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The dynamic linkages between crude oil and natural gas markets

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ABSTRACT

The time varying price spillovers between natural gas and crude oil markets for the period 1994 to 2014 are investigated. Contrary to earlier research, we show that in a large part of our sample the natural gas price leads the price of crude oil with price spillover effects lasting up to two weeks. This result is robust to a battery of tests including out-of-sample forecasting exercises. However, after 2006, we detect little price dependencies between these two energy commodities. These findings arise due to a conjunction of both demand and supply-side shocks arising from both natural and economic events, including Hurricane Katrina, the Tohoku earthquake and the Global Financial Crisis, as well as infrastructure and technological improvements. The increased use of new technologies such as hydraulic fracking for the extraction of gas and oil in particular affected supply in the latter part of the study. We conclude that the long term relation present in the early part of the sample has decoupled, such that price determination of these two energy sources is now independent.

1. Introduction

Crude oil and natural gas are major energy sources for the global economy. Thus, it is important to understand any price dependencies between these two commodities to better evaluate energy investment decisions, conduct policy decisions that may encourage the use of one fuel over another and also, to examine trading opportunities in highly active petroleum derivatives markets. Furthermore, energy commodities could be considered as alternatives to stock and bond portfolios to allow hedging against market risks. In fact, based on their energy contents, one could also derive a "burner tip parity" to facilitate arbitrage based on the theoretical price relationship of natural gas to that of crude oil (e.g. Ramberg and Parsons, 2012).

Papers investigating the relation between oil and gas typically report three key findings: the relation between gas and oil is unstable both in econometric and time terms; information transmission runs predominantly from oil to gas; and finally the linkages are generally asymmetric, in that positive and negative shocks behave differently. In this paper, our goal is to provide new empirical evidence on the transmission of shocks, between the crude oil and natural gas markets, by paying particular attention to their time-varying properties. Importantly, we do so through the lens of new empirical techniques. In fact one distinguishing feature of this study is that we do not impose any underlying economic structure, such as the long term and stable relation required for cointegration that is common in many recent works (see Brigida's, 2014 discussion). Neither do we impose crude oil as being weakly exogenous to natural gas. Instead, by using reduced form bivariate vector autoregressions (VARs), we allow for feedback between the two variables.

The VARs are estimated in a rolling scheme with Granger causality tests calculated at each step to provide a time-varying analysis of the one-step-ahead predictive power of these commodities for one other. Ferraro et al. (2015) recently applied the same intuition when analyzing the predictive linkages between crude oil and exchange rates. We supplement our results with a battery of causality tests, in the time and frequency domain, with out-of-sample predictive power tests, and with the more recently developed Hatemi-J (2012) asymmetric causality tests. Furthermore, we investigate whether the impact of shocks last longer than a day. Finally, we examine the economic significance of the findings of causality by comparing the predictive power generated by our models to the random walk benchmark, which is frequently suggested as the hardest to beat in prior work.

Overall, our empirical analysis shows no evidence for a stable relation between the oil and gas markets. Instability in supply is perhaps not surprising given the technologies and extraction methods involved in oil and gas production. However, the presence of common business cycles and environmental and climate factors is likely to drive demand, which would be consistent with potential spillover and causality effects. The interplay between these factors underpins the significant time variation in information spillover evident in the results and the interesting

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finding that after 2006, there is no evidence of a causal relationship. This conclusion is contrary to the view that crude oil and natural gas can be regarded as reliable substitutes, or that the price of one can be used to hedge the price of the other, which is a necessary condition for convergence-based trading strategies.

In addition, we show that for the period between 1999 and 2006, the natural gas market unilaterally Granger causes the crude oil market. The unilateral causality is strong enough to allow us to obtain better forecasts than the random walk model, implying potential trading opportunities in this time period. The only causality detected from crude oil to natural gas is in the beginning of the sample between 1994 and 1996: the latter time coincided with the January 1996 agreement for Iraq to sell oil under U.N. Resolution 986, while the former was characterized by a number of supply-side quota shocks that expanded both natural gas and oil production (see Van Robays, 2012; Fratzscher et al., 2014). It is noteworthy that this finding is against the conclusions of the significant majority of studies in the literature, such as Nick and Thoenes (2014), Hartley et al. (2008), Brown and Yücel (2008), Panagiotidis and Routledge (2007) and more recently Lin and Li (2015), who all argue that crude oil is dominant in information processing within energy markets. Note that Lin and Li (2015) did identify regional differences in volatility spillover effects between oil and gas in the U.S., Europe and Japan.

Asymmetric causality tests also show that both natural gas price increases *and* declines were transmitted to the crude oil market in the period between 1999 and 2006. However, these tests also reveal a noteworthy finding that crude oil price increases never caused price changes in the natural gas market. It becomes apparent that the causality that is detected from crude oil to natural gas in the beginning of the sample is caused by an asymmetric relationship—oil price declines preceded natural gas price increases in that period. There is a similar period around 2009, during the period of the Global Financial Crisis, when crude oil price declines also generated natural gas price increases. This is again evidence against the notion that these two markets can be reliably regarded as substitutes.

These results contribute to existing literature on the interconnectedness of the energy markets to one another and also to other asset markets, such as stocks. In the case of the former, Atil et al. (2014) also examine asymmetric linkages between oil and gas markets. However, they do so by modeling natural gas prices as dependent on crude oil prices. An example of the latter relationship between energy and stock markets is the paper by Gatfaoui (2016), who assesses the joint link between U.S. oil and gas markets and then uses this to assess the relationship with U.S. stock markets, while Sanusi and Ahmad (2016) employ asset pricing techniques to show that energy price factors affect the returns of U.K. based oil and gas companies. Our findings provide important insights into the general applicability of this and related approaches. Other recent papers, recognizing the time-varying nature of volatility and its spillover to other markets, employ GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) techniques to model spillovers between oil and gas markets. For example, Lin and Li (2015) extend the Vector Error Correction (VEC) model of oil and gas prices, but do so in a Multivariate GARCH (MGARCH) setting.

In further analysis in this study, time varying impulse response functions are estimated to examine the possibility that some shocks could have a longer term impact than others. We calculate accumulated impulse response functions from rolling bivariate VARs along with their standard errors. This exercise suggests that the unilateral impact from natural gas to crude oil is still statistically significant after 10-days. However, again, in the latter part of the sample, we do not detect dependency between these two markets.

The rest of the paper is organized as follows: In the next section, we expand upon the literature discussed briefly in the introduction; then, the statistical methods are discussed, along with an overview of the data used. The preliminary statistics and the main empirical findings are then presented, with concluding remarks in the final section of the paper.

2. Literature

A general review on the modeling of the oil market and its structure is provided in Alhajji and Huettner (2000), with the work by Balistreri et al. (2010) providing further and more recent insights. The nature of the linkage between crude oil and natural gas prices has been investigated by many researchers including Lin and Li (2015), Atil et al. (2014), Brigida (2014), Nick and Thoenes (2014), Ramberg and Parsons (2012), Brown and Yücel (2008), Hartley et al. (2008), Villar and Joutz (2006), Serletis and Herbert (1999) and Vücel and Guo (1994) among many others.

As mentioned earlier, these studies report three key empirical findings. The first relates to the instability in the crude oil–natural gas price. This is especially important because cointegration analysis is the chosen methodology in a large part of the prior work. Cointegration analysis looks for a stationary, or stable, relation between the price differential in the oil and gas markets. Instabilities in this relation make it difficult to reach conclusive results concerning the long term relationship between two assets. For example, Parsons and Ramberg (2012), Brown and Yücel (2008), Hartley et al. (2008) and Villar and Joutz (2006) argue that since the oil and gas markets are cointegrated, a vector error correction model is appropriate. However, Parsons and Ramberg (2012) argue that the evidence for cointegration is rather weak, while Brigida (2014) finds the cointegration relation between the two variables exhibits significant regime changes. More recent authors such as Geng et al. (2016) are able to consider the impact of the shale gas revolution and how this has destabilized the long-term oil and gas relationship, especially in the United States of America.

The second conclusion of the oil and gas literature is that information transmission runs from crude oil to natural gas. In other words, crude oil is exogenous with respect to the gas market. By using Granger causality tests, Brown and Yücel (2008), Hartley et al. (2008) and Asche et al. (2006) detect causality from crude oil to natural gas. This is usually explained by the fact that crude oil market is a global and much larger market, whereas natural gas prices are much more sensitive to local market conditions. It is important to note that based on these reported empirical findings, many recent studies impose weak exogenity of crude oil on natural gas as a structural assumption, without first testing for it, and therefore investigate the linkages between these prices in a single equation framework (see for example, Atil et al., 2014; Brigida, 2014; and Nick and Thoenes, 2014).

The third conclusion of the prior work is that the linkages between these commodities are likely to exhibit asymmetries, in that transmission of positive and negative shocks are likely different. Similarly, this is usually motivated by the argument that the price of crude oil in global markets is determined by international macro factors, while natural gas prices respond much more to regional factors, which may be part reflect the impediment of transport costs. Atil et al. (2014) is a recent example of this strand of the literature.

3. Statistical method of analysis

3.1. Time- and frequency-domain causality tests

As mentioned above, the primary focus in this study is to provide evidence on the time-varying price spillovers between prices in the crude oil and natural gas markets. Granger causality tests are our primary tools in this analysis. Specifically, a variable is said to Granger cause another if information contained in the first variable is useful to improve the forecast of the second variable. As originally introduced by Granger (1969), these tests have been applied in numerous articles for determining the nature of the relations between economic and financial variables.

Granger causality tests are conventionally conducted as in-sample *F*, or *Wald* tests in vector autoregression (VAR) models. The prices in the oil and gas markets can be expressed as described below:

$$\Delta Oil_t = \alpha_0 + \alpha_1 \Delta Oil_{t-1} + \ldots + \alpha_p \Delta Oil_{t-p} + \beta_1 \Delta Gas_{t-1} + \ldots + \beta_p \Delta Gas_{t-p} + \varepsilon_{1,t} \quad (1)$$

$$\Delta Gas_t = a_1 + a_1 \Delta Oil_{t-1} + \ldots + a_p \Delta Oil_{t-p} + b_1 \Delta Gas_{t-1} + \ldots + b_p \Delta Gas_{t-p} + \varepsilon_{2,t} \quad (2)$$

In which ΔOil and ΔGas denotes the first differences of logarithms of crude oil and natural gas prices (or returns if one assumes negligible carrying-costs due to the short holding period as discussed further below in the data section), and p is the lag length of the system. The primary advantage of the reduced from VAR models is that both variables are treated as jointly endogenous; hence, no structural assumption is needed in regards to the relation between crude oil and natural gas prices. The equations can be estimated using the ordinary least squares (OLS) method, while Granger causality testing amounts to testing the restrictions on coefficients. For example, Granger causality from natural gas returns to crude oil returns can be expressed by the following hypothesis, which can be tested by an *F*, or a *Wald*, test:

$$H_o : \beta_1 = \beta_2 = \ldots = \beta_p = 0 \quad (3)$$

If this null hypothesis is rejected, it can be concluded that there is causality from natural gas to crude oil, which in turn implies that past information in the natural gas market is helpful to forecast movements in the crude oil market.

As discussed in the Introduction, a goal of the present study is to account for instabilities in price linkages between the oil and gas markets. Therefore, in addition to the full sample analysis, rolling VARs—with a window size of 1000 observations—are estimated with recalculation of the causality tests at each iteration. This approach provides a series of test statistics that record the evolution of price spillovers between these two markets. The choice of window size of 1000 observations is somewhat arbitrary but corresponds to approximately four years of data (about 252 working days in each year). This should be sufficient to account for all lagged information. However, we also test shorter (750) and longer (1250) observation windows with the results being materially the same.

While commonly used in empirical research, a noteworthy point regarding the conventional tests discussed above is that they produce a single, one-shot statistic regarding predictability. Consequently, they implicitly ignore the possibility that causal dynamics could show variation across different frequencies across the spectrum. In many cases it could be useful to obtain information on short term, or temporary, spillovers versus long term, or permanent, causal relations. This can be accomplished by examining causality in the frequency domain. Specifically, high frequency shocks are those that disappear relatively fast, while low frequency shocks tend to be more permanent. By conducting the separate causality analysis at high and low frequencies, it is possible to gain a richer understanding of the dependency between any two variables.

These points have been well recognized in the literature (e.g. Geweke, 1984). However, the test statistics using frequency domain analysis are difficult to estimate due to the presence of nonlinearities. In this regard, Breitung and Candelon (2006) offer suitable statistical techniques for conducting causality tests at any given frequency. In particular, by building on earlier work by Geweke (1984), these authors show that the test statistics can be calculated by imposing linear restrictions on the autoregressive parameters in a VAR model. They also find that their method has good size properties in Monte Carlo experiments.

An example of a recent application is Yamada and Yanfeng (2014). These authors conduct a simulation study on the power properties of the Breitung–Candelon test. In the original paper, Breitung and Candelong state that theoretically their frequency domain causality test should suffer from low power when causality is examined at the extreme ends of the spectrum. However, Yamada and Yanfeng (2014) find that even at the extremes of the spectrum, the frequency domain causality test has high power.

The details of the Breitung and Candelon (2006) methodology have also been extensively discussed in prior studies, including Lemmens et al. (2008), Bodart and Candelon (2009) and Ciner (2013) among others. Thus, here we present their primary conclusions, which show that within the context of our study, Granger causality from ΔGas o ΔOil at any frequency (ω) can be tested by the following linear restriction:

$$H_0 : R(\omega)\beta = 0, \quad (4)$$

where $\beta = |\beta_1 \ldots .\beta_p|'$ and

$$R(\omega) = \begin{pmatrix} \cos(\omega) & \cos(2\omega) \ldots . \cos(pw) \\ \sin(\omega) & \sin(2\omega) \quad \sin(p\omega) \end{pmatrix}.$$

This null hypothesis can also be tested using an *F*-test, which follows an $F(2, T-2\text{p})$ distribution, for every ω between 0 and π, with T being the number of observations in the series. We calculate frequency domain causality tests at high and low frequencies, as discussed further below. Moreover, we similarly estimate rolling VARs and recalculate the test statistics at each step to obtain a time series of *F-tests* on high and low frequency dynamics

3.2. Asymmetric causality tests

The Granger causality tests discussed above are built on the inherent assumption that a symmetric relation exists between the variables. In other words, it is assumed that the causal impact of a negative price change is the same as the impact of a positive price change. Consequently, if there is an asymmetric relation between natural gas and crude oil prices, conventional causality tests may not uncover it. This could happen, for example, if crude oil price declines affect natural gas prices differently than price increases. As mentioned earlier, an asymmetric relation between these two markets has been motivated by the recent work of Atil et al. (2014), who proposes that the oil price is determined by global factors, while the natural gas price is affected by more regional economic factors as well as by its own supply and demand shocks. These include changes in local weather conditions.

We rely on a recent test for asymmetric causality proposed by Hatemi-J (2012). Note that Nguyen et al. (2015) recently applied the same test statistic to examine asymmetric causality between the US equity returns and commodity futures returns. The starting point of the analysis is to define the prices (in levels) as random walk processes as follows:

$$Oil_t = Oil_{t-1} + \varepsilon_{Oil,t} = Oil_0 + \sum_{i=1}^{T} \varepsilon_{oil,t-i} \quad (5)$$

$$Gas_t = Gas_{t-1} + \varepsilon_{Gas,t} = Gas_0 + \sum_{i=1}^{T} \varepsilon_{Gas,,t-i} \quad (6)$$

In which $i = 1 \ldots .T$ and the constants Oil_0 and Gas_0 are the initial values of the respective commodities. Hatemi-J (2012) then proceeds to calculate cumulative positive and negative sums of the underlying variables as:

$$Oil_t^+ = \sum_{i=1}^{T} \Delta Oil_{t-i}^+, \; Oil_t^- = \sum_{i=1}^{T} \Delta Oil_{t-i}^- \\ Gas_t^+ = \sum_{i=1}^{T} \Delta Gas_{t-i}^+ \text{ and } Gas_t^- = \sum_{i=1}^{T} \Delta Gas_{t-i}^- \quad (7)$$

in which, $\Delta Oil_{t-i}^{+} = \max(\Delta Oil_{t-i}, 0)$, $\Delta Oil_{t-i}^{-} = \min(\Delta Oil_{t-i}, 0)$, $\Delta Gas_{t-i}^{+} = \max(\Delta Gas_{t-i}, 0)$ and $\Delta Gas_{t-i}^{-} = \min(\Delta Gas_{t-i}, 0)$. Causality tests can now be calculated between Oil_t^{+} and Gas_t^{+}, for example, to evaluate the impact of oil price increases on gas price increases, separately, within the context of VAR models. Note that since this method decomposes price levels, which are nonstationary, VAR models and causality tests are conducted using the lag augmentation method of Dolado and Lütkepohl (1996). We calculate the full eight possible combinations of asymmetric causality tests similarly, by using rolling VARs, to capture the effects of possible time variation linkages.

3.3. Out-of-sample causality tests

Granger causality analysis can also be conducted by examining out-of-sample forecasting accuracy. While the in-sample tests described above have been more frequently used in the literature, it can be argued that out-of-sample analysis is more in line with the intuition of Granger causality (see Ashley et al. (1980) for a discussion of this point). Out-of-sample causality analysis can be conducted by estimating restricted and unrestricted models and then, comparing their forecasting accuracy. For example, the linear model in Eq. (1) is our unrestricted model to measure causality from natural gas to crude oil returns. To examine whether the information in the natural gas market improves the forecast of crude oil futures, which is in fact the definition of Granger causality, we estimate the following restricted model:

$$\Delta Oil_t = \alpha_0 + \alpha_1 \Delta Oil_{t-1} + \ldots + \alpha_p \Delta Oil_{t-p} + \varepsilon_{2,t} \tag{8}$$

If Granger causality exists, forecasts generated by the unrestricted model should be superior to forecasts from the restricted model. Hence, we first obtain one-step-ahead forecasts by both the unrestricted and restricted models. In the second step, we examine whether forecasts by the unrestricted model have a lower mean squared forecast error (MSFE), in which case we conclude that Granger causality from natural gas returns to crude oil returns is present.

Diebold and Mariano (1995) propose a simple test statistic to examine equality of mean squared forecast errors. While the well-known DM test has been popular in empirical research, it has also been argued that the test statistic will be upwardly biased when the models are nested, as in our case. That is because the null hypothesis of the test is equal MSFE. Therefore, under the null hypothesis, the restricted model is the "correct" model and the unrestricted model is necessarily misspecified since it includes extraneous explanatory variables (see, among others, Ye, Ashley and Guerard, 2014). To correct for this bias, Clark and West (2006, 2007) propose the following statistic:

$$CW = P^{1/2} \frac{\frac{1}{p} \sum \left[e_{r,t}^2 - e_{u,t}^2 + (f_{r,t} - f_{u,t}) \right]}{LTVAR(e_{r,t}^2 - e_{u,t}^2 + (f_{r,t} - f_{u,t})} \tag{9}$$

In which $f_{r,t}$ and $f_{u,t}$ represent the out-of-sample forecasts from restricted and unrestricted models, respectively and $e_{r,t}$ and $e_{u,t}$ are forecast errors from restricted and unrestricted models. In this equation, p stands for number of observations and *LTVAR(.)* is the long term variance function. Clark and West (2006, 2007) also show that this statistic has a standard normal distribution asymptotically similar to the DM test, under the null hypothesis of equal MSFE for the two models. This is true for rolling forecasting schemes as used in the present study. For recursive forecasting exercises, the distribution of the test statistic is not standard normal. Note that positive values of the CW test indicate that the unrestricted model outperforms the restricted model in forecasting and if the test statistic is greater than the critical value of 1.96, it would be regarded as evidence for Granger causality.

4. Data

In this study we rely upon the prices of financial future contracts for crude oil and natural gas, where the underlying asset is each commodity traded in US dollars in the spot market. Futures prices are preferred since they tend to reflect information faster than the spot market. Nearby (or near month) futures contracts are used due to the fact that they tend to be the most liquid. Our data includes daily settlement prices of the nearby contract (to the spot date) of natural gas (Henry Hub Natural Gas) and crude oil futures traded on the New York Mercantile Exchange (NYMEX). For simplicity we refer to the market prices of these contracts as simply oil and gas prices. Note the crude oil contract is deliverable, whereas natural gas is cash settled upon expiration of the contract. The sample period is between January 13, 1994 and December 9, 2014, for a total of 5243 observations.

Russia is the world's largest producer and exporter of natural gas. However, most of Russian exports are piped gas not natural gas in liquid form (termed Liquid Natural Gas (LNG)), which is in effect a separate market. The world's largest importers of LNG are all in Asia, much of which comes from Indonesia and Australia (Cassidy and Kosev, 2015). While pricing mechanisms vary by regional market, there has also been a shift from long term to short term pricing of gas contracts in Asia more or less over the last 10-years. These short term contracts are priced off oil, such as North Sea Brent or Japan customs-cleared crude (JCC) because of "the liquidity and transparency of crude oil prices and the substitutability of natural gas and petroleum products" (EIA, 2016). Thus, as these contracts increase as a proportion of the total then there should be a convergence between the oil and gas prices. This conclusion is supported by our findings for the later part of the sample, where the leading status of gas to oil evident in the earlier periods is no longer present.[1]

This sample period covers a unique episode of modern history where the interplay between changes in demand, supply and infrastructure related factors in both the oil and gas markets caused considerable variation in the long-term relationships between these two sources of energy. First, there was long term variation in demand due to both business cycle and substitution effects as energy users shifted to alternate less polluting, or environmental damaging energy resources. Second, there were long term changes in supply due to the introduction of additional producers of both oil (e.g. the end of the trade embargo against Iran) and gas (e.g. new production in Australia and elsewhere), the failure by OPEC to enforce supply restrictions, and the impact of horizontal drilling in US markets. Finally, there were improvements in infrastructure in the form of better transport and technology that have lowered the cost of producing energy products (see Cassidy and Kosev, 2015; EIA, 2015, 2016; and Kennedy, 2015).

In addition there were a number of key events that affected markets:

(a) Hurricane Katrina in August 2005 cased a spike in oil prices due to reduced U.S. oil production in the Gulf of Mexico (see CFR, 2005 and Fratzscher et al., 2014).
(b) The impact of the Global Financial Crisis (GFC) on the demand of energy products. Immediately after the GFC period there was global oversupply (of both oil and gas);
(c) Following the Tohoku earthquake and subsequent Fukushima reactor disaster of March 11, 2011, gas prices rose. The disaster also changed energy policy in Japan and elsewhere away from nuclear towards gas and oil as well as a shift in the nature of contract pricing. As noted by CME (2016) "When Japan's nuclear plants shut down from 2012 to 2014, domestic LNG demand rose significantly, and almost all available LNG was locked up in term contracts. Spot LNG accounted for less than 15% of the LNG-traded market. However, with the economic slowdown in Asia last year, the amount of LNG in the form of already purchased

[1] We thank an anonymous referee for this observation.

contracts now exceeds actual demand3". Hence, buyers locked into term-supply contracts are looking for ways to off-load their excess supply in the spot market (Reuters, 2015).

(d) These events aligned with technological advances associated with horizontal drilling and hydraulic fracturing, especially in Canada and the US. As noted by Brown (2013), "oil and natural gas from shale formations became a significant factor after 2008…with rising energy prices and the shale boom led to strong growth of U.S. oil and gas employment from 2005 to 2011".

While oil and gas prices are not just driven exclusively by events in the United States the impact of technological improvements associated with shale gas and oil in Canada and the US cannot be ignored (See Kennedy, 2015). For example, while oil prices, along with oil production, have fallen from a peak in July 2008 (e.g. WTI of US$145.31 on July 3, 2008) the production of gas has remained more resilient and has only recently declined. Increasing output has largely been driven by technological improvements associated with cost extraction: extraction has remained profitable despite significant falls in price due to declines in costs. For example, Lease Operating Expenses (LOE), which are the costs of maintaining and operating property and equipment on a producing oil and gas lease, have fallen nearly 50% (see EIA, 2015, 2016).

The descriptive statistics of futures price returns, calculated as log price differences, are presented in Table 1. We find that, consistent with the literature, returns are not statistically different from zero, on average and exhibit excess kurtosis. Note that the standard deviation of natural gas is greater than oil over the full sample period. This table also shows the significant and high positive Pearson correlation coefficient between oil and gas as levels ($\rho = 0.451$, $p = 0.000$) and as log differences ($\rho = 0.224$, $p = 0.000$). The presence of long term correlation in the series has underpinned much of the arbitrage and trading literature where these two commodities are treated as a pair-trade. One important feature of the two series is their different standard deviations, with oil being less than gas (F-test of 0.41, $p = 0.000$ rejects the null hypothesis that the two are equal).

Also, as mentioned above, a large number of studies have focused on the cointegration properties between crude oil and natural gas prices. We have also tested for cointegration between the variables as a preliminary analysis by using two different approaches: Johansen's (1991) full information maximum likelihood approach; and Saikkonen and Lütkepohl's (2000) system cointegration analysis, which accounts for the possibility of structural shifts. The results of these tests were consistent in that the null hypothesis of no cointegration between crude oil and natural gas prices cannot be rejected. The details of these tests are not reported in a table but are available upon request from the authors.

5. Empirical findings

5.1. Time domain causality

We first present conventional time causality tests, conducted within the context of bivariate VAR models. The lag length for the VAR model for the full sample is determined by the Akaike Information Criterion (AIC) and is selected to be 3, which eliminates all autocorrelation present in the residuals. We first report the causality tests using the full sample data in Table 2. We observe that there is unilateral causality running from natural gas to crude oil at comfortable significance levels. In other words, the natural gas market seems to lead the crude oil market in the information process.

As discussed above, one of the goals of this paper is to provide evidence on time variation in the causality relations between the two variables. Hence, the full sample result should be regarded as an average relation between the variables. Hence, we then proceed by estimating rolling bivariate VAR models with the calculation of a new causality test statistic at each rolling window. This provides us with a series of time domain causality tests. The time varying causality tests are reported in Figs. 1 to 6: Figs. 1 to 3 report time domain causality, and then low and high frequency causality tests for natural gas to oil, while Figs. 4 to 6 repeat these for the relation from oil to natural gas. These figures reveal key several findings.

Firstly, it can be observed that it is important to account for time variation to ensure a complete understanding of the linkages between these two variables. The full sample test indicates significant causality from natural gas to crude oil. However, it is clear from Figs. 1 to 3 that this conclusion is only valid for the period between 2003 and 2010. In particular, there is a noteworthy increase in the importance of shocks from the natural gas market to the crude oil market from 2003 to 2006 and then, a gradual decline. The background to this finding is the significant increase in the crude oil price from its historic average of under US$30 per barrel to near US$100 per barrel in late 2007, with corresponding increases in the price of natural gas. Importantly, we find that there was no causality after 2010.

Since we use a 1000-day window in rolling VARs, this finding suggests that causality from natural gas to crude oil began approximately in 1999 with the significance of spillovers increasing through to 2002. The presence of the gas to oil causality coincides with the introduction in March 1998 and March 1999 of production cuts by OPEC in an attempt to prevent falls in oil prices (Fattouh, 2007). Afterward, the statistical significance gradually disappears, approximately in 2006. In other words, there is unilateral price spillover from natural gas futures to crude oil futures between 1996 and 2006.

On the other hand, the graph for the time domain causality test from crude oil to natural gas in Fig. 4 indicates that the crude oil market produced spillover shocks only for a relatively short period at the beginning of the sample. The influence of crude oil on natural gas seems to completely disappear after 1999. Again, since a 1000-day window is used, the findings indicate causality from crude oil to natural gas futures prices for the period 1994 to 1995, only. Hence, coupled with the causality tests in Fig. 1, the analysis suggests that there was no information spillover between these two energy markets after 2006, indicating a noteworthy degree of independence in the price process.

5.2. Frequency domain causality

While the time domain tests (Figs. 1 and 4) provide a summary measure of the lead–lag relations between the variables, as discussed above frequency domain tests decompose causality into short term (transitory) and long term (permanent) components. Short term linkages are captured by higher frequency components of the spectra, while long term dynamics correspond to lower frequency components, or trend relations. Therefore, if there is a long term dynamic relationship between

Table 1
Summary statistics.

	Mean	Std. dev.	Skewness	Kurtosis
Oil	.0003	.0231	−0.1224	4.561
Natural gas	.0001	.0360	0.1329	7.737

Notes: Sample period = January 13, 1994 to December 9, 2014. N = 5243. The full sample period Pearson correlation between Oil and natural gas was 0.224 ($p = 0.000$) and between (levels) oil and natural gas = 0.451 ($p = 0.000$).

Table 2
Full sample causality tests.

	Conventional	Short term	Long term	OOS-CW
Oil-natural gas	0.44 (0.72)	0.37 (0.69)	0.65 (0.52)	−1.69 (0.99)
Natural gas oil	17.13 (0.00)	8.99 (0.00)	24.84 (0.00)	7.89 (0.00)

Notes: Sample period = January 13, 1994 to December 9, 2014. N = 5243.

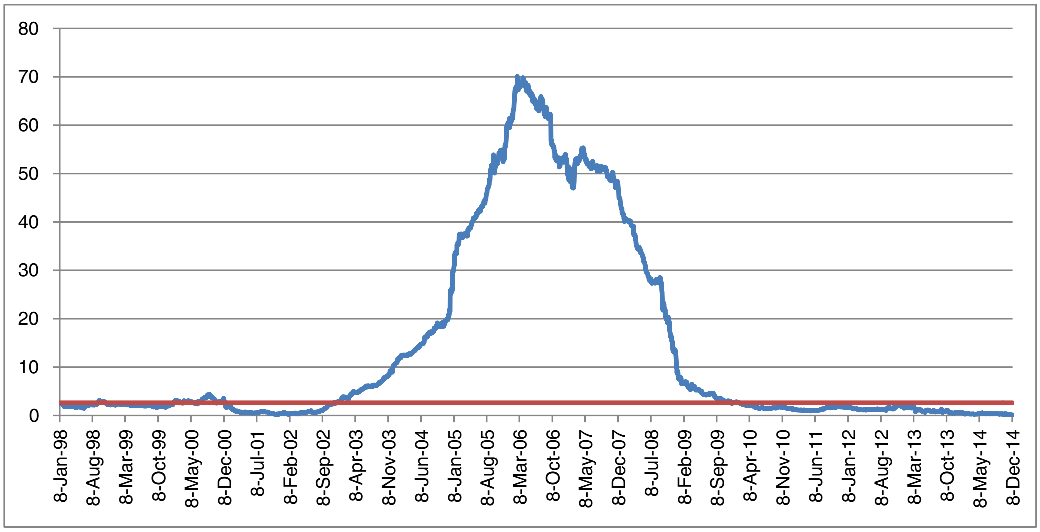

Fig. 1. Time domain causality from natural gas to oil.

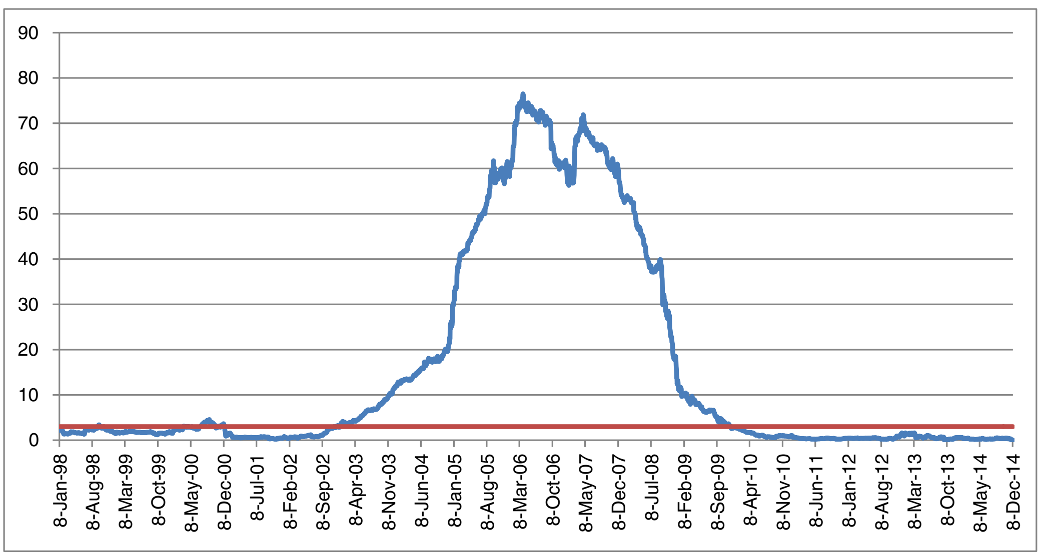

Fig. 2. Low frequency causality tests from natural gas to oil.

crude oil and natural gas prices in the data, omitted by the conventional causality tests, it is likely to be detected in this analysis.

In other words, consider the possible case of crude oil impacting the price of natural gas in the long run (as argued by several authors as mentioned in the introduction), while in the short run the price of natural gas was independent of crude oil. In this case we would expect a difference between short and long term causality tests from crude oil to natural gas, with long term causality tests being statistically significant. In this paper, short term causality tests are conducted at frequency $\omega = 2.5$, which corresponds to a periodicity of 2 to 3 trading days. These are shocks that tend to have a transitory impact. Long term causality tests are conducted at a frequency of $\omega = .5$, which corresponds to a periodicity of 12 to 13 trading days. These can be considered as permanent shocks with lasting effects.[2]

First, the full sample short and long term causality tests were calculated and are reported in the third and fourth column of Table 2. The results are similar to those from the time domain tests: There is unilateral, both short and long term, causality running from natural gas to crude oil futures. This indicates that examining short and long term causality separately does not change the conclusion that shocks from the crude oil market are not relevant for natural gas price movements. We then investigate time variation in the frequency domain causality tests by similarly conducting rolling VARs.

In Figs. 2 and 3, we present low and high frequency plots of the evolution in causality from natural gas to crude oil. These results are very similar to those from the time domain causality tests. The plot reveals significant causality from natural gas to crude oil between 2003 and 2010 and again, considering that 1000-day windows are used, this corresponds approximately to causality between 1999 and 2006. However, after 2006, there is no price spillover, which is also consistent with results presented in the time domain analysis.

Frequency domain tests for causality from crude oil to natural gas are reported in Figs. 4 and 5. The results are again similar to those

[2] We also conducted the long term causality analysis at frequency $\omega = .01$ at the very low end of the spectra. The results are qualitatively the same and are available from authors.

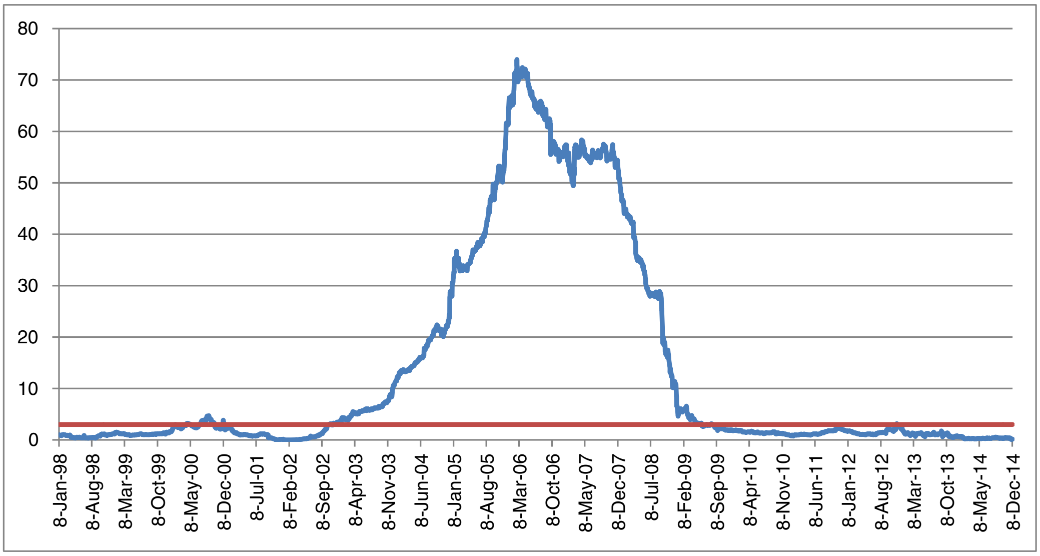

Fig. 3. High frequency causality tests from natural gas to oil.

from the time domain analysis. These results reveal causality from crude oil to natural gas only at the beginning of the sample period. It is particularly noteworthy that the findings are very similar for both short and long term causality tests. As argued above, if crude oil were a long term determinant of natural gas, even if not in the short term, we should have detected notable differences between the high and low frequency test statistics. There is no evidence to support this argument and overall, price shocks in the crude oil market do not appear to impact the natural gas market.

5.3. Asymmetric causality

We now proceed to determine whether there is any asymmetric dynamics not previously detected by the time and frequency domain causality tests conducted above. This could arise if crude oil and natural gas prices react differently to negative and positive price shocks. We use the decomposition and testing method suggested by Hatemi-J (2012), as described in the previous section, to construct asymmetric causality tests. We continue to rely on rolling bivariate VARs to obtain a series of test statistics to investigate potential time variation. We report the associated rolling *F-tests* for causality for the eight possible combinations between Oil_t^+, Oil_t^-, Gas_t^+ and Gas_t^- in Figs. 7 to 14.

These results confirm that asymmetric causality patterns from natural gas to crude oil are not materially different from those detected by time and frequency domain causality tests. Both natural gas price increases and decreases are informative for crude oil price changes for the period between 1999 and 2006. Again, after 2006, we do not observe any spillover from the natural gas market. Perhaps the more interesting results are observed when asymmetric causality is considered from crude oil to natural gas. Also, recall that time and frequency domain causality tests indicate a brief period at the beginning of the sample, between 1994 and 1996, when there was unilateral causality from crude oil to natural gas. The asymmetric causality tests reveal that this finding was due to spillovers from Oil_t^- to Gas_t^-. In other words, that causality occurred in a period in which both prices were falling.

A new finding revealed by the asymmetric causality tests is that there was spillover from Oil_t^- to Gas_t^+ between 1998 and 2000 and again, in a brief period around 2009, which coincides with the turmoil in financial markets due to the Global Financial Crisis. These linkages are not captured by conventional causality tests and indicate that in both periods oil price declines preceded natural gas price increases.

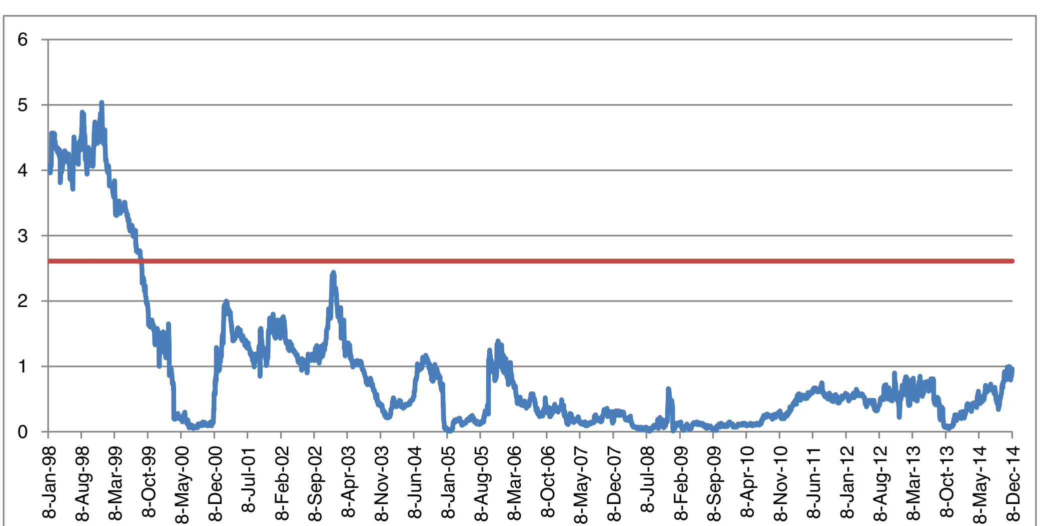

Fig. 4. Time domain causality tests from oil to natural gas.

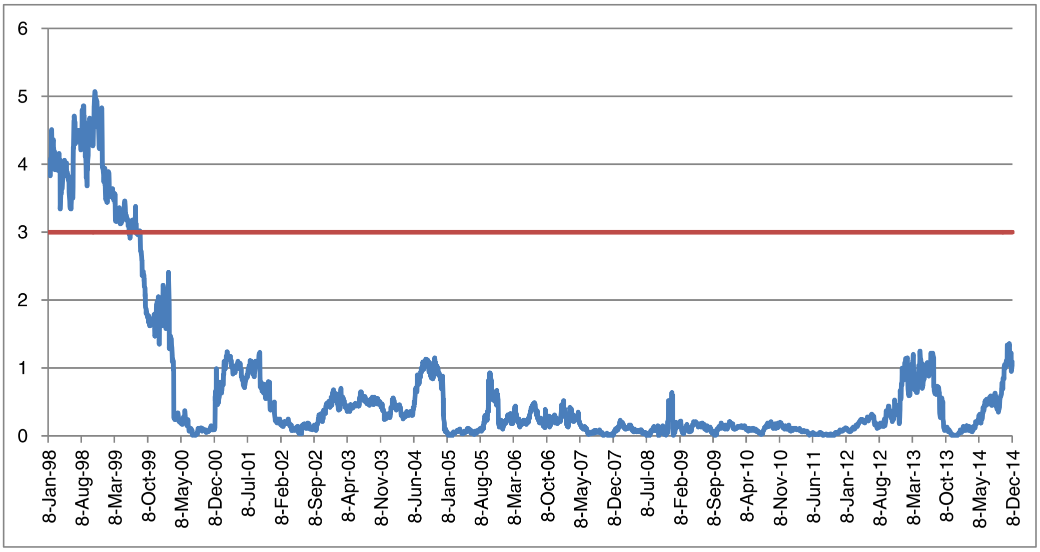

Fig. 5. High frequency causality tests from oil to natural gas.

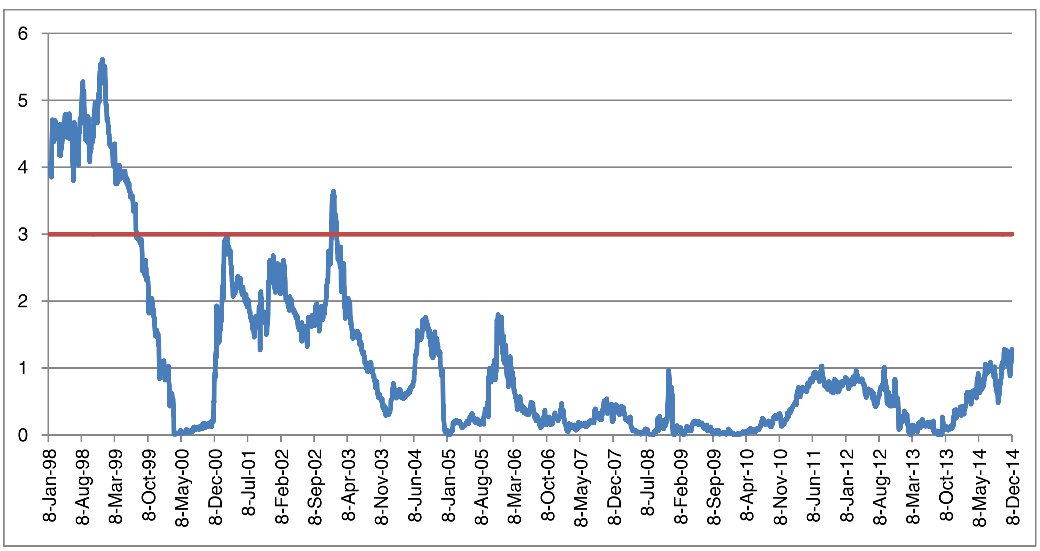

Fig. 6. Low frequency causality tests from oil to natural gas.

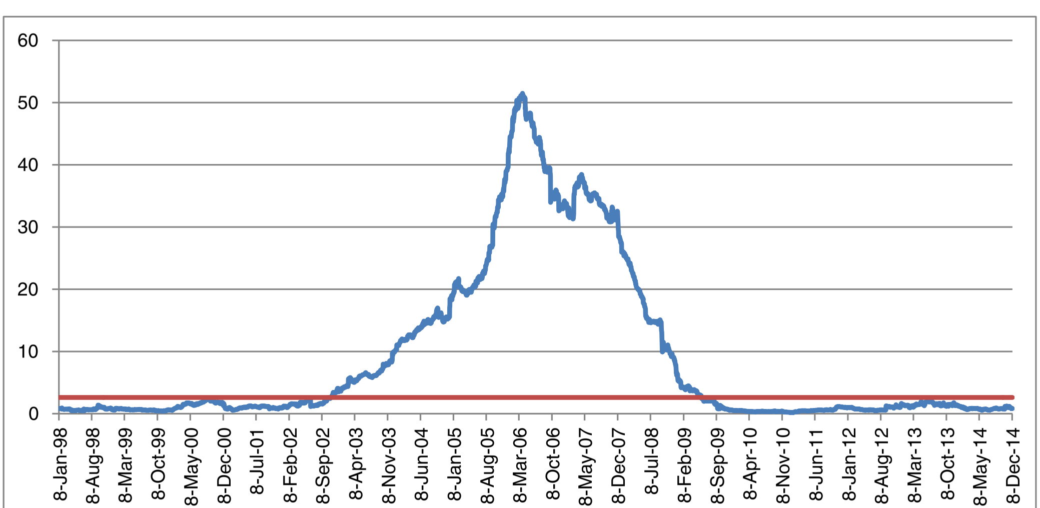

Fig. 7. Causality from Gas_t^+ to Oil_t^+.

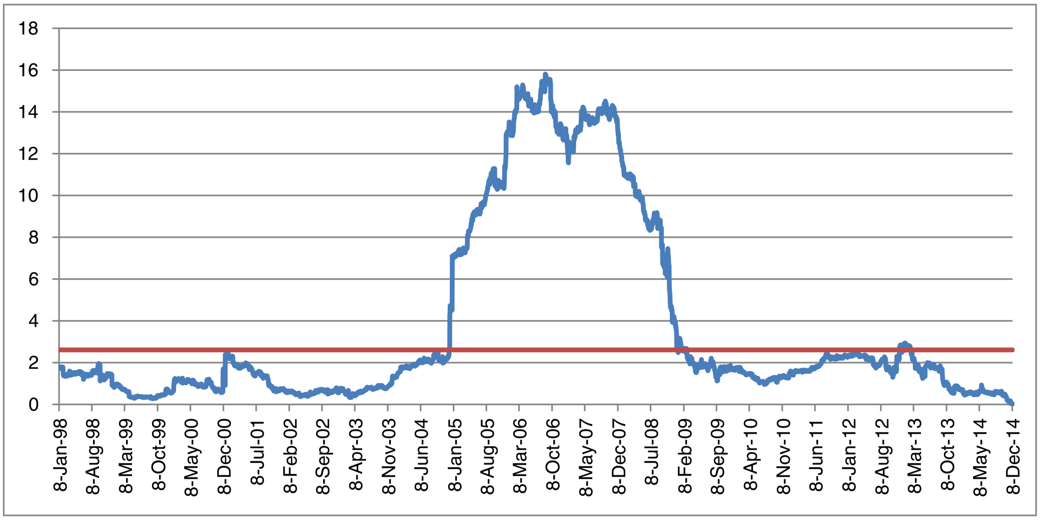

Fig. 8. Causality from Gas_t^+ to Oil_t^-.

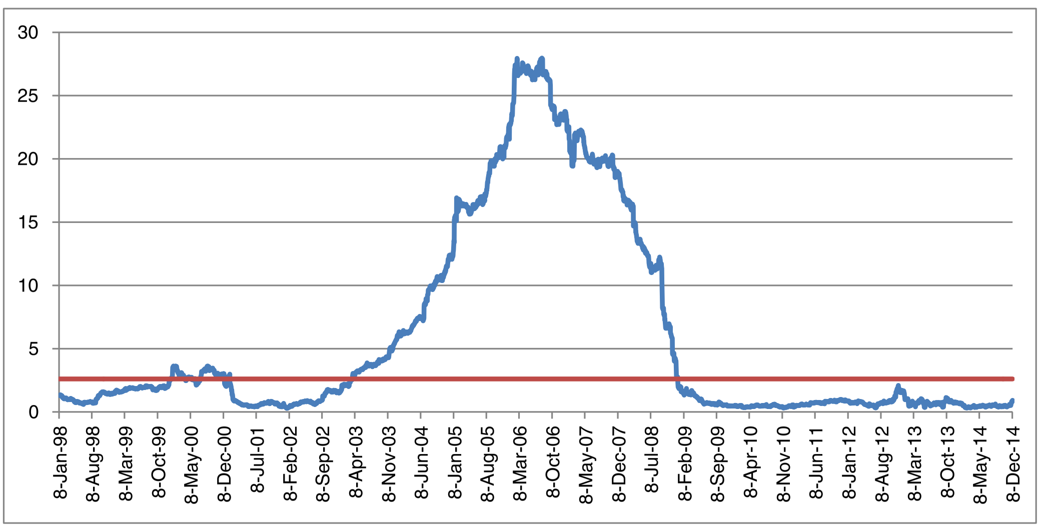

Fig. 9. Causality from Gas_t^- to Oil_t^+.

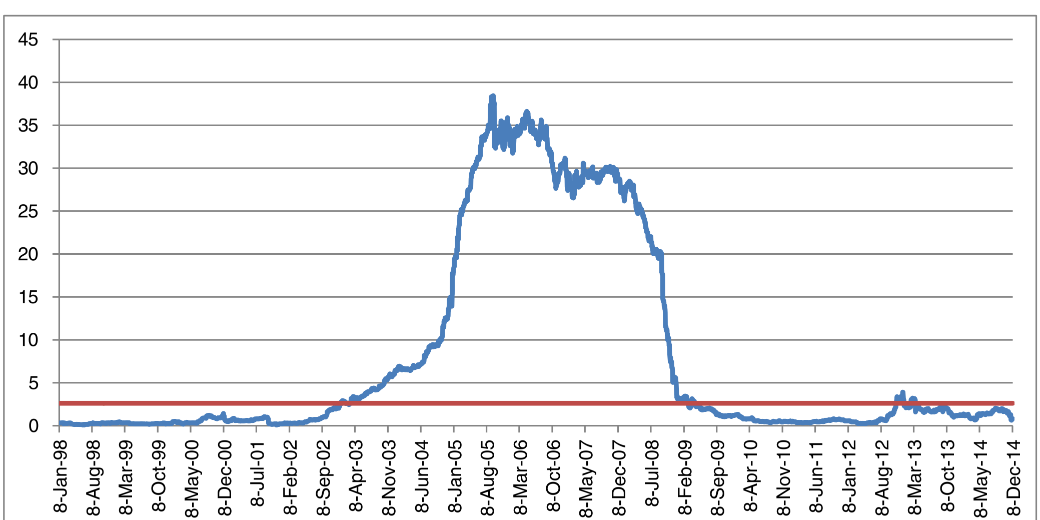

Fig. 10. Causality from Gas_t^- to Oil_t^-.

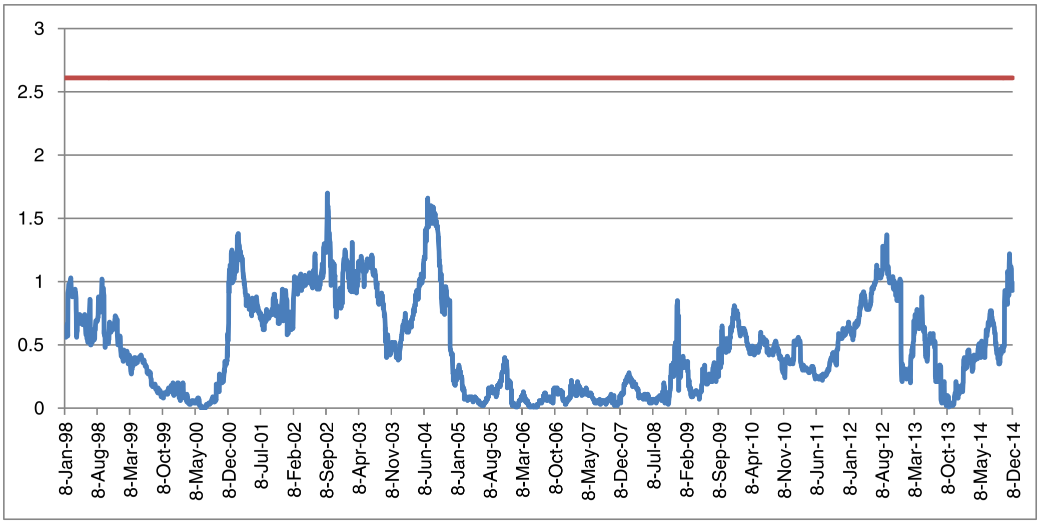

Fig. 11. Causality from Oil_t^+ to Gas_t^+.

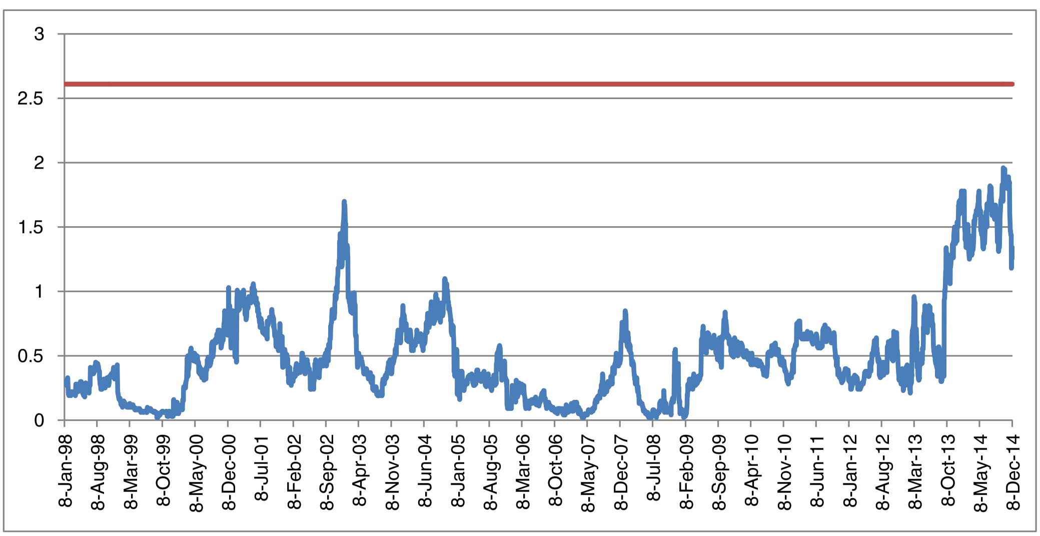

Fig. 12. Causality from Oil_t^+ to Gas_t^-.

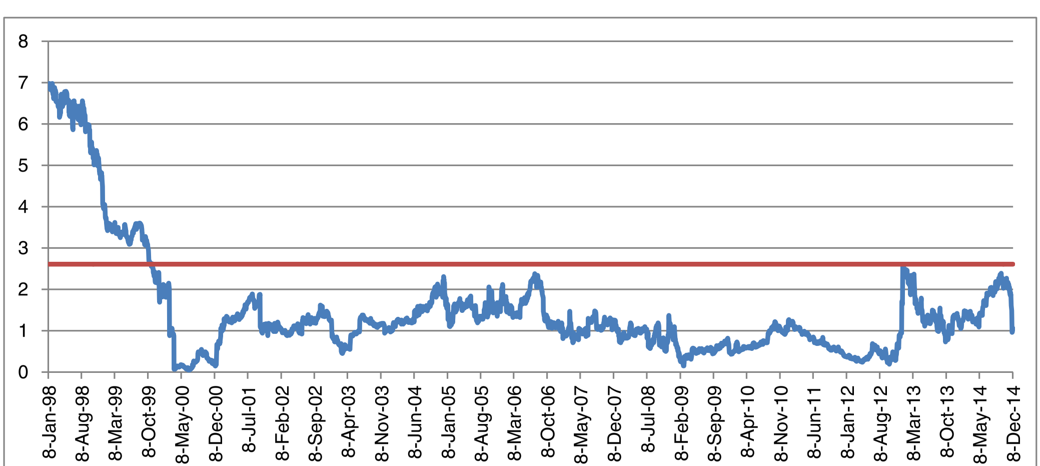

Fig. 13. Causality from Oil_t^- to Gas_t^-.

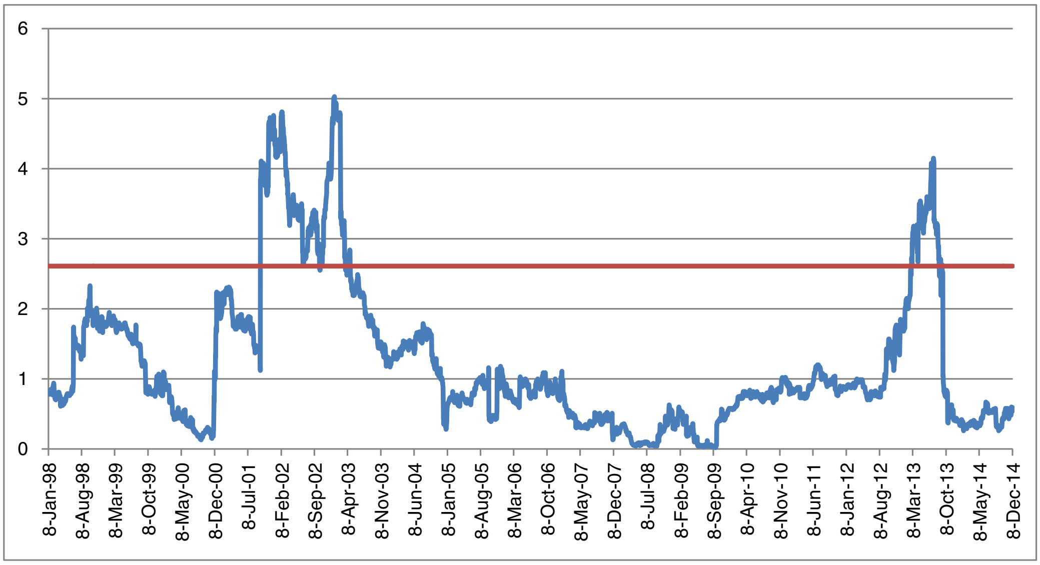

Fig. 14. Causality from Oil_t^- to Gas_t^+.

This is further evidence against a stable long term relation between these markets since it indicates that, at least for these periods, crude oil price declines can be viewed as positive news in the natural gas market.

At this junction, it is noteworthy that recently Atil et al. (2014) also examined asymmetric spillovers between crude oil and natural gas markets and report results that are rather different. They consider a similar decomposition method and find that crude oil and natural gas prices tend to move in the same direction. For example, they report that a 1% decline in the crude oil price is associated with a 1.6% decline in the natural gas price. They use monthly data and cover a shorter time period (between 1997 and 2012), which could account for some of the differences between their findings and those presented here.

However, the more likely explanation lies in the underlying assumption that Atil et al. (2014), along with many others in this branch of the literature such as Nick and Thoenes (2014) as recent examples, make in their analyses. Specifically, Atil et al. (2014) begin their empirical analysis by implicitly assuming that crude oil is (weakly) exogenous to natural gas. Thus, they construct a single equation structural model and consider only the unilateral impact from crude oil to natural gas. The findings of the present paper imply that this assumption is incorrect and there is statistically significant spillover from natural gas to crude oil at least in parts of the sample investigated. Hence, our approach, of estimating both prices jointly, appears to yield a richer analysis of the dynamic relationship.

5.4. Out-of-sample causality analysis

The tests above focus on the in-sample causality relations between the variables and identified significant causality running from natural gas prices to crude oil. A subsequent question of this finding for financial economists is whether causality findings are also significant in out-of-sample forecasting exercises. Moreover, a strand of the literature, beginning with Ashley et al. (1980), suggests that out-of-sample testing for predictability is a more appropriate way to test for causality dynamics. In this section, we conduct out-of-sample causality tests and investigate the robustness of the reported results.

To conduct this analysis, we first estimate restricted and unrestricted autoregressive models and obtain one-step-ahead forecasts by similarly using rolling regressions with 1000-day windows. Then, we use the CW test to examine the predictive power of lagged natural gas price changes for oil price changes and vice versa. We first report the CW tests for the entire sample in Table 2 and show that they are consistent with the in-

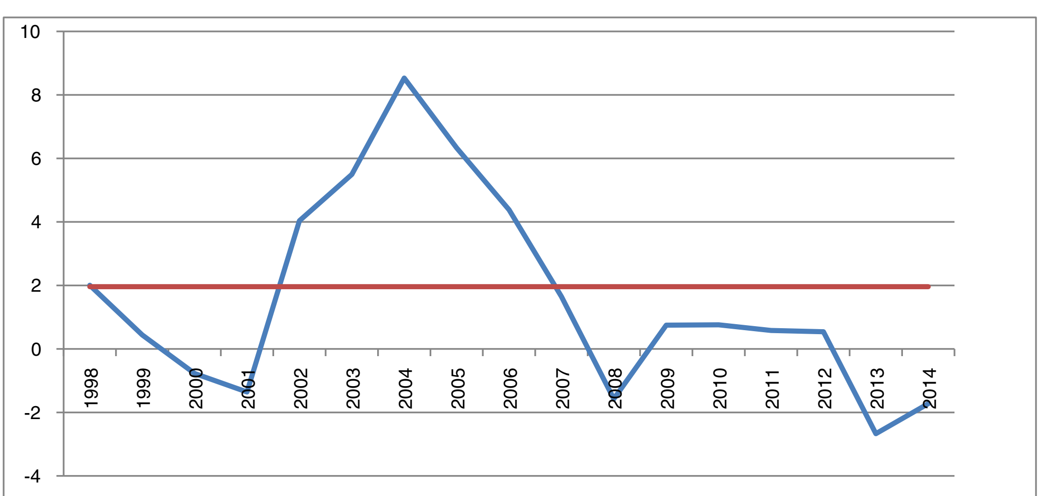

Fig. 15. Out-of-sample causality from natural gas to oil.

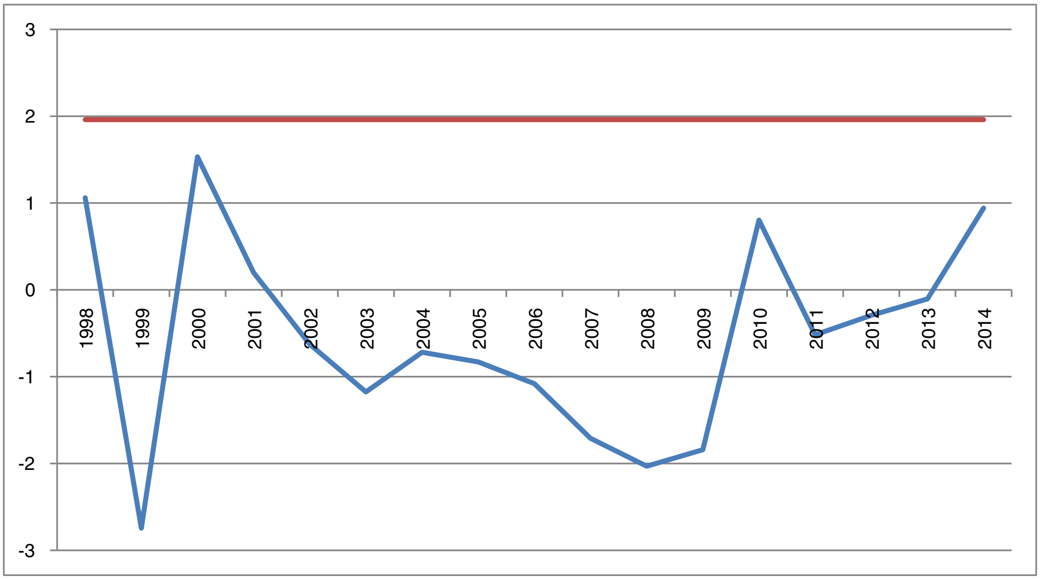

Fig. 16. Out-of-sample causality from oil to natural gas.

sample analysis. Specifically, the test statistics suggest unilateral causality from natural gas to crude oil.

However, the full sample CW test should be interpreted as evidence for *average* predictive power. The time-varying causal relations detected by the in-sample analysis presented above, leads us to examine potential instabilities in predictive power. It is noteworthy that instability of many economic variables in financial forecasting has attracted attention in recent literature (see Rossi, 2012 for a recent review). To investigate the time variation in forecasting power, we calculate the CW test for each year in the sample separately. This provides a series of CW tests, which are plotted in Figs. 15 and 16. These results are largely consistent with the in-sample analysis and reveal unilateral out-of-sample causality from natural gas to crude oil between approximately 2003 and 2007 with no price transmission occurring between the markets after 2009. In the case of causality from crude oil to natural gas, recall that the above in-sample analysis detects statistical significance in the beginning of the sample, between 1994 and 1999. The out-of-sample causality analysis also indicates a spike in the very beginning of the sample, while, in this case the statistical significance is not obtained.

These findings consistently point to statistically significant causality from natural gas futures prices to crude oil futures between 1999 and 2007. While researchers usually reach arguments based on statistical significance, an important further question is whether the findings are also economically significant. In this final part of the study, we focus on this issue. Since the influential work by Meese and Rogoff (1983) on exchange rate predictability, the gold standard of obtaining economically significant out-of-sample forecasting is comparing predictability against the simple random walk. Thus, we test whether our unrestricted autoregressive model for crude oil is able to generate forecasts better than a random walk in addition to the restricted model.

The method of analysis is the same as above, in other words we obtain one-step-ahead forecasts using rolling regressions and use the more reliable CW test to compare forecast accuracy. The full sample CW test produced by this exercise is 6.72, which is comfortably greater than the critical value of 1.96. In other words, over the entire sample, using lagged values of natural gas futures returns, improves crude oil futures price predictability and beats the random walk benchmark. This is a noteworthy finding since per the efficient markets hypothesis it is important to isolate economic and financial variables that could be significant predictors.

However, as mentioned above, the overall CW statistic is a summary measure that suggests predictive power over the entire sample of the

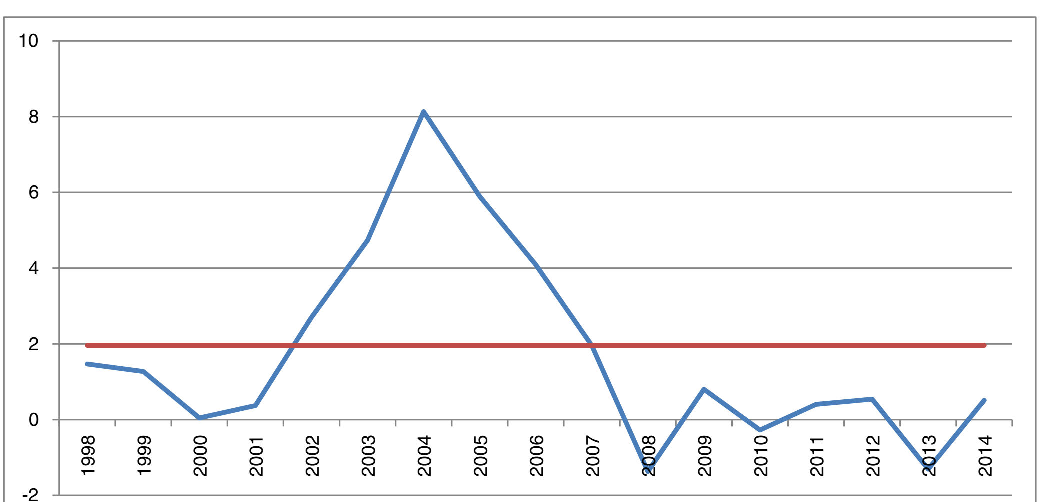

Fig. 17. Out-of-sample causality from natural gas to oil: random walk benchmark.

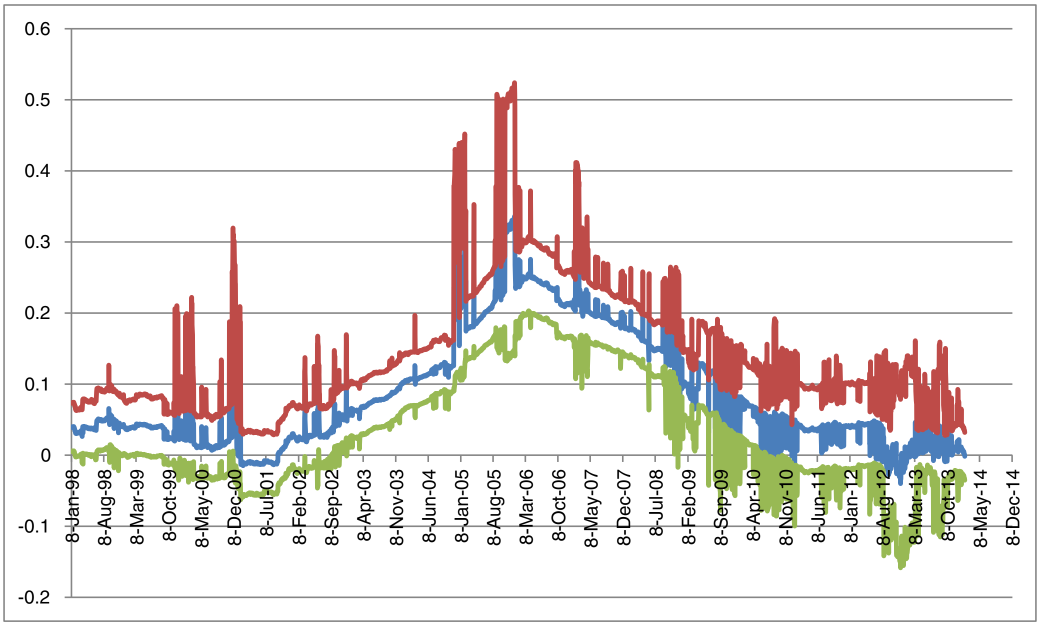

Fig. 18. 10-day horizon AIRF from gas to oil.

study. Therefore, similar to the above analysis, we also calculate CW statistics for each calendar year to gain insights into any time variation in predictability against the random walk. The results of this analysis are presented in Fig. 17. Similar to the previous analysis, we find that predictability only occurs in the period between 2001 and 2007.

5.5. Long term impacts

The Granger causality analysis discussed above examines one-step-ahead predictive ability. In the final part of the empirical analysis, we examine whether price spillovers between variables also have longer lasting impacts. For this purpose, we rely on impulse response functions, which can be calculated within the context of the same bivariate VAR models estimated to test for causality dynamics. Impulse response functions trace the impact of a one-unit in one variable on the system.

We calculate accumulated impulse response functions (AIRF), which are cumulative sums of the impulse response functions and hence, provide estimates of the total impact of a shock in one of the variables on the others in the system. These are calculated at a 10-day horizon, which corresponds to approximately two weeks of trading. While the horizon day choice is somewhat arbitrary, it is based on the notion that in sufficiently liquid markets 10-trading days should be sufficient to fully incorporate all information into prices. Also, noteworthy, we calculate the AIRFs using the *generalized* approach of Shin and Pesaran and Shin (1998). This method is robust to the ordering of the variables in the system, unlike the Cholesky decomposition method that is commonly used in empirical research.

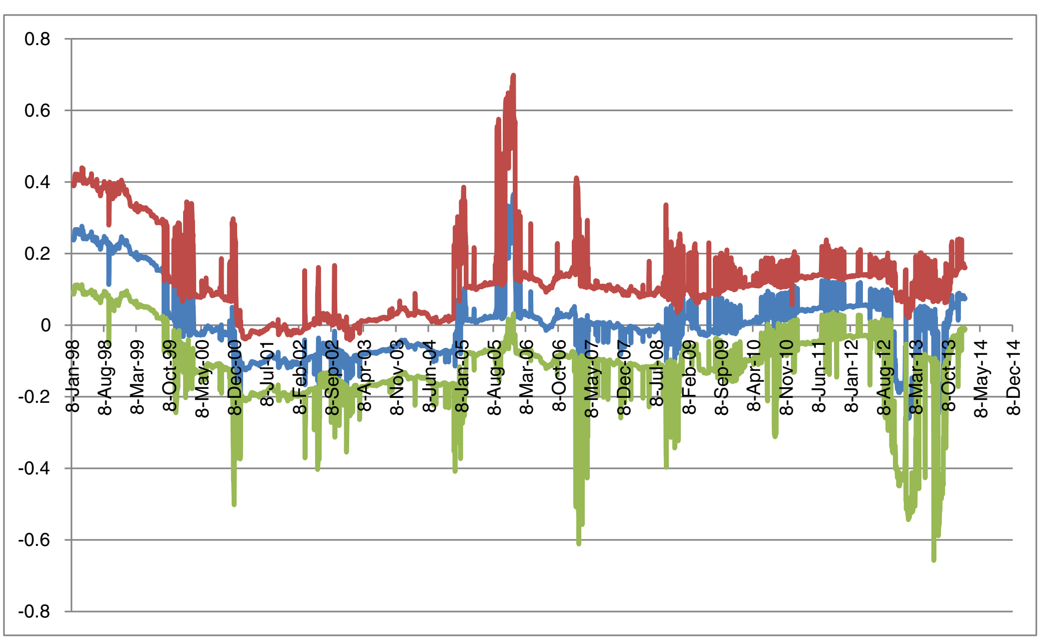

Fig. 19. 10-day horizon AIRF from oil to gas.

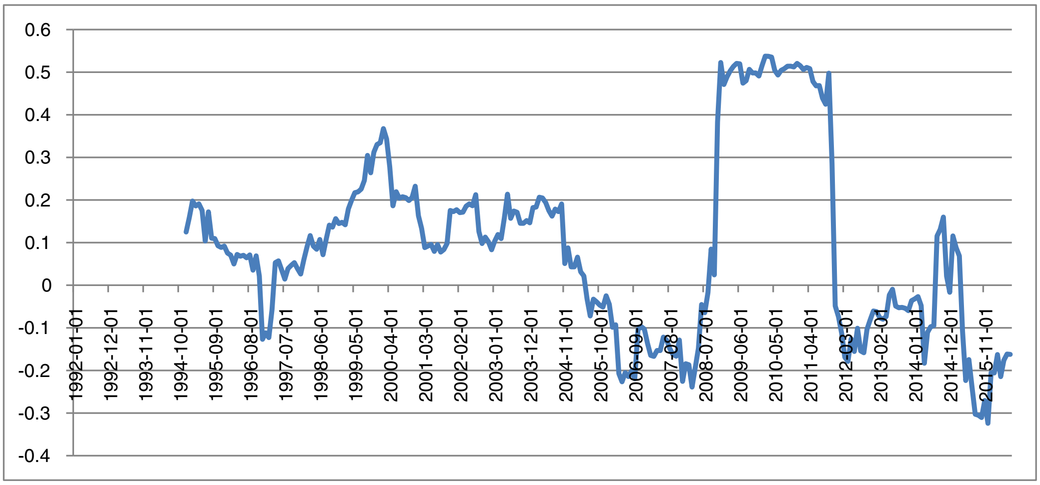

Fig. 20. Rolling correlation of changes in the price of ok wti (oil) and global price of gas (LNG) The figure plots the 36-month rolling correlation between WTI oil and LNG gas.

We continue to use rolling bivariate VARs with 1000-day windows. Within each window we calculate and save a 10-day horizon AIRF along with its standard error determined by the method of Lütkepohl (1993). In this manner, we have a series of estimates of the longer term impacts of shocks between natural gas and crude oil markets and are able to examine their time variation. We report the AIRFs along with their 5% confidence bands in Figs. 18 and 19. It can be observed, as expected, the AIRF graphs are very similar to the causality graphs discussed above. The contribution of this analysis, however, is that the total impact of shocks from natural gas to crude oil is statistically significant even after 10-days, and between 1999 and 2006 is always positive. At its peak, a 1 % increase in natural prices generates a 0.3% cumulative increase in oil prices after 10-days.

On the other hand, when we examine the time varying AIRFs from crude oil to natural gas in Fig. 19, we find that shocks from the crude oil market generate significant responses in the natural gas market only in the beginning of the sample between 1994 and 1996, which is again consistent with the causality analysis. Interestingly, we detect a negative reaction in the natural gas market to crude oil price shocks around 2009. This is, of course, the same relation captured by the asymmetric causality tests, discussed above. However, in this case, we can observe the cumulative impact is not statistically significant after the 10-day horizon. Hence, the asymmetric causality detected above from crude oil price declines to natural price increases was in fact short-lived.

5.6. Economic implications and interpretations

To better understand the relationships described in the paper we provide two figures that plot rolling 36 month correlations between changes in the price of WTI Oil and the global price of LNG. Fig. 20 plots the 36-month rolling correlation between WTI oil and LNG gas. The figure reveals a number of key episodes: (a) commencing from 1992 to 2000 there is an increasing correlation between oil and gas; (b) From 2000 to early 2008 the correlation declines; (c) then the onset of the Global Financial Crisis (GFC) and the regulatory and monetary developments that then occurred sees very high correlations. This episode includes the Tohoku earthquake shock and subsequent gas price spike shown in the figure of March 2011; (d) then high shale substitutes become available, the oil price falls, resulting in mostly a negative correlation until the present. The analysis reveals that the lead of gas to oil occurs during the correlation decline from 2000 until the onset of the GFC in episode (b). Overall, the results suggest more complex dynamics with the lead relationships—and links with economic activity—being episodic.

The last Fig. 21 plots the 36-month rolling correlation between changes in the global price of oil and gas and US Industrial Production. It is clear from this figure that the temporal correlations identified in Fig. 20 are closely linked to changes in US Industrial Production, which in turn is a proxy for demand driven factors affecting energy prices.

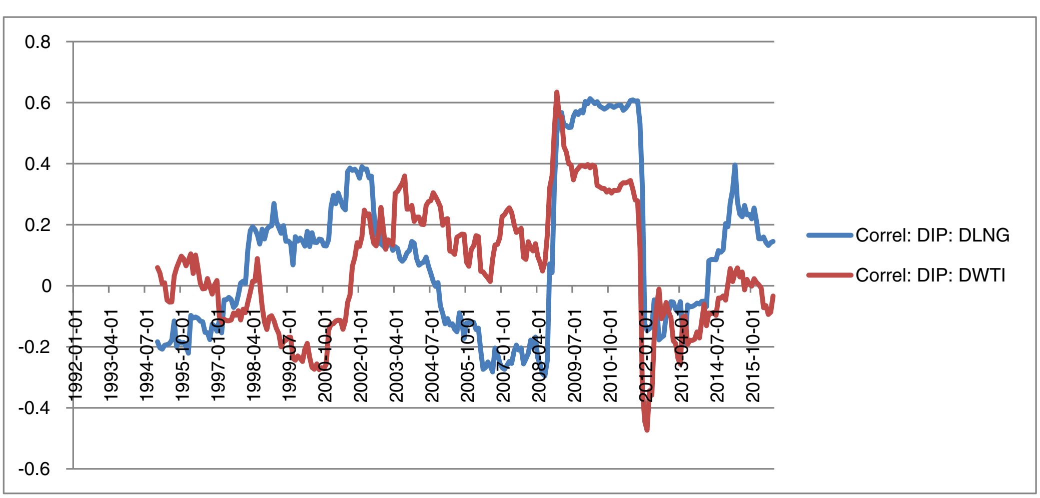

Fig. 21. Rolling correlation of changes in the price of OK WTI (DWTI), changes in the global price of gas (DLNG) and changes in US industrial production (DIP) This figure plots the 36-month rolling correlation between changes in the global price of oil and gas and US Industrial Production.

However, the correlations reveal significant temporal differences. For example, the period from 2003 to 2008 shows declining but still positive correlation between DIP and DWTI. This period also includes the price shock associated with Hurricane Katrina in August 2005 that affected oil prices and US production capacity in the Gulf of Mexico. However, while the direction is still the same for the correlation between DIP and DLNG, it becomes negative until the period around the Lehman default in September 2008. Both correlations then remain positive until after the Tohoku shock in 2011. After 2012 both correlations are negative. The positive correlations for DIP and DLNG and negative correlations to zero correlation for DIP and DWTI after 2014 are consistent with substitution and oil supply side shocks (rather than demand driven factors).

While the leading relationship of gas to oil does appear to arise from a conjunction of these otherwise independent events, with respect to the pricing of energy assets, price decoupling would also be consistent with a lack of, or reduced, integration between energy assets. This implies limits to arbitrage between prices (such as the burner tip parity trade) and also has implications for convergence trading (e.g. trading based on mean reversion). Differences in pricing between specific energy assets (such as gas) arise from the complex nature of how these assets are traded (e.g. different contractual pricing relationships), differing costs of production due to extraction technology and freight costs. Collectively, while specific energy asset prices have fallen due to both demand, supply and infrastructure driven factors, long term demand will likely shift towards cleaner energy sources, with gas being the most favored. If gas contracts become mostly short-term and priced off oil, then the relationships identified in the earlier paper of this paper (leading relationship of gas to oil), will likely remain an historical artifact. Nonetheless, it will be important in time series analysis to consider, or at least be mindful of, the more complex and temporal nature of the oil-gas dynamics.

6. Concluding remarks

In this paper, we provide evidence on the causality relations between crude oil and natural gas prices. Specific attention is directed on time variation in the relation. We employ a battery of tests and provide evidence that the relation between these two energy commodities is not stable. Evidence of time variation in the relation implies that these commodities are unlikely to be regarded as reliable substitutes to hedge against similar risks. Our asymmetric causality tests also indicate several periods when price increases in one of these markets preceded declines in the other one in a statistically significant manner. Moreover, the analysis points out that after 2007, price movements in these markets have been largely independent.

We also find that there is there is unilateral causality from natural gas to crude oil in a significant part of the sample, specifically between 1999 and 2007. This finding is robust to different causality tests employed and furthermore, by using lagged natural gas price changes, traders could obtain better prediction than the random walk model. Also, the impulse response analysis indicates that the effect of shocks from the natural gas market is statistically significant even after 10-days. To the best of our knowledge, the leading position of the natural gas market over the crude oil market in information processing is not recognized in prior work. In fact, many papers in the literature, as discussed earlier, simply assume that crude oil is a determinant of natural gas prices and that it as an exogenous variable. The findings of the present study cast doubt on this approach.

Since our study's focus is to simply let the data speak and highlight the time series properties of the relation between the variables, rather than specifying a structural model, our analysis is silent on the causes of the dynamic behavior of these variables. However, one could plausibly argue that it was initially related to supply shocks exerted by producers and later the adoption of new technologies in hydraulic fracturing and horizontal drilling. These techniques increased production in both oil and gas markets especially after 2007. It was after this time that the informational lead of natural gas prices ended and subsequently there was little feedback between these markets afterwards. Other authors, including De Bock and Gijon (2011) argue that technological advances and the resulting production boom affected natural gas and crude oil prices differently. Natural gas production increased by 26% between 2007 and 2014, almost all of it used in the US, and its price fell by approximately 45% in this time period. On the other hand, crude oil production in the US increased even more significantly, by 45%. However, despite recent technological innovations the US still produces approximately 10% of the global crude oil output. Thus, the reaction of the globally determined crude oil price differed in the sample period of our study, which likely offers a plausible explanation for our empirical findings. The fact that the only causal relation that we detect after 2007 is an asymmetric one, when crude oil price declines precede natural gas price increases appears also to be consistent with this view.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.10.019.

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