Risk Transmission Mechanism between Energy Markets: A VAR for VaR Approach

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Abstract

The Global Financial Crisis (GFC) of 2007-2009 that originated in the US has revealed the need for measuring and monitoring the transmission of extreme downside market risk. This paper investigates the risk transmission mechanism between the oil and natural gas markets. We apply the recently introduced test statistics based on cross-quantilogram function and the multivariate quantile regression model (VAR for VaR) to the US oil and natural gas prices, which are independently formed. Our results show two asymmetric patterns. First, the shocks in the oil market substantially increase the Value at Risk (VaR) in the natural gas market. However, the reverse impact does not exist. Second, we highlight the significant asymmetric response of gains and losses transmission in energy markets, cautioning about the underlying weakness of adopting volatility to measure risk in the energy market. Moreover, extreme market risk is more easily transmitted across markets than moderate risk. Our results are in general robust in application to other regional energy markets, such as Europe and Asia, but the heterogeneities in responses are underpinned by the differing role of natural gas in regions. The findings in this paper have important implications for academic researchers, policy makers in gas-dependent economies, and business practitioners in light of projected increases in the use of natural gas worldwide as well as development of independent gas-on-gas competitive prices in Asia.

JEL Classification: F21; F30; G15

Keywords: Energy Market Integration; Risk Spillovers; VAR for VaR

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1 Introduction

Measuring and monitoring the distributional interdependence between different financial series is a primary concern among academic researchers, policy makers, and business practitioners. The global financial crisis (GFC) in 2007-2009 that originated in the US has further heightened the need for research to evaluate the transmission mechanism of extreme downside market risk. Given the changing trend of market integration, understanding the risk transmission mechanism not only helps to improve portfolio allocation strategies in seeking the international investment opportunities, but also leads to the formulation of the best policy responses for maintaining financial stability and avoiding financial contagion.

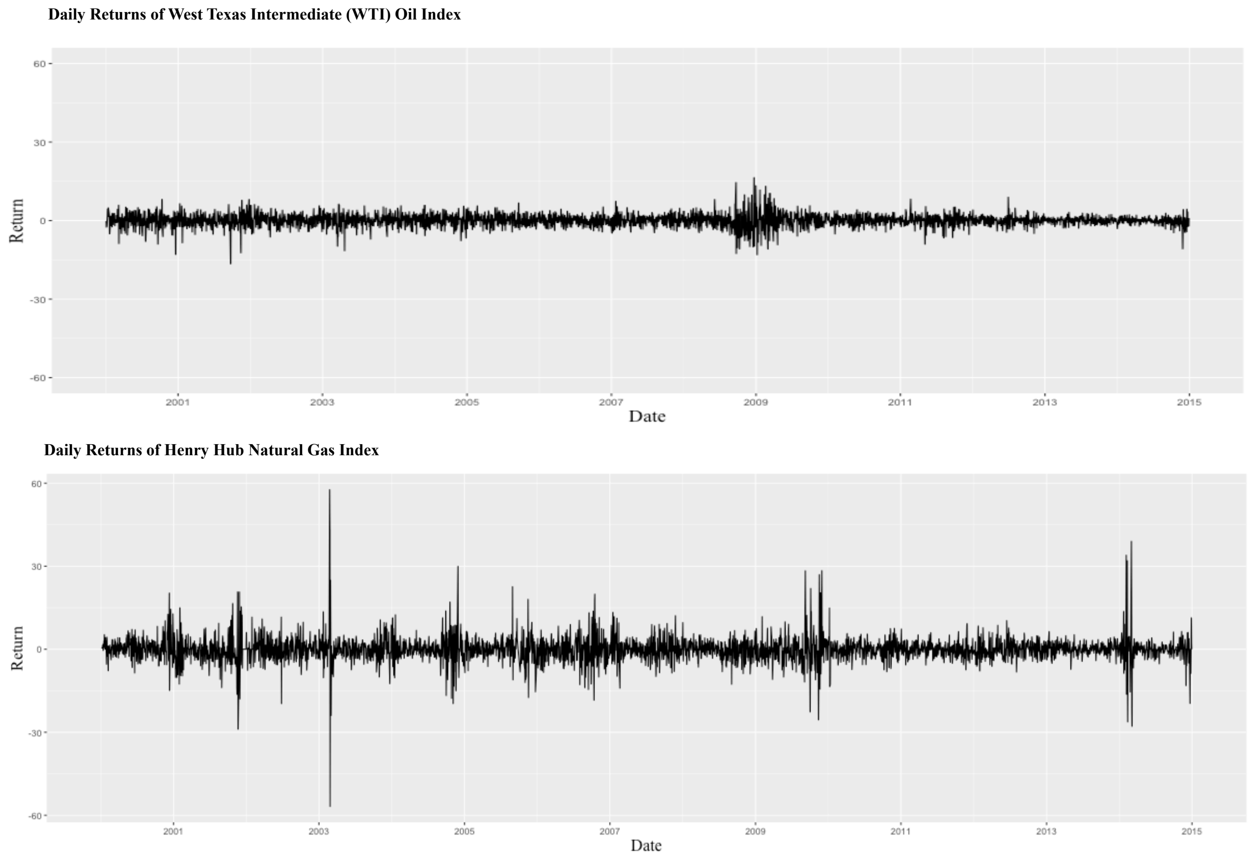
Understanding the risk spillover between energy markets has important implications for the academic researchers, policy makers, and business practitioners. Such a deepened understanding is particularly important for energy products that are being commoditized, such as natural gas (NG) and liquefied natural gas (LNG). East Asian countries are considering the development of their own oil and gas benchmark prices. From the 1960s until the early 1990s, natural gas prices were indexed to oil prices, a practice that changed in North America and is in transition in Europe but is still dominant in East Asia. The concept of Asian premium, which originated in crude oil markets, has also been extended to the natural gas market (Zhang et al., 2018). Motivated by the significant and unexplained gap between East Asian LNG prices and gas prices in North America and Europe (often called as Asian premium), East Asia is gearing up to change its dominant oil indexation in its long-term contracts to more flexible hub-indexed prices for LNG and gas imports (IEA, 2013; Shi and Padinjare Variam, 2016). One of the results of the pricing transition will be the development of regional benchmark prices for gas. Moreover, the pricing transition will cause the commoditization and financialization of gas, as new financial contracts tied to independent prices develop. This leads to a question of considerable interest to both academia and policy makers that how the commoditization, financialization, and subsequent integration of energy markets would affect the risk transmission mechanism across energy markets. Many studies observed that decoupled natural gas prices were much more volatile than oil prices (Serletis and Shahmoradi, 2005), which is illustrated in Figure 1.

In terms of policy front, a risk transmission study could generate insights that are relevant for policy makers in both gas importing and exporting countries. In particular, risk transmission presents a realistic policy question for those countries, mainly in East Asia, that face a decision on whether to change their current import pricing mechanism from oil indexation to gas-on-gas competitive prices (hub indexation).[1] If this volatility is generated by gas prices, but not passed from oil prices, the policy makers will face a significant negative consequence for their gas pricing transition decision. Revealing this latent relationship

[1]A gas trading hub is a trading market that promote gas-on-gas competition and the prices reflect gas's own market fundamentals if the competition is free from interventions and the market is liquid.

other than the price link would help them to make informed decisions about the transition and prepare for the consequences. Given the importance of East Asia in the current and future gas market, this policy concern has global policy significance. Natural gas demand growth in Asia is projected at a compound annual growth rate (CAGR) of 3.6% until 2040, thus making for almost 40% of the incremental demand for gas worldwide. As natural gas assumes an even larger role in Asia, Asian growth is driven by China and India, where gas consumption is projected to increase by 560 billion cubic metres (bcm) by 2040 from the 2014 levels (IEA, 2016). This increased role of natural gas in the Asian economy makes Asian policy makers increasingly concerned about the risk transmission mechanism between oil and gas markets. Additionally, for gas-exporting countries, especially those with a significant share of the gas-exporting sector in their national economy—such as Australia, Brunei, Malaysia, Indonesia, Qatar, and Russia—understanding the impact of a fall in crude oil prices on gas prices can help policy makers a better prepare for unexpected shocks from oil markets.

Figure 1. Daily Returns in the US Energy Market



This paper aims to trace out the dynamic risk transmission mechanism between energy markets. In particular, we address the following issues: Can information in the oil market help to predict the risk in the natural gas market? What will happen quantitatively to the natural gas market if there is a shock to the oil market? Does the risk interdependence structure change over time? Is there any different response patterns in the natural gas market between losses and gains, given the external shocks? Is the heterogeneity present in other representative regional energy markets?

In attempting to answer these questions above, we first construct recently introduced test statistics, which are based on the cross-quantilogram function, to investigate the existence of risk spillover. More specifically, a class of kernel-based tests proposed by Hong et al. (2009) is used to detect the extreme downside risk spillover between energy markets. These statistics have a convenient asymptotic standard normal distribution and can be used to check a large number of lags, thus we can detect risk spillover that occurs with time lags or that has weak spillover at each lag but carries over a very long distributional lag.[2]

After confirming the existence of the risk spillovers, we further apply a bilateral vector autoregressive model (VAR) for Value at Risk (VaR) (White et al., 2015) to quantitatively trace out dynamic risk transmission mechanism between energy markets. The idea of VaR naturally lends itself to the concept of quantile regression. Compared to the more traditional method, which models the whole multivariate distribution, the quantile approach has at least three appealing features. First, it directly models the quantile and links it to market risk. As a result, it avoids the indirect risk measure based on estimating the time-varying first and second moments. Second, the quantile regression is known to be robust to outliers, which is particularly important in analyzing financial time series. Third, the quantile regression is a semi-parametric approach and therefore imposes little distributional assumption on the underlying data-generating process (DGP). The multivariate quantile regression framework of a VAR for VaR model can be regarded as a multivariate extension of the univariate conditional autoregressive value at risk (CAViaR) model of Engle and Manganelli (2004).

To the best of our knowledge, this paper is the first study to provide a systemic analysis of an international risk-transmission mechanism, with a special emphasis on energy markets. Our paper makes the following contributions. First, we complement the studies that investigate the first- and second-moment relationships between energy markets. We extend these papers by directly focusing on the quantile interdependence structure of the energy market return distribution. In practice, the occurrence of a left quantile has a clear economic meaning as market risk. Second, our paper contributes to the current quantile regression studies by investigating the two-way quantile interdependence patterns between the US oil and natural gas markets, using the recently developed statistics based on the cross-quantilelogram function. More importantly, we extend quantile analysis used in early studies to the multivariate framework, and adopt the VAR for VaR method to explicitly capture these multilateral distributional relationships. The new method allows us to

[2] Han et al. (2016) further establish the asymptotic distribution of the cross-quantilogram and the corresponding test statistics, where the consistent confidence intervals are derived by the stationary bootstrap.

construct a dynamic tail-interdependence system, and quantitatively trace out the risk transmission patterns between energy markets. Our result shows that the shocks in the oil market substantially affect the VaR in the natural gas market. However, the risk in the natural gas market has no predictive power for the risk in the oil market. Moreover, extreme market risk is easier to transmitted across energy markets more easily than moderate risk. Third, we highlight the significant asymmetric response of gains and losses transmission in energy markets, thereby illustrating the potential weakness of adopting volatility to measure market risk. In sum, our results are valuable for anyone who needs evaluation and forecasts of the risk environment in international energy markets. Taking the extreme co-movement into account leads to an improvement in the accuracy of the out-of-sample VaR forecasts (Aloui et al., 2014).

The rest of this paper is organized as follows. Section 2 summarizes the relevant literature. Section 3 outlines the methodology used for this study, and section 4 analyzes the data sets and empirical results. The last section concludes with policy implications.

2 Literature review

Many empirical studies of energy market integration focus on market interdependence in the first and second moments (Asche et al., 2002; Siliverstovs et al., 2005; Panagiotidis and Rutledge, 2007; Zhang and Yao, 2016). In empirical financial studies, the first moment relationship between financial series refers to mean spillover, measuring the price discovery ability across the markets. The second moment relationships represent volatility spillover. In theory, it quantifies the mass of information transmits across different markets. Asche et al. (2002) tested the Law of One Price (LOP)—that is, focus on the first moment—and find that Russian gas is systematically cheaper than Norwegian and Dutch gas. Sheng et al. (2014) examine the role of energy market integration on price volatility focus on the second moment, and find that energy market integration will mitigate price volatility. Siliverstovs et al. (2005) investigate the degree of natural gas market integration in Europe, North America, and Japan between the early 1990s and 2004 and reveal that both of them show a high level of natural gas market integration within Europe, within the North American market, and between the European and Japanese markets, but the European and the North American markets are not integrated. Panagiotidis and Rutledge (2007) examine the UK wholesale gas prices and the Brent oil price over the period 1996-2003 and find that the two prices are coupled. Asche et al. (2006) tested market integration between natural gas and other energy sources in the UK and demonstrate that a single energy market exists. Furthermore, they find that the crude oil price is the driving force behind prices. Zhang and Yao (2016) analyze interdependence between crude oil, diesel and gasoline markets. They also explore the dynamic bubbles of oil prices and predict their crash time.

So far, most studies still focus on the first and second moments only. Lin and Tamvakis (2001) claim to have conducted the first study of an information transmission mechanism in the energy market, which finds that substantial spillover effects exist between two futures markets: the New York Mercantile Exchange (NYMEX) and London's International Petroleum Exchange (IPE), and IPE morning prices seem to be considerably affected by the close of the previous day on the NYMEX. A similar study with similar results was done by Lin and Tamvakis (2004). Hammoudeh et al. (2003) examine the spillover among the prices of three different petroleum products. Lin and Li (2015) explore the spillover effect between crude oil and natural gas markets in the US, European and Japanese markets within the first and second moments. The results suggest that crude oil and natural gas prices are cointegrated in Europe and Japan but decoupled in the US, and the price spillover direction is from crude oil to natural gas, not vice versa. Fan et al. (2008) assess both the extreme downside and upside VaR of returns in the West Texas Intermediate (WTI) and Brent crude oil spot markets and reveal a significant two-way risk spillover effect between the WTI and Brent markets. Chang et al. (2010) analyze the volatility spillover and asymmetric effects across and within four oil markets and reveal volatility spillovers and asymmetric effects on the conditional variances for most pairs of series.

Studies on VaR have been proliferated in the 2000s. Conventional techniques, such as generalized autoregressive conditional heteroskedasticity approach with generalized error distribution (GED-GARCH) (Fan et al., 2008), and historical simulation approach (David Cabedo and Moya, 2003), were applied in the early stage. Later, new methods, such as Extreme Value Theory (EVT) were applied. Marimoutou et al. (2009) model VaR for long and short trading positions in the oil market by applying both unconditional and conditional EVT to forecast VaR and find that the new methodology has better performance than those conventional methodologies. Aloui and Mabrouk (2010) show that considering long-range memory, fat-tails, and asymmetry is better at predicting a one-day-ahead VaR for both short and long trading positions, and the fractionally integrated asymmetric power ARCH (FIAPARCH) model outperforms the other models in the VaR's prediction. Meanwhile, the mean and volatility transmission studies have proliferated and extend beyond oil markets to between the oil and natural gas markets (Ewing et al., 2002) and between oil and other markets, such as equity markets (Arouri et al., 2012; Malik and Hammoudeh, 2007; Zhang et al., 2017), non-energy commodity markets (Ji and Fan, 2012), specifically agricultural commodity markets (Du et al., 2011; Nazlioglu et al., 2013; Serra, 2011) and, more recently, the carbon market (Balclar et al., 2016; Zhang and Sun, 2016). Recent studies also investigate the role of behavioral factors in determining oil prices, such as investor attention (Yao et al., 2017). Ewing et al. (2002) find that current oil volatility depends on past volatility and not so much on specific events or economic news, but natural gas return volatility responds more to unanticipated events. Joëts (2014) investigates transmission mechanisms across forward price returns for oil, gas, and coal and show that energy price co-movements, although they exist in normal times, increase during extreme fluctuations. Aloui et al. (2014) showed evidence of asymmetric dependence between the oil and natural gas markets: they tend to comove closely together during bullish periods, but not at all during bearish periods.

This paper uses a multivariate framework of quantile regressions, a recent development in econometrics, to increase the informational content of previous tests. The finance literature has frequently employed quantile regression to study quantile interdependence between financial series (e.g., Bassett Jr and Chen, 2002; Chuang et al., 2009; Tsai, 2012; Baur et al., 2012; Baur, 2013; Ciner et al., 2013; Gebka and Wohar, 2013; Mensi et al., 2014). In addition, studies have also used quantile regression to construct a new VaR measure (e.g., Engle and Manganelli, 2004; Rubia and Sanchis-Marco, 2013). Lee and Li (2012) and Li and Miu (2010) further apply quantile regression to firm-level data, examining the effect of diversification on firm performance and obtaining bankruptcy prediction, respectively. We extend quantile analysis used in early studies to the multivariate framework, and adopt the VAR for VaR method to explicitly capture the multilateral distributional relationships, with a particular focus on the energy markets.

3 Methodology

Our study employs two new statistical methods to study risk spillover between oil and gas markets and the tail interdependence structure. First, for the study of risk spillover between markets, we employ the recently introduced test statistics, which are based on the cross-quantilogram function. The definition of market risk is in line with the conventional idea of VaR. More specifically, a class of kernel-based tests proposed by Hong et al. (2009) is used to detect the extreme downside risk spillover between financial markets. As these statistics have a convenient asymptotic standard normal distribution and can be used to check a large number of lags, we can detect risk spillover that occurs with time lags or that has weak spillover at each lag but carries over a very long distributional lag.

Second, after confirming the existence of risk spillover, we employ the VAR for VaR model (White et al., 2015) to quantitatively uncover these tail-interdependency patterns. The VAR for VaR framework can be viewed as a vector autoregressive extension of traditional quantile models. This method allows us to go beyond the analysis of the univariate quantiles, and directly investigates dynamic risk-transmission mechanism between energy markets. Based on the results from our analysis of VAR for VaR, we offer conclusions and suggest some policy implications.

3.1 Value at risk

Given the rising need for monitoring and controlling financial risk, risk prediction plays an essential role in the field of banking and finance. The VaR concept, originally proposed by J.P. Morgan in 1994, has become a standard measure of market downside risk. The VaR is defined as a threshold of loss value, such that the losses will exceed this VaR threshold with only a small target probability, α. In practice, α is commonly chosen to be 1%, 5%, or 10%. Mathematically speaking, the VaR for period t of a portfolio is the negative α-quantile of the conditional return distribution, which has the following specification:

$$VaR_t^{\alpha} \equiv -Q_{\alpha}(r_t|\mathcal{F}_{t-1}) = -\inf_{x}\{x \in \mathbb{R} : \mathrm{P}(r_t \leq x|\mathcal{F}_{t-1}) \geq \alpha\}, 0 < \alpha < 1, \tag{1}$$

where Q_{α} denotes the quantile function, r_t is the return on an asset or portflio in period t, and $\mathcal{F}_t$ represents the information available at date t.

Despite its conceptual simplicity, the VaR prediction is a challenging statistical problem. The difficulty mainly lies in how to find a suitable model for the widely reported stylized facts of financial series—for example, volatility clustering, substantial kurtosis, and mild skewness of financial returns. The existing models for calculating VaR, which differ mainly in the way of estimating the empirical distribution, can be classified as follows: historical simulation methods, fully parametric models, extreme value theory methods, and quantile-regression methods.[3] In this study, we mainly employ the filtered historical simulations (FHS) to measure univariate VaR, which is a combination of the historical simulation method and fully parametric models. Kuester et al. (2006) show that this method performs relatively better by comparing the out-of-sample performance of existing methods. We also utilize the quantile-regression method as a robustness check for the risk-spillover results (Engle and Manganelli, 2004).

For implementing the FHS-based VaR measure, we first apply the univariate generalized autoregressive conditional heteroskedasticity (GARCH) model proposed by Bollerslev (1986) to filter out persistent volatility clustering and serial dependence in each series. For example, denoting r_t as the daily return of energy index, the AR(m)-GARCH(1,1) model can be defined as:

$$\begin{cases} r_t = b_0 + \sum\limits_{j=1}^{m} b_j r_{t-j} + \varepsilon_t, \\ \varepsilon_t = \xi_t \sigma_t, \\ \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1.}^2 \end{cases} \tag{2}$$

The error term ξ_t is assumed to follow a student t distribution.[4] Parameters in the above equations are

[3] An extensive review of these methods can be found in Kuester et al. (2006).

[4] We experiment with the alternative distribution of errors terms, such as generalized error distribution (GED), and skewed

estimated by quasi-maximum likelihood (QML) method to obtain the consistent estimator in the absence of normality in the conditional shocks.[5]

For the FHS, the VaR estimate forecasts are then generated by computing the VaR from paths simulated using draws from the filtered residuals. More specifically, we first estimate the unconditional quantile functions by solving the following minimization problem:

$$\hat{q}(\alpha) = arg \min_{v \in R} \sum_{t=1}^{T} \pi_\alpha (\xi_t - v), \tag{3}$$

where $\pi_\alpha(u) \equiv u(\alpha - 1[u < 0])$. The indicator function $1[\cdot]$ takes a value of 1 when its argument is true, and 0 otherwise. Then, the VaR estimate can be calculated by substituting it into an estimated GARCH model.

The idea of the VaR naturally lends itself to the concept of quantile regression. Instead of modeling the whole distribution, the specified left quantile of the time series can be explicitly modeled using any relevant information. One appealing feature of this method is that we do not need to impose any distributional assumptions on the return series. More specifically, the conditional quantile of a portfolio, $Q_\alpha(r_t|x_t) = -VaR_t^\alpha$, can be modeled as some functions of the information $x_t \in \mathcal{F}_{t-1}$, that is,

$$VaR_t^\alpha \equiv -g_\alpha(x_t; \beta_\alpha), \tag{4}$$

where $g_\alpha(x_t; \beta_\alpha)$ and parameter vector β_α explicitly depend on α. The objective function for the general, possibly non-linear case of equation (5), proposed by Engle and Manganelli (2004), is

$$\min_{\beta \in \mathbb{R}^K} \left\{ \sum_{r_t \geq VaR_t} \alpha \left| r_t + VaR_t \right| + \sum_{r_t < -VaR_t} (1 - \alpha) \left| r_t + VaR_t \right| \right\}, \tag{5}$$

with, according to equation (5), $VaR_t^\alpha = -g(x_t; \beta_\alpha)$ or, in the linear case, $VaR_t^\alpha \equiv x_t' \beta_\alpha$. Consistency and asymptotic normality of the nonlinear regression quantiles for the time-series case are established in Engle and Manganelli (2004). In particular, their CAViaR specifications includes VaR_{t-1}^α as an explanatory variable in x_t, to adapt to serial dependence in the first two moments. A function of r_t is also included to link the conditional quantile to return innovations. More specifically, the absolute value in the CAViaR specification can be written as:

$$VaR_t^\alpha = \beta_0 + \beta_1 VaR_{t-1}^\alpha + \beta_2 \left| r_{t-1} \right|. \tag{6}$$

It utilizes the autoregression parameter, β_1, to capture the response to the previous VaR_{t-1}^α, and introduces

generalized error distribution (SGED). The results in the following section are robust to these alternative distribution choices.

[5] We also experiment with the GJR GARCH, Exponential GARCH (EGARCH), and APARCH model to capture possible asymmetric volatility, the results in the following section are robust to these alternative modeling strategies.

a direct response of the quantile to the return process, treating the effect of extreme returns on VaR_t^{α} and volatility symmetrically.

3.2 Test statistics

To illustrate the test statistics for Granger causality in risk, we first introduce the cross-quantilogram function. The cross-quantilogram function (Linton and Whang, 2007; Hong et al., 2009; Han et al., 2016) is proposed to measure the quantile dependence between two series.

After calculating the VaR estimate, we may define the estimated quantile-hit or quantile-exceedance process for each return series $r_{i,t}$:

$$\hat{Z}_{i,t} \equiv 1[r_{i,t} < -VaR_{i,t}], i = 1, 2, ..., \tag{7}$$

where $1[\cdot]$ is the indicator function as before.

Then we can define our cross-quantilogram function between two series:

$$\hat{\rho}\,(j) = \hat{C}(j)/\left[\hat{C}_1(0) * \hat{C}_2(0)\right]^{1/2}, \tag{8}$$

where the numerator is the sample cross-covariance function:

$$\hat{C}(j) \equiv \begin{cases} T^{-1} \sum\limits_{t=j+1}^{T} (\hat{Z}_{1,t} - \hat{\alpha}_1)(\hat{Z}_{2,t-j} - \hat{\alpha}_2), J \geqslant 0, \\ T^{-1} \sum\limits_{t=1-j}^{T} (\hat{Z}_{1,t+j} - \hat{\alpha}_1)(\hat{Z}_{2,t} - \hat{\alpha}_2), J < 0, \end{cases} \tag{9}$$

where $\hat{\alpha}_i \equiv T^{-1}\Sigma_{t=1}^{T}\hat{Z}_{i,t}$ and the denominator in equation (9) is the corresponding variance: $\hat{C}_i(0) = T^{-1}\sum_{t=1}^{T}(\hat{Z}_{i,t} - \hat{\alpha}_i)^2$.

Given a set of quantiles, the cross-quantilogram considers dependence in terms of the direction of deviation from quantiles, and thus measures the directional predictability from one series to another. Hong et al. (2009) first propose a kernel-based test statistics to investigate the Granger causality in risk:

$$Q = T\sum_{j=1}^{T-1} k^2(j/M)\hat{\rho}^2(j), \tag{10}$$

where $k\,(.)$ is a weighting function and M defines the bandwidth, which is a positive integer. Examples of $k\,(.)$ include the truncated, Bartlett, Daniell, Parzen, quadratic-spectral (QS), and Tukey-Hanning kernels.

In this paper, we employ the Daniell kernel to investigate the empirical questions:

$$k(z) = \sin(\pi z)/\pi z, -\infty < z < +\infty. \tag{11}$$

Another appropriately standardized version of this statistic is

$$Q_1(M) = \{T\sum_{j=1}^{T-1} k^2(j/M)\hat{\rho}^2(j) - C_{1T}(M)\}/(2D_{1T}(M))^{1/2}, \tag{12}$$

where:

$$C_{1T}(M) = \sum_{j=1}^{T-1}(1 - j/T)k^2(j/M),$$

$$D_{1T}(M) = \sum_{j=1}^{T-1}(1 - j/T)\{1 - (j+1)/T\}k^4(j/M).$$

Under appropriate regularity conditions, it can be shown that under $H_0, Q_1(M) \to N(0,1)$ in distribution. In addition to Q_1, the test statistic for the bidirectional hypothesis has also been introduced:

$$Q_2(M) = \left\{T\sum_{|j|=1}^{T-1} k^2(j/M)\hat{\rho}^2(j) - C_{2T}(M)\right\}/\{2D_{2T}(M)\}^{1/2}, \tag{13}$$

where the centering and scaling factors are:

$$C_{2T}(M) = \sum_{|j|=1}^{T-1}(1 - |j|/T)k^2(j/M),$$

$$D_{2T}(M) = [1 + \hat{\rho}^4(0)]\sum_{|j|=1}^{T-1}(1 - |j|/T)(1 - (|j|+1)/T)k^4(j/M).$$

This statistic of Q_2 also converges to standard normal distribution under the null hypothesis, and it is a suitable statistic in the absence of prior information about the direction of causality. The proposed tests have the convenient asymptotic standard normal distribution under the null hypothesis of no Granger causality in risk. These tests check a large number of lags but avoid suffering from a severe loss of power due to the loss of a large number of degrees of freedom, by adopting a downward-weighting kernel function. This downward weighting is consistent with the stylized fact that today's financial markets are influenced more by more recent events than by remote past events, thus enhancing the power of the proposed tests.

3.3 VAR for VaR

After confirming the existence of risk spillover, we employ a VAR for VaR model (White et al., 2015) to trace out the dynamic tail-interdependence structure between financial markets. The VAR for VaR framework can be viewed as a vector autoregressive extension of traditional quantile models. This method allows us to go beyond the analysis of the univariate quantiles, and directly investigate the risk-transmission mechanism between energy markets.

A bivariate version used in this study relates the conditional quantiles of two random variables according to a VAR structure, conditional on the past information set $\mathcal{F}_{t-1}$. The later empirical analysis indicates that VAR(1) for VaR model is sufficient to capture the energy market tail interdependence. The model can be written as:

$$q_{1t} = c_1 + a_{11}\left|r_{1t-1}\right| + a_{12}\left|r_{2t-1}\right| + b_{11}q_{1t-1} + b_{12}q_{2t-1}, \tag{14}$$

$$q_{2t} = c_2 + a_{21}\left|r_{1t-1}\right| + a_{22}\left|r_{2t-1}\right| + b_{21}q_{1t-1} + b_{22}q_{2t-1},$$

where $|r_{1t-1}|$ and $|r_{2t-1}|$ represent the return series of the US and corresponding Asian markets, and q_{1t} and q_{2t} are the conditional quantiles. If $b_{12} = b_{21} = 0$, this model reduces to the CAViaR model of Engle and Manganelli (2004). This bivariate quantile model in equation (15) can be expressed more compactly in matrix form as follows:

$$q_t = c + A\left|r_{t-1}\right| + Bq_{t-1}, \tag{15}$$

Any empirical evidence for non-zero off-diagonal terms in either A or B will indicate the presence of tail interdependence between the two variables.

After we construct the VAR for VaR model, we can further quantify the impacts of the external shocks on the tail of returns by estimating the pseudo impulse response functions (PIRFs). PIRFs differ from traditional functions because they assume that intervention δ affects the observable return r_t only at time t. At all other periods, no change occurs in r_t. In this way, the pseudo αth-quantile impulse-response function (IRF) for the ith return $r_{i,t}$ can be written as:

$$\Delta_{i,s}(\tilde{r}_{i,t}) = \tilde{q}_{i,t+s} - q_{i,t+s}, s = 1, 2, 3... \tag{16}$$

where $\tilde{q}_{i,t+s}$ is the αth conditional quantile of the treated series $(\tilde{r}_{i,t})$, and $q_{i,t+s}$ is the αth conditional quantile of the unaffected series $(r_{i,t})$. One advantage of this setting of PIRFs is that they retain the traditional interpretation of IRFs, even now we can assess the responses of different quantiles of the distribution.

Table 1: Summary Statistics of Daily Returns

	Mean	Std	Min	Max	Skew	Kurt	JB.test	Q(10)	LM(10)
WTI	0.020	2.365	-16.545	16.410	-0.207	7.676	3456.30	51.47	498.95
Henry Hub	0.010	4.610	-56.818	57.666	0.643	24.997	75944.00	422.02	1052.30

Note 1: Q(10) is the Box-Pierce test statistic with 10 lags, which is asymptotically distributed as Chi-squared with 10 degrees of freedom.

Note 2: LM(10) is the Lagrange multiplier test statistic with 10 lags, which is asymptotically distributed as Chi-squared with 10 degrees of freedom.
Note 3: The 5% critical value for χ^2 (10) is 18.307 and the 1% critical value for χ^2 (10) is 23.209.

Therefore, we can directly model the tail interdependence structure across the financial series, and further examine how risk is transmitted from one market to another, instead of indirectly estimating risk spillover by recovering the first and second conditional moments of the financial series. In our empirical application, we also take into account the contemporaneous correlation by identifying the structural shocks using a standard Cholesky decomposition.

4 Empirical analysis

4.1 Data description

The energy data for this study are extracted from Bloomberg and the US Energy Information Administration (EIA) website. It consists of the daily closing prices of two primary energy market indices in the United States: the WTI Crude Oil Index (US Oil) and the Henry Hub Natural Gas Index (US NG).[6] The data sets span from January 3, 2000, to December 31, 2014. The daily returns of these indices are computed as:

$$r_{i,t} = \ln(P_{i,t}/P_{i,t-1}) * 100$$

where $r_{i,t}$ stands for the daily return of the indices, and $P_{i,t}$ stands for the closing price.

Table 1 displays the summary statistics of the daily returns of these two indices. It first shows that these markets experienced a positive average return during the sample period. Table 1 also reports that gas markets are in general featured with greater volatility. More specifically, we document the standard deviation of 4.610 in the US natural gas market and 2.365 in the US oil market. Compared with the standard deviation of 1.284 in the US stock market (S&P 500 Index), we highlight the instability of the investment in the energy markets.[7] Table 1 further reports that the oil series is left skewed, and both two return series are leptokurtic. Such non-normal properties are also captured by the highly significant Jarque-Bera test statistics. These results imply the potential weakness of treating the variance as the measure of risk for the energy series. Furthermore, the Box and Pierce (1970) type portmanteau statistics suggest the existence of mild autocorrelation in each

[6]In the later section, we further extract data for Brent Oil of the Europe, National Balancing Point (NBP) natural gas of the Europe, and Japan Korea Marker (JKM) Natural Gas of Asia from the same data source.
[7]We calculate the variance of the US stock index series in the same sample period for the comparison.

series. The Engle (1982) tests for an autoregressive conditional heteroskedasticity (ARCH) effect clearly reject the null hypothesis of no ARCH effect. As a result, appropriate AR-GARCH models seem adequate to accommodate the statistical feature of each series and thereafter filter out the volatility clustering.

4.2 Model estimation

In this section, we employ the FHS to calculate the univariate VaR. In the empirical finance literature, research has often found that GARCH(1,1) models can capture most volatility clustering in financial time series. Therefore, we apply the AR(4)-GARCH(1,1) model discussed in the previous section to both energy series. The results below show that this specification is adequate to clear out the autocorrelation.

Table 2 summarizes the estimation results of univariate GARCH models for each index. The coefficients correspond to equation (2). Table 2 first shows the minimal serial correlation in the mean of these return series, which is reflected by the limited number of significant autoregressive coefficients. In general, this result is in line with the efficient market hypothesis (EMH), indicating that past information has weak predictive power for future returns. However, regarding the second moment, we observe obvious volatility clustering, which is shown by the significant ARCH and GARCH coefficients for all the indices. In Table 2, we also present diagnostic statistics for model adequacy along with the estimated parameters. The corresponding p-values of portmanteau statistics for autocorrelation in standardized residuals are all above 0.10, as are the p-values of a similar test for autocorrelation in squared standardized residuals. These results imply the adequacy of the specified models for each index, which means our model can capture all the first- and second-moment variations that can be explained by its own past information for each index. Based on the model we construct, the VaR estimates can be easily calculated by substituting the draws from the filtered residuals into the estimated GARCH model.

4.3 The interdependence structure within the energy markets

4.3.1 Mean and volatility spillover

Before we investigate risk spillover, which is of major interest in this study, it is useful to revisit the interdependence structure of the energy markets within the first two moments. In particular, we examine the existence of mean and volatility spillover between the US oil and natural gas markets by adopting the test statistics presented earlier. Tables 3 and 4 reports the kernel-based test statistics, together with their p-values. We use the Daniell kernel and report the bandwidth as M=5, 10, 20.[8] The first row shows the two-way statistics for the existence of mean or volatility spillover between two markets. The second row presents

[8]Because commonly used non-uniform kernels deliver similar power, we only report the results based on the Daniell kernel.

Table 2: Estimation Results of AR-GARCH model

	US Oil	US NG
b_0	0.057**	-0.018
	(0.029)	(0.047)
b_1	-0.029*	0.042**
	(0.016)	(0.017)
b_2	-0.005	-0.105***
	(0.016)	(0.016)
b_3	0.007	-0.017
	(0.016)	(0.016)
b_4	0.015	0.019
	(0.016)	(0.016)
ω	0.021**	0.500***
	(0.008)	(0.099)
α_1	0.045***	0.146***
	(0.006)	(0.015)
β_1	0.952***	0.829***
	(0.006)	(0.015)
Q(10)	7.854	13.064
P-Value	*0.643*	*0.220*
LM(10)	14.169	3.514
P-Value	*0.165*	*0.967*
AIC	4.286	5.333
BIC	4.301	5.348

Note 1: Q(10) is the Box-Pierce test statistic on squared standardized residuals with 10 lags.
Note 2: LM(10) is the Lagrange Multiplier test statistic on the autocorrelation of the squared standardized residuals with 10 lags.
Note 3: The 1%, 5% and 10% critical value for χ^2 (10) are 23.209, 18.307 and 15.987, respectively.
*** $p<0.01$.
** $p<0.05$.
* $p<0.10$.

Table 3. Mean Spillover between the US Oil and Natural Gas Markets

	M=5	M=10	M=20
US_Oil↔US_NG	35.695***	28.369***	20.558***
	0.000	0.000	0.000
US_Oil→US_NG	36.638***	28.441***	20.289***
	0.000	0.000	0.000
US_Oil←US_NG	-0.702	-0.588	-0.682
	0.758	0.722	0.752

Note 1: M is the integer in Daniell kernel.
Note 2: "↔" represents the two-way tests (Q_2). "→" and "←" represents the one-way tests (Q_1) for causality from the former to the latter and the latter to the former with respect to with respect to F_{t-1}.
*** p<0.01.
** p<0.05.
* p<0.10.

Table 4. Volatility Spillover between the US Oil and Natural Gas Markets

	M=5	M=10	M=20
US_Oil↔US_NG	1.018	0.861	0.240
	0.154	0.195	0.405
US_Oil→US_NG	1.214	0.522	-0.536
	0.112	0.301	0.704
US_Oil←US_NG	0.967	1.094	1.089
	0.167	0.137	0.138

Note 1: M is the integer in Daniell kernel.
Note 2: "↔" represents the two-way tests (Q_2). "→" and "←" represents the one-way tests (Q_1) for causality from the former to the latter and the latter to the former with respect to with respect to F_{t-1}.
*** p<0.01.
** p<0.05.
* p<0.10.

one-way test statistics for whether the first index Granger-causes the second index in mean or volatility, with respect to the information $\mathcal{F}_{t-1}$. The third row documents the counterparts.

Table 3 presents the results of mean spillover. We document significant Q_2 statistics in the first row, implying the substantial two-way mean spillover between the US oil and US NG market. This result shows these energy markets are highly integrated in terms of the mean. Furthermore, we document that information in the oil market Granger causes price movements in the US NG market. In contrast, price movements in the NG market have no significant reverse impact on the oil market. These results are in line with the dominating status of the US oil market, implying that information in the US oil market has price discovery ability for the NG market.

Table 4 presents the results for the second moment, volatility spillover. The results first show that there is no significant two-way volatility spillover between the US oil and US NG market. Meanwhile, the similar insignificant Q_1 statistics in the second and third rows also indicate that the volatility in one market does not have predictive power for another. Notably, the patterns of the volatility spillover differ considerably from the previous mean spillover. These results provide the first evidence that interdependence structure between two financial series can be very different across different moments.

4.3.2 Value at risk and risk spillover

In this section, we examine the existence of risk spillover between the US oil and US NG markets. Table 5 reports the kernel-based test statistics at the 1% risk level, together with their p-values.[9] The first row shows the two-way statistics for the existence of risk spillover between the two markets. The second row presents one-way test statistics for whether the first index Granger-causes the second index in risk, with respect to the information $\mathcal{F}_{t-1}$. The third row documents the counterparts.

We document the following stylized facts:

First, the Q_2 statistics are highly significant, implying the two-way risk spillover between the US oil and US NG market. As a result, we confirm these two energy markets are integrated in terms of market risk. Moreover, the risk spillover pattern is largely different from the volatility spillover pattern. This observation further highlights the importance of using the left tail of the distribution (VaR), instead of conventional volatility, to measure the market risk.

Second, risk in the US oil market has strong predictive power for the risk in the US NG market. These observations are supported by highly significant one-way test statistics Q_1 in the second row. Meanwhile, risk in the NG market has few impacts on the oil market. These results show that we could utilize the information in the oil market to estimate the extreme downside market movements in the NG market.

Table 5. Risk Spillover between the US Oil and Natural Gas Markets

	M=5	M=10	M=20
US_Oil↔US_NG	18.661***	14.310***	10.229***
	0.000	0.000	0.000
US_Oil→US_NG	31.897***	22.512***	15.891***
	0.000	0.000	0.000
US_Oil←US_NG	-0.352	-0.561	-0.849
	0.638	0.713	0.802

Note 1: M is the integer in Daniell kernel.
Note 2: "↔" represents the two-way tests (Q_2). "→" and "←" represents the one-way tests (Q_1) for causality from the former to the latter and the latter to the former with respect to with respect to F_{t-1}.
*** p<0.01.
** p<0.05.
* p<0.10.

[9] We also experiment test statistics at the 5% and 10% risk levels. In general, they deliver similar risk interdependence patterns. To conserve space, we concentrate on results at the 1% risk levels as a baseline case. We further discuss downside risk at the 5% and 10% levels in section 4.5.1, which investigates the asymmetric property of international transmission patterns.

Table 6. Estimates and Standard Errors, VAR for VaR Model

US_OIL on US_NG				
c_1	a_{11}	a_{12}	b_{11}	b_{12}
-0.21***	-0.32***	0.06***	0.82***	0.04**
(0.08)	(0.04)	(0.01)	(0.03)	(0.02)
c_2	a_{21}	a_{22}	b_{21}	b_{22}
-0.45*	-0.33*	-0.55***	-0.08	0.78***
(0.24)	(0.17)	(0.02)	(0.13)	(0.06)

Note: Estimated coefficients are in the first row. Standard errors are reported in brackets in second row. The coefficients correspond to the VAR for VaR model reported in Eq.(14) of the paper.
*** p<0.01.
** p<0.05.
* p<0.10.

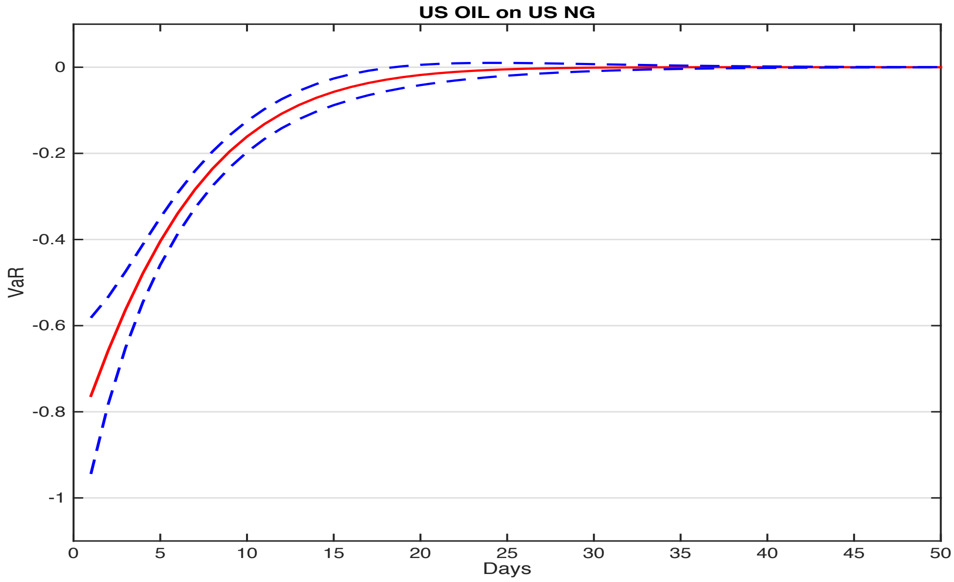
4.4 VAR for VaR

After confirming the existence of two-way risk spillovers, we employ a bivariate VAR for VaR model (White et al., 2015) to trace out the dynamic tail-interdependence structure between these markets. In our bivariate framework (Eq. 14), the first equation describes the quantile responses of the oil market, and the second equation describes the quantile responses of the corresponding NG market. Because conventional wisdom and previous test statistics both suggest that the oil market plays a dominating role in energy markets, we focus on how risk in the oil market can help to predict the risk in the NG market. We assume shocks to oil markets Granger-cause changes in the NG market contemporaneously, but shocks to the NG market do not have the instant direct impact on the oil market the same day.

Table 6 reports the estimation results for the bivariate VAR for VaR system, showing that some of the non-diagonal coefficients in the A or B matrices are significantly different from zero. This finding illustrates that multivariate quantile model can reveal dynamics that cannot be detected by estimating univariate quantile models, hence capturing two-way risk spillovers. For example, we document the significance of the coefficient a_{21}, implying that the VaR of the gas market depends not only on its own past information, but also on information in oil markets.

Figure 2 displays the PIRFs of risks in the NG markets to a one-standard-deviation shock to the oil market, together with the 95% confidence interval. The horizontal axis measures the time (expressed in days), and the vertical axis measures the change in the 1% quantiles of the NG indices (expressed in percentage returns) as a reaction to the oil shock. The PIRFs document that this shock propagates in the international risk-transmission mechanism and how long it takes to absorb it. The shock is completely absorbed when the PIRFs have converged to zero. Careful inspection of the PIRFs of NG markets reveals similar patterns

Figure 2. Quantile Impulse-Response Function

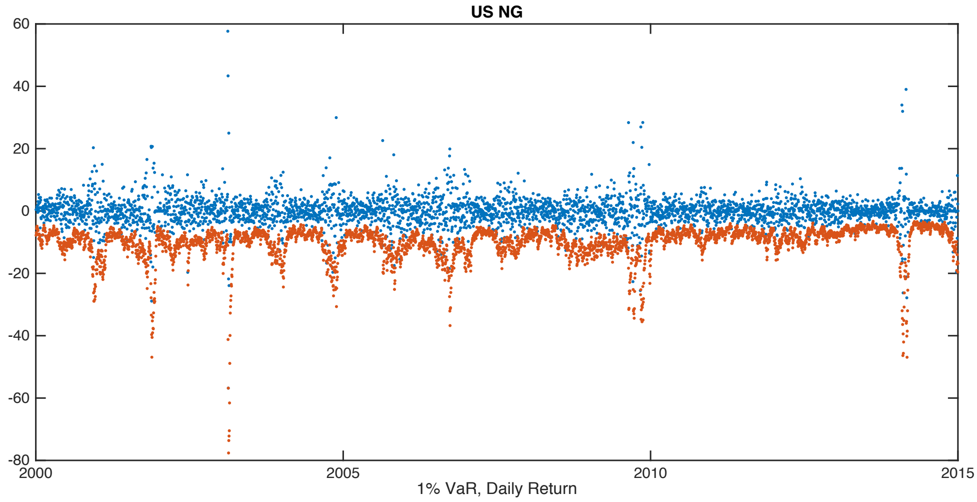


Note: The plot reports the quantile impulse-reponse functions between the US oil and natural gas market at 1% level, together with 95% confidence intervals.

in how their long-run risks react to oil shocks. More specifically, a one-standard-deviation decline in the oil market generates 0.78-percentage-point increase in the VaR for the US NG market. This effect is also statistically significant, and the NG markets absorb the shocks slowly in the following 50 days. These results confirm that the information in the oil market can help to predict risk in the NG market.

Based on the multivariate quantile model we estimated, we construct a multivariate VaR measure for natural gas markets. The resulting estimated 1% quantiles are reported in Figure 3. These quantile plots clearly capture extreme downside movements, providing the evidence that this multivariate VaR measure is suitable for capturing the dynamics of energy market risk. The absolute value of VaR in the NG market is much bigger than the oil market, suggesting huge risk in investing in this market.

Figure 3. Estimated 1% Quantile for the US Natural Gas Market



Note: The chart reports the in-sample 1% daily Value at Risk (VaR) for natrual gas market, together with the daily return. The VaR is computed from a bivariate VAR for VaR model, where the first equation contains the quantile of the oil market and the second equation contains the quantile of the corresponding natural gas market.

4.5 Further discussion

4.5.1 Responses across different risk levels

In most of the existing literature, researchers adopt volatility to measure risk, and focus on volatility spillovers. One underlying limitation of these studies is that they treat gains and losses in a symmetric way. However, in practice, the different quantiles of a return series may respond in a very different fashion given that external shocks originated in different markets.[10]

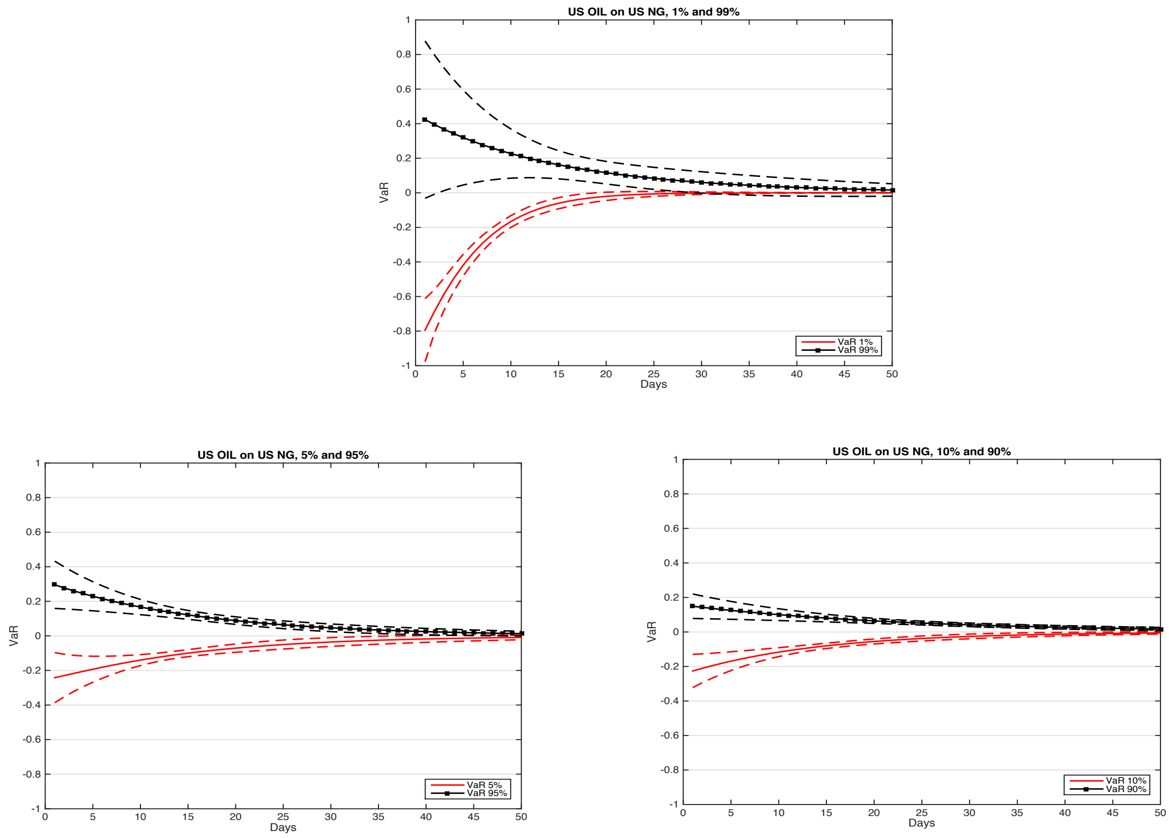
In this section, we explicitly examine the responses across different risk levels. The objective is to show how the energy market reactions vary across different magnitudes of market losses and gains. We present the impacts of an external shock on energy market across different quantiles in Figure 4. We pick 1%, 5%, and 10% to measure the losses because they are the commonly used VaR levels. We also pick 99%, 95%, and 90% to measure the corresponding market gains. The red solid line represents the down side risk, and the black solid line reports the upside side risk. The corresponding dashed lines are the 95% confidence intervals.

Figure 4 delivers some interesting observations.

First, we show that the extreme losses and gains (e.g., 1% and 99% quantile pair) are more likely to be transmitted across the market, compared to moderate losses and gains (e.g., 5% and 95% quantile pair, 10% and 90% quantile pair). For example, we document a substantial 0.8-percentage-point instant increase in VaR at the 1% level, and the moderate 0.2-percentage-point instant changes of VaR at the 5% and 10%

[10]One explanation is that market participants behave asymmetrically in response to the positive or negative market information.

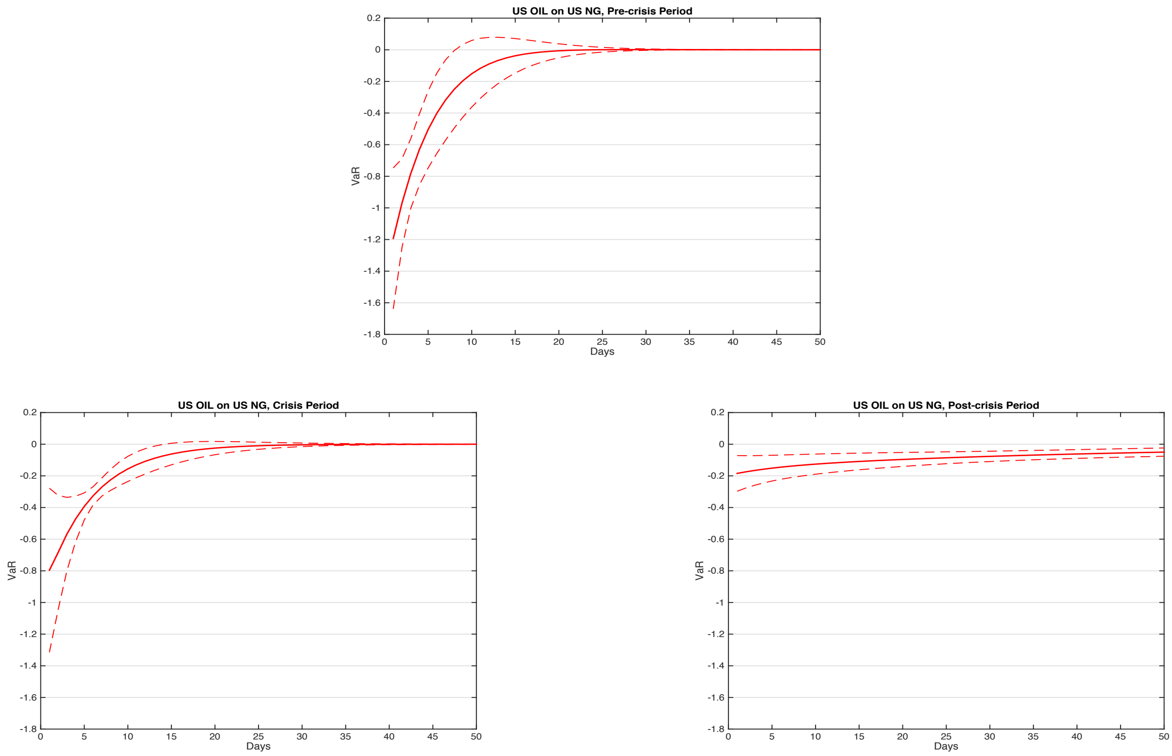
Figure 4. Responses of Gas Market across Different Quantiles



level. Results are similar when we consider the market gains. These disproportionate patterns show that the market is more sensitive the extreme events, highlighting the policy instruments to control for extreme risk spillover.

Second, the significant asymmetric pattern has been identified in the extreme downside movements, namely 1% risk. More specifically, we document 0.8-percentage-point instant changes in market losses and 0.4-percentage-point instant changes in market gains, given the external oil shocks. Meanwhile, regarding the moderate risk level, the response pattern is in general symmetric. These empirical results are in line with our expectation, which reflect the financial property of energy prices since market participants behave asymmetrically when provided with extreme market gains and losses. Extreme market losses are more likely to trigger financial contagion, easily transmitting across the markets and leading to a surge in the VaR. Based on the asymmetric pattern we observe, we illustrate the potential weakness of adopting volatility to measure the market risk. We suggest that future research to treat the losses and gains separately when attempting to investigate the interdependence structure between financial series, such as the energy series in our case. Our analysis on the distributional interdependence across different quantiles also contributes to a better understanding of how different types of information are transmitted between commodity markets.

Figure 5. Time-varying Pattern of Tail Interdependence.



4.5.2 Time-varying Risk Transmission Patterns

The world economic and energy consumption landscape has shifted dramatically in recent years. On the one hand, informatization spurs increasing financial integration and enhances financial linkages between the commodity markets. On the other hand, with the rise of demand for the clear energy and the development of energy infrastructure such as pipeline, the world markets have experienced astonishing growth in natural gas consumption. These stylized facts lead to a question of considerable interest regarding how the shift in the global economic landscape and energy demand structure affects the risk-transmission patterns across the time.

In this section, we investigate the time-varying property of the international risk-transmission mechanism we trace out between the oil and natural gas markets. To shed light on this issue, we divide our sample into three parts: the pre-crisis period from January 1, 2000, to December 31, 2006; the crisis-period from January 1, 2007, to December 31, 2009; and the post-crisis period from January 1, 2010, to December 31, 2014.[11] To make the results more comparable, we also standardize the shocks in the crisis period and post-crisis period to the pre-crisis period level.

[11] Note that because the crisis period contains only a relatively shorter time span with fewer observations, quantile analysis based on that may lead to distorted results. Also, the financial crisis may create the extraordinary multilateral relationships.

Figure 5 summarizes the pseudo impulse response patterns between the two markets across the pre-crisis period, crisis period, and post-crisis period. First, we document the risk integration between oil and gas markets has declined over time. The US oil market experienced an decreasing predictive power for risk in the natural gas market. Quantitatively speaking, the instant impact of oil shocks on natural gas markets has decreased dramatically, from -1.20 in the pre-crisis period to -0.80 and -0.18 in the crisis and post-crisis periods, respectively. Our findings are in line with the observation that natural gas market is more isolated from the oil market in the recent years, and providing the further evidence on this topic in the risk transmission perspective. Meanwhile, these empirical findings suggest an extreme market event, such as the global financial crisis, does not necessarily amplify the risk linkages between the commodity prices since we do not document a surge in risk spillover during the financial crisis period. Last but not least, given the declining patterns of risk spillover over time, our results also indicate that investing in oil and nature gas commodity provides some opportunities if one seeks for risk sharing and portfolio diversification in energy market.

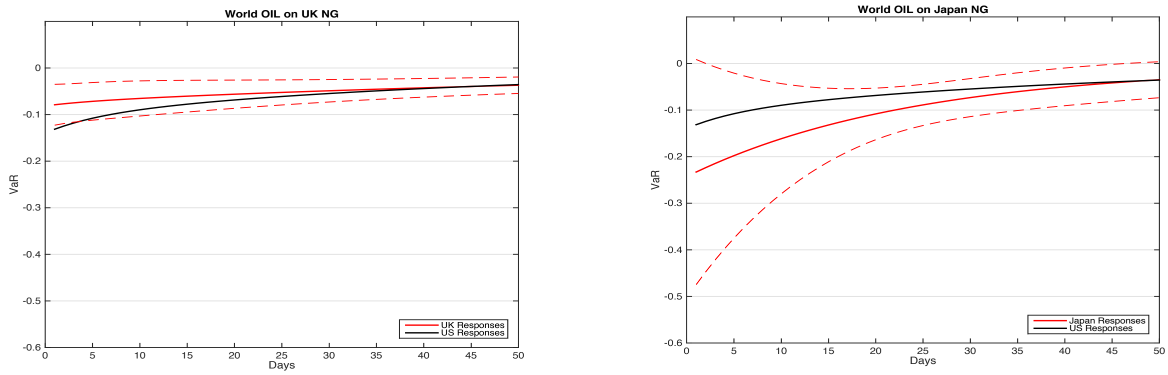
4.5.3 Impacts on other regional natural gas market.

In the recent decades, the world NG markets have developed rapidly. Hub-based gas prices in Northwest European markets have reached market acceptance and a dominant position in gas pricing. More and more price indices are also being developed for other parts of Europe as well as in Asia, which are applicable to different regions. In this section, we include representatives of these natural gas price indices, the UK's National Balancing Point (NBP) and Asian Japan Korea Marker (JKM) indices, and discuss the risk spillover patterns related to these markets. We utilize WTI oil price as the world oil index for these regions.[12] One important question we attempt to shed light on is whether any difference exists across the markets in different areas. Notably, the time span of these indices is relatively short. Our data for these series are from March 1, 2009, to December 30, 2014.[13] Basically, we estimate the risk transmission patterns between these markets in the post crisis period like before, which is more insightful for the current situation. To facilitate the comparison, we also estimate the US results in this period. Our results are summarized in Figure 6.

Figure 6 delivers some interesting observations. On the one hand, we document the significant risk transmission patterns in these regional markets. These findings show that the risk integration between oil to natural gas market is not only a regional phenomenon in the US, but also a global phenomenon across world major markets. On the other hand, our empirical findings also report substantial heterogeneities in risk responses across different regional natural gas markets. More specifically, the instant impact on the UK is -0.08, and -0.12 on the US. These results show that the risk shocks in the oil market still have the stronger impact on the corresponding NG market, compared to the UK market. Meanwhile, the Asian gas market is more integrated with the oil market in terms of risk transmission among these three markets. The instant impact is around twofold compared to that of the US, and is statistically significant. This result is in line with the current market structure of the Asian natural gas market.

[12] Our results are robust to the alternative well accepted oil index such as Brent Oil.
[13] The starting date of JKM series is Feb 03, 2009 from the Platts dataset.

Figure 6. Responses of Gas Market across Different Regions



5 Conclusion and policy implications

The GFC in 2007-2009 that originated in the US has brought to surface the need for measuring and monitoring the transmission of extreme downside market risk. This paper investigates the risk transmission mechanism between the oil and gas markets. By applying the recently introduced test statistics based on cross-quantilogram function, we first confirm the existence of risk spillover between these two energy markets. Furthermore, we apply the multivariate quantile regression model (VAR for VaR) to quantitatively reveal these tail-interdependence patterns.

Our results show that the shocks in the oil market substantially affect the VaR in the natural gas market. However, risk in the natural gas market has no predictive power for risk in the oil market. Moreover, extreme market risk is easier to transmit across the energy markets, compared to the moderate risk. Another key message this paper reveals is an asymmetric tail-interdependency structure between energy markets, warning of underlying weakness of adopting volatility to measure the market risk. We also report the significant time-varying risk interdependence patterns between the oil and natural gas markets. Our results are in general robust in application to other regional energy markets, such as Europe and Asia, but heterogeneities also arise. Compared to the US and European markets, the Asian gas market is more integrated with the oil market in terms of risk transmission. The risk transmission response of gas prices to oil price shocks is stronger in Asia than in the US and European markets.

The results in this paper offers clear practical insights and relevant policy implications for academia, policy makers, and business sectors. The main practical insights and policy implications can be summarized as follows. First, the evidence of substantial risk transmission from oil markets to natural gas markets suggests the need for sound policies to stabilize energy markets during large price movements in oil market, as well as the need for good instruments to effectively hedge the positions. One possible direction is to adopt market regulation mechanisms in price controls, such as setting the downside price limits in trades.

Second, the evidence of asymmetry in risk transmission on extreme downside market moves should be considered in drafting gas market policy. The development of instruments to hedge against price risks should be prioritized. This is increasingly important because of expanding role of natural gas in Asian economies as well as countries with significant dependence on natural gas export revenue. Asia is projected to increase its gas usage and hence, both gas-exporting-dependent countries and major natural gas and LNG importers, will become economically vulnerable to volatility in gas prices, because gas prices show significant risk transmission from oil markets at the left tail of the return distribution even the two prices are determined by their own fundamentals. The perceived independence of market-determined natural gas prices mask the risk of tail dependent risk transmission from the oil market.

Third, the observed tail dependence of oil and gas prices, especially during volatile price regimes, does not also make them hedges (in light of differing growth opportunities in both fuels) in diversified portfolios. But their co-movements make them candidates for investment strategies such as pair trade if they eventually converge to some parity. These strategies entail that traders go long on contracts that are underperformers and short contracts that are overperformers based on a parity target price.

Lastly, for policy makers and the gas industry, which are facing a decision on a gas pricing transition from oil indexation to gas-on-gas competitive prices, such as those in East Asia, our results suggest that even though hub prices formed independently from oil prices are used as benchmark prices, appropriate mechanisms are still required to manage and hedge the negative consequences of high volatility and the possibility of risk transmission from oil markets. Even though gas prices can be independent of oil prices, results from our study of the US and European markets show that left-tail risk transmission still exist in such a setting.

References

Aloui, C. and S. Mabrouk (2010). Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed GARCH models. *Energy Policy 38*(5), 2326–2339.

Aloui, R., M. Ben Aissa, S. Hammoudeh, and D. K. Nguyen (2014). Dependence and extreme dependence of crude oil and natural gas prices with applications to risk management. *Energy Economics 42*(C), 332–342.

Arouri, M. E. H., J. Jouini, and D. K. Nguyen (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics 34*(2), 611–617.

Asche, F., P. Osmundsen, and M. Sandsmark (2006). The UK Market for Natural Gas, Oil and Electricity: Are the Prices Decoupled? *The Energy Journal 27*(2), 27–40.

Asche, F., P. Osmundsen, and R. Tveterås (2002). European market integration for gas? Volume flexibility and political risk. *Energy Economics 24*(3), 249–265.

Balclar, M., R. Demirer, S. Hammoudeh, and D. K. Nguyen (2016). Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. *Energy Economics 54*, 159–172.

Bassett Jr, G. W. and H.-L. Chen (2002). Portfolio style: Return-based attribution using quantile regression. In *Economic Applications of Quantile Regression*, pp. 293–305. Springer.

Baur, D. G. (2013). The structure and degree of dependence: a quantile regression approach. *Journal of Banking & Finance 37*(3), 786–798.

Baur, D. G., T. Dimpfl, and R. C. Jung (2012). Stock return autocorrelations revisited: A quantile regression approach. *Journal of Empirical Finance 19*(2), 254–265.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 31*(3), 307–327.

Box, G. and D. Pierce (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American Statistical Association 65*, 1509–1526.

Chang, C.-L., M. McAleer, and R. Tansuchat (2010). Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. *Energy Economics 32*(6), 1445–1455.

Chuang, C.-C., C.-M. Kuan, and H.-Y. Lin (2009). Causality in quantiles and dynamic stock returnvolume relations. *Journal of Banking & Finance 33*(7), 1351–1360.

Ciner, C., C. Gurdgiev, and B. M. Lucey (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis 29*, 202–211.

David Cabedo, J. and I. Moya (2003). Estimating oil price Value at Risk' using the historical simulation approach. *Energy Economics 25*(3), 239–253.

Du, X., C. L. Yu, and D. J. Hayes (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics 33*(3), 497–503.

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society 50*(4), 987–1007.

Engle, R. and S. Manganelli (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic 22*(4), 367–381.

Ewing, B. T., F. Malik, and O. Ozfidan (2002). Volatility transmission in the oil and natural gas markets. *Energy Economics 24*(6), 525–538.

Fan, Y., Y.-J. Zhang, H.-T. Tsai, and Y.-M. Wei (2008). Estimating Value at Risk' of crude oil price and its spillover effect using the GED-GARCH approach. *Energy Economics 30*(6), 3156–3171.

Gebka, B. and M. E. Wohar (2013). Causality between trading volume and returns: Evidence from quantile regressions. *International Review of Economics & Finance 27*, 144–159.

Hammoudeh, S., H. Li, and B. Jeon (2003). Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. *The North American Journal of Economics and Finance 14*(1), 89–114.

Han, H., O. Linton, T. Oka, and Y.-J. Whang (2016). The cross-quantilogram: measuring quantile dependence and testing directional predictability between time series. *Journal of Econometrics 193*(1), 251–270.

Hong, Y., Y. Liu, and S. Wang (2009). Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics 150*(2), 271–287.

IEA (2013). Developing a Natural Gas Trading Hub in Asia: Obstacles and Opportunities. *International Energy Agency, Paris.*.

IEA (2016). World Energy Outlook. *International Energy Agency, Paris.*.

Ji, Q. and Y. Fan (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy 89*(1), 273–280.

Joëts, M. (2014). Energy price transmissions during extreme movements. *Economic Modelling 40*, 392–399.

Kuester, K., S. Mittnik, and M. S. Paolella (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics 4*(1), 53–89.

Lee, B. S. and M.-Y. L. Li (2012). Diversification and risk-adjusted performance: A quantile regression approach. *Journal of Banking & Finance 36*(7), 2157–2173.

Li, M.-Y. L. and P. Miu (2010). A hybrid bankruptcy prediction model with dynamic loadings on accounting-ratio-based and market-based information: A binary quantile regression approach. *Journal of Empirical Finance 17*(4), 818–833.

Lin, B. and J. Li (2015). The spillover effects across natural gas and oil markets: Based on the VECMGARCH framework. *Applied Energy 155*, 229–241.

Lin, S. X. and M. N. Tamvakis (2001). Spillover effects in energy futures markets. *Energy Economics 23*(1), 43–56.

Lin, S. X. and M. N. Tamvakis (2004). Effects of NYMEX trading on IPE Brent Crude futures markets: a duration analysis. *Energy Policy 32*(1), 77–82.

Linton, O. and Y.-J. Whang (2007). The quantilogram: With an application to evaluating directional predictability. *Journal of Econometrics 141*(1), 250–282.

Malik, F. and S. Hammoudeh (2007). Shock and volatility transmission in the oil, US and Gulf equity markets. *International Review of Economics & Finance 16*(3), 357–368.

Marimoutou, V., B. Raggad, and A. Trabelsi (2009). Extreme Value Theory and Value at Risk: Application to oil market. *Energy Economics 31*(4), 519–530.

Mensi, W., S. Hammoudeh, J. C. Reboredo, and D. K. Nguyen (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review 19*, 1–17.

Nazlioglu, S., C. Erdem, and U. Soytas (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics 36*, 658–665.

Panagiotidis, T. and E. Rutledge (2007). Oil and gas markets in the UK: Evidence from a cointegrating approach. *Energy Economics 29*(2), 329–347.

Rubia, A. and L. Sanchis-Marco (2013). On downside risk predictability through liquidity and trading activity: A dynamic quantile approach. *International Journal of Forecasting 29*(1), 202–219.

Serletis, A. and A. Shahmoradi (2005). Business cycles and natural gas prices. *OPEC Review 29*(1), 75–84.

Serra, T. (2011). Volatility spillovers between food and energy markets: A semiparametric approach. *Energy Economics 33*(6), 1155–1164.

Sheng, Y., X. Shi, and D. Zhang (2014). Economic growth, regional disparities and energy demand in China. *Energy Policy 71*, 31–39.

Shi, X. and H. M. Padinjare Variam (2016). Gas and LNG trading hubs, hub indexation and destination flexibility in East Asia. *Energy Policy 96*, 587–596.

Siliverstovs, B., G. L'Hégaret, A. Neumann, and C. von Hirschhausen (2005). International market integration for natural gas? A cointegration analysis of prices in Europe, North America and Japan. *Energy Economics 27*(4), 603–615.

Tsai, I.-C. (2012). The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. *Journal of International Financial Markets, Institutions and Money 22*(3), 609–621.

White, H., T.-H. Kim, and S. Manganelli (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics 187*(1), 169–188.

Yao, T., Y.-J. Zhang, and C.-Q. Ma (2017). How does investor attention affect international crude oil prices? *Applied Energy 205*, 336–344.

Zhang, D., M. Shi, and X. Shi (2018). Oil indexation, market fundamentals, and natural gas prices: An investigation of the Asian premium in natural gas trade. *Energy Economics*.

Zhang, Y.-J., J. Chevallier, and K. Guesmi (2017). De-financialization of commodities? Evidence from stock, crude oil and natural gas markets. *Energy Economics 68*, 228–239.

Zhang, Y.-J. and Y.-F. Sun (2016). The dynamic volatility spillover between European carbon trading market and fossil energy market. *Journal of Cleaner Production 112*, 2654–2663.

Zhang, Y.-J. and T. Yao (2016). Interpreting the movement of oil prices: Driven by fundamentals or bubbles? *Economic Modelling 55*, 226–240.