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Revisiting global economic activity and crude oil prices: A wavelet analysis

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ABSTRACT

Based on the wavelet analysis approach, this paper firstly examines the dynamic relationship between global economic activity (proxied by the Kilian economic index) and crude oil prices in both time- and frequency-domains. Our empirical results demonstrate significant correlation between crude oil prices and global economic activity at high frequencies (in the short run) during the entire sample period; however, the co-movement between the two at low frequencies (in the long run) is weaker and exists only during certain proportions of the sample period. We also document evidence that global economic activity and oil price are positively correlated, with dynamic lead-lag relationships across time. Our findings are robust to alternative choices of oil price indexes and controlling for other confounding factors such as geopolitical risk, armed conflicts, economic policy uncertainty and equity market uncertainty. The current study provides valuable implications for oil market investors based on the information of global economic situation and its dynamic relationships with oil prices.

1. Introduction

As one of the most important sources of energy, crude oil plays a fundamental role in a country's macroeconomy. Accordingly, the determinants of crude oil prices and how they impact the fluctuations of crude oil prices have attracted considerable attention of scholars.[1] Exerting critical impact on the demand side of the crude oil market, global economic activity is widely considered as a key factor in explaining the dynamics of oil prices (Kilian, 2009; He et al., 2010; Wang and Sun, 2017). Since the crude oil supply is not completely elastic, *ceteris paribus*, global economic expansion (slump) would increase (decrease) demand for crude oil, and consequently result in a rise (fall) in crude oil prices. Despite the close nexus and great policy implication, there have been limited studies that specifically investigate the interaction between global economic activity and oil prices.[2] Most previous econometricians have merely controlled for global economic activity along with oil prices in the demand equation under a supply-demand framework to estimate the price and income elasticities of oil demand (e.g., Pesaran et al., 1998; Gately and Huntington, 2002; Griffin and Schulman, 2005; Krichene, 2006). Recently, there have been a growing body of literature that investigate the relationship between global economic activity and oil prices by applying a multi-country framework where data of critical countries (e.g., developed countries, emerging countries and oil exporters) are pooled together for analysis or by exploiting a single indicator of global economic activity to perform time-series analysis.[3] This strand of literature investigate the nexus exclusively from a time-domain perspective.

However, another critical perspective missed in previous studies is

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[1] See Lynch (2002), Hamilton (2009), Mu and Ye (2011), Benhmad (2012), Kilian and Hicks (2013), Ratti and Vespignani (2013), Tiwari et al. (2013), Wang and Sun (2017), etc.

[2] Vast majority of previous researches on oil price-macroeconomy relationship are carried out at national level, especially in developed countries and the OPEC members. However, owning to rapid economic development, emerging countries have been playing in a key role in contributing to the growth of world oil consumption and driving up the oil prices (Hamilton, 2009; Kilian and Hicks, 2013). Therefore, the relationship between global economic activity and oil prices deserves attention.

[3] See Kilian (2009), He et al. (2010), Cashin et al. (2014), Mohaddes and Raissi (2015), Mohaddes and Pesaran (2016), Ratti and Vespignani (2016) and Mohaddes and Pesaran (2017). Methodologies applied in these studies include the Global vector autoregressive (GVAR) model, the Johansen test and the vector error correction model (VECM), which all incorporate time information only while ignoring important information in the frequency domain (Power and Turvey, 2010; Huang et al., 2016). More detailed discussion of the above literature is elaborated in Section 2.

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the frequency domain, from which researchers can capture useful and important information when analyzing oil prices. First, oil prices are generated from a process that consists of different components operating at various frequencies (Vacha and Barunik, 2012; Tiwari et al., 2013). On the one hand, the crude oil market is comprised of interacting agents with different time horizons and term objectives. According to the heterogeneous market hypothesis for financial markets, such market heterogeneity leads to the presence of different dealing frequencies. On the other hand, oil price fluctuations may be induced by factors that operate at very different time scales (e.g., from a few months of strikes in Nigeria to a few years of wars such as the 2nd Gulf War). Heterogeneity in these time horizons leads to diverse underlying cycles in the oil price changes. Second, the relations between oil and macroeconomic variables may also vary at different frequencies (Aguiar-Conraria and Soares, 2011; Naccache, 2011; Benhmad, 2012; Tiwari et al., 2013). 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. Third, decomposing data into different frequencies can also offer useful insight for heterogenous agents with different time horizons to effectively manage their asset portfolio (Chang and Lee, 2015). If global economic activities and oil prices co-move in high (low) frequencies, it implies that short-term (long-term) investors should particularly pay attention to and exploit the information of global economic fluctuations to guide their investment. Meanwhile, understanding of not only the time-varying but also the frequency-varying causal relationship between global economic activity and the oil price can also significantly improve price prediction accuracy and decision-making process for heterogenous market participants.

We contribute to the literature by investigating the dynamic interaction between global economic activity and the crude oil price in both frequency- and time-domains based on a novel approach of wavelet analysis.[4] The wavelet analysis measures co-movement and causality between two series under the consideration of time and frequency simultaneously.[5] Different with conventional time series or panel data approaches (e.g, cointegration analysis, vector correction model and vector autoregressive model) that only divide time scale into short-run and long-run, the wavelet analysis detects multi-scale relationships between variables (Aguiar-Conraria et al., 2012). Specifically, two tools of wavelet analysis are employed: (1) wavelet coherency, which assesses the dynamic co-movement between crude oil prices and global economic activity across different frequencies and time periods, and (2) wavelet phase-difference, which is a non-linear technique that allows us to derive the time-varying causality between the two. In such fashion, we can observe high-frequency (short-term) and low-frequency (long-term) relationships between the crude oil price and the global economic activity. Meanwhile, we are also able to examine the relationship between the two regarding possible structural changes, time variations and non-linearity without making ex-ante assumptions on model specifications. Previous literature have shown that when researchers investigate energy prices, ignoring these concerns may invalidate the empirical results (Beckmann et al., 2014).[6]

We measure the global economic activity by the Kilian economic index and the oil price by the West Texas Intermediate (WTI) crude oil spot price and the Brent crude oil spot price.[7] We exploit a monthly data set between mid-1980s and 2018 to investigate the dynamic co-movement and causality across time and frequency domains. Our empirical works begins with tests for the crude oil prices and the Kilian economic index for unit roots and cointegration. After providing the presence of long-run cointegration relationships among variables, we perform generalized impulse response analysis to observe the dynamic response of the crude oil prices to global economic activity shocks and vice versa. We then conduct the Toda and Yamamoto (1995) causality test to examine the causality between the two and the causality direction. Finally, we apply the wavelet coherency analysis to investigate how the strength of co-movement between crude oil prices and the Kilian economic index changes across different time periods and frequencies, and the phase-difference technique to derive the time-varying causal relationship between the two.

Overall, our empirical results offer evidence of dynamic relationship between the crude oil prices and the Kilian economic index across both time and frequencies. First, the wavelet coherency analysis demonstrates high degree of co-movement between the crude oil prices and the Kilian economic index at high frequencies (in the short run) during the entire sample period, whereas at low frequencies (in the long run) the co-movement is weak and only exists during certain periods of the sample. Second, as for (partial) phase difference analysis, we find that the causal relationship is bi-directional: global economic activity and oil price are positively correlated, and yet the lead-lag relationships vary across time. For robustness checks, we also apply the partial wavelet coherency and partial phase difference to account for simultaneous impacts of other confounding factors, including geopolitical risk, armed conflict, economic policy uncertainty and equity market uncertainty on the Kilian economic index and the oil prices, aiming to reveal the true co-movement and causality between the two variables. We obtain robust empirical results. Our findings are also consistent when we change to use the OECD industrial output production as an alternative measure of global economic activity.

Our findings provide important policy implications in several aspects. First, the information of variations in global economic activity is particularly relevant for short-term oil market investors (e.g., arbitragers or speculators) with a horizon of less than 1.5 years. Our results suggest that they should keep a close eye on global economic activity 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 at the signal of global economic prosperity. Second, the time-varying relationship between global economic activity and the crude oil prices implies that oil market participants should incorporate such dynamic pattern when managing their portfolios. Particularly, we find

[4] 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; Vacha et al., 2013; Chang and Lee, 2015; Pal and Mitra, 2017).

[5] Frequency in wavelet analysis implies the different relationships between variables at different time scales.

[6] Structural breaks and non-linearity are generally missing in conventional time-domain methods. Recent empirical researches employing time-domain methods pay increasing attention to accounting for non-linearity of oil prices. Approaches used or proposed all requires making certain assumptions on model specifications which may or may not be completely realistic. Such methods include the threshold vector error correction model (Mamatzakis and Remoundos, 2011), multi-threshold nonlinear autoregressive distributed lag model (Pal and Mitra, 2015, 2016), the neural networks approach (Ghaffari and Zare, 2009), and the Markov switching model (Janczura and Weron, 2010). Kilian and Vigfusson (2013) compare alternative non-linear models and examine their forecasting power for predicting the U.S. real GDP based on oil prices.

[7] Proposed by Kilian (2009), the Kilian economic index is constructed as a monthly global indicator based on the dry cargo single voyage freight rates, which is collected by a consulting firm for various bulk dry cargoes, such as coal, iron ore, fertilizer and scrap metal. The Kilian economic index has been a common indicator to approximate the fluctuations of global economic activities, especially among researches on oil prices. For papers that also employ the index, see Apergis and Miller (2009), Alquist and Kilian (2010), He et al. (2010), Basher et al. (2012), Baumeister and Kilian (2015), and Ratti and Vespignani (2013). We also use an alternative measure of global economic activities: the OECD monthly industrial output production for robustness checks.

that after 2005 the oil prices also co-move with global economic activity in the long run (at the frequency band of 8 years). This suggests potential opportunities for long-term investors (e.g., oil producers) to also take advantage of global economic activity information to earn excess returns. Third, consistent with previous findings, we find that oil is not a good energy commodity for investment risk diversification (Chang and Lee, 2015). Since oil prices both move in phase with global economic activity in the WTI and Brent markets, there seems to be no room for hedging and diversify risk across different oil markets purely based on global economic activity.

The remainder of this paper is organized as follows. Section 2 reviews the relevant existing literature. Section 3 illustrates the methodological framework of wavelet analysis. Section 4 talks about the data used in this paper and presents the empirical results, interpretation and implications. Section 5 concludes.

2. Literature review

The interaction between the crude oil price and economic activity has received tremendous attention among economists and policy makers. Initial researches typically look into this issue based on a single-country framework, with the U.S. or other developed countries most commonly considered as the sample. This line of studies have been the vast majority of the literature on the price-macroeconomy relationship. Among many of others, typical papers under this strand of literature include Hamilton (1983), Mork (1989), Hooker (1996), Cunado and De Gracia (2003), etc.

Nevertheless, there has been a growing recognition that the oil market should be best viewed as a global market (Killian, 2009; Baumeister and Peersman, 2013; Killian and Murphy, 2012). A single-country framework fails to account for economic interlinkages and spillovers that exist between different countries and regions under oil price shocks. Moreover, owning to rapid economic development, emerging countries have been playing a key role in contributing to the growth of world oil consumption and driving up the oil prices (Hamilton, 2009; Chai et al., 2011; Li and Lin, 2011; Kilian and Hicks, 2013). Therefore, the relationship between global economic activity and the oil price deserves attention. Accordingly, recent researchers switch their horizon to the interaction between the oil price and global economic activity rather than the economy of a single country or a handful of countries.

One common approach to present the global economy is to use a multi-country framework, where representative countries of different types (e.g., developed and emerging countries, oil exporters and importers, etc.) are incorporated. Several recent studies utilize this approach to study the economic consequences of oil shocks for the global economy, including impacts on real output. For instance, Cashin et al. (2014) utilize the Global Vector Autoregressive (GVAR) approach and exploit a sample of 38 countries/regions during 1979Q1-2011Q2 to differentiate the effects of supply-driven and demand-driven oil-price shocks on different countries. The authors show that facing supply-driven surge in oil prices, oil-importing countries typically experience a long-lived fall in economic activity, whereas oil-exporting countries respond by an increase in economic activity. As for oil-demand disturbance, real output increases in almost all sample countries. Similarly, based on the GVAR model estimated for 38 countries/regions, Mohaddes and Raissi (2015) examine the global macroeconomic consequences of the fall in oil prices due to the U.S. oil revolution. The empirical findings demonstrate significant heterogeneities in responses across different countries: real GDP increases in both developed and emerging oil importers, whereas output declines in oil exporters. Mohaddes and Pesaran (2016) conduct the GVAR approach to investigate macroeconomic consequences of country-specific oil-supply shocks. Based on a sample of 27 countries over the period of 1979Q2 to 2013Q1, the authors show that oil-supply shocks have considerably inconsistent implications on the global economy depending on which country is subject to the shock. Saudi Arabian oil supply shocks lead to significant adverse effects on real GDP in both advanced and emerging economies. In contrast, the effects of adverse Iranian oil output shocks on real GDP are neutralized mainly due to an increase in Saudi Arabian oil production. Based on a global factor-augmented error correction model, Ratti and Vespignani (2016) examine the relationships between oil prices and various global macroeconomic variables including global industrial production. They demonstrate that granger causality goes from oil prices to global industrial production and positive innovation in the world oil price is associate with positive effects on global industrial production. Mohaddes and Pesaran (2017) also employ the GVAR modeling approach to analyze this topic from a different angle. They find that the effects of oil price plunge on global real output are positive and they take longer period to materialize (approximately 4 quarters after the shock) relative to those on interest rate, inflation and global equity prices.

Another way to investigate global economic activity is to find an appropriate measuring indicator. Kilian (2009) construct a monthly measure of global economic activity based on data for dry cargo bulk freight rates. Taking advantage of the data, Kilian (2009) decompose the real crude oil prices into three components: crude oil supply shocks, shocks due to global demand for all industrial commodities, and demand shocks specific to the global crude oil market. Kilian (2009) finds that demand expansion shock in global commodity markets due to global economic activity leads to substantial and sustained increase in oil prices. However, Kilian (2009) only considers the dynamic effects of structural economic shocks. Utilizing the Johansen test and the error-correction model, He et al. (2010) demonstrate that crude oil prices are significantly influenced by variations in global economic activity (also proxied by the Kilian economic Index) through both long-run equilibrium conditions and short-run impacts. Yet, the study fails to account for potential structural breaks, which may lead to biased results.[8] Jo (2014) exploits a different indicator of world industrial production to proxy global economic activity and studies how it is impacted by oil price uncertainty based on an autoregressive model with time-varying stochastic volatility in mean. Jo (2014) finds a negative effect of oil price uncertainty shock on world industrial production.

A common feature of the previous literature is that the analyses are all conducted in the time-domain and fail to capture the dynamic co-movement and causality between global economic activity and crude oil prices across different frequencies. In addition, the researches usually only focus on one direction of the causality, while ignoring the reverse causality. We contribute to the literature by employing a novel wavelet approach to investigate dynamic co-movement and causality between global economic activity and oil prices not only in the time domain but also in the frequency domain. We also allow for the lead-lag relationship between global economic activity and oil prices to vary across time and frequencies.

3. Wavelet analysis

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 (Aguiar-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

[8] During their sample period (1988–2007), structural breaks are likely to exist and exert critical impacts on the relationship between global economic activity and the oil price, given the incidents of critical international economic events such as the Asian Financial crisis and geopolitical conflicts such as the Gulf war.

locally stationary series, while the Fourier analysis is merely suitable for stationary series (Roueff and Sachs, 2011).

In general, there are two types of wavelet transforms, which are discrete wavelet transform (DWT) and continuous wavelet transform (CWT) respectively.[9] 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:

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

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:

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

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,

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

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

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

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

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

where $\widehat{\psi}(\omega)$ 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:

$$\psi(t) = \pi^{-1/4}e^{i\omega_0 t}e^{-\omega_0^2/2}. \tag{6}$$

Following Grinsted et al. (2004), we set ω_0 to be 6, which makes the Morlet wavelet reach the optimal trade-off between time and frequency localization. Since Aguiar-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 the 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 a 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:

$$\left|W_{xy}(s,\tau)\right|^2 = |W_x(s,\tau)|^2\left|W_y{}^*(s,\tau)\right|^2 \tag{7}$$

where $x(t)$ and $y(t)$ are the two series, and the asterisk presents the complex conjugation. 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):

$$R^2_{xy}(s,\tau) = \frac{\left|S\left(s^{-1}W_{xy}(s,\tau)\right)\right|^2}{S\left(s^{-1}|W_x(s,\tau)|^2\right)S\left(s^{-1}|W_y(s,\tau)|^2\right)} \tag{8}$$

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 the Kilian economic 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:

$$\phi_{xy} = \tan^{-1}\left(\frac{I\left\{S\left(s^{-1}W_{xy}(s,\tau)\right)\right\}}{R\left\{S\left(s^{-1}W_{xy}(s,\tau)\right)\right\}}\right), \text{ with } \phi_{xy} \in [-\pi,\pi]. \tag{9}$$

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 $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, 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 $\phi_{xy} \in \left(-\frac{\pi}{2}, -\pi\right)$, 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).

Crude oil prices and global economic activity may be impacted by other confounding factors, such as geopolitical risk, armed conflict, economic policy uncertainty and equity market uncertainty. In order to account for the effects of these factors and to reveal the true co-movement and causality between the crude oil price and global economic activity, we utilize the partial coherency and partial phase difference to achieve the goal. As suggested by Aguiar-Conraria and Soares (2013), the squared partial wavelet coherency between series $x(t)$ and $y(t)$ with $z(t)$ controlled can be defined as:

$$R^2_{xy|z}(s,\tau) = \frac{\left|R_{xy}(s,\tau) - R_{xz}(s,\tau)R^*_{yz}(s,\tau)\right|^2}{\left(1-\left(R_{xy}(s,\tau)\right)^2\right)\left(1-\left(R_{yz}(s,\tau)\right)^2\right)} \tag{10}$$

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:

$$\phi_{xy|z} = \left(\frac{I\left(C_{xy|z}(s,\tau)\right)}{R\left(C_{xy|z}(s,\tau)\right)}\right) \tag{11}$$

[9] Discrete wavelet transforms (DWT) can reduce noise and compress data, while continuous wavelet transforms (CWT) possesses function of feature extraction that simplifies the resources required to provide relevant information and perform the desired task. Thus, CWT is relatively advantageous owning to its convenience of using reduced representation rather than full-sized sample data (Chang et al., 2013).

where I and R are 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.

4. Data description and empirical results

4.1. The data

In this section, we explain the data we utilize in the current study and discuss correspondent summary statistics. We choose a monthly data set that spans from May 1985 to February 2018.[10]

We measure global economic activity using the Kilian economic index, proposed by Kilian (2009).[11] The Kilian economic index is widely adopted by researchers as a proxy for global economic activity, especially among studies on oil prices (Apergis and Miller, 2009; Alquist and Kilian, 2010; He et al., 2010; Basher et al., 2012; Ratti and Vespignani, 2013; Baumeister and Kilian, 2015). The index is constructed based on the data of representative dry cargo single-voyage ocean freight rates, available in the monthly report on "Shipping Statistics and Economics" published by Drewry Shipping Consultants Ltd.[12] Various bulk dry cargoes include grain, oilseeds, coal, iron ore, fertilizer and scrap mental. In order to eliminate fixed effects (due to different routes, commodities and ship sizes) of each series of freight rates in the raw data, Kilian (2009) first computes the monthly growth rates for each series and then takes the equal-weighted averages and normalizes the time-series such that January of 1968 is set as the benchmark unit. Finally, Kilian (2009) deflates the series with the U.S. CPI and then detrends the real index to account for technological advances in shipbuilding.

The Kilian economic index presents a direct measure of global economic activity. It automatically aggregates real economic activity in all countries and incorporates shifts in country weights, changes in real output composition and changes in the propensity of imports of industrial commodities required for a given unit of real output. This offers advantages compared to other measures since the relative contribution of individual countries for global economic activity changes over time and it is not straightforward to assign each country's contribution to global economic activity with a proper weight.

Panel (a) of Fig. 1 depicts how the Kilian economic index varies month by month during May 1987–February 2018. We can see the index approximately ranges between −120 and 40. The reader should keep in mind that the index has been normalized such that a negative figure does not necessarily indicate negative economic growth. The global economic activity witnesses a significant expansion at the end of the 1980s and stays relatively steady during the first half of 1990s. After that, the index manifests higher degree of volatility indicating economic expansions and slumps. The global economic slumps implied by the index include the 1997 Asia financial crisis, the early 2000s recession, the 2008 financial crisis, the European sovereign debt crisis in early 2010s and the continuously depressed economic environment in 2014–2015.[13]

We obtain the spot crude oil prices (dollar/barrel) of 2 origins (the West Texas Intermediate market and the Brent market) from the BP Statistical Review of World Energy. The evolution of the 2 price time series is also shown in panel (a) of Fig. 1. At the first glance, we can tell that the 2 oil price indexes move closely together. The only notable difference is that the spike of the WTI oil price in 2010–2014 is not as large as that of the Brent oil prices. 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 attributed to the rapid economic growth of developing countries, such as China and India (Wang and Wu, 2013). However, we find that a structural break point exists in 2008, where the global financial crisis may account for the remarkable plunge of the oil prices (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 again that is likely to be driven by the boom of shale gas/oil fracturing.

There might be other factors that influence both the crude oil prices and global economic activity. To reveal the true relationship between the two, we need to tease out impacts of these confounding factors. We check for robustness whether other factors may have affected our baseline results by conducting partial wavelet coherency and partial phase difference analyses where we control for geopolitical risk, armed conflict, economic policy uncertainty and equity market uncertainty. We explain below the reason why we want to control for the above variables and the corresponding data sources we utilize.

Geopolitical events, such as political unrest, terrorist attacks, civil and international wars, which are common phenomena that plagued many nations in the world, could exert huge impact on the business cycle and result in dramatic changes in the financial markets (Gaibulloev and Sandler, 2009; Guidolin and La Ferrara, 2010). The risk of incidents of such events, namely, geopolitical risk, is considered as a crucial factor for interpreting oil price behaviors because it can alter investors' expectation on the oil market conditions (Wacziarg, 2012; Noguera-Santaella, 2016; Wang and Sun, 2017).[14] We take advantage of a novel data set to measure geopolitical risk: the geopolitical risk (GPR) index, with higher value indicating higher risk. Constructed by Caldara and Iacoviello (2018), the data set is the first to evaluate geopolitical risk properly and comprehensively. The authors built the GPR index by reflecting automated text-search results of the electronic archives of 11 national and international newspapers. The index is calculated based on the number of articles that contained words regarding geopolitical risk for each month (as a share of the total number of news articles). It incorporates not only pure geopolitical threats and tensions but also actual geopolitical events and activities.[15] 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

[10] Sample period may vary slightly across different empirical specifications due to data availability of specific variables.

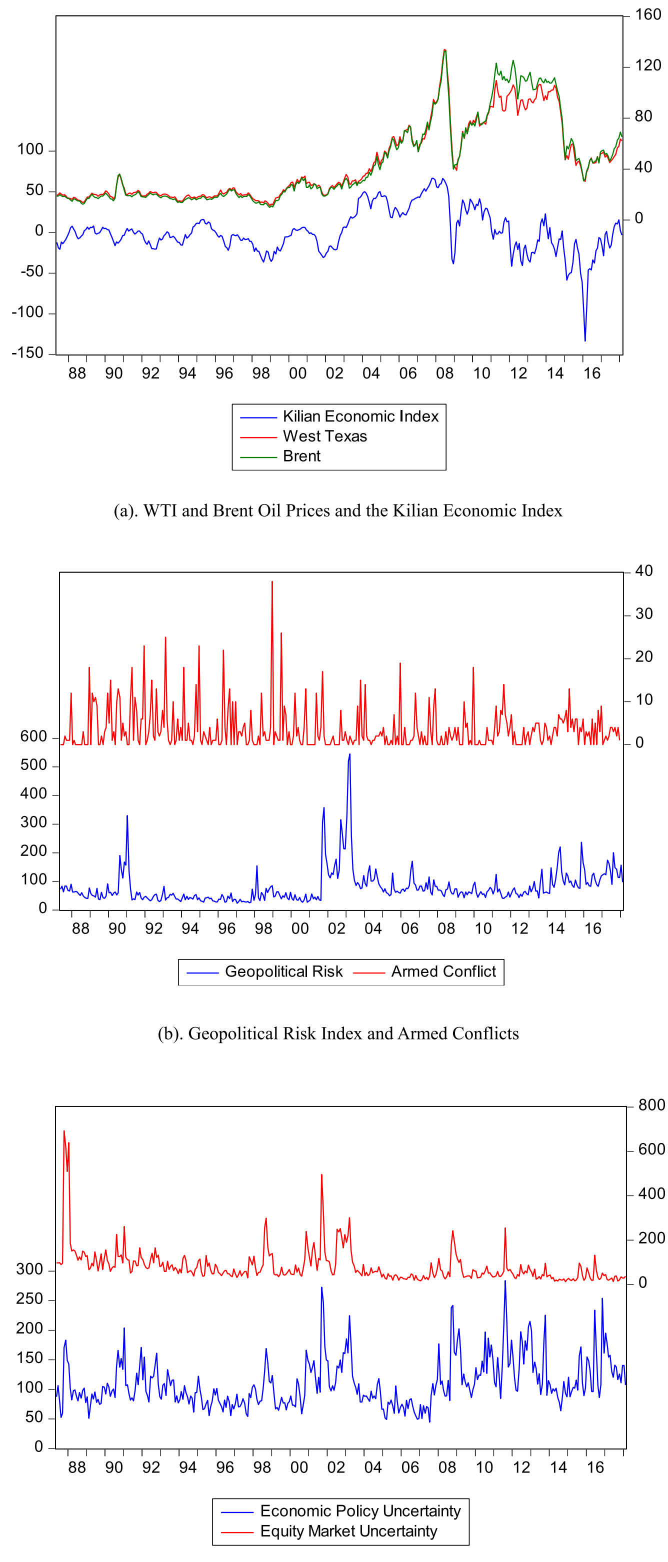
[11] Another measure of global economic activity commonly adopted by previous empirical researchers is the index of Industrial Production in OECD countries, which aggregates industrial production for OECD countries. The data is available from the OECD Monthly Economic Indicators (MEI). We argue the Kilian economic index is a more suitable measure because the OECD Industrial Production index fails to capture the influence of emerging market economies (specifically China and India), which have become major contributors to the growth of world output since 2003 (Kilian, 2009; Engel and Rogers, 2006; Crucini et al., 2011; Kose et al., 2012). We thus use the Kilian economic index for our main analyses. We also check the data of the OECD output production for robustness of our findings.

[12] Klovland (2004) points that the world economic activity is the most influential factor in determining demand for sea transport services, and empirically proves that economic activity cycles can explain the short-term behaviors of shipping freight rate during the period 1850–1918. Thus, Kilian (2009) argues that dry cargo single freight rate index can capture the changes in demand for industrial commodities in the global market.

[13] According to the World Trade Statistical Review 2016 by the WTO, the dramatic fall in world trade during 2014–2015 was due to a number reasons including an economic slowdown in China, a severe recession in Brazil, exchange rate volatility, etc.

[14] Such effect is particularly pronounced for the crude oil market since a large share of global crude oil supply is produced in the Middle East, where tensions, conflicts and wars have plagued for several decades. Moreover, Wang and Sun (2017) provide empirical evidence that geopolitical risk (wars or political tensions) leads to the rise of crude oil price by causing oil supply disruptions.

[15] The automated text-search of GPR index contains 6 groups of words: Group 1 includes words related to explicit mentions of geopolitical risk and mentions of military-related tensions; Group 2 includes words directly associated with nuclear tensions; Group 3 and 4 contain words related to war threats and terrorist threats; Group 5 and 6 capture press coverage of actual adverse geopolitical events that are expected to increase geopolitical uncertainty.



(a). WTI and Brent Oil Prices and the Kilian Economic Index

(b). Geopolitical Risk Index and Armed Conflicts

(c). Economic Policy Uncertainty Index and Equity Market Uncertainty Index

Fig. 1. Time plots of variables.

geopolitical risk in that month were twice as frequent as during the 2000s.

We also check for a narrow definition of geopolitical events: armed conflict. We utilize the armed conflict data available from the Uppsala Conflict Data Program (UCDP). The data is updated annually and records armed conflicts that result in at least 25 battle-related deaths and in which at least one actor is the government of a state.

Panel (b) of Fig. 1 plots how geopolitical risk index and the number of armed conflicts evolve over time during the sample period. The geopolitical risk index ranges from about 50 to over 500 and it is characterized by several peaks associated with key geopolitical events. The first peak occurs between 1990 and 1991, corresponding to the Kuwait invasion and the subsequent Gulf War. The most significant spike happens around the 911 terrorist attack in 2001 and remains high until the US-Iraq war ended. Afterward, the index rises in correspondence to major terrorist events in the E.U. such as the March 2004 Madrid bombing, and the July 2005 London bombing. The most recent spikes of the geopolitical risk index correspond to geopolitical tensions in Ukraine and Iraq, as well as the terrorist attacks organized by the ISIS (Islamic State of Iraq and Syria). As for armed conflicts, the number ranges from 0 to around 40 and is significantly more volatile. The most dramatic spike appears during year 1999, when large-scaled armed conflicts between India and Pakistan occurred in the Kashmir region. The number of conflicts experiences spikes periodically, the example of which include the US-Iraq war and the 2014 Russia-Ukraine crisis, etc.

Economic policy uncertainty, which exerts significant impact for economic and financial activities, is found to have close relationship with oil prices and provide useful information for understanding behaviors of oil prices (Kang and Ratti, 2013; Antonakakis et al., 2014; Bekiros et al., 2015). We resort to the economic policy uncertainty (EPU) index, constructed by Baker et al. (2016)), to control for its impact.[16] As a news-based measure, the EPU index is a normalized index of the volume of news article discussing economic policy uncertainty based on screening related key words in newspapers.[17] More details of the methodology of data construction can be found in Baker et al. (2016). The index is available at the country level and we choose the index for the U.S. as our control.

Equity market uncertainty is perceived as another influencing factor of crude oil prices (Onour, 2011; Ciner, 2013). We thus account for the U.S. equity market uncertainty index into the partial wavelet coherence as well as the partial phase difference analyses. The data shares the same source and construction methodology as the economic policy uncertainty index. The difference is that the authors switch their attention to volumes of news articles containing terms related to equity market uncertainty among U.S. newspapers available from the Access World New's NewsBank service.

The evolution of economic policy uncertainty index and equity market uncertain index is depicted in panel (c) of Fig. 1. The U.S. economic policy uncertainty index spikes during tight presidential elections, the Gulf Wars, Asian financial crisis, the 9/11 attacks, the 2008 financial crisis, the 2011 debt-ceiling dispute and other major battles over fiscal policy in the U.S. As for the equity market uncertainty, it generally follows the fluctuations of the U.S. economic uncertainty index, yet with smaller volatility.

4.2. *Empirical findings*

4.2.1. *Evidence from the unit root tests, degree of stationarity test and cointegration test*

Before determining whether all series are cointegrated, we first test for the unit root for oil prices, the Kilian economic index and other relevant factors discussed in the last section to examine the integrated order. We adopt the Augmented Dickey-Fuller (ADF) unit root test

[16] The data is available at www.policyuncertainty.com.

[17] The EPU index is built based on the coverage of policy-related economic uncertainty in 10 leading newspapers. The index reflects the frequency of articles containing the following triple: “uncertainty” or “uncertain”; “economic” or “economy”; and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation” or “White House”.

developed by Dickey and Fuller (1979), the Phillips-Perron (PP, hereafter) unit root test proposed by Phillips and Perron (1988) and the KPSS unit root test developed by Kwiatkowski et al. (1992). We apply these tests to the levels of the series and their first differences respectively. The lag lengths of the ADF test are chosen based on the Akaike information criterion (AIC). The results are reported in Table 1. When the ADF test is applied to the levels of series, we fail to reject the null hypothesis of a unit root for all series. Nevertheless, when we re-apply the test to first differences, the null hypothesis is rejected for all series at the 1% level. Thus, we find evidence that all variables are integrated of order one. Our findings are robust when we perform the PP test and the KPSS tests. For the PP tests, we show that the null hypothesis of a unit root cannot be rejected for all level series, while it is rejected for all first-differenced series at the 1% significance level. For the KPSS test, the null hypothesis of stationarity is rejected for all level series, but not for any of the first-differenced series. We thus conclude that all variables are integrated of order one.

Out of the concern for potential existence of nonlinearity due to high fluctuations of the variables, we also conduct the degree of stationarity (DS) test developed by Huang et al. (1998) to supplement the conventional unit root test. Comparing with conventional unit root tests, the merit of the DS test is that it can accurately examine the stationarity of any data without destroying its features of nonlinearity as well as the non-stationarity (Dash et al., 2018). An index of stationarity, DS(ω), can be derived from the Hilbert spectrum, which is expressed as below:

$$DS(\omega) = \frac{1}{T}\int_0^T \left(1 - \frac{H(\omega,t)}{n(\omega)}\right)^2 dt \tag{12}$$

where [0, T] is the chosen time window, $H(\omega,t)$ represents the Hilbert spectrum. $n(\omega)$ equals $\frac{1}{T}h(\omega)$, where $h(\omega)$ stands for the marginal spectrum. For a stationary process, the Hilbert spectrum cannot be a function of time. Thus, it should consist of only horizontal contour line, implying that $DS(\omega)$ should oscillate around zero.

The results of the DS test for the two oil prices and the Kilian index are presented in Fig. 2. The upper figures in the panels reflect $DS(\omega)$ for the original data, and the lower figures depict $DS(\omega)$ for data transformed in the first-difference form. The results suggest that all the variables are stationary after they are first-differenced, confirming again the conclusion we obtain from the unit root tests.

Next, we employ the Johansen (1988) maximum likelihood approach to test for pairwise cointegrating relationships between the 2 oil price indexes and the Kilian economic index. The test for the number of cointegrating vectors is based on maximal eigenvalue and trace eigenvalue statistics of the stochastic matrix in the multivariate framework. As documented in Table 2, we can tell that both tests confirm the existence of one cointegrating vector: for both pairs, the null hypothesis of no cointegration is rejected at least at the 5% significance level under both equations, whereas the null hypothesis of at most 1 cointegrating vector cannot be statistically rejected in either equation. Hence, we show existence of cointegrating relation between the oil prices and the Kilian economic index, meaning that there exists a long-run equilibrium between each crude oil price and the Kilian economic index.

We further re-apply the Johansen techniques while adding separately the data of *Geopolitical Risk*, *Armed Conflict*, *Economic Policy Uncertainty* and *Equity Market Uncertainty* into above pairs. Shown in Table 2, no matter whether we choose the criterion of the maximum eigenvalue statistics or trace eigenvalue statistics, we find at most 2 cointegrating vectors in almost all cases: the null hypothesis of no cointegration can be rejected at least at the 5% significance level, the null hypothesis of at most 1 cointegrating vector can be rejected at least at the 10% significance level, whereas the null of at most 2 cointegrating vectors cannot be rejected at even 10% significant level. The only exception is the case of cointegration test for the Brent oil price, the Kilian index and the Geopolitical Risk index, where we find evidence of 3 cointegrating vectors since we even reject the null of at most 2 cointegrating vectors. In sum, we demonstrate the cointegrating relationships between the oil prices and the Kilian economic index after other confounding factors are controlled for.

4.2.2. Evidence from the generalized impulse response and causality test

Van Dijk et al. (2007) propose that it is hard to understand and interpret nonlinear time series models if only the estimated values of model parameters are considered. Therefore, after confirming fundamental cointegration relationships between the crude oil prices and the Kilian economic index, we employ the generalized impulse response analysis developed by Koop et al. (1996) and Pesaran and Shin (1998) to further quantify the dynamic responses of the crude oil prices and global economic activity to a one-time shock (or innovation) from each other and trace the effects. The generalized impulse response approach dominates the conventional orthogonalized impulse response function due to its property of being invariant to the ordering of the variables.[18] Generalized impulse response analysis can be applied to both linear and nonlinear models and performs efficiently when dealing with multiple linear or nonlinear time series (Koop et al., 1996; Pesaran and Shin, 1998).

Panel (a) and (b) of Fig. 3 present the cases where the shock is from the Kilian economic index to the Brent oil price and vice versa. The graphs show the dynamic responses of one series to a shock instantaneously and after one period (1 month), two periods and up to thirty periods. The horizontal axis presents the number of months, and the vertical axis represents the impulse response coefficient. From panel (a), we can tell that a one-standard-deviation innovation (shock) of the Kilian economic index in the current period generates a jump of the Brent oil price during the first 20 months, after which the positive impact starts to gradually diminish in magnitude. Overall, although the response in each period is not statistically different from zero, the accumulated sum of responses is significantly positive, indicating that an increase in the Kilian economic index leads to a noticeable rise in the Brent oil price. It is also worth stressing that such impact largely exists in the short run. Fig. 3(b) shows the dynamic responses of the Kilian economic index given a one-standard-deviation shock of the Brent oil prices. The response maintains significantly positive during the first 10 months and the positive impact begins to decay after about 5 months. We find that the response of the Kilian economic index under a shock of the Brent oil prices lasts for a shorter period, relative to what is shown in Fig. 3(a). This implies that the causality may run from the global economic activity to the Brent oil prices, while the reverse causality is less likely to hold.

We also perform the same analysis to the relationship between the WTI crude oil price and the Kilian economic index, the results of which are shown in Fig. 3(c) and 3(d). We find the results manifests quite similar patterns as those shown in Fig. 3(a) and 3(b). We thus show our results are robust to the choice of oil price indexes.

We also conduct the causality test proposed by Toda and Yamamoto (1995) to examine the causal relationship between the crude oil prices and the Kilian economic index. The Toda-Yamamoto causality test is a simple method of adding extra lags intentionally in estimation. Besides, compared with conventional Granger causality test, it is very useful in practice since it does not require pretests of a unit root and cointegrating rank. The results of the test are presented in Table 3. The null hypothesis that the Kilian economic index is not the Granger cause of the Brent oil price is rejected at the 1% significance level, whereas the hypothesis that

[18] A conventional orthogonalized impulse response function, measuring the time profile of the effect of a shock on the behavior of a series, is not invariant to the ordering of the variables in the vector autoregressive (VAR) models. This is because underlying shocks to the model are orthogonalized using the Cholesky decomposition before impulse responses are computed. Such impulse response function can be only applied to univariate linear model. Otherwise, it will have conceptual problems such as history, shock or composition dependence (Koop et al., 1996).

Table 1
Unit root tests.

Variables	ADF		PP		KPSS	
	Level	First Difference	Level	First Difference	Level	First Difference
Brent	−0.717(1)	−12.921(0)***	−0.405	−13.042***	1.689***	0.074
WTI	−0.389(6)	−9.540(5)***	−0.305	−12.721***	1.702***	0.065
Kilian economic index	−1.745(2)	−5.858(13)***	−2.660	−14.605***	43.599***	0.034
Geopolitical Risk	−1.184(10)	−6.014(16)***	−1.490	−72.158***	10.086***	0.000
Armed Conflict	−1.404(15)	−8.853(14)***	−1.404	−18.200***	5.447***	0.002
Economic Policy Uncertainty	−0.587(9)	−11.139(8)***	−0.854	−24.295***	7.517***	0.050
Equity Market Uncertainty	−1.356(3)	−10.976(8)***	−0.365	−4.830***	1.146***	0.068

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 the PP test is a unit root, while the null hypothesis of KPSS test is stationary. The *** indicates significance at the 1% level.

the Brent oil price is not the Granger cause of the Kilian economic index cannot be rejected. We therefore provide evidence that the causality runs from the Kilian economic index to the Brent oil price, but not in the opposite direction. Similar results are reached when we replace the Brent oil price by the WTI oil price. In sum, again we confirm the existence of a causal relationship between the crude oil price and global economic activity.

4.2.3. Evidence from conventional structural break test

As discussed earlier, there might exist certain structural breaks in the time series of the crude oil prices and the Kilian economic index during the sample period. To investigate this issue, we adopt the Perron and Vogelsang (1992)'s approach of unit root test which allows for one structural break at an unknown time. They propose the following model to test for the unit root hypothesis:

$$Y_t = c_0 + \rho Y_{t-1} + d_1 {*} D(TB)_t + u_t \tag{13}$$

where *TB* denotes the date of structural break and should be assigned somewhere in the sample period, and *D(TB)*is a dummy variable for the structural break.u_t represents the error term. The results of the Perron and Vogelsang (1992) unit root test are presented in Table 4. We can see that for the WTI and Brent oil prices and the Kilian economic index, the series are all stationary after one structural break is accounted for. The estimated structural breaks occur at October 2005, September 2005 and December 2015 respectively for the WTI oil price, the Brent oil price and the Kilian economic index.

To relax the assumption of only one structural break in the data evolution, we further conduct the Narayan and Popp (2010) structural break test for both crude oil prices and the Kilian economic index to allow for two endogenous breaks.[19] The results are shown in Table 5. It can be found that for the WTI oil price, the two break points occur in June 2004 and September 2014, while for the Brent oil price, the structural breaks lie in January 2004 and September 2014. The first structural break of the oil prices in 2004 may be attributed to the significant growth of the world economy, especially for emerging countries such as China, India and Russia, which in turn raised the demand of oil consumption and thus drove up the oil prices. Conversely, the second break of the oil price, which is associated a remarkable fall in 2014 (shown in Fig. 1), is likely to be owning to the hydraulic fracturing shale gas/oil boom. The results of the Narayan and Popp (2010) structural break test also indicate two break points in the Kilian economic index in year 1998 and 2008. Our best guess is that the former may be caused by the Asian financial crisis and the latter may be ascribed to the world-wide financial crisis.

4.2.4. Empirical results of the wavelet analysis

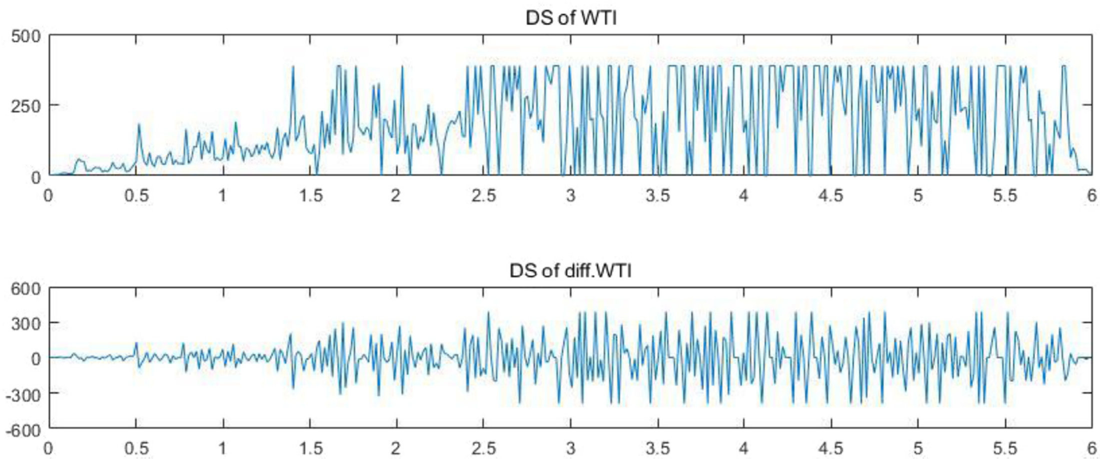
Although traditional cointegration tests provide evidence of cointegrated relationships between the oil price and the Kilian economic index, yet, we are dissatisfied with the fact that only one cointegration is discovered to proxy the long-run co-movement in the historical interactive process of the two variables. Next, we resort to the wavelet analysis to investigate the dynamic interaction between the oil price and the Kilian economic index in both frequency and time domains.[20]

Figs. 4–8 depict the (partial) wavelet coherencies and (partial) phase differences among the WTI/Brent oil price, the Kilian economic index and various aforementioned control variables. The upper graphs in each figure document the results of (partial) wavelet coherency, while the lower graphs show the results of (partial) phase differences. In the wavelet coherency analysis graphs, the y-axis refers to the frequencies, which is converted to time units (years) for ease of interpretation; the x-axis refers to the sample period, which varies slightly due to data availability differences across each case. The wavelet coherency finds "regions" in time-frequency sphere where the two series co-vary. The cone of influence depicted with a black line describes such a "region", indicating that the contour is significant at the 5% level. The color of the graph reflects the strength of coherency at each frequency across time, 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. We choose the frequency band of 3–8 years to perform the wavelet analysis. This is out of two concerns: (1) the response of oil prices to external shocks usually takes 3–8 years (Chang and Lee, 2015); (2) business cycles typically last for 3–8 years (Bergman et al., 1998).

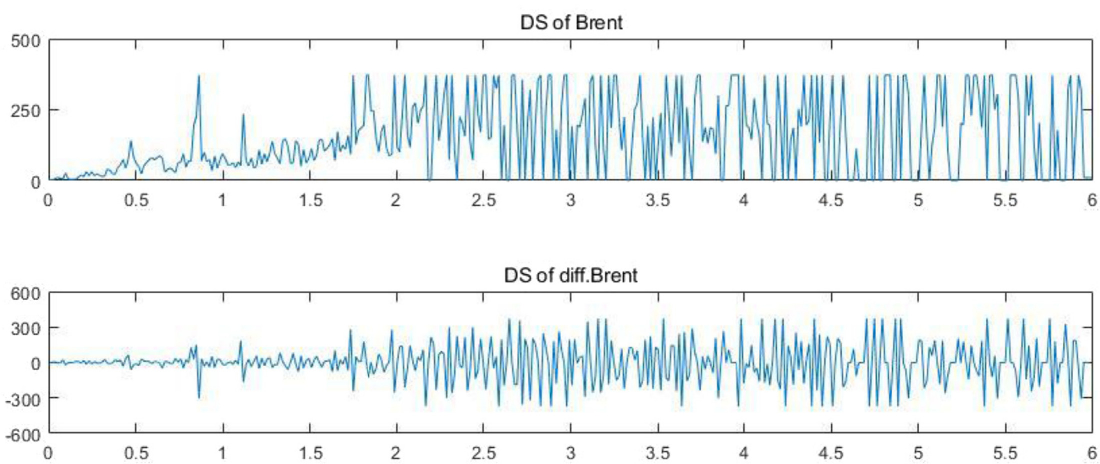
Since the WTI oil price is the mostly commonly used oil price index, we start with the pair of the WTI oil price and the Kilian economic index for our wavelet analysis. The wavelet coherency and phase difference analyses for the relationship between the two are illustrated in Fig. 4.1 and 4.2. From the wavelet coherency results, we obtain interesting patterns. Different from traditional cointegration analysis where only a single integration relationship is found, we observe significant dynamic correlations between the WTI crude oil price and the Kilian economic index in both time and frequency domains. First, all area corresponding to high frequencies (specifically fluctuations with duration of less than 1.5 years) is red, indicating that the degree of co-movement between the WTI oil price and the Kilian economic index is strong at high frequencies (in the short run) for the entire sample period. The short-term dependence suggests that global economic activity is an important factor to be taken into consideration for short-term investors (e.g., arbitragers and

[19] Narayan and Popp (2013) demonstrate that the endogenous structural break unit root test of Narayan and Popp (2010) is superior to the other two widely used two break unit root tests, namely the Lumsdaine and Papell (1997) and Lee and Strazicich (2003). Specifically, according to Monte Carlo simulations, the Narayan and Popp (2010) test performs better in power and size comparisons. This is because different from the other two tests, the Narayan and Popp (2010) test chooses the break date by maximizing the significance of the break dummy coefficient. The test has been applied in a number of studies, including Apergis and Payne (2010), Narayan and Liu (2011), Makin and Narayan (2013), Salisu and Fasanya (2013), Salisu and Mobolaji (2013) and Narayan et al. (2015), etc.

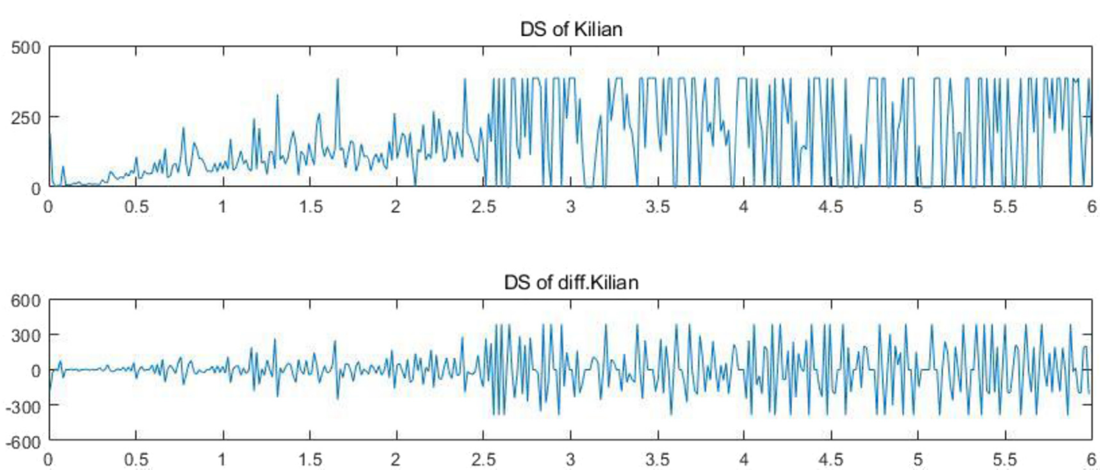
[20] Both the oil prices and the Killian index are transformed in the growth rate form to avoid the erroneous problems associated with non-stationarity in wavelet analysis.



(a) Degree of Stationarity: West Texas Crude Oil Price



(b) Degree of Stationarity: Brent Crude Oil Price



(c) Degree of Stationarity: Kilian Economic Index

Fig. 2. Degree of stationarity (DS) tests of oil prices and the Kilian economic index.

Table 2
Johansen's cointegration test.

Null Hypothesis	Maximum Eigenvalue Statistics	Trace Eigenvalue Statistics
No. of CE(s)	Cointegration test for Brent and Kilian	
None	19.834(0.006)***	24.938(0.001)***
At most 1	0.053(0.204)	0.404(0.589)
	Cointegration test for West Texas and Kilian	
None	18.170(0.011)**	23.353(0.003)***
At most 1	0.104(0.240)	0.406(0.687)
	Cointegration test for Brent, Kilian and Geopolitical Risk	
None	20.543(0.060)*	39.263(0.003)***
At most 1	14.768(0.042)**	18.710(0.016)**
At most 2	3.952(0.047)**	3.952(0.047)**
	Cointegration test for West Texas, Kilian and Geopolitical Risk	
None	22.099(0.037)**	41.382(0.002)***
At most 1	14.159(0.052)*	19.282(0.013)**
At most 2	2.682(0.102)	2.682(0.102)
	Cointegration test for Brent, Kilian and Armed Conflict	
None	71.060(0.000)***	88.888(0.000)***
At most 1	13.881(0.057)*	17.818(0.022)**
At most 2	5.029(0.592)	5.029(0.592)
	Cointegration test for West Texas, Kilian and Armed Conflict	
None	71.399(0.000)***	90.291(0.000)***
At most 1	13.685(0.062)*	18.892(0.015)**
At most 2	5.208(0.483)	5.208(0.483)
	Cointegration test for Brent, Kilian and Economic Policy Uncertainty	
None	30.512(0.002)***	47.844(0.000)***
At most 1	13.463(0.067)*	17.333(0.026)**
At most 2	3.870(0.193)	3.870(0.193)
	Cointegration test for West Texas, Kilian and Economic Policy Uncertainty	
None	31.098(0.001)***	49.614(0.000)***
At most 1	13.918(0.057)*	18.516(0.017)**
At most 2	1.445(0.229)	1.445(0.229)
	Cointegration test for Brent, Kilian and Equity Market Uncertainty	
None	30.263(0.002)***	48.206(0.000)***
At most 1	14.136(0.052)*	17.944(0.021)**
At most 2	1.675(0.155)	1.675(0.155)
	Cointegration test for West Texas, Kilian and Equity Market Uncertainty	
None	32.768(0.001)***	51.659(0.000)***
At most 1	13.941(0.056)*	18.892(0.015)**
At most 2	1.544(0.214)	1.544(0.214)

Notes: ***, ** and * denote rejection at 1%, 5% and 10% levels. P-values are in parenthesis.

speculators) in the oil market. Second, on the contrary, the correlation between the two series becomes weaker at lower frequencies. The Kilian economic index and the WTI oil price only have high degree of co-movement for the frequency bands of 5–8 years in the period of 1995–1997, 2000–2002 and 2005–2010. This implies that new information of global economic activity is generally less of a concern for oil market participants with a long horizon (e.g., oil producers and policy makers). Third, nevertheless, our results also demonstrate a dynamic relationship between global economic activity and the WTI oil price, which should be incorporated in the decision-making process for oil market investors. For instance, the structural breaks at the above periods during which the two series also strongly co-move at low frequencies suggests the potential reoccurrence of such co-movement in the future. In this sense, long-term investors should also pay attention to the fluctuations of global economic activities for excess return.

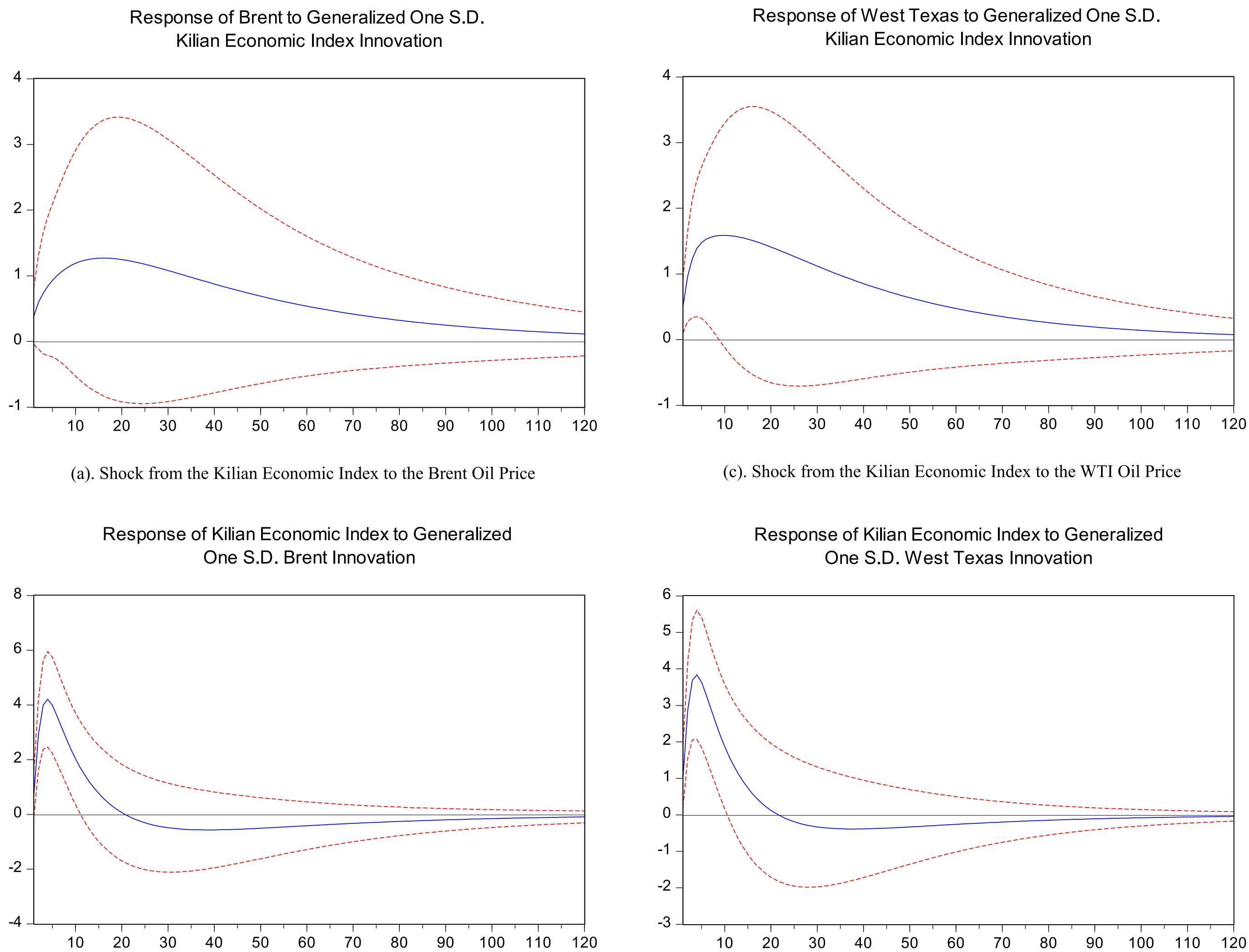
Because the wavelet coherency is squared, it cannot distinguish between positive and negative co-movements. Therefore, we subsequently utilize the phase difference analysis to investigate the positive and negative correlation as well as the lead-lag relationships between the two series. Shown in Fig. 4.2, the phase difference lies in between $(0, \pi/2)$ during multiple periods including 1987–1989, 1990–1991, 1993–1995, 1996–1997, 2002–2004, 2010–2012 and 2016–2018. The interpretation is that in these time slots the two series was moving in phase (i.e., positively correlated), with the Kilian economic index leading the WTI oil price. In other words, an increase in global economic activity contributes to a rise in the WTI oil prices. This is consistent with our intuition and pervious findings in the literature (He et al., 2010). However, distinct from He et al. (2010), who only find short-run and long-run relationships between global economic activity and the oil price in general, we aim to detect multi-scale relationships between the two: our results identify (1) a strong correlation at high frequency band, specifically with a fluctuation duration of less than 1.5 years, and (2) a relatively weaker correlation at the lower frequencies. In terms of investment recommendations, this suggests that short-term investors in the oil market should consider purchasing more assets if they predict a possible improvement in world economic outlook.

In contrast, during almost all remaining periods, the phase difference lies in between $(-\pi/2, 0)$, providing evidence that the WTI oil price was leading the Kilian economic index with a positive correlation.[21] This might be somewhat counter-intuitive as normally one would think that an increase in oil prices would serve to damage the economy, the support of which has been found in some previous studies. However, as discussed in Section 2, recent studies have demonstrated that one need to keep in mind the heterogeneous responses across country types and differential impacts between supply-driven and demand-driven oil price shocks (Cashin et al., 2014; Mohaddes and Raissi, 2015). Although supply-driven oil price increases dampen economic activities for oil-importing countries, conversely, real outputs are boosted in oil-exporting countries under such scenarios. Moreover, Cashin et al. (2014) also show that a demand-driven oil price spike generally leads to an increase in real output in a country, no matter it is an oil importer or exporter. It is likely that as we take a global perspective, the net effect is dominated by the positive effect of oil prices on global economic activities in our sample period. Our findings are consistent with Ratti and Vespignani (2016) who examine the relationships between oil prices and various global macroeconomic variables including global industrial production. Based on a global factor-augmented error correction model, they demonstrate that granger causality goes from oil prices to global industrial production and positive innovation in world oil price are associated with positive effects on global industrial production. Overall, the changes in the lead-lag relationship between the WTI oil price and the Kilian economic index further confirm the existence of structural breaks and clear dynamic dependence between the two.

We next perform the partial wavelet coherency as well as partial phase difference to tease out simultaneous effects of factors discussed in Section 4.1 on the WTI oil price and the Kilian economic index. We start with the geopolitical risk. The results are documented in Fig. 4.3 and 4.4. The evidence is to a large extent consistent with what we have shown above. For the partial wavelet coherency analysis, again the correlation between the two series are strong at high frequencies (in the fluctuation duration of less than 1.5 years). Yet, although still relatively weak, the co-movement in low frequencies turns to be somewhat stronger when geopolitical risk is taken into consideration. The oil price and the Kilian index are correlated at the frequency band of 8 years during 1995–2000 and notably, for almost the entire period after 2005. This further suggests potential opportunity for long-term market participants in the oil market to take advantage of global economic information for excess return. As for partial phase difference, the statistics also exhibit quite similar pattern. We thus find robust credence supporting the existence of dynamic causality between the WTI oil price and the Kilian economic index.

To check the robustness of our findings, we use the Brent crude oil price instead and re-apply the above analysis, the results of which are reported in Fig. 5. We obtain consistent findings. Both wavelet coherency and phase difference analyses provide very similar results as what we

[21] We also find the phase difference can be marginally above $\pi/2$ or below $-\pi/2$ in very short periods. But since the evidence is rather weak, we argue that there exists dynamic causality between the WTI oil price and the Kilian economic index, with two variables moving in phase.



(a). Shock from the Kilian Economic Index to the Brent Oil Price

(c). Shock from the Kilian Economic Index to the WTI Oil Price

(b). Shock from the Brent Oil Price to the Kilian Economic Index

(d). Shock from the WTI Oil Price to the Kilian Economic Index

Fig. 3. General impulse responses.

Table 3
Toda-Yamamoto causality test for crude oil prices and the Kilian economic index.

Null Hypothesis	Chi-Square	P-Value	Conclusion
Kilian is not the Granger cause of Brent	30.427	0.000	Reject
Brent is not the Granger cause of Kilian	3.660	0.301	Fail to reject
Kilian is not the Granger cause of WTI	21.526	0.000	Reject
WTI is not the Granger cause of Kilian	4.267	0.234	Fail to reject

Table 4
Perron and Vogelsang (1992) Unit root test.

		d_1	(rho-1)	constant	Optimal Breakpoint
WTI	Coefficient	50.978	−0.069	23.621	2005M10
	T-statistic	30.489	−4.608		
	P-value	0.000	−3.560 (5% critical value)		
Brent	Coefficient	56.426	−0.067	22.485	2005M09
	T-statistic	29.522	−3.813		
	P-value	0.000	−3.560 (5% critical value)		
Kilian	Coefficient	−25.857	−0.046	1.315	2015–12
	T-statistic	−4.781	−5.506		
	P-value	0.000	−3.560 (5% critical value)		

have interpreted when the WTI oil price is used as the proxy.

Shown in Figs. 6–8, we next discuss the results when other confounding factors are controlled for: armed conflicts, economic policy uncertainty and equity market uncertainty. The results where the WTI oil price index is used are reported in the left two panels, while the results where the Brent oil price index is used are reported in the right two panels. As for partial wavelet coherency analysis, we observe similar patterns across different choices of oil price proxies and control variables: relationship between global economic activity and oil prices are significantly strong at higher frequencies (especially for frequencies less than 1.5 years) during all the sample period. Strong dependence and co-movement between global economic activity and crude oil prices indicates that oil market participants of shorter investment horizons should pay special attention to such nexus for decision makings. On the other hand, like partial phase difference analysis where we control for geopolitical risk, the correlation at lower frequencies also tends to be slightly stronger compared to the results of phase difference shown in Fig. 4.1 and 5.1. Additionally, the results again stress the relevance of fluctuations of global economic activity for long-term investors after 2005. Nevertheless, the general pattern of co-movement between the oil prices and Kilian index does not change: it is strong in the short run, while it becomes weaker in the long run.

The results of partial phase difference are also robust and similar as

Table 5
Narayan and Popp (2010) Unit root Test.

Variables	M1 (Break in intercept)				M2 (Break in intercept and trend)			
	t-statistics	TB-1	TB-2	k	t-statistics	TB-1	TB-2	k
WTI	−6.386***	2004–06	2014–09	12	−7.499***	2004–06	2014–09	12
Brent	−5.949***	2004–01	2014–09	12	−5.016***	2004–02	2014–09	10
Kilian	−6.041***	1998–01	2008–03	12	−7.130***	1998–05	2008–03	12

Notes: *** indicates significance at the 1% level. The finite sample critical values are computed by the Monte Carlo simulation and *k* is the number of lagged differences in the Narayan and Popp (2010) unit root test.

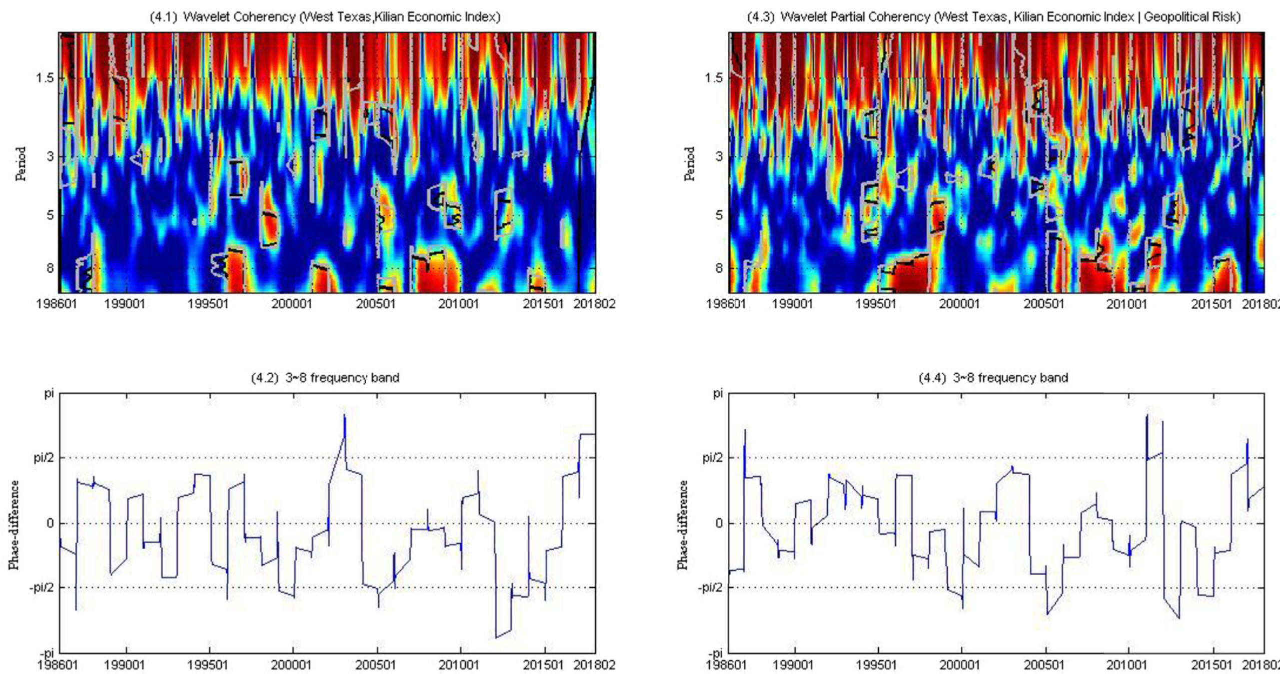


Fig. 4. Wavelet coherency and phase difference of Kilian economic Index-WTI.

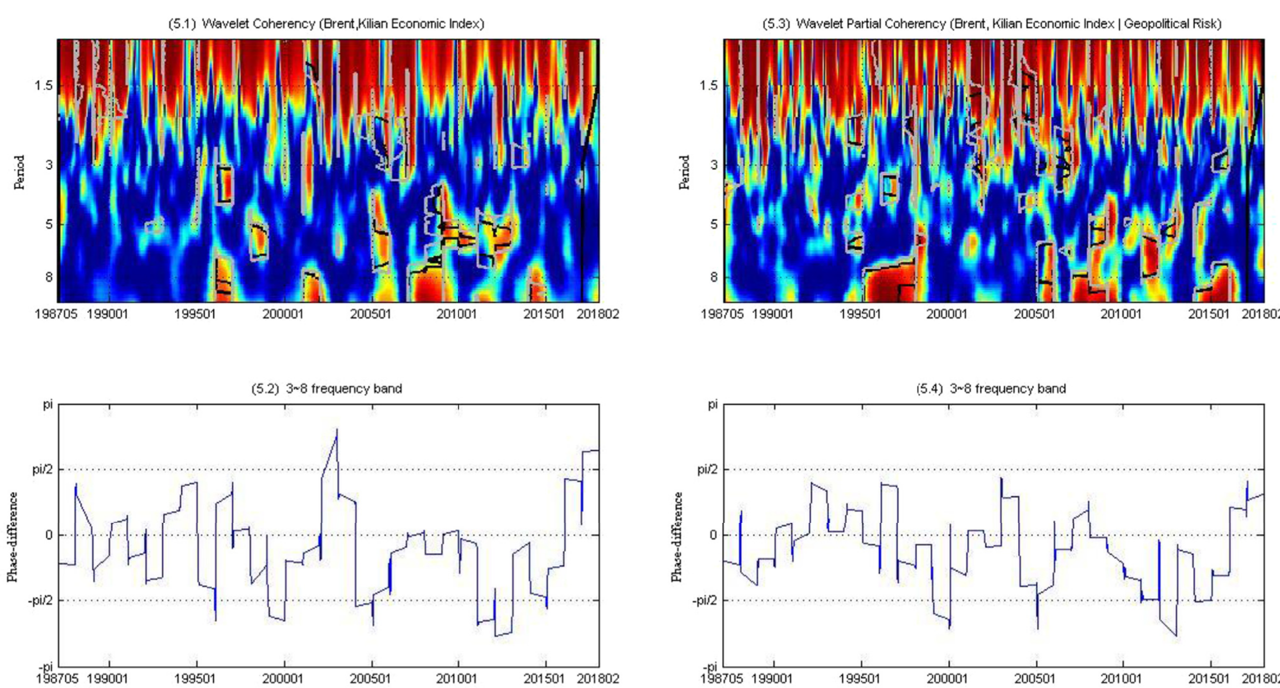


Fig. 5. Wavelet coherency and phase difference of Kilian economic index-Brent.

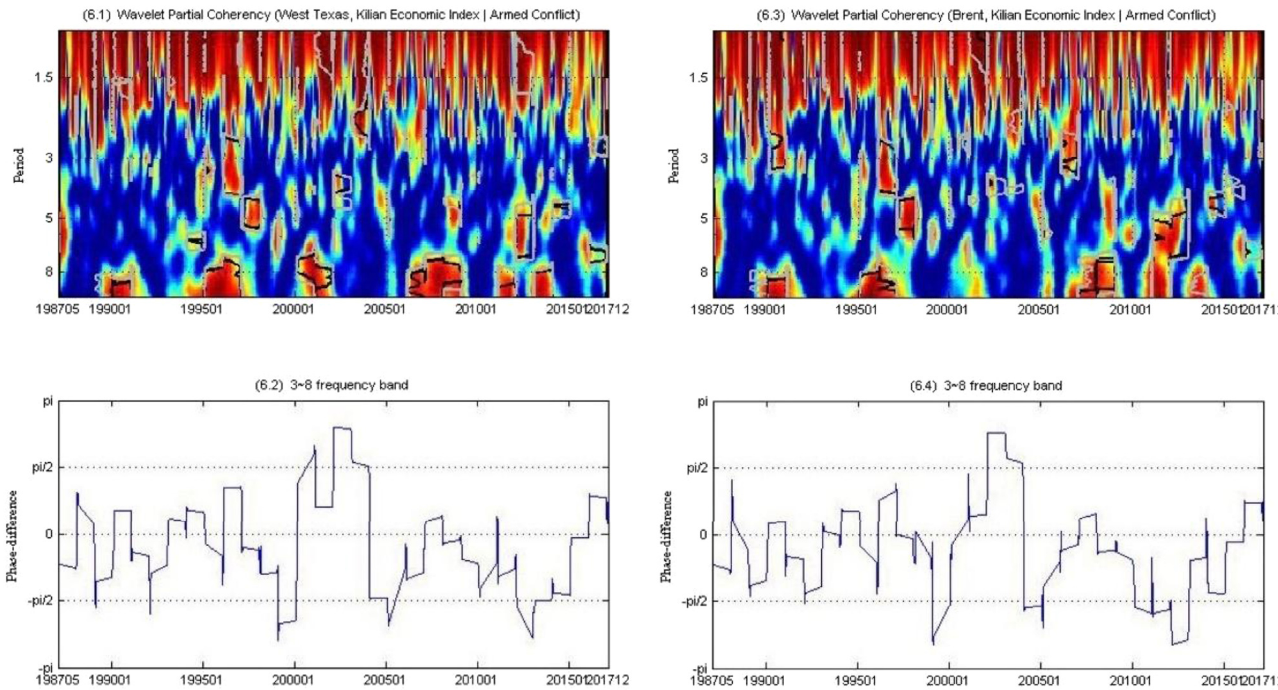


Fig. 6. Partial wavelet coherency and partial phase difference: Armed conflicts controlled.

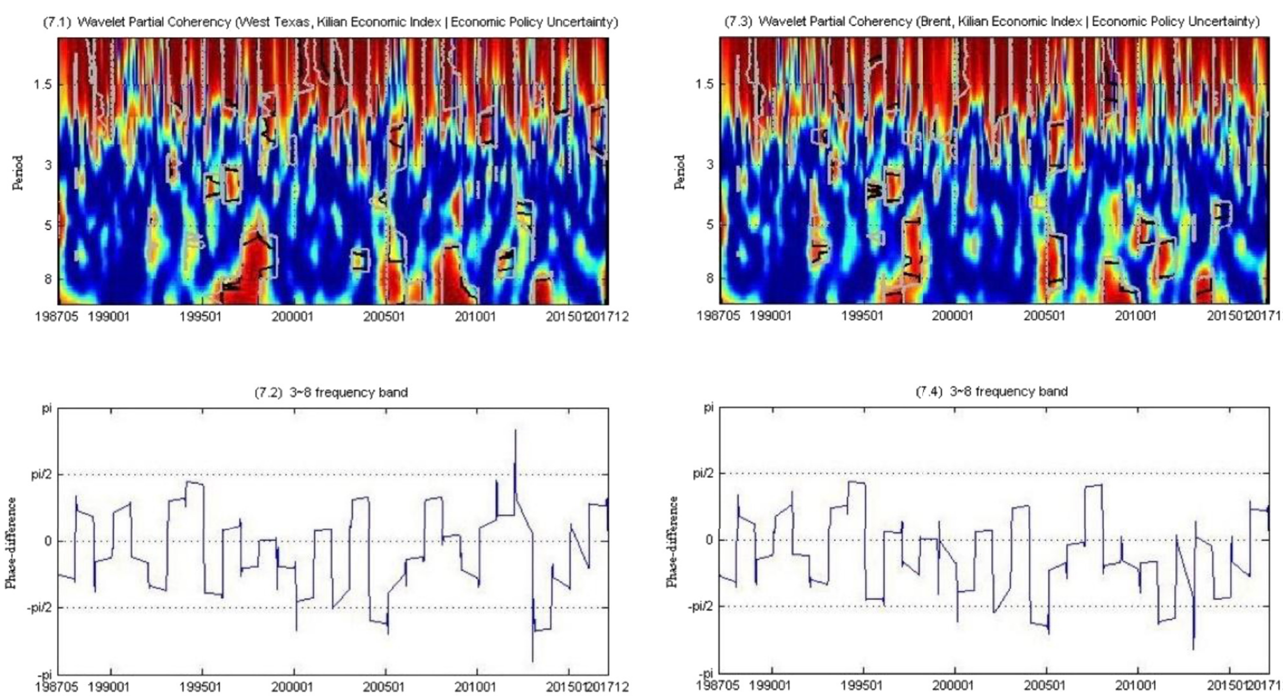


Fig. 7. Partial wavelet coherency and partial phase difference: Economic policy uncertainty controlled.

those where we control for geopolitical risk. The correlation between the Kilian economic index and the crude oil prices maintains positive in almost all sample period, and the lead-lag relationship varies across time. Overall, we find robust evidence that the two series move in phase and that there exists significantly dynamic causality between the two variables.

4.2.5. More evidence using the OECD industrial production as a proxy for global economics activity

Finally, we check whether our conclusions are sensitive to our choice of indicator for global economic activity. We resort to an alternative measure: the OECD industrial production.[22] We re-apply the wavelet analysis, the results of which are documented in Fig. 9. The left panels present the results where the WTI oil price index is used, and the right

[22] The OECD industrial production refers to the volume of output in OECD countries generated by production units classified under the industrial sectors, including mining, manufacturing, electricity, etc. This indicator is available at the monthly frequency and is obtained from the OECD Statistics.

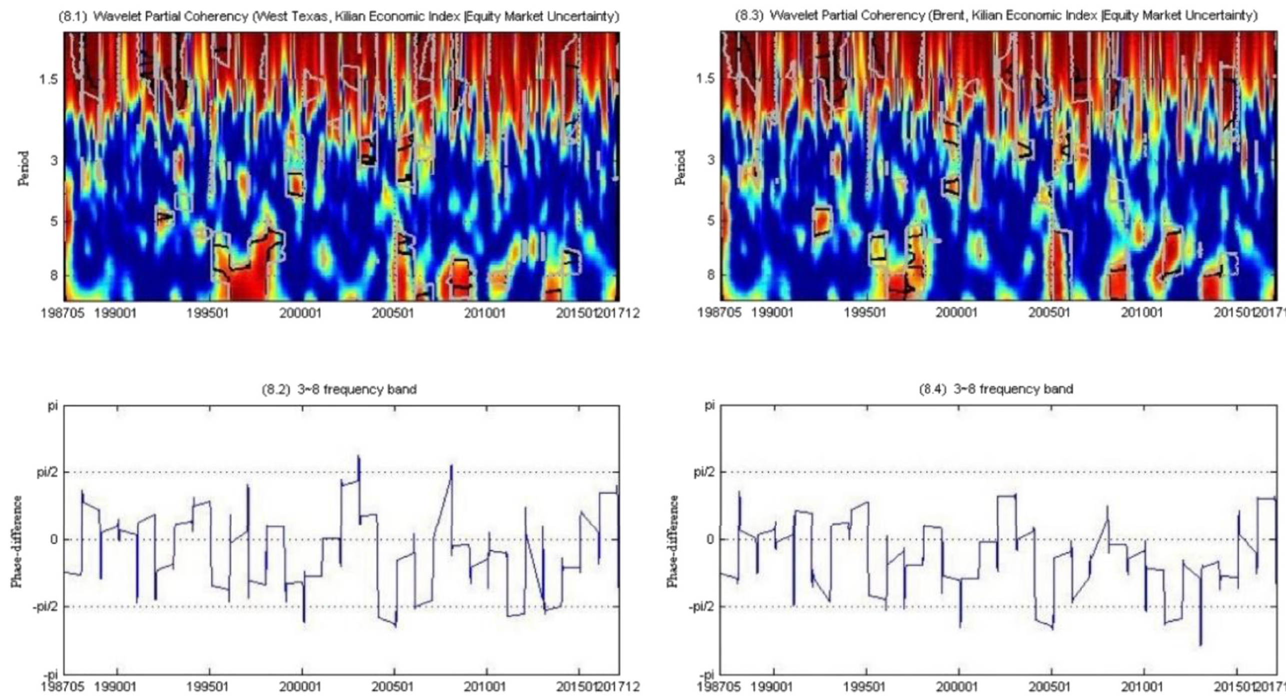


Fig. 8. Partial wavelet coherency and partial phase difference: Equity market uncertainty controlled.

panels present those where the Brent oil price index is used. Compared with earlier results, consistent findings can be observed: the crude oil prices and OECD industrial production has strong co-movement in the short run but rather weak and less persistent correlation in the long run; the lead-lag relationship between the oil prices and the Kilian economic index are dynamic with a positive correlation.

5. Concluding remarks

Although global economic activity is widely perceived as a key factor impacting the world demand for oil and thus oil prices, there have been limited studies that specifically focus on the nexus between the global economic activity and oil prices. Compared with previous literature which all conduct analysis exclusively in the time domain, we attempt to revisit the relation between crude oil prices and global economic activity from a dynamic perspective in both time- and frequency domains. We do so by utilizing a novel approach of wavelet analysis. We provide robust evidence that correlation between crude oil prices and global economic activity varies across not only frequencies but also time. Generally, we find that the two series have strong degree of co-movement in high

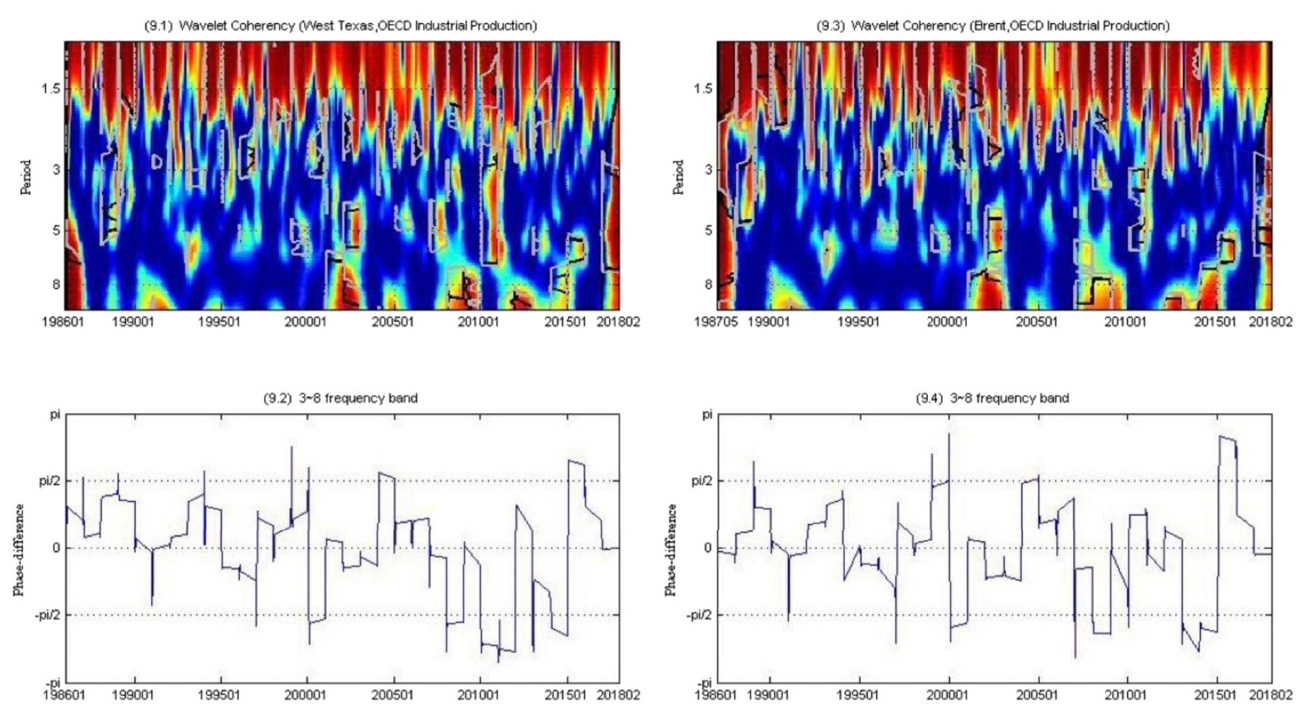


Fig. 9. Wavelet coherency and phase difference of OECD industrial production - crude oil prices.

frequencies (short-term fluctuations), whereas the evidence of co-movement in low frequencies (long-term fluctuations) is relatively weaker. We also demonstrate dynamic lead-lag relationship between global economic activity and oil prices, with a positive correlation.

Our finding provides critical implications for participants in the oil market. First, global economic activity offers particularly useful information for short-term investors, which they should incorporate in their market forecast and decision making. Given our results that global economic prosperity results in higher oil prices, the short-term oil investors should consider adding assets in front of new information under which global economic outlook can be stimulated. Second, although the relevance of global economic activity is generally not as strong for long-term investors in the past 30 years, our results also indicate potential room of profitability for long-term investors by taking advantage of information in global economic activity. This is especially the case given the structural break of the relationship at 2005, since when global economic activity and oil prices manifest to some extent close nexus again. Third, we observe that oil prices move in phase with the global economic activity, no matter in the WTI market or the Brent market, no matter in low or high frequencies. The results suggest no room for hedging or risk diversification through investing across different oil markets or oil financial assets with different maturity lengths.

We admit our study has certain limitations. Taking a global economy perspective indicates inadequate information offered for a specific country under certain circumstances. For instance, if the objective is to understand the impact of oil price fluctuations on macroeconomy, then the results of our study may be less informative to provide country-specific implications. Nevertheless, we believe that our findings provide critical implications when one looks into how the oil price is impacted by the global economic activity. Since the oil market should be viewed as a global market, the information on global economic variations offers general implications on the world oil price to investors in any country, at least among oil importers. Particularly, our results stress that oil market investors or policy makers in any country should understand that the impact of global economic activities is mostly relevant for world oil price fluctuations during the short run, whereas it is not so much in the long run. On the other hand, we also admit that oil prices may vary across different local markets and may be significantly affected by region- or country-specific factors such as geopolitical situation. Our study only investigates the relationship between global economic activity and world benchmark oil prices. We do not claim to answer how global economic activity influences differentially prices at country-specific markets.

Some questions remain unanswered and should be examined later. For instance, as a reduced-form study, our paper does not offer precise answers for why the oil price and global economic activity co-moves strongly in high frequencies but not in the low frequencies. Future study can revisit and further investigate the question and other related issues as more and richer data becomes available. Econometricians may also incorporate such dynamics to propose empirical models which can better understand and predict oil price behaviors.

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