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Aviral Kumar Tiwari
Montpellier Business School
Zinnia Mukherjee
Simmons College
Rangan Gupta
University of Pretoria
Mehmet Balcilar
Eastern Mediterranean University, University of Pretoria and Montpellier Business School
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

A Wavelet Analysis of the Relationship between Oil and Natural Gas Prices

Aviral Kumar Tiwari[*], Zinnia Mukherjee[**], Rangan Gupta[***] and Mehmet Balcilar[****]

Abstract: In this paper, we aim to explore the relationship between natural gas and crude oil prices for the U.S. economy over the time period 1997 and 2017 in both the unconditional and conditional framework by conditioning the relationship on natural gas production. The time period covers the recent shale gas supply boom. Our results indicate that during the shale gas revolution period of 2007 – 2013, oil and natural gas prices were cyclical and oil prices were leading natural gas prices. Once we control for the natural gas production we find that significant or high wavelet coherency is observed during 2000-2015 for 3 to 4 years scale. These results have implications for cross market policy effects.

Keywords: Oil and Natural Gas Prices, Shale Gas Revolution, Wavelet Analysis
JEL Codes: C49, Q31

[*] Montpellier Business School, Montpellier, France, Email: aviral.eco@gmail.com.
[**] Corresponding author. Department of Economics, Simmons College, Boston, USA. Email: zinnia.mukherjee@simmons.edu.
[***] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.
[****] Department of Economics, Eastern Mediterranean University, Famagusta, via Mersin 10, Northern Cyprus, Turkey; Department of Economics, University of Pretoria, Pretoria, 0002, South Africa; Montpellier Business School, Montpellier, France. Email: mehmet@mbalcilar.net.

1. Introduction

The United States has long been on the search for alternative energy sources to meet its growing energy demand and reduce dependency on coal and oil based energy sources. The oil crises of the 1970s served as a major boost to increase research and development efforts to find new and alternative domestic energy sources as they would make the U.S. economy less dependent on foreign energy sources and, hence, more resistent to external shocks such as those brought about the oil crises. Natural gas, one of the major fossil fuels, is an alternative energy source that can be economically viable. In the United States, natural gas is classified into two types: (1) natural gas from conventional gas fields, and (2) unconventional natural gas. Historically, conventional natural gases have been more easily extractable because they are found trapped in permeable material in the earth.[1] In contrast, uncoventional natural gases are difficult to exploit because they are often dispersed over large areas that are not easily accesible. Compared to conventional natural gases, unconventional gases involve advanced methods of extraction, which are relatively new and costly.

Among the four types of unconventional natural gases, shale gas has steadily grown in importance as an alternative energy source for the United States. The gas is found trapped between the layers of shale formation known as "shale plays". Shale is a sedimentary rock composed of fine-grained particles. In the United States, shale gas was first produced commercially in 1821 in Fredonia, NY.[2] Since 1930, the development of large pipelines for extracting and transmitting this natural gas to different parts of the country led to steady increase in the volume of commercially produced shale gas. In 1947, a hydraulic fracturing experiment was carried out in Grant, Kansas, to stimulate oil and gas wells for increasing production levels. Hydraulic fracturing is a technique used for stimulating oil and gas wells by fracturing the rock where the gas is trapped with the help of a pressurized liquid such as

[1] Source: https://pubs.usgs.gov/fs/fs-0113-01/fs-0113-01textonly.pdf
[2] Source: https://www.energy.gov/sites/prod/files/2013/04/f0/where_is_shale_gas_found.pdf

water. The cracks created in the rocks help to move the trapped oil (petroleum) or natural gas freely. Since 2000, advancement in extraction technology such as hydraulic fracturing and horizontal drilling made access to large deposits of shale gas economically feasible, which resulted in a rapid increase in U.S. shale gas production. In 2014, shale gas comprised more than 40% of total U.S. natural gas production (US Energy Information Administration 2014a). Currently, the United States is one of only four countries that produce shale gas commercially, the other being Canada, China, and Argentina.

In the United States, shale gas is found in many areas. About 91 percent of total U.S. shale gas proved reserves are contained in the seven shale plays (reference). The following table lists the major shale plays in the United States with the proved shale gas reserves available there.[3]

Basin	**Shale Play**	**States**	**2015 Reserves (trillion cubic feet)**
Appalachian	Marcellus	PA, WV	72.7
Western Gulf	Eagle Ford	TX	19.6
Arkoma, Anadarko, S.OK	Woodford	OK	18.6
Fort Worth	Barnett	TX	17.0
TX-LA Salt	Haynesville/Bossier	LA, TX	12.8
Appalachian	Utica/Pt. Pleasant	OH	12.4
Arkoma	Fayetteville	AR	7.1
Sub-total			**160.3**
Other Shale			
All U.S. shale			**175.6**

Table 1: Distribution of shale gas reserves in the United States

The growing importance of shale gas as an alternative energy source and its recent (rapid) increase in production, have generated an interest in scholars across disciplines that study different aspects of energy sources and their environmental and economic impact. The recent shale gas revolution has important widespread implications for the U.S. economy. To understand the potential impact of an abundance of supply in this market, Brown and

[3] Table 1 reference: https://www.eia.gov/naturalgas/crudeoilreserves/pdf/usreserves.pdf

Krupnick (2010) simulate the effects of a lower gas price under varying scenarios of natural gas availability, demand for natural, climate change related policies, and the availability of competing resources. Their model findings indicate that the rise in shale gas production and the projected increase in its use can lead to a small drop (less than 1 percent) in total U.S. carbon dioxide emissions. Hausman and Kellogg (2016) conducted a comprehensive analysis of the welfare effects associated with shale gas production in the United States. Specifically, they analyse the impact of the recent shale gas supply boom on the welfare of consumers and producers of natural gas. They find the expansion of natural gas supply between 2007 and 2013 reduced U.S. natural gas price by $3.45 per thousand cubic feet (mcf). The supply boom led to large increases in surplus for consumers of natural gas and a reduction in production surplus because the fall in price outweighed the gain in supply. Shale gas production and use can result in both positive and negative externalities. An example of a positive external effect would be when shale gas is substituted for coal, such as in electricity production, and hence, potentially lower emissions from coal use, which are known to impact human health adversely (Mason et al., 2016). However, the discussion on the environmental impact of shale gas production has been more about the negative external effects associated with its production. The production process has a direct impact on current and future water supply because hydraulic fracturing uses large amount of water. The technology involves drilling wellbores through drinking water aquifers, and generates large volumes of wastewater. Also, there are serious concerns associated with fracking at the city, town, and state level. Although natural gas, in particular shale gas, can have some positive impact on greenhouse gas emissions, shale gas production is also associated greenhouse gas (GHG) emissions. Howarth et al., (2011) were the first to provide estimates of the GHG footprint of shale gas by focusing on methane emissions associated with shale gas production. The authors find that in the long run, the GHG footprint of shale gas is to be significantly larger than that of conventional gas or oil, which raises concerns about its long term potential to mitigate global warming. The

more immediate impact of shale gas production is the viability as a substitute for conventional fossil fuel energy sources such as coal and oil. Given the recent supply boom as a result of advancement in extraction technology, there is a growing interest among scholars and policymakers about the impact of the rise in shale gas production on the U.S. energy market, particularly the impacts on alternative energy prices.

In this paper, we aim to explore the relationship between natural gas and crude oil prices for the U.S. economy over the time period 1997 and 2017. The period covers the period of the shale gas production boom, a major event in the natural gas market. We advance the existing literature by conducting a wavelet analysis of the relationship between the variables of interest. Wavelet is a time-varying methodology across time and frequency domains. The method requires the decomposition of a time series into time-frequency space, which allows researchers to identify the dominant modes of variability and the variations of those modes over time (Torrence and Compo, 1998). It is often used in geophysical applications when time series data may be non-stationary and the series can contain dominant periodic signals, which can vary in both amplitude and frequency over long time frames. For example, in the context of equatorial sea surface temperature in the Pacific Ocean, the dominant mode of variability is identified as El Niño-Southern Oscillation (ENSO). To capture the interdecadal changes in variance and coherence in ENSO and Indian monsoons over 125 years, Torrence and Webster (1999) applied a wavelet analysis to isolate the timescales of the ENSO-monsoon variability and used significance tests to assess the robustness of their results.

In the economics literature, wavelet analysis have been used to study economic time series data that at contain combinations of components operating on different frequencies. In economics literature, Lee (2004) was one of the first to apply the wavelet methodology to analyse the international transmission mechanism of stock market movements. Conraria et al. (2008) applied the methodology to study the time-frequency effects of U.S. monetary policy.

Using long term monthly data on macroeconomic variables from 1921 to 2007, the authors were able to disentangle the short, medium, and long relations between the variables that determine the impact of monetary policy. Yogo (2008) used the wavelet analysis to decompose U.S. real GDP data from 1947 to 2003 into trend, cycle, and noise.

Our paper is related to two papers - Caporin et al., (2016) and Monge et al., (2017). Caporin et al. (2016) use data from 1997 to 2013 and find the presence of a structural break around 2007 that corresponds with the sharp rise in shale gas supply. Then they apply a Vector Error Correction Model (VECM) to show that shale production between 1997 and 2013 impacted the relationship between oil and natural gas prices. They conclude that on the basis of available data, they are unable to state unequivocally that there exists a long run relationship between oil and gas prices. A VECM specification depends only on time domain and constant parameter whereas the application of wavelet methodology allows us to study both short- and long run frequencies and thereby recognize how the relationships among the key variables have evolved in the short, medium, and long term. Monge (2017) study the relationship between U.S. crude oil production and WTI crude oil prices between 2000 and 2016. They study the performance of the relationship in the time-frequency domain by applying wavelet tool for its resolution. They observe higher frequencies between 2003 and 2009, which suggest a short term relationship, and low frequencies for the period between 2009 and 2014, which indicates a presence of a long term component in the relationship between crude oil production and crude oil prices.

However, in terms of the question we ask dealing with effect of natural gas on oil prices in the wake of the shale gas revolution, our paper is most closely related to the works of Geng et al., (2016a, b, c, 2017), Ji et al., (2018), Zhang and Ji (2018). These studies using variety of econometric methods covering nonparametric, regime-switching, directed acyclic graphs, multi-scale perspective, in general tends to suggest weak relationship between the two prices of concern. We aim to build on the above mentioned works, especially nonlinear

causality approach of Geng et al., (2017) and to some extent the correlation analyses of Geng et al., (2016 a, b), with the variables being disaggregated into their various frequencies based on Ensemble Empirical Mode Decomposition (EEMD). We do this by relying on coherency and phase-differences in a wavelet analysis, which allows us to provide time-varying causal relationship across frequencies between natural gas and oil prices, without having to look at sub-sample analysis based on pre and post- the shale gas revolution.

The structure of this paper is as follows. In the following section, we describe the dataset we use in the analysis and provide the descriptive statistics of it. Section 3 presents an overview of the methodology applied. In section 4, we discuss the results of the empirical model. Finally, Section 5, provides a few concluding remarks on the policy implications of our findings.

2. Data

We use monthly data from January 1997 to July 2017 for all our variables. Data on natural gas prices are the Henry Hub Natural Gas Spot Price. The data on natural gas quantity, measured in million cubic feet (MMcf), are given by the U.S. natural gas gross withdrawals obtained from the EIA database. We include data on crude oil given by the Crude Oil Real Spot Prices (WTI, dollars per barrel) at Cushing, Oklahoma obtained from the EIA database. All variables are included in the analysis in their natural logarithmic form. The following table (Table 2) provides the descriptive statistics of the data for the full sample.

Variable Name	Mean	Median	STD	Max	Min
Henry Hub Natural Gas Spot Price (Dollars per Million Btu)	4.428	3.830	2.235	13.420	1.720
Cushing, OK WTI Spot Price FOB (Dollars per Barrel)	55.601	49.780	29.915	133.880	11.350
U.S. Natural Gas Gross Withdrawals (MMcf) [NGW]	2211930.522	2080504.000	278852.752	2828428.000	1766603.000
CPI	203.790	206.755	27.036	246.373	159.400
Real Natural Gas Price [NGP]	2.198	1.798	1.120	6.740	0.727
Real WTI Price [WTI]	26.257	22.509	12.338	61.564	6.904

Table 2: Descriptive Statistics

3. Methodology

The objective of the wavelet analysis is to determine the frequency content of a variable with a view to extracting the temporal variation of this frequency content (Labat, 2005). A wavelet is a function with zero mean localized in both time and frequency. It grows quickly and decays within a limited period (Fan and Gençay, 2010) thereby obeying the conditions that $\int \psi(\eta)d\eta = 0$ and $\int |\psi(\eta)|^2 d\eta = 1$. We can characterize a wavelet by its localization in time (Δt) and frequency ($\Delta\omega$ or the bandwidth). Thus, for a CWT of series $x(t)$

$$W_x(s,\tau) = \langle x(t), \psi(t) \rangle \equiv \int_{-\infty}^{\infty} x(t) \circ \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) dt \tag{1}$$

where s and τ are the scale and location parameters and $\psi((t-\tau)/s)$ is known as the mother wavelet function that is possibly complex-valued. The symbol $\circ$ is the convolution operator. A complex wavelet function is of valuable utility in economic analysis as it gives information on local phase. One such function having this property is the Morlet wavelet function. Besides, the Morlet wavelet function can be shown to achieve an optimal localization between the resolution in time and in frequency due to its Gaussian envelop. This property is guaranteed by Heisenberg's uncertainty theorem stating that there is a lower limit to the product of time and frequency resolution. Also implying a trade-off between the resolution in time and in frequency, the theorem ensures that any improvement in time degrades the frequency resolution and any improvement in frequency degrades the time resolution. Thus, to achieve optimal balance, we employ the Morlet wavelet function given by

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2} \tag{2}$$

where ω_0 is dimensionless frequency and η is dimensionless time. For optimal balance, we set $\omega_0 = 6$ as suggested by Torrence and Compo (1998). Since the idea behind the CWT is

to apply the wavelet as a band pass filter to the time series, the wavelet is stretched in time by varying its scale s, so that $\eta = s \cdot t$ and normalizing it to have unit energy. For the Morlet wavelet, the Fourier period (λ_{wt}) is almost equal to the scale $(\lambda_{wt} = 1.03)$ s. The wavelet transform also inherits this property. The discretized version of Equation (1) for time series $\{x_n : n = 1,...,N\}$ is given by

$$W_m^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \cdot \psi^* \left((m-n) \frac{\delta t}{s} \right), \quad m = 1,2,\ldots,N-1 \tag{3}$$

where δt is the uniform step size. From the expression above, the wavelet power that measures the variability in the time series both in time and in frequency is defined as $\left| W_m^x(s) \right|^2$. The CWT suffers from edge effects caused by a discontinuity at the edge because wavelet is not completely localized in time. To cope with this challenge, the cone of influence (COI) has been introduced. The COI earmarks the area where edge effects cannot be ignored and determines the set of CWT coefficients influenced by the value of the signal at a specified position. Outside COI, edge effects are predominant and can distort the result. Here we take the COI as the area in which the wavelet power drops to e^{-2} of the value at the edge.

2.2 Wavelet coherence (WTC)

Since our intention is to measure the extent of synchronization between two given time series, it is informative to use coherence between them. Wavelet coherence is a time-frequency counterpart of the time-domain coefficient of determination and shares property with traditional correlation coefficient. Aguiar-Conraria et al. (2008, p. 2872) defines wavelet coherence as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series". Following Torrence and Webster (1999), we define the wavelet coherence between two time series as

$$R_m^2(s) = \frac{\left|S\left(s^{-1}W_m^{xy}(s)\right)\right|}{S\left(s^{-1}\left|W_m^x\right|^{\frac{1}{2}}\right)\cdot S\left(s^{-1}\left|W_m^y\right|^{\frac{1}{2}}\right)}, \tag{4}$$

where S is a smoothing operator and $W_m^{xy} = E[W_m^x \widetilde{W}_m^y]$ is the cross-spectrum, with $\widetilde{W}_m^y$ as the complex conjugate of W_m^y. Notice that $0 \le R_m(s) \le 1$ while for the traditional correlation coefficient (ρ) $0 \le \rho \le 1$. Without smoothing coherency is identically 1 at all scales and times. We may further write the smoothing operator S as a convolution in time and scale:

$$S(W) = S_{scale}(S_{time}(W_m(s))), \tag{5}$$

where S_{scale} denotes smoothing along the wavelet scale axis and S_{time} denotes smoothing in time. The time convolution is done with a Gaussian and the scale convolution is performed with a rectangular window (see, for more details, Torrence and Compo 1998). For partial continuous wavelet transform, Aguiar-Conraria, and Soares (2011) define coherence as

$$R_m^2(s)_{X,Y|Z} = \frac{\left|Q_{XY}^M\right|^2}{Q_{XX}^M Q_{YY}^M}, \tag{6}$$

where Q_{XY}^M, Q_{XX}^M and Q_{YY}^M are the minors associated with the smoothed cross wavelet transforms $\left|S\left(s^{-1}W_m^{XY}(s)\right)\right|^2$, $S\left(s^{-1}\left|W_m^X(s)\right|^2\right)$ and $S\left(s^{-1}\left|W_m^Y(s)\right|^2\right)$ respectively in a 3×3 matrix Q. This trivariate model was used in Ng and Chan (2012) and is a specific form of the multivariate case, where the effects of all other variables are removed from the coherence between x and y. It is important to conceptualize the lead-lag relationship between two time series. This is achieved by computing the phase difference given by

$$\phi_{x,y} = \tan^{-1}\frac{\Im\{W_m^{xy}\}}{\Re\{W_m^{xy}\}}, \qquad \phi_{x,y} \in [-\pi, \pi] \tag{7}$$

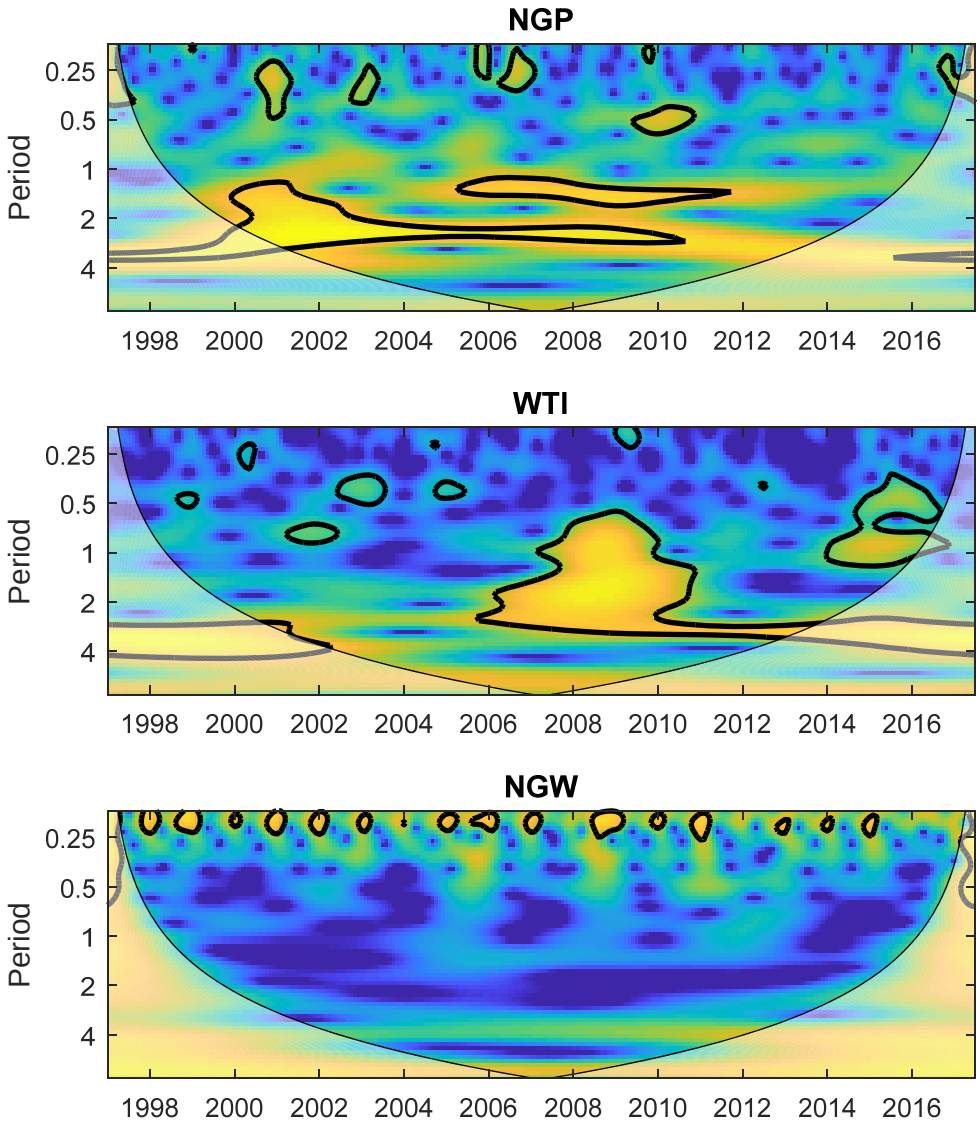
where $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum respectively. Phase differences are useful to characterize phase relationship between any two time series. A phase difference of zero indicates that the time series move together at the specified frequency. If $\phi_{x,y} \in [0, \pi/2]$, then the series move in-phase, with the time-series y leading x. On the other hand, if $\phi_{x,y} \in [-\pi/2, 0]$ then x is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of π (or $-\pi$) meaning $\phi_{x,y} \in [-\pi/2, \pi] \bigcup [-\pi, \pi/2]$. If $\phi_{x,y} \in [\pi/2, \pi]$ then x is leading, and the time series y is leading if $\phi_{x,y} \in [-\pi, -\pi/2]$.

3. Results analysis and discussion

In this paper, our objective is to examine the relationship between natural gas price and oil price in the unconditional and conditional framework by conditioning the relationship on natural gas production. For this purpose, we used monthly data from January 1997 to July 2017 for the analysis.

Figure (1) below has three panels in which we present results of continuous wavelet power spectrum. In the first panel, it is evident from Figure 1 that there are some common features in the wavelet power of between natural gas price and oil price. Specifically, the common features in the high (or significant) wavelet power of the two-time series are evident in 1~4 years scales that belong to 2005 to 2013. However, the observed similarity between the portrayed patterns of the two series in these periods may merely be a coincidence rather a results of a cause and effect relationship. To analyse the relationship between natural gas price and oil price we used conditional and unconditional framework of continuous wavelet transform, namely wavelet coherency and partial wavelet coherency and phase difference associated with each model.

Figure 1: Continuous Wavelet Power Spectra of the series



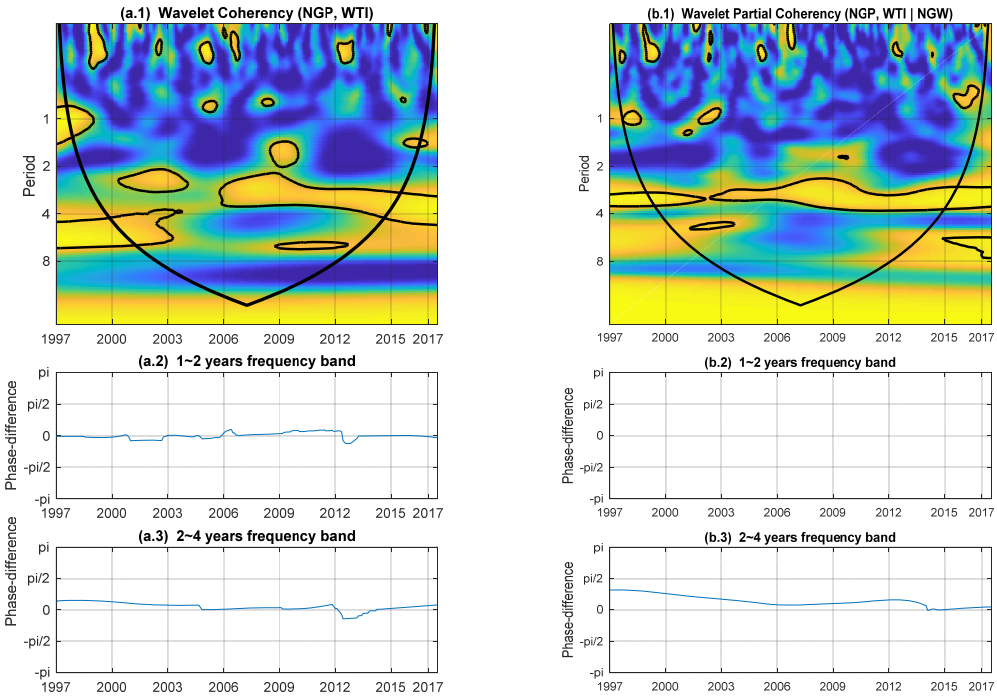
The results of wavelet coherence, partial wavelet coherence and associated phase-differences are presented in Figure 2. In figure 2, part a.1 presents results of wavelet coherency and b.1 shows the results of partial wavelet coherency while explicitly controlling for natural gas production. Part a.2 presents the phase-differences associated with the wavelet coherency exhibited by a.1. Similarly part b.2 presents results related to the phase-differences associated with the partial wavelet coherency exhibited by b.1 by explicitly controlling for natural gas production over the time period. The wavelet coherencey between natural gas price and oil

price in panel (a.1) show that there is evidence of significant wavelet coherency during 2006 – 2015 for 2 to 4 years scale. However, once we control for the natural gas production we find that significant or high wavelet coherency is observed during 2000 -2015 for 3 to 4 years scale. We also notice that between 2007 to 2009 there is increase the wavelet power of the coherency i.e., the region of yellow color is increased and high wavelet coherency power is observed during the scale of 1.5 to 2 years period. Now if we analyse the results from the phase-differences we find from Figure A1 and A2 that during 2006-2015 for both scales i.e., 1 to 2 years scale and 2 to 4 years scale phase-differences are between $[0, \pi/2]$ indicating that both series move cyclically and oil price leading natural gas price throughout period except in 2013 when phase difference are between $[0, -\pi/2]$ which indicates that during this period natural gas production is leading.

Finally, when we analyse the results obtained from the phase-difference of partial wavelet coherency as reported in b.2 and b.3 for 1 to 2 years scale and 2 to 4 years scale respectively, we find that till 2004 phase-differences lie between $[0, -\pi/2]$ which indicates that during this period natural gas price is leading. Further, evidence show that from 2007 to 2010 the phase-differences are between $[0, \pi/2]$, indicating that both series move cyclically and oil price leading natural gas price. Last but not least, if we study the case of 2 to 4 years' phase-difference we find that phase-differences always are between $[0, \pi/2]$ indicating that both series move cyclically and oil price leading natural gas price. So in general, the effect of natural gas price on WTI price, especially in the wake of the so-called shale gas revolution is not evident, and tends to support the works of Geng et al., (2016a, b, c, 2017), Ji et al., (2018), Zhang and Ji (2018).[4]

[4] As a robustness check, we also conducted (1000) bootstrapped time-varying Granger causality tests in the time domain, using rolling-, recursive-rolling, and recursive-windows (of 40 months) as developed by Balcilar et al., (2010), under both homoscedastic and heteroscedastic error distributions. These results have been reported in Figures A1 and A2 in the Appendix of the paper, and in general, confirms the findings in terms of lack of causality running from natural gas prices to crude oil prices during the shale gas revolution, especially under the rolling and recursive-rolling schemes.

Figure 2: Wavelet Coherency and Phase-differences



5. Conclusion:

The advancement of technology such as hydraulic fracking and fracturing in recent years has led to a sharp increase in production of shale gas in the United States. This supply boom has implications for the U.S. natural gas market, and more broadly the energy market. In this paper, we analysed the relationship between U.S. natural gas and crude oil prices between 1997 and 2017. We used wavelet methodology to demonstrate the impact of shale gas production on this relationship. Results indicate that when natural gas production is controlled for, there is a high wavelet coherency between the variables of interest during the years 2000 to 2015 for 3 to 4 years scale. Between 2007 and 2009, the wavelet power of the coherency further increased on the scale of 1.5 to 2 years. The results of the phase-differences show that except for a single year (2013) natural gas prices and oil prices moved cyclically between 2006 and 2015 with oil price leading natural gas prices. This indicates that when oil and natural gas prices are in-phase, they move together in the same direction with oil prices leading natural gas prices. The results of the phase differences of partial wavelet coherency

show that natural gas price was leading till 2004. The results illustrate the degree of substitutability between oil and natural gas with the crude oil market leading the natural gas market. The results imply that policies imposed on one market have implications for the market outcomes in the other market (though the net effects) will depend on which market the policy is imposed. As indicated by our results, since oil prices tend to lead natural gas prices and since the oil market is the dominant market, then a policy on the oil market can potentially have a stronger impact on the natural gas market than the other way around. For example, a tax on crude oil production , which can be expected to increase oil prices, can potentially have a stronger impact on the natural gas market outcome (through an increase in demand for natural gas and, hence, price) than a policy targeted to boost natural gas supply would have on the oil market. The cross market effects would depend on the direction of the co-movement of the variables of interest. We do not find any evidence of shale gas prices affecting oil price indicating that the in spite of the shale gas revolution, the shale gas market is still relatively small compared to the U.S. oil market. Our findings indicate that in spite of the recent spike in production, in the short run U.S. shale gas supply will not significantly reduce the economy's crude oil demand from both domestic and foreign sources. This conclusion is consistent with the arguments put forth by Kilian (2016).

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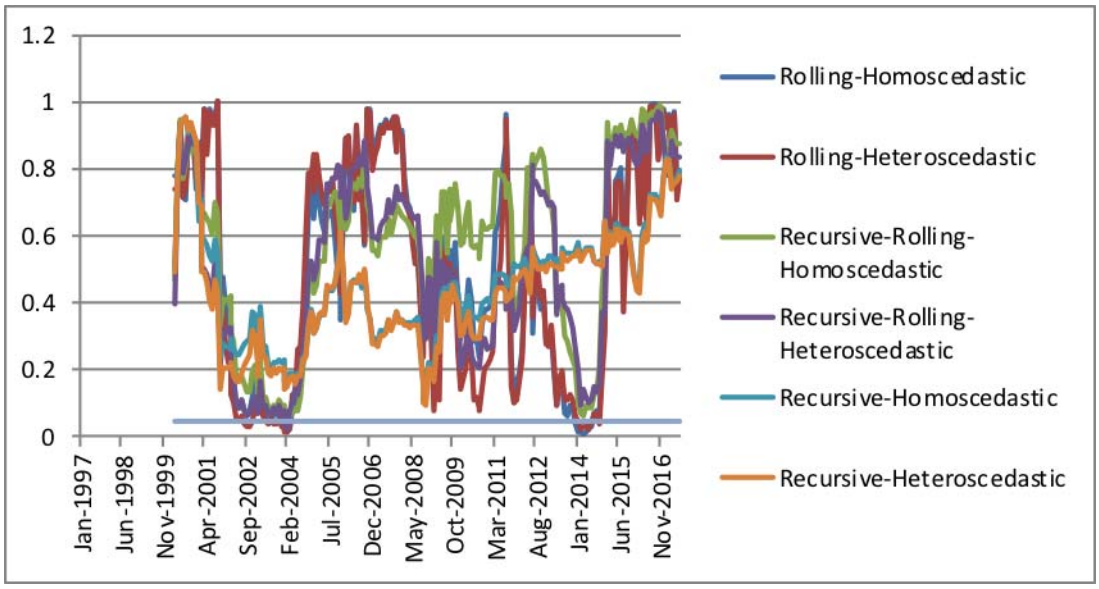
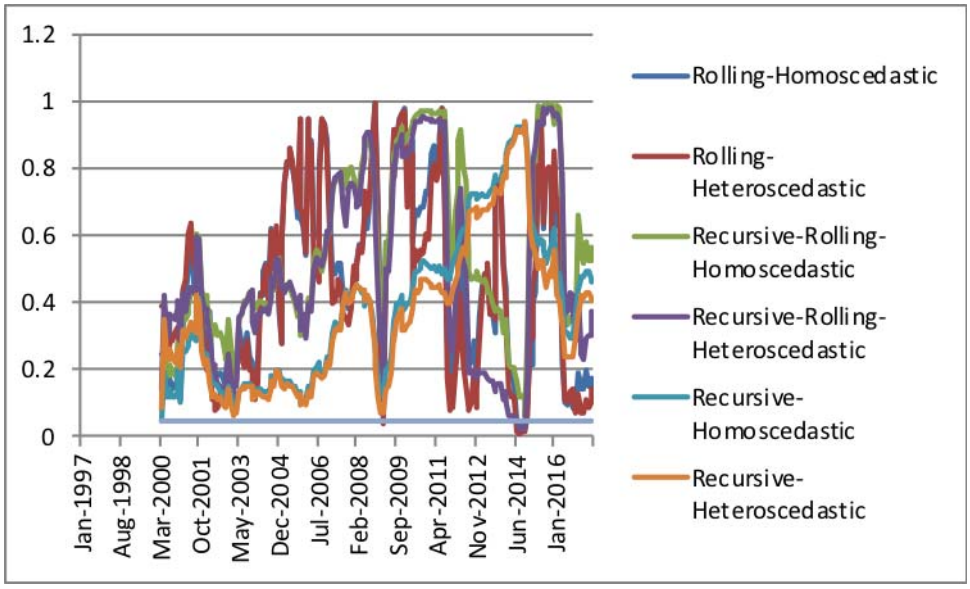
APPENDIX:

Figure A1. Time-varying causality from NGP to WTI



Note: The figure presents the bootstrap *p*-values of the rolling, recursive-rolling and recursive Wald tests which are obtained from a VAR model with a varying lag order and a window size of 40 observations. For each sub-sample, the BIC is used to select the optimal lag orders with a maximum lag order of 12. The *p*-values of the tests are obtained using 1,000 bootstrap repetitions. A horizontal line is drawn at 5%.

Figure A2. Time-varying causality from WTI to NGP



Note: See note to Figure A1.