1.784 (0)	-4.950 (0) ***	-2.046 (3)	-4.940(2) ***
West Texas	-1.967 (0)	-5.878 (0)***	-2.060 (2)	-5.883(2) ***
GPR	-1.297 (0)	-5.441 (1)***	-1.022 (4)	-9.796(5) ***
Economic Outlook	-0.593 (2)	-6.805 (1)***	-0.938 (6)	-9.968(3) ***

Notes: The null hypothesis of ADF tests is a unit root. The numbers in parentheses are the lag order and lag parameters are selected on the basis of the AIC. The null hypothesis of PP tests is a unit root. The numbers in parentheses are the bandwidths are selected on the basis of the Bartlett Kernel. The *** indicates significance at the 1% level.

Table 3. Johansen's Cointegration Test: without *Economics Outlook*

Null hypothesis	Maximum eigenvalue statistics	Trace eigenvalue statistics
No. of CE(s)	Cointegration test for *Brent* and *GPR*	
None	18.520*	26.157**
	(0.066)	(0.046)
At most 1	7.636	7.636
	(0.282)	(0.282)
	Cointegration test for *Dubai* and *GPR*	
None	13.429**	13.432**
	(0.020)	(0.032)
At most 1	0.003	0.003
	(0.964)	(0.964)
	Cointegration test for *Nigerian* and *GPR*	
None	10.598*	10.600*
	(0.064)	(0.095)
At most 1	0.003	0.003
	(0.961)	(0.961)
	Cointegration test for *WTI* and *GPR*	
None	10.550*	10.552*
	(0.065)	(0.097)
At most 1	0.001	0.001
	(0.975)	(0.975)

Notes: ***, ** and * denote rejection at1%, 5% and 10% levels. P-values are in parenthesis.

Table 4. Johansen's Cointegration Test: with *Economics Outlook*

Null hypothesis	Maximum eigenvalue statistics	Trace eigenvalue statistics
No. of CE(s)	Cointegration test for *Brent , GPR and Economic Outlook*	
None	32.613***	45.505***
	(0.000)	(0.000)
At most 1	10.860	12.892
	(0.161)	(0.119)
At most 2	2.032	2.032
	(0.154)	(0.154)
	Cointegration test for *Dubai , GPR and Economic Outlook*	
None	32.088***	45.068***
	(0.001)	(0.000)
At most 1	11.016	12.979
	(0.153)	(0.116)
At most 2	1.963	1.963
	(0.161)	(0.161)
	Cointegration test for *Nigerian , GPR and Economic Outlook*	
None	33.206***	46.127***
	(0.001)	(0.000)
At most 1	10.840	12.922
	(0.162)	(0.118)
At most 2	2.081	2.081
	(0.149)	(0.149)
	Cointegration test for *WTI, GPR and Economic Outlook*	
None	31.962***	44.842***
	(0.001)	(0.001)
At most 1	10.756	12.879
	(0.167)	(0.119)
At most 2	2.124	2.124
	(0.145)	(0.145)

Notes: ***, ** and * denote rejection at1%, 5% and 10% levels. P-values are in parenthesis.

Table 5. Engle-Granger Cointegration Test

Null hypothesis:series are not cointegrated		
	Z-statistic	Lag order
Cointegration test for *Brent* and *GPR*	-17.186**(0.049)	0
Cointegration test for *Dubai* and *GPR*	-17.219**(0.049)	0
Cointegration test for *Nigerian* and *GPR*	-17.194**(0.049)	0
Cointegration test for *West Texas* and *GPR*	-17.169**(0.049)	0
Cointegration test for *Brent , GPR and Economic Outlook*	-30.088***(0.002)	0
Cointegration test for *Dubai , GPR and Economic Outlook*	-30.148***(0.002)	0
Cointegration test for *Nigerian , GPR and Economic Outlook*	-30.099**(0.002)	0
Cointegration test for *West Texas, GPR and Economic Outlook*	-29.987***(0.002)	0

Notes: *** and** denote rejection at1% and 5% levels. P-values are in parenthesis.

Terrorism and Commodity Prices: An Exploratory Study

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Abstract

This paper attempts to empirically establish the impact of terrorism on the most commonly traded commodity, Crude oil. The study covers all major global terrorist events for a long time period of 1991-2016 to institute any causality between terrorism and oil prices. The results indicate that the oil prices get negatively affected by the terrorist events. Using S&P global oil index and US oil fund data, the results further confirm the relationship between the two. The study also found that the impact of a terrorist attack in a developed country has a stronger negative impact on the global oil prices as compared to an attack in a developing and underdeveloped country. Additionally, the attack in a net oil exporter country tend to have a stronger impact on oil prices compared to a net oil importer nation. The findings of the paper are instrumental to commodity investors and fund managers for portfolio diversification strategies against terrorism risk. The outcome of the study will also provide an insight to supervising authorities to be more efficient in absorbing exogenous geopolitical risk.

I. Introduction

International terrorism is a complex geopolitical issue that threatens to undermine the financial market and economy worldwide. Unprovoked attacks upon civilians and infrastructure carried out by regional and international terrorist groups create a sense of fear and uneasiness in the mind of general public which spillover to financial market. Terrorist activities has a tendency to send shock waves through both domestic and foreign markets by creating a state of insecurity within the marketplace, which can lead to investor apprehension and many unforeseen financial consequences. The impact that an act of terror has on the financial market and commodities varies depending on the type of attack, locale, extent of casualty and time in which it was committed. Some terrorist activities can cause only a national or regional disturbance spiking volatility at local level, while others may cause economic repercussions through the entire financial system. No matter the size and scope of the act, it brings uncertainty to the marketplace and ensures enhanced volatility facing a wide variety of asset classes including commodity market.

A lot of research on terrorism has been done in the fields of sociology and political science but with respect to economics and finance, terrorism has not received much attention from researchers. Even within the financial sector most of the studies has been concentrated on the stock market reaction to terrorist activities (inter alia: Arin, Ciferri, and Spagnolo 2008; Brounen and Derwall 2010; Charles and Darne 2006; Chen and Siems 2004; Chesney, Reshetar, and Karaman 2011; Drakos, 2010; Eldor and Melnick, 2004; Kollias, Papadamou and Stagiannis, 2011; Kollias, Papadamou and Arvanitis, 2013; Nikkinen and Vahamaa, 2010).

If we focus on the implications of terrorist activities on the most traded commodity, crude oil we are unable to find any significant empirical research. Guo & Kleisen (2005) using daily prices of crude oil futures traded on the New York Mercantile Exchange (NYMEX) over the period 1984-2004 found out that crude oil price volatility is mainly driven by exogenous (random) events such as significant terrorist attacks and conflicts in the Middle East. Plante and Traum (2012) noted that oil price index rose due to terrorist attacks and political upheaval in oil producing countries. In a recent paper, Sartori (2016) noted that growing terrorist activities in major oil producing country Libya is affecting oil production and distribution giving a rise in oil price volatility.

Even though there is no direct evidence to show that terrorism has a direct impact on oil prices, one way to argue this correlation is that oil producing countries might be favored for their terrorist activities to shock the national or world economy at large. Luft and Korin (2004) highlighted that terrorist might have an incentive to attack oil producing countries to damage their target countries' geopolitical interest. To substantiate this argument, we can find that in 2012, there were at least thirty-five terror attacks that targeted oil or gas pipelines, tankers and refineries (Taylor, 2012). The closest of evidence which showed the impact of terrorism on oil price can be tracked back to series of terrorist attacks in Saudi Arabia in May 2004, caused oil prices to rise to the highest point since 1990 (Luft and Korin, 2004). Pirog (2005) also acknowledged that the fear of terrorism and war are quickly reflected in the current oil price as well as future markets like NYMEX.

In terms of the locale of the terrorist attack and its impact of oil price can be explained from the argument that oil producing countries (mostly oil exporting countries) have tactical values to developed countries such as importance of oil rich Saudi Arabia to the United States. In terrorism literature in can be established from research of Pape (2003) and Savun & Philips

(2009) that developed countries are more likely to become terrorist targets because of their active foreign involvements. Oil producing countries may be more likely targets of terrorist attacks because targeting strategic assets of developed countries in oil exporting countries might be more cost effective for terrorist.

Thus it can be seen from above discussion that there has been no single study which has empirically established how terrorism will affect oil prices and its volatility. The current study is an attempt to fill in this research gap. The study will make use of daily oil prices and will be tested against all the major terrorist attacks since 1991. We will also try to establish how the terrorist attack with affect one and two-month oil futures. In contrast to impact studies which often employ only event-study methodology, in this paper we investigate the impact of terrorism using filtered generalized autoregressive conditionally heteroscedastic (GARCH) approach. Another contribution of this paper is that most of the literature on commodity price is explained from macroeconomic shocks but not from unexpected event such as terrorist attacks.

The findings of our empirical investigation are useful for investors, fund managers, insurance agencies, banks and government. This study is among the first one to give insights into possible portfolio diversification strategies in commodities market with respect to the risk of terrorism. We organize the remainder of the paper as follows. In the next section, we discuss the data set. The main findings are presented in Section III, and the final section summarizes the key messages emerging from our paper.

II. Data and methodology:

We sourced data from two sources to compile the final dataset, namely U.S. Energy Information Administration (EIA) and Global Terrorism Database (GTD). The daily oil prices (WTI spot) are sourced from EIA whereas the terrorism related data is sourced from GTD. We compile daily WTI prices from 1/11/1991 to 9/8/2016. The timespan is chosen to match the oil data with terrorism data. The terrorism data starts from the attack that took place in France, Spain and Greece and includes the recent attack in Germany. We further segregate terrorist attacks (TER) at regional level, developing vs developed, and also on the basis of oil-importing and oil exporting countries. The segregation is based on World Bank classifications. Finally, we also limit our sample to most developed countries.

Once, we compile the dataset, we run following estimations:

$$OIL_t = \alpha + \beta_1 \, TER_t + \beta_2 \, OIL_{t-1} + \beta_3 \, OIL_{t-1} + OIL_t{}^2 + \varepsilon_t$$

The model is estimated based on GARCH (1,1) with t distribution. The OIL is oil returns, estimated as log WTI – log WTI(-1) which is plotted in Figure 1. Terrorist attacks (TER) is measured by several variables starting with attack day. The attack day variable takes the value of 1 in case TER occur, otherwise zero otherwise. We also use other measures of TER such as number of attacks (in a day), number of casualties, number of injured, property destroyed (1 if yes zero otherwise), number of properties destroyed. We have more than 50000 observations spanning over 191 countries.

[Insert Figure 1 here]

Descriptive statistics:

The OIL is plotted in Figure 1 which displays volatility and volatility clustering. The descriptive statistics is provided in Table 1. The full sample indicates that there are total of 51061 attack days whereas the total number of attacks are 108478. The statistics on the number of killings and injuries are 301138 and 433310 respectively. The attacks that involve destruction of property are 33086 whereas the total number of property destroyed are 56874.

[Insert Table 1 here]

Further statistics reveal that the most number of these attacks took place in oil importing and the developing countries. Similarly, the total number of casualties and injuries from attacks is observed in oil importing and developing economies as compared oil exporting and developed economies. The further segregation of data based on region reveals that Middle East and North Africa (MENA) and South Asia leads in number of attack days followed by the Sub Sahara Africa (SSA) and South East Asia (SEA). Similarly, the total number of attacks, casualties and injuries reveal the similar pattern. Western Europe witnessed the highest number of attack days and attacks among the western countries. The least number of attack days are witnessed by Australasia & Oceania (115), East Asia (324) and Central Asia (411). The Pearson correlation coefficients are presented in Table 2. The coefficients reveal that all the TER variables, except number of casualties, is significantly correlated with the OIL. Furthermore, the attack days, property destroyed and the number of property destroyed is positively related with the OIL whereas the other variables such as number of attacks and the number of injuries is negatively related with OIL.

[Insert Table 2 here]

III. Findings

The effect of TER on OIL based on GARCH (1,1) with t distribution is provided in Table 3. The results based on full sample indicate that TER negatively affect the OIL. The results are consistent across all the proxies except number of casualties and injuries. Further segregation of data reveals that terror attacks in oil importing countries are almost similar to full results. However, in case of oil exporting countries, the number of attacks, number of casualties and injuries exert positive pressure on OIL.

[Insert Table 3 here]

We further segregate the results based on per capita income. The classification is based on World Bank. The impact of TER on OIL may be contingent on the importance of country as the TER in developing economies may not have similar affect as compared to developed or most developed economy. In other words, we expect TER in developing economy to have no or weak effects on the OIL as compared to developed or most developed nations. The results are reported in Table 4. Although the impact of TER are negative in case of developing economies, the magnitude is lower as compared to developed/most developed. The important point to note here is that the number of attack days and the total number of attacks in developing economies are 46500 and 101934 respectively as compared to developed economies where the total number of attack days and number of attacks are 4481 and 6544 respectively.

[Insert Table 4 here]

The sample is further divided based on region. The sample segregation is based on the TER in the region (see Table 5). These regions have witnessed significant TER over the sample period. In case of Eastern Europe (EE), almost all the variables are insignificant indicating that TER in EE do not have any effect on the OIL. The results based on other regions reveal that the TER exerts negative and significant effect on the OIL. On average, it can be argued that the TER negatively affects the OIL.

Robustness:
Finally, we test the relationship by replacing oil spot prices by 1 and 2 month futures. Testing the relationship between oil futures (FUTURES) and TER provides a natural framework to test the lagged effect of TER. If there is lagged effect of TER on OIL, it should be reflected in FUTURES. The results are provided in Table 6. The findings indicate that, in almost all the cases, the TER negatively affects the FUTURES (1 AND 2). These findings indicate that the TER not only effects the oil sport prices but also effects the futures.

IV. Conclusion

In this study, we examine the effects of terrorist attacks on crude oil price both in the spot market as well as in the future market. The results indicate that the oil prices get negatively affected by the terrorist events. Using S&P global oil index and US oil fund data, the results further confirm the relationship between the two. The study also found that the impact of a terrorist attack in a developed country has a stronger negative impact on the global oil prices as compared to an attack in a developing and underdeveloped country. Additionally, the attack in a net oil exporter country tend to have a stronger impact on oil prices compared to a net oil importer nation. The results of our study suggest several diversification strategies against terrorism risk in the commodity market. If concerned about this risk, investors should hold assets that have little or no negative sensitivity to this risk which is still an are3a to explore in the future research.

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Figure 1: Daily Oil returns

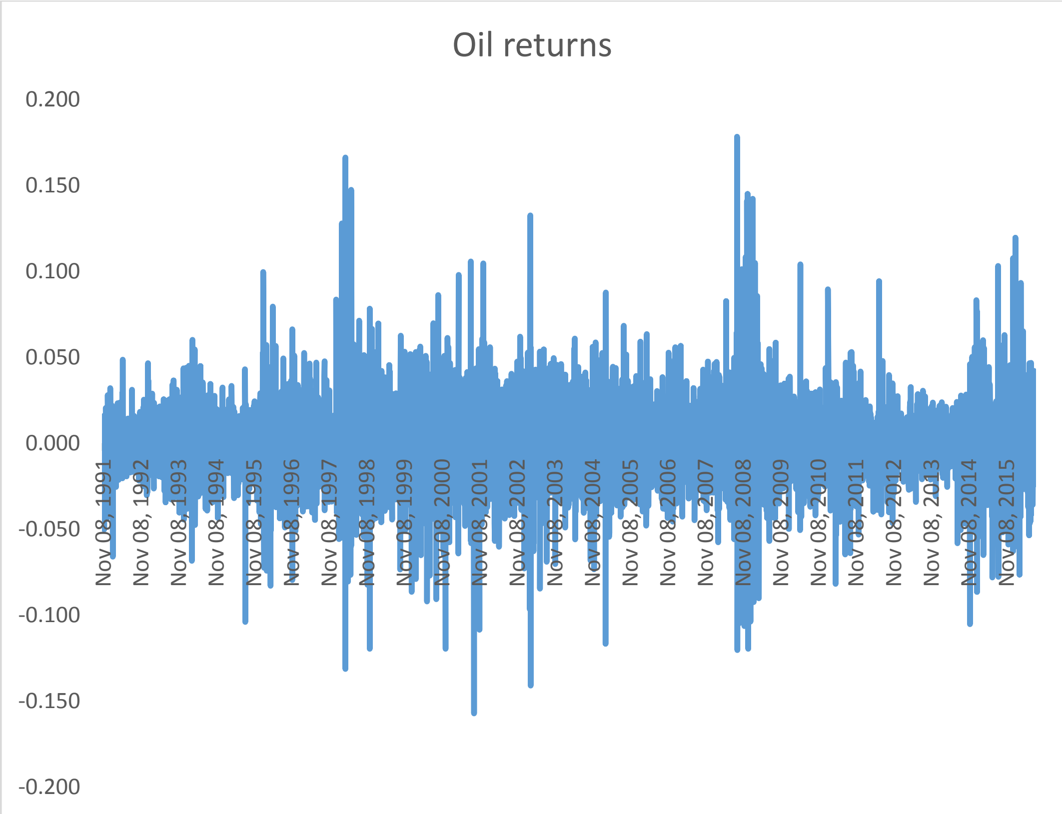

Table 1: Descriptive statistics

Region	Attack days	No. of attack	No. of casualties	No. of injuries	Property destroyed	No. of Property destroyed
Full sample						
Mean	0.909	1.931	5.457	8.029	0.589	1.012
SD	0.288	2.550	22.524	75.521	0.492	1.767
Total	51061	108478	301138	433310	33086	56874
Oil exporting						
Mean	0.903	1.766	5.660	9.474	0.572	0.969
SD	0.297	2.189	17.343	35.779	0.495	1.618
Total	10332	20221	64089	104648	6552	11094
Oil importing						
Mean	0.910	1.972	5.405	7.657	0.593	1.023
SD	0.286	2.633	23.678	82.711	0.491	1.803
Total	40729	88257	237049	328662	26534	45780
Developing						
Mean	0.916	2.004	5.929	8.233	0.577	1.009
SD	0.277	2.606	19.387	32.575	0.494	1.763
Total	46580	101934	295786	401065	29338	51324
Developed						
Mean	0.839	1.226	1.011	6.137	0.702	1.040
SD	0.367	1.795	41.525	220.795	0.457	1.801
Total	4481	6544	5352	32245	3748	5550
Australasia & Oceania						
Mean	0.833	0.957	0.574	0.956	0.725	0.848
SD	0.374	0.603	2.064	3.423	0.448	0.672
Total	115	132	78	129	100	117
Central America						
Mean	0.912	1.566	1.407	2.082	0.665	1.245
SD	0.284	2.058	5.352	5.852	0.472	2.042
Total	879	1510	1354	1997	641	1200
Central Asia						
Mean	0.871	1.015	2.122	4.303	0.523	0.627
SD	0.336	0.650	5.602	38.045	0.500	0.760
Total	411	479	993	2001	247	296
East Asia						
Mean	0.885	1.221	2.961	25.057	0.596	0.913
SD	0.319	2.591	12.698	296.508	0.491	2.647
Total	324	447	1060	8820	218	334
Eastern Europe						
Mean	0.879	1.247	2.457	4.031	0.573	0.752
SD	0.327	1.151	12.896	20.040	0.495	0.961
Total	2619	3718	7203	11649	1709	2242

MENA						
Mean	0.918	2.432	7.840	12.889	0.577	1.069
SD	0.275	3.461	25.009	37.113	0.494	1.962
Total	14111	37391	118336	191071	8866	16429
North America						
Mean	0.866	1.053	4.436	18.894	0.653	0.790
SD	0.341	0.785	99.228	491.744	0.476	0.828
Total	800	973	4068	17250	603	730
South America						
Mean	0.887	1.645	2.914	2.688	0.645	1.230
SD	0.317	2.492	9.773	10.552	0.478	2.451
Total	3320	6159	10804	9787	2417	4606
South Asia						
Mean	0.938	2.381	6.042	9.103	0.624	1.197
SD	0.241	2.523	13.491	25.690	0.484	1.766
Total	12638	32072	80836	119681	8406	16127
Southeast Asia						
Mean	0.907	1.543	1.919	3.871	0.522	0.796
SD	0.290	1.604	5.220	12.843	0.500	1.429
Total	4856	8257	10110	20158	2796	4262
Sub-Saharan Africa						
Mean	0.914	1.459	8.356	5.817	0.508	0.726
SD	0.280	1.416	26.719	50.710	0.500	1.205
Total	7453	11894	64716	42202	4144	5921
Western Europe						
Mean	0.831	1.281	0.374	2.049	0.691	1.084
SD	0.375	1.979	4.364	32.758	0.462	1.981
Total	3535	5446	1580	8565	2939	4610

Table 2: Pearson correlation

	OIL	**Attack days**	**No. of attack**	**No. of casualties**	**No. of injuries**	**Property destroyed**	**No. of Property destroyed**
OIL	1						
Attack days	0.0283*	1					
No. of attack	-0.0449*	0.2400*	1				
No. of casualties	0.0023	0.0776*	0.2518*	1			
No. of injuries	-0.0176*	0.0345*	0.1152*	0.6405*	1		
Property destroyed	0.0623*	0.3793*	0.2693*	0.0773*	0.0483*	1	
No. of Property destroyed	0.0229*	0.1816*	0.7846*	0.1406*	0.0717*	0.4787*	1

Table 3: Oil (spot) and terrorist attacks (Oil importing vs Oil exporting)

Dependent variable: Oil returns	**(1) Attack days**	**(2) No. of attack**	**(3) No. of casualties**	**(4) No. of injuries**	**(5) Property destroyed**	**(6) No. of property destroyed**
Full sample	-0.0684***	-0.00939***	0.0000805	0.0000903	-0.134***	-0.0183***
	(-4.27)	(-3.91)	(0.47)	(1.20)	(-14.20)	(-6.21)
Oil importing	-0.0725***	0.00704**	-0.000144	0.0000245	-0.147***	-0.0189***
	(-4.07)	(2.67)	(-0.92)	(0.71)	(-13.69)	(-5.51)
Oil exporting	-0.0837**	0.0159**	0.00180***	0.00147***	-0.0886***	-0.0605**
	(-2.12)	(2.55)	(3.57)	(4.00)	(-4.38)	(-2.06)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Oil (spot) and terrorist attacks

Dependent variable: Oil returns	**(1)** **Attack days**	**(2)** **No. of attack**	**(3)** **No. of casualties**	**(4)** **No. of injuries**	**(5)** **Property destroyed**	**(6)** **No. of property destroyed**
Developing	-0.0480** (-2.76)	0.0110*** (4.61)	-0.000080 (-0.35)	0.000586* (2.19)	-0.119*** (-11.74)	-0.0156*** (-5.04)
Developed	-0.298*** (-6.95)	-0.0283*** (-3.43)	0.0000191 (0.03)	-0.0000069 (-0.36)	-0.145*** (-4.32)	-0.0232** (-2.95)
Most developed	-0.325*** (-6.14)	-0.0261** (-2.99)	-0.000087 (-0.10)	-0.0000112 (-0.49)	-0.177*** (-4.54)	-0.0226** (-2.62)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Oil (spot) and terrorist attacks (Regional results)

Dependent variable: Oil returns	**(1) Attack days**	**(2) No. of attack**	**(3) No. of casualties**	**(4) No. of injuries**	**(5) Property destroyed**	**(6) No. of property destroyed**
Eastern Europe	-0.0914 (-1.59)	0.0140 (0.94)	0.000682 (0.83)	0.000275 (0.44)	-0.135*** (-3.43)	-0.0258 (-1.31)
MENA	-0.0991*** (-3.06)	0.0141*** (4.23)	0.000698 (1.23)	0.00113*** (3.55)	-0.0373** (-2.00)	0.00286 (0.42)
South America	-0.130** (-2.30)	-0.0204** (-2.06)	-0.00184** (-2.23)	0.00135 (0.86)	-0.154*** (-3.82)	-0.0212** (-2.00)
South Asia	-0.0719* (-1.93)	0.0109** (2.42)	-0.000984 (-1.40)	0.00000618 (0.02)	-0.0707*** (-3.41)	-0.00415 (-0.81)
Southeast Asia	0.0584 (1.14)	0.0213** (2.08)	-0.0104*** (-2.77)	0.00336** (-2.10)	-0.162*** (-5.20)	-0.0329*** (-3.26)
Sub-Sahara Africa	-0.0865** (-2.01)	-0.00886 (-0.96)	-0.00113*** (-2.65)	-0.000193*** (-3.14)	-0.222*** (-8.39)	-0.0352*** (-2.90)
Western Europe	-0.331*** (-6.69)	-0.0275*** (-3.29)	-0.00139 (-0.38)	-0.00000964 (-0.02)	-0.134*** (-3.47)	-0.0214*** (-2.74)

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Oil (futures) and terrorist attacks

	(1) Attack days (1 Month Futures)	(2) Number of Attacks (1 Month Futures)	(3) Attack days (2 Month Futures)	(4) Number of Attacks (2 Month Futures)
Full sample	-0.0624***	-0.0980***	-0.507***	0.00795***
	(-3.96)	(-6.46)	(-61.31)	(3.59)
Oil exporting	-0.614***	-0.0150*	-0.584***	0.0101
	(-35.21)	(-2.52)	(-31.70)	(1.84)
Oil importing	-0.0594***	-0.00682**	-0.0889***	0.00598**
	(-3.37)	(-2.60)	(-5.35)	(2.83)
Developing	-0.339***	-0.0276**	-0.339***	-0.0159**
	(-7.29)	(-3.23)	(-7.29)	(-2.76)
Developed	-0.0415*	-0.0100***	-0.0751***	0.00863***
	(-2.43)	(-4.37)	(-4.59)	(3.75)
Most developed	-0.315***	-0.0260**	-0.340***	-0.0126*
	(-5.88)	(-2.82)	(-5.80)	(-2.41)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effects of crude oil price on investment

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Abstract

Using a comprehensive dataset of more than 33,000 firms from 54 countries in the period 1984-2015, we show that crude oil price uncertainty negatively influences corporate investment. More importantly, the effect is dependent on the market and stock characteristics of the firms. In addition, we discover that the effect is stronger in the crude oil producers group than for crude consumers. Our analysis reveals that the global financial crisis and market volatility phases significantly affect this relationship. Our results survive a range of robustness tests.

Keywords: Crude oil price uncertainty; Corporate investment; Producer and consumer, Firm characteristics.

I. Introduction

Investment decision is one of the most fundamental and important corporate activities, affecting a firm's value and therefore the investors' wealth. Both prior empirical and theoretical literature has conclusively suggested the negative impact of uncertainty on investment.[24] Uncertainties may come from various sources, such as input cost and output price uncertainty (Pindyck, 1991; Dixit and Pindyck, 1994; Bloom et al., 2007), macro uncertainty (Bloom, 2009), policy uncertainty (Gulen and Ion, 2016) and political uncertainty (Julio and Yook, 2011, 2012; An et al., 2016).

Given that crude oil is one of input costs faced by firms, either directly or indirectly, then uncertainty regarding its prices can make the investment decision more difficult (Henriques and Sadorsky, 2011). The intuition underlying the relationship between crude oil price uncertainty and corporate investment is simple. Pindyck (1991) argues that uncertainty in the energy price leads to uncertainty about future energy prices, which causes firms to postpone investments. There are two channels through which crude price can affect a firm's investments (Edelstein and Kilian, 2007; Hamilton, 2008; and Kilian, 2008). First, via "supply channel", in which rising crude oil price pushes up the marginal cost of production as crude oil is an important input cost in the whole production chain.[25] Second, via "demand channel", in which oil price increase reduces consumer expenditure and leads to a decrease in demand for the firm's product.

Despite the broad and growing literature studying the impact of oil price uncertainty on investment at the aggregate level (Uri, 1980; Bernanke, 1983; Mohn and Misund, 2009; Elder and Serletis, 2010a, b), considerably less attention has been given to the oil price uncertainty effect on firm-level investment. Notable exceptions are Henriques and Sadorsky (2011) and Wang et al. (2017).[26] Wang et al. (2017) develop and estimate a dynamic model of investment to investigate the impact in China's market and reveal that the oil price uncertainty has a negative impact on corporate investment expenditures in this market. They also investigate the effect of state ownership and degrees of marketisation on the relationship between oil price uncertainty and corporate investment. They discover that the effect is stronger in state-owned firms and high-degree marketization periods compared to non-state-owned firms and low-degree marketization periods. Henriques and Sadorsky (2011) investigate how oil price volatility affects the strategic investment decisions of US firms and find the effect is negative.

This study is motivated not only to extend the scarce literature examining the impact of crude oil price uncertainty on firm-level investment, but it also attempts to address a series of unanswered questions regarding this relationship. In particular, we aim to shed light on the following questions: first, how does the oil price uncertainty affect corporate investment from a global standpoint? Is this relationship homogeneous across different continents and between developed and emerging countries? Does this relationship depend on the firm's characteristics? Does this relationship vary between oil consumers and oil producers? Finally, have the global financial crisis and market volatility phases affected this relationship? The answers to these questions are of particular importance as crude oil is not only the main input in modern industry but also the most traded commodity in the world. A comprehensive

[24] The exceptions are the studies by Hartman (1972) and Abel (1983) that find that increased uncertainty may raise investment due to its positive effect on the value of a marginal unit of capital. See Carruth et al. (2000) and Bond et al. (2005), that provide a comprehensive survey of studies on uncertainty and investment, for more detail of this literature.

[25] Although some firms may not directly consume crude oil as part of their production process, crude oil could be an indirect cost to firms.

[26] It is worth noting that a number of papers test the effect of energy price on corporate investment, namely Yoon and Ratti (2011), Ratti et al. (2011), and Sadath and Acharya (2015). Yoon and Ratti (2011) examine the effect of energy price uncertainty on US manufacturing, while Sadath and Acharya (2015) test Indian manufacturing firms. They find that higher energy price uncertainty causes firms to be more cautious by reducing the responsiveness of investment to sales growth. Ratti et al. (2011) construct a dynamic model of investment for non-financial firms in 15 European countries and observe that a real energy price increase reduces the persistence degree in the investment adjustment cost function.

understanding of the impact of its price uncertainty on investment decisions and factors affecting such an effect is critical to a firm's success.

Our analysis is based on a large sample of 33,075 firms from 54 countries. The sample consists of 405,711 firm-year observations for the period 1984-2014. Our study distinguishes itself from the prior literature and contributes to the crude oil uncertainty and investment literature through five important directions.

First, a very few empirical works that have been done on the effect of crude oil price uncertainty on firm-level investment have paid attention to individual countries, such as the US (Henriques and Sadorsky, 2011) and China (Wang et al., 2017). This study, on the other hand, provides a complete picture, the global perspective. In addition, our large set of data, which spans a wide range of countries, allows us to divide the data into different aggregate market sample groups, namely: developed, emerging, Africa, Americas, Asia, Australasia, and Europe. Given national differences in industrial structure, energy structure, energy consumption intensity, energy import dependence and energy pricing mechanisms, the impact of oil price shocks may be different across markets (Crompton and Wu, 2005). In fact, our findings consistently show a negative and statistically significant predictive effect in all aggregate markets. The magnitude of the effect, however, is heterogeneous. For the sample of 33,075 firms, the crude oil price uncertainty negatively, and statistically significantly, predicts the corporate investment. One percent rises in crude oil price uncertainty reduce corporate investment by 0.487%. The negative and statistically significant predictive effect is found in both developed and emerging country panels, but the effect is stronger in the developed panel compared to the emerging panel. In continent-based panels, the negative predictive effect is consistently observed in five continent panels. However, the effect is panel-dependent in terms of magnitude, where the effect is strongest on the Australasia panel (0.697%) and weakest on the Africa panel (0.258%). The findings give credence to our approach of forming a wide range of panels.

Second, to our knowledge, this study is the first to empirically investigate how the effect of crude oil price uncertainty on corporate investment is subject to the characteristics of a firm. The existing literature documents that the effects of crude oil on equity markets are sensitive to characteristics of firms. For example, Phan et al. (2015), Tsai (2015), Narayan and Sharma (2011, 2014), and Sadorsky (2008) document that the effect of crude oil price movements on stock returns varies with firm size. However, nothing is known about the effect of firm characteristics on the relationship between crude oil price uncertainty and corporate investment. We enhance the literature by testing this question. We perceive that the crude oil price uncertainty statistically significantly predicts corporate investment, the predictive effect is, however, subject to the characteristics of a firm. The small firms, growth firms, and most volatile firms are affected more by crude oil price uncertainty compared to large firms, value firms, and least volatile firms. A one percent increase in crude oil price uncertainty reduces corporate investments by 0.999%, 0.654%, and 0.670%, respectively. For the firm age-based panels, corporate investment in young firms is positively affected by the crude oil price uncertainty while the mature firms are negatively affected. In considering the trading volume-based firms, the results suggest that firms at different trading volume levels are almost equally impacted by crude oil price uncertainty.

Third, a common limitation of previous studies is that they only focus on a single oil consuming country, such as the US or China, and do not differentiate oil-producer countries (industries) from oil-consumer countries (industries) when investigating the effect of crude oil price uncertainty on corporate investment. In fact, a few studies have found the heterogeneous impacts of oil price shocks on stock markets in oil-consuming countries and oil-producing countries. For instance, Park and Ratti (2008) reveal that effects of oil price shocks and oil price volatility on real stock returns are different between oil exporting and importing countries. Jung and Park (2011) find a significant difference in the response of stock market returns to oil supply and demand shocks in an oil-exporting country (Norway) and an oil-importing country (Korea). More recently, Phan et al. (2015) find that oil price changes affect producers and consumers differently, where oil price increase has a positive effect on the stock returns of oil producing sectors but a negative effect on the stock returns of oil consuming sectors. Thus, it is of great importance to investigate whether the differences in the oil price uncertainty impacts on corporate investment widely vary between oil-producers and oil-consumers. In this paper, we aim to address previous studies' limitations by classifying our sample into oil producers and consumers using two approaches: (1) we use the Global Industry Classification Scheme to define crude oil producing and consuming industries, (2) we categorise crude oil producing and consuming countries based on the country's crude oil consumption and production. We expect that corporate investments in crude oil producing countries and industries are affected more strongly than crude oil consuming countries and industries. This expectation is reasonable as exposure to the oil price is stronger for the crude oil producer than for the crude oil consumer. In other words, crude oil is of greater importance for oil producers compared to oil consumers. For example, the profitability of crude oil is strongly dependent on oil price uncertainty while, in contrast, the profitability of crude consumers can be determined by a wide range of factors and oil price is only a part of them. The crude oil price uncertainty can affect the consumers either directly (via the increase in petroleum and gas prices) or indirectly (via the rise in prices of goods and services whose production depends on the usage of oil). Consistent with our prediction, the empirical results show that the magnitude of the predictive effect of crude oil uncertainty on corporate investment is statistically significantly different between oil consumers and producers. That is, this effect is more pronounced in the crude oil producing countries (industries) than the crude oil consuming countries (industries).

Fourth, we investigate the effect of the global financial crisis on the predictive effect in our baseline findings. The previous studies provide strong evidence for the effect of the global financial crisis on the relationship between crude oil and stock market (Wen et al., 2012; Aloui et al., 2013; Tsai, 2015; and others). Wen et al. (2012) find a significantly increasing dependence between crude oil (WTI oil spot price) and the US stock market (S&P500 index) during the global financial crisis, while it weakens in the China market (Shanghai stock market composite index). Aloui et al. (2013) show evidence of a positive dependence between the oil and stock markets of the Central and Eastern European countries but the dependence patterns change during the global financial crisis. Tsai (2015) shows that the oil prices negatively influence firms' stock returns in the US stock market before the global financial crisis, but the effect turns to positive during and after such a crisis. This paper contributes to the literature by offering a new finding, that the global financial crisis dampens the negative impact of a rise in crude oil price uncertainty on corporate investment. This finding is consistent regardless to the panels at both aggregate market and stock-characterised panel levels.

Last, but not least, we extend the existing literature of crude oil uncertainty and corporate investment by examining how different market volatility phases change the response of corporate investment decisions to oil price uncertainty. Using daily stock market price data, we compute one-year stock return variance of the world market (proxied by the MSCI World Index). When the market stock return variance is higher than the its median over the sample period, the market is considered as in a volatile phase. We find that the negative effect of crude oil price uncertainty on corporate investment is stronger when the market is volatile.

Our aforementioned findings survive through a range of robustness tests: (a) using two alternative measures of corporate investments, (b) using an alternative measure of crude oil price uncertainty, and (c) using an alternative regression model with additional firm-related control variables.

The remainder of this paper is organised as follows. In the next section, we develop our main hypothesis. Section III describes the data and discusses preliminary statistics on the data while section IV describes our main results, additional tests, and robustness tests. Finally, Section V sets forth our conclusions.

II. Hypothesis development

In this section, we develop a testable hypothesis by discussing several mechanisms through which crude oil price uncertainty affects corporate investments, basing the hypothesis on both theories and empirical findings in the existing literature. A firm's investment decision is made based on its net present value, which is equal to the sum of all discounted expected cash flows produced by that investment.

Accordingly, oil price uncertainty can affect firm investment decisions either by affecting future cash flows or by affecting the discount rate.

First, crude oil is one of the essential inputs for most goods and services production. Although some firms may not directly consume crude oil as part of their production processes, crude oil could be an indirect cost to firms. [27] While a rising crude oil price pushes up the marginal cost of production via the "supply channel", it reduces consumer expenditures and leads to a decrease in demand for the firm's product via the "demand channel" (Pindyck, 1991). Accordingly, the more uncertain the oil price, the greater movements of expected cash flow produced by investment opportunities. Second, any volatility in oil price is often seen as inflationary or deflationary, which is responded to by central banks through adjusting interest rates (Ferderer, 1996; Sadorsky, 1999). Together, by affecting future cash flows and/or the discount rate, a firm's investment decision is likely to be affected by the crude oil uncertainty.

In addition, firms invest if the net present value of an investment opportunity is greater than the option value of waiting. The theoretical foundations for real options in firm-level investment decisions under uncertainty are earliest developed by Bernanke (1983), McDonald and Siegel (1986), Pindyck (1988, 1991) and Dixit and Pindyck (1994). They show that a firm faced with heightened uncertainty may delay implementing investment in capital equipment until new information emerges. Bloom et al. (2007) present a model utilising different types of adjustment costs, uncertainty effects, and functional form of revenue functions in a panel of the UK manufacturing firms. They reveal that uncertainty reduces a firm's irreversible investment in response to sales shocks. This is because during times of increased volatility of a firm's demand shock, firms become more cautious and respond less. Bloom (2009) builds a model simulating a macro uncertainty shock on hiring and investment, suggesting that higher uncertainty increases the real option value to waiting, which causes firms to temporarily pause investment until the resolution of uncertainty. In the context of political uncertainty and corporate investment, Julio and Yook (2011, 2012) and An et al. (2016) document that political uncertainty leads firms to reduce investment expenditures. They state that around election times, firms are likely to be more cautious and delay investment expenditures until the uncertainty of the election outcome is resolved.

Consistent with the literature on real options, an increase in oil price uncertainty raises the option value of waiting to invest as waiting for uncertainty to be resolved will improve the chances of making the correct investment decision. (Pindyck, 1991; Dixit and Pindyck, 1994). Oil price uncertainty thereby causes firms to postpone their firms' investment. The above discussions lead us to the following hypotheses:

Hypothesis 1: **Oil price uncertainty leads to lower corporate investment.**

III. Data

In this section, we first describe the datasets, their sources, and panel construction. We then summarize the data using commonly noted statistics.

A. Data

Our data sample comprises two sets of data: firms' specific data and crude oil price uncertainty data. In our econometric framework that we discuss later (see, Julio and Yook, 2012), besides the corporate investment, the main variable of interest, we also control for cash flow (*CF*), Tobin's Q (*Q*), and growth rate of GDP (*GDP*). All data are collected from DATASTREAM, except for GDP data downloaded from the Global Financial Database. Specific details on each of these variables are provided in Table I. Data is collected for the period 1984 to 2015 at the annual frequency.[28] We apply the common data

[27] This is because most firms, which do not consume crude oil, do consume petroleum products (gasoline, diesel fuel, heating oil, jet fuel, etc.) whose prices move in line with oil price.

[28] The start date of our sample is dictated by the availability of crude oil price data.

filtering process, namely, (1) excluding all financial and utility stocks, (2) including only stocks that have data for all variables, (3) and winsorizing variables at 1st and 99th percentiles to remove the influence of outliers,[29] we end up with a total of 33,075 firms from 54 countries which consist of 405,711 firm-year observations.[30]

[Insert Table I here]

We group our 33,075 firms into various panels based on their location and stock characteristics. First, we have aggregate market panels such as a global (includes all stocks in our sample) panel, a developed country panel, an emerging country panel, and five continent-based panels. Second, we construct a number of panels based on stock characteristics including size (proxied by market capitalization), age, book-to-market ratio, trading volume and stock return volatility. The stocks are independently sorted in ascending order into three equal groups based on each of these five characteristics. We have: (i) three size-based panels, from low market capitalization (MV1) to high market capitalization (MV3); (ii) three firm age-based panels, from youngest firms (FA1) to oldest firms (FA3); (iii) three book-to-market (BM) ratio-based panels, from low BM (BM1) to high BM (BM3); (iv) three trading volume-based panels, from low trading volume (TV1) to high trading volume (TV3); and (v) three stock return volatility-based panels, from low volatility (VO1) to high volatility (VO3). Consequently, we end up with 23 panels of firms in total.

To understand the features of corporate investment data, we plot the series of equal-weighted average corporate investments of firms for aggregate market panels in Figure I. There are two main observations from this figure. First, there is a significant disparity in terms of magnitude and fluctuation in corporate investment across the various panels of firms. Second, the overall trend of corporate investment in all panels of firms (the exception is Australasia) is declining over time.
[Insert figure 1 and 2 here]

The second type of data is crude oil price uncertainty. Two measures of oil price uncertainty are widely used in the existing literature include the standard deviation of daily returns of international oil prices (Sadorsky, 2008; Henriques and Sadorsky, 2011), and the one generated from a GARCH model (Hamilton, 2003; Sadorsky, 2006; Yoon and Ratti, 2011). In this paper, we use both of the methods to measure international oil price uncertainty. The former measure is considered as the main measure while the latter measure is considered as a robustness test. We use the daily oil price obtained from the US Energy Information Agency website, and choose the daily closing oil price of the nearest contract to maturity of West Texas Intermediate. Annual oil price volatility is measured following Sadorsky (2008):

$$\sigma_t = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t^o - E(r_t^o)^2} \, .\sqrt{N}$$

The crude oil price volatility and end of the year closing prices are plotted in Figure 2. The figure shows that both oil price and volatility have changed over the estimation period of 1984-2015. Oil price volatility was particularly high in 1986 (Saudi Arabia and other OPEC members increase their share of

[29] This data filtering process is widely used in the corporate investment literature (Bates et al., 2009; Duchin et al., 2010; Julio and Yook, 2012; Asker et al., 2014; An et al., 2016)

[30] Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Macedonia, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Oman, Pakistan, Peru, the Philippines, Poland, Portugal, Russia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Tunisia, Turkey, Ukraine, the United Kingdom, the United States, Venezuela, and Vietnam.

the oil market), 1990 (the Gulf War), 1998 (Iraq War), 2008 (oil price bubble). Regarding the oil price, it reached its peaks in years 2008 and 2011-2013.

B. Summary statistics

Table II presents the summary statistics of our data set. Column 1 shows all 23 panels of firms and column 2 lists the number of firms per panel. The 23 panels consist of eight aggregate market-based panels and 15 stock characteristic-based panels. Several features of this data are evident. First, there are large variations in corporate investment across samples of aggregate markets and stock characteristics. The average corporate investment for a panel of all firms, for example, is 7.35% of prior-year total assets. The average corporate investment of the emerging panel (7.72%) is slightly higher than that of the developed panel (7.08%). For the continental markets, the average corporate investment varies between 6.58% (Europe) and 11.07% (Australasia) of prior-year total assets. Reading the corporate investment for panels based on the stock characteristics, we find that it declines with firm size, firm age, and book-to-market ratios but increases with trading volume and volatility.
[Insert Table II here]

Second, a strong heterogeneity feature is observed from data on *CF* (as a percentage of total assets). At the continent level, for instance, *CF* ranges from 1.42% (Australasia) to 10.08% (Africa). At the stock characteristic-based panel level, *CF* increases with size, age, and trading volume but decreases with volatility and no clear pattern for the book-to-market ratio. Third, concerning *Q* (market value to book value of assets), we observe a similar heterogeneity. The incentive to invest, as reflected by *Q*, is highest in Australasia (2.53) and lowest in Asia (2.13) at the continent level. At the stock characteristic-level, *Q* declines with book-to-market ratio and volatility while it increases with market value, age, and trading volume.

In summary, we observe that the corporate investment and other firm control variable are heterogeneous across 23 panels. This finding gives credence to our approach of forming a wide range of panels of firms based on aggregate markets and stock characteristics.

IV. Empirical Findings

The results are analysed in multiple subsections. First, we present evidence on the relationship between crude oil price uncertainty and corporate investment by using preliminary analysis (section A) and panel data regression models (section B). Next, we have additional analyses (section C) on our baseline results and, finally, we implement a range of robustness tests (section D).

A. Preliminary result

This section aims to understand preliminary evidence on the relationship between crude oil price uncertainty and corporate investment before we embark on more formal tests. To achieve this aim, we consider two tests: (i) a univariate analysis to capture corporate investment during high and low crude oil price uncertainty; and (ii) a Granger causality test to disclose the causation significance of crude oil price uncertainty on corporate investment. The main outcome observed from these tests is that crude oil price uncertainty does negatively influence corporate investment.
[Insert Table III here]

We start with a univariate analysis, the results of which are reported in Table III. This table reports the average values of corporate investment in the years with high crude oil price uncertainty (column 2) versus the years with low crude oil price uncertainty (column 3). High crude oil price uncertainty is when crude oil price uncertainty greater than its median over the sample period and it is low crude oil price uncertainty otherwise. The difference between corporate investments in high and low crude oil price uncertainty and its *t*-statistics are reported in columns 4 and 5, respectively. Out of the 23 panels , there are 20 panels (87%) that have higher corporate investment in low oil price uncertainty years compared to that in high crude oil price uncertainty years. In these 20 panels, the difference (high minus

low) is negative and statistically significant in 19 panels, which is 83% of the total number of panels. Considering the global panel that contains all stocks, high crude oil price uncertainty years have a corporate investment that is 5.41% lower than corporate investment in low crude oil price uncertainty years. Across statistically significant stock characteristic-based panels, corporate investment is, on average, 5.54% lower in high crude oil price uncertainty years. This implies that for the majority of firm-panels, there is statistical evidence of the negative effect of crude oil price uncertainty on corporate investment.
[Insert Table IV here]

We turn now to the Granger's causality test, which is reported in Table IV. We test the hypothesis that crude oil price uncertainty does not cause corporate investment. The null hypothesis is tested based on the F-statistic (column 2) and *p*-value (column 3). Out of 23 panels, the hypothesis that crude oil price uncertainty does not cause investment is rejected at least at the 10% level in all panels, except Africa. In most of the cases, the hypothesis is comfortably rejected at 1% level. Therefore, the results of the Granger causality test suggest a solid evidence for the effect of crude oil on corporate investment.

B. Main findings

Our preliminary analysis suggests a statistically significant and negative influence of crude oil price uncertainty on corporate investments. However, it is important to note that the univariate analysis or Granger causality does not control for other variables and cross-firm variations. To eliminate these limitations of those tests, we now employ more formal multivariate regression models in order to test our proposed hypotheses. Our main regression model is based on a standard investment-type specification that is widely used in the literature (see, for instance, Blundell et al., 1992; Blundell et al., 1999; Julio and Yook, 2012), and has the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 Q_{i,t-1} + \beta_3 CF_{i,t} + \beta_4 GDP_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

where i and t are index firm and time, respectively. The dependent variable, investment (*INV*), is defined as capital expenditure scaled by total assets in the preceding year. The variable *OILVOL* is the measure of crude oil price uncertainty, which is described in the previous section. *Q* is Tobin's *q*, a popular determinant for corporate investment, measured by the ratio of the market value of assets to the book value of assets. *CF* is cash flow, measured as earnings before interest and taxes, minus taxes and interest expenses, plus depreciation and amortization. Following (see Julio and Yook, 2012; and Gulen and Ion, 2015), we use the growth rate of GDP to control for general economic conditions. Firm and year effects are also modeled using a panel fixed effect model. As is common practice, standard errors are clustered at the firm level to correct for potential cross-sectional and serial correlation in the regression's error term, $\varepsilon_{i,t}$.

Before we examine the outcomes from the regression model, we test for the stationary of each of the variables by implementing the Levin, Lin, and Chu (2002) and Im, Pesaran and Shin (2013) panel unit root tests, which examine the null hypothesis of a panel unit root. The results, which are not reported, suggest that all variables in our model are panel stationary. Therefore, our estimates are free of any bias resulting from the persistency of the explanatory variables.

[Insert Table V here]

The results of the regression model testing predictive effect of crude oil price uncertainty on corporate investment are presented in Table V. First, we consider the results in aggregate market panels, reported in Panel A. There, three observations stood out. The first observation relates to the sign of the effect of crude oil price uncertainty on corporate investment. In all panel models, the sign is negative, suggesting that crude oil price uncertainty reduces corporate investment. The second observation regards the statistical significance of the results. We find that negative coefficients of crude oil price uncertainty are statistically significant at least at the 10% level in all panels. Third, although the predictive effect is consistently negative and statistically significant in all panels, the magnitude of the effect is heterogeneous. In the other words, the strength of the predictive effect is different across panels. The global panel experiences that one percent rises in crude uncertainty reduce corporate investment by 0.487%. Developed countries evidence a larger effect of crude oil price uncertainty on corporate investment compared to that of emerging countries (0.452% compared to 0.362%, respectively). Among five continents, the effect is strongest for Australasia and lowest for Africa. For every one percent increase in crude uncertainty, the corporate investment of firms in Australasia and Africa panels decreases by 0.697% and 0.258%, respectively.

We now turn our attention to the predictive effect of crude oil on corporate investment for panels sorted by stock characteristics. We find that for 15 out of 15 panels, the crude oil price uncertainty statistically significantly predicts corporate investment. A number of very interesting highlights emerges. First, the magnitude of the negative effect decreases with firm size. That is, corresponding to a one percent increase in crude oil price uncertainty, large firms' investments are likely to decrease by 0.444% while small firms' investments fall by 0.999%. Similarly, we find that increases in firms' book-to-market ratio also reduce oil price uncertainty exposure. However, this trend does not apply to firm age panels. In particular, crude oil price uncertainty positively affects young firms' investments while the effect is negatively significant for mature firms. A one percent increase in crude oil price uncertainty reduces the corporate investment of mature firms by 0.38%. Next, we find that firms at different trading volume levels are almost equally impacted by crude oil price uncertainty. A one percent increase in crude oil price uncertainty reduces corporate investment by 0.418% to 0.522%. With VO-based panels, the panels of most volatile firms are more severely affected by crude oil price uncertainty, where a one percent increase in crude oil price uncertainty reduces corporate investment by 0.670%.

In brief, in terms of the economic importance of crude oil price uncertainty, the most negatively affected panels based on stock characteristics are small firms, mature firms, growth firms, and high VO firms. For these panels of firms, a one percent increase in crude oil price uncertainty reduces the corporate investments by 0.999%, 0.380%, 0.654%, and 0.670%, respectively. Finally, we examine the results for the other determinants of corporate investment, *Q*, *CF*, and *GDP*. Their coefficients are, as expected, statistically significant in at least 21/23 panels. Moreover, the adjusted R-squared varies in the range of 28.3% to 43.3%.

C. Additional tests

Having shown that investment is systematically lower when the crude oil price uncertainty increases in most panels, we now deepen the analysis by investigating (a) whether the impact varies between crude oil producers and crude oil consumers, (b) whether there is an effect of global financial crisis on the predictive effect of crude oil price uncertainty on corporate investment, and c) whether the volatility phases of stock market affect this relationship.

C.1 Results based on crude oil producer/consumer

We expect that the overall impact of oil price uncertainty on corporate investment depends on whether a firm is a consumer or producer of oil and oil related products. We use two approaches to categorize crude oil consumers and producers. In the first approach, we utilize the Global Industry Classification Scheme and a firm is defined as crude oil producer if it belongs to one of the crude oil producing industries.[31] In the second approach, we collect data on crude oil consumption and production by country for the 54 countries in our sample, from the US Energy Information Administration (EIA) website. A country is defined as a crude oil producer if its crude oil production is higher than its crude oil consumption. Conversely, a country is defined

[31] Oil & gas drilling; oil & gas equipment & services; integrated oil & gas; oil & gas exploration & production; oil & gas refining & marketing; and oil & gas storage & transportation.

as a crude oil consumer if its crude oil production is less than its crude oil consumption. The regression model is of the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * PRODUCER\_INDUSTRY_i + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * PRODUCER\_COUNTRY_i + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

where all variables are as previously described except *PRODUCER_INDUSTRY*, which is crude oil producer dummy that equals 1 if the firm is a crude oil producing industry and zero otherwise; and *PRODUCER_COUNTRY,* which is crude oil producer dummy that equals 1 if the firm is a crude oil producing country and zero otherwise. The regressions control for the firm and year fixed effects and *t*-statistics are corrected for clustering of the residual at the firm level.
[Insert Table VI here]

The results are reported in Table VI. This table reports the coefficients and their *t*-statistics for crude oil price uncertainty and its interaction with producer dummy variables.[32] Our findings from this test have a number of following features. First, the results from earlier analysis still hold after controlling for the crude oil consumer/producer characteristic. The effect of crude oil price uncertainty on corporate investment is still negative and statistically significant in most cases. Second, the majority of the interaction between crude oil price uncertainty, *OILVOL*, and either crude oil producing industry, *PRODUCER_INDUSTRY*, or crude oil producing country, *PRODUCER_COUNTRY*, is negative and statistically significant. This result suggests that the negative effect of crude oil price uncertainty on corporate investment is strengthened in the crude oil producing industries or countries. In the other words, when the crude oil price uncertainty increases, the firms in producing industries or countries reduce their corporate investment more than the firms in crude oil consuming industries or countries. In considering the coefficients of interaction between *OILVOL* and *PRODUCER_INDUSTRY*, we find they are negative and statistically significant in four out of eight aggregate markets, which are the global, developed, Americas, and Australasia panels. This result is also found in nine out of 15 panels at the stock characteristic-based panel level (MV1, MV3, FA2, FA3, BM2, TV2, TV3, VO2 and VO3). In the case of the interaction between *OILVOL* and *PRODUCER_COUNTRY*, the coefficients are negative and statistically significant in four aggregate markets (global, emerging, Asia, and Europe) and seven firm-characterized panels (MV2, MV3, FA2, FA3, BM2, TV3, and VO3)

C.2 Results based on global financial crisis

We now examine the effect of the global financial crisis on the relationship between crude oil price uncertainty and corporate investment. In particular, we test whether crude oil price uncertainty exerts different effects on corporate investment during the crisis. The regression model takes the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * CRISIS_{t-1} + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where *CRISIS* is a dummy variable which equals 1 if the year is in global financial crisis (2007-2009) and zero otherwise. The regressions control for the firm and year fixed effects and *t*-statistics are

[32] In Australasia panel, we cannot run the equation (3) due the *PRODUCER_COUNTRY* variable in this panel is a constant. The results are represented as "---".

corrected for clustering of the residual at the firm level. The results for estimating equation (4) are reported in Table VII. In this table, we report the coefficients of crude oil price uncertainty and its interaction with global financial crisis dummy variable. As a general observation, we find consistent results with earlier analysis after controlling for the global financial crisis effect. However, the global financial crisis does significantly influence on the relationship between crude oil price uncertainty and corporate investment. In considering the coefficients of the interaction between crude oil price uncertainty variable and global financial crisis dummy, we observe that they are positive and statistically significant in most cases. This result implies that the negative impact of a rise in crude oil price uncertainty on corporate investment is weaker in the global financial crisis period. This finding is consistent regardless to panel levels. The coefficients are positive and statistically significant at the one percent level of significance in all aggregate market panels and 14 out of 15 firm-characterized panels.

[Insert Table VII here]

C.3 Results based on phases of market volatility

Market volatility phases can potentially also influence the effect of crude oil price uncertainty on corporate investment. Using daily stock market price data, we compute one-year stock return variance of the world market (proxied by the MSCI World Index). When the market variance is higher than its median over the sample period, the market is considered as in a volatile phase and the *VOLATILE* dummy variable takes a value of one. It takes a value of zero otherwise. We check for robustness of the baseline results by allowing outcomes to vary over the market volatility phases using the following regression model:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_t + \beta_2 OILVOL_{t-1} * VOLATILE_{t-1} + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t} \qquad (5)$$

The results are presented in Table VIII. We find consistent results in term of predictive effect of crude oil price uncertainty on corporate investment after controlling for the market volatility phases. With respect to the effect of market volatility phases, we examine the interaction of *OILVO*L and *VOLATILE* variables. There are three main features of the results. First, the coefficients are negative in all panels. Second, we can comfortably reject in all cases the null hypothesis of the coefficient is not different from zero at one percent significance level in 20 out 21 panels. Third, the findings are consistent regardless of panel levels. These findings imply that the negative effect of crude oil price uncertainty on the corporate investment is stronger when the market is volatile. In the other words, the point of conclusion here is that firms tend to reduce their investments due to the rise in crude oil price uncertainty more when the market is volatile.

[Insert Table VIII here]

D. Robustness tests

The goal of this section is to check the robustness of our main findings. We investigate whether the documented effect of crude oil price uncertainty on corporate investment is robust to (a) two alternative measures for corporate investment, (b) an alternative measure of crude oil price uncertainty, and (c) alternative specifications of the main model, where we include additional firm control variables into the regression. The results are reported in the Appendix of this article.

D.1 Alternative proxy for corporate investment

We use two alternative measures of corporate investment *INV_A1 and INV_A2* to test the robustness of our earlier findings. *INV_A1* is calculated as capital expenditure scaled by property, plant, and equipment of previous year while *INV_A2* is calculated as the total asset growth rate. Several studies use these two measures of investment; see, inter alia, Hoshi et al. (1991), Kaplan and Zingales (1997), Mayers (1998), Korkeamaki and Moore (2004), Duchin et al. (2010), Eisdofer et al. (2013), Kahle and Stulz (2013), Asker et al. (2015), and González (2016)

The results are reported in the Table A.1 in the appendix. We find that with alternative measures of corporate investment, the results from the alternative measure are precisely consistent with the main measure's results. The alternative measures' results are even stronger in terms of magnitude. Using *INV_A1*, the effect of crude oil price uncertainty on corporate investment is negative and statistically significant at the one percent level in all aggregate market panels and 14 out of 15 stock characterized panels. On the other hand, the effect is negative and statistically significant in six out of eight aggregate market panels and 13 out of 15 stock characterized panels when we utilize *INV_A2*. We also find a similar pattern with earlier results in firm-characterized panels using the new measures, which is the most negatively affected panels based on stock characteristics are small firms, mature firm, growth firms, and high VO firms. In other words, while our results on the effect of crude oil price uncertainty on corporate investment are sensitive to the definition of corporate investments, they do not detract from the notion that crude oil price uncertainty influences corporate investment.

D.2 Alternative measure of crude oil price uncertainty

For the second robustness test, we use the variance generated from a GARCH(1,1) model as a proxy for crude oil price uncertainty. This measure has been used widely in the literature (see Sadorsky, 2008; Henriques and Sadorsky, 2011; Wang et al., 2017). The results are reported in Table A.2 in the appendix. In short, we observe very similar results to the ones using the standard deviation of daily crude oil returns reported earlier. Regardless of the measures of crude oil price uncertainty, we observe a strong negative relation between crude oil price uncertainty and corporate investment, consistent with the baseline results.

D.3 Alternative regression model with additional firm control variables

We next test the consistency of our findings by adding further firm control variables into the standard investment model by (Blundell, Bond, Devereux, and Schiantarelli, 1992; Blundell, Griffith, and Van Reenen, 1999; Julio and Yook, 2012). We add the one period lagged *INV* and two additional variables: *GROWTH*, which is sales growth rate calculated as the change in sales scaled by sales previous year; and *LEVERAGE*, which is firm leverage ratio calculated as total debt scaled by total assets.[33] The regression takes the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 Q_{i,t-1} + \beta_3 CF_{i,t} + \beta_4 GDP_{i,t-1} + \beta_5 INV_{i,t-1} + \beta_6 GROWTH_{i,t-1} + \beta_7 LEVERAGE_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

The results are reported in Table A.3. Our main finding is that the baseline results on the predictive effect of crude oil price uncertainty on corporate investment are consistent. From this exercise, we conclude that the choice of model's specifications did not in any way influence the relationship between crude oil price uncertainty and corporate investment.

V. Concluding remarks

This paper is motivated by our lack of understanding of the influence of crude oil price uncertainty on corporate investment. We analyze this effect for a sample of 33,075 firms that belong to 54 countries by categorizing firms into panels: a global panel of all firms, developed country panel, emerging country

[33] These variables have been used by An et al. (2016) and Wang et al. (2017) to explain the corporate investment.

panel, five continent-based panels, and into 15 panels constructed using firm characteristics, such as size, age, book-to-market ratio, trading volume, and volatility.

Our key findings can be summarized as follows, (1) our main findings reveal a negative and statistically significant predictive effect of crude oil price uncertainty on corporate investment expenditures, (2) the corporate investments of small firms, mature firms, growth firms, and high VO firms are negatively affected by crude oil price uncertainty the most, (3) we discover that the effect is stronger in the crude oil producing countries and industries than the crude oil consuming countries and industries, (4) the predictive effect of crude oil price uncertainty was weaker during the global financial crisis, (5) during a volatile market, the effect is stronger, (6) our findings survive through a wide range of robustness tests.

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Figure I: Plot of corporate investment

This figure plots time-series averages (equal-weighted) of the corporate investment for aggregate market panels over the period 1984-2015.

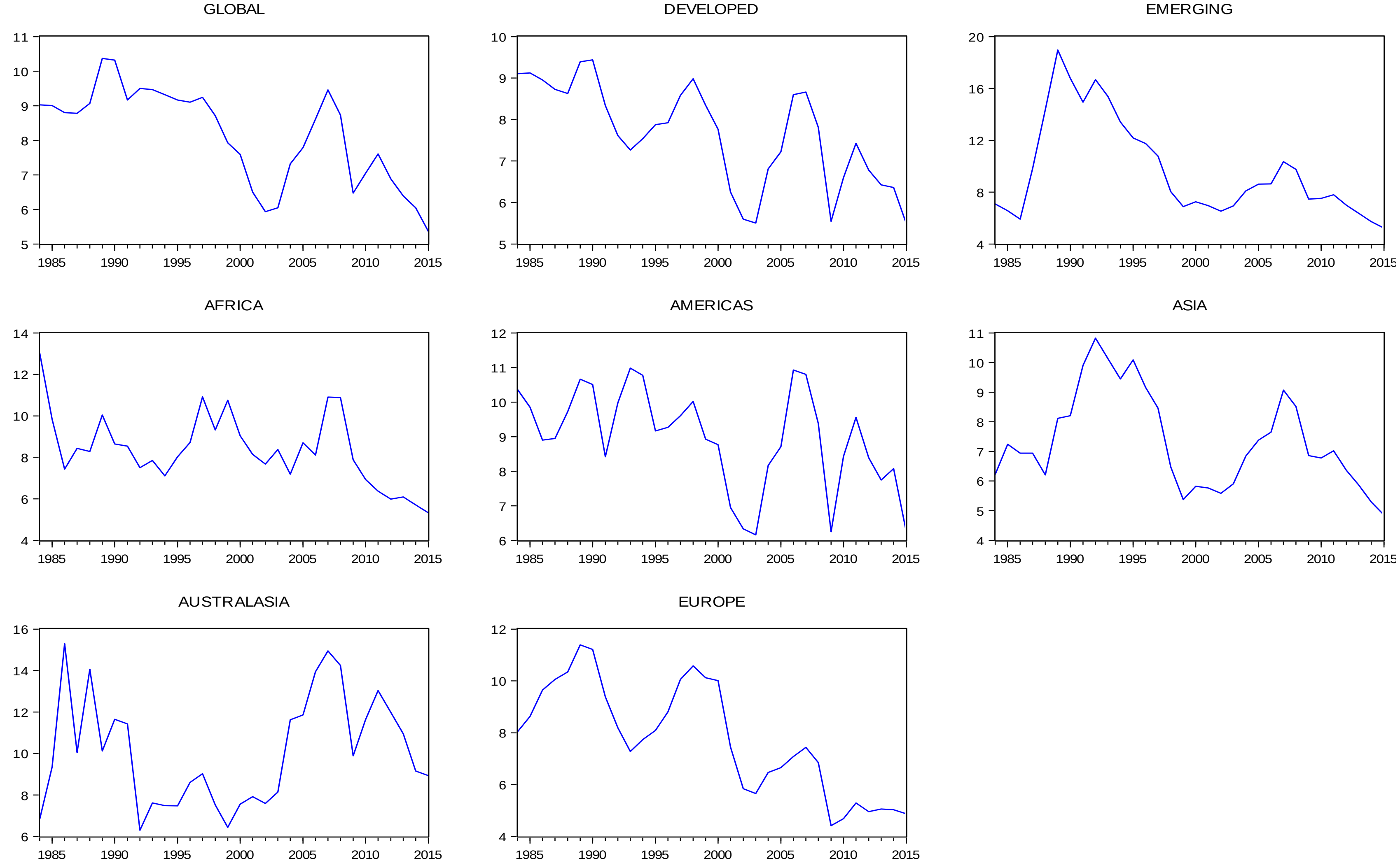

Figure II: Plot of crude oil prices and price uncertainty

This figure plots crude oil prices and price uncertainty over the period 1984-2015.

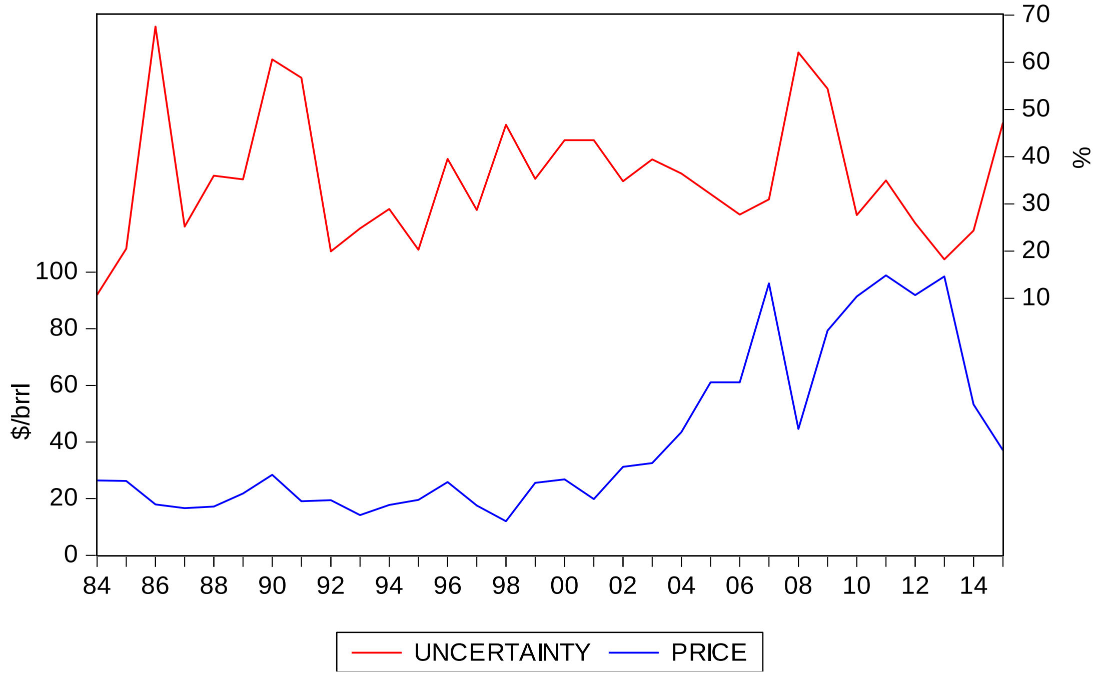

Table I: Variables description

Variable	Description
INV	Corporate investment: calculated as capital expenditure scaled by total assets in a previous year
OILVOL	Oil uncertainty measured by the standard deviation of daily returns of oil prices
OILVAR	Oil uncertainty measured by the GARCH variance from a GARCH(1,1) model
Q	Tobin Q: the ratio of the market value of assets to the book value of assets
CF	Cash flow: calculated as earnings before interest and taxes minus taxes and interest expense plus depreciation and amortization, scaled by total assets
PRODUCER_COUNTRY	Crude oil producing country dummy: equals 1 if the firm is a crude oil producing country and zero otherwise
PRODUCER_INDUSTRY	Crude oil producing dummy: equals 1 if the firm is a crude oil producing industry and zero otherwise
GDP	A country's GDP growth rate
CRISIS	Crisis dummy: equals 1 if the year is in the global financial crisis (2007-2009) and zero otherwise
VOLATILE	High volatile market dummy: equals 1 when the variance of one-year daily returns of the world market (proxied by the MSCI World Index) is higher than the its median over the sample period and zero otherwise
INV_A1	Corporate investment alternative measure 1: calculated as capital expenditure scaled by property, plant, and equipment of previous year
INV_A2	Corporate investment alternative measure 2: calculated as the total asset growth rate
GROWTH	Sales growth rate, calculated as the change in sales scaled by sales of the previous year.
LEVERAGE	Firm leverage ratio, calculated as total debt scaled by total assets.

Table II: Summary statistics of stock data.

This table reports the number of firms and the average value of stock variables and its standard deviation for: global panel, developed and emerging panels, five continent-based panels, and 15 firm-characterized panels.

Panels	No. of firm	INV		Q		CF		GDP	
		Mean (%)	SD	Mean	SD	Mean (%)	SD	Mean (%)	SD
Panel A: Aggregate market panels									
Global	33,075	7.35	11.35	2.32	5.16	6.18	8.50	4.09	3.51
Developed	17,678	7.08	11.78	2.27	5.52	5.29	8.72	2.63	2.32
Emerging	15,397	7.72	10.74	2.39	4.59	7.35	8.06	6.17	3.86
Africa	356	7.77	9.56	2.44	4.21	10.08	8.75	4.00	7.94
Americas	8,339	8.52	13.97	2.51	7.40	5.13	10.75	2.80	2.03
Asia	17,328	6.75	9.72	2.13	3.74	6.83	7.19	5.44	3.84
Australasia	1,667	11.07	17.14	2.53	5.38	1.42	11.31	3.32	1.46
Europe	5,385	6.58	9.59	2.52	4.68	6.47	7.34	2.36	2.78
Panel B: Firm-characterized panels									
MV1	11,025	8.11	15.29	2.29	7.48	3.91	9.89	3.58	2.85
MV2	11,025	6.90	10.48	2.22	4.20	6.75	8.35	4.60	3.76
MV3	11,025	7.28	9.23	2.41	3.89	7.23	7.25	4.08	3.77
FA1	11,025	9.84	15.44	2.20	6.62	5.43	9.02	4.43	3.45
FA2	11,025	8.09	13.11	2.23	5.33	5.99	9.03	4.22	3.39
FA3	11,025	6.29	8.56	2.40	4.56	6.63	7.86	3.64	3.63
BM1	11,025	7.95	12.79	3.84	8.27	5.80	10.21	4.24	3.55
BM2	11,025	7.49	10.47	2.30	3.35	6.93	7.84	4.01	3.52
BM3	11,025	6.71	11.00	1.18	2.75	5.68	7.43	4.01	3.45
TV1	11,025	6.76	11.59	1.88	5.62	5.44	8.60	3.26	2.96
TV2	11,025	7.39	11.74	2.18	4.75	5.85	8.77	3.78	3.23
TV3	11,025	7.81	10.75	2.86	5.05	7.11	8.07	5.24	3.96
VO1	11,025	6.62	9.22	2.34	4.17	7.07	7.60	3.69	3.50
VO2	11,025	6.87	9.75	2.34	4.19	6.84	7.94	4.59	3.84
VO3	11,025	8.75	14.71	2.27	6.79	4.34	9.78	4.00	3.10

Table III: Univariate analysis

This table reports the average value of corporate investment in the years with high crude oil price uncertainty versus the years with low crude oil price uncertainty. High crude oil price uncertainty is the years when *OILVOL* greater than its median over the sample period and it is low crude oil price uncertainty otherwise. The difference (high minus low) and *t*-statistic for the null hypothesis that the difference is equal zero are also reported.

	High Uncertainty	Low Uncertainty	Difference	*t*-statistic
Panel A: Aggregate market panels				
Global	7.101	7.507	-0.406***	-11.058
Developed	6.758	7.284	-0.526***	-10.512
Emerging	7.599	7.794	-0.195***	-3.642
Africa	8.149	7.539	0.610**	2.092
Americas	7.757	8.994	-1.237***	-13.746
Asia	6.563	6.854	-0.292***	-6.647
Australasia	10.296	11.512	-1.216***	-4.490
Europe	6.912	6.376	0.536***	7.375
Panel B: Firm-characterized panels				
MV1	7.429	8.481	-1.052***	-10.238
MV2	6.728	7.000	-0.272***	-4.563
MV3	7.202	7.332	-0.129***	-2.884
FA1	9.205	10.119	-0.914***	-6.578
FA2	7.915	8.185	-0.270***	-3.436
FA3	6.341	6.256	0.085**	2.316
BM1	7.569	8.181	-0.612***	-7.793
BM2	7.383	7.559	-0.176***	-3.209
BM3	6.410	6.889	-0.480***	-7.876
TV1	6.459	6.939	-0.480***	-7.032
TV2	7.094	7.567	-0.472***	-7.143
TV3	7.632	7.922	-0.291***	-5.073
VO1	6.353	6.787	-0.434***	-8.215
VO2	6.849	6.891	-0.042	-0.838
VO3	8.269	9.038	-0.769***	-8.760

Table IV: Granger causality test

This table reports the F-statistic and p-value of the Granger causality test with the null hypothesis that oil uncertainty does not Granger cause corporate investment.

	F-statistic	p-value
Panel A: Aggregate market panels		
Global	125.227	0.000
Developed	120.570	0.000
Emerging	13.050	0.000
Africa	1.259	0.262
Americas	66.215	0.000
Asia	10.996	0.001
Australasia	3.247	0.072
Europe	94.589	0.000
Panel B: Firm-characterized panels		
MV1	36.838	0.000
MV2	31.773	0.000
MV3	115.824	0.000
FA1	47.901	0.000
FA2	56.726	0.000
FA3	168.661	0.000
BM1	19.309	0.000
BM2	66.080	0.000
BM3	50.577	0.000
TV1	56.672	0.000
TV2	55.932	0.000
TV3	17.598	0.000
VO1	73.529	0.000
VO2	31.009	0.000
VO3	46.427	0.000

Table V: Estimation results

This table reports the regression results of crude oil price uncertainty influence on corporate investment. The regression model takes the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 Q_{i,t-1} + \beta_3 CF_{i,t} + \beta_4 GDP_{i,t-1} + \varepsilon_{i,t}$$

The coefficient and its *t*-statistic are reported. The regression controls for the firm and year fixed effects and *t*-statistics are corrected for clustering of the residual at the firm level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$OILVOL_{t-1}$		$Q_{i,t-1}$		$CF_{i,t}$		$GDP_{i,t-1}$		α		$\bar{R}^2$
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	
Panel A: Aggregate market panels											
Global	-0.487***	-16.86	0.106***	14.78	0.070***	17.62	0.095***	12.45	15.193***	21.80	0.344
Developed	-0.452***	-14.89	0.081***	9.30	0.051***	9.43	0.074***	3.87	14.781***	20.31	0.382
Emerging	-0.362***	-2.86	0.171***	13.72	0.092***	16.23	0.066***	8.39	11.841***	3.85	0.283
Africa	-0.258*	-1.88	0.124**	1.98	0.080***	2.65	0.009	0.65	10.134***	3.18	0.322
Americas	-0.543***	-12.60	0.068***	6.48	0.056***	8.01	0.165***	4.93	16.788***	16.38	0.364
Asia	-0.401***	-9.69	0.166***	13.62	0.105***	19.72	0.121***	9.31	12.223***	12.12	0.312
Australasia	-0.697***	-2.60	0.126***	3.87	-0.011	-0.59	0.160	0.91	23.215***	3.53	0.354
Europe	-0.270***	-5.52	0.094***	5.84	0.043***	5.01	0.119***	4.99	10.131***	8.62	0.318
Panel B: Firm-characterized panels											
MV1	-0.999*	-1.89	0.057***	5.14	0.022***	2.76	0.039**	2.22	28.695**	2.23	0.283
MV2	-0.448***	-7.13	0.154***	10.94	0.086***	13.20	0.063***	4.93	13.857***	9.10	0.327
MV3	-0.444***	-15.11	0.164***	15.54	0.102***	17.39	0.150***	13.33	13.526***	19.12	0.421
FA1	0.457***	10.00	0.056**	2.16	0.074***	4.03	-0.071*	-1.90	-6.425***	-5.11	0.311
FA2	0.209***	4.28	0.113***	9.03	0.048***	6.55	0.035**	2.42	-0.933	-0.77	0.318
FA3	-0.380***	-13.46	0.101***	12.09	0.077***	17.12	0.125***	12.88	12.436***	18.26	0.334
BM1	-0.654***	-9.40	0.057***	7.00	0.061***	8.44	0.125***	6.04	19.513***	11.62	0.309
BM2	-0.415***	-12.52	0.190***	11.36	0.073***	11.59	0.101***	9.13	13.453***	16.91	0.377
BM3	-0.389***	-7.07	0.341***	10.71	0.072***	10.39	0.058***	4.82	12.317***	9.23	0.344
TV1	-0.477***	-4.49	0.071***	5.51	0.049***	6.85	0.115***	7.39	15.002***	5.81	0.320
TV2	-0.418***	-12.39	0.107***	8.14	0.069***	10.20	0.077***	6.66	13.646***	16.86	0.348
TV3	-0.522***	-13.48	0.136***	11.96	0.090***	13.19	0.110***	8.51	15.777***	16.95	0.358
VO1	-0.399***	-12.43	0.085***	5.84	0.062***	8.58	0.092***	6.88	13.028***	16.93	0.433
VO2	-0.478***	-7.27	0.136***	12.03	0.080***	14.29	0.098***	9.50	14.549***	9.13	0.344
VO3	-0.670***	-6.01	0.089***	8.63	0.061***	8.71	0.093***	5.50	20.218***	7.48	0.304

Table VI: Crude oil producers versus consumers

This table reports the effect of crude oil producing industry and country on the relationship between crude oil price uncertainty and corporate investment. The regression models take the following forms:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * PRODUCER\_INDUSTRY_i + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t}$$

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * PRODUCER\_COUNTRY_i + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t}$$

The coefficient β_1 and β_2 and their *t*-statistics are reported. The regressions control for the firm and year fixed effects and *t*-statistics are corrected for clustering of the residual at the firm level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$PRODUCER\_INDUSTRY$				$PRODUCER\_COUNTRY$			
	β_1		β_2		β_1		β_2	
Panel A: Aggregate market panels								
Global	-0.484***	-16.66	-0.038***	-3.21	-0.488*	-11.09	-0.005*	-7.59
Developed	-0.447***	-14.62	-0.053***	-3.81	-0.451***	-14.87	0.008	1.11
Emerging	-0.362***	-2.86	0.036	1.03	-0.365***	-2.88	-0.019***	-3.35
Africa	-0.258*	-1.88	-0.017	-0.24	-0.252***	-13.78	-0.007	-1.27
Americas	-0.538***	-12.35	-0.065***	-3.50	-0.545***	-12.63	0.005	0.44
Asia	-0.401***	-9.68	0.052	1.59	-0.402***	-9.72	-0.015**	-2.33
Australasia	-0.700***	-2.61	-0.078*	-1.82	---	---	---	---
Europe	-0.270***	-5.52	0.003	0.16	-0.273***	-5.58	-0.011*	-1.84
Panel B: Firm-characterized panels								
MV1	-0.987*	-1.86	-0.086***	-2.96	-0.993*	-1.88	0.017	1.63
MV2	-0.448***	-7.14	0.009	0.29	-0.449***	-5.56	-0.011*	-1.89
MV3	-0.442***	-14.97	-0.026**	-2.18	-0.446***	-15.19	-0.021***	-3.64
FA1	0.457***	10.00	0.010	0.22	0.456***	10.00	0.022	0.95
FA2	0.210***	4.29	-0.046**	-2.15	0.210***	4.30	-0.015*	-1.84
FA3	-0.376***	-13.22	-0.048***	-3.83	-0.382***	-13.52	-0.014***	-2.91
BM1	-0.654***	-9.38	-0.026	-0.85	-0.654***	-9.40	0.000	-0.02
BM2	-0.411***	-12.24	-0.047***	-3.22	-0.417***	-12.58	-0.015*	-1.91
BM3	-0.385***	-7.04	-0.034	-1.47	-0.389***	-7.07	0.000	0.03
TV1	-0.475***	-4.46	-0.026	-0.90	-0.475***	-4.47	0.013	1.26
TV2	-0.417***	-12.43	-0.062**	-2.55	-0.418***	-12.38	0.002	0.30
TV3	-0.519***	-13.32	-0.029**	-2.11	-0.525***	-13.58	-0.032***	-4.94
VO1	-0.398***	-12.36	-0.012	-0.77	-0.400***	-16.69	0.007	1.55
VO2	-0.473***	-7.15	-0.039**	-2.32	-0.479***	-7.28	-0.005	-0.89
VO3	-0.665***	-5.75	-0.048**	-2.21	-0.675***	-6.05	-0.019*	-1.89

Table VII: Effect of global financial crisis

This table reports the effect of the global financial crisis on the relationship between crude oil price uncertainty and corporate investment. The regression model takes the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * CRISIS_{t-1} + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t}$$

The coefficient β_1 and β_2 and their *t*-statistic are reported. The regressions control for the firm and year fixed effects and *t*-statistics are corrected for clustering of the residual at the firm level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$OILVOL_{t-1}$		$OILVOL_{t-1} * CRISIS_{t-1}$		$\bar{R}^2$
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	
Panel A: Aggregate market panels					
Global	-0.487***	-16.86	0.305***	18.87	0.344
Developed	-0.452***	-14.89	0.276***	16.30	0.382
Emerging	-0.362***	-2.86	0.241***	3.44	0.283
Africa	-0.258*	-1.88	0.173**	2.12	0.322
Americas	-0.543***	-12.60	0.354***	14.50	0.364
Asia	-0.401***	-9.69	0.256***	11.17	0.312
Australasia	-0.697***	-2.60	0.459***	3.08	0.354
Europe	-0.270***	-5.52	0.161***	5.85	0.318
Panel B: Firm-characterized panels					
MV1	-0.999*	-1.89	0.598**	2.04	0.283
MV2	-0.448***	-7.13	0.276***	7.93	0.327
MV3	-0.444***	-15.11	0.280***	17.14	0.421
FA1	-0.148***	-4.94	0.346***	10.74	0.311
FA2	0.209***	4.28	-0.081***	-2.98	0.318
FA3	-0.380***	-13.46	0.227***	14.44	0.334
BM1	-0.654***	-9.40	0.401***	10.31	0.309
BM2	-0.415***	-12.52	0.264***	14.13	0.377
BM3	-0.389***	-7.07	0.249***	8.11	0.344
TV1	-0.477***	-4.49	0.296***	5.02	0.320
TV2	-0.418***	-12.39	0.265***	13.79	0.348
TV3	-0.522***	-13.48	0.329***	15.18	0.358
VO1	-0.399***	-12.43	0.245***	13.62	0.433
VO2	-0.478***	-7.27	0.295***	8.10	0.344
VO3	-0.670***	-6.01	0.423***	6.82	0.304

Table VIII: Effect of market volatility phases

This table reports the effect of market volatility phases on the relationship between crude oil price uncertainty and corporate investment. The regression model takes the following form:

$$INV_{i,t} = \alpha + \beta_1 OILVOL_{t-1} + \beta_2 OILVOL_{t-1} * VOLATILE_{t-1} + \beta_3 Q_{i,t-1} + \beta_4 CF_{i,t} + \beta_5 GDP_{i,t-1} + \varepsilon_{i,t}$$

The coefficient β_1 and β_2 and their *t*-statistic are reported. The regressions control for the firm and year fixed effects and *t*-statistics are corrected for clustering of the residual at the firm level. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$OILVOL_{t-1}$		$OILVOL_{t-1} * VOLATILE_{t-1}$		$\bar{R}^2$
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	
Panel A: Aggregate market panels					
Global	-0.417***	-15.43	-0.070***	-20.78	0.344
Developed	-0.394***	-13.97	-0.058***	-11.95	0.382
Emerging	-0.290**	-2.44	-0.072***	-8.31	0.283
Africa	-0.203	-1.64	-0.054*	-1.93	0.322
Americas	-0.461***	-11.62	-0.082***	-9.13	0.364
Asia	-0.336***	-8.69	-0.065***	-15.94	0.312
Australasia	-0.575**	-2.30	-0.122***	-4.28	0.354
Europe	-0.238***	-5.21	-0.032***	-4.64	0.318
Panel B: Firm-characterized panels					
MV1	-0.880*	-1.77	-0.119***	-3.49	0.283
MV2	-0.387***	-6.58	-0.061***	-10.66	0.327
MV3	-0.380***	-13.79	-0.065***	-19.66	0.421
FA1	0.197***	6.96	-0.346***	-10.74	0.311
FA2	0.234***	5.06	-0.025***	-4.33	0.318
FA3	-0.335***	-12.67	-0.045***	-13.83	0.334
BM1	-0.568***	-8.73	-0.086***	-10.84	0.309
BM2	-0.349***	-11.26	-0.066***	-13.81	0.377
BM3	-0.328***	-6.36	-0.061***	-11.01	0.344
TV1	-0.415***	-4.17	-0.062***	-7.02	0.320
TV2	-0.354***	-11.26	-0.064***	-11.50	0.348
TV3	-0.442***	-12.21	-0.079***	-16.70	0.358
VO1	-0.347***	-11.58	-0.052***	-11.50	0.433
VO2	-0.405***	-6.57	-0.073***	-12.99	0.344
VO3	-0.576***	-5.51	-0.094***	-9.61	0.304

Exchange rate volatility, oil price volatility and bilateral exports of Malaysia with China[34]

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Abstract

This study examines the impact of exchange rate volatility and oil price volatility on Malaysia's bilateral total export and on sub-categories of Malaysia's bilateral exports with China. Exchange rate volatility and oil price volatility are estimated by a stochastic volatility model. The autoregressive distributed lag (ARDL) models are used to examine the impact of exchange rate volatility and oil price volatility on Malaysia's bilateral exports. Exchange rate volatility and oil price volatility in many cases are found to have significant impact on Malaysia's sub-categories of Malaysia's bilateral exports in the short run and long run.

Keywords: Exchange rate volatility; Oil price volatility; Stochastic volatility; Autoregressive distributed lag; Bilateral exports; Malaysia

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1. Introduction

Volatility implies uncertainty and risk, which can adversely influence exports. Volatility can be due to exchange rate and other factor such as oil price. Generally, exchange rate is volatile for countries adopt a flexible or managed exchange system after the breakdown of the Bretton Woods system in 1973. A risk averse exporter would reduce exports with increase in exchange rate volatility (De Grauwe, 1988). Thus, exchange rate volatility discourages exports (Asteriou, Masatci and Pılbeam, 2016; Chi and Cheng, 2016; Bahmani-Oskooee and Aftab, 2017). Conversely, a few study reports that exchange rate volatility has a positive impact on exports (De Grauwe, 1988). Several studies report that there is no significant impact of exchange rate volatility on exports (Bahmani-Oskooee, Iqbal and Salam, 2016). This may due to amongst other inelasticity of export demand or incomplete exchange rate pass-through. The impact of exchange rate volatility on exports is actively researched (Aftab, et al. 2016; Pino, Tas and Sharma, 2016; Soleymani, Chua and Hamat, 2017).

Oil is an important source of energy in economy. The world oil price highly fluctuated in the 2010s. The fluctuation of the world oil price has adversely impact on the real and financial sectors in economy (Riggi and Venditti, 2015; Diaz, Molero and De Gracia, 2016). Therefore, export would be adversely affected when the real and financial sectors in economy had been adversely affected. Oil price shock can reduce export duration. Wang, Zhu and Wang (2017) find that oil price shock has significantly negative impact on China’s export duration. Oil price shock reduces export duration in non-energy intensive industries more than in energy intensive industries. Moreover, oil price shock influences non-processing firms more than processing firms. There are many studies reported the negative impact of oil price shock on stock returns (Singhal and Ghosh, 2016) or the impact of oil price shock and oil price volatility on stock returns (Diaz, Molero and De Gracia, 2016; Luo and Qin, 2017). The impact of oil price shock on economy can be asymmetric, that is, an increase in oil price shock has a more significant impact on economy than a decrease in oil price shock on economy (Bastianin, Conti and Manera, 2016).

This study examines the impact of exchange rate volatility and oil price volatility on Malaysia’s bilateral total export and sub-categories of Malaysia’s bilateral exports by standard international trade code (SITC) from 0 to 9 with China. Thus, this study provides some evidence of the impact of exchange rate volatility and oil price volatility on bilateral total export and sub-categories of bilateral exports. The impact of exchange rate volatility and oil price volatility on bilateral total export and sub-categories of bilateral exports can be different due to different degree of sensitivity of industries to volatility. Moreover, there are not many studies examined the impact of oil price volatility on bilateral exports of Malaysia with China. Exchange rate volatility and oil price volatility are estimated by a stochastic volatility model (Chan and Hsiao, 2014; Chan and Grant, 2016). The stochastic volatility model is selected from a group of stochastic volatility models. The stochastic volatility models are demonstrated to be good models in estimating volatility. Chan and Grant (2016) amongst other estimate oil price volatility using the stochastic volatility models. The measurement of volatility can be a matter of the significant impact of exchange rate volatility and oil price volatility on bilateral exports (Chi and Cheng, 2016). There are not many studies examined the impact of exchange rate volatility on exports using a stochastic volatility model. The asymmetric autoregressive distributed lag (ARDL) approach is used to investigate the positive and negative impacts of exchange rate volatility and oil price volatility on bilateral exports (Choudhry and Hassan, 2015). Hence, this study provides some evidence of the importance of the asymmetric impact of exchange rate volatility and oil price volatility on bilateral exports.

Exchange rate volatility and oil price volatility are found to have significant impact on some Malaysia's bilateral exports in the short run and long run and their impact differ across sub-categories of bilateral exports. Positive exchange rate volatility, negative exchange rate volatility, positive oil price volatility and negative oil price volatility are also found to have significant impact on Malaysia's bilateral exports in the short run and long run although their impact differ across sub-categories of bilateral exports.

2. Literature Review

Exchange rate volatility is found to have negative significant impact on exports. However, the impact of exchange rate volatility varies across categories of exports. Aftab, et al. (2016) examine the impact of exchange rate volatility on Malaysia's bilateral trade with European Union using industry level monthly data for the period from January, 2000 to December 2013. The results of the ARDL approach show that exchange rate volatility is found to have significant impact on many imports and exports in the short run and a few imports and exports of Malaysia's bilateral trade is found to have significant impact in the long run. Furthermore, the global financial crisis, 2007-2008 is found to have significant impact on Malaysia's bilateral trade with European Union. Bahmani-Oskooee and Aftab (2017) investigate the asymmetric impact of exchange rate volatility on 54 Malaysia's bilateral exports to the US and 63 Malaysia's bilateral imports from the US using the ARDL approach. The study reports that the asymmetric impact of exchange rate volatility is found to be significant for about 1/3 of the bilateral imports and exports between the US and Malaysia.

Soleymani, Chua and Hamat (2017) analyse the impact of real exchange rate volatility and third country exchange rate volatility on trade of four countries of Association of South East Asian (ASEAN), namely Indonesia, Malaysia, Singapore and Thailand using annual data for the period from 1980 to 2012. The results of the ARDL approach demonstrate that real exchange rate volatility has a significant negative impact on 15 export and four import models in the short run and long run. The impact of four countries of ASEAN's currency against yuan exchange rate volatility respectively dominates the effect of the third country exchange rate volatility on four countries of ASEAN's trade.

Asteriou, Masatci and Pılbeam (2016) probe the impact of nominal and real effective exchange rate volatility on export and import volumes for Mexico, Indonesia, Nigeria, and Turkey using monthly data for the period from January, 1995 to December, 2012. Exchange rate volatility is estimated by the generalized autoregressive conditional heteroskedasticity (GARCH) models. The ARDL approach and Granger causality models are used. In the long run, there is no relationship between exchange rate volatility and international trade, except for Turkey but the impact of exchange rate volatility is small. In the short run, there is a significant causal relationship from exchange rate volatility to import and export demand for Indonesia and Mexico. For Nigeria, unidirectional causality from export demand to exchange rate volatility is found and no causality between exchange rate volatility and import/export demand is found for Turkey.

The impact of exchange rate volatility on export varies across countries. Chi and Cheng (2016) examine the impact of exchange rate volatility on Australia's maritime export volume with its Asian trading partners, namely China, Japan, Republic of Korea, Taiwan, India, Indonesia and Malaysia respectively using quarterly data for the period from quarter 1, 2000 to quarter 2, 2013. Two measures of exchange rate volatility are used, namely the (GARCH) (1,1) and mean adjusted relative change measures. Exchange rate volatility is found to have a significant negative impact on maritime export volume in the long run but the impact is found to vary across country pairs. Moreover, different measure of exchange rate volatility can produce different impact.

Pino, Tas and Sharma (2016) investigate the impact of exchange rate volatility on exports of Indonesia, Malaysia, Korea, Singapore, Thailand, and the Philippines for the period from 1974 to 2011. Exchange rate volatility is derived from an autoregressive conditional heteroscedasticity (ARCH) model, a GARCH model and a moving-average standard deviation measure. The results show that exchange rate volatility is found to have a significant impact on exports in the short run and long run. The negative impact of exchange rate volatility is dominated for all countries examined, except for Singapore. However, the impact of exchange rate volatility varies across countries in the short run. The conclusions are about the same to different measurements of exchange rate volatility.

The impact of exchange rate volatility can be different across measurements of exchange rate volatility. Wang and Zhu (2016) inspect the impact of Reminbi (RMB) exchange rate on trade in China using the spatial panel model and Markov Chain Monte Carlo estimation method for the period from quarter 1, 1993 to quarter 3, 2013. The results reveal that the RMB against the US dollar exchange rate is widely used in trade settlement has more significant impact on Chinese export. One per cent appreciation of the RMB against the US dollar exchange rate will lead to about 1.532 per cent decline in Chinese export. Conversely, one per cent appreciation of the RMB against the nominal effective exchange rate will lead to about 0.42 per cent decline in Chinese export. One per cent increases in the RMB against the US dollar exchange rate volatility will lead to about 0.579 per cent decline in Chinese export. China should improve the foreign exchange derivatives market to reduce the adverse impact of exchange rate volatility.

There are studies found insignificant impact of exchange rate volatility on exports. Bahmani-Oskooee, Iqbal and Salam (2016) study the impact of exchange rate volatility on 44 Pakistani export industries to Japan and 60 Pakistani import industries from Japan using the ARDL approach for annual data from 1980 to 2014. The results show that exchange rate volatility is mainly found not to have significant impact on trade between Pakistan and Japan in the short run and long run. Bouoiyour and Selmi (2016) survey literature of exchange rate volatility on trade using the meta-regression analysis on 41 studies. The results show exchange rate volatility impact to have a significant impact on trade after correction of publication bias, that is, the result is heterogeneity with respect to model specifications, samples, time horizons and countries' characteristics.

The impact of exchange rate volatility can be sensitive to countries included in the examination. Vieira and MacDonald (2016) investigate the impact of real effective exchange rate (REER) volatility and the global financial crisis, 2008 on export volume using the system generalized method of moments (GMM) in a panel data of 106 developing and emerging economies for annual data from 2000 to 2011. The results show that an increase in REER volatility will lead to a decrease in export volume whereas a decrease in REER volatility will lead to an increase in export volume. However, the conclusions are not the same when the oil export countries are excluded from the estimation. The global financial crisis is found to have positive impact export volume. REER and income are inelastic to export volume. Exchange rate volatility shall be reduced to increase export volume.

In a summary, the impact of exchange rate volatility on exports is actively researched. The ARDL approach is widely used in the estimation. The measurement of exchange rate volatility is mostly non-stochastic such as estimated by an ARCH model or a moving-average standard deviation measure. The aggregated data and bilateral data are used to examine the impact of exchange rate volatility on exports. Generally, exchange rate volatility is found to have a significant impact on export. However, the impact of exchange rate volatility can be varied across categories of exports, across countries and across measurements of exchange rate volatility. There are several studies found insignificant impact of exchange rate volatility on exports.

3. Bilateral Exports of Malaysia

China was the second largest for exports of Malaysia. In 2015, exports of Malaysia to China were about 13.1 per cent of total exports (Table 1). The main exports of Malaysia to China were SITC

7, SITC 3 and SITC 5. The exports values of SITC 7, SITC 3 and SITC 5 were Malaysian ringgit (RM) 46,595.0 million, RM14,640.6 million and RM10,817.9 million or about 45.9 per cent, about 14.4 per cent and about 10.7 per cent of exports Malaysia to China, respectively (*Malaysia External Trade Statistics System*, Department of Statistics Malaysia).

The main components of exports of SITC 7 are thermionic valves and tubes, photocells and parts thereof, automatic data processing machines and units thereof, and telecommunications equipment. The main components of exports of SITC 3 are natural gas, whether or not liquefied, petroleum products, refined and petroleum oils, crude and crude oils obtained from bituminous minerals. Finally, the main components of exports of SITC 5 are polymer of ethylene in primary forms, other plastics in primary forms, alcohols, phenols, phenol- alcohols and their derivatives, and radio-active and associated materials (*Malaysia External Trade Statistics System*, Department of Statistics Malaysia).

[Insert Table 1 about here]

4. Data and Methodology

Bilateral total export ($x_{t,t}$) is the sum of export values of SITC from 0 to 9 divided by total export price index (2005 = 100). Bilateral exports of SITC from 0 to 9 ($x_{i,t}$, $i = 0, \ldots, 9$) are export values of SITC from 0 to 9 divided by export price indexes (2005 = 100) of SITC from 0 to 9, respectively. SITC 0 is food and live animals. SITC 1 is beverages and tobacco. SITC 2 is crude materials, inedible, except fuels. SITC 3 is mineral fuels, lubricants and related materials. SITC 4 is animal and vegetable oils, fats and waxes. SITC 5 is chemicals and related products. SITC 6 is manufactured goods classified by material. SITC 7 is machinery and transport equipment. SITC 8 is miscellaneous manufactured articles. SITC 9 is commodities and transactions not classified elsewhere in SITC. Exchange rate (e_t) is the Malaysian ringgit (RM) against renminbi multiplied by relative consumer price index (CPI, 2005 = 100) of Malaysia over CPI (2005 = 100) of China. Exchange rate volatility (v_t) or oil price volatility (o_t) is exchange rate or oil price (*3 spot price index*, 2005 = 100) estimated by a group of stochastic volatility models, namely the standard stochastic volatility (SV) model, the stochastic volatility with a second order of autoregressive log volatility process (SV2) model, the stochastic volatility in mean (SV-M) model, the stochastic volatility with moving average (SVMA) model and the stochastic volatility with t-distribution (SVT) model. Foreign demand (y_t) is expressed by industrial value-added of China (2005 = 100). Total export, export values of SITC from 0 to 9, export price indexes and export values of the trading partner of Malaysia were obtained from *Malaysia External Trade Statistics System*, Department of Statistics Malaysia. Industrial value-added of China was obtained from the website of National Bureau of Statistics of China. Exchange rates were obtained from *Monthly Statistical Bulletin*, Central Bank of Malaysia. Oil price was obtained from *International Financial Statistics*, International Monetary Fund. The data were seasonal adjusted using the census X13 multiplicative or additive method and were transformed into the logarithm. The sample period is from January, 2010 to July, 2016. The beginning of sample period is restricted by the availability of the monthly export price indexes in Malaysia, which begins from January, 2010.

The standard stochastic volatility (SV) model is expressed as follows:

Model 1

$$y_t = \mu + \epsilon_t^y, \epsilon_t^y \sim N(0, exp^{h_t})$$
$$h_t = \mu_h + \phi_h\left(h_{t-1} - \mu_h\right) + \epsilon_t^h, \epsilon_t^h \sim N(0, \omega_h^2) \quad (1)$$

where y_t is $\ln e_t$, N denotes normally distributed and exp denotes exponential. The logarithm volatility, h_t is assumed to follows a stationary autoregressive with order one process with $|\phi_h| < 1$ and unconditional mean, μ_h. The process is initialised with $h_t \sim N(\mu_h, \omega_h^2/(1 - \phi_h^2)$.

The stochastic volatility with h_t follows a stationary autoregressive with order two process (SV2) model is expressed as follows:

Model 2

$$y_t = \mu + \epsilon_t^y, \epsilon_t^y \sim N(0, exp^{h_t})$$
$$h_t = \mu_h + \phi_h\left(h_{t-1} - \mu_h\right) + \rho_h\left(h_{t-2} - \mu_h\right) + \epsilon_t^h, \epsilon_t^h \sim N(0, \omega_h^2) \quad (2)$$

where when ρ_h = 0, model 2 is reduced to model 1.

The stochastic volatility in mean (SVM) model is expressed as follows:

Model 3

$$y_t = \mu + \lambda^{h_t} + \epsilon_t^y, \epsilon_t^y \sim N(0, exp^{h_t})$$
$$h_t = \mu_h + \phi_h\left(h_{t-1} - \mu_h\right) + \epsilon_t^h, \epsilon_t^h \sim N(0, \omega_h^2) \quad (3)$$

where λ captures the extent of volatility feedback and when $\lambda = 0$, the SVM model is reduced to the SV model.

The stochastic volatility with *t* error (SVT) model is expressed as follows:

Model 4 $$y_t = \mu + \epsilon_t^y, \epsilon_t^y \sim t_v(0, exp^{h_t})$$
$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \epsilon_t^h, \epsilon_t^h \sim N(0, \omega_h^2) \quad (4)$$

The stochastic volatility with moving average (SVMA) model is expressed as follows:

Model 5 $$y_t = \mu + \epsilon_t^y$$
$$\epsilon_t^y = u_t + \psi u_{t-1}, u_t \sim N(0, exp^{h_t})$$
$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \epsilon_t^h, \epsilon_t^h \sim N(0, \omega_h^2) \quad (5)$$

where u_0 and $|\psi| < 1$ (Chan and Hsiao, 2014). The marginal likelihood is used to select the best model.

The export models to be estimated are specified as follows:

Model 1 $$\ln x_t = \beta_{11} \ln e_t + \beta_{12} \ln y_t + \beta_{13} v_t + \beta_{14} o_t + u_{1,t} \quad (6)$$

Model 2 $$\ln x_t = \beta_{21} \ln e_t + \beta_{22} \ln y_t + \beta_{23} v_t^+ + \beta_{24} v_t^- + \beta_{25} o_t^+ + \beta_{26} o_t^- + u_{2,t} \quad (7)$$

where ln is logarithm, x_t is bilateral exports, namely bilateral total export or bilateral exports of SITC from 0 to 9, e_t is exchange rate, y_t is foreign demand, v_t is exchange rate volatility, o_t is oil price volatility, $v_t^+ = \sum_{j=1}^t \Delta v_j^+$, $\Delta v_t^+ = \max(\Delta v_t, 0)$ and $v_t^- = \sum_{j=1}^t \Delta v_j^-$, $\Delta v_t^- = \min(\Delta v_t, 0)$ are partial sum process of positive and negative changes in v_t, $o_t^+ = \sum_{j=1}^t \Delta o_j^+$, $\Delta o_t^+ = \max(\Delta o_t, 0)$ and $o_t^- = \sum_{j=1}^t \Delta o_j^-$, $\Delta o_t^- = \min(\Delta o_t, 0)$ are partial sum process of positive and negative changes in o_t and $u_{i,t}$ $(i = 1, 2)$ is a disturbance term (Schorderet, 2001; Shin, Yu and Greenwood-Nimmo, 2014; Choudhry and Hassan, 2015).

The error correction models of the export models are as follows:

Model 1
$$\Delta \ln x_t = \beta_{30} + \sum_{i=0}^{a} \beta_{31i} \Delta \ln e_{t-i} + \sum_{i=0}^{b} \beta_{32i} \Delta \ln y_{t-i} + \sum_{i=0}^{c} \beta_{33i} \Delta v_{t-i} + \sum_{i=0}^{d} \beta_{34i} \Delta o_{t-i} + \sum_{i=1}^{f} \beta_{35i} \Delta \ln x_{t-i} + \beta_{36}\, ec_{t-1} + u_{3,t} \quad (8)$$

Model 2
$$\Delta \ln x_t = \beta_{40} + \sum_{i=0}^{a} \beta_{41i} \Delta \ln e_{t-i} + \sum_{i=0}^{b} \beta_{42i} \Delta \ln y_{t-i} + \sum_{i=0}^{c} \beta_{43i} \Delta v_{t-i}^{+} + \sum_{i=0}^{d} \beta_{44i} \Delta v_{t-i}^{-} + \sum_{i=0}^{f} \beta_{45i} \Delta o_{t-i}^{+} + \sum_{i=0}^{g} \beta_{46i} \Delta o_{t-i}^{-} + \sum_{i=1}^{h} \beta_{47i} \Delta \ln x_{t-i} + \beta_{48}\, ec_{t-1} + u_{4,t} \quad (9)$$

where Δ is the first difference operator, ec_{t-1} is an error correction term and $u_{i,t}$ (i = 3, 4) is a disturbance term.

5. Results and Discussions

The results of the Dickey and Fuller unit root test statistic are reported in Table 2. The lag length used to compute the Dickey and Fuller unit root statistic is based on the Akaike information criterion. The Dickey and Fuller unit root test statistic shows that all the variables are non-stationary in their levels but become stationary after taking the first differences, except Malaysia's total export to China The variables in this study are the mixture of I(1) and I(0) variables.

[Insert Table 2 about here]

The results of the stochastic volatility models are given in Table 3. The estimations are based on the means of the 21000 draws from the posterior distribution using the Gibbs sampler after a burn-in period of 1000 (Chan and Hsiao, 2014). The marginal likelihood is used to select the best stochastic volatility model. Exchange rate volatility is found the best estimated by the SVMA model. The SVM model is found the best to estimate oil price volatility. The Ljung-Box tests of the null hypothesis of no serial correlation in the standardised residuals are all not rejected. The McLeod-Li tests of the null hypothesis of no serial correlation in the squared standardised residuals are also all not rejected. The SVMA models is said to be good to capture the time-varying volatility of the data. The parameters estimated are found mainly to be statistically significant. The stochastic volatility process is highly persistent. The plots of exchange rate volatility, which is computed by the moving standard deviation with order three (MSD(3)) and estimated by the SVMA model are shown in Figure 1. Exchange rate volatility moves in the same direction. However, the exchange rate volatility estimated by the SVMA model tended to be non-stationary compared with exchange rate volatility computed by the MSD(3), which is stationary. This may imply that the SVMA model captures better the exchange rate volatility clustering.

[Insert Table 3 about here]

[Insert Figure 1 about here]

The ARDL bounds testing approach and the long run coefficients of the ARDL approach are given in Table 4. The ordinary least squares (OLS) estimator with Newey-West standard error is used when no-autocorrelation of the disturbance term is found to be statistically significant and the OLS estimator with Huber-White standard error is used when homoscedasticity of the disturbance term is found to be statistically significant. The Wald statistics are found to be statistically significant. Therefore, there are long-run relationships between exports and their determinants. Generally, exchange rate volatility has no significant long-run impact on Malaysia's export to China, except export of SITC 8, that is, miscellaneous manufactured goods. Conversely, oil price volatility has significant long-run impact on Malaysia's total export and exports of SITC 4, SITC 5, SITC 6, SITC 8 and SITC 9 to China.

In the long run, positive exchange rate volatility and negative exchange rate volatility are found to have more significant impact than positive oil price volatility and negative oil price volatility on Malaysia's exports to China. Positive exchange rate volatility is found to have significant impact on Malaysia's total export and exports of SITC 0, SITC 1, SITC 2, SITC 3, SITC 5, SITC 7 and SITC 9 to China. Negative exchange rate volatility is found to have significant impact on Malaysia's exports of SITC 1, SITC 2, SITC 3, SITC 4, SITC 5, SITC 6 and SITC 7 to China. Positive oil price volatility is found to have significant impact on Malaysia's export of SITC 6 to China. Negative oil price volatility is found to have significant impact on Malaysia's exports of SITC 4, SITC 8 and SITC 9 to China.

[Insert Table 4 about here]

The summary results of the error correction models are reported in Table 5. The OLS estimator with Newey-West standard error is used when no-autocorrelation of the disturbance term is found to be statistically significant and the OLS estimator with Huber-White standard error is used when homoscedasticity of the disturbance term is found to be statistically significant. The coefficients of the one lag of error correction terms are found to be less than one or about one and to have the expected negative signs and statistically significant. This implies the validity of an equilibrium relationship among the variables in the estimated model. The coefficients of exchange rate and foreign demand are found in many cases to be statistically significant. There are many cases of exchange rate volatility and oil price volatility found to have a significant impact on exports. Hence, some sectors of exports are sensitive to exchange rate volatility or oil price volatility whilst some sectors of exports are less sensitive to exchange rate volatility or oil price volatility. Moreover, some sectors of exports react negatively or positively to exchange rate volatility and oil price volatility, respectively. For Malaysia's exports to China, exchange rate volatility has relative more significant impact on exports in the short run than in the long run. Exchange rate volatility is found to have significant impact on bilateral total export and exports of SITC 4 and SITC 7. Oil price volatility is found to significant impact on exports of SITC 0, SITC 2, SITC 7, SITC 8 and SITC 9. Thus, many categories of bilateral exports are affected by exchange rate volatility.

In the short run, positive and negative exchange rate volatility and positive and negative oil price volatility are mostly found to have significant impact on Malaysia's exports to China. Positive exchange rate volatility is found to have significant impact on total export and exports of SITC 0, SITC 2, SITC 6, SITC 7, SITC 8 and SITC 9. Negative exchange rate volatility is found to have significant impact on exports of SITC 2, SITC 4, SITC 5 and SITC 8. Positive oil price volatility is found to have significant impact on exports of SITC 6 and SITC 9. Negative oil price volatility is found to significant impact on exports of SITC 0, SITC 4, SITC 5, SITC 7 and SITC 9.

[Insert Table 5 about here]

The finding that exchange rate volatility to have significant impact on exports is same with the findings such as Pino, Tas and Sharma (2016) and Bahmani-Oskooee and Aftab (2017), amongst other. Exchange rate volatility and oil price volatility have insignificant impact on exports can be due to incomplete transmission between exchange rate volatility or oil price volatility and export price because exporting firm absorbs lose temporarily to maintain its market share in foreign country (Gopinath, Itskhoki and Rigobon, 2010; Bandt and Razafindrabe, 2014: 64; Bernini and Tomasi, 2015; Choudhri, and Hakura, 2015). Also, there is no connection between exchange rate volatility and the real economy may be due to local currency pricing, heterogeneous international distribution of commodities and noise traders in the foreign exchange rate markets (Devereux and Engel, 2002).

A more stable international environment would encourage export. It can be achieved through more effectively international cooperation to minimise international shocks. A more stable exchange rate and a more stable oil price would encourage exports. Nonetheless, exchange rate volatility is unlikely to be fully eliminated under flexible exchange rate regime. However, exchange rate volatility can be reduced or minimised through various methods of exchange rate risk hedging in the forward market, future market or money market. Exchange rate volatility can be an opportunity to exporters to obtain higher profits. Oil price shall be volatile under free market and therefore It is not easy to eliminate oil price volatility. A more diversified export can reduce overall shocks. Exporters from Malaysia can reduce their risks through a more diversified of their exports with more focus on exports to Association of Southeast Asian Nations Economic Community (AEC), which is not fully exploited by exporters of Malaysia. AEC can provide an alternative export market to exporters from Malaysia.

6. Concluding Remarks

This study examines the impact of exchange rate volatility on Malaysia's bilateral total export and sub-categories of Malaysia's bilateral exports by SITC from 0 to 9 to China. Exchange rate volatility and oil price volatility are both found in many cases to have significant impact on Malaysia's bilateral exports in the short run and long run although their impact differ across sub-categories of bilateral exports. Moreover, positive exchange rate volatility, negative exchange rate volatility, positive oil price volatility and negative oil price volatility are found to have significant impact on Malaysia's bilateral exports in the short run and long run although their impact differ across sub-categories of bilateral exports. Exchange rate volatility and oil price volatility can influence many categories of bilateral exports. A more stable international environment and a more stable exchange rate would encourage exports. It can be achieved more effectively through international cooperation to minimise those shocks. A more diversified export can reduce the impact of overall shocks on bilateral exports.

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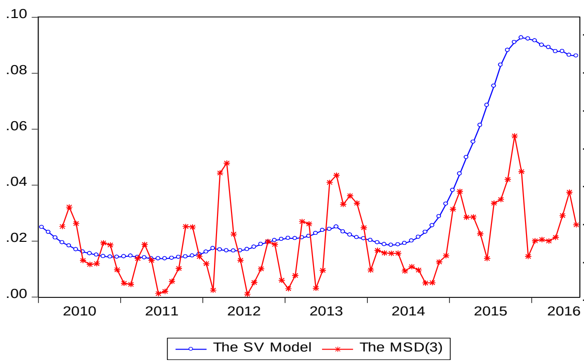
Figure 1

Exchange Rate Volatility or Oil Price Volatility Computed by the MSD(3) and Estimated by the SV Model, Respectively, January, 2010 – July, 2016

China



Oil Price

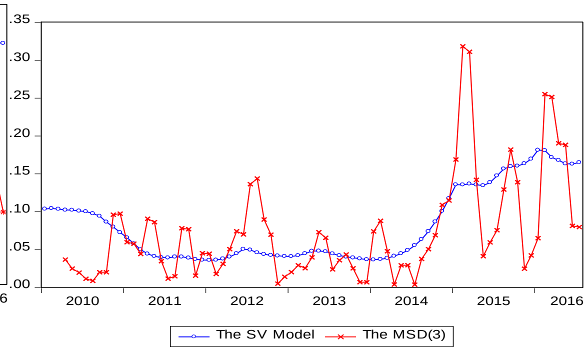


Table 1

Bilateral Exports of Malaysia, 2011-2015 (RM Million)

	2011	2012	2013	2014	2015
Singapore	88,191	95,553	100,257	108,728	108,388
	(12.6%)	(13.6%)	(13.9%)	(14.2%)	(13.9%)
China	91,551	88,793	97,043	92,286	101,537
	(13.1%)	(12.6%)	(13.5%)	(12.1%)	(13.1%)
The US	57,653	60,791	58,055	64,405	73,669
	(8.3%)	(8.7%)	(8.1%)	(8.4%)	(9.5%)
Japan	81,368	83,401	79,197	82,617	72,683
	(11.7%)	(11.9%)	(11.0%)	(10.8%)	(9.4%)
Korea	26,252	25,368	26,199	27,941	24,668
	(3.8%)	(3.6%)	(3.6%)	(3.7%)	(3.2%)
Germany	18,456	16,512	17,859	12,233	19,639
	(2.6%)	(2.3%)	(2.5%)	(1.6%)	(2.5%)
The UK	7,157	6,848	7,922	5,923	9,318
	(1.0%)	(1.0%)	(1.1%)	(0.8%)	(1.2%)
Total Exports	697,862	702,641	719,992	765,417	777,355

Source: MOF (2015, 2016).

Note: Values in the parentheses are the percentages of the total exports.

Table 2

The Results of the Dickey and Fuller Unit Root Test Statistic

$\ln x_{t,t}$	-2.6485*(1)
$\Delta \ln x_{t,t}$	-14.9232***(0)
$\ln x_{0,t}$	-1.2120(2)
$\Delta \ln x_{0,t}$	-9.2191***(1)
$\ln x_{1,t}$	-1.6659(2)
$\Delta \ln x_{1,t}$	-7.3953***(2)
$\ln x_{2,t}$	-1.8799(2)
$\Delta \ln x_{2,t}$	-11.3152***(0)
$\ln x_{3,t}$	-1.3520(1)
$\Delta \ln x_{3,t}$	-19.7395***(0)
$\ln x_{4,t}$	-2.2086(2)
$\Delta \ln x_{4,t}$	-8.7405***(1)
$\ln x_{5,t}$	-2.5316(2)
$\Delta \ln x_{5,t}$	-9.4273***(1)
$\ln x_{6,t}$	-1.6628(2)
$\Delta \ln x_{6,t}$	-11.9672***(0)
$\ln x_{7,t}$	-2.5145(3)
$\Delta \ln x_{7,t}$	-16.6192***(0)
$\ln x_{8,t}$	-2.3269(1)
$\Delta \ln x_{8,t}$	-14.6615***(0)
$\ln x_{9,t}$	-1.0295(2)
$\Delta \ln x_{9,t}$	-8.5720***(1)
$\ln e_t$	-0.8245(0)
$\Delta \ln e_t$	-6.8754***(0)
$\ln y_t$	-1.7425(0)
$\Delta \ln y_t$	-9.3933***(1)
v_t	-0.5183(3)
Δv_t	-2.7993*(2)
o_t	-0.8756(1)
Δo_t	-2.9617**(0)

Notes: $x_{t,t}$ is total export at time t. $x_{i,t}$ is export of SITC i at time t ($i = 0, \ldots, 9$). e_t is exchange rate at time t. y_t is foreign demand at time t. v_t is exchange rate volatility estimated by the SVMA model at time t. o_t is oil price volatility estimated by the SVM model at time t. The Dickey and Fuller unit root statistic is estimated based on the model including an intercept. Values in the parentheses are the lags used in the estimations. *** (**, *) denotes significance at the 1% (5%, 10%) level.

Table 3:The Parameters Posterior Means of the SV Models, January, 2010 - July, 2016

	China	Oil Price

μ	-0.87	5.35
	(0.00)	(0.02)
μ_h	-4.11	-3.52
	(2.81)	(1.82)
ϕ_h	0.99	0.98
	(0.02)	(0.01)
ω_h^2	0.10	0.06
	(0.05)	(0.02)
ρ_h	0.73	-
	(0.06)	
λ	-	-36.31
		(6.39)
ML	155.3	66.5
Q(20)	115.22	47.42
	(24.98)	(18.94)
$Q^2(20)$	26.36	16.11
	(11.14)	(6.46)

Notes: Exchange rate volatility is estimated by the SVMA model. Oil price volatility is estimated by the SVM model. ML denotes the marginal likelihood. Q(20) and $Q^2(20)$ denote the Ljung-Box and McLeod-Li statistics of order 20 computed based on the standardised errors and squared standardised errors, respectively. Values in the parentheses are the standard deviations.

Table 4

The Results of Bounds Testing Approach for Cointegration and the Long Run Coefficients of the ARDL Approach

Model 1

	ln $x_{t,t}$	ln $x_{0,t}$	ln $x_{1,t}$	ln $x_{2,t}$	ln $x_{3,t}$	ln $x_{4,t}$
Wald-Statistic	7.2732$^{@@@}$	7.9495$^{@@@}$	15.9758$^{@@@}$	6.0968$^{@@@}$	12.7633$^{@@@}$	6.2568$^{@@@}$
	ln $x_{5,t}$	ln $x_{6,t}$	ln $x_{7,t}$	ln $x_{8,t}$	ln $x_{9,t}$	
Wald-Statistic	6.6360$^{@@@}$	6.1350$^{@@@}$	12.0708$^{@@@}$	10.5881$^{@@@}$	3.8930$^{@}$	

	ln $x_{t,t}$	ln $x_{0,t}$	ln $x_{1,t}$	ln $x_{2,t}$	ln $x_{3,t}$	ln $x_{4,t}$
ln e_t	1.2416**	2.9784***	0.5787	3.8662**	3.3711*	0.7630
	(2.0615)	(2.7905)	(0.1862)	(2.6156)	(1.9843)	(0.4401)
ln y_t	0.1250**	-0.8501***	-0.7865*	-0.2177	-0.8657***	0.7588***
	(2.0358)	(-5.7375)	(-1.9810)	(-0.9944)	(-5.5187)	(2.9036)
v_t	2.3362 (1.6510)	-5.5265	7.4943	-3.6482	2.0283	3.0888
		(-1.4196)	(0.8383)	(-0.6312)	(0.5443)	(0.4742)
o_t	-1.8838***	-0.5175	-3.2753	1.2575	-0.4813	-5.6256***
	(-3.4823)	(-0.5702)	(-0.7878)	(0.6960)	(-0.2598)	(-2.9470)
Diagnostic Tests						
LM	4.1168$^{@@}$	1.4254	0.5911	0.9675	3.2102$^{@@}$	1.0854
Reset	0.3912	5.5547$^{@@}$	0.0145	1.1479	5.1896$^{@@}$	0.4697
Hetero	2.1570$^{@}$	1.1223	5.5937$^{@@@}$	1.4055	0.8064	1.3429

	ln $x_{5,t}$	ln $x_{6,t}$	ln $x_{7,t}$	ln $x_{8,t}$	ln $x_{9,t}$
ln e_t	-0.2594	7.3060***	0.8506**	-1.8691**	2.2173
	(-0.2803)	(3.3530)	(2.0074)	(-2.1698)	(0.9975)
ln y_t	-0.2087**	-0.0834	0.2076**	-0.0504	-0.0978
	(-2.0327)	(-0.3082)	(2.4888)	(-0.4771)	(-0.3492)
v_t	2.8189	-7.2782	-1.3984	5.7951*	-4.3503
	(0.9184)	(-0.9420)	(-0.7738)	(1.9775)	(-0.5173)
o_t	-1.6293*	-8.8542***	-0.0966	2.1566**	-3.9702*
	(-1.6821)	(-3.7850)	(-0.1845)	(2.5230)	(-1.7433)
Diagnostic Tests					
LM	1.0962	1.0417	1.3366	0.2539	0.1261
Reset	0.6390	0.1168	0.2161	1.2485	1.7831
Hetero	0.3508	1.6067	2.5054$^{@@}$	0.8544	0.3576

Table 4 (Continued)

Model 2

	ln $x_{t,t}$	ln $x_{0,t}$	ln $x_{1,t}$	ln $x_{2,t}$	ln $x_{3,t}$	ln $x_{4,t}$
Wald-Statistic	$4.2664^{@@}$	3.1754	$9.3907^{@@@}$	$3.8556^{@@}$	$5.8582^{@@@}$	$5.1188^{@@@}$
	ln $x_{5,t}$	ln $x_{6,t}$	ln $x_{7,t}$	ln $x_{8,t}$	ln $x_{9,t}$	
Wald-Statistic	$7.7713^{@@@}$	$4.2301^{@@}$	$6.4359^{@@@}$	$5.4943^{@@@}$	$3.9500^{@@}$	

	ln $x_{t,t}$	ln $x_{0,t}$	ln $x_{1,t}$	ln $x_{2,t}$	ln $x_{3,t}$	ln $x_{4,t}$
ln e_t	-0.4927	2.3670**	5.3155**	-0.1594	-0.1274	-0.2476
	(-0.5682)	(2.1122)	(2.5524)	(-0.0784)	(-0.0814)	(-0.1255)
ln y_t	0.0993	-0.6348***	-1.0061**	0.4269*	-1.1149***	0.8267***
	(1.1181)	(-4.4380)	(-2.9499)	(2.0061)	(-4.9695)	(3.1985)
v_t^+	7.0902**	-7.4489*	-13.4218**	20.5297**	14.4789***	4.2991
	(2.1540)	(-1.7053)	(-2.8741)	(2.5557)	(3.0445)	(0.5482)
v_t^-	-3.6033	7.6443	34.1240**	-24.8528**	-29.6143***	16.0780*
	(-0.6947)	(1.0853)	(2.6405)	(-2.1884)	(-3.0579)	(1.8262)
o_t^+	-0.8968	1.8289	-1.2761	-1.6316	-2.1915	-2.1345
	(-0.7123)	(1.0792)	(-0.6281)	(-0.5689)	(-1.2316)	(-0.5818)
o_t^-	-1.3297	-0.7971	-0.7843	-1.4905	-1.4612	-5.4624**
	(-1.6722)	(-0.6980)	(-0.3043)	(-0.9832)	(-0.9175)	(-2.3559)
Diagnostic Tests						
LM	0.5485	0.5575	0.1666	0.7829	0.1822	0.5708
Reset	0.5549	1.3699	0.0220	0.2063	$2.8795^{@}$	1.1220
Hetero	1.3736	0.7888	$3.1842^{@@@}$	1.2319	0.6399	0.7063

	ln $x_{5,t}$	ln $x_{6,t}$	ln $x_{7,t}$	ln $x_{8,t}$	ln $x_{9,t}$
ln e_t	0.4194	11.9708**	-0.3589	1.9847*	-6.7718
	(0.5424)	(2.4694)	(-1.0977)	(1.9721)	(-1.5682)
ln y_t	-0.4683***	-1.3005***	0.2159***	-0.1685	1.1179
	(-4.7307)	(-3.2060)	(3.6700)	(-1.1748)	(1.4070)
v_t^+	-4.3424**	-9.8058	2.1931***	0.3344 (0.1093)	37.8969*
	(-2.2949)	(-0.8270)	(2.9148)		(1.9625)
v_t^-	13.4607**	54.1194**	-3.4835*	2.0072 (0.3178)	0.0919
	(2.8159)	(2.0583)	(-1.6818)		(0.0103)
o_t^+	-0.9613	-32.2650***	0.5176	-0.6802	-1.4804
	(-0.8034)	(-3.2096)	(1.0717)	(-0.5775)	(-0.2474)
o_t^-	-1.0061	8.1425	0.3583	1.9954*	-10.4410**
	(-1.0776)	(1.5286)	(0.8157)	(1.8050)	(-2.1077)
Diagnostic Tests					
LM	1.4820	1.6070	$3.0026^{@}$	0.2873	$3.9907^{@@}$
Reset	1.2159	1.2735	0.0033	0.1389	0.1436
Hetero	1.4257	1.1152	$2.4022^{@@}$	1.2941	0.4630

Notes: $x_{t,t}$ is total export at time t. $x_{i,t}$ is export of SITC i (i = 0, … , 9) at time t. e_t is exchange rate at time t. y_t is foreign demand at time t. v_t is exchange rate volatility estimated by the SVMA/SVM model at time t. o_t is oil price volatility estimated by the SVM model at time t. LM is the Lagrange multiplier test of disturbance serial correlation. Reset is the test of functional form. Hetero is the test of heteroscedasticity. The ordinary least squares (OLS) estimator with Newey-West standard error is used when the Lagrange multiplier test of disturbance serial correlation is found to be significant. The OLS estimator with Huber-White standard error is used when the test of heteroscedasticity is found to be significant. Values in the parentheses are the t-statistics. *** (**, *) denotes significance of the t-statistic at the 1% (5%, 10%) level. $^{@@@}$ ($^{@@}$, $^{@}$) denotes significance of the F-statistics at the 1% (5%, 10%) level.

Table 5
The Results of the Error-Correction Models

Model 1

	$\Delta \ln x_{t,t}$	$\Delta \ln x_{0,t}$	$\Delta \ln x_{1,t}$	$\Delta \ln x_{2,t}$	$\Delta \ln x_{3,t}$	$\Delta \ln x_{4,t}$
constant	8.0866***	8.3609***	6.6644***	7.2123***	15.3088***	4.7548***
$\Delta \ln e_{t-i}$	0.5976	2.3548@@	5.0920	1.9473	5.7115**	1.1063
$\Delta \ln y_{t-i}$	0.1277**	-0.8258(F)	0.3299	-0.2809	-0.5960**	0.8807***
Δv_{t-i}	15.2984**	-4.5107	-21.0258	16.6957	9.2489	49.0068***
Δo_{t-i}	-1.5183	12.0301**	10.9129	-22.0376@@@	-4.7104	-9.7926
$\Delta \ln x_{j,t-i}$	-	-0.8258(F)	-	-	-	0.1120
ec_{t-1}	-0.7013***	-0.6463***	-0.8975***	-0.5851***	-1.0311***	-0.7646***
Diagnostic Tests						
Adj. R^2	0.3449	0.4611	0.5262	0.3636	0.4963	0.4381
LM	4.1254@@	1.3145	0.4305	0.9772	2.5045@	1.0662
Reset	0.0745	0.1530	0.0407	2.8387@	0.2281	0.1670
Hetero	0.1863	1.3502	0.9856	1.2138	0.4817	0.8436

	$\Delta \ln x_{5,t}$	$\Delta \ln x_{6,t}$	$\Delta \ln x_{7,t}$	$\Delta \ln x_{8,t}$	$\Delta \ln x_{9,t}$
constant	6.1439***	9.4919***	9.4796***	4.9230***	2.9201***
$\Delta \ln e_{t-i}$	0.0229	3.7272**	0.1513	-3.8772***	1.7545
$\Delta \ln y_{t-i}$	-0.1425*	0.1768	0.1685**	-0.1455	0.0859
Δv_{t-i}	2.2700	-5.2631	12.4862**	2.0733	2.9942
Δo_{t-i}	0.2565	-7.3449(F)	4.7269**	7.6347**	-9.0157**
ec_{t-1}	-0.6631***	-0.6049***	-0.9305***	-0.8536***	-0.3832***
Diagnostic Tests					
Adj. R^2	0.2856	0.3171	0.4641	0.4396	0.2046
LM	3.5010@@	0.8149	1.0957	0.2123	0.7868
Reset	0.1950	0.3797	0.4550	0.7042	0.1222
Hetero	0.4896	0.7391	2.4452@@	1.8031	0.8001

Table 5 (Continued)

Model 2

	Δ ln $x_{t,t}$	Δ ln $x_{0,t}$	Δ ln $x_{1,t}$	Δ ln $x_{2,t}$	Δ ln $x_{3,t}$	Δ ln $x_{4,t}$
constant	5.0892***	5.2399***	12.0100***	3.0657***	11.8665***	3.3185***
Δ ln e_{t-i}	1.4481@@	1.2828	7.0256	4.5928@@@	4.4216*	1.4688
Δ ln y_{t-i}	0.1166	-0.3328***	-0.1639	-0.0861	0.9159(F)	-2.2428@@
Δ v_{t-i}^{+}	-5.1191@@@	3.8164@@	-9.3739	-21.2646@@@	0.2602	-7.2598(F)
Δ v_{t-i}^{-}	-0.4006(F)	-2.2566	21.6908	17.2299@@	6.9972	17.956**
Δ o_{t-i}^{+}	-0.5483(F)	0.6404	-0.2203	1.2927	-2.0141	1.8456(F)
Δ o_{t-i}^{-}	1.2529(F)	1.5472@@	-1.3807	-0.6659	0.9361	5.9468@@@
Δ ln $x_{j,t-i}$	-	-	-	-	-0.2094**	0.1715*
ec_{t-1}	-0.5091***	-0.4614***	-0.9495***	-0.5243***	-0.9388***	-0.7136***
Diagnostic Tests						
Adj. R^2	0.5245	0.3815	0.4628	0.4194	0.6636	0.5578
LM	0.3676	0.7089	0.2123	0.6374	0.1644	0.1720
Reset	0.0055	1.7686	0.0167	3.6344@	0.3044	0.0159
Hetero	1.0587	0.6903	1.3197	0.9221	0.3740	0.4966

	Δ ln $x_{5,t}$	Δ ln $x_{6,t}$	Δ ln $x_{7,t}$	Δ ln $x_{8,t}$	Δ ln $x_{9,t}$
constant	8.6524***	9.5366***	7.9097***	5.1175***	-1.8342***
Δ ln e_{t-i}	2.8580@@	18.4411@@@	0.2067	-0.9442	-2.4647(F)
Δ ln y_{t-i}	0.0804(F)	-0.5612**	0.1936**	0.0531	-1.6958@@@
Δ v_{t-i}^{+}	-0.9744	-18.3360@@@	0.9776*	-2.9187**	-17.5217@@@
Δ v_{t-i}^{-}	-14.6606@@	-14.3794(F)	-0.5334	8.4607**	-3.2467
Δ o_{t-i}^{+}	-0.7222(F)	16.4047@@@	-0.0504	-0.3337	-10.6639@@@
Δ o_{t-i}^{-}	2.6040@@	-4.3938(F)	1.0536**	1.1418	12.3999@@@
Δ ln $x_{j,t-i}$	-	-1.0115@@@	-	-	-0.9141@@
ec_{t-1}	-0.7865***	-0.3772***	-0.8736***	-0.5138***	-0.2944***
Diagnostic Tests					
Adj. R^2	0.4231	0.7102	0.4555	0.4014	0.5886
LM	1.7727	1.6160	3.3257@@	0.4807	2.8297@
Reset	0.3479	0.4522	0.0297	1.7239	0.0077
Hetero	1.3788	1.4266	1.6698	1.6674	0.4284

Notes: $x_{t,t}$ is total export at time t. $x_{i,t}$ is export of SITC i (i = 0, … , 9) at time t. e_t is exchange rate at time t. $x_{j,t-k}$ is lag of total export or export of SITC i (i = 0, … , 9) (k = 1, 2, 3) at time t. y_t is foreign demand at time t. v_t is exchange rate volatility estimated by the SVMA/SVM model at time t. o_t is oil price volatility estimated by the SVM model at time t. Adj. R^2 is the adjusted R^2. LM is the Lagrange multiplier test of serial correlation in the disturbance term. Reset is the test of functional form. Hetero is the test of heteroscedasticity. The ordinary least squares (OLS) estimator with Newey-West standard error is used when the Lagrange multiplier test of serial correlation in the disturbance is found to be significant. The OLS estimator with Huber-White standard error is used when the test of heteroscedasticity is found to be significant. *** (**, *) denotes significance of the t-statistics at the 1% (5%, 10%) level. @@@ (@@, @) denotes significance of the F-statistics at the 1% (5%, 10%) level. (F) denotes the F-statistics.

Can Tax on Energy Consumption Reduce CO_2 Emissions?

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Abstract

China made a commitment in the 2015 United Nations Climate Change Conference in Paris to reduce CO_2 emissions per unit of GDP by 60 percent by year 2030. The current study attempts to explore the measures to reduce CO_2 emissions caused by energy consumption. In particular, it examines the effectiveness of energy consumption tax on reduction of CO_2 emissions. This is made possible by investigating the impacts of energy price, energy consumption and their interaction on CO_2 emissions, using times series data on three sources of energy, namely fossil fuel, coal and gas, over 1984-2013 in China. Empirical analysis suggests that tax on total energy consumption does not reduce CO_2 emissions from oil and coal consumption, but reduces CO_2 emissions from gas consumption; and that tax on energy consumption exceeding threshold levels effectively hurdles further increases in CO_2 emissions from all three sources of energy.

1. Introduction

This study examines the influences of energy price and energy consumption on environmental pollution (CO2 emissions) in China. There has been a significant rise in CO_2 emissions from energy consumption in the new industrialized countries compared to developed countries over the last two decades. Deterioration of environment has triggered major concerns about global warming and climate change. Hence, understanding the reasons behind environmental degradation and its relation with economic development and energy use has become common ground of research among economists.

There is an extensive existing literature examining the debate about the relationship between energy consumption, income and pollution in both developed and developing countries, which can be broadly classified into three groups. The first group examines the relationship between income and environmental pollution under the Environmental Kuznets Curve (EKC). The EKC hypothesis asserts that pollution rises with rising income at the initial stage and then turns to decline after both pollution and income reach threshold levels (Grossman and Krueger, 1994). A number of studies (Stern, 2004; Dinda, 2004; Kijima et al., 2010; Seldon and Song, 1994; Unruh and Moomaw, 1998; Managi and Jena, 2008; Shafik, 1994) empirically test the EKC hypothesis but fail to produce conclusive evidence.

The second group of studies examine the nexus between energy consumption and economic growth using different econometric methodologies, and reveal varied and inconclusive results (Kraft and Kraft, 1978; Masih and Masih, 1996; Narayan et al., 2008). The third group of studies claim that the lack of conclusive evidence in the first two groups of studies is due to omitted variable bias, and examine dynamic relationships among carbon emissions, energy consumption, and economic growth in a single framework. See, for example, Ang (2007), Zhang and Cheng (2009), Ghosh (2010), Halicioglu (2009) for Turkey, Jail and Mahmud (2009) for China, Iwata et al. (2010) for France, and Saboori and Sulaiman (2013) for five Asian countries. Findings from these studies are again generally inclusive, continuing to arouse interests among researchers and policy makers.

The main objective of this paper is to investigate the impacts of disaggregate energy consumption and energy price on CO_2 emissions in China. Further, with the inclusion of the interaction between energy consumption and energy price in explaining CO_2 emissions, we aim to examine whether tax on excessive energy consumption effectively hurdle CO_2 emissions. This study is important for the following reason. Energy prices increased multifold over the period from early 2000s to 2012; this has become a substantive concern in the world's macroeconomic environment. Despite surges in energy prices, CO_2 emissions worldwide increased contemporarily; in particular, China has overtaken the US and became the largest emitter of CO_2. The major increase in CO_2 emissions in China was attributed to fast increasing coal consumption which grew at 10 percent annually from early 2000s to 2012. Coal consumption in China declined after 2012. In contrast, oil and gas consumption have persisted continuous and strong growth over time. Concurrent increases in energy prices and CO_2 emissions in China raise an important paradox which needs further investigation.

Contribution of this paper to the literature is threefold: first, to the best of our knowledge, the existing literature on China utilizes aggregate data to investigate the nexus between energy consumption, income and CO_2 emissions. However, different energy sources are heterogenous in terms of efficiency and contribution to CO_2 emissions. Natural gas has the highest thermal efficiency, followed by oil and coal (Hao et al., 2016). In producing same quantity of heat, coal combustion emits largest quality of CO_2, followed by oil and gas. Hence, an analysis of differentiating between impacts of disaggregate energy sources on CO_2 emissions is important for policy makers to formulate heterogeneous policies for different energy sources.

Second, most existing studies ignore energy price in CO_2 emissions models. An analysis of impacts of both energy consumption and prices on CO_2 emissions in China is timely and imperative from policy perspective. China made a commitment in the 2015 United Nations Climate Change Conference in Paris to reduce CO_2 emissions per unit of GDP by 60 percent by year 2030. The current study is essential for framing appropriate energy tax policies to in order to achieve the goal. Ideally, a rise in energy price would encourage consumers to adopt more efficient energy mix or more energy efficient technologies (Selden et al., 1999; Stern, 2004) and hence reduce energy consumption and CO_2 emissions. However, given that China is an influential producer and consumer of energy, an increase in energy price is likely to affect CO_2 emissions through many channels. Some channels contribute to increase CO_2 emissions while others mitigate emissions.

First of all, an increase in coal and oil prices would boost wealth of coal and oil producers in China, which consequently creates demand for other goods and services and heighten CO_2 emissions. Secondly, given other conditions unchanged, increases in price are associated with decreases in consumption; however, due to strong economic growth, demand for energy grows strongly and continuously over time in China. As a matter of fact, China is able to mitigate part of the losses arising from rising energy prices. Thirdly, China's capability of substituting labour with more capital input leads to significant increases in China's labour productivity, creating more demand for Chinese products from the global market; consequently, energy demand and CO_2 emissions rise even in circumstances when energy prices increase (Faria et al., 2009). Furthermore, improvements in income and export earnings create demand for energy related goods and services such as transport and vehicles; as a result, CO_2 emissions rise (Skeer and Wang, 2007). Therefore, given substitutions of energy sources and China's characteristics of being an open economy as well as an oil and coal producer, energy prices' influences on CO_2 emissions are multifold; it is essential in policy perspective to find out the overall effects of energy prices on China's CO_2 emissions.

The third contribution of the current study is the assessment of tax's influences on CO2 emissions. We include in the models not only energy price but also the interactive term between energy price and energy consumption, and hypothesize a negative relationship between the interactive term and CO_2 emissions. Non-rejection of the hypothesis would imply that imposition of tax on energy consumption exceeding threshold levels (or, excessive energy consumption) effectively reduces marginal CO_2 emissions (or, hurdles excessive CO_2 emissions).
The rest of the paper is organized as follows. Section 2 illustrates some stylish facts. Section 3 proposes the models. Section 4 describes data. Section 5 presents empirical findings. And Section 6 provides conclusions and policy advices.

2. Stylish Facts

People's Bank of China and the China Banking Regulatory Commission (2017) announced that from 1st January 2018 maximum loan ratios for new energy cars, traditional cars and second-hand cars will be respectively 85 percent, 80 percent and 70 percent.

3. Models

To examine the relationships between output, disaggregate energy consumption, disaggregate energy prices, and CO_2 emissions, Bloch, Rafig and Salim (2015) propose a framework including one supply-side model and two demand-side models (henceforth, the BRS framework). In the supply-side model, the authors explain output with factors including capital stock, labor and disaggregate energy consumption; in the first demand-side model, the authors explain disaggregate energy consumption with factors including output and disaggregate energy prices; and in the second demand-side model, the authors explain CO2 emissions with factors including output and disaggregate energy consumption. Note that the authors exclude energy prices in the CO_2 emissions model.

We amend the BRS framework by, (1) incorporating our hypotheses on the energy price-CO_2 emissions nexus in the second demand-side model, i.e., the CO2 emissions model; (2) endogenizing energy prices as hypothesized by Apergis and Payne (2014). Our proposed framework is as follows:

$$Y_t = \alpha_0^Y + \alpha_1^Y KPC_t + \alpha_2^Y EO_t + \alpha_3^Y EC_t + \alpha_4^Y EG_t + \alpha_5^Y T_t + \varepsilon_t^Y \tag{1}$$

$$CO_t = \alpha_0^{CO} + \alpha_1^{CO} PO_t + \alpha_2^{CO} Y_t + \alpha_3^{CO} PO_t \cdot Y_t + \varepsilon_t^{CO} \tag{2.1}$$

$$CC_t = \alpha_0^{CC} + \alpha_1^{CC} PC_t + \alpha_2^{CC} Y_t + \alpha_3^{CC} PC_t \cdot Y_t + \varepsilon_t^{CC} \tag{2.2}$$

$$CG_t = \alpha_0^{CG} + \alpha_1^{CG} PG_t + \alpha_2^{CG} Y_t + \alpha_3^{CG} PG_t \cdot Y_t + \varepsilon_t^{CG} \tag{2.3}$$

$$EO_t = \alpha_0^{EO} + \alpha_1^{EO} PO_t + \alpha_2^{EO} CO_t + \alpha_3^{EO} (PO_t \cdot CO_t) + \varepsilon_t^{EO} \tag{3.1}$$

$$EC_t = \alpha_0^{EC} + \alpha_1^{EC} PC_t + \alpha_2^{EC} CC_t + \alpha_3^{EC} (PC_t \cdot CC_t) + \varepsilon_t^{EC} \tag{3.2}$$

$$EG_t = \alpha_0^{EG} + \alpha_1^{EG} PG_t + \alpha_2^{EG} CG_t + \alpha_3^{EG} (PG_t \cdot CG_t) + \varepsilon_t^{EG} \tag{3.3}$$

$$PO_t = \alpha_0^{PO} + \alpha_1^{PO} PC_t + \alpha_2^{PO} PG_t + \alpha_3^{PO} CO_t + \varepsilon_t^{PO} \tag{4.1}$$

$$PC_t = \alpha_0^{PC} + \alpha_1^{PC} PO_t + \alpha_2^{PC} PG_t + \alpha_3^{PC} CC_t + \varepsilon_t^{PC} \tag{4.2}$$

$$PG_t = \alpha_0^{PG} + \alpha_1^{PG} PO_t + \alpha_2^{PG} PC_t + \alpha_3^{PG} CG_t + \varepsilon_t^{PG} \tag{4.3}$$

The above framework displays a multiple equations system, where Equation (1) is the supply-side model, Equations (2.1)-(2.3) are demand-side equations modelling oil, coal and gas consumption respectively, Equations (3.1)-(3.3) are demand-side equations modelling CO_2 emissions from using oil, coal and gas respectively; and Equations (4.1)-(4.3) model energy prices. Notations in the above system are described as follows:

Y = per capita GDP (at constant 2010 price, \$, natural logarithm);
KPC = per capita capital stock at current price (at constant 2010 price, \$, natural logarithm). This series is estimated with the perpetual inventory method with depreciation rate of 9.6% and initial capital stock in year 1960 being 10 times investment of the same year;

T = time trend, with value 1 for year 1984, 2 for year 1985, and so on (natural logarithm);
EO = CO_2 emissions from oil consumption (% of total, natural logarithm);
EC = CO_2 emissions from coal consumption (% of total, natural logarithm);
EG = CO_2 emissions from gas consumption (% of total, natural logarithm);
CO = Consumption of oil (% of total, natural logarithm);
CC = Electricity production from coal (% of total, natural logarithm);
CG = Electricity production from coal (% of total, natural logarithm);
PO = Price of oil (constant 2010 prices, \$, natural logarithm);
PC = Price of coal (constant 2010 prices, \$, natural logarithm);
PG = Price of gas (constant 2010 prices, \$, natural logarithm);
α = parameter to be estimated; and
ε = error term.

Further, superscript of parameter and error term represents the dependent variable of corresponding equation; and subscript t represents time. Note in the above system, prices of substitutions of energy sources are not considered in demand equations, due to high correlation between prices of energy sources.

As robustness tests of prices' influences on energy consumption as well as on CO_2 emissions, we set up another two multiple equations frameworks. First, we remove the hypothesis of endogenous energy prices and a new framework consists only Equations (1)-(3.3); Second, we set up another multiple equations framework, where the interactive terms ($PO_t \cdot Y_t$, $PC_t \cdot Y_t$, $PG_t \cdot Y_t$) in demand equations (2.1)-(2.3) are replaced with squared income (Y_t^2), and the interactive terms ($PO_t \cdot CO_t$, $PC_t \cdot CC_t$, $PG_t \cdot CG_t$) are replaced with respective squared energy consumption ratios (CO_t^2, CC_t^2, CG_t^2) in demand equations (3.1)-(3.3). With this setup, we assume that income has quadratic impacts on energy consumption in a way that income beyond threshold level reduces marginal energy consumption, and that energy consumption has quadratic impacts on CO_2 emissions in a way that energy consumption beyond threshold level reduces marginal CO_2 emissions. Non-rejection of these hypotheses further provides incentives for policy makers to take measures to reduce excessive CO_2 emissions from excessive energy consumption.

4. Data

Data on prices are obtained from the Quandl website, and the rest are from World Development Indicators (WDI) database. Trends of major variables, including GDP, per capita GDP, energy prices, energy consumption as percent of total energy, and CO_2 emissions as percent of total emissions, are presented in Figures 1-4. The following observations are noted. Clear upward trends are noted in GDP and per capita GDP at 2010 prices, associated with increasing demands for energy and CO2 emissions volume; oil price and coal price at constant 2010 prices are generally on the rise with substantial declines were seen in early 1990s and late 2000s; there was clear rise in natural gas price from late 1990s to late 2000s, and after 2008 gas price declined significantly; oil consumption as percent of total energy increased over time; electricity generation from coal source as percent of total electricity has generally stabilized since early 1990s, given availability of substitutions such as hydropower, nuclear power and wind power; and trends of CO_2 emissions from the three sources of energy as percent of total emissions are in general consistent with energy consumption ratios.

[Insert Figure 1-5 here]

Pairwise correlation diagrams between energy prices and CO_2 emissions volume are shown in Figure 5. There are clear positive associations between energy price and CO_2 emissions volume in the cases of oil and coal, and such association is not evident in the case of natural gas. Summary statistics and coefficients of pairwise correlation between major variables are respectively presented in Table 1 and Table 2. From Table 2 we see high correlations amongst variables such as *EG*, *CO*, *CC*, *CG* and *PO*, hence combination of these variables in corresponding equations should be chosen with care in order to avoid multicollinearity problem.

[Insert Tables 1 and 2 here]

5. 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 is addressed by using the three-stage least squares estimator.

5.1. 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 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.

[Insert Tables 3-6 here]

[Insert Figure 6 here]

The multiple equations system is estimated by the three-stage least squares estimator. It is found that:
(1). CO_2 emissions are harmful to income;
(2). Oil and coal prices are positively associated with CO_2 emissions, while natural gas price is negatively associated with CO_2 emissions. This suggests that tax on general consumption of oil and coal (i.e., addition to energy price) doesn't help reduce CO_2 emissions caused by using oil and coal;
(3). Energy consumption is positively associated with CO_2 emissions in all three sources of energy;
(4). Interaction between price and energy consumption reduces CO_2 emissions in all three sources of energy, indicating that tax on the portion of consumption of three energy sources exceeding threshold levels effectively reduces CO_2 emissions;
(5) In the cases of oil and coal, energy price and income are positively associated with energy consumption, and interaction between price and income is negatively associated with energy consumption. such associations are not significant in the case of gas.
(6) In the robustness analysis, we found that the hypothesis of income's quadratic effects on energy consumption is not rejected, consistent with findings from Jalil and Mahmud (2009); however, this finding doesn't mean that income's non-linear impacts can only take the quadratic form. The performance of income squared suggests that income beyond certain level reduces income's marginal effect on energy consumption. This is phenomenon we observed; but what is the mechanism to such phenomenon? We propose that, marginal energy consumption is reduced if government imposes energy consumption tax on those with high income.

Other macroeconomic indicators such as openness, urbanization and transport development are not included in this framework due to high correlation between any of these indicators with variables currently included. As further robustness analyses, we also try different forms of variables, for instance, energy consumption per capita in place of energy consumption ratio, CO_2 emissions per capita in place of CO_2 emissions ratio, values at current prices in place of values at constant prices, and values in US dollar in place of values in local currency yuan. Quantitative analyses using different forms of variables yield similar results.

6. Conclusions

This study examined the impact of energy tax on CO_2 emission in China. We found that a tax on income beyond a threshold levels of income will reduce excessive energy consumption of coal and oil in China. We further note that tax on energy consumption exceeding threshold levels will reduce Co_2 emissions from using oil, coal and gas.

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Figure 1. GDP and GDP per capita (constant 2010 prices)

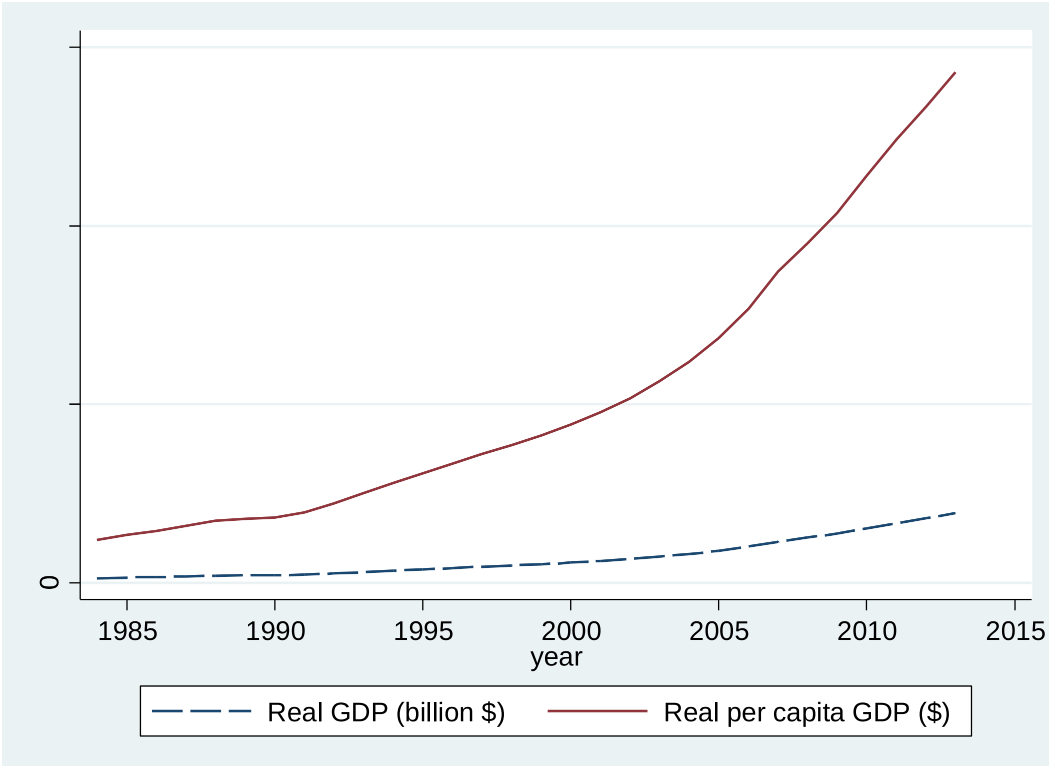
0
1985
1990
1995
2000
2005
2010
2015
year
Real GDP (billion $)
Real per capita GDP ($)

Figure 2. Energy prices by energy source

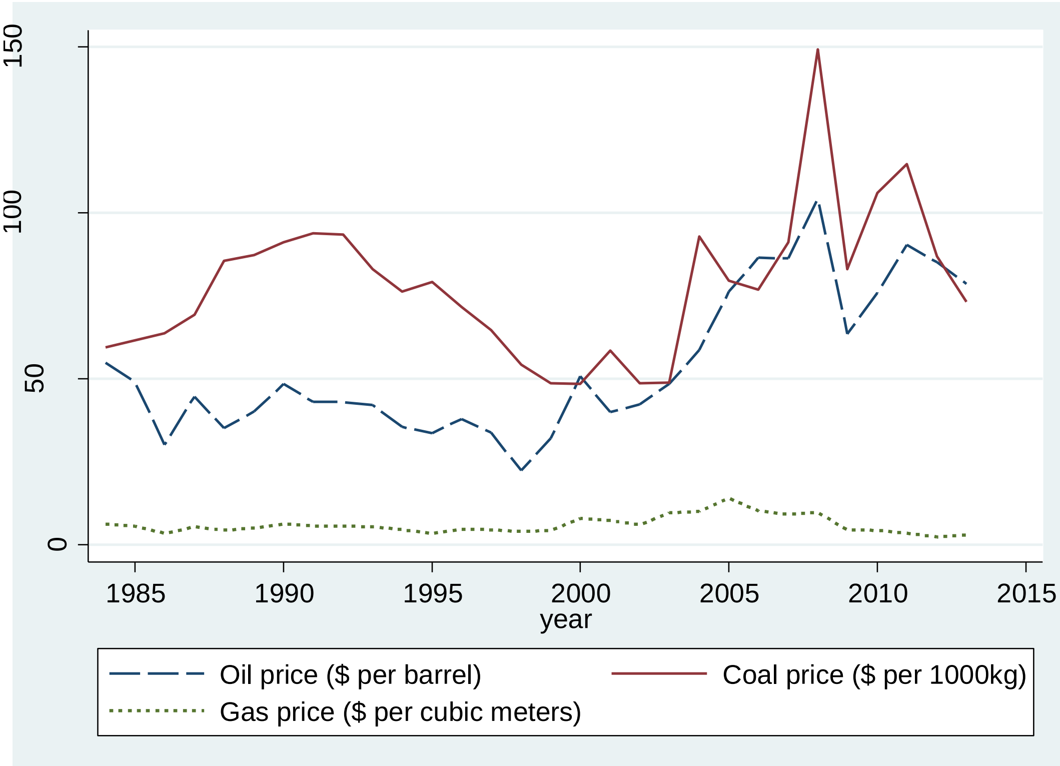

Figure 3. Energy consumption by energy source

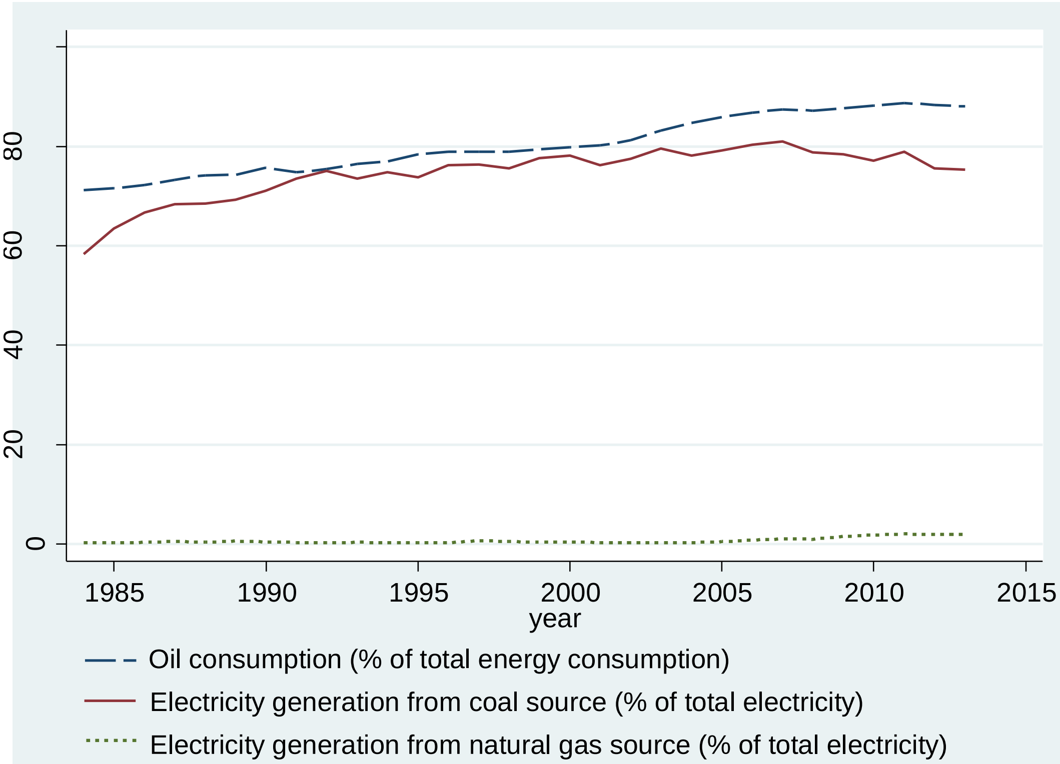

Figure 4. CO_2 emissions from energy consumption by energy source

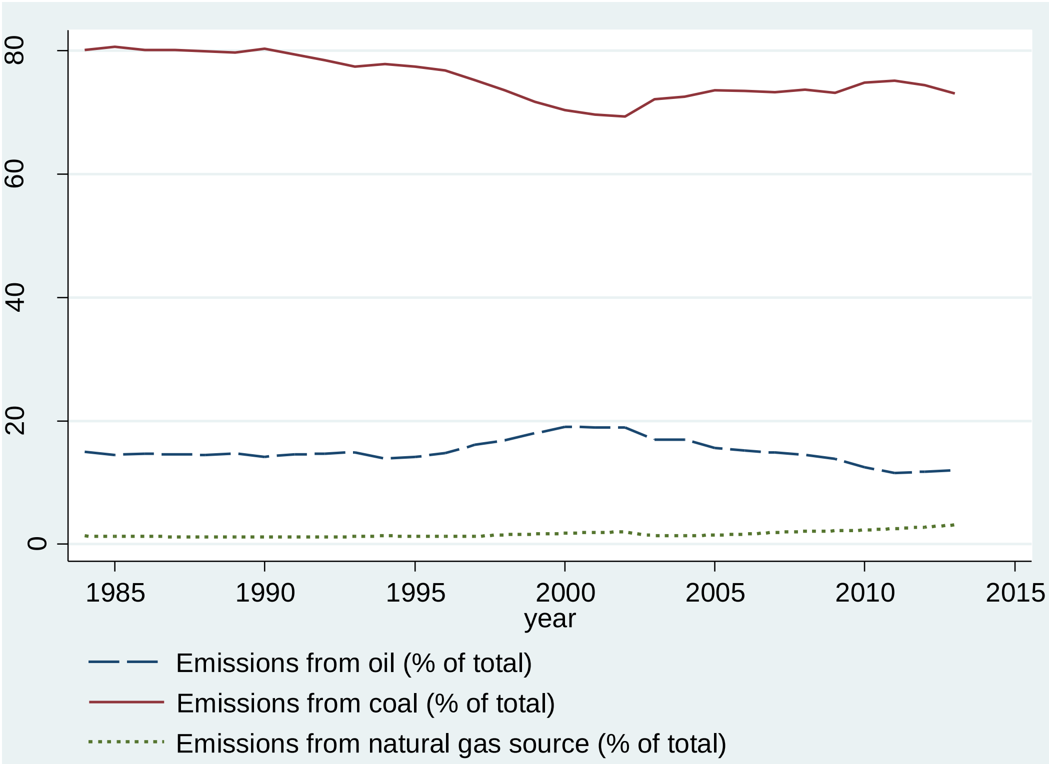

Figure 5. Scatter diagrams between energy price and CO_2 emissions by energy source

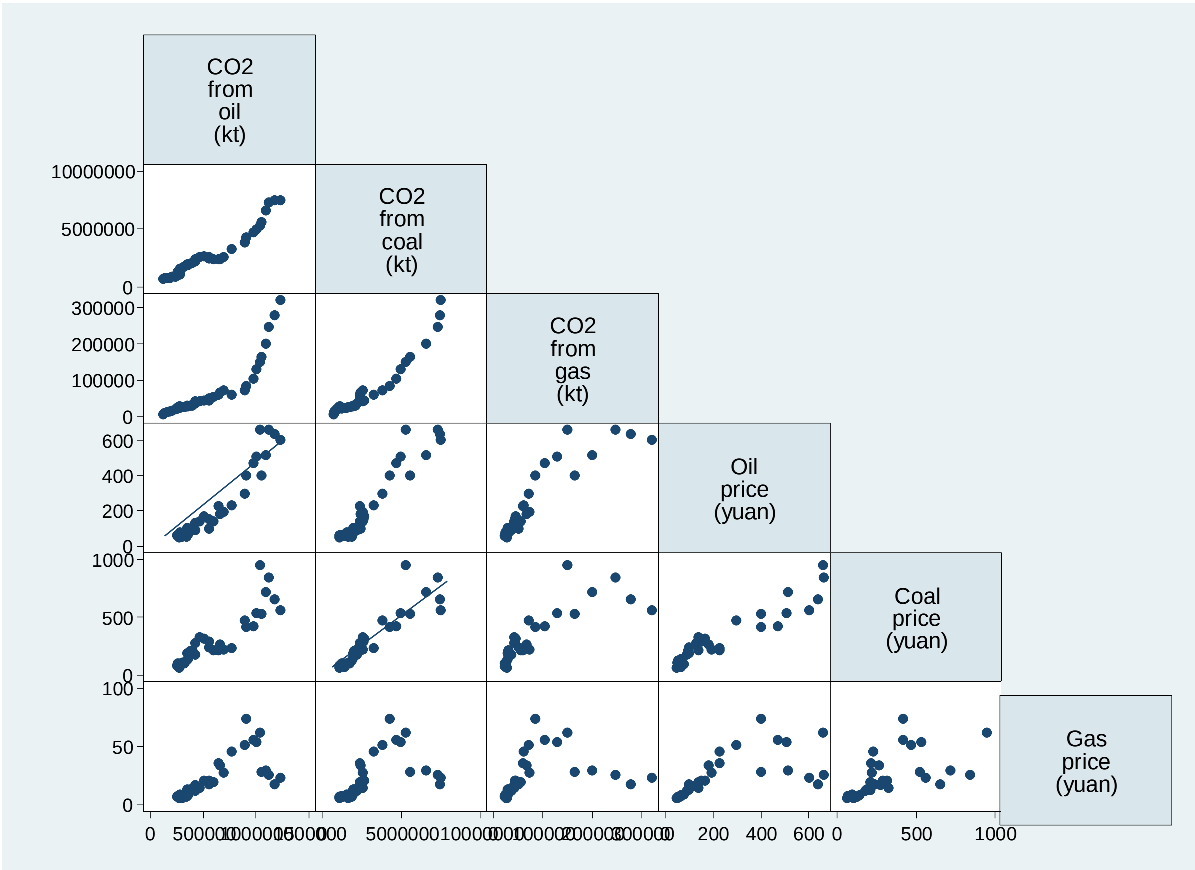

Figure 6. Simultaneous impacts of oil price and oil consumption on CO2 emissions

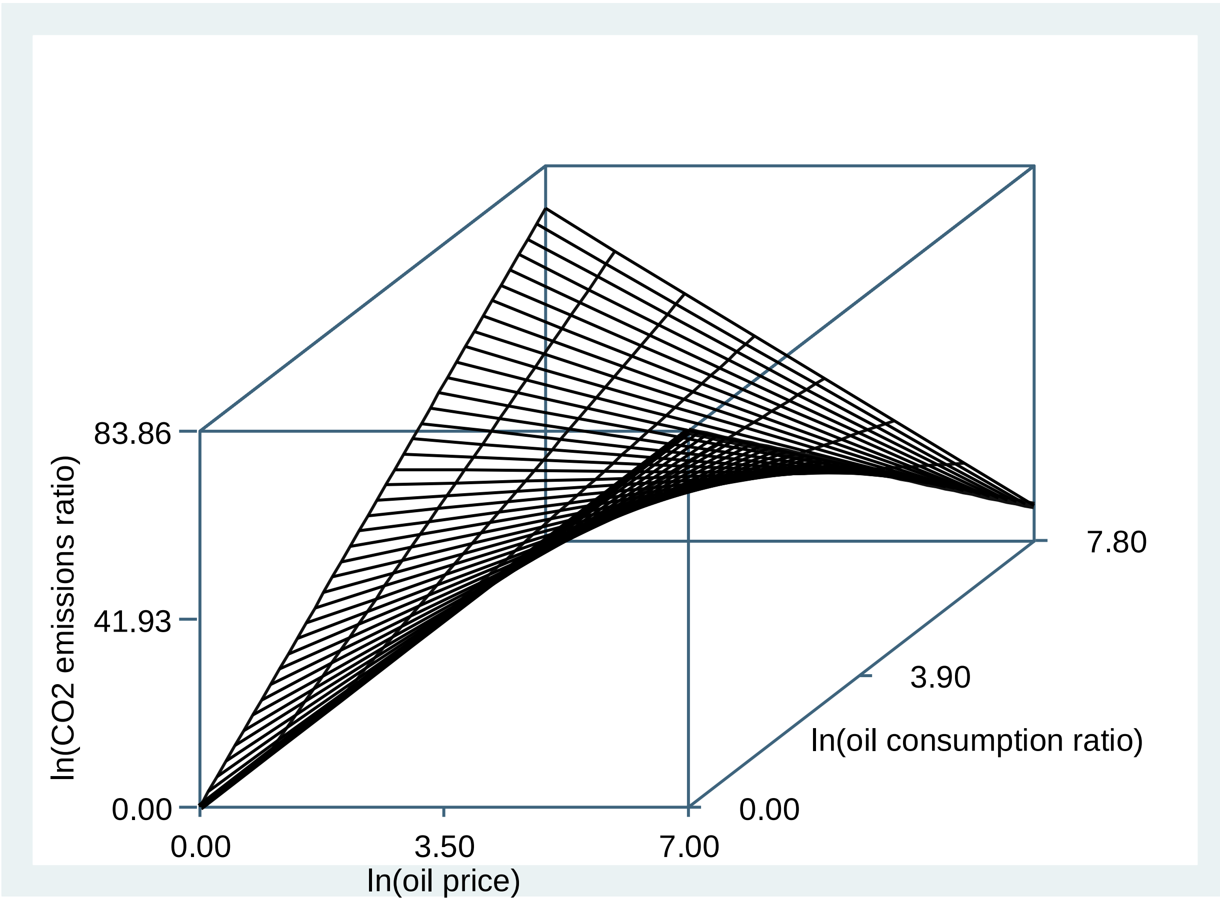

Table 1. Summary statistics

Series	Mean	Standard deviation	Minimum	Maximum
CO2 emissions from oil consumption (% of total)	15.08	1.96	11.57	19.07
CO2 emissions from coal consumption (% of total)	75.63	3.50	69.36	80.64
CO2 emissions from gas consumption (% of total)	1.63	0.52	1.12	3.13
Oil consumption (% of total energy consumption)	80.29	5.79	71.16	88.73
Electricity production from coal sources (% of total)	74.55	5.26	58.29	80.95
Electricity production from gas sources (% of total)	0.69	0.58	0.24	2.04
GDP per capita (constant 2010 price, $)	2122	1570	481	5722
Capital stock per capita (constant 2010 price, $)	4362	3757	818	13910
Oil price (constant 2010 price, $)	50.96	18.71	22.37	104.10
Coal price (constant 2010 price, $)	76.93	20.96	48.48	149.28
Gas price (constant 2010 price, $)	6.54	2.44	3.41	14.08

Note: Data on prices are obtained from the Quandl website, and the rest are from World Development Indicators (WDI).

Table 2. Correlation Matrix

	Y	*KPC*	*EO*	*EC*	*EG*	*CO*	*CC*	*CG*	*PO*	*PC*	*PG*
Y	1.0000										
KPC	0.9992	1.0000									
EO	-0.2346	-0.2492	1.0000								
EC	-0.7318	-0.7230	-0.4669	1.0000							
EG	0.8634	0.8736	-0.3236	-0.6181	1.0000						
CO	0.9886	0.9866	-0.2274	-0.7039	0.7969	1.0000					
CC	0.7775	0.7576	0.1393	-0.7511	0.4547	0.8011	1.0000				
CG	0.7425	0.7520	-0.6375	-0.2211	0.7672	0.7198	0.3898	1.0000			
PO	0.6825	0.6950	-0.4550	-0.2581	0.6337	0.7141	0.3264	0.6555	1.0000		
PC	0.2750	0.2745	-0.6629	0.2877	0.1572	0.3311	0.1579	0.5099	0.5567	1.0000	
PG	0.0331	0.0255	0.5295	-0.2850	-0.2301	0.1288	0.2522	-0.3029	0.2973	0.0095	1.0000

Table 3. Clemente, Montanes and Reyes (1998) two-break unit root tests

Variable	Optimal breakpoint 1 (p-value)	Optimal breakpoint 2 (p-value)	Observed t-stat (H_0: $rho - 1 = 0$)	5% critical value
Y	1993 (0.000)	2004 (0.000)	-2.711	-5.490
KPC	1995 (0.000)	2005(0.000)	-2.597	-5.490
EO	1998 (0.001)	2006 (0.000)	-3.375	-5.490
EC	1994 (0.000)	2000 (0.171)	-3.680	-5.490
EG	1995 (0.001)	2008 (0.000)	-3.563	-5.490
CO	1991 (0.000)	2004 (0.000)	-2.743	-5.490
CC	1986 (0.000)	1993 (0.000)	-3.503	-5.490
CG	1987 (0.005)	2006 (0.000)	-4.383	-5.490
PO	1996 (0.080)	2003 (0.000)	-4.255	-5.490
PC	1997 (0.002)	2005 (0.000)	-4.118	-5.490
PG	2001 (0.000)	2008 (0.000)	-3.670	-5.490
ε^{Y}	1985 (0.004)	1992 (0.684)	-5.656	-5.490
ε^{EO}	1994 (0.000)	2009 (0.000)	-5.879	-5.490
ε^{EC}	1999 (0.109)	2002 (0.106)	-5.668	-5.490
ε^{EG}	1999 (0.037)	2004 (0.144)	-5.746	-5.490
ε^{CO}	1983 (0.777)	1988 (0.183)	-5.524	-5.490
ε^{CC}	1996 (0.000)	2005 (0.000)	-5.511	-5.490
ε^{CG}	1993 (0.000)	2005 (0.000)	-5.548	-5.490
ε^{PO}	1987 (0.001)	2000 (0.048)	-5.536	-5.490
ε^{PC}	1987 (0.000)	1996 (0.001)	-5.592	-5.490
ε^{PG}	1998 (0.029)	2010 (0.000)	-5.813	-5.490

Note: Numbers before parentheses are optimal breakpoints; numbers in parentheses are p-values; ε with superscripts are estimated errors from corresponding Equations (1)-(4.3).

Table 4. Estimation of the multiple equations system

Dependent variable	Income	CO2 emissions			Energy consumption			Energy prices		
	Y	*EO*	*EC*	*EG*	*CO*	*CC*	*CG*	*PO*	*PC*	*PG*
Explanatory	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Constant	16.4	-44.98	-12.70	.621	3.088	-.341	-2.628	-11.49	3.840	-1.319
	(4.56)	(-3.23)	(-2.55)	(6.70)	(13.39)	(-0.27)	(-1.00)	(-4.76)	(1.43)	(-2.10)
Y					.167	.596	.308			
					(2.94)	(3.55)	(0.92)			
KPC	.597									
	(7.84)									
EO	-.688									
	(-4.15)									
EC	-2.826									
	(-3.86)									
EG	-.192									
	(-3.90)									
PO		13.52			.171				.713	.897
		(3.95)			(5.51)				(3.66)	(6.28)
PC			4.627			.963		.798		-.162
			(3.88)			(3.24)		(5.74)		(-1.17)
PG				-.240			.506	.316	-.198	
				(-4.20)			(0.32)	(3.50)	(-1.89)	
CO		10.88						2.604		
		(3.43)						(4.51)		
CC			3.852						-.447	
			(3.36)						(-0.77)	
CG				.390						-.351
				(3.29)						(-4.82)
$PO \cdot CO$		-3.091								
		(-3.97)								
$PC \cdot CC$			-1.050							
			(-3.83)							
$PG \cdot CG$				-.236						
				(-3.39)						
$PO \cdot Y$					-.021					
					(-2.80)					
$PC \cdot Y$						-.125				
						(-3.27)				
$PG \cdot Y$							-.126			
							(-0.63)			
T	.013									
	(1.76)									
D1986						.057				
						(2.26)				
D1987							.159			
							(0.98)			

D1993						.042				
						(2.51)				
D1995	.054			.170						
	(3.99)			(3.72)						
D1998		.231								
		(5.97)								
D2001										.191
										(2.14)
D2003					.019					
					(3.72)					
D2005										-.582
										(-4.60)
D2006	.083			.375			1.138			
	(4.76)			(4.12)			(6.62)			
RMSE	.0186	.0724	.0207	.1137	.0086	.0288	.2648	.2321	.2287	.2000
R squares	0.9994	0.6739	0.7922	0.8360	0.9850	0.8461	0.8474	0.6289	0.2675	0.7550

Note: Equations are estimated simultaneously with three-stage least squares estimator; (*)(**)(***) represent significance at the 10%, 5% and 1% levels respectively; last eight variables are dummy variables; RMSE is root mean squared error.

Table 5. Robustness analysis: Estimation of the multiple equations system

Dependent variable	Income	CO2 emissions			Energy consumption		
	Y	*EO*	*EC*	*EG*	*CO*	*CC*	*CG*
Explanatory variables	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)
Constant	15.59*** (4.00)	-38.19*** (-2.78)	-9.902** (-2.11)	.606*** (6.46)	3.332*** (13.07)	1.388 (1.13)	-4.177 (-1.49)
Y					.139*** (3.99)	.374** (2.34)	.438 (1.22)
KPC	.517*** (5.91)						
EO	-.656*** (-3.66)						
EC	-2.542*** (-3.20)						
EG	-.189*** (-3.45)						
PO		11.864*** (3.52)			.109* (1.71)		
PC			3.959*** (3.54)			.562*** (1.99)	
PG				-.226*** (-3.90)			1.677 (0.98)
CO		9.35*** (2.99)					
CC			3.214*** (2.98)				
CG				.434*** (3.48)			
$PO \cdot CO$		-2.717*** (-3.55)					
$PC \cdot CC$			-.898*** (-3.49)				
$PG \cdot CG$				-.253*** (-3.42)			
$PO \cdot Y$					-.014* (-1.70)		
$PC \cdot Y$						-.074*** (-2.04)	
$PG \cdot Y$							-.253 (-1.18)
T	.023*** (2.60)						
D1986						.084*** (3.29)	
D1987							.360** (1.91)
D1993						.039**	

						(2.28)	
D1995	.051***			.175***			
	(3.30)			(3.75)			
D1998		.244***					
		(6.27)					
D2003					.022***		
					(3.59)		
D2006	.077***			.356***			1.208***
	(3.92)			(3.71)			(6.43)
RMSE	0.0194	0.0716	0.0210	0.1130	0.0083	0.0276	0.2477
R squares	0.9993	0.6810	0.7872	0.8382	0.9862	0.8579	0.8664

Note: Equations are estimated simultaneously with three-stage least squares estimator; (*)(**)(***) represent significance at the 10%, 5% and 1% levels respectively; last eight variables are dummy variables; RMSE is root mean squared error.

Table 6. Robustness analysis: Estimation of the multiple equations system

Dependent variable	Income	CO2 emissions			Energy consumption		
	Y	*EO*	*EC*	*EG*	*CO*	*CC*	*CG*
Explanatory variables	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)	Coef. (z stat)
Constant	17.49*** (4.15)	-449.7*** (-6.96)	-25.17*** (-2.99)	.311*** (3.25)	2.836*** (20.27)	-1.668*** (-3.56)	28.23*** (3.47)
Y					.323*** (8.94)	1.513*** (12.28)	-8.214*** (-3.58)
KPC	.484*** (5.08)						
EO	-.731*** (-3.82)						
EC	-2.883*** (-3.32)						
EG	-.212*** (-3.49)						
PO		.143*** (2.72)			.016*** (3.34)		
PC			.048*** (3.92)			.012 (1.18)	
PG				.017 (0.30)			-.260** (-2.30)
CO		208.8*** (7.07)					
CC			14.31*** (3.60)				
CG				.297*** (2.95)			
Y^2					-.016*** (-6.67)	-.095*** (-12.01)	.570*** (3.61)
CO^2		-24.13*** (-7.12)					
CC^2			-1.744*** (-3.73)				
CG^2				.164*** (2.93)			
T	.025*** (2.56)						

D1986						.039***	
						(3.12)	
D1987							.749***
							(3.75)
D1993						-.051***	
						(-4.62)	
D1995	.048***			.177***			
	(2.98)			(4.03)			
D1998		.304***					
		(8.83)					
D2003					.023***		
					(4.97)		
D2006	.083***			.139			.605***
	(3.96)			(1.34)			(2.65)
RMSE	.0194	.0529	.0209	.1174	.0056	.0142	.2315
R squares	0.9993	0.8264	0.7886	0.8252	0.9936	0.9623	0.8833

Note: Equations are estimated simultaneously with three-stage least squares estimator; (*)(**)(***) represent significance at the 10%, 5% and 1% levels respectively; last eight variables are dummy variables; RMSE is root mean squared error.

Electricity Production Mix and the EKC Hypothesis: Evidence from 18 OECD Countries

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Abstract

This study aims to examine the EKC hypothesis by taking into account one of the most important clean electricity sources, that is, nuclear energy in 18 OECD countries for the period 1995-2013. We employ Panel FMOLS, Panel DOLS and PMG estimators to investigate the effects of electricity production from nuclear source, electricity production from non-renewables and trade openness underlying the EKC hypothesis. It is found that the EKC hypothesis is valid in OECD countries. Nuclear energy is beneficial to the environment. In contrast, non-renewable energy sources tend to increase CO_2 emissions. The results are consistent regardless of the methodology used.

Keywords: Nuclear energy, Non-renewables, CO_2 emissions, EKC, Electricity production.

1. Introduction

While many people around the world are still debating on whether global warming is real (some treat it as a hoax), the climate scientists have agreed that the Earth is warming by looking at the facts and data. It is recorded that the average world temperature has increased between 0.4 and 0.8°C over the last century. According to the World Meteorological Organization (2017), the year 2016 is confirmed as the warmest year on record, with a temperature 1.1°C above pre-industrial era. By the year 2100, it is predicted that the average global temperature could increase between 1.4 and 5.8°C. The effects of global warming can be devastating. Events that cause huge socio-economic disruption such as extreme weather conditions (including hotter summers and colder winters) and rising sea levels (due to faster melting of sea ice) have prevailed as a result of global warming. These phenomena would persist in the years to come if nothing serious is in place to curb the problem of global warming. Thus far, some international mitigation efforts have been made to reduce greenhouse gases. Unfortunately, these initiatives are unable to achieve the set targets when it comes to carbon dioxide (CO_2) reduction. For example, many industrial nations came to an agreement known as the Kyoto Protocol in 1997, but failed to reduce CO_2 emissions levels subsequently. Most recently, the Paris Agreement[35] had suffered a blow when the United States−the world second largest emitter−decided to withdraw from the agreement.

The increased amount of CO_2 and other greenhouse gases such as methane, nitrous oxide and fluorinated gas via the burning of fossil fuels and other human activities have caused heat to be trapped in the Earth's atmosphere, leading to greenhouse effect that causes global warming. Ultimately, reducing emissions particularly CO_2 seem to be the best solution for overcoming the issue of climate change. However, reducing CO_2 may imply cutting down on human activities such as electricity generation that can in turn affect economic performance of a country. In this regard, policy makers together with environmentalists are facing challenging tasks of reducing CO_2 while maintaining a country's economic growth simultaneously. Studies in the past have indicated that there is an inverted U-shaped relationship between GDP and CO_2 emissions in most occasions (for instance, Apergis & Ozturk, 2015; Dijkgraaf & Vollebergh,1998; Galeotti, Lanza, & Pauli, 2005), which can also be coined as the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis states that as GDP increases initially in a country, pollution tends to rise as well. However, as income keeps increasing and reaches a threshold, environmental deterioration reduces. This threshold level further suggests that economic growth could be a solution to environmental problems.

The Intergovernmental Panel on Climate Change (IPCC) (2014) reported that electricity and heat production constitutes the largest share, i.e. 25 per cent of global CO_2 emissions. Electricity generation involves the burning of fossil fuels such as coal, oil and natural gas. The increased use of these non-renewable energy sources in electricity production to cater for rising demand in electricity has worsened the environmental quality globally. As GDP of a country increases along an EKC, the demand for electricity increases. As stated, the more electricity is produced using non-renewable sources, the more pollutants will be emitted into the atmosphere. In other words, a country would find it more difficult to reach the turning point of EKC with more non-renewables used.

[35] A climate agreement within United Nations Framework Convention on Climate Change (UNFCCC) aiming to reduce greenhouse gases through mitigation, adaptation and finance that will start in year 2020.

Today, many sources of energy are being used to produce electricity besides fossil fuels. Nuclear energy is one of these sources of energy that has been in the limelight in recent years. It is a clean-air source of energy that can minimize greenhouse gases and most importantly it is able to produce electricity 24 hours in a day. As mentioned by Apergis, Payne, Menyah and Wolde-Rufael (2010) and Adamantiades and Kessides (2009), nuclear energy does not only fulfil the energy needs of many countries, but also helps to reduce CO_2 emissions in the long run. Accordingly, nuclear plants have recently saved about 10 per cent of CO2 emissions from the world energy use. Another advantage of nuclear energy lies with the fact that unlike renewable energy sources such as solar and wind power, it is not subject to unpredictable weather conditions. In its Fifth Assessment Report published in 2014, IPCC highlighted the difficulties of encouraging the development and adoption of renewable energies. The report warns that “No single mitigation option in the energy supply sector will be sufficient. Achieving deep cuts in greenhouse gas (GHG) emissions will require more intensive use of low-GHG technologies such as renewable energy and nuclear energy.”(IPCC, 2014). However, there are concerns with the use of nuclear energy such as reactor safety, nuclear proliferation as well as radioactive-waste transport and disposal.

As part of their strategies to reduce dependence on foreign fuels and to avoid unpredictable oil price fluctuations, countries have built nuclear power plants for the purpose of electricity generation. (Toth & Rogner, 2006). Since 1990s, the need for switching to nuclear power increased among countries as signatories of Kyoto agreement were required to reduce CO_2 emissions (Saidi & Mbarek, 2016). In the case of OECD countries, nuclear energy gathered momentum in 1970s and today the OECD countries account for approximately 85 per cent of the installed nuclear capacity worldwide. In addition, nuclear power is responsible for 18.4 per cent of the electricity generated in these countries (Nuclear Energy Agency, 2016).

Our study differs from the existing literature in several important ways. First, most of the existing studies focus on time series analysis (Begum et al., 2015; Iwata, Okada, & Samreth, 2010; Menyah & Wolde-Rufael, 2010) which has the problems in controlling for heteroscedasticity, endogeneity, serial correlation and reliability (Baltagi, 2005). Therefore, our study will make use of panel data analysis to overcome these weaknesses. Second, our study is unique in the sense that we employ Panel Fully Modified Ordinary Least Squares (FMOLS), Panel Dynamic Ordinary Least Squares and Pooled Mean Group (PMG) estimators to check the consistency of our results. Third, past researches tend to consider “nuclear energy consumption” in their studies (Al-Mulali, 2014; Baek, 2016). However, this study attempts to take a step further by employing “electricity production from nuclear source” as electricity generation is one of the most polluting human activities on Earth. Thus, our study aims to investigate the relationship among CO2 emissions, electricity production from nuclear energy, non-renewable energy, and GDP in 18 OECD countries using a mixture of econometric estimators namely, FMOLS, DOLS and PMG.

The rest of the paper is organized as follow. The second section reviews the literatures. Section three discusses the data, model, estimation procedures, and results interpretations. The concluding remarks and policy implications are presented in the final section.

2. Literature Review

In the recent decades, the interaction of economic growth and environmental degradation has been studied extensively. The relationships among energy production, economic growth and CO_2 emissions have been explored from different dimensions. The CO_2 emissions and economic growth nexus was first investigated, followed by energy-growth-pollution nexus. At a later date, researchers have extended the research by incorporating different energy sources such as nuclear energy into the EKC literature to examine the dynamic relationships among the environmental pollution, economic growth and a specific type of energy.

Grossman and Krueger (1991) were the pioneers who studied the relationship between environmental pollution and economic growth. It is found that there is an inverted U-shaped relationship between these two variables. The inverted U-shaped relationship was further proven by the findings of Apergis and Ozturk (2015), Chiu (2017), Dijkgraaf and Vollebergh (1998), Galeotti, Lanza, and Pauli (2005), Jalil and Mahmud (2009), Kristrom and Lungren (2003), Li, Wang and Zhao (2016) and Narayan and Narayan (2010).The inverted U-shaped relationship, which is named as Environmental Kuznets Curve thereafter, suggests that the increase in level of CO_2 emissions follows the upward trend of GDP at the early stage of economic development. However, when the economy grows further and meets a stabilization point, the level of CO_2 emissions decreases. It can be explained by the fact that the later stage of economy is developed along with the structural and technological changes which could diminish the environmental degradation. While the inverted U-shaped hypothesis exists in most of the studies, mixed results have been found by other researchers. Friedl and Getzner (2003) and Zanin and Marra (2012) found an invalid U-shaped EKC, that is, N-shaped curve in the pollution-growth nexus. Meanwhile, Bertinelli and Strobl (2005), Cialani (2007) as well as Rezek and Rogers (2008) have revealed a monotonically upward curve but Focacci (2003) found a monotonically downward curve.

Numerous studies have been done on the relationships among energy, economic growth and CO_2 emissions. Bastola and Sapkota (2015) discovered that economic growth Granger causes both carbon emissions and energy consumption unidirectionally in Nepal. In addition, Zhang and Cheng (2009) found a long run unidirectional causal relationship running from economic growth to energy consumption and from energy consumption to CO_2 emissions in China. A study by Saboori, Sapri, and Baba (2014) revealed a positive long run relationship among CO_2 emissions, energy consumption and economic growth in OECD countries. Most recently, a provincial analysis was done by Wang, Zhou, Li, and Feng (2016) on the link among GDP, energy consumption and CO_2 using data related to cement manufacturing and combustion of fossil fuels. It is found that cointegration occurs among the three variables with the existence of a long run positive relationship. Other researchers such as Apergis and Payne (2009), Baek (2015), Nasir and Rehman (2011), and Shahbaz and Lean (2012) have confirmed that energy consumption contributes to environmental degradation.

Recently, researchers have pursued the energy-growth-pollution nexus from a general to specific manner by studying the energy in the form of renewable energy and non-renewable energy. Some of the researches even narrow the focus into different sources of energy, i.e. studying the effect of the consumption of natural gas, coal, crude oil, nuclear energy and electricity on CO_2 emissions. The role of electricity in altering the level of economic growth and environmental pollution has attracted much attention of researchers. Similarly, the sources of electricity production are decomposed into renewable and non-renewable sources when the relationships between electricity production, economic growth and CO_2 emissions are studied. The renewable electricity sources are found important in reducing CO_2 emissions in Portugal, Denmark, Spain and USA but the usage of renewable electricity production may decrease economic growth at the beginning stage in Denmark, Portugal and Spain (Silva, Soares & Pinho, 2012).Similar result has been obtained by Onafowora and Owoye (2015) who studied the effect of shocks in the portion of renewable electricity out of total electricity generation on

CO_2 emissions and economic growth in China, India and Japan over the period of 1970 to 2011. Furthermore, Menegaki and Tsagarakis (2015) and Bento and Mountinho (2016) confirmed that EKC hypothesis exists in 33 European countries and Italy respectively when the renewable energy sources are used. More recently, Al-Mulali, Ozturk and Solarin (2016) discovered that the existence of EKC hypothesis is related to the significance of renewable energy consumption in reducing CO_2 emissions. By studying seven selected regions over the period of 1980 to 2010 using DOLS and VECM Granger causality, they found that EKC hypothesis is only confirmed in five regions in which the renewable energy consumption does contribute to a reduction in CO_2 emissions. The inverted U-shaped relationship does not exist in Middle East, North Africa and Sub Saharan Africa regions as renewable energy consumption has no effect on CO_2 emissions in these regions. On the contrary, the greater usage of renewable energy sources does not improve environmental quality in France but CO_2 emissions have motivated the usage of renewable energy sources (Marques, Fuinhas & Nunes, 2016). On the other hand, non-renewable electricity sources have a positive relationship with CO_2 emissions in Italy (Bento & Mountinho, 2016). However, Menegaki and Tsagarakis (2015) found that EKC hypothesis does not exist in the production of fossil energy by using gas and coal in 33 European countries over the period 1990 to 2010.

Apart from electricity production from renewable and non-renewable sources, a number of past researches have explored the effect of nuclear energy on CO_2 emissions. By using panel data, many researchers have found that nuclear energy consumption can reduce CO_2 emissions, as shown by Apergis, Payne, Menyah and Wolde-Rufael (2010) in 19 developed and developing countries; Baek and Pride (2014) in six major nuclear generating countries; Baek (2015) in 12 major nuclear energy consuming countries and Iwata, Okada and Samreth (2011) in 17 OECD countries and 11 non-OECD countries. However, mixed results have been found by Al-Mulali (2014) who studied the effect of nuclear energy consumption on CO_2 emissions in 30 major nuclear energy consuming countries. There is a reduction of CO_2 emissions in most of the countries except France and Sweden. A positive effect is found in Korea Republic instead. Besides, Iwata, Okada and Samreth (2012) found similar results by examining 11 OECD countries. They revealed that nuclear energy consumption does not have an effect on CO_2 emissions in seven countries other than Finland, Japan, Korea and Spain. For country-specified data, nuclear energy is shown to have a favourable impact on CO_2 emissions in France (Iwata, Okada & Samreth, 2010; Marques, Fuinhas & Nunes, 2016) and Korea (Baek & Kim, 2013) in both short run and long run. Similar result has been reached by Menyah and Wolde-Rufael (2010) and Baek (2016) in the context of United States by using VAR techniques and ARDL approach respectively. However, Jaforullah and King (2015) found that the nuclear energy consumption has no relationship with CO_2 emissions in United States over the period of 1965 to 2012 by using VECMs. Table 1 presents a summary of some recent literature on EKC.

[Insert Table 1 here]

3. Data, Model and Results

3.1 Data and variables

A balanced panel dataset from 1995 to 2013 is constructed for 18 OECD countries. All data are retrieved from the World Development Indicator (WDI), World Bank. The selection of countries is based on the availability of data, mainly on the electricity production from nuclear source. The list of countries, variables and summary statistics are presented in Table 2.

[Insert Table 2 here]

3.2 Model Specification

The objective of this study is to examine the EKC hypothesis in the presence of electricity production from nuclear energy and non-renewable energy sources. Hence, a panel model underlying the EKC hypothesis is specified as follow:

$$CO_{2it} = f(Y_{it}, Y_{it}^2, NUC_{it}, NONR_{it}, TO_{it},) \quad (1)$$

Where CO_2 represents CO_2 emissions measured in metric ton per capita, Y and Y^2 represents GDP and GDP^2 measured in constant 2010 US$ per capita, NUC is nuclear electricity output measured in % of total electricity output, NONR is electricity production from non-renewable sources including oil, gas, and coal, and lastly trade openness (TO) measured in % of GDP, enters the model as a control variable to avoid bias caused by the omission of relevant variables. For the sake of econometric estimation, the model specification mentioned above is estimated in natural logarithm form as shown below:

$$lnCO2it = \beta 0 + \beta 1 lnYit + \beta 2 lnY2it + \beta 3 lnNUCit + \beta 4 lnNONRit + \beta 5 lnTOit + \varepsilon it \quad (2)$$

Since the model is in double log form, the coefficients of the independent variables can be used to measure elasticities. Based on the EKC hypothesis, β_1 is expected to have a positive sign while β_2 is expected to have an opposite sign to dictate the inverted U-shaped curve. β_3 is expected to have a negative sign because renewable electricity production would reduce the emissions of CO_2. Non-renewable electricity production would increase the CO_2 emissions and thus β_4 is expected to have a positive sign. Lastly, the sign of β_5 is ambiguous because of inconsistent results from past studies.[36]

3.3 Estimation Procedures and Results Interpretations

The empirical analysis begins with the test of stationarity of variables. Three panel unit root tests are used in this study, namely LLC, IPS and Fisher ADF panel unit root test. Levin, Lin and Chu (2002) extended the time series Augmented Dickey-Fuller (ADF) unit root test to a panel framework as follow:

$$\Delta y_{it} = \emptyset_{it}\omega_i + \rho y_{it-1} + \sum_{j=1}^{n_i} \varphi_{ij}\, \Delta y_{i,t-j} + \varepsilon_{it} \quad (3)$$

where $\emptyset_{it}$ considers individual deterministic components and trends, ρ represents the autoregressive coefficient, ε_{it} is the error term and the lag order which is indicated by n. However, the LLC test may suffer from the loss of power as the test assumes a constant ρ across panels. Im, Pesaran, and Shin (2003) relaxed the assumption of the LLC test by allowing ρ to be varied across panels. Besides, the Fisher ADF test by Choi (2001) has a distinctive feature over the LLC test, that the test uses the time series ADF and Philip-Perron (PP) tests as a framework and combines each series p-value resulting from their unit root tests. All three tests examine the null hypothesis of non-stationarity of variables.

[Insert Table 3 here]

[36] A positive relationship between trade and emission is found by Shahbaz et al. (2015) and Atici (2012). However, the opposite relationship is proposed by Shahbaz, Lean, and Shabbir (2012), and Shahbaz et al. (2013).

Table 3 presents the results of panel unit root tests for the LLC, IPS, and Fisher ADF unit root tests. The results show that all variables are not stationary in the level form as the null hypotheses of these three test are not rejected based on the test statistics. However, the test statistics reject the null hypothesis when the variables are at their first differences. With this, it can be concluded that all variables are stationary at first difference or they are integrated at I(1).

Next, panel cointegration tests can be utilised after the variables are confirmed to be stationary at first difference. This step is done by using Pedroni and Kao tests for cointegration. Pedroni (1999, 2004) proposed two sets of panel cointegration tests. The first set is based on the within dimension approach which includes four test statistics: panel v-statistic, panel rho-statistic, panel PP-statistic, and panel ADF-statistic. These statistics pool the autoregressive coefficients across countries for the unit root tests on the estimated residuals by considering common time factor and heterogeneity across countries. The second set is based on the between dimension approach which consists of three statistics: group rho-statistic, group PP-statistic, and group ADF-statistic. These statistics are based on the averages of the individual autoregressive coefficients associated with the unit root tests of the residuals for each country. Similarly, Kao test uses ADF as a framework and assumes homogeneity in the panels. The t-statistic is derived from panel least squared dummy variable analysis.

[Insert Table 4 here]

The results of Pedroni and Kao test for panel cointegration are reported in Table 4. Both tests indicate that there is long run cointegration for the variables used in this study as the null hypothesis of no cointegration is rejected. In other words, the variables tend to move together in the long run. As the variables are confirmed to be cointegrated, the next step is to estimate the long run relationship. Two classical estimators are used in this study, namely fully modified OLS (FMOLS) and dynamic OLS (DOLS). The FMOLS is a single cointegration equation developed by Pedroni (2000). It has the advantages of eliminating the long run correlation between the cointegrating variables and stochastic regressors innovations. Moreover, it is unbiased and has fully efficient mixture normal asymptotic allowing for standard Wald tests using asymptotic Chi-square statistical inference.

Unlike FMOLS, the DOLS uses leads and lags of the first difference regressors for long run estimation. According to Kao and Chiang (1999), the finite sample properties of the DOLS are superior to the FMOLS by using Monte Carlo simulation. However, both FMOLS and DOLS do not provide any short run information. Hence, to obtain short run estimates and ascertain the relevance of the findings, Pooled Mean Group (PMG) estimator is added into the analysis. Other than providing short run estimates, the PMG estimator can solve the multicolinearity problem arises from the EKC framework. [37]By using PMG, the inverted U-shaped relation in the EKC hypothesis is captured by short run and long run elasticities instead of GDP and GDP squared as in FMOLS and DOLS.

[Insert Table 5 here]

From Table 5, it can be noticed that the long run estimates of FMOLS and DOLS are complementing each other. First, the EKC hypothesis is supported. This is observed from the

[37] See Stern (2004) and Cerdeira Bento and Moutinho (2016) for the critics on the multicolinearity issue and the use of ARDL of overcome the problem.

expected sign and significance of GDP and its squared term. GDP has the correct positive sign and its squared term shows the reverse. This result indicates a turning point for a decrease in environmental degradation after certain level of economic growth is achieved. When it comes to PMG estimation, the result reveals that economic growth increases CO_2 emissions in the short run as shown by the sign of D(Y) and it is significant. Then the reverse holds in the long run. This suggests that the EKC hypothesis is valid and consistent for all the three estimators. In addition, the Error Correction Term (ECT) in the PMG explains the restoration of equilibrium in the long run due to short run shock, is adjusted by around 32% in a year.

More interestingly, for the role of nuclear and non-renewable electricity production on CO_2 emissions, the results from all the three estimators are in favour with our prior hypothesis formed. Non-renewable electricity production has a significant positive effect on CO_2 emissions. Specifically, 1% increase in non-renewable electricity production increases CO_2 emissions by 0.15%, 0.11%, and 0.08% from FMOLS, DOLS, and PMG respectively. On the other hand, nuclear electricity production imposes a significant negative impact on CO_2 emissions. The results from these three estimators indicate that nuclear electricity production can be served as a substitute for conventional electricity sources to ensure better environmental quality. The estimated coefficients are consistently ranged from -0.02 to -0.03.

Despite using three different estimators, the role of trade openness is found to be ambiguous in this study. Using FMOLS and DOLS, it is found that there is a positive effect of trade openness on CO_2 emissions. This result is not matching with the estimation from the PMG which indicates a negative relationship. This implies that the impact of trade openness on CO_2 emissions remains inconclusive and ought to be addressed by future research.

The last part of the analysis concentrates on the direction of causality between the variables by using Dumitrescu-Hurlin (D-H) Granger causality test. The D-H causality test has a few advantages. First, it can be used in both situations where the number of years is smaller than the number of cross sections or vice versa. Second, it can be applied in unbalanced and heterogeneous panel even in the presence of cross-sectional dependence. Furthermore, this test is more superior as compared to the standard Pairwise Granger causality as it is able to solve the bias posed by homogeneity assumption. The results of the D-H causality test are presented in Table 6.

[Insert Table 6 here]

From Table 6, it can be concluded that three bidirectional causalities exist between non-renewable electricity production and CO_2 emissions, GDP and non-renewable electricity production, as well as electricity production from nuclear source and non-renewable electricity production. Other than bidirectional causality, unidirectional causality is found from GDP to CO_2 emissions, electricity production from nuclear source, and trade openness, from CO_2 emissions to electricity production from nuclear source and lastly from trade openness to CO_2 emissions, non-renewable electricity production, and electricity production from nuclear source. A graphical illustration of the direction of causality from Table 6 is presented in Figure 1.

[Insert Figure 1 here]

4. Conclusion and Policy Implications

The phenomenon of global warming leading to climate change is seen as a worldwide concern. Reducing CO_2 emissions is considered as the best solution to the problem of global warming. In relation to this, nuclear energy has gained global attention as one of the most significant means in limiting pollution by providing low-carbon electricity. By employing three panel estimators, namely Panel Fully Modified Ordinary Least Squares (FMOLS), Panel Dynamic Ordinary Least Squares (DOLS) and Pooled Mean Group (PMG) estimators to check for result consistency and robustness, this paper tests the validity of EKC hypothesis in 18 OECD countries with the inclusion of electricity production from nuclear energy and non-renewable energy sources for the period 1995-2013. The empirical evidence shows that an inverted U-shaped EKC does exist in OECD countries, confirming that pollution increases with income level during early stage of economic development and subsequently declines as income reaches a threshold. As expected, it is found that nuclear energy, as a so called clean energy, contributes to better environmental quality by lowering CO_2 emissions. However, electricity production from non-renewables such as fossil fuels tends to worsen the environmental degradation. It is worth highlighting that the above results are consistent for all methods used, suggesting that our findings are robust.

Several important policy implications can be drawn from the results obtained. First, it is vital for the policy makers of OECD countries to design growth-oriented policies and strategies in order to reduce CO_2 emissions persistently in these countries. For instance, growth–oriented fiscal and monetary packages can be designed and implemented as an extra effort to further stimulate economic growth. As income rises in these countries, there would be a switch towards information-based industries and services, improved environmental awareness, enforcement of stricter environmental laws and adoption of clean technologies that would further lead to a reduction in CO_2 emissions. Second, as electricity production using fossil fuels is harmful to the environment in these OECD countries, policy makers should design energy policies in such a way that aim to regulate and further discourage the adoption of fossil fuels at power plants. Third, it is necessary for OECD countries to increase investment in nuclear energy particularly in electricity production since it decreases CO_2 emissions. In other words, nuclear power should be considered as the key energy source in the future low-carbon electricity generation mix of OECD countries.

Despite the fact that nuclear power is a low-carbon electricity supply, it is important to note that the generation of electricity using nuclear energy requires special attention on safety issues. For instance, issues pertaining to radioactive waste management and nuclear installation should be treated with due care in order to avoid any accident that may potentially harm the environment and human health.

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Table 1: Some Recent EKC Studies

Authors	**Countries/ Regions**	**Period**	**Methodology**	**Variables (CO_2 as dependent)**	**Major Findings**
Zoundi (2016)	25 African countries	1980-2012	DOLS, GMM, DFE, PMG and MG	GDP, Renewable energy consumption, Primary energy	EKC is not supported. Renewable energy consumption has a negative effect on CO_2 emissions.

				consumption, and population growth	
Alam et al. (2016)	India, Indonesia, China, and Brazil	1970-2012	ARDL	Income, energy consumption, and population growth	EKC is confirmed in Brazil, China, and Indonesia only.
Bilgili et al. (2016)	17 OECD countries	1977-2010	FMOLS and DOLS	GDP, GDP^2, and renewable energy consumption	EKC is valid. Renewable energy consumption has negative relationship with CO_2 emissions.
Chiu (2017)	99 countries	1971-2010	Non-linear	Income, energy, and investment	EKC is supported.
Baek (2016)	United States	1960-2010	ARDL	Nuclear energy consumption, renewable energy consumption, income	EKC is found in the short run. Income increases CO2 emissions in the long-run. Energy consumption reduces CO_2 emissions in the short- and long-run.
Bento and Moutinho (2016)	Italy	1960-2011	ARDL	GDP, non-renewable and renewable electricity production, and trade	EKC is confirmed. Renewable electricity production reduces. CO_2 emissions
Al-mulali et al. (2016)	7 regions	1980-2010	DOLS	Renewable energy consumption	Renewable energy is significant in the EKC hypothesis.
Li et al. (2016)	28 provinces in China	1996-2012	GMM and ARDL	GDP, energy consumption, trade, and urbanization	EKC is valid.

Table 2: Summary Statistics

Country	Statistics	CO_2 emissions (metric ton per capita)	GDP per capita (constant 2010 US$)	Electricity production from nuclear (% of total electricity output)	Electricity production from non-renewable energy (% of total electricity output)	Trade openness (% of GDP)
Belgium	Mean	10.3100	35097.71	55.6773	39.0637	140.3248
	Std. Dev.	1.0364	9527.46	2.9495	2.5066	15.3602
	Min.	8.2848	23121.57	49.3684	31.9263	115.5111
	Max.	11.6238	48424.59	60.8880	42.0420	163.9951
Canada	Mean	16.0704	34297.48	14.2020	24.6089	69.7406
	Std. Dev.	1.2192	12231.79	1.4838	2.5628	7.0789
	Min.	13.5323	20577.49	12.0210	20.6928	58.3482
	Max.	17.4639	52496.70	17.4720	28.9542	82.8577
Czech Republic	Mean	11.3526	12802.91	27.3241	67.8567	110.7577
	Std. Dev.	0.9124	6432.72	6.2187	7.9372	22.6398
	Min.	9.3835	5765.05	18.6392	53.4401	81.7504
	Max.	12.3653	22649.38	35.6836	78.2200	147.9782
Finland	Mean	11.0563	36751.68	30.3091	38.2235	73.5849
	Std. Dev.	1.2403	10858.53	2.1554	5.9151	6.6933
	Min.	8.5126	24253.25	26.4616	26.0030	64.0692
	Max.	13.2611	53401.31	33.1280	49.9277	86.5119
France	Mean	5.8035	33112.58	77.5548	9.1982	52.4613
	Std. Dev.	0.4061	8272.37	1.3823	0.9279	4.6441
	Min.	5.0505	22465.64	74.3033	7.6830	43.2720
	Max.	6.2805	45413.07	79.5118	10.8015	59.2004
Germany	Mean	9.8499	34747.17	25.4678	62.2912	66.7357
	Std. Dev.	0.5578	8167.93	4.8908	2.0014	13.9550

	Min.	8.8147	23687.32	15.3710	59.2383	43.5447
	Max.	10.8602	46807.42	31.0811	65.4127	85.8748
Hungary	Mean	5.4317	9309.24	39.7972	56.3077	131.6883
	Std. Dev.	0.5146	4125.68	4.084	6.7131	28.0932
	Min.	4.1889	4481.41	32.2536	39.6157	78.4848
	Max.	6.0187	15669.26	50.7411	66.6657	168.2131
Japan	Mean	9.4999	38527.77	23.6005	66.6612	24.8029
	Std. Dev.	0.2915	4856.74	9.2715	8.3792	5.9642
	Min.	8.6194	31902.77	0.8786	58.3331	16.6795
	Max.	9.9092	48629.20	31.7328	86.9730	34.3990
Korea, Rep.	Mean	9.9281	16884.31	35.0487	63.5526	77.1786
	Std. Dev.	1.1466	5519.25	4.3894	4.4218	18.4347
	Min.	7.8820	8133.73	25.8015	54.4428	54.3156
	Max.	11.8402	25997.88	43.7460	72.3371	110.0000
Mexico	Mean	3.8200	7336.25	4.2238	78.9794	54.8669
	Std. Dev.	0.1644	1994.75	0.9455	4.1500	5.8043
	Min.	3.4767	3640.83	2.1337	70.3395	46.1116
	Max.	4.1270	10198.65	6.2426	83.4284	66.4083
Netherlands	Mean	10.5554	39317.13	3.9236	88.3554	125.4671
	Std. Dev.	0.3117	11412.72	0.5686	3.3386	14.1168
	Min.	10.1092	25921.13	2.7830	82.2533	108.3758
	Max.	11.2778	56928.82	4.9503	93.4387	154.2709
Slovak Republic	Mean	7.0507	11029.27	52.5304	30.4526	139.0511
	Std. Dev.	0.2549	5496.24	5.1363	5.5097	26.9405
	Min.	6.0590	4799.15	43.2761	26.2267	99.3564
	Max.	7.8544	18650.36	58.0772	39.5681	183.4055

Slovenia	Mean	7.6686	17217.97	36.5824	37.1042	114.9197
	Std. Dev.	0.3747	6246.43	1.5501	1.5613	18.3663
	Min.	7.0102	10227.74	33.5252	34.1072	92.6291
	Max.	8.5864	27501.87	39.0512	40.0000	144.7576
Spain	Mean	6.7900	23505.55	24.2247	53.8061	54.3095
	Std. Dev.	0.9306	7604.87	5.0700	6.5716	4.6410
	Min.	5.0830	14676.71	18.0769	40.0188	44.8303
	Max.	8.0970	35578.74	33.4881	63.6383	61.1831
Sweden	Mean	5.6373	41687.12	44.8009	3.8667	81.3006
	Std. Dev.	0.5250	11894.48	4.2690	1.7542	7.1068
	Min.	4.6172	26969.24	38.1929	1.6944	67.4888
	Max.	6.4342	60283.25	52.8163	8.7295	93.3591
Switzerland	Mean	5.4066	57042.97	40.8346	1.6594	101.7237
	Std. Dev.	0.3711	16925.55	2.1528	0.2972	15.6035
	Min.	4.6720	37813.23	37.3363	1.1860	77.3043
	Max.	5.9398	88002.61	44.7711	2.3931	132.4984
United Kingdom	Mean	8.5903	35336.10	21.5926	72.9966	53.7845
	Std. Dev.	0.7822	8328.80	4.1845	3.6715	4.6054
	Min.	7.0810	22755.56	13.6396	64.4632	48.6229
	Max.	9.4802	49949.15	28.1076	80.2219	65.7065
United States	Mean	18.8153	41475.27	19.4109	70.4645	25.5800
	Std. Dev.	1.2611	7687.17	0.5790	1.3900	3.1523
	Min.	16.2871	28782.78	18.1461	67.8246	22.1497
	Max.	20.2076	52749.91	20.6470	72.1990	30.8851
All countries	Mean	9.0909	29192.92	32.0781	48.0805	83.2377
	Std. Dev.	3.7845	16.47.18	18.2904	25.9790	38.8260
	Min.	3.4767	3640.83	0.8786	1.1860	16.6795
	Max.	20.2076	88002.61	79.5118	93.4387	183.4055

Table 3: Panel Unit Root Tests

	LLC		**IPS**		**Fisher ADF**	
	Level (trend and intercept)	First difference (intercept)	Level (trend and intercept)	First difference (intercept)	Level (trend and intercept)	First difference (intercept)
CO2	-0.2602 (0.3973) (1)	-15.2393*** (0.0000) (2)	0.1609 (0.5639) (3)	-13.7715*** (0.0000) (2)	39.9290 (0.2997) (3)	222.3570*** (0.0000) (2)
Y	0.0943 (0.5376) (0)	-9.6692*** (0.0000) (2)	-1.2583 (0.1041) (1)	-6.6889*** (0.0000) (2)	41.8078 (0.2332) (1)	107.411*** (0.0000) (2)
Y2	-0.0649 (0.4741) (0)	-9.7559*** (0.0000) (2)	-1.2613 (0.1036) (1)	-6.8184*** (0.0000) (2)	41.7695 (0.2344) (1)	109.3170*** (0.0000) (2)
NUC	0.0063 (0.5025) (1)	-18.5146*** (0.0000) (3)	-0.3403 (0.3668) (1)	-16.0752*** (0.0000) (3)	45.4800 (0.1337) (1)	259.084*** (0.0000) (3)
NONR	4.6969 (1.0000) (3)	-10.5920*** (0.0000) (3)	-0.6492 (0.2581) (1)	-10.6461*** (0.0000) (3)	40.7491 (0.2694) (0)	180.688*** (0.0000) (3)
TO	0.6258 (0.7343) (3)	-16.2590*** (0.0000) (1)	-0.8442 (0.1993) (3)	-12.6641*** (0.0000) (1)	44.9871 (0.1448) (0)	198.332*** (0.0000) (1)

Note: LLC, IPS, and Fisher ADF indicate the Levin et al. (2002), Im et al. (2003), Maddala and Wu (1999) panel unit root and stationary tests. All three tests examine the null hypothesis of non-stationary. *, ** and *** represent the rejection of null hypothesis at 10%, 5% and 1%. The figures without bracket is the test statistic value, the first bracket shows the probability value, while the subsequent bracket shows the lag length selected based on SIC. The probability values for the Fisher ADF are computed using asymptotic χ^2 distribution, while the rest follow the asymptotic normal distribution.

Table 4: Panel Cointegration Tests

Pedroni	
Panel cointegration statistics (within-dimension)	
Panel v-statistic	-1.7003(0.9555)
Panel rho-statistic	1.9851 (0.9764)
Panel PP-statistic	-5.1414*** (0.0000)
Panel ADF-statistic	-4.2900*** (0.0000)
Group mean panel cointegration statistics (between-dimension)	
Group rho-statistic	3.0426 (0.9988)
Group PP-statistic	-5.9121*** (0.0000)
Group ADF-statistic	-4.6435*** (0.0000)
Kao	
ADF	-2.4323*** (0.0075)

Note: Both tests examine the null hypothesis of no cointegration for the variables. *** indicates the rejection of null hypothesis at 1%. The figures without bracket represent test statistic values. Probability values are shown in the bracket. The lag length is selected automatically based on SIC.

Table 5: Panel Long Run and Short Run Estimation

Dependent: CO2	**FMOLS**	**DOLS**	**PMG**
Independent variable	Coefficient (t-stat) (p-value)	Coefficient (t-stat) (p-value)	Coefficient (t-stat) (p-value)
Y	0.7967***	0.7280***	-0.1537***
	(3.1166) (0.0020)	(3.2211) (0.0015)	(-7.4076) (0.000)
Y2	-0.0353***	-0.0326***	-
	(-2.7385) (0.0066)	(-2.8783) (0.0045)	
NONR	0.1538***	0.1061***	0.0816***
	(7.3652) (0.0000)	(3.8690) (0.0002)	(3.2846) (0.0012)
NUC	-0.0311**	-0.0179**	-0.0207**
	(-2.3814) (0.0180)	(-2.2106) (0.0284)	(-2.0027) (0.0464)
TO	0.0990***	0.0596***	-0.0835***
	(3.2029) (0.0015)	(3.6504) (0.0003)	(-2.7991) (0.0056)
Short Run Equation			
ECT(-1)			-0.3235***
			(-4.8711) (0.0000)
D(Y)			0.1689***
			(4.3723) (0.0000)
D(NONR)			0.3402**
			(2.1510) (0.0325)
D(NUC)			0.0253
			(0.1842) (0.8540)
D(TO)			0.1356***
			(4.0692) (0.0001)
C			1.2304***
			(4.8155) (0.0000)

Note: *,** and *** indicate significance at 10%, 5%, and 1% respectively.

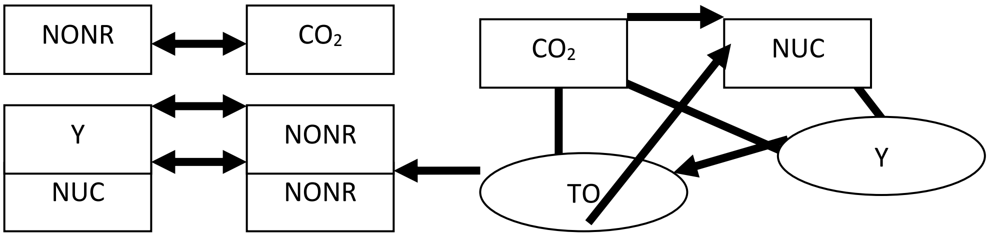
Table 6: Dumitrescu-Hurlin Granger Causality Test

Null hypothesis	Prob.	Conclusion
Y does not homogeneously cause CO_2	0.0000***	Unidirectional causality from Y to CO_2
CO_2 does not homogeneously cause Y	0.3946	
NONR does not homogeneously cause CO_2	0.0177**	Bidirectional causality between NONRENEW and CO_2
CO_2 does not homogeneously cause NONR	0.0000***	
NUC does not homogeneously cause CO_2	0.9573	Unidirectional causality from CO_2 to NUC
CO_2 does not homogeneously cause NUC	0.0000***	
TO does not homogeneously cause CO_2	0.0000***	Unidirectional causality from TO to CO_2
CO_2 does not homogeneously cause TO	0.4394	
NONR does not homogeneously cause Y	0.0350**	Bidirectional causality between Y and NONR
Y does not homogeneously cause NONR	0.0000***	
NUC does not homogeneously cause Y	0.5706	Unidirectional causality from Y to NUC
Y does not homogeneously cause NUC	0.0000***	
TO does not homogeneously cause Y	0.2480	Unidirectional causality from Y to TO
Y does not homogeneously cause TO	0.0005***	
NUC does not homogeneously cause NONR	0.0641*	Bidirectional causality between NUC and NONR
NONR does not homogeneously cause NUC	0.0226**	

TO does not homogeneously cause NONR	0.0000***	Unidirectional causality from TO to NONR
NONR does not homogeneously cause TO	0.1478	
TO does not homogeneously cause NUC	0.0075***	Unidirectional causality from TO to NUC
NUC does not homogeneously cause TO	0.6877	

Note: *,** and *** denote rejection of null hypothesis at 10%, 5% and 1% respectively. The optimal lag length is 2, the results for Y^2 is not reported. However, it will be made available upon request.

Figure 1: Direction of causality



A Novel Market Efficiency Index for Energy Futures and their Term Structure Risk Premiums

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Abstract

This paper proposes a novel futures market efficiency index that measures the ability for price discovery of a long-term futures contract on its nearby short-term contract, accounting for heteroscedastic prices and time varying risk premiums using crude oil, natural gas, heating oil and gasoil futures during 1990 – 2016. The spillover dynamics of information across futures markets is investigated using conditionally heteroscedastic common factors extracted for each commodity from the estimated term-premiums. Evidence of variation in efficiency across terms and commodities along with significant delayed, contemporaneous, and potential information spillovers among term premiums can help investors to optimally diversify their portfolios.

Keywords: Futures efficiency, Term premium, Energy futures, Efficiency index, Time-varying risk premium.

1. Introduction

The strand of literature on testing the efficient market hypothesis (EMH) was originated with the seminal work of Fama (1965) who used the random walk definition of market efficiency. The EMH is based on the principal that prices of an asset reflect all publicly available information. Samuelson (1965) pioneered testing of the futures market efficiency using the martingale definition of efficiency. Subsequently, several authors proposed various test procedures for testing the efficient futures market hypothesis (EFMH) which is based on the definition that a futures market is efficient under the joint assumption of risk neutrality and rationality if the current futures price of an asset for delivery at a specified date in the future is an unbiased predictor of the future spot price. Among the many approaches used to investigate the efficiency of commodity markets, efficiency tests based on price discovery (specifically cointegration based approaches) seem to be popular in the literature. See for example, Hansen and Hodrick (1980), Bilson (1981), Longworth (1981), Baillie (1989), Boothe and Longworth (1986), Chowdhury (1991), Chung (1991), Luo (1998), Lee and Mathur (1999), Wang and Ke (2005), Switzer and El-Khoury (2007), Joyeux and Milunovich (2010), Arouri et al. (2013), Narayan, Liu, and Westerlund (2015), among others. These conventional market efficiency tests assume a constant risk premium and homoscedastic futures prices, that is, these tests ignore the information contained in the heteroscedasticity of prices and time-varying risk premiums. Westerlund and Narayan (2013) propose a more powerful test using the WLS (weighted least square) model which accounts for heteroscedastic prices, but they assume a constant risk premium in their model. Kuruppuarachchi et al. (2017) introduce a more general futures market efficiency test accounting for both heteroscedastic prices and time-varying risk premiums. However, applications of these tests so far have mostly been focussed on investigating the market efficiency of a single security (commodity) during a given time period.

Market efficiency indices are used to investigate the overall efficiency of a group of securities (or portfolio of securities) such as market sectors, exchanges etc., however such indices are sparse in the literature. This study addresses the gap in the literature by proposing a novel futures market efficiency index. Kristoufek and Vosvrda (2013) introduce such an index for capital markets taking into consideration the correlation structure of the returns i.e., the long- and short-term memory. They extend the index for the futures market in Kristoufek and Vosvrda (2014) and use it to analyze the market efficiencies of 25 commodity futures. To the best of the authors' knowledge, this is the only such index we could find in the literature. Their index is based on the martingale definition of efficiency which assumes that the returns of a financial asset in an efficient market are serially uncorrelated with a finite variance. Furthermore, their approach doesn't take into account the information on the time varying risk premiums and the heteroscedasticity of prices. Brenner and Kroner (1995) document that serially correlated risk premiums in futures market efficiency tests which are based on the martingale property of prices, may produce misleading results. The proposed index in this paper overcomes such drawbacks.

The proposed efficiency index is based on the price discovery from long- to short-term futures (similar to the concept of nearby futures to the spot price) across the term structure of the underlying futures. This is a significant novelty feature of the index. That is, the index corresponding to a futures contract is calculated by repeatedly applying the futures market efficiency test proposed in Kuruppuarachchi et al. (2017) between short- and long-term maturity futures price series across the term structure while estimating the term-premium of the underlying commodity. The term-premium is defined as the expected excess return between the current long-maturity futures price and the expected future short-maturity futures price on the next maturity date. Recent studies such as Chaves (2017) extends the literature on futures risk premiums using its term structure and documents that the term structure of futures prices has a strong impact on the returns earned by the investors in those markets. Chaves (2017) also reports that the term structure of futures prices contains significant information corresponding to the time-varying risk premiums between nearby maturities. Furthermore, the proposed efficiency index depicts the magnitude of the consistency of the market efficiency along the futures term structure as it repeatedly tests the market efficiency across the term structure. The index helps investors to understand the ability of price discovery of the underlying commodity across terms and hence is practically very appealing (see for example Baruník and Malinská, 2016).

We also extract a conditionally heteroscedastic principal component common factor (CHCF) of the term-premiums for each commodity using the Kuruppuarachchi et al. (2016) approach. These CHCFs are used to investigate the spillover effects of the macroeconomic shocks on the term-premiums of one commodity on another. Such an investigation can help investors to determine the exposure of their investments to macroeconomic risks.

The proposed index is used to investigate the market efficiencies of four major energy futures, namely WTI crude oil, heating oil, natural gas, and gasoil. Daily futures prices were collected over the sample period January 1990 – December 2016 from Bloomberg which includes the term structures of each contact from 1 to 12 months prior to maturity, respectively.

We document some interesting results in this paper. First, the degree of market efficiency is varying across energy commodities and the highest efficiency is recorded by the gasoil futures traded at ICE. This implies that the price discovery along the term structures is not consistent among commodity futures in the energy sector. Second, CHCFs of term premiums indicate both delayed and contemporaneous information spillovers among the commodity futures in the energy sector. Volatility and extreme risks corresponding to CHCFs of term premiums in crude oil, natural gas, and gasoil futures tend to transmit information across them. These results elaborate on how investors' sentiment for perceived investment risk behaves in the energy sector futures.

The remainder of the paper is organized as follows. Section 2 explains the methodology including the construction of market efficiency index and computation of CHCF of futures term premiums. Section 3 presents data and summary statistics while section 4 presents numerical results obtained for market efficiency and risk premiums. Section 5 concludes the paper.

2. Methodology

2.1 Computing the Consistence Efficiency Index

We define the log price of a long-maturity futures contract ($the\ N^{th}$ period contract) at time t with N months to maturity as $f^N(t)$ and the log price of a short-maturity futures contract ($the\ (N-1)^{th}$ period contract) at time $t+1$ with $N-1$ months to maturity as $f^{N-1}(t+1)$. According to the risk premium theory, the expected log price of the $(N-1)^{th}$ period futures contract, $E_t[f^{N-1}(t+1)]$, is equal to its current log price corresponding to $(N)^{th}$ contract, $f^N(t)$, plus an expected return premium (or price discount), $E[\pi^N(t+1)]$, as illustrated by equation (1),

$$E_t[f^{N-1}(t+1)] = f^N(t) + E[\pi^N(t+1)], \quad (1)$$

where N is the term (number of months to maturity) such that $N = 1, \ldots\ldots, 12$ and $\pi^N(t+1)$ is the term-premium (risk premium) between the consecutive short- and long-maturity futures contracts.

Thus, the one-period expected term-premium is identical to $E[\pi^N(t+1)] = E[f^{N-1}(t+1)] - f^N(t)$ which depicts the roll yield between two consecutive futures contracts. Similarly, the price of a short-term contract, $f^0(t)$, can be used to determine the expected value of the spot price at the expiration, $s(t+1)$, such that, $E_t[s(t+1)] = f^0(t) + E[\pi^1(t+1)]$ according to Fama and French (1987). Moreover, since the spot prices are imprecise or simply unavailable in the case of commodities, we use the price of the nearby contract, denoted by $f^0(t)$, as a proxy for the spot price following Fama and French (1987).

Conventional EFMH is based on the principle that the futures price is the market expectation of a spot price at some future time. Following this principal, Kawamoto and Hamori (2011) document that long-maturity futures price can be considered as the market expectation of a short-maturity futures price at a future time. By repeatedly applying a market efficiency test between short- and long-maturity futures they tested for the consistency of efficiency in a futures market. We extend this line of research to develop the proposed efficiency index by using the market efficiency test proposed in Kuruppuarachchi et al. (2017) as stated by equations (2a) – (2e). In this state-space model the term- premium, $\pi^N(t+1)$, is assumed to be time varying according to an AR(1) process as stated in equation (2b) and the futures prices are heteroscedastic following a GARCH process. We use to test One-period market efficiency is tested using the efficiency test in (2), that is, the market efficiency of the $(N)^{th}$ period futures contract price on its $(N-1)^{th}$ period futures contract price. The test involves two-steps, namely (i) testing for the cointegration relationship between the two futures price series $f^{N-1}(t+1)$ and $f^N(t)$ and (ii) testing the hypothesis $\beta_1 = 1$. Tests of one-period market efficiency simultaneously estimate the term premium, $\pi^N(t+1)$.

$$f^{N-1}(t+1) = \beta_1 f^N(t) + \pi^N(t+1) + \varepsilon(t+1) \tag{2a}$$
$$\pi^N(t+1) = \gamma_0 + \gamma_1 \pi^N(t) + \eta(t+1) \tag{2b}$$
$$\begin{pmatrix} \varepsilon(t+1) \\ \eta(t+1) \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2(t+1) & C \\ C & Q \end{pmatrix}\right] \tag{2c}$$
$$\varepsilon(t+1) = \xi(t+1)\sigma(t+1) \tag{2d}$$
$$\sigma^2(t+1) = \varphi_0 + \varphi_1 \varepsilon^2(t) + \varphi_2 \sigma^2(t) \tag{2e}$$

In order to calculate the proposed efficiency index, we repeat the one-period efficiency test for all the N^{th} period futures contracts of a commodity i.e., $N = 1, \ldots .12$, and define an efficiency indicator $I(N)$ such that, $I(N) = 1$, if the efficient market hypothesis is accepted at the α level of significance for the N^{th} period futures contract, $I(N) = 0$ otherwise. The consistent efficiency index (CEI) for a commodity future is defined as the weighted average of the efficiency indicator values, $I(N)$ and is given by equation (3).

$$CEI = \frac{\sum_{N=1}^{12} I(N)W(N)}{\sum_{N=1}^{12} W(N)} \tag{3}$$

In equation (3), $W(N)$ is the weight assigned for the market efficiency of the N^{th} period futures contract (i.e., the futures contract with N-months to maturity). CEI can take a maximum value of 1, if it is efficient at all terms $N = 1, \ldots, 12$, and a minimum value of zero, otherwise. According to the rational expectation of futures prices, the probability of a market efficiency hypothesis being accepted for an N^{th} period contract, $\Pr\{I(N) = 1\}$, is an increasing function of decreasing N. Therefore, we use a Daniel kernel weight[38] in (3) defined as $W(N) = sin\left(\pi \frac{N-0.5}{12}\right) / \left(\pi \frac{N-0.5}{12}\right)$, following Priestley's theory of spectral analysis (1981).

2.2 Computing the Risk Premium CHCF

The building blocks to extract the information contained in the term structure of futures contracts are roll yields, estimated from the underlying risk premiums between two consecutive futures contracts, $\pi^N(t+1)$ in equation (2b). The roll yield has a positive sign when the futures term structure curve is downward sloping (backwardation) and a negative sign when the curve is upward sloping (contango). Contango hurts the performance of long positions in futures, because futures prices tend to fall over time (negative roll yield and return). Backwardation is beneficial to investors with long positions in futures, because futures prices have a tendency to move up over time (positive roll yield and return) (Chaves, 2017). Moreover, $\pi^N(t+1) - \pi^N(t+1)$ represents the additional risk premium earned by buying a long-term instrument relative to buying the nearby short-term instrument.

[38] We have selected the squared Daniel kernel function because of its performance and relevance experienced during the analysis.

In this paper, we extract a principle component common factor for each of the energy futures using the respective term-premiums over a one-year period. This common factor represents the systematic risk component of the term-premiums of the underlying energy futures. That is, we estimate $\pi^N(t+1)$ for all $N = 1, \dots, 12$ using equation (2b) and then adopt the method developed in Kuruppuarachchi et al. (2016) to compute the common factor of term premiums. Compared to the usual principal components this approach accounts for the heteroscedastic properties of the underlying term-premiums. Hence, these common factors are referred to as conditionally heteroscedastic common factors (CHCFs).

Let, $\Psi(t)$ be the vector of a cross section of N number of term-premiums. Kuruppuarachchi et a. (2016) defines the CHCF of $\Psi(t)$ as $M(t)$ by eliminating the idiosyncratic variations, $e(t)$ of the series of $\Psi(t)$ as in (4a)

$$\Psi(t) = M(t)\Lambda' + e(t) \tag{4a}$$

Here, Λ is the factor loading matrix obeying the rule $\frac{\Lambda'\Lambda}{N} = \mathrm{I}$, where I is an identity matrix. Moreover, $var[M(t)] = R(t)$, $var[\Psi(t)] = \Sigma(t)$, and $var[e(t)] = \Omega(t)$, satisfy equation (4b)

$$\Sigma(t) = \Lambda(t)R(t)\Lambda'(\mathrm{t}) + \Omega(t) \tag{4b}$$

Kuruppuarachchi et al. (2016) estimate $\Sigma(t)$ using the dynamic conditional correlation (DCC-GARCH) specification in Engle (2002).[39] Hence, the percentage of variation, $E[V(t)]$, explained by the extracted common factor $M(t)$ at time *t*, is also time-varying.

3. Data and Summary Statistics

We retrieve energy futures data from Bloomberg over the period January 1990 to December 2016. The data includes the term structures of each contract extending from 1 month to 12 months prior to maturity. Our sample of commodity futures includes WTI crude oil, heating oil, natural gas traded on the Chicago Mercantile Exchange (CME), and gasoil traded on the Intercontinental Exchange (ICE). The monthly data sets are organized by the price at the maturity date for each N where $N = 1, \dots, 12$. Log price series for each maturity period is used for the analysis. Table 1 presents the summary statistics of prices of all the energy futures contracts in the sample.
<Insert Table 1 here >

In Table 1 the average price at maturity is typically less than the prices at different maturity terms implying a long-term contango effect.[40] WTI crude oil indicates its highest average price over 3-5 month terms while all other energy commodities report increasing averages corresponding with maturity terms. All the series in the sample are unit root and heteroscedastic.[41] Therefore, we use log prices and log returns which are stationary to measure continuous compounded returns.

4. Numerical results

Each panel of Table 2 illustrates the results corresponding to the first and the second steps of the market efficiency test (see columns 2 and 3), value of the indicator function (column 4), and the average (column 9) and the standard deviations (column 10) of the estimated term-premiums for each commodity at each term to maturity, N, in the sample. Commodity CEIs for are reported at the end of each panel, respectively. It is evident from the Panel D of Table 2 that gasoil futures traded on the ICE, report efficiency at all terms i.e., $N = 1, \dots .12$ and have the highest consistent efficiency level ($CEI_{QS} = 1.00$) compared to other commodity futures in Panels A to C of Table 2. The high efficiency of these contracts reflects their importance as an efficient hedging and trading mechanism.

<Insert Table 2 here >

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[39] See Kuruppuarachchi and Premachandra (2016) for more details in estimating CHCFs
[40] One exception is the Gasoil mean futures contract price at maturity is U$388.90 and the one month contract price is U$388.51.
[41] These results are not presented here to conserve the space but available upon request.

Heating oil traded on the CME in Panel B has the second highest consistent efficiency ($CEI_{HO} = 0.8591$) while WTI crude oil futures traded on the CME in Panel A has the third highest value, the efficiency index is $CEI_{CL} = 0.6913$. Natural gas futures traded on the CME in Panel C indicates the lowest consistent efficiency ($CEI_{NG} = 0.4005$) when compared to the other futures in the sample.

Graphs of the average and the standard deviation of the estimated risk premiums at each month to maturity, for each commodity in the sample are given in Figure 1. Average risk premiums are similar for contracts with 12 months prior to maturity. The difference in the average premium increases as the contracts move closer to maturity. Natural gas shows the greatest change in the mean risk premium varying from 0.2817%, one month prior to maturity to -0.0288% with nine months remaining to maturity. ICE gasoil has the lowest change in mean risk premium, moving from 0.0220% at seven months until maturity and -0.0293% with one month to maturity. The higher mean risk premiums for contracts closer to maturity suggest that a strategy of buying the short-term futures contract and selling the long-term futures contract when the risk premium is negative is lucrative for investors (Chaves, 2017).
<Insert Figure 1 here >
The annualized standard deviation of the risk premium for each commodity increases as the contract approaches maturity. Great standard deviation implies more uncertainly and suggests greater risk exposure for investors. Natural gas demonstrates the greatest shift in volatility. Annualized standard deviation changes from 1.1208% for one month contracts to 0.2149% for 11 month contracts. WTI crude oil risk premiums are also quite volatile, varying from 0.4925% at one month to maturity out to 0.0588% for futures maturing in 7 months. ICE Gasoil volatility is less marked, moving between 0.3372% and 0.0849% for one month and 11 month contracts, respectively. Heating oil has a similar increase in volatility over the 12 month maturity period. Heating oil risk premium standard deviation is greatest for three month contracts (0.3271%) and lowest for contracts with 12 months to maturity (0.0680%). Consistent with Chaves (2017) the commodity risk premium graphs show that the risk premiums are time varying and depend on the yield spread.

4.1 CHCFs of the Energy Futures

We compute a CHCF for each of the energy futures in the sample using the 12 estimated term-premiums corresponding to the underlying energy futures in order to investigate systematic variations behind those term-premiums. The CHCF indicates the size of the corresponding energy market's premium being paid to the investors in general regardless of the investment term. Table 3 illustrates the descriptive statistics of the CHCFs computed for the energy futures in our sample.

<Insert Table 3 here >

It is evident from Table 3 that the average term premium CHCFs for crude oil, natural gas, and gasoil contracts are negative and close to zero implying zero expected returns in the long-run for these futures with potential contango term structures. The percentage of positive term premium CHCFs for these commodities are also less than 50% implying a relatively higher possibility of contango effects than backwardation. In contrast, the term premium CHCFs of heating oil futures are more positive with close to zero returns in the long-run. Skewness and kurtosis values do not show significant deviations from symmetric behavior in term premium CHCFs. Although stationarity is evident from the ADF tests, serial correlations and heteroscedastic properties exist in all term premium CHCFs as reported by the LBQ and ARCH tests respectively.

In order to examine the time-varying nature of the term premium CHCFs for the commodities, we plot the cumulative values of each CHCF in Figure 2. From Figure 2 there is a cumulative negative, downward trend from year 2000 for all the commodities except heating oil. Continuous investment in crude oil, natural gas, and gasoil results in negative cumulative returns until around year 2010. The risk premiums of these three commodities dropped further as a result of the GFC. In contrast, heating oil futures demonstrate a cumulative positive and upward trend in risk-premiums until the GFC, followed

by a downward trend until 2011. All energy sector futures indicate positive trends after 2011 in varying magnitudes.
<Insert Figure 2 here >

Decreasing risk premiums in Figure 2 indicate the contango effect in those markets causing higher prices in short-term futures than long-term futures contracts. Booming commodity index investments and diversification of portfolios with commodity derivatives might be the possible causes for such behaviour in risk premiums. This phenomenon is well documented in Falkowski (2011) and Cheng and Xiong (2014) among others. They document that the large inflow of investment capital to the commodity futures markets in the past decade due to financialization of futures has distorted the commodity prices. Nikitopoulos, Squires, Thorp and Yeung (2017) find that OECD petroleum country shocks are transmitted through backwardated markets. During contango markets, US consumption shocks create a small initial price increase in the spot relative to the future market that is later reversed.

4.2 Spillover of Information in Term Premiums

Next, we consider if these energy futures share information related to their market risks among themselves. If information is shared we want to determine the form of the information spillover. It may be contemporaneous, delayed or potential? In this section, we answer these questions using the CHCFs computed in section 4.1.

First, we investigate contemporary information spillovers using dynamic conditional correlations in Engle (2002) with ADCC (1,1,1) specification. Contemporary spillovers indicate how the information related to a market shock on one futures market in the current month affects another futures market in the same month. Figure 3 illustrates the computed conditional correlations between pairs of energy futures term-premium CHCFs. Figure 3 illustrates positive correlations between term premium CHCFs most of the time during the sample period. This indicates that the information related to market risks in one futures market is spilled over to the other futures market during the same month causing an increase in risk premiums across energy futures. This is true for all the pairs of energy futures examined in Figure 3. However, the correlations between natural gas and the two commodities, heating oil and gasoil, appear to be negative in the early 90s indicating diversification opportunities of these futures in order to minimize investment risks. Moreover, the correlation between natural gas and crude oil indicate alternative signs over the sample period. When the market risk rises, the benefits of diversification appreciate and investors tend to choose commodities as refuge instruments (Chong and Miffre, 2010; Silvennoinen and Thorp, 2013). This potential demand for commodities from noncommercial traders has been increased in the past causing an increase in prices and hence, negative risk premiums. The increase in cross-commodity correlations in Figure 3 is also consistent with this conjecture that these fundamental demand factors are shaping not only oil prices, but other energy commodity prices as well.

<Insert Figure 3 here >

Second, we examine delayed information spillovers among these futures markets using their CHCFs. Delayed spillover indicates how the information related to the market shocks in one futures market during the past five months affects another futures market in the current month. We use Hong (2001) causality test for mean and variance spillovers, and Hong et. al. (2009) test for extreme risk spillovers. Hong (2001) interprets the volatility spillover as one large shock increases the volatility not only its own market but also other markets as well. Therefore, the causation (spillover) patterns in variance provide vital information for investors when hedging their investments against uncertainty. On the other hand, volatility is a two-sided risk measure and hence it cannot capture the spillover effects in the heavy tails due to jumps. Therefore, Hong et al. (2009) introduce a new concept of spillover called extreme risk spillover where the past history of the occurrences of extreme risks in one market has predictive ability for the occurrence of such risks in another market. This is known as Granger causality in value-at-risk. Granger causality in risk considers on the co-movements between the left tails of the return distributions corresponding to two markets. This type of risk spillover can arise not only from co-movements in mean and in variance, but also from the co-movements in higher order moments such as skewness and kurtosis. Also, they may arise even in the absence of Granger causality in mean and variance. With respect to the four energy futures that we consider in this paper, the Granger causality tests in extreme downside (upside) risk reflect the impact of downside (upside) risks of very low (high) term-premiums in one energy sector commodity on the term-premiums of another energy sector commodity.

<Insert Table 4 here >

Table 4 summarizes the results corresponding to the one-way Granger causality in-mean, in-variance, and in-risk tests. It is interesting to observe from Panel A that none of the term- premium CHCFs transmit information on change in their mean term-premium levels during the past 5-month period to other markets. More specifically, causality-in-mean is not significant for any of the CHCFs. However, other panels of Table 4 indicate significant information spillovers due to changes in variance and extreme risks of their term-premiums. Panel B shows that variance in the gasoil term premium is significantly affected by the past variances in crude oil and natural gas term premiums. That is, small market shocks that change the variance of term-premiums of crude oil and natural gas markets significantly affect the variance of term-premiums of the gasoil market. Also, the information on change of variance in gasoil term-premiums is spilled over to the term-premiums in the crude oil sector indicating feedback causality-in-variance between crude oil and gasoil term premiums. Moreover, variance in heating oil term premium Granger causes to variance in natural gas term premiums.

As far as downside risk spillovers in Panel C are concerned, crude oil plays a major role by transmitting information due to extreme decreases (extreme down-side shocks) in crude oil term-premiums on to both heating oil and gasoil term-premium down side risks. That is, an extreme drop in crude oil term-premiums tends to Granger cause to decrease term premiums in both heating oil and gasoil extremely. Moreover, extreme downside risk in natural gas term- premiums Granger causes to crude oil term-premiums and gasoil term-premiums Granger causes heating oil term-premiums. Panel D of Table 4 indicates that term premium in gasoil is affected by extreme upside risks in all other energy commodities in the sample. In summary, gasoil becomes the mostly affected energy futures commodity due to variance-, downside-, and upside- risk spillovers from other energy sector commodity markets. Robe and Wallen (2016) empirically examine what drives market expectations of crude oil price volatility. These forecasts matter to physical market participants as economic agents seek to trade oil price volatility. Their study finds a positive association between the VIX and short-dated oil implied volatilities (IVs) and the West Texas Intermediate IV term structure.

Finally, using the impulse response function developed by Pesaran and Shin (1998) we investigate how the potential impact of a shock to term premiums in one futures market affects that market as well as the term-premiums in other futures markets. In Figure 4 we construct the impulse response plots from one futures market sector, with the corresponding 90% simulated confidence intervals, using a VAR(2) specification.[42] It is evident from the graphs in Figure 4 that a shock on the term-premiums of any energy futures market has a potential impact on the term-premiums of all other futures markets, with shocks being absorbed over a period of up to two months. The result indicates that investors' fear of shocks to their investment premiums lasts approximately two months on average in any energy futures market.
<Insert Figure 4 here >

In a related study, Robe and Wallen (2016) show that shocks to physical oil market fundamentals are important. Their study documents a relation between oil IVs, output constraints and storage market tightness.

[42] We limit the model for VAR(2) (i.e., $p = 2$) as the inclusion of further lags does not make a significant contribution over the loss of degrees of freedom.

5. Conclusion

This study introduces a novel futures market efficiency index which is based on the aggregate efficiency of the futures along its term structure spanning from 1 month to 12 months. The index uses a market efficiency test recently developed in Kuruppuarachchi et al. (2017) that accounts for both heteroscedastic prices and time-varying risk premiums. The efficiency test simultaneously estimates the time-varying term-premiums of futures providing valuable information to the investor. The index assesses the efficiencies of four major energy futures commodities, namely WTI crude oil, heating oil, natural gas, and gasoil. The contracts of these commodities are available each month during sample period 1990 to 2016. Our findings are interesting and very appealing to the investor. We document that futures market efficiency is not consistent across different terms to maturity for all the energy commodities considered in this paper, except gasoil. Moreover, the estimated term premiums between successive contracts of the same commodity reveal important information on the market dynamics of energy futures due to backwardation and contango. We propose for the first time in the literature a conditionally heteroscedastic common factor (CHCF) for each energy sector commodity considered in this paper. The CHCFs represent the common systematic variations of the term-premiums of all the contracts of a given commodity. We use the CHCFs to investigate the information spillovers between term-premiums of energy sector commodities. Results reveal that spillovers do exist in three different forms namely, contemporaneous, delayed, and potential impact.

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Table 1: Summary statistics of the sample of futures

This table presents descriptive statistics of energy futures contracts selected in this study during January 1990 to December 2016. Summary measures are presented for each term from 2 months to 12 months to the maturity. First row presents summary statistics for the prices at the maturity day.

	WTI Crude Oil		*Heating Oil*		*Natural Gas*		*Gasoil*	
Term	*($ per barrel)*		*($per gallon)*		*($per MMBtu)*		*(per metric tonne)*	
	Mean	*Stdev*	*Mean*	*Stdev*	*Mean*	*Stdev*	*Mean*	*Stdev*
Maturity	46.55	30.56	135.18	93.12	3.81	2.37	388.90	315.32
1 month	46.78	30.71	135.62	93.45	3.91	2.43	388.51	314.60
2 months	46.90	30.85	135.97	93.82	3.97	2.47	389.19	314.94
3 months	46.94	30.96	136.18	94.15	4.00	2.47	389.79	315.33
4 months	46.96	31.05	136.32	94.44	4.03	2.49	390.45	315.82
5 months	46.94	31.12	136.39	94.66	4.05	2.50	391.03	316.31
6 months	46.91	31.16	136.42	94.81	4.07	2.51	391.55	316.76
7 months	46.87	31.18	136.42	94.90	4.08	2.51	391.87	317.03
8 months	46.82	31.20	136.40	94.92	4.10	2.51	392.09	317.24
9 months	46.77	31.20	136.34	94.88	4.10	2.49	392.25	317.40
10 months	46.72	31.20	136.29	94.84	4.10	2.47	392.37	317.48
11 months	46.68	31.19	136.24	94.82	4.10	2.46	392.50	317.55
12 months	46.79	31.11	136.58	94.52	4.11	2.46	393.74	316.93

Table 2: Numerical Results

This table summarizes the results of the market efficiency of four energy futures in the sample. *, ** , and *** indicate the significance of the stationarity at 10%, 5% and 1%, respectively. Each panel illustrates corresponding results for WTI crude oil, heating oil, natural gas, and gasoil futures. Computed efficiency index is illustrated at the end of each panel.

Panel A: Computation of E_i for WTI Crude Oil (EI_{CL})

Term N	Stationarity test of $\varepsilon(t)$ Step-(i)	Test of H$_0$: $\beta_1 = 1$ Step-(ii)	$I(N)$	$W(N)$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	Average $\pi_{an}^N(t+1)$ (annualized %)	Stdev $\pi_{an}^N(t+1)$ (annualized %)
1	-8.187***	0.195	1	0.997	0.9996	-0.000028***	0.90000	-0.0972	0.4925
2	-5.834***	0.467	1	0.974	1.0000	-0.00006	0.84690	-0.0932	0.2766
3	-5.223***	25.441	0	0.930	0.9997***	-0.000098***	0.8765***	-0.0083	0.2736
4	-4.697***	0.175	1	0.866	1.0000	-0.000048***	0.89950	-0.0345	0.1247
5	-4.578***	27.255	0	0.784	0.9999***	-0.000014***	0.8044***	0.0167	0.1585
6	-4.305***	0.439	1	0.689	0.9998	-0.000034***	0.70340	0.0176	0.1180
7	-4.201***	0.190	1	0.583	1.0004	-0.00003	0.54850	-0.0074	0.0588
8	-4.357***	76.859	0	0.471	1.0002***	-0.000023***	0.8974***	0.0040	0.0914
9	-4.401***	0.092	1	0.357	1.0005	-0.00002	0.79770	-0.0072	0.0651
10	-4.409***	0.962	1	0.245	1.0005	-0.000006***	0.89990	-0.0054	0.0626
11	-3.992***	0.756	1	0.139	1.0004	-0.00001	0.01090	-0.0008	0.0059
12	-17.715***	0.879	1	0.043	0.9999	0.00000	0.16780	-0.0014	0.1526

$\boldsymbol{CEI_{CL} = 0.6913}$

Panel B: Computation of E_i for Heating Oil (EI_{HO})

Term N	Stationarity test of $\varepsilon(t)$ Step-(i)	Test of H$_0$: $\beta_1 = 1$ Step-(ii)	$I(N)$	$W(N)$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	Average $\pi_{an}^N(t+1)$ (annualized %)	Stdev $\pi_{an}^N(t+1)$ (annualized %)
1	-7.351***	20.591	0	0.997	0.9988***	0.00000	0.16780	-0.0014	0.1526
2	-6.515***	0.345	1	0.974	0.9993	-0.000006***	0.89490	-0.0198	0.3215
3	-6.250***	0.472	1	0.930	0.9997	-0.00003	0.84230	-0.0277	0.3271
4	-6.217***	0.706	1	0.866	0.9995	-0.00002	0.84540	-0.0667	0.2369
5	-6.461***	0.343	1	0.784	0.9994	-0.00001	0.74250	-0.0447	0.1841
6	-6.500***	0.064	1	0.689	0.9994	0.000011***	0.82190	0.0181	0.2069
7	-6.615***	0.460	1	0.583	0.9996	0.000012***	0.83980	0.0507	0.1954
8	-6.635***	0.641	1	0.471	1.0000	0.000016***	0.89330	0.0188	0.1845
9	-6.775***	0.433	1	0.357	1.0001	0.00001	0.75220	-0.0343	0.1049
10	-6.740***	0.751	1	0.245	1.0001	0.00001	0.49960	-0.0057	0.0823
11	-6.920***	0.375	1	0.139	0.9996	-0.000003***	0.80680	-0.0120	0.0919
12	-17.463***	0.152	1	0.043	1.0002	-0.000025***	0.74140	-0.0143	0.0680

$\boldsymbol{CEI_{HO} = 0.8591}$

Panel C: Computation of E_i for Natural Gas (EI_{NG})

Term *N*	*Stationarity test of* $\varepsilon(t)$ *Step-(i)*	*Test of* H₀: $\beta_1 = 1$ *Step-(ii)*	$I(N)$	$W(N)$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	*Average* $\pi_{an}^N(t+1)$ *(annualized %)*	*Stdev* $\pi_{an}^N(t+1)$ *(annualized %)*
1	-8.994***	0.878	1	0.997	0.9820	0.000038***	0.80130	0.2817	1.1208
2	-8.675***	25.549	0	0.974	0.9913***	0.000029**	0.6753***	-0.0263	0.8099
3	-9.312***	28.390	0	0.930	0.9884***	0.00004	0.59940	0.1596	0.5781
4	-8.078***	6.812	0	0.866	0.9928***	0.00004	0.81870	0.1137	0.5591
5	-8.665***	19.804	0	0.784	0.9943***	-0.000021***	0.8635***	0.0656	0.4183
6	-8.865***	19.821	0	0.689	0.9948***	-0.000001**	0.6697***	0.0452	0.2851
7	-8.980***	0.284	1	0.583	0.9994	0.00000	0.85530	-0.0492	0.2985
8	-8.737***	0.063	1	0.471	0.9977	0.00003	0.67030	0.0019	0.2673
9	-9.520***	0.949	1	0.357	0.9995	0.00000	0.61320	-0.0288	0.2439
10	-9.331***	0.845	1	0.245	0.9993	-0.00001	0.70780	-0.0086	0.2152
11	-9.408***	0.940	1	0.139	0.9996	-0.00005	0.72330	-0.0124	0.2149
12	-15.289***	0.547	1	0.043	0.9997	0.00005	0.58710	0.0133	0.3213

$\boldsymbol{CEI_{NG} = 0.4005}$

Panel D: Computation of E_i for ICE Gasoil (EI_{QS})

Term *N*	*Stationarity test of* $\varepsilon(t)$ *Step-(i)*	*Test of* H₀: $\beta_1 = 1$ *Step-(ii)*	$I(N)$	$W(N)$	$\hat{\beta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	*Average* $\pi_{an}^N(t+1)$ *(annualized %)*	*Stdev* $\pi_{an}^N(t+1)$ *(annualized %)*
1	-11.686***	0.172	1	0.997	0.9999	-0.00002	0.64140	-0.0293	0.3372
2	-6.414***	0.864	1	0.974	0.9995	-0.00001	0.72460	-0.0182	0.2706
3	-5.501***	0.771	1	0.930	0.9995	-0.00001	0.89980	-0.0051	0.2683
4	-5.379***	0.292	1	0.866	0.9995	0.00000	0.89440	0.0039	0.2489
5	-5.459***	0.030	1	0.784	0.9998	0.00002	0.89270	-0.0061	0.2010
6	-5.560***	0.349	1	0.689	0.9996	0.00002	0.89930	0.0190	0.1784

7	-5.555***	0.714	1	0.583	0.9997	0.00001	0.83550	0.0220	0.1102
8	-5.869***	0.618	1	0.471	0.9999	-0.000001**	0.89910	0.0051	0.1177
9	-6.105***	0.947	1	0.357	0.9999	-0.000014***	0.8881***	0.0129	0.1143
10	-6.834***	0.002	1	0.245	0.9999	-0.000030***	0.85760	0.0062	0.0886
11	-7.102***	0.007	1	0.139	0.9999	-0.00010	0.89740	-0.0074	0.0849
12	-16.409***	0.956	1	0.043	0.9998	0.00000	-0.22880	-0.0115	0.2052

$\boldsymbol{CEI_{QS} = 1.0000}$

Table 3: Summary of Term Premium CHCFs

This table presents a summary of descriptive statistics of term premium CHCFs of four energy commodities for the sample period of January 1990 to December 2016. % Positive corresponds to the percentage of positive term premium CHCF values during the sample period ADF (Augmented Dickey-Fuller), LBQ (Ljung-Box), and ARCH (Engle's ARCH) tests are performed to test for stationarity (H_0: unit root process), autocorrelations, and heteroscedasticity in CHCFs respectively. The H_0 of the ADF is the unit root hypothesis. The H0 of the LBQ test is the existence of a serially unautocorrelated series. The H_0 of the ARCH test is the homoscedasticity of the underlying series. All tests are performed at 5 lags and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	WTI Crude Oil	*Heating Oil*	*Natural Gas*	*Gasoil*
Mean	-0.0334	0.0119	-0.0410	-0.0849
Stdev	0.4210	0.4829	0.8593	0.4915
% Positive	46.21%	51.62%	48.01%	42.24%
Skewness	0.1428	-0.0437	0.0393	0.2702
Kurtosis	1.5623	1.5597	2.0881	1.5177
Sample Size	277	277	277	277
ADF Test	-5.8510^{***}	-6.9350^{***}	-6.2779^{***}	-5.7345^{***}
LBQ Test	101.1326^{***}	53.8044^{***}	35.4376^{***}	32.9477^{***}
ARCH Test	156.7196^{***}	136.8848^{***}	78.3172^{***}	93.8656^{***}

Table 4. Results of Granger Causality Tests

This table presents the results of the Granger causality tests using the causality in mean and variance tests due to Hong (2001), and causality in risk tests due to Hong et al. (2009) for the term premium CHCFs. Daniel kernel with 5 months lag is used in all Hong's tests of causality. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Causality to	*Causality from*			
Panel A: Causality-in-Mean	*WTI Crude Oil*	*Heating Oil*	*Natural Gas*	*Gasoil*
WTI Crude Oil		0.0505	0.2431	0.9745
Heating Oil	-0.8582		-0.214	1.1946
Natural Gas	-0.6112	-0.3071		-0.4343
Gasoil	-0.2926	0.5444	0.7839	
Panel B: Causality-in-Variance				
WTI Crude Oil		-0.5329	-0.5745	3.3139***
Heating Oil	-0.5664		-0.8088	0.9452
Natural Gas	-0.5473	2.0295**		-0.3959
Gasoil	4.6829***	-1.0247	4.0972***	
Panel C: Causality-in-Downside Risk				
WTI Crude Oil		-0.6239	4.1087***	-0.0231
Heating Oil	4.8828***	-0.3315	-0.4195	4.8828***
Natural Gas	-0.9843	-0.7458		0.2092
Gasoil	5.5265***	0.5420	1.1176	
Panel D: Causality-in-Upside Risk				
WTI Crude Oil		-0.5731	-0.4800	-0.2643
Heating Oil	-0.1569		-0.3992	0.3523
Natural Gas	-0.2301	1.1177		0.7504
Gasoil	2.3345***	1.6131*	2.9447***	

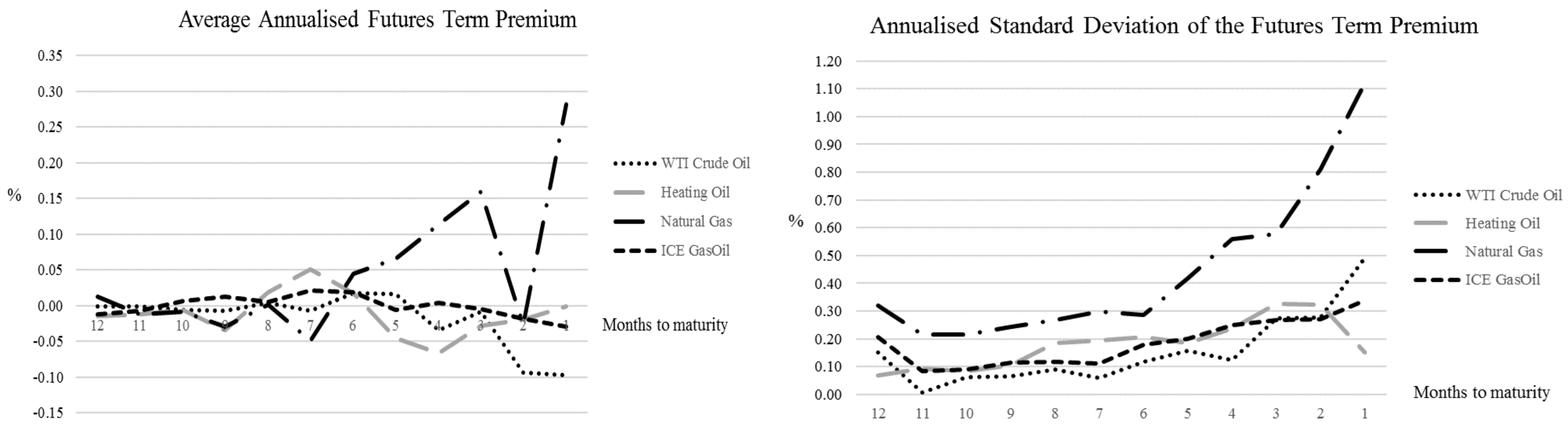

Figure 1. Futures Term Premium
The two panels in this figure display the annualized mean and annualized standard deviation of the futures term period estimated by equation (2) for the for energy sector commodity futures namely, WTI futures, heating oil, natural gas, and gasoil. The values are reported for contracts with maturities ranging from 12 months to one month.

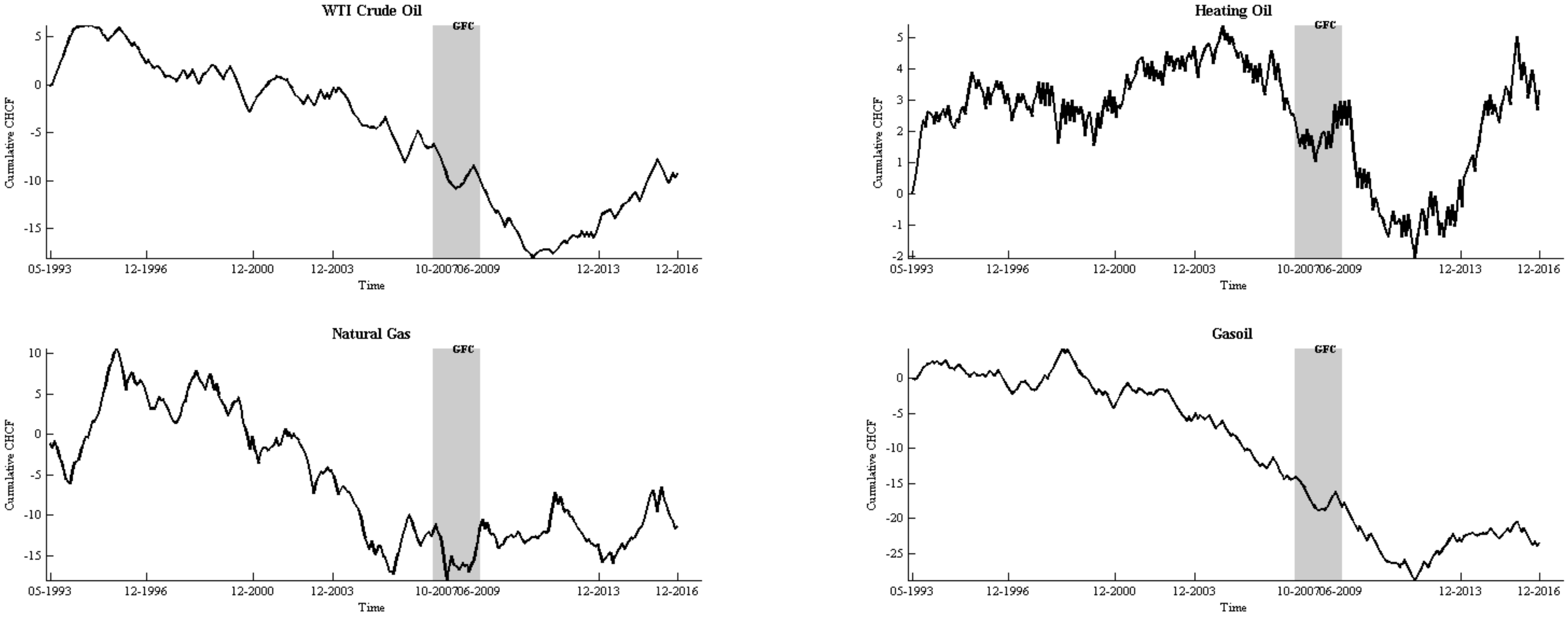

Figure 2. Cumulative Term Premium CHCFs
The four panels in this figure display the cumulative performance of term premium CHCFs during the sample period for the four energy sector commodity futures namely, WTI futures, heating oil, natural gas, and gasoil. A term premium CHCF demonstrates the systematic variation of term premiums covering a term structure from 2 months to 12 months until maturity. Shaded area represents the GFC during 2007/12/01 to 2009/6/30.

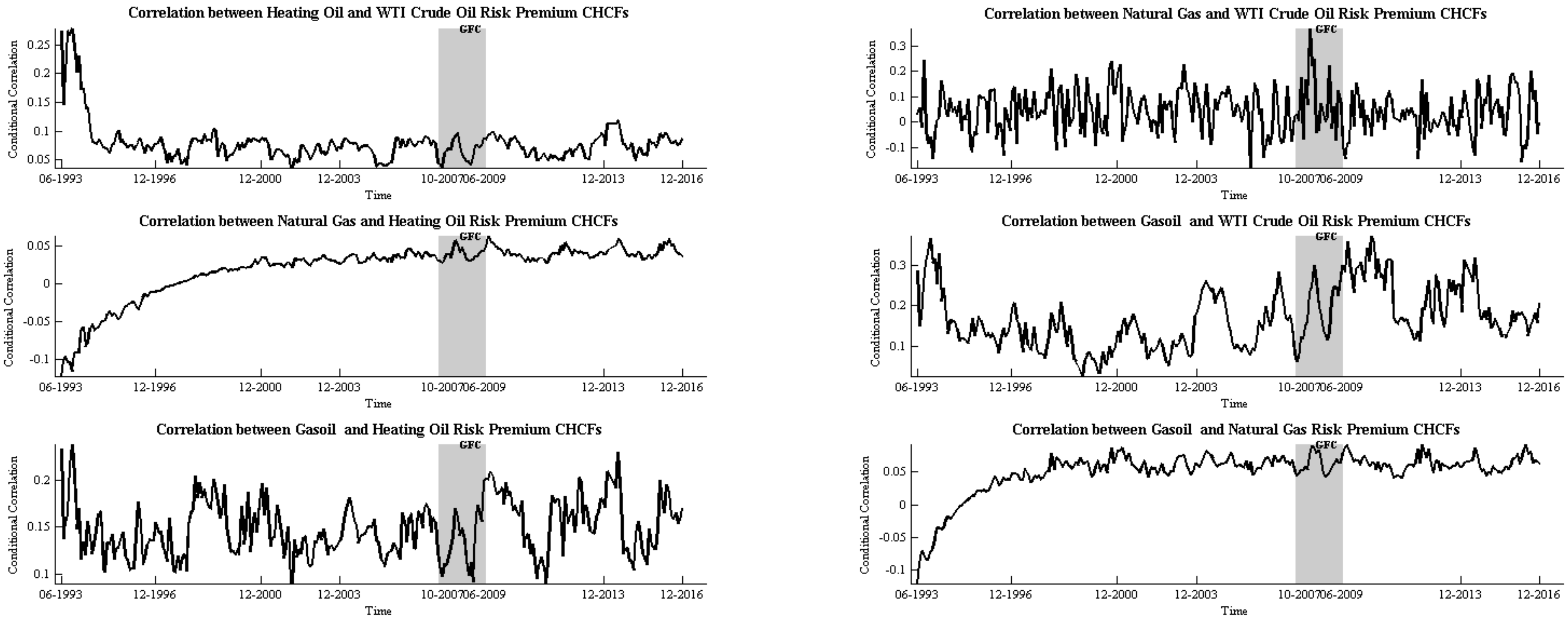

Figure 3. Conditional Correlation Analysis

This figure illustrates the conditional correlations between term premium CHCFs corresponding to each energy commodity in the sample. The conditional correlations are estimated using the ADCC (1,1,1). Shaded area represents the GFC during 2007/12/01 to 2009/6/30.

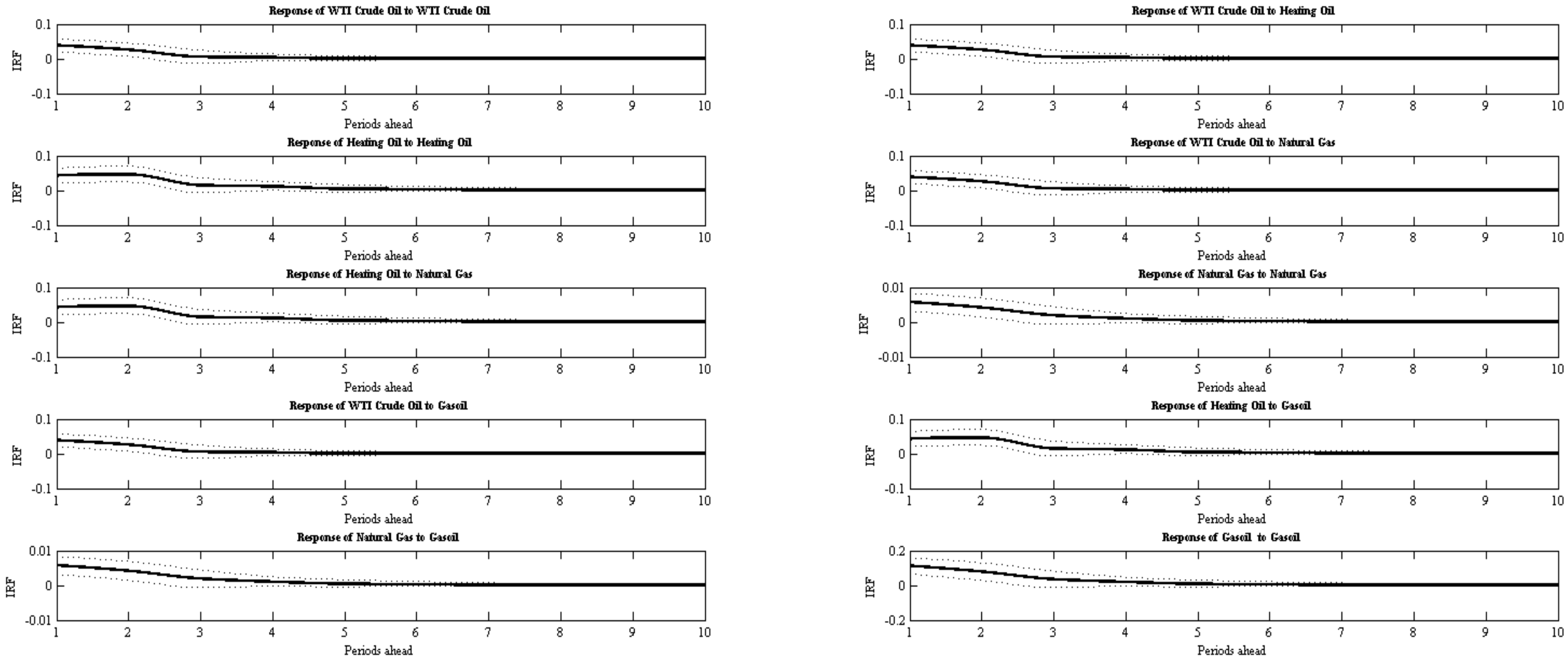

Figure 4. Impulse Response Analysis

This figure illustrates the generalized impulse response functions for each term premium CHCF. Dotted lines represent 90% simulated confidence bands.

Understanding corporate debt for global energy firms

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ABSTRACT

In this paper, we design a new hypothesis that for energy firms' oil market activities impact capital structure. We test this hypothesis using an extensive and unique sample of 726 energy firms from 56 countries covering the 1986 to 2015 period. We find that oil market activities do influence capital structure. Specifically, we discover that speed of adjustment (SOA) to leverage for energy firms when not exposed to oil market activities is between 0.54 and 1.69 years. When exposed to oil price growth (market liquidity) the corresponding SOA is between 1.03 and 2.15 (0.48 and 1.32) years. In other words, oil price growth slows down while market liquidity improves SOA to leverage for energy firms.

Keywords: Capital Structure; Energy Firms; Leverage, Speed of Adjustment; Oil Prices.

I. Introduction

The speed of adjustment (SOA) to a target leverage occupies significant interest in corporate finance research. The reason is strong. The motivation for estimating SOA has roots in the works of, among others, Fama and French (2002), Flannery and Rangan (2006), and Shyam-Sunder and Myers (1999). The key motivating message of these studies is that a slow SOA is tantamount to inconsequential target leverage. In other words, when firms adjust to a target leverage slowly the implication is that the trade-off theory, which argues that to embrace a change in leverage firms have to consider the marginal benefit and cost of such a change, has little relevance to capital structure. The relevance of trade-off theory has been, as a result, a subject of tension mounted with mixed empirical results; see Graham and Leary (2011) and Welch (2004).

Our goal in this paper is to revisit the issue of the relevance of capital structure trade-off theory. With respect to the vast literature on trade-off theory, our position is novel and different in the following way. Motivated by the fact that asymmetric information and other costs, such as transactions costs and taxes, contribute to market imperfections and these imperfections impact a firm's leverage rebalancing decisions, we ask what precisely the role of oil market activities is. Oil market activities are an important consideration because they create market imperfections (see Section II for a detailed discussion on this). For energy firms, oil prices and related measures, such as price basis and price return volatility, constitute key sources of information asymmetry. The existence of hedgers and speculators in oil spot and futures trading, for instance, is a source of information asymmetry. It follows that oil market prices, their volatility, and price basis can potentially signal information asymmetry. On the other hand, trading volume and open interest in the oil market can, by improving liquidity, potentially reduce information asymmetry. The fact that the role of oil market activities in shaping a firm's capital structure has not been studied represents a research gap worthy of investigation. Doing so will allow us to understand capital structure from a different (oil market) point of view. Our paper, therefore, is a response to this research gap. Precisely for this reason, we consider only energy firms because they are the most directly impacted by oil prices (see Narayan and Sharma 2011). We collect a sample of energy firms that belongs to 56 countries. We have annual data over the 1986 to 2015 period for 726 firms, totaling no less than 8,641 firm-year observations. The sample is unique because it represents the first study on capital structure of energy firms and rich because it considers data from 56 countries. We, therefore, have a global sample.

Our empirical approach is motivated by the evidence that estimated SOA can be estimator dependent. The implication is that the estimation of SOA and its robustness go together. We are not ignorant about it, and respond by applying multiple estimators, namely, the panel fixed effects (FE) estimator, the Arellano and Bond (1991) difference generalized method of moments (GMM) estimator, the least squares dummy variable correction (LSDVC) estimator of Bruno (2005) and Kiviet (1995), the long difference (LD) estimator of Hahn, Hausman, and Kuersteiner (2007), and the iterative bootstrap-based correction (BC) procedure proposed by Everaert and Pozzi (2007).

Our main story revolves around using oil market activities to test the hypothesis that they matter to leverage and the speed at which leverage reverts to equilibrium. Together, broadly, we consider eight measures, namely, oil spot/futures price growth, their volatility, basis, volume of trade, liquidity (open interest), and the US$100 oil price psychological barrier, to represent oil market activities. We proxy oil prices with the annual growth rate in oil prices. As an alternative measure of the effect of oil prices, we consider the psychological barrier effect—

that is, the effect on leverage when oil price reached the US$100 per barrel mark for the first time in history. We capture this using a dummy variable following Narayan and Narayan (2014), who show that when the oil price reached US$100 or more per barrel it negatively affected US stock returns. Oil price futures, its trading volume, open interest (liquidity), and price basis are used as additional variables that proxy oil market activities.

Our investigation concludes with three key findings. Our first finding is that oil prices do matter to corporate leverage decision making. For example, in trade-off theory-based regression models, both oil spot prices and the dummy variable capturing the US$100 per barrel psychological barrier effect appear statistically significantly, suggesting that they determine leverage. Apart from their statistical significance, we also estimate whether they are economically significant. We find that they are economically relevant as well. Specifically, we find that the effect of the growth rate in oil price reduces leverage by around 10% of mean leverage (where mean leverage is around 17% of total assets). We also discover that both the growth rate of oil price and the perceived psychological barrier influence also SOA. The SOA without oil effects, depending on the estimator used, falls in the 0.54 years to 1.69 years range. With the oil price growth rate, SOA increases to between 1 year and 2.15 years range. With the psychological barrier effect, SOA is in the 0.94 years to 1.85 years. The message is that, on average, these estimates are sufficiently high compared to estimates obtained without the two oil price variables.

Our second finding is that there is limited evidence from our regression analysis that trading volume and price basis matter to leverage and SOA. They appear economically irrelevant as well. The other price variables, namely oil futures price and its volatility, do matter to leverage but not so much to SOA. A one standard deviation increase in oil futures price and its volatility, for instance, influence leverage by at most 10.8% and 5.3%, respectively. Our third most important result relates to the effect of liquidity. We find that a one standard deviation increase in liquidity has the most (magnitude-wise) effect on leverage. It reduces leverage by 13% of mean leverage and improves SOA from about 1.7 years to 1.3 years.

These results are robustness along multiple counts. First, we show that the results hold regardless of the measure of leverage—both market debt ratio and book debt ratio provide consistent results. Second, we document that there is a size effect story in our hypotheses test. The effect both on leverage and on SOA is mainly on the large sized firms; however, the role of oil price growth, psychological barrier and liquidity stand out in a robust manner. Third, we test for nonlinear effects and find that the SOA is insensitive to positive and negative changes in oil prices although economically negative oil price changes reduce leverage more than positive oil price changes.

Our empirical investigation contributes to two literatures. First, we connect to the literature that directly studies SOA. There is a vast literature documenting the magnitude of SOA but without consensus (e.g., Alti, 2006; Fama and French, 2002; Flannery and Rangan, 2006; Leary and Roberts, 2005; Lemmon, Roberts, and Zender, 2008; in contrast with Elsas and Florysiak, 2015; Frank and Goyal, 2008; Graham and Leary; 2011; Huang and Ritter, 2009). This literature finds the SOA to be in the 7–36% range. Several of these studies question the validity of trade-off theory as a result. Fama and French (2002) and Graham and Leary (2011), among others, question the relevance of a target leverage upon finding slow SOAs to leverage. In our story, such concerns are eased, with our results supporting faster SOAs across a broad range of estimators. Even when allowing for asymmetric effects arising from oil prices, SOA suggests a much faster half-life (1 year to 2.15 years) compared to the non-energy firm leverage SOA literature. In fact, when we study the effect of oil market liquidity, we discover an even faster SOA (half-live of between 0.48 years and 1.32 years).

The second literature we contribute to is on the broader role of oil prices in understanding the economic and financial systems. Studies have shown that oil prices predict economic growth (Hamilton, 1983; Rotemberg and Woodford, 1996) and stock prices (Driesprong, Jacobsen, Maat, 2008; Kilian and Park, 2009). Our study is the first to develop the relation between oil and corporate debt, and show how oil prices and other oil market variables impact corporate leverage. Overall, therefore, our study identifies a role for oil market activities that go beyond merely understanding their relevance to shaping economic growth and stock prices.

The remainder of the paper proceeds as follows. Section II contains hypothesis development, focusing specifically on how oil market activities, by creating asymmetric information, contribute to capital structure decision making. Section III presents the data and discusses results. Section IV discusses the results from robustness tests. The final section provides concluding remarks.

II. Hypothesis development

A well-established fact of capital structure theories relates is the role played by information asymmetry is determining optimal leverage. This role can be traced to the relation between information asymmetry and external financing costs. As Myers (1984) and Myers and Majluf (1984) make clear, firms' external financing costs rise with information asymmetry. The implication is clear: Information asymmetry dictates the composition of debt and equity issuance for a firm (Noe, 1988; Ross, 1977), which in turn dictates how the stock market reacts, an idea consistent with the signaling theory of capital structure.

The key point of our hypothesis is that oil market activities matter to corporate capital structure of energy firms. The speed at which energy firms adjust their leverage depends on the evolution of the oil price—both its first and second order moments, volume of oil contracts traded, liquidity in the oil market and the price basis. There are several channels through which the oil market related activities introduce information asymmetry and transaction costs to energy firms. The starting point is to recognize that there are two types of traders in the oil market—hedgers and speculators. A key characteristic of speculators is that they possess different information on selected variables. To avoid strategic participation in the spot market, Perrakis and Khoury (1998) assume that speculators only participate in the futures market while speculators and hedgers both are active in the spot market. Hedgers are generally less well informed but possess private information (Johnson, 1960) but they do not possess private information sufficient to impact futures market equilibrium (Perrakis and Khoury, 1998). Speculators thrive on information extracted from the informational asymmetry and randomness of the spot market supplies (see Grossman, 1978 and Bray, 1981). The key message of this discussion is that because hedgers and speculators take positions in both spot and futures markets and each possesses different degree of information, a source of information asymmetry in the oil market is hedgers and speculators themselves.

A second channel of information asymmetry is informational frictions in commodity markets, a subject that is illustrated neatly in Sockin and Xiong (2015). The key message of this paper is that commodity market participants are exposed to severe informational frictions regarding global supply, demand and inventory of these commodities. They attribute this to the greater global importance (hence globalization) of crude oil. The theoretical model of Scokin and

Xiong (2015) has several unique features, from which we can infer and generalize that: (1) a higher oil price depicts a stronger global economy, enticing producers to increase oil production; (2) an oil supply shock constitutes informational noise, thereby oil price does not fully reveal the strength of the global economy; and (3) because the futures market attracts different participants than the spot market, it may have its own informational effects on commodity demand and the spot price.

There is empirical support for point (3) also. There is, for instance, disagreement about future oil prices by professional market participants. As shown in Singleton (2011), the time-series dispersion in the standard deviation of the one-year ahead forecasts of oil prices by the professionals surveyed by Consensus Economics and the level of WTI oil prices has widened. This reflects information asymmetry in the oil market. Finally, energy price bubbles also contribute to asymmetric information. Narayan and Narayan (2017) show that the oil market is characterized by price bubbles. Their findings reveal that bubbles are responsible for optimal energy pricing. This result has connections to the idea that one key source of asymmetric information is bubbles, as, for example, demonstrated in the work of Abreu and Brunnermeier (AB, 2003) and Asako and Ueda (2014). The AB model rests on the idea that when investors receive a private signal (asymmetric information) they have an incentive to ride a bubble compared to when they receive a public signal (symmetric information). These discussions motivate the following hypothesis.

Hypothesis 1: Increased information asymmetry and transaction costs lead to a slower SOA.
In contrast to the discussions relating to the design of hypothesis 1, oil market liquidity can obviate information asymmetry and transaction costs. Futures market open interest—our measure of oil market liquidity—reveals the number of outstanding contracts that are active. A high number of open interest implies higher volume of market participants, which reduces information asymmetry and transaction costs. From the work of Easley et al. (1996), we learn that higher trading volume is associated with probability of information event, higher intensity of informed and uniformed trading. They point out that higher liquidity tends to attract more uninformed traders compared to informed traders. In other words, while higher volume sees both informed and uninformed trading increase, liquidity has a larger effect on uninformed trading, thus it is easy to follow how liquidity reduces information asymmetry. Moreover, from the work of Edmans (2009), it is clear that increasing market liquidity can lower transaction costs. This leads to our second hypothesis.

Hypothesis 2: Increased liquidity by reducing information asymmetry and transaction costs lead to a faster SOA.

III. Data and main results

A. Data

We use two types of data to test our proposed hypotheses. First is the corporate leverage related data for energy firms. A list of all variables used are noted in column 2 of Table I. Market debt (*MDR*) and book debt (*BDR*) ratios are used as dependent variables. A range of control variables, such as profitability (*EBIT_TA*), depreciation (*DEP_TA*), total assets (*SIZE*), fixed asset proportion (*FA_TA*), and research and development variables (*R&D_TA*) are used. Full details are provided in Table I. These data are downloaded from the Compustat database. The second data series is with respect to crude oil; we use the Brent crude oil price as a proxy for the spot market and use it to identify the dates on which the oil price reached the US$100 per barrel mark. Using these dates, we form a dummy variable to capture the oil price psychological barrier effect. This data are from the US Energy Information Administration website. We obtain the oil price futures, contracts traded (volume) and open interest data from the Commodity Research Bureau database. Finally, we use a GARCH (1,1) model to estimate oil price spot and futures price return volatility.

The specific steps involved in data construction are noted in Table II. These can be summarized as follows. We begin by considering energy firms from the Compustat database. We specifically consider SIC codes 1311 (crude petroleum & natural gas), 1381 (drilling oil and gas wells), 1382 (oil & gas field exploration services), and 1389 (oil & gas field services). We consider a period 1986 to 2015 because it allowed us to maximise the number of countries for which we could obtain data. This period contains data for 56 countries and has 726 firms for a total of 8,641 firm-year observations. We remove firms with at least two years of missing data and we winsorize data at the 1% and 99% levels to remove outliers. This financial data are supplemented with the securities price data for the corresponding firms, as listed in Table I.

[Insert Table I and II here]

Table I presents descriptive statistics of the data. Our main interest variables are *MDR* and *BDR*. The literature uses both measures of leverage as a dependent variable, although in testing the trade-off theory *MDR* is the preferred dependent variable. The difference between the two is that *MDR* is forward looking (accounts instantaneously for all information available through the financial market), whereas *BDR* is a historical accounting-based measure, implying that firm management may have an influence on the reported figures. By definition, therefore, *MDR* is expected to be more volatile than *BDR*. This is what we find as reported in Table III. The standard deviation of *MDR* is at most 0.242 while that of *BDR* is 0.215 for the sample of entire 756 firms.

Appendix A contains a plot of the seven time-series oil market activity variables and a table of descriptive statistics. These provide a snapshot of the data series with respect to the oil market activity. Some key features of the data are as follows. Annual average growth rates in trading volume and open interest have been highest at 18.7% and 16.8%, respectively. This is followed by spot price growth (6.3%) and futures price growth (4.7%). These four series with the highest growth are also amongst the most volatile. In terms of persistence, the ADF unit root test, which examines the null hypothesis of a unit root, is reported in the last column. The *t*-statistic reported in parenthesis suggests that the unit root null hypothesis can be rejected at the 5% level of better for all seven series. It is therefore clear that all series are stationary. We also observe that, based on the AR(1) coefficient, there is some level of persistence in series such as basis, open interest and volume growth but they are all less than 0.42. The implication is that these series are statistically suitable for our regression analysis.

B. Empirical design

The empirical specification for a partial SOA to leverage (*MDR*) widely used in the literature (e.g., Flannery and Rangan, 2006) has the following form:

$$MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \gamma\alpha_i + \varepsilon_{it+1} \tag{1}$$

where γ is the SOA coefficient and *MDR* (or *BDR* in models for robustness/additional tests) proxies leverage. See Table II for descriptions and details of the variables. A range of theoretically motivated variables that help explain *MDR* is represented by $\boldsymbol{X}$ (see Table I).

These variables are common in this literature and therefore we refrain from repeating a discussion on them. A final note concerns the time it takes to achieve target leverage: From the estimates of the SOA, we compute the implied half-life as [log(0.5)/log(1 - γ)], which is the number of years it takes to revert to half of the target level. The regression model is estimated using five estimators, namely, the FE, LSDVC, BC, LD, and GMM. The idea behind reporting results from multiple estimators is to judge the robustness of the results from the estimator point of view. We will however use the difference GMM estimator as our preferred estimator for making general inference since it is the most widely used estimator.

C. Results

C1. Oil spot and futures price effects

We begin with the results reported in Table III without oil market activity variables. We consider this regression as our baseline model, allowing us to compare SOA when oil market activity variables are included (Table IV). Across the five estimators, the coefficient on the one-period-lagged *MDR* falls in the 0.275 (*t*-statistic = 5.22) to 0.664 (*t*-statistic = 6.04) range. This result suggests a SOA of 33.6–72.5%. With our preferred estimator, GMM, the SOA is 72.5%, which translates to a half-life of 0.54 years. Across all other estimators the half-life is in the 0.94–1.69 years. These results imply a fast rate of adjustment to leverage consistent with the trade-off theory.

[Insert Table III and IV here]

We now examine results from the regression model where we include the growth rate in oil spot price (Table IV). We see that the SOA is slightly slower now in the range of 27.6 - 43.1%, with a half-live of between 1.08 years to 2.15 years. When we include an oil price dummy variable capturing the psychological effect of price reaching the US$100 per barrel mark (Table V), we again observe half-lives higher (in the 0.94 years to 1.85 years range) than when oil effects are excluded. These results are consistent with Hypothesis 1. They imply that oil prices by introducing information asymmetry delay SOA to leverage for energy firms.

[Insert Table V and VI here]

Oil price futures effect on SOA is reported in Panel B of Table VI. We see that across all estimators the slope coefficient on oil price futures growth rate is statistically different from zero. The *t*-statistic (in absolute terms) is in the 2.30 and 4.43 range. The effect is negative suggesting that like spot oil price growth the futures price growth reduces debt. However, we do not observe any remarkable difference in SOA. The half-lives are within the 0.81 to 1.53 years range. Finally, we consider basis, which is the difference between spot and futures oil price. The results are reported in Panel C (Table VI). Across all five models, basis is statistically insignificant. The *t*-statistic is in the 0.28 to 1.29 range.

C2. Oil price volatility effects

Oil price spot and futures volatility also represents asymmetry in the oil market. This sub-section is devoted to understanding precisely the role of price volatilities in influencing SOA. The results are reported in Panel D (spot price return volatility) and Panel E (futures price return volatility). Prices volatilities are bad for debt; they increase debt. All estimators suggest that a rise in price volatilities increases debt by between 0.048% and 0.056% (spot price volatility) and by between 0.046% and 0.057% (futures price volatility). The SOA though remains very close to those observed from the baseline model, particularly at the lower end of the range of estimated half-live. For example, we see half-live in the 0.49 years to 1.34 years range with price return volatilities compared to the half-live obtained from the baseline model, which is in the 0.54 to 1.69 years range. It follows that like oil price futures, while price volatilities are statistically significant determinants of leverage their effect on SOA is limited.

C3. Volume and futures contracts

We also consider other measures of oil market activity, namely, the volume of oil traded and the open interest. The use of volume and open interest constitute oil market activity because it reflects the number of futures contracts traded while open interest is a measure of liquidity in oil futures market because it represents the number of outstanding futures contracts held by market participants. In other words, as volume of open interest increases, so do market activity and therefore liquidity. As Dolatabadi, Narayan, Nielsen and Xu (2017) note, out of all commodities the volume of contracts and outstanding futures contracts are the largest for crude oil. Crude oil makes up appropriately 1/3 of all commodity contracts. The results of the effect of volume and open interest are reported in Panels F and G of Table VI. We find that the slope coefficient of volume growth is statistically insignificant; the estimated *t*-statistic is in the 0.35 to 0.54 range in absolute terms.

The growth rate of open interest, on the other hand, is statistically different from zero in 4/5 estimators. The sign suggests that as liquidity improves it reduces debt, which is just as expected. Liquidity, we find, improves SOA. Across the four estimators where the slope coefficient is statistically different from zero, we see that the half-live falls in the 0.48 to 1.32 years range. This compares to the half-live from the baseline model of 0.54 to 1.69 years range. We conclude that liquidity helps negate asymmetric information in the market thereby contributing to a faster SOA, consistent with Hypothesis 2.

C4. Economic significance of the role of oil market

We have ascertained that SOA is influenced by oil market activities. To this end, we have shown that not only oil spot price growth matter to SOA, the US$100 psychological barrier and market liquidity also matter to SOA. Even when variables such as the spot/futures price volatilities and oil futures price growth do not strongly influence SOA they appear statistically significantly in the regression model. This evidence, though, is statistical. The goal of this sub-section is to test the economic significance of the role of oil market activities in influencing SOA.

[Insert Table VII here]

The economic significance results are presented in Table VII. The absolute value of the effect, which is the slope coefficient multiplied by the standard deviation, and the effect on leverage from a one standard deviation increase in the oil market activity variable, are reported. We will focus directly on the latter since it makes more economic sense. We see that the largest effect results from oil market liquidity: a one standard deviation increase in its growth reduces *MDR* by 13.04% of its mean. Both oil spot and futures prices reduce mean *MDR* by at least 10% from a one standard deviation increase in these price growths. Even the volatility of these two prices are meaningful; that is, a one standard deviation increase in price volatilities increases *MDR* by at least 5.27% of mean *MDR*.

IV. Robustness tests

Up to this point, we have tested the robustness of our results on two fronts. First, we have employed a large number of estimators and our results on the SOA and the role of the determinants of leverage remain broadly intact. Second, we have utilized a wide range of

control variables in the leverage model. From this analysis, again, our main conclusion that oil market activities influence capital structure holds.
Several studies allude to the possibility that the relevance of trade-off theory is sensitive to the different compositions of stocks, market phases, data subsamples, firm size, leverage measures, and nonlinear effects. These issues can shape conclusions on SOA and should, thus, not be ignored. We, therefore, investigate the robustness of our conclusions from these perspectives. Specifically, we run the following tests: (1) we use an alternative measure of leverage, namely *BDR*, to test the effect of oil market activity on leverage and SOA; (2) we categorize stocks into three different sizes to check the sensitivity of SOA to firm size; and (3) we test whether positive and negative rates of growth in oil price influence leverage differently.

Our first robustness test deals with an alternative measure of leverage (BDR). We notice that the SOA across the five estimators are broadly similar. The effect on SOA from oil price growth and market liquidity stand out. Price volatility measures do have an impact but not as remarkable as oil price growth and the psychological barrier effects. Volume and basis almost have no effects, neither on SOA nor on the leverage directly. Our second robustness test deals with potential size effects. We divide our sample of firms using market capitalization into small, medium and large firms. We see that the effect both on leverage and on SOA is mainly on the large sized firms. In this, the role of oil price growth, psychological barrier and liquidity stand out. There is, therefore, a size-based effect story in our analysis.

We ideally would like to sub-sample our data and re-run estimation models. However, when we do this split, because our sample is small (1986 to 2015) sub-sampling weakens our sample and in fact given the unbalanced nature of the dataset some of the estimators do not work parsimoniously. We, therefore, do not engage in a sub-sampling exercise. Finally, oil prices are shown to exert a nonlinear effect on stock prices (Narayan and Sharma, 2011). Motivated by this evidence, we test the sensitivity of leverage (*MDR*) to positive and negative changes in oil prices. To test this hypothesis, we propose:

$$MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \delta\, GOP_{it} * POS_{it} + \gamma\alpha_i + \varepsilon_{it+1} \qquad (2)$$

$$MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \delta\, GOP_{it} * (1-POS_{it}) + \gamma\alpha_i + \varepsilon_{it+1} \qquad (3)$$

We set *POS* = 1 when the spot price growth rate is positive and *POS* = 0 when it is negative. We report the SOA, half-live, the slope coefficient, δ, the absolute value of the effect, which is the slope coefficient multiplied by the standard deviation, and the effect on leverage from a one standard deviation increase in the oil spot price positive and negative change (% SD).

[Insert Table VIII here]

The results are reported in Table VIII. We see that while leverage SOA is insensitive to negative and positive oil price changes, the economic effects from a one standard deviation increase in positive and negative growths in oil prices on leverage are different. A one standard deviation increase in positive change in oil price is between 10% and 13% (positive change) and between 11% and 17% (negative change). This implies that while there is some evidence of nonlinear effects of oil prices on leverage there is largely no effect on SOA.

V. Concluding remarks

This paper uses a unique firm level data on corporate debt to study whether global energy firms' (756 firms, from 56 countries, over the period 1986 to 2015) leverage decisions are influenced by oil market activities. We proxy oil market activities with spot/futures oil price growth, their volatilities, the US$100 oil price psychological barrier, price basis, volume of contracts traded and open interest (liquidity). We design two hypotheses that have roots in the idea that the oil market is characterized by informational asymmetry (or lack of), which would either delay or improve SOA to leverage. We find both statistical and economic significance in support of our hypotheses. Using oil price growth and the US$100 psychological barrier, we find SOA to leverage is slower for energy firms. The SOA for energy firms when not exposed to these prices is in the range of 33.6–72.5%, culminating into a half-life of between 0.54 and 1.69 years. However, when exposed to these two oil market activity variables, the corresponding half-life is between 1.03 and 2.15 years. We also find that market liquidity influences SOA. We find that a one standard deviation increase in liquidity has the most (magnitude-wise) effect on leverage. It reduces leverage by 13% of mean leverage and improves SOA from about 1.7 years to 1.3 years.

The key implication of this result is that an oil market activity-augmented trade-off theory model of the determinants of debt offers a better representation of the determinants of capital structure for global energy firms.

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Table I: Descriptive statistics

This table provides information about variable definition, number of observation, and statistics on the minimum, maximum, mean and standard deviation for each variable used in our empirical analysis. The firm data are obtained from the Compustat database, while the source of Brent spot price is the US Energy Information Administration website (EIA). We obtain the oil price futures, contracts trade (volume), and open interest data from the Commodity Research Bureau database.

Variable	Definition	N	Minimum	Maximum	Mean	Std Dev
MDR	Market debt ratio = book value of (short-term plus long-term) debt (Compustat items [9]+[34])/ market value of assets (Compustat items [9]+[34]+[199] [25]).	6303	0	0.878	0.170	0.218
BDR	Book debt ratio: (long-term [9] +short-term [34] debt)/total assets [6].	6303	0	0.945	0.179	0.215
EBIT_TA	Profitability: earnings before interest and taxes (Compustat items [18]+[15] +[16])/total assets (Compustat item [6]).	6303	-2.850	0.461	-0.097	0.424
MB	Market to book ratio of assets: book liabilities plus market value of equity (Compustat items [9] + [34]+[10]+[199] [25])/total assets (Compustat item [6]).	6303	0.142	69.749	2.773	7.872
DEP_TA	Depreciation (Compustat item [14])/total assets (Compustat item [6]).	6303	0	0.290	0.043	0.051
SIZE	Log (total asset).	6303	0	14.994	5.682	3.126
FA_TA	Fixed asset proportion: property, plant, and equipment (Compustat item [14)]/total assets (Compustat Item [6]).	6303	0	0.951	0.439	0.296
R&D_TA	R&D expenses (Compustat item (46))/total assets (Compustat item [6]).	716	0	0.535	0.021	0.066
R&D_Dummy	Dummy variable equal to one if firm did not report	6303	0	1.000	0.887	0.317

	R&D expenses and zero otherwise.					
IND_MED	Median industry MDR, calculated for each year based on the GIC industry groups.	6303	0	0.441	0.088	0.099
GOP_SPOT	Growth rate of Brent oil spot price (p), computed as p(t)-p(t-1)/p(t-1)]*100.	32	-45.446	54.010	4.754	24.189
GOP_FUTURE	Growth rate of oil futures price (p) computed as p(t)-p(t-1)/p(t-1)]*100.	32	-44.587	51.588	4.659	23.607
VAR_SPOT	Volatility of spot price return computed using a GARCH (1,1) model.	32	0.530	1.820	0.881	0.283
VAR_FUTURE	Volatility of futures price return computed using a GARCH (1,1) model.	32	0.463	1.609	0.765	0.250
VOL_GROWTH	Growth in the number of contracts traded per annum.	32	-26.803	143.968	18.727	31.951
OI_GROWTH	Open interest growth: growth in the total number of outstanding contracts that are held by market participants per annum.	32	-22.436	136.933	16.678	28.439
BASIS	Crude oil spot price less crude oil futures price.	32	-1.325	0.715	-0.028	0.494
D_OIL	Dummy variable which is equal to 1 when the Brent oil price is greater than or equal to $100 and 0 otherwise.					

Table II: Dataset construction

This table shows the steps undertaken to construct our data set. The financial data are obtained from the Compustat database while the West Texas Intermediate (Brent) crude oil price is downloaded from US Energy Information Administration website.

Steps	Countries	Firms	Firm-Year
Annual financial data of all energy firms (SIC codes 1311; Crude Petroleum & Natural Gas, 1381; Drilling Oil & Gas Wells, 1382; Oil & Gas Field Exploration Services, 1389; and Oil & Gas Field Services, NEC) are downloaded for the 1986 to 2015 period.	56	726	8641
Daily security prices are downloaded from CRSP and converted to annual data.	56	726	7904
Annual market equity data and annual financial data are merged.	56	726	9484
Missing values are removed.	56	701	6365
Firms with less than two years data are removed and data are winsorized at 1% and 99%.	56	673	6303
Data for Brent crude oil are downloaded and merged with financial data.	56	673	6303

Table III: Regression results from the baseline model (without oil price variable)

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on the different estimation methods and different dependent variables. We adopt the panel fixed effects (FE) estimator, the least squares dummy variable correction (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) estimator (Hahn, Hausman, and Kuersteiner, 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (*MDR*) and, for robustness, the book debt ratio (*BDR*) as the dependent variables. Our model is: $MDR(BDR)_{it+1} = (1-\gamma)MDR(BDR)_{it} + \gamma\beta X_{it} + \gamma\alpha_i + \varepsilon_{it+1}$. X_{it} is a vector of control variables, such as earnings before interest and tax divided by total asset *(EBIT_TA*), market-to-book ratio (*MB*), depreciation scaled by total assets (*DEP_TA*), *size* (proxied by the log of total asset), fixed asset proportion (*FA_TA*), research and development expenses as a proportion of total assets (*R&D_TA*), dummy variable for unreported R&D expenses (*R&D_Dummy*), and the median industry market debt ratio (*IND_MED*). Finally, ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	FF	LSDVC	BC	LD	Difference GMM
MDR	0.479***	0.636***	0.664***	0.560***	0.275***
	(10.02)	(11.27)	(6.04)	(4.53)	(5.22)
EBIT_TA	-0.026	-0.38	-0.038	-0.028	-0.061
	(-0.87)	(-0.96)	(0.71)	(-0.76)	(-1.87)
MB	0.001	0.003	0.002	0.003	0.002
	(0.62)	(0.73)	(0.69)	(1.78)	(0.60)
DEP_TA	-0.070	-0.211	-0.343	-1.085***	-0.097
	(-0.34)	(-0.87)	(-0.7)	(-3.56)	(-0.44)
Size	0.039***	0.031**	0.027*	0.039**	0.033***
	(4.64)	(2.81)	(1.85)	(2.68)	(3.07)
FA_TA	0.079*	0.075	0.083	00.078	0.041
	(1.68)	(1.12)	(1.08)	(1.20)	(0.87)
R&D Dummy	0.005	0.005	0.041	-0.020	0.040**
	(0.32)	(0.32)	(1.67)	(-0.53)	(2.58)
R&D_TA	0.011	-0.084	-0.071	0.266***	-0.065
	(0.10)	(-0.54)	(-0.40)	(4.49)	(-0.58)
IND_MED	0.146**	0.119	0.165*	-0.093	0.274***
	(1.86)	(1.40)	(1.81)	(-1.14)	(3.38)

Table IV: Regression results with the inclusion of oil price variable

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on the different estimation methods and different dependent variables. We adopt the panel fixed effects (FE) estimator, the least squares dummy variable correction (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) estimator (Hahn, Hausman, and Kuersteiner, 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (*MDR*) and, for robustness, the book debt ratio (*BDR*) as the dependent variables. Our model is: $MDR(BDR)_{it+1} = (1-\gamma)MDR(BDR)_{it} + \gamma\beta X_{it} + \delta GOP_{it} + \gamma\alpha_i + \varepsilon_{it+1}$. Here, *GOP* is the growth rate of Brent oil price, and X_{it} is a vector of control variables, such as earnings before interest and tax divided by total asset *(EBIT_TA*), market-to-book ratio (*MB*), depreciation scaled by total assets (*DEP_TA*), *size* (proxied by the log of total asset), fixed asset proportion (*FA_TA*), research and development expenses as a proportion of total assets (*R&A_TA*), dummy variable for unreported R&D expenses (*R&D_Dummy*), and the median industry market debt ratio (*IND_MED*). Finally, ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	FF	LSDVC	BC	LD	Difference GMM
MDR	0.511***	0.680***	0.724***	0.526***	0.569***
	(10.94)	(11.56)	(7.99)	(4.24)	(16.80)
GOP	-0.0008***	-0.0009***	-0.0009***	-0.0007***	-0.0009***
	(-5.18)	(-5.29)	(-3.96)	(-2.61)	(-6.12)
EBIT_TA	-0.017	-0.013	-0.007	-0.041	-0.025
	(-0.58)	(-0.47)	(-0.22)	(-1.04)	(-0.88)
MB	0.002	0.002	0.0004	0.003	-0.002
	(0.84)	(0.73)	(0.15)	(1.71)	(-0.72)
DEP_TA	0.144	-0.182	-0.326	-1.077***	-0.262
	(-0.71)	(-0.76)	(-0.80)	(-3.51)	(-1.50)
Size	0.028***	0.018*	0.012	0.035**	0.008*
	(3.30)	(1.76)	(0.91)	(2.58)	(1.25)
FA_TA	0.091**	0.071	0.087	0.075	0.155***
	(1.98)	(1.02)	(1.32)	(1.15)	(3.91)
R&D Dummy	0.012	0.013	0.037	-0.012	0.040***
	(0.77)	(0.64)	(1.61)	(-0.28)	(2.65)
R&D_TA	0.001	-0.024	-0.004	0.247***	0.008
	(0.01)	(-0.20)	(-0.04)	(3.53)	(0.07)
IND_MED	0.133*	0.076	0.080	-0.064	0.108
	(1.70)	(0.86)	(0.91)	(-0.75)	(1.54)

Table V: Regression results with the inclusion of oil price psychological barrier effect

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on the different estimation methods and different dependent variables. We adopt the panel fixed effects (FE) estimator, the least squares dummy variable correction (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) estimator (Hahn, Hausman, and Kuersteiner, 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (*MDR*) and, for robustness, the book debt ratio (*BDR*) as the dependent variables. Our model is: $MDR(BDR)_{it+1} = (1-\gamma)MDR(BDR)_{it} + \gamma\beta X_{it} + \delta D\_OIL_{it} + \gamma\alpha_i + \varepsilon_{it+1}$, where *D_OIL* is the dummy variable, which is equal to 1 when Brent crude oil price is greater than or equal to $100 and 0 otherwise, and X_{it} is a vector of control variables, such as earnings before interest and tax divided by total asset (*EBIT_TA*), market-to-book ratio (*MB*), depreciation scaled by total assets (*DEP_TA*), *size* (proxied by the log of total asset), fixed asset proportion (*FA_TA*), research and development expenses as a proportion of total assets (*R&A_TA*), dummy variable for unreported R&D expenses (*R&D_Dummy*), and the median industry market debt ratio (*IND_MED*). Finally, ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	FF	LSDVC	BC	LD	Difference GMM
MDR	0.478***	0.644***	0.688***	0.557***	0.534***
	(10.09)	(11.38)	(6.88)	(4.88)	(15.90)
D_OIL	-0.029**	-0.028**	-0.026**	0.019	-0.026**
	(-2.54)	(-2.36)	(-2.48)	(1.14)	(-2.43)
EBIT_TA	-0.027	-0.022	-0.018	-0.026	-0.022
	(-0.93)	(-0.79)	(-0.45)	(-0.73)	(-0.81)
MB	0.001	0.001	0.000	0.003**	-0.003
	(0.55)	(0.48)	(0.06)	(2.11)	(-1.09)
DEP_TA	0.087	-0.114	-0.234	-1.11***	-0.322*
	(-0.42)	(-0.46)	(-0.61)	(-3.58)	(-1.84)
Size	0.042***	0.033***	0.030**	0.034**	0.013**
	(4.96)	(2.95)	(2.43)	(2.43)	(2.05)
FA_TA	0.070	0.052	0.064	0.076	0.144***
	(1.48)	(0.74)	(0.81)	(1.15)	(3.64)
R&D Dummy	0.009	0.009	0.041*	-0.024	0.041***
	(0.57)	(0.46)	(0.81)	(-0.60)	(2.71)
R&D_TA	0.021	0.003	0.048	0.241***	0.039
	(0.19)	(0.02)	(0.26)	(3.56)	(0.35)
IND_MED	0.23	0.073	0.088	-0.115	0.121*
	(1.55)	(0.80)	(0.99)	(-1.41)	(1.73)

Table VI: Regression results from other proxies of oil market activities

This table provides results from the estimation of the partial adjustment model (of speed of adjustment) based on the different estimation methods and different dependent variables. We adopt the panel fixed effects (FE) estimator, the least squares dummy variable correction (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) estimator (Hahn, Hausman, and Kuersteiner, 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (*MDR*) as the dependent variable. Our base model is: $MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \gamma\alpha_i + \varepsilon_{it+1}$. In panel B through panel G, we include each of the proxy variable representing oil market activity, from futures price growth (*GOP_FUTURE*) to open interest growth (*OI_GROWTH*). Future/spot price (p) growth is computed as: [p(t)-p(t-1)/p(t-1)]*100. Future/spot price return volatility is extracted through estimating a GARCH(1,1) model, and call this *VAR_SPOT* and *VAR_FUTURE* representing spot price return volatility and futures price return volatility, respectively. Volume growth (*VOL_GROWTH*) computed by log [vol(t)/vol(t-1)] *100, where vol is volume. Open interest growth (*OI_GROWTH*) is computed as log [OI(t)/OI(t-1)]*100, where OI is open interest. In addition, *D_OIL* represents the oil price psychological barrier effect, it is a dummy variable which takes a value 1 in the year in which the Brent crude oil price is at least US$100 and a value of 0 otherwise. BASIS as the difference between WTI spot and futures prices. In each panel, we report the slope coefficient associated with $1-\gamma$, the SOA which is the γ, the half- life statistic, which is computed as log(0.5)/log($1-\gamma$). Finally, ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

	FE	BC	Difference GMM	LSDVC	LD
Panel A: Base Model					
$1-\gamma$	0.497***	0.664***	0.275***	0.636***	0.56***
	(10.02)	(6.04)	(5.22)	(11.27)	(4.53)
SOA (%)	0.503	0.336	0.725	0.364	0.44
half-life (year)	0.991	1.693	0.537	1.532	1.195
Panel B: With inclusion of Future price growth (*GOP_FUTURE*)					
Coefficient	-0.0008***	-0.0010***	-0.0008***	-0.001***	-0.0007*
	(-4.30)	(-4.10)	(-4.43)	(-4.08)	(-2.30)
$1-\gamma$	0.426***	0.635***	0.276***	0.603***	0.527***
	(8.23)	(6.48)	(5.19)	(11.12)	(4.30)
SOA (%)	0.574	0.365	0.724	0.397	0.473
half-life (year)	0.812	1.526	0.538	1.370	1.082
Panel C: With inclusion of *BASIS*					
Coefficient	-0.003	0.003	0.004	-0.005	0.014
	(-0.32)	(0.28)	(0.47)	(-0.42)	(1.29)
$1-\gamma$	0.39***	0.582***	0.22***	0.562***	0.513***
	(7.45)	(6.00)	(4.15)	(10.02)	(3.84)
SOA (%)	0.61	0.418	0.78	0.438	0.487
half-life (year)	0.736	1.281	0.458	1.203	1.038
Panel D: With inclusion of Spot return volatility(*VAR_SPOT*)					
Coefficient	0.053***	0.049**	0.048***	0.056***	0.004
	(2.72)	(2.43)	(2.82)	(2.61)	(0.17)
$1-\gamma$	0.398***	0.597***	0.246***	0.571***	0.567***
	(7.69)	(5.58)	(4.69)	(10.23)	(4.52)
SOA (%)	0.602	0.403	0.754	0.429	0.433
half-life (year)	0.752	1.344	0.494	1.237	1.222

Panel E: With inclusion of Future return volatility (*VAR_FUTURE*)					
Coefficient	0.053**	0.046**	0.046**	0.057**	0.002
	(2.57)	(2.18)	(2.50)	(2.45)	(0.07)
$1-\gamma$	0.397***	0.597***	0.245***	0.57***	0.565***
	(7.66)	(5.59)	(4.66)	(10.22)	(4.49)
SOA (%)	0.603	0.403	0.755	0.43	0.998
half-life (year)	0.750	1.344	0.493	1.233	0.112
Panel F: With inclusion of volume growth (*VOL_GROWTH*)					
Coefficient	0.0001	0.000	-0.0001	0.0001	0.0001
	(0.48)	(0.35)	(-0.54)	(0.47)	(0.36)
$1-\gamma$	0.387***	0.586***	0.234***	0.560***	0.59***
	(7.44)	(5.90)	(4.45)	(10.07)	(4.94)
SOA (%)	0.613	0.414	0.766	0.460	0.41
half-life (year)	0.730	1.297	0.477	0.893	1.314
Panel G :With inclusion of open interest growth (*OI_GROWTH*)					
Coefficient	-0.0001***	-0.001***	-0.001***	-0.001***	0.0002
	(-2.62)	(-2.65)	(-3.31)	(-2.70)	(0.31)
$1-\gamma$	0.394***	0.591***	0.239***	0.566***	0.573***
	(7.62)	(5.39)	(4.55)	(10.06)	(4.84)
SOA (%)	0.606	0.409	0.761	0.434	0.427
half-life (year)	0.744	1.318	0.484	1.218	1.245

Table VII: Economic Significance

This table provides results from the economic significance analysis of the importance of the oil market variables. The statistical results obtained on the slope coefficient relating to each oil market variable from the iterative bootstrap-based correction procedure (BC) and the difference generalized method of moments (GMM) methods are used to estimate economic significance. We report the absolute value of the effect, which is the slope coefficient multiplied by the standard deviation, and the effect on leverage from a one standard deviation increase in the oil market activity variable (% SD).

Variables		BC	Difference GMM
GOP_SPOT	Absolute value	-0.022	-0.022
	% SD	-9.986	-9.986
GOP_FUTURE	Absolute value	-0.024	-0.019
	% SD	-10.829	-8.663
VAR_SPOT	Absolute value	0.014	0.014
	% SD	6.361	6.231
VAR_FUTURE	Absolute value	0.012	0.012
	% SD	5.275	5.275
VOL_GROWTH	Absolute value	0.000	-0.003
	% SD	0.000	-1.466
OI_GROWTH	Absolute value	-0.028	-0.028
	% SD	-13.045	-13.045
BASIS	Absolute value	0.001	0.002
	% SD	0.680	0.906

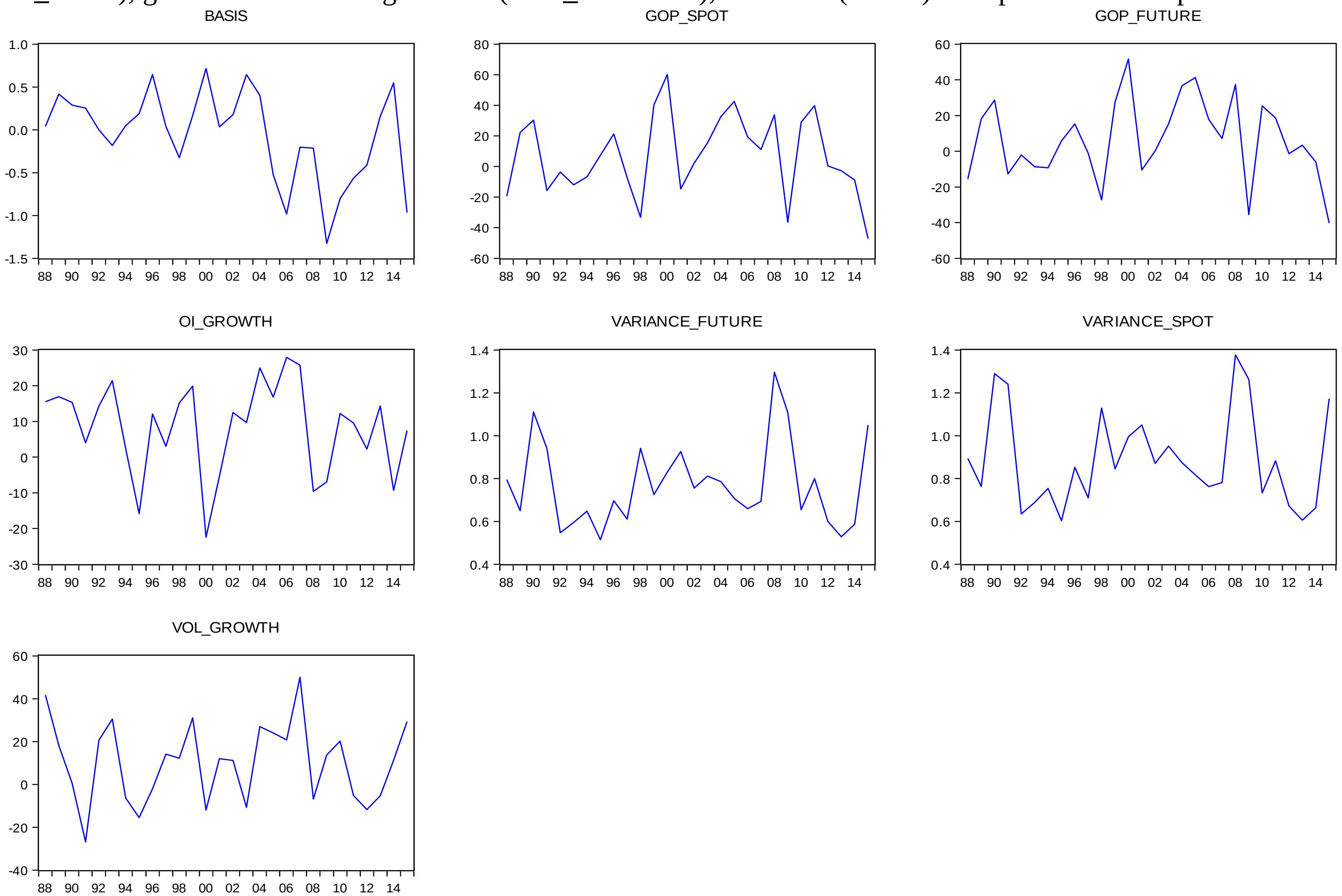
Table VIII: Nonlinear effects of oil price on leverage

This table provides results for the effect of positive and negative spot price growth rate on leverage. We adopt the panel fixed effects (FE) estimator, the least squares dummy variable correction (LSDVC) estimator (Bruno, 2005; Kiviet, 1995), the iterative bootstrap-based correction procedure (BC) proposed by Everaert and Pozzi (2007), the long difference (LD) estimator (Hahn, Hausman, and Kuersteiner, 2007), and the generalized method of moments (difference GMM) with initial estimators proposed by Arellano and Bond (1991). We consider market debt ratio (*MDR*) as the dependent variable. Our considered models are $MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \delta\, GOP_{it} * POS_{it} + \gamma\alpha_i + \varepsilon_{it+1}$ and $MDR_{it+1} = (1-\gamma)MDR_{it} + \gamma\beta X_{it} + \delta\, GOP_{it} * (1 - POS_{it}) + \gamma\alpha_i + \varepsilon_{it+1}$. We set *POS* = 1 when the spot price growth rate is positive and *POS* = 0 when it is negative. We report the SOA, the half-live, the slop coefficient, δ, the absolute value of the effect, which is the slope coefficient multiplied by the standard deviation, and the effect on leverage from a one standard deviation increase in the oil spot price change (% SD).

Type of effect	Statistics	FF	LSDVC	BC	LD	GMM
Positive growth	$1-\gamma$	0.506	0.68	0.713	0.522	-0.23
	SOA (%)	0.494	0.32	0.287	0.478	N/A
	half-life (years)	1.018	1.797	2.049	1.066	N/A
	Coefficient	-0.0010	-0.0011	-0.0010	-0.0012	-0.0009
		(-3.88)	(-3.70)	(-2.84)	(-2.26)	(-3.64)
	Absolute value	-0.024	-0.027	-0.024	-0.029	-0.022
	% SD	-11.10	-12.21	-11.10	-13.32	-9.99
Negative growth	$1-\gamma$	0.499	0.671	0.710	0.548	0.331
	SOA (%)	0.501	0.329	0.29	0.452	0.669
	half-life (years)	0.997	1.737	2.024	1.152	0.627
	Coefficient	-0.0014	-0.0015	-0.0014	-0.0010	-0.0013
		(-4.89)	(-5.40)	(-4.71)	(-2.74)	(-5.00)
	Absolute value	-0.034	-0.036	-0.034	-0.024	-0.031
	% SD	-15.53	-16.64	-15.53	-11.10	-14.42

APPENDIX A: A plot of market activity variables and descriptive statistics

This figure plots time-series data on the growth rate of oil price (*GOP_SPOT*), growth rate of futures price (*GOP_FUTURE*), growth rate of open interest (*OI_GROWTH*), variance of futures price returns (*VARIANCE_FUTURE*), variance of spot price returns (*VARIANCE_SPOT*), growth rate of trading volume (*VOL_GROWTH*), and basis (*BASIS*). The plot covers the period 1986 to 2015.



Descriptive statistics for oil market activity variables

This table presents descriptive statistics for each of the seven oil market activity variables for the time period 1986-2015. Each variable is described in column 1. Mean and standard deviation appear in columns 2 and 3, respectively. The first order autoregressive (AR(1)) coefficient together with the t-statistic testing the null hypothesis that the coefficient is zero is reported in parenthesis. Column 5 reports unconditional correlation between the market activity variable and *MDR*, and in parenthesis the t-statistic examining the null hypothesis that the correlation is zero is reported. The last column reports results from a unit root test based on the augmented Dickey-Fuller model, which includes a constant term but no time trend and the optimal lag length to control for serial correlation is selected using the Schwarz Information Criterion. The t-statistic testing the null of a unit root is reported in parenthesis in column 6.

1		2	3	4	5	6
Variables		Mean	Standard deviation	AR(1) coefficient (t-stat.)	Unconditional correlation (t-stat.)	ADF Unit root test
Oil spot price growth	*GOP_SPOT*	6.328	26.245	0.123 (0.637)	-0.105 (-8.348)	-0.877 (-4.523)
Oil future price growth	*GOP_FUTURE*	4.659	23.607	-0.018 (-0.092)	-0.098 (-7.617)	-1.018 (-5.153)
Variance of spot price return	*VAR_SPOT*	0.881	0.283	0.009 (0.052)	0.051 (3.896)	-0.991 (-5.470)
Variance of future price return	*VAR_FUTURE*	0.765	0.250	0.014 (0.080)	0.046 (3.521)	-0.985 (-5.413)
Difference between spot and future price	*BASIS*	-0.028	0.494	0.425 (2.391)	-0.007 (-0.526)	-0.575 (-3.233)
Open interest growth	*OI_GROWTH*	16.678	28.439	0.402 (4.382)	-0.066 (-5.066)	-0.598 (-6.513)
Volume growth	*VOL_GROWTH*	18.727	31.951	0.384 (3.538)	-0.022 (-1.718)	-0.616 (-5.665)

Determinants of Power Spreads in Electricity Markets: A Multinational Analysis

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Abstract

We study the impacts of variable renewable energy (vRES), prices of substitute fuels, power price volatility, structural breaks, and seasonality on the hedgeable power spreads (profit margins) of the main providers of flexibility in the current power systems - gas and coal power plants. We focus on three European electricity markets (Germany, UK, Nordic) over the time period 2009-2016. We show that the total vRES capacity installed during 2009-2016 is associated with a drop of 3-22% in hedgable profit margins of coal and especially gas power generators. We also find significant persistence (and asymmetric effects) in the power spreads volatility using a univariate TGARCH model.

Keywords: Financial risk management; Hedging; Futures markets; Electricity markets

1. Introduction

The electric power sector is undergoing a rapid transition where the share of net electricity generation in the total energy consumption is increasing globally due to digitalization (Helm 2017). The growth of electric vehicles, demand response programs, energy storage, self-generation, internet of things (IoT), and variable renewable energy sources (vRES) in national energy mixes are some factors changing the risk profiles market participants will face. In this transforming energy market environment, a question arises whether the traditional hedging mechanisms and tradable products are still relevant and sufficient for risk management. Financial derivatives were adopted by electricity market participants relatively recently, in 1990s, when the markets were liberalized. However, these products were designed for centralized power systems with a dispatchable generation fleet, which is not the case of the current market characterised by rapid adoption of intermittent renewable energy sources, such as wind and solar power. It is therefore essential to clearly understand the newly emerging factors shaping the risks market participants face.

In electricity markets, power generators use derivatives to lock-in long-run prices to cover fixed costs, retailers use derivatives to lock-in volatile wholesale prices, and commodity traders/speculators look for profits from short-term price fluctuations. This work primarily focuses on the first group, namely power generators who typically lock-in a portion of their revenue margin in advance by selling derivatives contracts on outputs (electricity) and buying derivatives contracts on inputs (fuel and carbon) ahead of the actual delivery.

Specifically, we are interested in technologies that provide flexibility and dispatchability to the power system, meaning technologies with the capability to balance changes in power supply and demand and to provide power when vRES are not available. Coal and gas-fired power plants are flexible technologies that we focus on. This is in contrast to typical must-run baseload technologies, such as nuclear, or more variable generation, such as wind and solar. We concentrate particularly on these technologies because the outlined transformative trends, such as the increase in vRES production dependent on local weather, increase the need for flexibility (Belderbos and Delarue 2015). At the same time, flexibility providers in liberalized electricity markets need to recover costs and gain reasonable profits to stay in the market. We define a proxy for hedgeable profitability of a given energy technology as power spread.

For gas-fired assets, the differential between prices of electricity and fuel is called spark spread, for coal-fired assets, this differential is called dark spread. Because gas and coal are sources of greenhouse gases, power generators using these fuels in Europe need to acquire CO_2 emission allowances. When carbon costs are considered in spark and dark spreads, they are called clean spark and clean dark spreads.

In this work, we carry out cross-country analysis of three different European electricity markets, namely Germany, UK and Nordics[43], and explore the drivers of hedgeable revenue margins proxied by the two clean power spreads just described. This work contrasts the incentives to provide flexibility, as manifested by power spreads (revenue margins), with the underlying fundamental factors impacting these spreads. In addition to seasonality, fuel prices, and power price volatility, we particularly focus on the impacts of solar and wind generation, which we hypothesize decrease the clean spark and clean dark spreads.

Ultimately, the underlying issue is the energy policy trilemma, which is environmental sustainability, reliability of supply, and economic competitiveness. The support of vRES is associated with environmental sustainability, while the question of adequate hedging mechanisms for dispatchable and flexible generation is associated with both reliability of supply and economic competitiveness. Hence, the key motivation of this work is to evaluate the impacts of current policy which promotes rapid deployment of vRES under the requirement of greater system flexibility on the one hand, with the risk management reality of flexibility providers on the other hand. If there are fundamental factors impeding risk management of flexibility

[43] By the term Nordic we refer jointly to Norway, Sweden, Finland and Denmark.

providers, these have to be first identified and understood before designing new market mechanisms, such as capacity markets, aligned with the objectives of a sustainable, competitive and secure energy market. Misaligned policies may lead to consumers paying risk premia for the increased risk exposure of flexibility providers or lead to higher electricity prices because of the lack of investments into flexible capacity.

We estimate a jointed model for the mean and variance of the futures power spreads on front-month contracts in daily frequency for the period 2009-2016. Our statistical model quantifies the effects of changes in fuel futures prices (gas and coal), volatility of power futures prices, seasonality, and expected wind and solar generation on power spreads. By explicitly modelling variance (volatility) of power spreads with asymmetric threshold generalized autoregressive conditional heteroscedasticity (TGARCH), we reach two methodological benefits and contributions.

First, because volatility is a key input in option pricing formulas, which is an area typically dominated by reduced-form (stochastic) models (Cartea and Villaplana 2008, Carmona, Coulon and Schwarz 2012), our econometric approach presents a practical alternative for multi-asset derivatives pricing. Simplified derivatives valuation and risk management may be appreciated especially by risk managers who often rely on complex third party software. Practicality and model agility may be highly valued to reduce cash-flow variation, especially with the growth of vRES and CO_2 prices. The second methodological benefit of explicitly modelling volatility is that our hypothesized determinants of power spreads are more robust and less prone to false sense of precision. This is because treating expected squared error terms equally at any given point (homoscedasticity) when this assumption does not hold (heteroscedasticity) leads to biased standard errors and confidence intervals, thus giving a false sense of precision (R. Engle 2001).

The current state of the art econometric literature has typically focused on modelling determinants of commodity prices, such as weather, market tightness, or demand flexibility, in the spot market. This is understandable, because spot prices drive optimization decisions and physical portfolio dispatch. In contrast, the literature focusing on the futures market prices has mostly focused on hedging effectiveness, cashflow at risk analyses, and volatility forecasting. This is also understandable, because the uncertainty of future supply and demand factors affecting derivatives' prices is inherently high and dependent on how far on the forward curve we go. For instance, short-term futures are typically impacted by storage conditions, whereas long-term futures are impacted by the future potential energy supply (Pilipovic 2007). We attempt to fill this gap between spot and futures commodity price research and explicitly model the determinants of the hedgeable profit margins in the futures market.

Finally, our approach enables us to distinguish and quantify the individual factors affecting the hedgeable profit margins of flexibility providers. Such distinction of factors may better inform policy makers and regulators in designing adequate and reliable power markets. Additionally, by linking electricity, emissions, and fuels across three different electricity markets in Europe, we bring comprehensive empirical evidence on evolution and determinants of hedgeable profit margins for supply-side providers of flexibility.

The paper is structured as follows. Section 2 reviews mostly modelling literature on power spreads valuation. Section 3 initially outlines the main drivers of electricity supply and demand in the studied regions before proposing the main drivers of power spreads. The section continues with data and model description. Section 4 summarizes the main results which are further discussed in section 5. The paper ends with conclusions in section 6.

2. Literature review

The literature on commodity spot and derivatives pricing is vast. As a starting point, the research field can be classified according to modelling approaches of electricity prices[44]. Five general modelling approaches can be identified (Weron 2014): i) Multi-agent (multi-agent simulation, equilibrium, game theoretic), ii) Fundamental (structural), iii) Reduced-form (quantitative, stochastic), iv) Statistical (econometric, technical analysis), and v) Computational intelligence techniques (artificial intelligence-based, non-parametric, non-linear statistical). Next, we focus on the two most widely applied approaches in derivatives pricing – reduced-form, and statistical.

Reduced-form models, also called financial mathematical models (Möst and Keles 2010), are dominating the electricity derivatives valuation field which focuses on the stochastic behaviour of commodity prices in one- or multi-factor models (Mahringer and Prokopczuk 2015, Carmona, Coulon and Schwarz 2012, Islayev and Date 2015, Barlow 2002). These stochastic factors are typically mean-reversion (Brownian motion), jump diffusion (Poisson process with jump terms), and regime switching (Markov models), which undisputedly play a central role in valuing power derivatives. These models take prices as exogenous and focus on modelling the futures and volatility curves. Their main usage is in pricing financial derivatives and short term forecasting of spot and futures prices (Suren and Date 2015). Some of the studies applying stochastic approaches particularly focus on seasonality in volatility (Fanelli, Maddalena and Musti 2016, Paschke and Prokopzuk 2010, Back, Prokopzuk and Rudolf 2013), which is an important factor in the valuation of commodity derivatives. Reduced-form models applied to power spreads predominantly focus on the value of spread options (Carmona, Coulon and Schwarz 2012, Deng, Johnson and Sogomonian 2001, Mahringer and Prokopczuk 2015, Hsu 1998, Dempster, Medova and Tang 2008), which is mainly because of the versatility of options (keeping the upside while protecting the downside). Additionally, the choice of running a power plant or storage, if the operating margin between power price and the operating cost is positive, gives a rise to an option value of a power plant. The choice to run a power plant or not can then be valued as option according to option value methods, such as Black-Scholes. Option spreads are often approximated by Monte Carlo, tree methods, and partial differentiation equation (PDE) solvers (Carmono and Durrleman 2003). A survey of reduced-form models in power futures setting is present in (Eydeland and Wolyniec 2003, Pilipovic 2007).

Statistical (econometric) techniques do not solely focus on the replication of price dynamics as the reduce-form models do and they deal with stochastic processes differently (Möst and Keles 2010). In addition to using past price characteristics to explain price fluctuations, statistical models incorporate also the current and/or past values of exogenous factors (Weron 2014). In an electricity price modelling setting, the typical exogenous factors are, for example, electricity consumption and production, weather, and fuel prices. Statistical models thus focus on the impact of explanatory variables on the price fluctuations, which enables interpretation of the physical (fundamental) components in the analysis. Since the main purpose of this study is to explain the impacts of exogenous variables on the hedgeable profit margins, we embrace the econometric approach to price modelling.

Econometric models have to address the typical and complex empirical features of (daily) electricity prices, namely extreme volatility, excess kurtosis, positive skewness, price jumps, seasonality, and conditional heteroscedasticity. Weron and Zator (2014) point out important methodological pitfalls of applying linear regression models for explaining the relationship between spot and futures electricity prices, which can be generalized to electricity prices (spreads). They mention three issues needing attention: (1) bias originating from simultaneity (endogeneity) problems, i.e. there is often a loop of causality between dependent and independent variables; (2) the effect of correlated measurement error; and (3) the impact of seasonality on

[44] Alternative classification could be along the electricity derivatives pricing approaches, namely 1) Theory of storage (Kaldor 1939), where forward commodity contract price is equal to the spot discounted by interest rate and the storage costs; 2) Equilibrium pricing (Keynes 1930), where futures prices are related to the expected spot prices; and 3) Stochastic pricing models (Benth and Koekabakker 2008, Eydeland and Wolyniec 2003), vis discussion on the reduced-form modelling.

regression models. We explain in detail how we address these fundamental issues in the methods section below.

The mean-reverting and seasonal behaviour of electricity prices is often modelled by autoregressive (AR-type) time series models (Weron 2014) and volatility clustering by conditional heteroscedasticity models (ARCH). Non-linear effects, especially price-spikes, are modelled by regime-switching and authors typically combine and/or compare model performance under different specifications. For example, Karakatsani and Bunn (2008) build a fundamental regression model for intra-day electricity prices and compare its day-ahead forecasting performance to time-varying and regime-switching models. In their specification, they include multiple economic, technical, strategic, risk, behavioural and market design price effects, such as demand forecast, demand slope, demand volatility, margin (excess of generation capacity), price volatility, and seasonality. Weron and Misiorek (2008) show that AR electricity price models with system load as the exogenous variable generally perform better than pure price models. Also Kristiansen (2012) uses the Nordic demand and Danish wind power as exogenous variables in an AR model to forecast the Nordic hourly day-ahead prices. Applied directly to spot spark spreads, Woo, et al. (2012) estimate a twostep regression model applying a logistic and ARCH log linear regression using demand, wind generation and fuel prices, among others. Illustrated on European Union Allowance (EUA) future returns, Boersen and Scholtens (2014) employ a threshold GARCH model and study the impacts of natural gas, oil prices, fuel switching, electricity futures price, and weather (heating degree days) on the yearly futures carbon price.

As was briefly illustrated, most of the statistical models focus on spot prices rather than derivatives prices, which is understandable because spot prices drive optimization decisions and physical portfolio dispatch. An additional reason is that derivatives prices are not simple forecasts of expected future outcome. Instead, in addition to being a function of the basic fundamental drivers of supply and demand for the physical commodity, derivatives prices also reflect the relative risk aversion of participants, the speculative positions and the perceived cost of risk (Roques, Newbery and Nuttall 2004, Karakatsani and Bunn 2008). Hence, electricity spot price modelling with econometric techniques need to capture all factors affecting the current supply and demand. Nonetheless, similar techniques applied to derivatives prices need to consider the future factors of supply and demand affecting the expected value of a derivative during its settlement period. Forecasting input factors by, for example, exponential smoothing methods, bears obvious risks of forecasting errors that just surge with the increase of forecasting window.

The uncertainty of future inputs presents the biggest challenge for applying econometric techniques to derivatives valuation. To overcome this limitation, instead of relying on point estimates, the econometric model can work with different input scenarios which establish probable boundaries. Other approaches to overcome the uncertainty of forecasted inputs include use of the nearest forward contract, such as front-month, which is convergent with the spot price because disparities between the two are quickly arbitraged away. The nearest contracts are usually the most traded and liquid representing the short-term portion of the forward curve which is often used as a spot price indicator. In fact, the influence of past spot electricity prices on the future electricity prices has been repeatedly documented (Karakatsani and Bunn 2008, Redl, et al. 2009). In such a case, the present supply and demand factors could be used to explain the nearest contract price dynamics without inherently increasing the model's uncertainty and complexity.

An additional challenge in modelling derivatives of power spreads lies in the fundamental structure of the spread itself. Power spreads, be it clean dark or clean spark, are by design cross-commodity derivatives consisting of fuel prices, electricity prices and carbon allowance prices. Each of these price series typically constitutes a separate pricing model. Nonetheless, to uncover the average price formation process of such derivatives, a joint model for all commodities is required (Carmona, Coulon and Schwarz 2012).

3 Material and methods

In this section, we first shed light on electricity supply and demand in the three European electricity markets here considered. Then, we discuss, propose and define a set of influential determinants of power spreads. Finally, we present data used in the empirical analysis and the modelling details.

3.1 Fundamentals of electricity supply and demand

This work focuses on three European electricity markets (Nordic, German, and UK) which are set in specific techno-economic environments exerting influence on the types and levels of risks the flexibility providers face. It is therefore essential to first outline and understand the relevant local factors of electricity supply and demand[45] before proposing relevant determinants of power spreads. As a reminder, by Nordic we jointly refer to Norway, Sweden, Finland, and Denmark.

On the supply side, the power systems in Germany and the UK have traditionally relied on thermal generation (coal, gas, nuclear). However, since the introduction of EU targets for reductions in carbon emissions and the promotion of RES, both countries have since 2008 seen a rapid growth in capacity and power generation from vRES (particularly wind and solar)[46]. On the contrary, the Nordic electricity market is a hydro-dominated system with a large share of indigenous generation from biomass, making the adoption of vRES less rapid, compared to the two other cases. With respect to market design, the UK slightly differs from the two other markets due to the introduction of separate carbon price floor and capacity market mechanisms in 2013 and 2014, respectively. The UK and Nordics are generally less interconnected by cross-border transmission lines compared to Germany which is part of the highly meshed transmission grid of the Continental Europe synchronous area.

On the *demand side*, the studied markets share similarities with respect to energy intensity (mining, manufacturing, etc.), macroeconomic development (omitting the recent Brexit) and demographic structure, but differ with respect to weather characteristics and deployment of energy saving technology, such as smart metering. The peak demand in 2016 was comparable across the regions, namely 82GW, 72GW, and 70GW for Germany, Nordics, and the UK, respectively (ENTSO-E 2017). The wholesale electricity prices in all three markets have systematically decreased since 2008 generally due to the decreasing fuel commodity prices and increasing production from vRES.

3.2 Drivers of power spreads

Next, we propose a set of potential influential drivers of power spreads, define how they are measured and provide explanations for their selection based on theoretical considerations and market intuition. The summary of proposed power spread drivers is presented in

[45] See (ENTSO-E 2017) for an overview of European electricity supply and demand, and (OME 2007) for their drivers.
[46] See

Figure in Appendix for a summary of yearly development of installed vRES and electricity consumption in the three studied markets.

Table .

Market participants who use power spreads for hedging (flexibility and dispatchability providers) need to pay attention to the fundamental supply and demand changes of the underlying[47] assets (electricity, coal/gas, CO_2). As discussed in section 0 and 3.1, the effects of vRES production, especially solar and wind, on electricity prices, are well known. For this reason, we study the effect of *expected solar and wind production* (EP_{vRES}) on future power spreads. Our empirical estimation will work with front-month futures, so we need to estimate the expected solar and wind generation in the next month. We utilize the available data set on hourly PV and wind capacity factors for the EU-28 plus Norway (Pfenninger and Lain 2016, Lain and Pfenninger 2016) and calculate twelve long-run capacity factors ($LCF_{vRES,m,c}$) for country c and month m based on the mean capacity factors from the years 2006-2016. Then, we take the installed capacity values for wind and solar in each country during the month of the underlying contract ($IC_{vRES,c,m+1}$) [48] and multiply them with the long-run capacity factors and the number of hours in the underlying month (h_{m+1}). Eq. 1 expresses the next month's expected production (GWh) of vRES technology in a country c.

$$EP_{vRES,c,m+1} = LCF_{vRES,c,m+1} * IC_{vRES,c,m+1} * \mathrm{h}_{\mathrm{m+1}} \qquad (1)$$

Other studies also consider the impacts of installed solar and wind generation capacity on electricity spot (Rubin and Babcock 2013) and futures (Cartea and Villaplana 2008, Carmona and Coulon 2014) prices. However, in an econometric setting, using installed capacities leads to high collinearity between solar and wind capacity for the considered countries, possibly biasing the results.

Price of the substitute fuel is an important driver of future (Carmona, Coulon and Schwarz 2012) and spot (C.-K. Woo, et al. 2012) power spreads. Fuel prices also impact the cost of CO_2 (Mansanet-Betaller, Pardo and Valor 2007, C.-K. Woo, et al. 2012). We consider the price of the substitute fuel, meaning the price of gas in the clean dark spread model and the price of coal in the clean spark spread model. We expect to see a positive relationship between the price of fuel substitute and the power spread in question. The interpretation is that when the substitute fuel gets more expensive, using the current fuel becomes more profitable.

Volatility of power futures prices has been also shown to affect spot (Karakatsani and Bunn 2008) and futures (Fanelli, Maddalena and Musti 2016) electricity prices. In our definition of power spreads (Eq.2 below), we use peak load power prices for gas and baseload power prices for coal technologies. This is because during our sample period (2009-2016) coal-fired power plants were typically run to meet continuous energy demand (baseload) and gas-fired power plants typically operated during high energy demand (peak load)[49]. To keep our analysis comparable, we estimate the volatilities of power futures prices based on a five-day rolling window, defined as coefficient of variation of front-month electricity peak load price when studying clean spark spreads and front-month electricity baseload price when studying clean dark spreads. The volatility in futures power prices reflects risks for hedgers and traders, so investigating the effects on power spreads may reveal who is bearing these risks (buyers or sellers).

We further address *seasonality* in the mean of power spreads by the season-of-the-year effect, namely spring (Mar-May), summer (Jun-Aug), fall (Sep-Nov) and winter (Dec-Feb). The impact of seasonality in mean equations is typically captured by daily, monthly, and quarterly dummies (Karakatsani and Bunn 2008), and sine/cosine-based specifications. Properly addressing seasonality in the price series nets out the average change in power spreads resulting from seasonal fluctuations. Cartea and Villaplana (2008) also

[47] Other *outputs*, such as capacity or ancillary services, and *inputs*, such as chemicals, spare parts, or labour, could be considered to affect the power spreads. However, over the near-term planning horizons, the impacts of these additional factors on cash flow uncertainty of flexibility providers are far less than that of fuel, carbon and power prices.
[48] From the current trading month (m), this is the next month's installed capacity (m+1). Since the installed capacities do not drastically change month-to-month, we consider this approach realistic and reliable.
[49] These dynamics might have changed in the more recent time, i.e. 2017, especially in the UK, however, such time period is not included in our sample.

show a seasonal component (summer, spring, fall, and winter) of the time-dependent volatility. We have tested the seasonal effect in volatility and have not found any significant effects, thus they are not reported.

Finally, we need to control for possible *structural breaks* in our time series (2009-2016). We identified two main country-specific events with possible spillover effects. The first event followed the Fukushima nuclear disaster in 11th March 2011, which led the German government to temporarily (but effectively) shut down 8 out of 17 German nuclear reactors on 15th March 2011. We hypothesize that the effect of removing over 8GW of capacity had a strong and positive impact on German power spreads. The second major event happened in the UK where a carbon price floor was introduced from the beginning of 2013. The carbon price floor started at the level of 15.70 GBP/tCO_2 and progresses by approximately 2.04 GBP/tCO_2 per year to reach 30 GBP/tCO_2 in 2020 (Sandbag 2013). We hypothesize that the carbon price floor has negatively impacted the UK's power spreads, especially the more carbon intensive clean dark spread.

Our key modelling principles are parsimony and adequacy. By the first principle, we keep the number of coefficients in check instead of over-parametrizing the models. This is a fundamental principle in the Box-Jenkins approach. By the second principle, we verify that the main model assumptions and statistical properties of the price process are adequate. Next, we present the modelling details.

3.3 Data and model

We begin by formally defining how the power spreads are calculated. As mentioned in the introduction, clean dark and clean spark spreads represent cross-commodity derivatives consisting of fuel prices, electricity prices and carbon allowance prices. To calculate the future power spreads, we use daily closing prices of the front (prompt) month energy commodity futures contracts (electricity, gas, coal), which refer to contracts traded in the current month with a delivery in the next month. Futures power spreads represent a hedgeable payoff per unit of production from a dispatchable power plant, which is expressed in Eq. 2.

$$Cl.Spread\ (T)_t = \ (ELECTRICITY(T)_t - (\ FUEL(T)_t * ER)) - \ CO2\ (T)_t \qquad (2)$$

$\mathrm{Cl.Spread}\ (\mathrm{T})_\mathrm{t}$ in Eq. (2) is the daily futures clean dark $\mathrm{CDS}\ (\mathrm{T})_\mathrm{t}$ or clean spark spread $\mathrm{CSS}\ (\mathrm{T})_\mathrm{t}$ in EUR/MWh_{el} with delivery in month *T* traded at day *t*; $ELECTRICITY(T)_t$ is the daily futures electricity price (EUR/MWh) for baseload (clean dark spread) and peak load (clean spark spread) with delivery in month *T;* $\mathrm{FUEL(T)_t}$ is a daily closing monthly futures price (EUR/MWh) for natural gas (ICE UK Natural Gas for clean spark spread) or coal price (ICE Rotterdam Coal Future for clean dark spread) with delivery in month *T*; ER is an efficiency rate, which is the factor of how much gas (coal) is needed to produce 1 MWh of power, i.e. this considers the fuels' heating values and the efficiencies of coal and gas power plants, here assumed 36% and 50%, respectively; and $CO2(T)_t$ is the daily closing futures price of a front-month (T) EUA (ICE ECX EUA Future) carbon allowance (EUR/tCO_2) traded at time *t*. For the UK power spreads, the UK's carbon price floor is used from 2013 onwards as the CO_2 price, since the EUA price has stayed well below the carbon price floor, see

Figure in Appendix. Carbon emission intensity factor is assumed 0.41 tCO_2/MWh_{el} for clean spark spread and 0.95 tCO_2/MWh_{el} for clean dark spread. All data originates from Thomson Reuters Eikon database, except the German and Nordic monthly power futures data which originate from EEX and Nasdaq OMX, respectively. The time period covered is from the year 2009 to 2016, both included.

Figure and

Figure present the daily German, UK and Nordic clean dark (CDS) and clean spark spreads (CSS)

Because power produced from gas is typically used in times of high demand, we use the electricity peak futures in the pricing formula for clean spark spreads. Similarly, power produced from coal is, to date, considered baseload and that is why we use the electricity baseload futures in the pricing formula for clean dark spreads. *Baseload* hours are defined as 00am-12pm Mon-Sun, *peak load* hours are defined as 8am-8pm Mon- Fri, and *off-peak* hours are 8pm-8am Mon-Sun in all the studied markets.

To reach a common unit of EUR/MWh_{el} for all spreads, we did the following unit conversions. The gas futures were quoted in British pence/1000 therms and were converted to EUR/MWh_{el} (dividing the Euro converted price of natural gas by 2.93071 (1 therm = 29.3071 kilowatt hours). Coal futures were quoted in USD/tonne and were converted to EUR/MWh_{el}. Currency conversion from GBP and USD to EUR was done by using daily exchange rates from the European Central Bank, similarly as (Boersen and Scholtens 2014, Alberola, Chevallier and Chèze 2008). The choice for using National Balancing Point (NBP) gas futures (ICE UK Natural Gas) is that NBP is a benchmark for natural gas trading in Britain and continental Europe (Martinéz and Torró 2015). For the same reason, ICE Rotterdam Coal futures are used because they are settled against the API 2 index benchmark for coal imported into Norwest Europe. While the coal and gas prices differ between the three countries in terms of their absolute levels, the differences will be largely constant since they are largely driven by (rather constant) transport costs. The underlying market dynamics, however, are largely the same.

ICE ECX EUA is one of the main platforms auctioning EUA allowances since the first trading period of the EU ETS in 2005; hence the corresponding contract prices are considered representative. The UK's yearly carbon price floor was converted from GBP/tCO_2 into EUR/tCO_2 by using yearly median EUR/GBP conversion rate for each year.

Table 2 further presents detailed descriptive statistics for the power spreads during the studied period 2009-2016. It must be first noted that futures contracts are traded only during the business (trading) days, which excludes weekends and bank holidays, which further vary across the different exchanges and markets. Our sample size of this eight-year long sample for each of the markets is approximately 2000 observations (approximately 21 trading days/month). The sample size slightly varies across the market/spread combinations, because in some cases, the power spreads could not be calculated if one or more of the commodity future prices weren't available. The Nordic CSS is an exception with a sample size of 1624 due to the missing access to the Nordic power peak futures contracts that we possess only until 27th May 2015. The mean *spread* (P_t) is significantly higher for CDS than CSS, mainly due to the higher gas fuel prices. The changing fuel price dynamics, see

Figure in Appendix, are observable on the power spread levels, especially on the convergence between German CDS and CSS from 2014 to 2016. In general, the highest mean (median) CDS and CSS spreads are in the UK and the lowest in the Nordics, with Germany scoring in between. CSS spreads are more volatile (standard deviation) than CDS spreads while both exhibiting positive skewness.
Log transformation is a typical approach to limit and stabilize price volatility in electricity price modelling studies (Möst and Keles 2010). In the presence of negative spreads, we apply a common method (Sewalt and De Jong 2003, Knittel and Roberts 2005) and add a small constant *log(x + constant)*, where *min(x + constant)* is equal to 0.1. To preserve the sign of the spread, the log of the constant is further subtracted, making the full transformation equal to *log(x + constant) – log (constant)*. Transforming the daily power spreads by *natural logarithm* (lnP_t) shows the stabilization and normalization effects on the distribution, as shown by reduced values of standard deviation, skewness, and kurtosis.

The visual inspection of the power spreads in

Figure and

Figure implies that the time series may not be stationary, which is further confirmed by the traditional unit-root tests (KPSS, ADF, and DFGLS). Using nonstationary time series for estimation would lead to spurious regression, hence we calculate *daily spread changes* (P_t-P_{t-1}), and *daily log spread returns* (lnP_t-lnP_{t-1}). Log-returns are widely used in energy research (Boersen and Scholtens 2014, Pilipovic 2007, Mansanet-Bataller, Pardo and Valor 2007) because they promote stationarity and represent continuously compounded price changes. Also, when both the left hand side and the right hand side variables in a regression equation are in logs, the coefficients are interpreted as elasticities. We will use this property in our model described in detail further below.

The daily log returns (*lnPt-lnPt-1*) in Table 2 exhibit mostly positive skewness, which implies long right tails possibly caused by positive outliers, and excessive kurtosis, which often exceed value 3, a benchmark for normal distribution in financial econometrics. High kurtosis values imply that more frequent extreme (positive and negative) returns can be expected (fat-tails). All of the mean and median log returns are close to zero or slightly negative, which implies the negative tendency of power spread returns. The standard deviation of log returns also points out to high volatility, which is the highest for UK CDS (0.083), which translates into 132% annualized volatility[50].Next, we test whether the daily log returns contain a time dependent volatility using the ARCH Lagrange multiplier (LM) test. Residuals from a simple regression of log return spreads on a constant are tested for the presence of autoregressive conditional heteroscedasticity (ARCH) and in all cases the null hypothesis of no volatility clustering is rejected. Hence ARCH-type models are appropriate to this modelling problem. As outlined above, the distribution of log returns is fat-tailed, as implied by large kurtosis values, which may be better described by a t-distribution than a Gaussian distribution. In the model selection process, we compared normal and t-distribution alternatives with the latter leading to a better goodness of fit (AIC, BIC, LL). The thickness of the tails of the error distribution is confirmed by the degrees of freedom (values of around 2) under the t-distribution assumption, which are far from the value 30 which would imply normal distribution. Specifically, we have tested one symmetric GARCH(1,1) and two asymmetric SAARCH(1,1), and TGARCH(1,1) ARCH-type models with normal and t-distributions.

Our baseline model is the symmetric GARCH(1,1) model, which is frequently used for volatility forecasting and in the derivatives literature (Hull 2012). The first asymmetric GARCH is simple asymmetry ARCH (SAARCH(1,1)) first proposed by Engle (1990). The asymmetric term γ accounts for the leverage effect of volatility. In SAARCH model, the sign of γ is expected to be negative, implying the greater impact of negative news on volatility than positive news. The asymmetric term γ in the threshold GARCH (TGARCH(1,1)), first introduced by (Zakoian 1994), is expected to be negative, because this coefficient loads only the absolute positive innovations, which should have a smaller (negative) impact on variance rather than the negative news. TGARCH(1,1) with t-distribution has systematically outperformed other specifications and is selected as the best-fitting model for further estimation. In Table 3 we present the model selection summary for the German CDS exemplarily, however, the results are systematically similar for the other country-spread combinations.
After defining the log returns and identifying the best fitting model (TGARCH with t-distribution), we jointly estimate the mean and variance equations for log power spread returns by the method of conditional maximum likelihood. The mean equation is expressed in Eq.3 and the conditional variance in Eq. 4.

$$\begin{aligned}\Delta R(T)_t = {} & c + \Delta\beta_1 SolarProduction(T) + \Delta\beta_2 WindProduction(T) \\ & + \Delta\beta_3 SubstituteFuel(t) + \Delta\beta_4 PowerPriceVolatility(t) \\ & + \Delta\beta_5 StructuralBreaks(t) + \Delta\beta_6 Seasons(t) + \epsilon_t\end{aligned} \tag{3}$$

$$\sigma_t = \alpha_0 + \alpha_i|\varepsilon_{t-1}| + \gamma_i|\varepsilon_{t-1}|I(\varepsilon_{t-1} > 0) + \beta_7\sigma_{t-1} \tag{4}$$

[50] This is calculated by multiplying the square root of 252 (the number of trading days in a year) by the standard deviation.

In Eq.3, $R(T)_t$ refers to the daily log return of the power spread for the delivery in month T traded during time *t; Solar* and *Wind production* refers to the expected generation of the respective technology in the next month T at time *t; SubstituteFuel* stands for the daily futures price of the substitute fuel, which is coal (ICE Rotterdam Coal Future) for the clean spark spread equation and gas (ICE UK Natural Gas) for the clean dark spread equation*; PowerPriceVolatility* stands for a five-day rolling volatility of electricity futures prices, defined as coefficient of variation of front-month electricity peak load price for the clean spark spread and front-month electricity baseload price for the clean dark spread; *StructuralBreaks* are two dummy variables referring to the German nuclear moratorium (15March2011) and the introduction of the carbon price floor in the UK (since year 2013)*; Seasons* stands for spring (March-May), summer (June-August) and fall (September-November) seasonal dummies of the trading time *t*, where winter (December-February) is the reference season. Exactly in the same manner as the dependent variables (power spreads), all the independent variables are transformed by the natural logarithm and first differenced, which maintains the property of coefficients representing elasticities.

In Eq.4, σ_t denotes conditional variance, α_i accounts for the symmetric impact of innovations (lagged squared errors) irrespective of their sign, and γ_i accounts for the leverage effect by loading only positive innovations (I(.) is an indicator function, equalling 1 when true, otherwise 0). As discussed above, the coefficient γ_i is expected to be negative because positive news typically have a smaller impact on the variance than negative news; finally β_j is a coefficient of the lagged conditional variance addressing the heteroscedasticity effect.

In sum, we have first defined power spreads and investigated their statistical properties, such as skewness, kurtosis and volatility. Then, we identified volatility clustering and selected a best fitting model (TGARCH with t-distribution). Finally, we have proposed a statistical model that in its mean equation accounts for the supply and demand effects in power spreads, and in its variance equation for the volatility clustering. Next, we present the estimation results.

4 Results

In this section, we present and discuss the estimation results for the mean and variance models of German, Nordic, and UK clean dark (CDS) and clean spark (CSS) spreads from the period 2009 to 2016. Table 4 summarizes the results for clean dark spreads and Table 5 for clean spark spreads. We begin with the results in the mean equation, move to the results in the variance equation, and end the section with the model fit and performance summary. As a reminder, both the left hand side and the right hand side variables are log-differenced, representing a log-log regression model where the coefficients in the mean equation represent marginal effects (elasticities).

The expected wind production only seems to have a significant, negative effect on the German CSS (at 1% significance level). It also has a negative effect on the German CDS, but at a 20% significance level only. The interpretation is that 1% increase in monthly wind production reduces the German CSS by 0.42% and the German CDS by 0.22%. To put this into an installed capacity perspective, the monthly average wind production in Germany was approximately 6000GWh/month in 2016. To produce an extra 60GWh/month (1%) approximately 410MW of additional installed wind capacity would be needed[51]. To put the values into Euro perspective[52], holding everything else constant, additional 1GW of installed wind capacity reduces the German CSS by 0.051 EUR/MWh_{el} and the German CDS by 0.032 EUR/MWh_{el}. The values may seem rather small, however, considering that there were 22 GW of new installed wind capacity added

[51] Here we assume average 20% wind capacity factor, 13% PV capacity factor, and average of 730 hours/month.
[52] Here we use the mean daily clean spark and clean dark spread values over 2009-2016, see

Table and Table 2.

in Germany during our sample period (2009-2016), the total negative effect for the German CSS is 1.122 EUR/MWh_{el} (-22.3%) and 0.704 EUR/MWh_{el} (-11.8%) for the German CDS.

The effect of expected PV production on CSS and CDS is more systematic, with negative and highly significant coefficients across the three markets. The coefficients of the PV generation, however, are much smaller than those for wind, implying a smaller negative impact. PV has the strongest negative effect on the German CSS (0.24%) and CDS (0.17%) followed by the impacts on the Nordic CSS (0.046%) and CDS (0.037%), and the UK's CSS (0.024%). Again, to put this into installed capacity perspective, the monthly average PV production was approximately 3800 GWh in Germany, 1000 GWh in the UK, and 72 GWh in the Nordics in 2016. To increase the monthly generation values by 1%, approximately 400 MW in Germany, 105 MW in the UK, and 8 MW in the Nordics would be needed[8]. In Euro values[9] and holding everything else constant, an additional 1 GW of PV capacity would reduce the German CSS by 0.030 EUR/MWh_{el}, the German CDS by 0.026 EUR/MWh_{el}, the Nordic CSS by 0.889 EUR/MWh_{el}, the Nordic CDS by 0.105 EUR/MWh_{el}, and the UK's CSS by 0.008 EUR/MWh_{el}. Again, the values may seem rather small, however, considering that there were around 32 GW of new installed PV capacity added in Germany during our sample period (2009-2016), the total negative effect for the German CSS is 0.962 EUR/MWh_{el} (-19.1%) and 0.815 EUR/MWh_{el} (-13.6%) for the German CDS. Similarly, approximately 11 GW of new solar PV capacity was built in the UK during the studied period. Effectively, the new PV capacity is associated with a 0.088 EUR/MWh_{el} drop in the UK's CSS, which is approximately 2.6% of the UK's average CSS during the studied period. For the Nordic market, the mentioned 1GW increase in solar PV capacity would mean more than doubling its total capacity, because only approximately 900 MW of solar PV capacity was added during 2009-2016. Hence, the total effect of solar PV on the Nordic CSS has been 0.800 EUR/MWh_{el} (-5.5%) and on the Nordic CDS 0.094 EUR/MWh_{el} (-4.4%) over the studied period 2009-2016.

The effect of the substitute fuel, i.e. gas in the CDS and coal in the CSS, is found to be significant only for the CDS, especially in the UK. The estimated elasticities of the CDS for the substitute fuel (gas) are 1.69% for UK, 0.16% for Germany, and 0.05% for the Nordics. In Euro perspective, 1% increase in gas price would increase the UK CDS by 0.186 EUR/MWh_{el}, the German CDS by 0.011 EUR/MWh_{el} and the Nordic CDS by 0.001 EUR/MWh_{el}. Given the domination of flexible hydro-generation in the Nordic power system, we would not expect a very strong effect of changes in gas price on the Nordic power spreads. However, Germany's and the UK's power systems are much more reliant on gas generation, which explains the stronger effects.

The volatility of power futures contracts has small but significant positive effects on the CDS in Germany and the UK. The increased volatility in baseload power futures contracts used in the CDS seems to allow market participants to capture a small positive risk premium. This premium may represent a compensation for coal power generators facing the increased uncertainty around the futures power price.

The two structural events studied in this work, namely the UK carbon price floor and the nuclear moratorium in Germany, both significantly affected the clean dark and clean spark spreads in the affected markets. Specifically, the carbon price floor had a more negative effect on the UK CDS than the CSS, which is to be expected given the greater carbon intensity of coal. Also, the German nuclear moratorium that led to a large and sudden drop in generation capacity has had a positive and significant impact on the German CSS and more so on the German CDS. The sudden drop in German capacity was largely substituted by coal generators, who have, temporarily, seen an increase in their hedgeable profits. Since these events represent binary variables that are not log-transformed, we can take the exponential of their coefficient to find out the exact percentage difference between the pre- and post-event. Holding everything else fixed, we can say that after the introduction of the UK carbon price floor in 2013, we would expect a 55% drop in UK's CDS and a 38% drop in UK's CSS, as compared to the pre-carbon price floor period. Similarly, after the German nuclear moratorium and holding everything else fixed, we would expect a 56% increase in the German CDS and a 36% increase in the German CSS in comparison to the pre-moratorium period.

Our final results from the mean equation refer to the seasonality (spring, summer, fall), which is referenced to the winter season. We have found significant and negative seasonality especially in the German power spreads. Using the same exponentiation as described above to find the percentage impact of seasons on power spreads, we find that in the non-winter seasons, the mean German CDS and CSS are approximately 16% and 20% lower, respectively. We also find a significantly negative effect of summer (7%) and fall (7%) on the Nordic CDS and a significantly negative effect of fall (9%) on the Nordic CSS, holding everything else constant.

In the variance equation, we find significant leverage effects in the CDS and CSS volatility, specifically for the CDS in the UK and Germany, and the CSS in the Nordics and Germany. This means that positive news have a lower impact on the volatility of the mentioned power spreads than negative news. Also, the sum of ARCH and GARCH terms is close to unity, indicating that the volatility is also highly persistent.

4.1 Model fit and performance

Next, we present a summary of the model fit and performance. After each model was estimated, we have tested for the presence of autocorrelation in the standardized residuals with portmanteau Q test, which was rejected at 10% level of significance in all models. The test is applied to evaluate whether the residuals are free of systematic variation and are normally distributed. Additionally, the ARCH Lagrange multiplier test was applied on the standardized residuals to check for the presence of heteroscedasticity, which was again rejected for various lags.

As a visual summary of the model fit, we present multiple diagnostics of standardized residuals, namely their distribution against time, histogram, autocorrelation and partial-autocorrelation functions, as displayed in

Figure . We present these diagnostics for the German CDS model only; however, the results for the remaining models are very similar.

The efficient market hypothesis postulates that returns follow a martingale process and thus cannot be predicted. Within our model specification, we can explicitly forecast the volatility of power spread returns, and thus measure the model's performance. We do this by in-sample one-step ahead (one trading day ahead) volatility forecast and reporting four different loss functions (Degiannakis and Floros 2016). Specifically, these functions are root mean square error (RMSE), mean-absolute error (MAE), mean heteroscedasticity adjusted absolute error (HMAE), and mean heteroscedasticity adjusted squared error (HMSE), as defined in Eq. (5-8).

$$MSE = 1/(n)\sum_{t=1}^{n}(\hat{\sigma}_t^2 - \sigma_t^2)^2 \tag{5}$$

$$MAE = 1/(n)\sum_{t=1}^{n}|\hat{\sigma}_t^2 - \sigma_t^2| \tag{6}$$

$$HMSE = 1/(n)\sum_{t=1}^{n}(1 - \sigma_t^2/\hat{\sigma}_t^2)^2 \tag{7}$$

$$HMAE = 1/(n)\sum_{t=1}^{n}|1 - \sigma_t^2/\hat{\sigma}_t^2| \tag{8}$$

where σ_t^2 is the actual volatility and $\hat{\sigma}_t^2$ is the predicted volatility at day *t*. The in-sample prediction provides only the historical performance of the model, which is sufficient given the main purpose of the paper focusing on the determinants of power spreads. The out-of-sample hedging effectiveness and out-of-sample forecasting of the power spreads volatility are natural extensions, as shown earlier on crack spreads (Wang and Wu 2012). Table 6 summarizes the forecast evaluation statistics showing good in-sample performance and fit.

5 Discussion

In this section, we come back to the key motivations of this work and attempt to shed more light on these based on the results summarized above. In this work, we focused on the energy policy trilemma, which is environmental sustainability, reliability of supply, and economic competitiveness. The promotion of vRES is associated with environmental sustainability, while the question of adequate hedging mechanisms for dispatchable and flexible generation is associated with both reliability of supply and economic competitiveness. To jointly study these policies, we have focused on the risk management reality of dispatchable flexibility providers (coal and gas power generators) and the fundamental factors impacting the risk management, proxied by hedgeable power spreads. Below, we first deepen the discussion around some of the main results and then follow with broader implications that span beyond the country-specific drivers of hedgeable profit margins.

First, the finding of negative effects of vRES on hedgeable power spreads concurs with studies on spot markets. This suggests that the risk management of flexible conventional generation becomes more challenging with the growth in vRES. The statistical significance (insignificance) of the vRES effects on some hedgeable power spreads can be mostly explained by the structure of a power generation fleet in a given country. Germany has seen the largest increase in solar PV and wind capacity, where especially the latter substituted the conventional generation (coal, lignite, nuclear and natural gas) in the daily operation. The stronger negative effect of wind generation on the CSS rather than the CDS can be explained by the structure of the merit order curve: gas generation is typically dispatched after coal. The close-to-zero marginal variable costs of vRES push gas off the merit order curve first, making the negative effect stronger for the CSS than for the CDS. In the UK, the share of coal-fired power generation in the overall electricity supply has been steadily declining and the major drop in the UK's CDS seems to be explained by the carbon price floor rather than by vRES. The UK's CSS is negatively impacted by solar PV generation mostly because the day-time peak demand typically coincides with peak solar PV generation which pushes the peaking gas generators off the merit order curve. With respect to the Nordic market, it may seem surprising that the limited solar PV generation has significantly negative impacts on both the CDS and the CSS. Despite the fact that the Nordic electricity market is a hydro-dominated system with natural access to flexibility, there are national differences which may be confounding some of the estimated effects. Disaggregation of the individual Nordic countries, which would need to take into consideration futures zonal prices of the individual countries[53], could reveal more nuanced relationships between hedgeable power spreads and vRES. Perhaps more interesting for the Nordic market, a study of hedgeable peak/off-peak spreads could reveal the hedging dynamics of hydro-generating power plants which also function as energy storage.

Second, we find a systematic effect of gas, as a substitute fuel, on the clean dark spread. Depending on the power generating fleet in a given market, we typically expect a stronger impact of the substitute fuel on the CDS than the CSS. This is because in the past, coal was typically a cheaper fuel than gas, which means that coal-fired power plants (depending on their efficiency) would be dispatched before gas-fired power plants. Consequently, when gas-fired power plants are needed to cover the demand, they set the power price and gas prices would therefore drive the clean dark spread. On the contrary, increasing coal prices would not drive the clean spark spread to the same extent. These dynamics, though, may be also changing in the future. For example, Ofgem (2016) highlights a wholesale market situation in May 2016 when CCGTs pushed all coal off merit order curve for four hours. Increasing coal prices, increasing efficiencies of gas-fired power plants, and higher carbon prices are just some factors behind the changing dynamics between CDS and CSS.

Third, the large negative impact of the UK's carbon price floor on power spreads reveals the following issues. First, the increased cost of carbon was not fully passed through to the power prices, so the externality was paid for by the polluters rather than end-users. This may be explained by increasing electricity imports into the UK following the introduction of the carbon price floor since the floor was introduced in the UK only. This shows that, as opposed to a continent-wide or global policy on carbon, a single-country policy may lead to carbon leakage. In the case of EU and the UK, the UK's carbon emitting power generators faced approximately four times higher costs for carbon than their European counterparts. Inside the single electricity market with cross-border transmission connections, the more expensive generators are easily substituted by less expensive imports, irrespective of their carbon intensity.

Now, we may move towards broader implications of the results. First, many countries currently have an overcapacity in their power systems so the negative or low power spreads are sending "correct" market signals to not invest into new flexible generation. However, the exit of large-scale nuclear power plants and decommissioning of old dispatchable units puts pressure on the transmission system operators (TSO) to run the system reliably already in the short-term.[54] The design of efficient, market-based solutions to promote adequate risk management of existing assets or, if needed, investments into new flexible capacity is therefore an important challenge.

[53] This would involve combining the Nordic baseload and peak load power futures with electricity area price differential (EPAD) contracts.
[54] For instance, the German TSO's have been calling for new flexible gas power plants to run the transmission system reliably (Frankfurter Allgemeine Zeitung 2017).

Second, given the acclaimed role of natural gas as a transition fuel, it is interesting to see that vRES seems to have a stronger negative impact on the CSS than on the CDS. With the shut-down of coal-fired power plants in the medium term and continuous adoption of vRES, gas-fired power plants may find economic challenges, particularly when relying on energy-only markets exclusively. New markets rewarding capacity, reliability or flexibility may be needed to enable flexibility providers to stay in or enter the market.

Third, the effects of vRES on hedgeable power spreads may change with the change in subsidy-based economics of vRES. Moving towards a subsidy-free vRES market, wholesale power prices may start to reflect scarcity and under the assumption of sufficiently high price caps, power prices may again start sending investment signals into flexible generation and storage, if these are needed. The change in vRES subsidies would relatively quickly translate into the wholesale electricity prices, underlying the relevance of an energy-only market. The current prolonged downward pressure on electricity prices has led to the introduction of regulatory-driven solutions, such as the capacity markets / payment mechanisms. Depending on the length and further development of vRES economics, and the development of commodity and CO_2 prices all jointly impacting the power prices, capacity markets may be justified. However, in addition to the security of supply as the core purpose of capacity markets, the regulatory and cost burden should be also accounted for when justifying their existence.

6 Conclusions

This work has studied the impacts of power market fundamentals on risk management of technologies that provide flexibility and dispatchability to the power system. By explicitly studying the relationships between fundamentals and hedgeable power spreads, we have revealed important dynamics. Namely, the growth in variable renewable energy generation and capacity reduces the possibility of coal and especially gas power plants to manage risk ahead of actual operation. This finding is especially relevant for markets that do not have abundance of flexible renewable generation, such as the hydro-based Nordic power market. Methodologically, we have attempted to bridge a gap between the spot and futures pricing models and empirically quantify the impacts of fundamentals on the futures market.

The time period analysed here captured the transition period in which traditional business models and risk management strategies designed for the centralized power system are ceasing to work. This effect is manifested by the increasing challenge to secure profit margins by traditional hedging methods. Great emphasis has been put on the environmental sustainability as one policy of the energy trilemma. However, without addressing the remaining two energy policies of the energy trilemma, issues such as lack of investment in flexible and dispatchable generation, and high electricity prices may become more pronounced in the near future. New hedging strategies and hedging products, portfolios of integrated energy technologies, and the possibility to participate in multiple markets may aid smoothing the transition.

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Figure 1 German, UK and Nordic daily clean dark spreads (CDS), 2009-2016

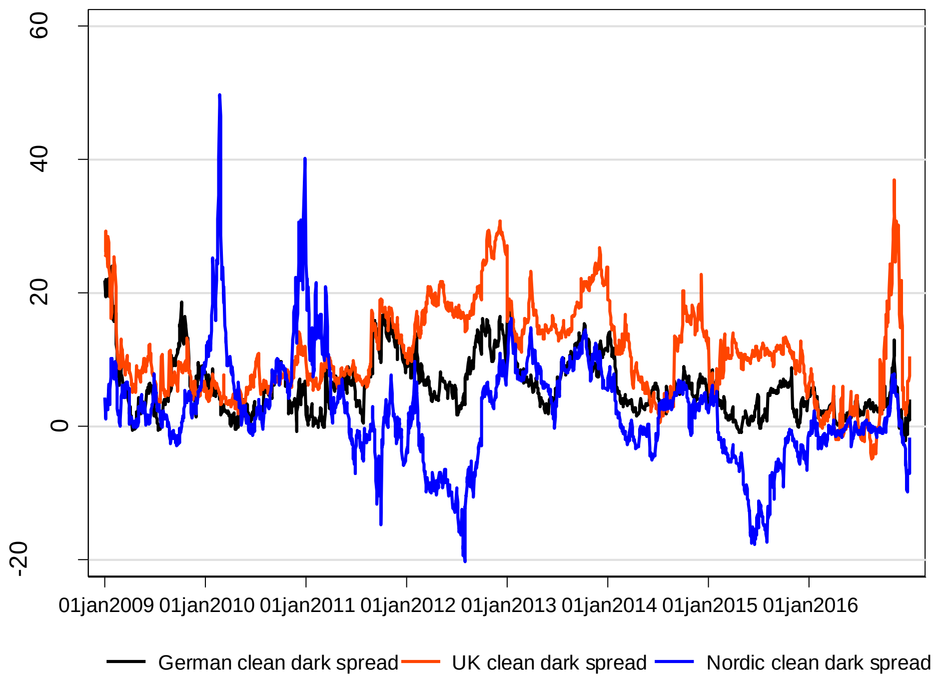

Figure 2 German, UK and Nordic daily clean spark spreads (CSS), 2009-2016

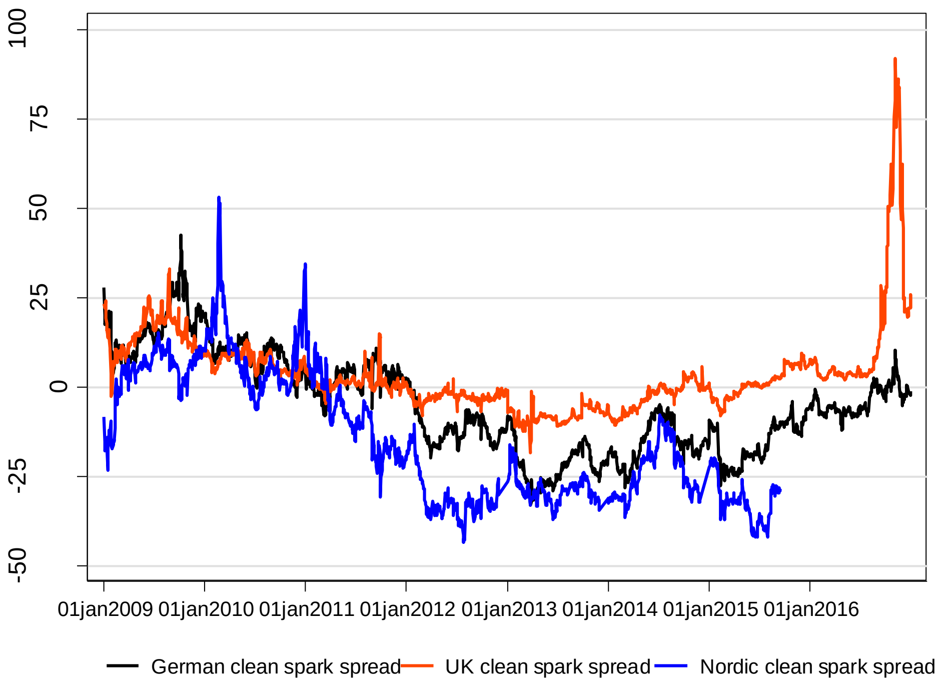

Figure 3 Diagnostics for German clean dark spreads (CDS) with TGARCH model specified in Eq.(3-4): (a) Daily standardized residuals against time. (b) Autocorrelation function of standardized residuals against lag in days. (c) Histogram with normal and kernel distribution of standardized residuals. (d) Partial autocorrelation function of standardized residuals against lag in days.

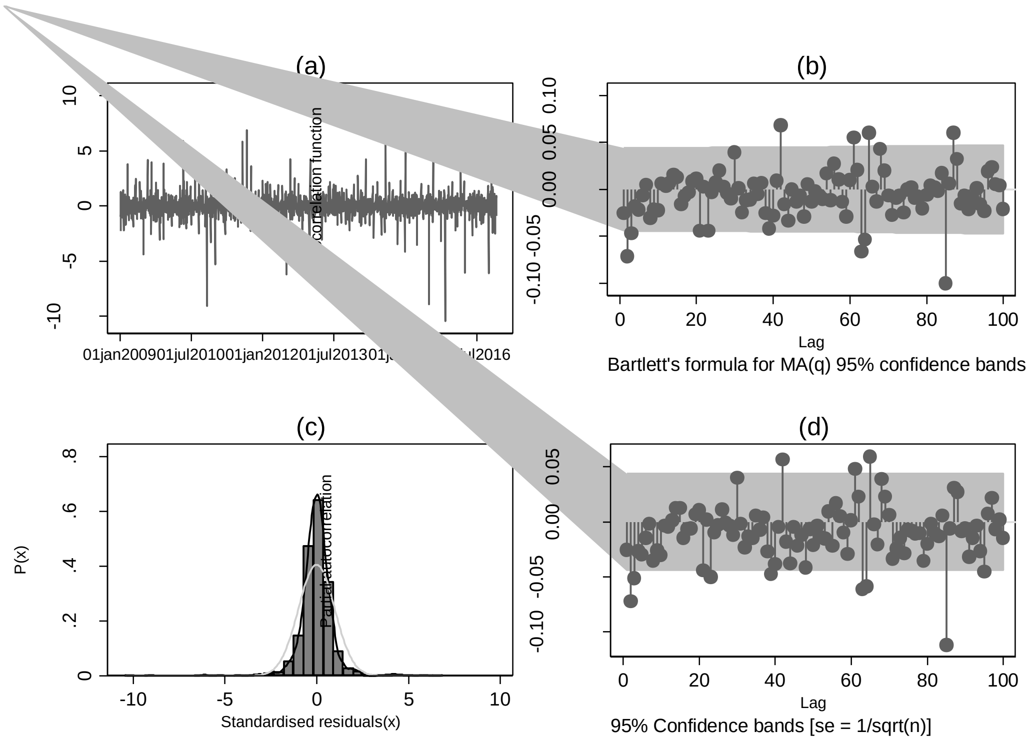

Figure 4 Electricity consumption and installed vRES capacity in Germany, UK and Nordic

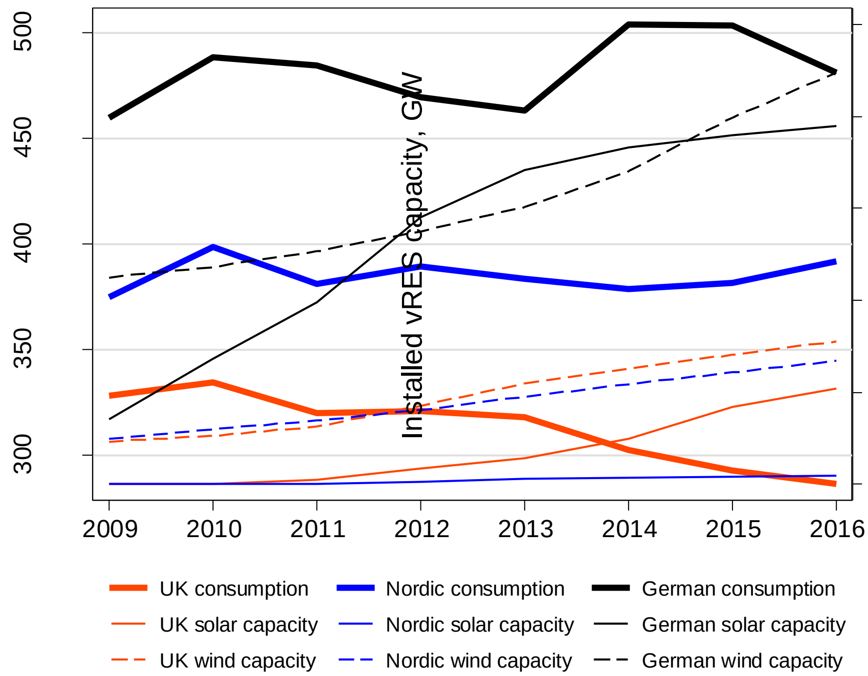

Figure 5 Fuel, EU ETS and UK carbon price floor prices

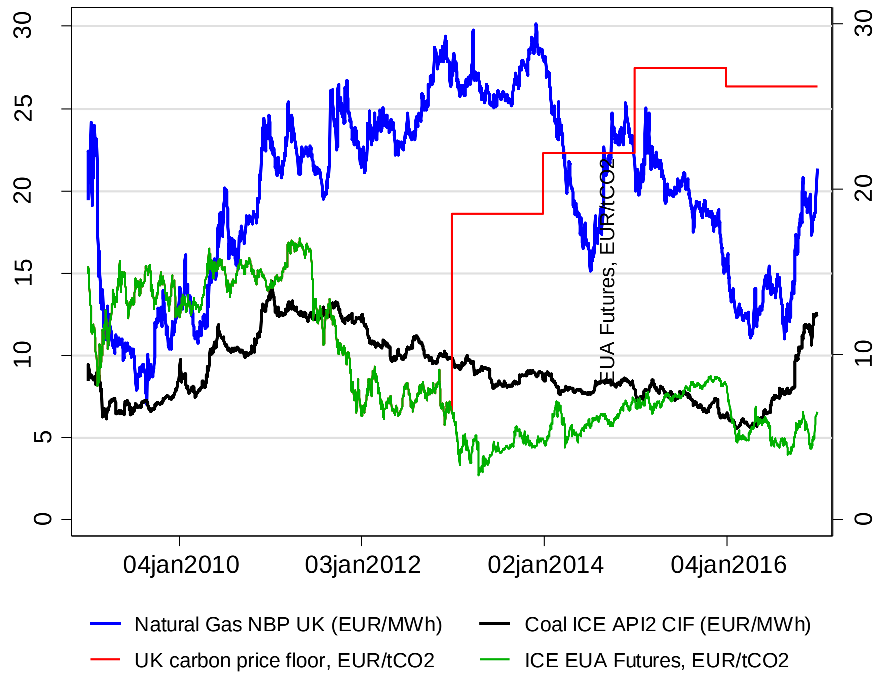

Table 1 Fundamental drivers of power spreads and studies applying them in electricity futures and spot markets

Driver	Definition	Futures market	Spot market
Expected solar and wind generation	Expected next-month PV and wind productions are calculated as the product of the national long-run PV and wind capacity factors, installed capacity of solar and wind, and the number of hours in a month.	(Kristiansen 2017)	(C.-K. Woo, et al. 2012, Woo, Horowitz and Pacheco 2011)
Price of fuel (substitute)	Price of gas when studying clean dark spreads (CDS) and price of coal when studying clean spark spread (CSS), in EUR/unit of fuel.	(Carmona and Coulon 2014, Carmona, Coulon and Schwarz 2012, Boersen and Scholtens 2014)	(Mansanet-Bataller, Pardo and Valor 2007, C.-K. Woo, et al. 2012)
Volatility of electricity futures price	Five-day rolling volatility of electricity futures prices, defined as coefficient of variation (standard deviation/mean) of front-month electricity peak load price when studying clean spark spreads and front-month electricity baseload price when studying clean dark spread.	(Fanelli, Maddalena and Musti 2016)	(Karakatsani and Bunn 2008)
Seasonality	Season-of the year effect on the mean of power spreads, measured as dummies for spring (March-May), summer (June-August), fall (September-November), and winter (December-February), with reference to winter as the coldest and typically the most volatile season.	(Cartea and Villaplana 2008)	(Karakatsani and Bunn 2008)
Structural breaks	We consider two country-specific events captured by dummy variables. The first event is the introduction of carbon price floor in the UK in 2013. The second event is the announcement of the so-called nuclear moratorium by the German government, which stated a temporary* shut down of 8 out of 17 German nuclear reactors.	(Arouri, et al. 2012)	(Alberola, Chevallier and Chèze 2008)

Note: *The temporary shut-down resulted to permanent shut down announced August 6th 2011. The affected reactors were Biblis A (1167MWe) and B (1240MWe), Brunsbüttel (771MWe), Isar 1 (878 MWe), Krümmel (1346 MWe), Neckarwestheim 1 (785 MWe), Philippsburg 1 (890 MWe) and Unterweser (1345 MWe), a total of 8422 MWe (IAEA 2011).

Table 2 Summary statistics for German, Nordic, and UK daily power spreads, 2009-2016

		Variable	N	mean	med	min	max	sd	skew	kurt
Clean dark spread (CDS)	Germany	P_t	2010	5.983	5.158	-2.090	24.044	4.394	0.991	3.789
		P_t-P_{t-1}	2010	-0.008	-0.026	-5.821	8.575	0.922	1.333	19.254
		lnP_t	2010	0.353	0.333	-0.175	1.045	0.218	0.467	2.746
		lnP_t-lnP_{t-1}	2010	0.000	-0.001	-0.310	0.447	0.049	1.106	18.076
	Nordic	P_t	1989	2.130	1.756	-20.276	49.613	7.972	0.834	6.947
		P_t-P_{t-1}	1989	-0.005	0.013	-17.868	10.627	1.379	-1.222	32.651
		lnP_t	1989	0.034	0.043	-0.709	0.808	0.190	-0.322	4.766
		lnP_t-lnP_{t-1}	1989	0.000	0.000	-0.232	0.353	0.031	1.257	25.237
	UK	P_t	2036	11.012	10.303	-4.890	36.920	6.833	0.514	3.055
		P_t-P_{t-1}	2036	-0.007	-0.034	-11.304	8.297	1.155	-0.391	21.584
		lnP_t	2036	1.056	1.120	-3.910	2.128	0.516	-1.720	11.835
		lnP_t-lnP_{t-1}	2036	0.000	-0.002	-0.584	0.594	0.083	0.499	14.423
Clean spark spread (CSS)	Germany	P_t	1998	-5.026	-6.971	-33.069	42.428	13.712	0.360	2.486
		P_t-P_{t-1}	1998	-0.010	-0.026	-10.448	14.571	1.491	0.444	16.350
		lnP_t	1998	-0.314	-0.236	-5.804	0.824	0.607	-1.379	8.435
		lnP_t-lnP_{t-1}	1998	0.000	-0.001	-0.523	0.532	0.070	0.343	14.876
	Nordic	P_t	1624	-14.652	-19.419	-43.440	52.991	17.795	0.534	2.371
		P_t-P_{t-1}	1624	-0.012	-0.013	-19.620	12.680	1.920	-0.937	20.553
		lnP_t	1624	-0.553	-0.540	-2.715	0.760	0.618	-0.323	2.348
		lnP_t-lnP_{t-1}	1624	-0.002	0.000	-0.506	0.487	0.077	-0.447	10.588
	UK	P_t	2021	3.423	1.122	-18.372	92.018	11.938	3.227	19.295
		P_t-P_{t-1}	2021	0.001	-0.014	-19.797	15.255	1.662	-0.280	36.959
		lnP_t	2021	0.063	0.059	-5.219	1.789	0.458	-0.489	12.699
		lnP_t-lnP_{t-1}	2021	0.000	-0.001	-0.593	0.521	0.066	0.135	21.092

Note: This table shows descriptive statistics for the daily spread (P_t), daily log spread (lnP_t), daily spread change (P_t-P_{t-1}), and daily log returns (lnP_t-lnP_{t-1}) of power spreads - clean dark spread (CDS) and clean spark spread (CSS). Outliers in the log returns series, defined as log returns greater 0.6 (60%), were substituted by the nearby past log return. The following numbers of log returns were affected: 12 UK CDS, 3 Nordic CSS, 3 UK CSS, 6 DE CSS.

Table 3 Model selection, example of German CDS daily log returns

	GARCH	GARCH(t)	SAARCH	SAARCH(t)	TGARCH	TGARCH(t)
Constant	-0.001	-0.001*	-0.001	-0.001**	-0.003***	-0.001**
	(-0.53)	(-1.93)	(-1.32)	(-2.17)	(-5.16)	(-2.27)
ARCH(-1)	0.392**	0.026**	0.383**	0.027***	0.344**	0.106***
	(2.24)	(2.46)	(2.25)	(2.94)	(2.57)	(4.64)
GARCH(-1)	0.127	0.962***	0.094	0.957***	0.381*	0.939***
	(1.02)	(66.94)	(1.04)	(77.97)	(1.90)	(73.15)
Leverage effect γ	-	-	-0.007	-0.003**	-0.078	-0.068***
	-	-	(-1.04)	(-2.42)	(-0.43)	(-2.68)
Constant	0.001***	0.000	0.002***	0.000**	0.021**	0.001**
	(4.75)	(1.52)	(5.54)	(2.11)	(2.34)	(2.57)
Log degrees of freedom (t-dist.)	-	-0.680**	-	-0.713***	-	-0.670**
	-	(-2.50)	-	(-2.65)	-	(-2.47)
Akaike Information Criterion	-6572.14	-7517.15	-6576.45	-7525.11	-6613.97	-7570.87
Bayesian Information Criterion	-6549.72	-7489.13	-6548.43	-7491.48	-6585.94	-7537.24
Log likelihood	3290.071	3763.576	3293.227	3768.555	3311.985	3791.437
Degrees of freedom		2.506		2.490		2.512
N	2009	2009	2009	2009	2009	2009

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; The table displays model selection with different volatility specifications (GARCH(1,1), SAARCH(1,1), and TGARCH(1,1)) and distribution assumptions (t-distribution, indicated by symbol (t)). The best fitting model that captures the time dependence structure of the series is selected based on the information criteria and log likelihood statistics.

Table 4 Estimation results of TGARCH model for German, Nordic, and UK clean dark spreads (CDS), 2009-2016

	DE CDS	NORD CDS	UK CDS
Mean equation			
Expected Wind Production (GWh/month)	-0.2145	0.0067	0.056
	(-1.21)	(0.08)	(1.18)
Expected Solar Production (GWh/month)	-0.1704***	-0.0373***	0.0179
	(-3.63)	(-5.22)	(1.27)
Gas price (EUR/MWh)	0.1621***	0.0446*	1.6911***
	(6.51)	(1.66)	(28.42)
Base power futures price volatility	0.0036**	-0.0013	0.0039**
	(2.25)	(-0.84)	(2.46)
German nuclear moratorium(15March2011)	0.4460***	-	-
	(67.85)	-	-
UK Carbon floor (y2013)	-	-	-0.4386***
	-	-	(-29.25)
Spring	-0.1624***	-0.0033	0.0063
	(-3.03)	(-0.21)	(0.31)
Summer	-0.1193**	-0.0645***	-0.0185
	(-2.17)	(-3.72)	(-1.20)
Fall	-0.1518***	-0.0635***	-0.007
	(-3.77)	(-9.83)	(-0.63)
Constant	-0.0008	-0.0002	0.0002
	(-1.34)	(-0.29)	(0.30)
Variance equation			
ARCH(-1)	0.0907***	0.1103***	0.3934***
	(4.88)	(5.70)	(5.76)
ARCH(-2)	-	-	-0.2880***
	-	-	(-4.29)
Leverage effect γ	-0.0859***	0.0103	-0.0786***
	(-3.83)	(0.44)	(-3.29)
GARCH(-1)	0.9563***	0.8950***	0.9588***
	(68.91)	(55.14)	(129.14)
Constant	0.0008**	0.0007***	0.0002*
	(1.98)	(3.30)	(1.83)
Akaike Information Criterion	-7671.0118	-9271.1837	-7025.506
Bayesian Information Criterion	-7592.6834	-9198.5882	-6935.78
Log likelihood	3849.5059	4648.5918	3528.753
Degrees of freedom	2.6994	3.6766	2.6185
Durbin-Watson statistic	2.0477	1.9646	2.1411
N	1988	1967	2014
Time interval	5Jan2009-28Nov2016		

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; the table shows estimation results of TGARCH(1,1) model (DE & NORD CDS) and TGARCH(2,1) model (UK CDS) with t-distribution on daily log returns. All the explanatory variables are also log-differenced, therefore the coefficients of this log-log regression model represent marginal effects (elasticities).

Table 5 Estimation results of TGARCH model for German, Nordic, and UK clean spark spreads (CSS), 2009-2016

	DE CSS	NORD CSS	UK CSS
Mean equation			
Expected Wind Production (GWh/month)	-0.4185***	0.0936	0.0221
	(-11.44)	(0.91)	(0.72)
Expected Solar Production (GWh/month)	-0.2395***	-0.0460**	-0.0236**
	(-23.42)	(-2.26)	(-2.53)
Coal price (EUR/MWh)	-0.3013	-0.2126	0.0428
	(.)	(-1.17)	(0.74)
Peak power futures price volatility	0.0017	-0.0051	-0.0029
	(1.07)	(-1.28)	(-1.36)
German nuclear moratorium(15March2011)	0.3101***	-	-
	(49.06)	-	-
UK Carbon floor (y2013)	-	-	-0.3193***
	-	-	(-20.10)
Spring	-0.2103***	-0.023	0.0157**
	(-312.07)	(-0.74)	(2.06)
Summer	-0.1565***	-0.0369	0.0107
	(-13.95)	(-0.90)	(0.92)
Fall	-0.1805***	-0.0835***	-0.0182
	(-11.16)	(-2.77)	(-1.39)
Constant	-0.0008	-0.0008	-0.0003
	(-1.26)	(-0.65)	(-0.37)
Variance equation			
ARCH(-1)	0.1380***	0.1946***	0.4708***
	(5.50)	(3.85)	(5.84)
ARCH(-2)	-	-	-0.3343***
	-	-	(-4.46)
Leverage effect γ	-0.1163***	-0.0761**	-0.0346
	(-5.22)	(-2.44)	(-0.94)
GARCH(-1)	0.9428***	0.8832***	0.9271***
	(74.88)	(24.58)	(54.94)
Constant	0.0006**	0.0011*	0.0010**
	(2.56)	(1.77)	(2.39)
Akaike Information Criterion	-6548.9012	-4628.1019	-7013.5527
Bayesian Information Criterion	-6481.8291	-4558.2481	-6929.5392
Log likelihood	3286.4506	2327.051	3521.7764
Degrees of freedom	2.8010	3.2198	2.3953
Durbin-Watson statistic	2.0594	1.4515	1.4550
N	1977	1593	2000
Time interval	5Jan2009-30Nov2016*		

Note: Significance levels are *p< 0.10, **p< 0.05, *** p<0.01; Z-statistics based on Bollerslev-Woodridge robust standard errors in parentheses; the table shows estimation results of TGARCH(1,1) model (DE & NORD CSS) and TGARCH(2,1) model (UK CSS) model with t-distribution on daily log returns; All the explanatory variables are also log-differenced, therefore the coefficients of this log-log regression model represent marginal effects (elasticities). *NORD CSS estimation sample is 5Jan2009-28Aug2015.

Table 6 Comparison of in-sample forecasting performance of volatility models for power spreads

Loss function	DE CDS	UK CDS	NORD CDS	DE CSS	UK CSS	NORD CSS
MSE	4.50E-06	0.00075	0.000032	0.00079	0.01356	0.002268
MAE	0.0031	0.00827	0.001134	0.00614	0.00739	0.007707
HMSE	22.08326	120.047	12.55427	12.24601	11.0894	11.91409
HMAE	-0.07084	-0.58742	-0.105445	0.02459	0.27927	0.022787

*Note: RMSE refers to root mean square error, MAE refers to mean absolute error, HMSE and HMAE refer to heteroscedasticity adjusted MSE and MAE, respectively, as defined in Eq. (5-8).