Bidirectional Causality in Oil and Gas Markets

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Abstract

Do events in the natural gas market cause repercussions in the crude oil market? This paper studies linkages between the two markets using high-frequency, intraday oil and gas futures prices. By analyzing the effect of weekly oil and gas inventory announcements on price volatility, we show a bidirectional causal relationship. Both inventory gluts and shortages have cross-commodity effect on price volatility not only for the next-month nearby futures contract but also for the following six months' contracts.

JEL Classification: Energy Demand and Supply Q41, Energy and the Macroeconomy Q43, Energy Forecasting Q47, Futures Pricing G13
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1 Introduction

Weekly inventory reports made by the Energy Information Administration (EIA) of the Department of Energy are the key news announcements in the oil and gas markets. As such, they are closely followed by the energy industry. This paper uses these inventory announcements and high-frequency, intraday oil and gas futures prices to study linkages between the oil and gas markets and show a bi-directional causality. Both inventory gluts and shortages have a cross-commodity effect on futures prices for both the next-month nearby futures contract and the following six months' contracts.

The relationship between the oil and gas markets has been of interest to researchers before. Several papers have shown a cointegrating relationship between oil and gas prices (see, for example, Villar and Joutz, 2006, for a review of this literature). This paper goes further by analyzing how strongly specific fundamentals-based shocks from one market are transmitted to the other market. We show the gas market has a causal effect on the oil market in addition to the oil market affecting the gas market, a result that has not been shown before. We find that the effect of gas inventory announcements on oil price volatility is more than twice as strong as the effect of oil inventory announcements on gas price volatility. Moreover, the spillover effects from the gas market into the oil market, while small individually, amount to substantial swings in the values of futures contracts. These results add to, and sometimes differ from, studies that used lower frequency data, such as daily, weekly or monthly prices, and applied different empirical approaches, such as Granger-causality or cointegration procedures. For example, Asche, Osmundsen and Sandsmark (2007) analyzed monthly oil, gas and electricity prices in the U.K. from 1985 to 2002 and concluded that the energy market was integrated with the oil price being the exogenous leading price. Similarly, Pindyck (2004) conducted Granger causality tests between daily oil and gas price volatility from 1990 to 2003 and concluded that the oil price affected the gas price but not the other way around.[1]

Economic theory suggests there should be bidirectional causality between oil and gas markets for several reasons as outlined by Villar and Joutz (2006). From the demand perspective, oil and gas are substitutes because portions of both the power generation and industrial sectors have the ability to switch between gas and products refined from crude oil as the production input. An increase in the relative price of one energy source might move some firms to the other source. The situation is more complex from the supply perspective. An increasing oil price will simultaneously exert positive and negative pressures on the gas price. Oil and gas are often jointly produced from the same underground reservoirs. If the oil price increases, then potentially gas supply will also increase with new drilling for oil. As a result, this could push gas prices lower. At the same time, however, an increasing oil price may intensify competition for resources, such as drilling rigs, production facilities, and engineering and operations staff, used in exploration and production of both oil and gas, causing an increase in the cost of supplying gas, and hence having a commensurate impact on its price. Which effect is stronger is an empirical question.

Understanding the linkages between the two energy markets has increasing importance as evolving energy policies promote natural gas as a cleaner fuel and a domestic source of

[1] Several studies analyzed the effect of own inventory announcements on energy prices, although none focused on the cross-commodity effect between oil and gas markets. Generally, these studies find that oil inventory announcements affect the oil price and gas inventory announcements affect the gas price (Chang, Daouk and Wang, 2009 and Bjursell, Gentle and Wang, 2009 for oil, and Linn and Zhu, 2004, Ates and Wang, 2007, Mu, 2007, Gregoire and Boucher, 2008, Bjursell, Gentle and Wang, 2009, and Gay, Simkins and Turac, 2009 for gas).

energy, leading to the energy mix in the U.S. changing in favor of gas. In 2003, crude oil and natural gas comprised 40% and 23% of the U.S. energy consumption, respectively. By 2010, the mix between oil and gas has changed to 37% and 25%, respectively.[2] This trend is likely to continue as North America has witnessed unprecedented discoveries of shale gas in the last several years. In addition, trading in the oil and gas futures markets has increased dramatically, ranking the oil and gas futures as the first and the second largest energy futures, and the first and the ninth largest commodity futures by volume in 2008, respectively.[3] Understanding of how commodity markets relate to one another can help policy-makers, consumers and investors more efficiently incorporate risk spillovers into their decisions.

2 Methodology

To study linkages between the oil and gas markets, we use high-frequency, intraday oil and gas futures prices. Our choice of the 10-minute time interval trades off noise due to the data microstructure and loss of information. One approach, the volatility signature plot technique, graphs the scaled realized volatility (daily average of squared returns), against time intervals in multiples of one minute (Andersen, Bollerslev, Diebold & Labys, 2000). We choose the 10-minute interval as the appropriate length since realized volatility stabilizes at that interval length.[4]

[2]EIA Annual Energy Review 2010.

[3]Futures Industry Magazine Annual Volume Survey: 2008 A Wild Ride.

[4]See Dacorogna, Gencay, Muller, Olsen and Pictet (2001) for a discussion of scaling factors. Also, note that the realized volatility is used only to choose the appropriate interval. It is not used in the regressions. The dependent variable in the volatility regressions is defined as the absolute return. As a robustness check, the regressions are repeated using 15-minute and 30-minute intervals. The results do not change materially.

Oil trading ceases on the third business day prior to the twenty-fifth calendar day of the month preceding delivery. At expiration, oil has to be physically delivered to Cushing, OK. Gas trading ceases three business days prior to the first day of the delivery month. At expiration, gas has to be physically delivered to Henry Hub, LA. Very few market participants make physical delivery at contract expiration opting instead to roll over positions into a new contract. We create a continuous record of the futures contract prices by using current contracts until expiration date. Because trading may be thin during the last few days before the contract expiration date, we tested switching to the next contract as soon as its daily contract volume exceeds the current contract volume as an alternative method for creating a continuous record of prices. The results do not materially differ between the two methods, so only the results using the expiration date method are reported.

As is customary in these studies, we measure volatility as the absolute value of returns, $|R_j|$, where R_j is the difference between the log price at the end of interval j and the log price at the end of interval *j-1*: $R_j \equiv \ln(P_j) - \ln(P_{j-1})$ where P_j is the price at the end of period j. To validly undertake hypothesis testing about the regression parameters, we test for stationarity of the return series. The series is stationary as gauged by an augmented Dickey-Fuller test.

Following Ding, Granger and Engle (1993), Ederington and Lee (1993), Gwilym, McMillan and Speight (1999), McKenzie (1999), Bollerslev, Cai and Song (2000), and Ederington and Guan (2005), we measure the response of volatility to unexpected changes in inventories.

Using unexpected changes in inventories assumes efficient markets, implying that only the unanticipated component of news announcements matters: the anticipated component has already been built into market participants' price forecasts. The unexpected component is the difference between the actual value, A_{kj}, and the expected value, E_{kj}, where $k \in \{O, G\}$ stands for oil and gas announcements. To come up with a common metric of "surprise" for oil and gas, which are measured, respectively, in thousands of barrels and billions of cubic feet, the unexpected component is divided by the actual value and then multiplied by 100. The resulting "surprise", $S_{kj} \equiv \frac{A_{kj}-E_{kj}}{A_{kj}} \times 100$, is the percentage of actual inventory by which the expected inventory falls short of actual inventory.[5] Measuring surprise this way means that a positive surprise occurs when the analysts under-forecast inventory. We call this an inventory glut. A negative surprise, which we term an inventory "shortage", occurs when the analysts over-forecast inventories.

To allow for the possibility of asymmetric reaction of the price volatility to shortages and gluts, indicators, $I(S_{kj} > 0)$, are created that take on value of 1 if $S_{kj} > 0$ and 0 otherwise. These indicators are then multiplied by the surprise, i.e., $S_{kj} \times I(S_{kj} > 0)$ and used as an additional explanatory variable in our equation measuring volatility response to surprises. This means the coefficient on the surprise, S_{kj}, measures the effect of a shortage while the sum of the coefficients on S_{kj} and $S_{kj} \times I(S_{kj} > 0)$ measures the effect of a glut.[6]

The effect of the surprise is analyzed using ordinary least squares (OLS) regression. Several control variables are also included in the regressions. As suggested by Andersen, Bollerslev, Diebold and Vega (2003), lags of surprise and dependent variable are added to allow for autocorrelation.

[5] Balduzzi, Elton and Green (2001) implement another methodology for standardizing announcement units. They divide the difference between the actual and expected values by its sample standard deviation σ_k and interpret the coefficient as the change in oil price return for one standard deviation change in the surprise. In this paper, dividing by the actual value is preferred to allow for interpreting the surprise as a percentage deviation of the expectation from the actual value.

[6] Except for Gregoire and Boucher (2008), who analyze only the effect of gas inventory announcements on gas price using daily data, previous papers have not distinguished between inventory gluts and shortages.

A beginning-of-day dummy is included to account for unusual price movements at the beginning of the day. This dummy takes on the value of 1 during the first interval of the day and 0 in all other intervals. An end-of-day dummy is included in the same way to account for unusual price movements at the end of the day. These time-of-the-day effects have been identified in many financial markets, for example by Becker, Finnerty and Kopecky (1993), Bollerslev, Cai and Song (2000), and Linn and Zhu (2004). Alternative specifications are run where the beginning-of-day (end-of-day) dummy takes on the value of 1 for the first (last) two and three intervals. The results do not change.

A first-trading-day dummy is included that takes on the value of 1 in all intervals on the day after a non-trading day, i.e., after a weekend or a holiday, to allow for effects due to the market being closed for an extended period of time. A trader composition variable, defined as the ratio of non-commercial financial traders volume to the traditional commercial traders volume, is added to account for a change in the composition of firms trading oil futures. As documented by Buyuksahin et al (2008), the proportion of non-commercial financial traders has been on the rise and the proportion of traditional commercial traders has declined. The three-month Treasury bill rate is included to account for the cost of holding inventory (Pindyck, 2004). Trading volume (measured in 1000s of executed contracts) is added to account for various unobservable sources of volatility. We tried both contemporaneous and lagged volume as a control variable. The results were very similar and the lagged volume specification is reported in this paper. Additional controls for unobservable sources of general market volatility including the daily Chicago Board Options Exchange Volatility Index (VIX) and intraday returns and absolute returns on S&P 500 futures did not change results of the analysis.

Control variables for gasoline inventory, distillate fuel oil (referred to as "distillate") inventory and refinery utilization are also included because these data are released at the the same time as the oil inventory data, hence their announcements could possibly provide additional information that could affects futures prices.[7] There are no other weekly announcements made by any U.S. government agency which coincide with the oil and gas inventory announcements.

For both oil and gas we estimate separate regression equations:

$$|R_j| = \alpha + \Sigma_{i=1}^{I}\beta_i|R_{j-i}| + \Sigma_{k=1}^{K}\Sigma_{l=0}^{L}\gamma_{kl}S_{k,j-l} + \Sigma_{k=1}^{K}\Sigma_{l=0}^{L}\delta_{kl}S_{k,j-l} \times I(S_{k,j-l} > 0) + \Sigma_{m=1}^{M}\theta_m\{Z_m\} + \varepsilon_j, \quad (1)$$

where $\{k\}$ includes oil, gas, gasoline, distillate and refinery utilization, i and l stand for lags of absolute returns and surprises, respectively, and $\{Z_m\}$ includes dummies for the beginning-of-day, end-of-day and the first-trading-day, and controls for trader composition, three-month Treasury bill rate, lagged volume, VIX, and S&P 500 return and absolute return.[8]

Newey-West standard errors are used to account for heteroskedasticity and autocorrelation in the error term ε_j. There is no endogeneity from a two-way relationship between oil (or gas) prices and oil (or gas) inventory because the variable on the right-hand side is the *unanticipated* component of the inventory changes. As such, inventory surprises cannot be a causal factor for the decisions of the market participants.

[7] Distillate includes diesel fuels used in on-highway engines, e.g., automobiles and trucks, and off-highway engines, e.g., railroad locomotives and agricultural machinery, as well as fuel oils used for heating and power generation. Refinery utilization is defined by the EIA as the ratio of gross inputs used in the atmospheric oil distillation units to the operable capacity of the units. The Weekly Petroleum Storage Report includes other data, e.g., propane inventory and jet fuel inventory. However, Bloomberg does not conduct surveys for these commodities. Therefore, they cannot be included in the regression. It is unlikely they would have a major effect on the results of this paper.

[8] 33 lags are used since a trading day includes 33 10-minute intervals. In an alternative specification, the model is modified to include lagged cross-commodity terms, i.e., the *oil* price volatility equations include *gas* price volatility lags. The results do not change and they are not sensitive to the number of lags.

3 Data

Our price data consists of weekday transactions prices from 9 a.m. to 2:30 p.m. ET for oil futures with maturities of one month to nine years and gas futures with maturities of one month to 12 years traded on NYMEX during the period from June 13, 2003 to September 24, 2010.[9] There are 27 and 33 intervals within a trading day depending on whether the market opened at 10 a.m. or 9 a.m. ET.[10] This proprietary data is provided by Tick Data, Inc., a company that specializes in intraday time series data for equities, futures and options. The data are transaction data, i.e., not bid-ask quotes.[11]

In our sample period, there are 20 days when the NYMEX market closes earlier than normal, usually due to an upcoming holiday. These days are eliminated to prevent skewing intraday patterns. Only 0.20% and 0.45% of all observations for the oil and gas nearby contracts, respectively, are missing because no trade occurred in a 10-minute interval. These missing prices are set equal to the previous prices. The resulting sample contains 54,884 10-minute intervals on 1,826 days, a period of 380 weeks.

The data on the U.S. oil and gas inventory come from, respectively, the Weekly Petroleum Status Report and the Weekly Natural Gas Report, both published by the EIA based on companies submitting weekly forms stating their current inventory, as mandated by law.[12]

[9]The sample starts as of June 13, 2003 because Bloomberg surveys of market expectations are not available for oil prior to this date. This sample period is interesting because it captures a recent period of high volatility in energy prices.

[10]Until January 31, 2007, the trading day starts at 10:00 a.m. ET whereas after January 31, 2007, the trading day starts at 9:00 a.m. A variable added to control for this change was insignificant at conventional p-values. Night trading is not analyzed in this paper since the day and night trading sessions may differ from the information arrival standpoint.

[11]Oil and gas futures contracts are also traded on the InterContinental Exchange (ICE) in London. This paper focuses on the NYMEX futures data because the NYMEX market is approximately twice as liquid as the ICE market during the sample period.

[12]Only commercial inventory is considered in this paper. The Strategic Petroleum Reserves (SPR) held by the U.S. government are excluded since weekly changes in the SPR inventory on average amount to only

The oil report is released weekly on Wednesday at 10:30 am ET for the week ending on the previous Friday. [13] The data are in thousands of barrels. The gas report is released weekly on Thursday at 10:30 am ET for the week ending on the previous Friday unless Thursday falls on a public holiday. The data are in billions of cubic feet.

Our market expectations data of oil inventories are the median forecasts of Bloomberg's weekly survey of approximately twenty industry experts of expected EIA reported oil inventory (excluding the Strategic Petroleum Reserves). This paper uses the median forecast. The survey is published on Monday or Tuesday, prior to the actual values being released by the EIA. Similarly, Bloomberg conducts a weekly survey of approximately twenty-five industry experts asking them what they expect the gas inventory to be once released by the EIA. We again use the median forecast.

Statistics for the oil inventory surprise, S_O, and the gas inventory surprise, S_G, are summarized in Table 1. In our sample period, there are no observations where the inventory surprise variables, S_O and S_G, are exactly zero. The mean values of these variables are close to zero, so it appears that the Bloomberg survey can be considered unbiased, i.e., the analysts do not systematically overforecast or underforecast inventories.

Table 1: Summary statistics for oil and gas inventory surprise variables

	Min	Max	Mean	Standard Deviation
Oil inventory surprise, S_O	-2.85%	2.82%	-.02%	.94%
Gas inventory surprise, S_G	-1.55%	2.93%	.05%	.46%

3% of the weekly commercial inventory changes during the sample period.

[13] If Monday, Tuesday or Wednesday fall on a public holiday, the report is released on the following Thursday at 11:00 am ET. These holiday weeks are skewing the intraday pattern graph in Figure 1. The regressions are correct because the data show the inventory reports on the days and intervals when they are actually released. As a robustness check, however, these weeks are eliminated from the data. The results do not change materially. The results reported in this paper include the holiday weeks.

4 Results

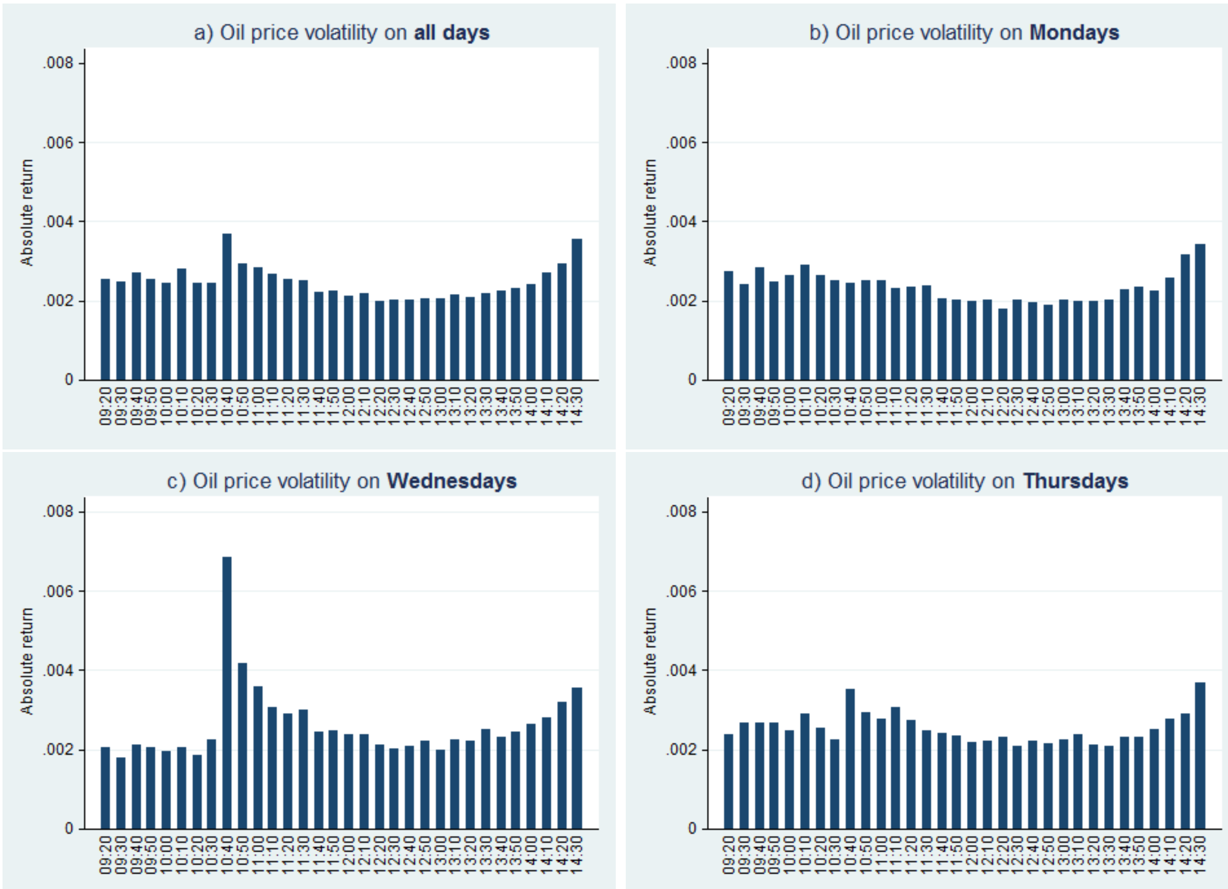
4.1 Oil Price Volatility

4.1.1 Intraday Pattern Graphs

Figure 1 shows the intraday pattern of oil price volatility. In panel a), absolute returns for each 10-minute interval are averaged across all days in the data sample. In addition to a U-shaped pattern corresponding to the market opening and closing, one feature stands out. The 10:40 a.m. interval shows a spike in volatility. Panels b), c) and d) display the intraday pattern of volatility by day. Panel b) gives the absolute returns for each interval averaged only for Mondays. While the U-shaped pattern is still visible, the 10:40 a.m. spike disappears. The graphs for Tuesdays and Fridays, not shown in this paper, look similar. Panel c) shows the intraday volatility pattern for Wednesdays (the day when the Weekly Petroleum Storage Report is released at 10:30 a.m.) Bjursell, Gentle and Wang (2009) find the 10:40 a.m. spike is due to the oil inventory news announcement. However, panel d) for Thursdays shows a similar pattern, albeit with a smaller magnitude. We hypothesize that the 10:40 a.m. spike is due to the release of the Weekly Natural Gas Storage Report at 10:30 a.m., suggesting that gas market surprises affect oil futures prices, something that has not been observed in previous research. [14]

[14] The fact that the data sample includes the period from June 13, 2003 till January 31, 2007 when the market opened at 10 a.m. as well as the period from February 1, 2007 till September 24, 2010 when the market opened at 9 a.m. creates a “double-U” because the volatility is higher after 9 a.m. and after 10 a.m. The smaller spike on Thursdays in the 11:10 a.m. interval is due to the Weekly Petroleum Storage Report being released on Thursdays at 11:00 a.m. if Monday, Tuesday or Wednesday fall on a holiday, as discussed in Section 3.2.

Figure 1: Intraday pattern of oil price volatility



Notes: This figure shows the intraday pattern of the NYMEX crude oil nearby contract futures price volatility. The volatility is defined as the absolute return. The first interval is not displayed to avoid skewing the graphs by the overnight gap as the first interval is affected by not only the first ten minutes of the trading day but also the period since the market closed on the previous day. Source: Tick Data, Inc.

4.1.2 Cross-Commodity Effect

Table 2 shows results for the price volatility of the oil nearby futures contract. Specification (1) includes the oil inventory variables as well as control variables that have been used in other papers to explain the oil price volatility, as described in Section 4. The oil glut variable stands for the situation in which $S_{kj} > 0$ (actual inventorys exceeded expected inventory) and the oil shortage variable stands for the situation in which $S_{kj} < 0$ (expected inventory exceeded actual inventory). The coefficient of -.00425 on the oil shortage means that when analysts overforecasted actual inventory by 1%, there was an .00425 increase in volatility.[15] The coefficient of +.00626 on the oil glut indicates that an under forecast of the actual inventory by 1% caused an .00626 increase in volatility.

Table 2: Price volatility regressions for oil nearby contract

	(1)	(2)	(3)
Oil shortage $S < 0$	***-.00425 (.00051)	***-.00426 (.00051)	***-.00231 (.00066)
Oil glut $S > 0$	***.00626 (.00074)	***.00627 (.00074)	***.00433 (.00077)
Gas shortage $S < 0$		**-.00205 (.00075)	***-.00209 (.00075)
Gas glut $S > 0$		***.00191 (.00052)	***.00194 (.00053)
Gasoline shortage $S < 0$			**-.00107 (.00048)
Gasoline glut $S > 0$			***.00212 (.00068)
Distillate shortage $S < 0$			**-.00139 (.00062)
Distillate glut $S > 0$			*.00093 (.00051)
Beg-of-day dummy	***.00795 (.00026)	***.00796 (.00026)	***.00797 (.00026)
End-of-day dummy	***.00098 (.00008)	***.00099 (.00008)	***.00100 (.00008)
Trader composition	***-.00010 (.00003)	***-.00010 (.00003)	***-.00010 (.00003)
T-bill rate	***-.00008 (.00001)	***-.00008 (.00001)	***-0.00008 (0.00001)
Volume 1st lag	***.00006 (.00001)	***.00006 (.00001)	***.00006 .00001
$\|R_j\|$ 1st lag	***.07220 (.01127)	***.07248 (.01129)	***0.07239 (.01130)
R^2	0.27	0.28	0.28
$RMSE$	0.00318	0.00317	0.00317

*Notes: ***, ** and * represent 99%, 95% and 90% significance levels, respectively. Standard errors are shown in parenthesis. The number of observations is 54,850 in all specifications. The control variables that are not significant are excluded from the specification reported in this paper. Only the first lags of volume and absolute return are reported to save space.*

Specification (2) adds the gas inventory variables. The oil inventory variables are un-

[15] The change is an increase even though the coefficient has a negative sign because shortage stands for $S_{kj} < 0$, so the coefficient is multiplied by a negative number.

affected. The coefficients of -.00205 and +.00191 on the gas shortage and the gas glut are about one-half and one-third the size of their oil counterparts, respectively, although gas inventory announcements still have a sizeable effect on the oil price volatility, especially when compared to the mean intraday absolute return of .00272 shown in Figure 1.[16]

Specification (3) adds control variables for the gasoline and distillate inventory. Even though adding these variables decreases the oil shortage and oil glut estimates, the gas shortage and gas glut estimates are unaffected, and, in fact, the gas inventory variables become more important relative to the oil inventory variables. The gas shortage impact becomes almost as large as that of an oil shortage while a gas glut has about one-half the impact of an oil glut.

We would expect that a gas shortage means anticipated increases in the price of gas, so firms that can use either fuel move, when possible, to oil, and similarly, a gas glut would attract those firms that can use either source of energy as they expect a drop in the price of gas. Hence, just as it is puzzling that we find the impact of oil surprises on the price of oil is asymmetric (consistent with what Kuper and van Soest, 2006, among others, have found in earlier studies), it is reassuring that we find the impact of gas gluts and shortages to be relatively symmetric in magnitude.

4.1.3 Joint Model of Oil and Gas Price Volatility

To put the effect of *gas* inventory announcements on the *oil* price volatility in perspective, the effect of *oil* inventory announcements on the *gas* price volatility is analyzed for comparison. Since errors may be correlated across the oil and gas regressions, a seemingly unrelated

[16] A concern arises in large samples that statistical significance of results is driven by sample size. This is less of a concern here since several control variables, such as weekly refinery utilization announcements, daily VIX data, and intraday S&P 500 returns and absolute returns are not statistically significant.

regression (SUR) is estimated using the oil and gas equations specified by (1). Table 3 displays the results. Again, the coefficients are sizeable given the intraday absolute returns shown in Figure 1.

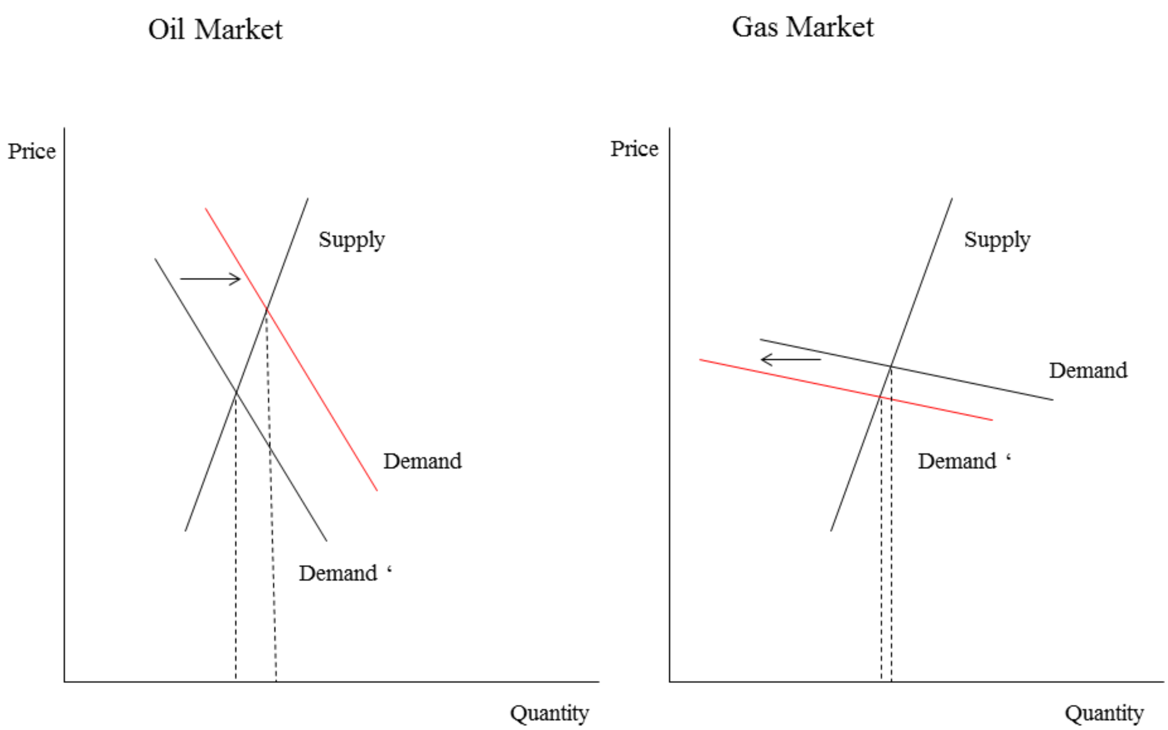
Table 3: SUR model for oil and gas price volatility

	Oil price volatility	Gas price volatility
Oil shortage	***-.00235	**-.00101
$S < 0$	(.00030)	(.00041)
Oil glut	***.00436	**.00104
$S > 0$	(.00030)	(.00040)
Gas shortage	***-.00212	***-.02432
$S < 0$	(.00061)	(.00087)
Gas glut	***.00198	***.02110
$S > 0$	(.00044)	(.00064)

*Notes: ***, ** and * represent 99%, 95% and 90% significance levels, respectively. Standard errors are shown in parenthesis. The number of observations is 54,850. Only the oil and gas inventory variables are reported to save space.*

As would be expected, there is little change in the estimated impacts of gas gluts and shortages on the volatility of oil. And consistent with spillover effects across the markets, surprise oil gluts and shortages have the expected directional impact on gas volatility. What perhaps needs explaining is that the effect of both *gas gluts and gas shortages* on the *oil* price volatility is more than twice as strong as the effect of *oil gluts and oil shortages* on the *gas* price volatility. At first thought, the stronger effect of gas gluts and shortages on oil prices when compared to the effect of oil gluts and shortages on gas prices may seem counterintuitive, especially since the oil market is so much larger. But as shown in Figure 2, if the demand for gas is flatter than the demand for oil, as would be expected since many more users of gas can switch to oil, proportionately, than the share of oil users who can switch to gas, an equal shift of demand curves (from users switching back and forth) will have a greater impact on the price of gas, all else equal. Interestingly, the own-effects for oil and for gas shortages are nearly equal in sign and magnitude.

Figure 2: Comparison of effect of inventory change on oil and gas markets



4.1.4 Effect across Futures Contract Maturities

To investigate how current news announcements affect futures price volatility further into the future, we ran the model for the nearby contract, denoted as Contract 1, and the following six months' contracts for oil and gas. Again, since errors may be correlated across the regressions for the different maturities, SUR is applied.[17]

[17]This leads to the slight differences between results for the nearby contract reported in Table 2 that uses OLS and Table 4 that uses SUR. Also, since contracts with longer maturities are traded less frequently, these contracts have more missing observations than the nearby contract. Oil contracts 2 through 8 have 0.42%,

Table 4 displays the results for the oil and gas inventory variables. The two-way causality indicated by the cross-commodity effect holds across the maturity structure as the oil and gas inventory variables remain significant for the longer maturities. The results described above are, therefore, robust to the maturity structure. In general, the coefficients increase as the length of the contract decreases, supporting the Samuelson (1965) theorem, which states that futures contracts become more volatile as their expiration date approaches.

Table 4: Price volatility of contracts with longer maturities

Panel a): Oil contracts

	Contract 1	Contract 2	Contract 3	Contract 4	Contract 5	Contract 6	Contract 7	Contract 8
Oil shortage	***-.00223	***-.00197	***-.00185	**-.00067	***-.00124	*-.00057	-.00005	-.00048
$S < 0$	(.00030)	(.00026)	(.00026)	(.00028)	(.00030)	(.00031)	(.00031)	(.00031)
Oil glut	***.00428	***.00352	***.00334	***.00208	***.00224	***.00083	***.00116	.00043
$S > 0$	(.00031)	(.00027)	(.00027)	(.00029)	(.00031)	(.00031)	(.00032)	(.00032)
Gas shortage	***-.00233	***-.00243	**-.00136	*-.00095	***-.00178	*-.00105	-4.35e-06	-.00021
$S < 0$	(.00062)	(.00054)	(.00054)	(.00058)	(.00063)	(.00063)	(.00065)	(.00064)
Gas glut	***.00241	***.00223	***.00206	***.00135	***.00247	***.00139	***.00167	.00011
$S > 0$	(.00045)	(.00040)	(.00039)	(.00042)	(.00046)	(.00046)	(.00047)	(.00047)

Panel b): Gas contracts

	Contract 1	Contract 2	Contract 3	Contract 4	Contract 5	Contract 6	Contract 7	Contract 8
Oil shortage	**-.00096	**-.00080	***-.00116	***-.00105	**-.00070	-.00053	-.00030	-.00001
$S < 0$	(.00043)	(.00041)	(.00038)	(.00035)	(.00035)	(.00033)	(.00034)	(.00032)
Oil glut	**.00100	.00063	**.00086	.00035	.00043	*.00061	.00038	***.00104
$S > 0$	(.00044)	(.00041)	(.00038)	(.00036)	(.00036)	(.00034)	(.00035)	(.00033)
Gas shortage	***-.02486	***-.02315	***-.02062	***-.01168	***-.01141	***-.01015	***-.00752	***-.00724
$S < 0$	(.00088)	(.00083)	(.00077)	(.00072)	(.00073)	(.00069)	(.00070)	(.00067)
Gas glut	***.02120	***.02059	***.01782	***.01515	***.01220	***.01194	***.00827	***.00766
$S > 0$	(.00064)	(.00061)	(.00056)	(.00052)	(.00053)	(.00050)	(.00051)	(.00049)

*Notes: ***, ** and * represent 99%, 95% and 90% significance levels, respectively. Standard errors are shown in parenthesis. The number of observations is 54,598. Only the oil and gas inventory variables are reported to save space.*

4.1.5 Pre-Announcement and Post-Announcement Effects

We also find that oil and gas inventory announcements affect the oil price volatility even prior to the announcement. Dummy variables for the intervals before and after the an-

6.79%, 25.69%, 46.43%, 60.76%, 71.30% and 77.54% missing observations, respectively. Gas contracts 2 through 8 have 1.19%, 5.83%, 11.83%, 17.97%, 24.81%, 33.24% and 40.07% missing observations, respectively. As in the nearby contract, the missing observations are set equal to the previous observation. However, since the number of missing observations varies across the contracts, an unbalanced SUR is applied as a robustness check. The results do not change. Contracts with maturities longer than eight months do not have significant coefficients on the inventory variables, so they are not reported.

nouncements indicate that volatility is lower than usual for approximately 70 minutes before the oil announcements and 30 minutes before the gas announcements. After the announcement, oil volatility remains higher than usual for approximately 60 minutes following the oil announcements and 20 minutes following the gas announcements. This suggests that oil market participants decrease their trading activity while waiting for the inventory report announcements and increase their trading activity once the reports are released.

We find similar results for gas futures volatility, which remains higher than usual for approximately 40 minutes after the oil announcements and 30 minutes after the gas announcements. This fast adjustment is consistent with what has been found in other financial markets, for example, the effect of macroeconomic announcements on bond price volatility (Balduzzi, Elton and Green, 2001).

4.2 Robustness Checks

4.2.1 Structural Breaks and Business Cycle

The oil and gas markets were subject to numerous shocks and developments during the sample period, such as the increase in futures trading, the introduction of LNG technology, and the development of the shale gas fields. Hence we repeated our estimations adding dummy variables for individual years and, separately, for individual months. The sample period was also split into sub-periods before and after the recent recession. In addition, a structural break test was performed following Hansen (2001). The results indicating bidirectional causality were unaffected nor were the magnitudes of the parameter estimates appreciably different. Controlling for seasonal effects, likewise, had no material impact on our findings.

Finally, because oil and gas volatility varies during the sample period, we included ratios of the absolute value of the daily return to the absolute value of average daily return for each day of the week and added dummy variables for periods when oil and gas prices were below mean values. Again, there was no substantive change in our results.

Because oil and gas prices exhibit time-varying volatility, generalized autoregressive conditional heteroskedasticity (GARCH) models lend themselves as tools for analyzing the data in addition to the OLS. We, therefore, implemented the EGARCH(1,1) model with one ARCH term and one GARCH term with the Gaussian distribution that allows for an asymmetric reaction to positive and negative innovations.

$$R_j = \alpha + \Sigma_{i=1}^{I}\beta_i R_{j-i} + \Sigma_{k=1}^{K}\Sigma_{l=0}^{L}\gamma_{kl}S_{k,j-l} + \Sigma_{k=1}^{K}\Sigma_{l=0}^{L}\delta_{kl}S_{k,j-l} \times I(S_{k,j-l} > 0) + \Sigma_{m=1}^{M}\theta_m\{Z_m\} + \varepsilon_j, \quad (2)$$

$$\log(h_j^2) = \nu + \phi\log(h_{j-1}^2) + \omega\left|\frac{\varepsilon_{j-1}}{\sqrt{h_{j-1}}}\right| + \rho\frac{\varepsilon_{j-1}}{\sqrt{h_{j-1}}}, \quad (3)$$

where equation (2) is the mean equation, equation (3) is the conditional variance equation, and the distribution of the error conditional on an information set at time j, Ψ_j, is assumed to be $\varepsilon_j|\Psi_j \sim N[0, h_j^2]$. The term $\rho\frac{\varepsilon_{j-1}}{\sqrt{h_{j-1}}}$ captures the asymmetry because positive innovations $\varepsilon_j > 0$ are allowed to have different effects on the conditional variance than negative innovations $\varepsilon_j < 0$. The results were identical to what we found with OLS in terms of signs, significance, and relative magnitudes.

5 Implications and Conclusions

Despite strong theoretical foundations to expect two-way causality and empirical results showing that the two markets are cointegrated, previous research on the relationship between the crude oil and natural gas markets concluded that the oil market affects the gas market but not vice versa. This paper dispels the notion of one-way causality, finding empirical support for bi-directional causality and lending support to a hypothesis of interrelated markets.

Our direct test measures how futures prices respond to surprises in inventory announcements. Our estimates indicate the immediate (meaning effect of the shock on the closest 10-minute interval) impact of a 1% surprise in gas inventory changes the oil price by $0.158. This compares to the average price change over 10-minute intervals on non-announcement days, i.e., Mondays, Tuesdays and Fridays, of $0.100 which is more than 50% increase. Applying this price impact on average daily open interest of futures contracts for the first six months to the worth of the market amounts to $84,000,000. This is a conservative estimate since it considers only the effect during the first 10-minute interval. And finally, as open interest contracts have been rising steadily, the magnitude of the impact on the worth of the market would be even higher now.

As documented by Buyuksahin, Haigh, Harris, Overdahl and Robe (2008) and Basu and Gavin (2011), the recent dramatic rise in oil and gas futures trading is mainly due to greater participation by financial institutions (investment banks, mutual funds, pension funds, university endowment funds and hedge funds) in trading commodity derivatives to increase gain and diversify risks. The results here allow commodity markets investors to better understand the sources of risks and price volatility spillovers between the markets. They also allow policymakers to better manage volatility spillovers between the energy markets and financial markets, mitigating risks and improving the efficiency of the economy.[18] Moreover, recent

[18]See, for example, Kilian and Park (2009), Cifarelli and Paladino (2010), and Hammoudeh, Yuan and McAleer (2010).

policy has promoted gas as a cleaner, cheaper and domestic alternative to oil. As shale gas discoveries lower the price of gas, supply shocks in the gas markets may increasingly reverberate through the oil market and economy in general.

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