Noisy Inventory Announcements and Energy Prices

Marketa W. Halova, Alexander Kurov* and Oleg Kucher

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* Corresponding author. Department of Finance, College of Business and Economics, West Virginia University, P.O. Box 6025, Morgantown, WV 26506, Tel: 304-293-7892, Fax: 304-293-3274, e-mail: alkurov@mail.wvu.edu.

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Marketa Halova is an assistant professor of economics at the Department of Economics, Washington State University, Pullman, Washington.

Alexander Kurov is an associate professor of finance at the Department of Finance, West Virginia University, Morgantown, West Virginia.

Oleg Kucher is an assistant professor of economics at the Department of Economics, Frostburg State University, Frostburg, Maryland.

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Abstract

This study examines the effect of oil and gas inventory announcements on energy prices. Previous estimates of this effect suffer from bias due to measurement error in inventory surprises. We utilize intraday futures data for three petroleum commodities and natural gas to estimate the price response coefficients using traditional event study regressions and the identification-through-censoring (ITC) technique proposed by Rigobon and Sack (2008). The results show that the bias in OLS estimates of the price impact of inventory surprises is quite large. The ITC coefficient estimates are about twice as large as OLS estimates for petroleum commodities and about four times as large as OLS estimates for natural gas. These results imply that energy prices are more strongly influenced by unexpected changes in inventory than shown in previous research.

1. Introduction

Commodity prices are volatile. There is much debate in the academic literature whether this volatility is driven primarily by supply and demand fundamentals or by speculative trading (e.g., Kilian and Murphy, 2012, Büyükşahin and Harris, 2011, Tang and Xiong, 2012). An important strand of this literature investigates the effect of public news on commodity prices.[1] Boudoukh, Richardson, Shen, and Whitelaw (2007) show that even when relevant fundamentals can be easily measured, modeling their impact on prices is not a trivial exercise.[2] When researchers are unable to explain the majority of commodity price variation by fundamental factors, the logical conclusion is that most of the volatility is generated by uninformed speculative trading.

We examine the effect of fundamentals, represented by news about inventory, on energy futures prices. Inventory reports for petroleum and natural gas are prepared by the U.S. Energy Information Administration (EIA). The oil and gas inventory reports are widely followed by market participants because the release of these reports often triggers large price moves. For example, on March 19, 2009, the price of natural gas futures for April delivery jumped almost 13% after EIA data showed a larger than expected withdrawal of natural gas from inventories.

Linn and Zhu (2004) find a large increase in volatility of natural gas futures returns after the release of the Natural Gas Storage Report. Gay, Simkins, and Turac (2009) show that a 1% unexpected increase in natural gas inventory results in an approximately 1% drop in the natural gas futures price. Chang, Daouk, and Wang (2009) find a significant response of crude oil futures returns to unexpected inventory changes immediately after the announcement. Using

[1] See, for example, Roll (1984), Bauer and Orazem (1994), Karali and Thurman (2009), Chatrath, Miao, and Ramchander (2012).
[2] Boudoukh et al. (2007, p. 411) write: "Even in the comparatively simple setting of the frozen concentrated orange juice futures market, the relation between returns and temperature is nonlinear, multidimensional, and state and path dependent. In other markets, identifying the fundamentals and modeling their relation to prices is likely to be even more difficult."

cross-sectional data on analyst forecasts of inventory, both Gay et al. (2009) and Chang et al. (2009) provide evidence that prices react more strongly to forecasts of analysts with better prior forecast accuracy. Halova (2012) finds that unexpected changes in natural gas inventory have a statistically significant effect on prices of crude oil futures. Similarly, unexpected changes in crude oil inventory move natural gas futures prices.

Despite using intraday futures returns, Gay et al. (2009) report an R^2 of only about 23% for an event study regression that allows for time variation in the response of natural gas futures to the Natural Gas Storage Report announcements. Chang et al. (2009) obtain an R^2 of about 35% in the regression of intraday crude oil futures returns on the aggregate forecast error for crude oil, gasoline and distillate fuel oil. It is surprising that much of the price variation remains unexplained by fundamental news even in a narrow intraday window around the most important and widely anticipated information release of the week. Limited explanatory power of event study regressions is consistent with substantial amount of noise in the measured inventory surprises. Due to the presence of noise in measures of inventory surprises, previous estimates of the response of energy prices to such news have been biased towards zero. We contribute to this literature by adjusting for the measurement error bias using the identification-through-censoring technique proposed by Rigobon and Sack (2008).

We examine own- and cross-commodity responses of four energy commodities to inventory news. The results show that the attenuation bias in event study estimates of price responsiveness to inventory surprises is quite large. For example, based on event study estimates, an unexpected 1% increase in natural gas inventory seems to result in a 2.4% decline in natural gas futures prices. In contrast, our estimates adjusted for the measurement error bias show that natural gas prices fall by almost 10% on average in response to a 1% inventory shock. In other words, energy futures prices are much more responsive to inventory announcements than shown in previous research.

Accurately measuring the effect of inventory news on energy prices is important for several reasons. First, unbiased estimates of the response coefficients allow indirect inferences about elasticity of supply and demand curves for energy commodities. Unexpected changes in commodity inventory are driven by supply and demand shocks. Commodity price responses to such shocks are determined by the price elasticity of supply and demand. The less elastic the supply and demand, the larger the price response to a given shock. Our results provide evidence that short-term supply and demand for energy commodities are less elastic than they appear based on traditional event study regression results. This finding helps to explain large fluctuations in energy prices in response to moderate demand and supply disturbances.[3]

Second, our results are useful for modeling price dynamics of energy commodities. Large jumps in energy prices are common, and are often triggered by inventory announcements (e.g., Chiou-Wei, Linn, and Zhu, 2010). Our estimates of the price response coefficients help explain such extreme price changes. This information can be incorporated into dynamic models of energy commodity prices. Finally, knowing sensitivity of energy futures prices to inventory news should help commercial users of energy and energy traders predict price moves based on their forecasts of inventory changes. For example, accurate estimates of the responsiveness of energy commodity prices to inventory news may influence the decision of power generation facilities to accumulate inventory or to acquire a capability to switch between natural gas and oil products.

[3] Baumeister and Peersman (2012) provide evidence that the increased volatility of crude oil prices since the mid-1980s is explained by declining short-term elasticities of oil demand and oil supply. They show that variance of oil demand and supply shocks actually declined during this period.

2. Identification-Through-Censoring

In a typical event study, asset returns are regressed on the unexpected component of the data release. In the context of inventory announcements with one inventory surprise and one commodity return, this approach implies the following specification:

$$R_t = \gamma z_t + \varepsilon_t ,$$
$$z_t = \Delta I_t - E_{t-\tau}[\Delta I_t], \tag{1}$$

where R_t is the commodity futures return in the event window around the announcement, ΔI_t is the actual change in inventory, $E_{t-\tau}[\Delta I_t]$ is the market's expectation of the inventory change before the release, and ε_t is an i.i.d error term representing price movements unrelated to the data release. The surprise component of the inventory announcement is z_t .

To estimate the response coefficient γ more precisely, previous studies use futures returns in a narrow intraday window surrounding the data release. This approach reduces the variance of the error term by excluding the influence of most other price-moving events that occur on the same day. To measure the unexpected change in inventory, previous studies use the Bloomberg consensus forecasts. Gay et al. (2009) provide evidence that this measure of market expectations is an improvement over forecasts obtained from historical inventory data using statistical approaches. However, the resulting measure of the unexpected change in inventory contains measurement error. This measurement error comes from two sources. First, the survey-based measure of expected inventory changes is an imprecise proxy for market expectations at the time of the announcement. For example, the analyst forecasts used to compute the Bloomberg consensus forecast may come from an unrepresentative sample of analysts, and at least some of these forecasts are likely to be out of date at the time of the release of inventory data. Second, the announced value of the inventory change is a noisy estimate of the true change in inventory, for example, because the EIA's data collection process covers only a sample of storage operators. Therefore, the measured inventory surprise z_t can be represented as follows:

$$z_t = z_t^* + \eta_t, \tag{2}$$

where z_t^* is the "true" inventory surprise and η_t is the measurement error.

The market response to the news is driven by the true inventory surprise z_t^*. However, the true surprise is unobservable. Substituting the measured inventory surprise for its true value leads to the following model, which is typically estimated with OLS:

$$\begin{aligned} R_t &= \gamma z_t + \upsilon_t, \\ \upsilon_t &= \varepsilon_t - \gamma \eta_t. \end{aligned} \tag{3}$$

Since the error term is correlated with the regressor, the OLS estimate of γ is biased. Under reasonable assumptions regarding the disturbance ε_t and the measurement error η_t, the OLS estimate of γ is:

$$\hat{\gamma}_{OLS} = \gamma\left(1 - \frac{\sigma_\eta^2}{\sigma_{z^*}^2 + \sigma_\eta^2}\right). \tag{4}$$

Equation (4) shows that the OLS estimate is biased downwards (towards zero), understating the market's response to the news. Rigobon and Sack (2008) argue that the problem of measurement error in the news variable is essentially an identification problem. One can readily compute three quantities: the variance of the asset returns, the variance of the measured news, and the covariance between them. However, these moments are determined by four unknown parameters: γ, $\sigma_{z^*}^2$, σ_η^2, and σ_ε^2. To solve this identification problem, Rigobon and

Sack (2008) propose a methodology called identification-through-censoring (ITC). Scheduled data releases occur at pre-specified times. On non-event days both the true surprise z_t^* and the measurement error η_t are zero. In effect, the measurement error is "censored" on non-event days. Returns on non-event days provide additional information needed for identification. This approach can be represented as follows:

$$R_t = \begin{cases} \gamma z_t^* + \varepsilon_t & t \in D \\ \varepsilon_t & t+1 \in D \end{cases}$$
$$z_t = z_t^* + \eta_t, \tag{5}$$

where *D* is the set of announcement days. Assuming that σ_ε^2 does not change on announcement days, we can estimate this variance using returns before the announcement.[4] This model leads to the following set of moment conditions:

$$\begin{gathered} \mathrm{var}(R_{t-1}) = \sigma_\varepsilon^2, \\ \mathrm{var}(R_t) = \gamma^2 \sigma_{z^*}^2 + \sigma_\varepsilon^2, \\ \mathrm{var}(z_t) = \sigma_{z^*}^2 + \sigma_\eta^2, \\ \mathrm{cov}(R_t, z_t) = \gamma \sigma_{z^*}^2. \end{gathered} \tag{6}$$

Solving these equations for the main parameter of interest, we get:

$$\gamma = \frac{\mathrm{var}(R_t) - \mathrm{var}(R_{t-1})}{\mathrm{cov}(R_t, z_t)}. \tag{7}$$

Volatility varies over the trading day in a predictable manner. Therefore, we use pre-event-day returns in the same intraday interval as the interval used to compute event-day returns.

[4] Returns do not have to be conditionally homoscedastic to satisfy this identifying assumption. Return volatility varies over time. Yet, unless the variance of the structural shocks is systematically different between the event and pre-event days, it is appropriate to use the pre-event-day returns to estimate the variance of the structural shocks.

For example, when the Petroleum Status Report is released on the regular schedule (Wednesday at 10:30 a.m.), the event-window returns are computed in the interval from 10:25 a.m. to 10:40 a.m. on the day of the announcement. Non-announcement returns are computed in the interval from 10:25 a.m. to 10:40 a.m. on the day before.

The Petroleum Status Report announcements include inventory estimates for three petroleum commodities: crude oil, gasoline, and distillate. Chang et al. (2009) show that gasoline and distillate inventory surprises move crude oil futures prices. Therefore, in addition to the inventory surprise for crude oil, they also use the aggregate petroleum inventory surprise. However, inventory surprises for crude oil, gasoline and distillate are likely to have a larger effect on prices of crude oil, gasoline, and heating oil, respectively. The ITC estimation can easily accommodate multiple markets and multiple data surprises. In the case of three data surprises and three markets, the model becomes:

$$
\begin{aligned}
R_{1,t} &= \gamma_{1,1} z^*_{1,t} + \gamma_{2,1} z^*_{2,t} + \gamma_{3,1} z^*_{3,t} + \varepsilon_{1,t}, \\
R_{2,t} &= \gamma_{2,1} z^*_{1,t} + \gamma_{2,2} z^*_{2,t} + \gamma_{3,2} z^*_{3,t} + \varepsilon_{2,t}, \\
R_{3,t} &= \gamma_{3,1} z^*_{1,t} + \gamma_{3,1} z^*_{2,t} + \gamma_{3,3} z^*_{3,t} + \varepsilon_{3,t}, \\
z_{1,t} &= z^*_{1,t} + \eta_{1,t}, \\
z_{2,t} &= z^*_{2,t} + \eta_{2,t}, \\
z_{3,t} &= z^*_{3,t} + \eta_{3,t}.
\end{aligned}
\tag{8}
$$

Estimating this model involves 27 unknown parameters (nine response coefficients, three variances of the structural shocks $\varepsilon_{i,t}$, three variances of the true surprises $z^*_{i,t}$, three variances of the noise terms $\eta_{i,t}$, three covariances of the structural shocks, three covariances of the surprises, and three covariances of the noise terms). Futures returns and the observed data surprises provide 27 moment equations. This number includes six moment equations provided by the variance-covariance matrix of non-announcement returns and 21 moment equations provided by the variance-covariance matrix of announcement window returns and inventory surprises. The model parameters can be estimated using the generalized method of moments (GMM).[5]

It is also interesting to examine the effect of the Petroleum Status Report announcements on natural gas futures prices. Therefore, we estimate a model that includes returns in all four energy futures markets and the three separate inventory surprises contained in the Petroleum Status Report. The model is similar to that shown in equation set (8) above, but includes one additional equation for the fourth futures return. Adding the fourth return equation involves estimating seven additional parameters. The expanded variance-covariance matrix of returns and inventory surprises provides eleven additional moment equations.[6] Therefore, the ITC estimator is over-identified, as in Rigobon and Sack (2008).

To compare the explanatory power of OLS and ITC estimations, we compute the following pseudo-R^2 statistic for our ITC models:

$$R_i^{2*} = 1 - \frac{\sigma_{\varepsilon_i}^2}{var(R_{it})} \tag{9}$$

This statistic represents the fraction of return variance explained by the model. Because variances of the structural shocks ε_i are estimated using non-event returns, this formula for pseudo-R^2 assumes that inventory surprises explain all of the increase in return variance around the announcement.

[5] The GMM estimation theory is based on asymptotic principles. To make sure that ITC estimates are reliable in a finite sample, we estimated an ITC model with one data surprise and two markets using artificial data. The ITC estimates were close to the assumed population parameter values, showing that the ITC estimates are reliable. A detailed description of this exercise is available upon request.

[6] The moment equations for this model are shown in the Appendix.

3. Data and Sample Selection

3.1. Energy Inventory Reports

Our data for the U.S. inventory of crude oil and other petroleum products are obtained from the Weekly Petroleum Status Report compiled by the EIA. The data include weekly ending commercial stocks of crude oil, gasoline, and distillate fuel oil. The data included in the Petroleum Status Report are collected by the EIA on weekly surveys from a sample of operators at several key points along the petroleum production and supply chain.[7] The key data in the Petroleum Status Report are released at 10:30 a.m. (Eastern Time) every Wednesday for the week ending the previous Friday. For some weeks which include holidays, releases are delayed by one day.

The inventory data for natural gas represent weekly estimates of natural gas in underground storage in the Lower 48 States. These estimates are reported in the EIA's Weekly Natural Gas Storage Report.[8] The data in this report are obtained from a survey of a sample of natural gas storage operators. The report is released at 10:30 a.m. (Eastern Time) every Thursday, except for certain weeks that include Federal holidays. Historical dates and times of release for both inventory reports are obtained from Bloomberg.

Figure 1 shows historical values of inventory for crude oil, distillate, gasoline, and natural gas over our sample period.[9] The natural gas inventory exhibits strong seasonality. On average, natural gas inventory increases from April to November and falls during the heating season in winter and early spring.

[Insert Figure 1 about here]

[7] The survey and estimation methodology used in the Weekly Petroleum Status Report are described at http://www.eia.gov/pub/oil_gas/petroleum/data_publications/weekly_petroleum_status_report/current/pdf/appendixb.pdf
[8] The methodology used in the Natural Gas Storage Report is described at http://ir.eia.gov/ngs/methodology.html.
[9] These data are available on the EIA's website at http://www.eia.gov/.

3.2. Sample Selection

Our sample period extends from July 16, 2003 through June 27, 2012.[10] This period contains 468 releases of the Petroleum Status Report and 467 releases of the Natural Gas Storage Report. During this period, there were 30 occasions when the two reports were released simultaneously, at 10:30 a.m. on Thursdays. We exclude such simultaneous announcements from the sample. A few observations are removed due to missing futures returns data. The final sample contains 435 observations for each of the two inventory reports.

3.3. Inventory Surprises

To compute the unexpected changes in inventory, or inventory surprises, we need a proxy for the market expectations at the time of the inventory announcement. Following the previous literature, we use the Bloomberg consensus forecasts to measure expected changes in inventory. The consensus forecast is computed as the median of individual analyst forecasts. We compute inventory surprises as the difference between the actual and expected change in inventory, divided by the inventory level.

Summary statistics for inventory surprises are shown in Panel A of Table I. The standard deviation of inventory surprises for natural gas is lower than those for crude oil and other petroleum products. This indicates that natural gas inventory changes are more predictable than petroleum inventory changes. This higher predictability is likely to be related to the seasonal pattern in the natural gas inventory.

[Insert Table I about here]

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[10] Our sample period begins in July 2003 because the first Weekly Petroleum Status Report announcement date for which Bloomberg forecast data is available for all three petroleum commodities is July 16, 2003.

3.4. Energy Futures Returns

To examine the response of energy prices to inventory news, we use intraday futures prices for WTI crude oil, gasoline, heating oil, and natural gas.[11] These futures contracts are traded on the New York Mercantile Exchange (NYMEX). Energy futures markets are very liquid, with the combined average daily trading volume in the four futures contracts that we examine exceeding 1.2 million contracts in the first six months of 2012. Futures markets have been shown to dominate price discovery in energy commodities (e.g., Schwarz and Szakmary, 1994).

We compute continuously compounded returns in an intraday event window surrounding the inventory announcement surprises using prices of the nearby futures contract. The nearby contract becomes relatively illiquid in its last few days of trading. Therefore, in the last three days of trading of the nearby contract we substitute prices of the next closest contract. The event window is from five minutes before to ten minutes after the announcement time.[12] The 15-minute event window allows for a comparison of our results with results of existing studies looking at the market response to energy inventory announcements. For example, Gay, Simkins, and Turac (2009) also use 15-minute intervals containing the announcement.

Summary statistics for futures returns are shown in Panel B of Table I. The table also provides non-announcement day returns, which are used in the ITC estimation. We use equally matched numbers of event and non-event days. The non-announcement day returns are computed in the same 15-minute intraday intervals as the announcement day returns. For the Petroleum Status Report, the non-announcement day returns are computed using futures prices from the day before the announcement. Because the Petroleum Status Report is normally released exactly one

[11] The futures market data are obtained from Genesis Financial Technologies.
[12] The results with longer event windows are similar.

day before the Natural Gas Storage Report, the non-announcement day returns for the Natural Gas Storage Report are computed using futures prices from two days before the announcement.

The table shows that volatility of petroleum futures returns approximately doubles when the Petroleum Status Report is released. The increase in volatility of the natural gas futures around releases of the Natural Gas Storage Report is even larger. Volatility of natural gas futures returns also increases somewhat after the release of the Petroleum Status Report. In contrast, volatility of petroleum futures seems to be unchanged after the release of the Natural Gas Storage Report.

Figure 2 shows cumulative average returns (CARs) for crude oil and natural gas futures around the inventory announcements. The CARs are presented separately for positive and negative inventory surprises. Futures prices tend to increase when the inventory is lower than expected and decline when the inventory is larger than expected. The negative relation between excess supply shocks and futures return movements is consistent with basic economic theory (prices fall when supply increases). The natural gas futures returns after the release of the Natural Gas Storage Report tend to be larger in absolute value than returns in the crude oil futures market following the release of the Petroleum Status Report. There also seems to be some asymmetry between the effects of positive and negative inventory surprises. Specifically, positive inventory surprises tend to be followed by bigger price moves, particularly in the natural gas futures market. Overall, the figure shows that the price impact of the news is immediate and appears to be permanent.

[Insert Figure 2 about here]

4. Empirical Results

4.1. Full Sample Results

Estimation results for the effect of petroleum inventory surprises on energy prices are presented in Table II.[13] According to the OLS estimates, a 1% unexpected increase in crude oil inventory leads to an approximately 0.5% drop in the crude oil futures price. The corresponding ITC estimate is more than twice as large. As expected, the response coefficients differ across the three inventory surprises. For example, the ITC estimate of the crude oil response coefficient for crude oil inventory surprises is about –1.06, whereas the crude oil response coefficient for gasoline inventory surprises is only about –0.55. The corresponding estimates for gasoline futures are about –0.52 and –1.25, respectively. All three petroleum inventory surprises have similar (and relatively small) impacts on the natural gas futures prices. The average ratio of ITC to OLS estimates ranges from about 1.7 for natural gas to about 1.9 for crude oil, showing that traditional event study regressions underestimate the energy market responses to news about petroleum inventory by approximately a factor of two. The estimated proportion of the variance of the measured inventory surprise due to noise ($\sigma_\eta^2 / \sigma_z^2$) ranges from about 49% for gasoline to about 59% for crude oil, showing that the measured inventory surprises are quite noisy. For comparison, the corresponding statistic for several major macroeconomic announcements reported in Rigobon and Sack (2008) exceeded 90%.

[Insert Table II about here]

To examine the effects of the natural gas inventory announcements on the four energy commodity markets, we estimate an ITC model with four markets and one inventory surprise. The model has 16 unknown parameters, and the variance-covariance matrix of futures returns

[13] Inventory surprises and futures returns are demeaned prior to estimation.

and inventory surprises provides 25 moment equations. The full sample ITC and OLS estimation results are presented in Panel A of Table III. The OLS estimate of the response coefficient for natural gas futures is about –2.4, implying that an unexpected 1% increase in natural gas in storage results in a 2.4% drop in natural gas futures prices. This estimate is somewhat larger in absolute value than the corresponding estimate for an earlier sample period in Gay et al. (2009). The ITC estimate of the response coefficient for natural gas is almost four times as large as the OLS estimate. The estimated proportion of the variance of the measured inventory surprise due to noise for natural gas inventory surprises is about 73%.

[Insert Table III about here]

Both the OLS and ITC estimates of the effect of natural gas inventory surprises on petroleum commodity prices are statistically significant. For the cross-commodity effects of the natural gas inventory surprises, the ratio of ITC to OLS estimates ranges from about 2.5 for gasoline to about 3.3 for crude oil. The difference between ITC and OLS coefficient estimates reported in Tables II and III is economically significant. It implies that supply and demand curves for energy commodities are much less elastic than suggested by the previous event study results. Based on the pseudo-R^2 values of the ITC estimations, inventory surprises explain a much larger fraction of return variance than it appears from the explanatory power of the OLS regressions.

Rigobon and Sack (2008) point out that macroeconomic surprises included in the model often coincide with the release of other important data. Volatility induced by information releases not accounted for in the model may lead to an upward bias in the ITC estimates. Similar considerations apply in our case. For example, the Natural Gas Storage Report includes not only the total amount of natural gas in storage (for which Bloomberg survey forecasts are available), but also the storage amounts for the East, West, and Producing regions. Even if the overall amount of gas in storage is equal to the market's expectations, there may be unexpected changes in regional gas inventories that may move energy futures prices. Therefore, ITC estimates may have some upward bias.

4.2. Injection and Withdrawal Seasons for Natural Gas

Natural gas storage involves two calendar periods: the "injection season" (April through October) and the "withdrawal season" (November through March). During injection, inventory surprises are determined to a large extent by supply shocks related to the technology of gas storage. During withdrawal, unexpected changes in natural gas inventory are driven primarily by demand shocks due to weather. Gay et al. (2009) argue that, since the demand curve for natural gas is less elastic than the supply curve, prices should respond more strongly to storage surprises during the injection season than during the withdrawal season. They find empirical support for this hypothesis. Gay et al. (2009) also provide evidence that inventory changes are less predictable during the withdrawal season.

An alternative explanation for the seasonal variation in the price response to inventory news is that, due to a larger proportion of noise in the variance of the measured inventory news, the OLS attenuation bias is larger during the withdrawal season. To examine this issue, we estimate the four-commodity model for the Natural Gas Storage Report announcements separately for injection and withdrawal seasons. The results are provided in Panels B and C of Table III. Consistent with Gay et al. (2009), the OLS estimate of the own-commodity response to natural gas storage surprises is about 55% larger in absolute value during the injection season than during withdrawal. The ITC estimate of the own-commodity response coefficient is still larger in absolute value during the injection season than during withdrawal, but only by about

33%. The OLS estimates of cross-commodity effects are not statistically significant during the withdrawal season. The corresponding ITC estimates for crude oil and heating oil are statistically significant. Consistent with our expectations, there is evidence that noise accounts for a larger proportion of the variance of the measured inventory surprises during the withdrawal season.

4.3. The Effect of Analyst Forecast Dispersion on Response Coefficients

Chiou-Wei et al. (2010) examine the effect of market uncertainty on the response of the natural gas futures prices to the storage surprises. They use the standard deviation of the individual analysts' forecasts of the change in inventory as a proxy for market uncertainty. They find that the market response to inventory surprises estimated with OLS is significantly weaker at times of greater dispersion in analyst forecasts. In a study of the response of stock returns to earnings surprises, Imhoff and Lobo (1992) also find that firms with high dispersion of analyst forecasts exhibit little or no price response to earnings surprises. They provide evidence that analyst forecast dispersion is more likely to proxy for noise in earnings surprises than for uncertainty about the firm's earnings prospects.

Abarbanell, Lanen and Verrecchia (1995) show theoretically that the price response coefficient is negatively related to forecast dispersion for two reasons. First, measurement error in earnings surprises increases in the dispersion of analyst forecasts and introduces a downward bias in the earnings response coefficients. Second, even when the earnings surprise is measured without error, the market response increases in forecast precision, which is negatively related to forecast dispersion. In the context of earnings forecasts, precision reflects the extent to which current earnings is informative about future earnings and therefore about the firm value. Permanent changes in earnings provide a more precise signal about future earnings than do transitory earnings changes.

Figure 3 shows the standard deviation of analyst forecasts of natural gas inventory changes divided by the reported level of inventory. Consistent with Gay et al. (2009), dispersion of analyst forecasts tends to be much larger during the withdrawal season. The figure also shows a decline in the average level of forecast dispersion over our sample period.

[Insert Figure 3 about here]

We examine whether the effect of analyst forecast dispersion on the estimates of the market response to the Natural Gas Storage Report announcements is driven by measurement error in inventory surprises.[14] The sample is partitioned into two parts based on whether the analyst forecast dispersion for a given announcement is above or below its median value for the entire sample. Panels D and E of Table III show OLS and ITC estimation results for these two subsamples. As expected, the OLS estimate of the response of natural gas prices to storage announcements is much larger in the low dispersion subsample. The difference between the two estimates is almost a factor of three (–5.0 in the low dispersion subsample versus –1.8 in the high dispersion subsample). The OLS R^2 of the natural gas regression is twice as high in the low dispersion subsample as in the high dispersion subsample.

The ITC estimate of the response coefficient for natural gas ranges from about –10.8 in the low dispersion subsample to –7.8 in the high dispersion subsample. The estimated proportion of the variance of the measured inventory surprise due to noise is about 77% in the high dispersion subsample compared to about 52% in the low dispersion subsample. These results imply that much of the effect of analyst forecast dispersion on the OLS estimate of the response coefficient for natural gas is due to the attenuation bias induced by measurement error in inventory surprises. These findings also provide support for using the dispersion of analyst

[14] This section focuses on the Natural Gas Storage Report announcements because their single inventory surprise allows for straightforward partitioning of the sample based on analyst forecast dispersion.

forecasts as a proxy for measurement error. Even after correcting for the bias induced by noise in inventory surprises, the market response to the news is somewhat stronger in the low dispersion subsample. This finding is consistent with the notion that the forecast dispersion conveys information about precision of analyst forecasts.[15]

The fact that forecast dispersion increases during the withdrawal season raises the question whether the difference in price response coefficients between the injection and withdrawal seasons is driven by variation in forecast dispersion. We estimated an OLS regression that included the inventory surprise and the inventory surprise interacted with a dummy variable for the withdrawal season. Consistent with the results in Panels B and C of Table III, the coefficient of the interaction term is positive and statistically significant. However, this coefficient becomes insignificant when an interaction of the inventory surprise with a dummy for high forecast dispersion is added to the model.[16] This finding supports the conclusion that the smaller OLS estimate of the response to inventory surprises during the withdrawal season is due, at least in part, to a larger proportion of noise in inventory surprises.

A possible reason behind the somewhat smaller ITC estimate of the price response during the withdrawal season is lower precision of inventory surprises during withdrawal. As mentioned above, inventory changes during withdrawal are driven primarily by demand shocks due to weather. Such demand shocks tend to be temporary (e.g., Pindyck, 2001), which implies lower precision of inventory surprises.

[15] Hautsch and Hess (2007) and Burgstahler and Chuk (2010) use the analyst forecast dispersion as a proxy for precision.
[16] These regression results are not tabulated to save space but are available upon request.

4.4. Decoupling of Natural Gas and Petroleum Markets

This subsection examines whether the cross-commodity effects of petroleum and natural gas inventory announcements have diminished in recent years. Figure 4 shows weekly spot prices of natural gas and energy equivalent prices of WTI crude oil.[17] After collapsing during the 2008 recession, oil prices resumed their climb. Natural gas prices, however, have drifted downwards, after briefly trading at energy parity with oil in December 2008. This divergence between natural gas and oil prices is consistent with Ramberg and Parsons (2012), who show that the cointegrating relationship between the two prices is not stable through time. By June 2012, the energy equivalent price of oil exceeded the price of natural gas by a factor of six. This apparent decoupling of oil and gas prices has coincided with the shale gas boom in the U.S.

[Insert Figure 4 about here]

We begin by computing the daily realized correlation between natural gas and crude oil futures returns as follows:[18]

$$RC_t = \frac{\sum_{i=1}^{m} R_{o,i} R_{g,i}}{\sqrt{\sum_{i=1}^{m} R_{o,i}^2 R_{g,i}^2}}, \tag{9}$$

where $R_{o,i}$ and $R_{g,i}$ are continuously compounded returns of the most actively traded crude oil and natural gas futures contracts, respectively, in a 5-minute intraday interval i, and m is the number of such intervals in trading day t.

[17] Natural gas prices are normally quoted in dollars per million British thermal units (BTU). One barrel of WTI crude oil contains 5.825 million BTUs. Therefore, energy equivalent price of crude oil can be computed by dividing the WTI crude price per barrel by 5.825.

[18] This measure is proposed by Andersen, Bollerslev, Diebold, and Labys (2001) and used by Wang, Wu, and Yang (2008), among others.

Figure 5 shows a pronounced decline in the correlation between the two energy futures markets in late 2009. The Quandt-Andrews breakpoint test for one or more unknown structural breakpoints identifies a shift in the mean of the realized correlations on December 11, 2009. The mean of the realized correlation declined from about 0.45 before December 2009 to about 0.09 after this structural break. This decline is strongly statistically significant.

[Insert Figure 5 about here]

Table IV presents correlations of event-window returns in the four energy futures markets. The correlations between natural gas and petroleum futures returns after the release of the Natural Gas Storage Report are both economically meaningful and strongly statistically significant during the period before December 11, 2009. These correlations become small and statistically insignificant in the more recent period. A similar pattern is observed for return correlations around the Petroleum Status Report announcements, although two of the three correlation coefficients for natural gas remain statistically significant after December 2009.

[Insert Table IV about here]

Table V shows estimates of the effect of the natural gas inventory announcements on the four energy commodity futures markets before and after the decoupling of oil and natural gas markets. The OLS estimate of the response coefficient for natural gas is more than twice as high in the more recent period compared to the period before December 11, 2009. However, the ITC estimates of this coefficient show little change from one subperiod to the next. The larger attenuation bias in the OLS estimate in the first subperiod is due to a greater proportion of noise in the measured inventory surprises. The proportion of the variance of the measured inventory surprise due to noise declines from about 78% to about 53% in the more recent subperiod.

The Natural Gas Storage Report is the EIA's only report designated a Principal Federal Economic Indicator. The report received this designation in January 2008.[19] In mid-2008, the EIA modified its weekly underground natural gas storage sample and sample selection procedure to reflect changes in the industry and improve data quality.[20] According to the EIA, the new procedure improves the accuracy of storage estimates. The finding of less noise in the natural gas inventory surprises in the post-2009 period may be due to increased accuracy of storage data.

Both the OLS and ITC estimates of the effect of the natural gas inventory news on petroleum commodities are statistically significant during the period before December 11, 2009. After this date, however, none of the cross-commodity effects are statistically significant. The OLS R^2 estimates for crude oil, gasoline and heating oil are close to zero in the period after December 11, 2009. These findings are consistent with decoupling of petroleum and natural gas markets.

[Insert Table V about here]

OLS and ITC estimation results for the Petroleum Status Report announcements before and after December 11, 2009 are reported in Table VI. Both OLS and ITC estimates indicate that inventory surprises have a significant effect on natural gas prices during the first subperiod. In the second subperiod, however, natural gas futures prices show significant response only to gasoline inventory surprises. The OLS R^2 of the natural gas regression falls from about 26% before December 11, 2009 to only about 5% thereafter.

[Insert Table VI about here]

Some power plants and industrial users of energy have the capability to switch between natural gas and petroleum products. This fuel substitution links natural gas and oil prices (e.g.,

[19] See http://ir.eia.gov/ngs/wngsrevaluation.pdf
[20] See http://ir.eia.gov/ngs/samplechg.html for a detailed discussion of these changes.

Brown and Yücel, 2008) and is likely to contribute to the cross-commodity effects of oil and gas inventory announcements. The increased shale gas production in the U.S. in recent years has led to a glut of natural gas and sent gas prices to historical lows relative to oil prices. As a result, most facilities with fuel-switching capability have probably switched to natural gas. Only a large move of oil and gas prices towards energy parity would induce these facilities to consider switching to oil products. Price changes caused by inventory news are small compared to the recently observed deviation of oil and gas from energy parity. Under these conditions, inventory surprises should have little effect on the relative attractiveness of oil and gas as substitute fuels. This may contribute to our finding that the fundamental link between petroleum and natural gas markets has weakened in recent years.

5. Summary and Conclusion

This study examines the effect of unexpected changes in inventory on energy prices. Using intraday futures data and inventory surprises for petroleum products and natural gas, we estimate the price response coefficients using traditional event study regressions and Rigobon and Sack's ITC methodology. The results show that the noise in estimated inventory surprises and the resulting attenuation bias in OLS estimates are quite large. The ITC coefficient estimates are about twice as large as OLS estimates for petroleum commodities and about four times as large as OLS estimates for natural gas. Thus, energy prices are more strongly influenced by excess supply and demand shocks than shown in previous studies. Our results help to explain why we often observe large movements in energy prices in response to moderate demand and supply shocks. These findings are a step towards showing that high volatility of energy prices can be explained by fundamental news.

Appendix. Moment Conditions Used in ITC Estimation of the Response of Crude Oil, Gasoline, Heating Oil, and Natural Gas Futures Prices to Petroleum Status Report Announcements

This estimation uses an ITC model with four markets and three inventory surprises. Estimating this model involves 34 unknown parameters. The variance-covariance matrix of returns and inventory surprises provides 38 moment conditions:

1). $var(R_{1t-1}) = \sigma^2_{\varepsilon_1}$

2). $var(R_{2t-1}) = \sigma^2_{\varepsilon_2}$

3). $var(R_{3t-1}) = \sigma^2_{\varepsilon_3}$

4). $var(R_{4t-1}) = \sigma^2_{\varepsilon_4}$

5). $var(R_{1t}) = \gamma^2_{11}\sigma^2_{z_1^*} + \gamma^2_{12}\sigma^2_{z_2^*} + \gamma^2_{13}\sigma^2_{z_3^*} + 2\gamma_{11}\gamma_{12}cov(z_1^*, z_2^*) + 2\gamma_{11}\gamma_{13}cov(z_1^*, z_3^*) + 2\gamma_{12}\gamma_{13}cov(z_2^*, z_3^*) + \sigma^2_{\varepsilon_1}$

6). $var(R_{2t}) = \gamma^2_{21}\sigma^2_{z_1^*} + \gamma^2_{22}\sigma^2_{z_2^*} + \gamma^2_{23}\sigma^2_{z_3^*} + 2\gamma_{21}\gamma_{22}cov(z_1^*, z_2^*) + 2\gamma_{21}\gamma_{23}cov(z_1^*, z_3^*) + 2\gamma_{22}\gamma_{23}cov(z_2^*, z_3^*) + \sigma^2_{\varepsilon_2}$

7). $var(R_{3t}) = \gamma^2_{31}\sigma^2_{z_1^*} + \gamma^2_{32}\sigma^2_{z_2^*} + \gamma^2_{33}\sigma^2_{z_3^*} + 2\gamma_{31}\gamma_{32}cov(z_1^*, z_2^*) + 2\gamma_{31}\gamma_{33}cov(z_1^*, z_3^*) + 2\gamma_{32}\gamma_{33}cov(z_2^*, z_3^*) + \sigma^2_{\varepsilon_3}$

8). $var(R_{4t}) = \gamma^2_{41}\sigma^2_{z_1^*} + \gamma^2_{42}\sigma^2_{z_2^*} + \gamma^2_{43}\sigma^2_{z_3^*} + 2\gamma_{41}\gamma_{42}cov(z_1^*, z_2^*) + 2\gamma_{41}\gamma_{43}cov(z_1^*, z_3^*) + 2\gamma_{42}\gamma_{43}cov(z_2^*, z_3^*) + \sigma^2_{\varepsilon_4}$

9). $var(z_{1t}) = \sigma^2_{z_1^*} + \sigma^2_{\eta_1}$

10). $var(z_{2t}) = \sigma^2_{z_2^*} + \sigma^2_{\eta_2}$

11). $var(z_{3t}) = \sigma^2_{z_3^*} + \sigma^2_{\eta_3}$

12). $cov(R_{1t}, z_{1t}) = \gamma_{11}\sigma^2_{z_1^*} + \gamma_{12}cov(z_1^*, z_2^*) + \gamma_{13}cov(z_1^*, z_3^*)$

13). $cov(R_{2t}, z_{1t}) = \gamma_{21}\sigma^2_{z_1^*} + \gamma_{22}cov(z_1^*, z_2^*) + \gamma_{23}cov(z_1^*, z_3^*)$

14). $cov(R_{3t}, z_{1t}) = \gamma_{31}\sigma^2_{z_1^*} + \gamma_{32}cov(z_1^*, z_2^*) + \gamma_{33}cov(z_1^*, z_3^*)$

15). $cov(R_{4t}, z_{1t}) = \gamma_{41}\sigma^2_{z_1^*} + \gamma_{42}cov(z_1^*, z_2^*) + \gamma_{43}cov(z_1^*, z_3^*)$

16). $cov(R_{1t}, z_{2t}) = \gamma_{11}cov(z_1^*, z_2^*) + \gamma_{12}\sigma^2_{z_2^*} + \gamma_{13}cov(z_2^*, z_3^*)$

17). $cov(R_{2t}, z_{2t}) = \gamma_{21}cov(z_1^*, z_2^*) + \gamma_{22}\sigma^2_{z_2^*} + \gamma_{23}cov(z_2^*, z_3^*)$

18). $cov(R_{3t}, z_{2t}) = \gamma_{31}cov(z_1^*, z_2^*) + \gamma_{32}\sigma^2_{z_2^*} + \gamma_{33}cov(z_2^*, z_3^*)$

19). $cov(R_{4t}, z_{2t}) = \gamma_{41}cov(z_1^*, z_2^*) + \gamma_{42}\sigma^2_{z_2^*} + \gamma_{43}cov(z_2^*, z_3^*)$

20). $cov(R_{1t}, z_{3t}) = \gamma_{11}cov(z_1^*, z_3^*) + \gamma_{12}cov(z_2^*, z_3^*) + \gamma_{13}\sigma_{z_3^*}^2$

21). $cov(R_{2t}, z_{3t}) = \gamma_{21}cov(z_1^*, z_3^*) + \gamma_{22}cov(z_2^*, z_3^*) + \gamma_{23}\sigma_{z_3^*}^2$

22). $cov(R_{3t}, z_{3t}) = \gamma_{31}cov(z_1^*, z_3^*) + \gamma_{32}cov(z_2^*, z_3^*) + \gamma_{33}\sigma_{z_3^*}^2$

23). $cov(R_{4t}, z_{3t}) = \gamma_{41}cov(z_1^*, z_3^*) + \gamma_{42}cov(z_2^*, z_3^*) + \gamma_{43}\sigma_{z_3^*}^2$

24). $cov(z_{1t}, z_{2t}) = cov(z_1^*, z_2^*) + cov(\eta_1, \eta_2)$

25). $cov(z_{1t}, z_{3t}) = cov(z_1^*, z_3^*) + cov(\eta_1, \eta_3)$

26). $cov(z_{2t}, z_{3t}) = cov(z_2^*, z_3^*) + cov(\eta_2, \eta_3)$

27). $cov(R_{1t}, R_{2t}) = \gamma_{11}\gamma_{21}\sigma_{z_1^*}^2 + \gamma_{12}\gamma_{22}\sigma_{z_2^*}^2 + \gamma_{13}\gamma_{23}\sigma_{z_3^*}^2 + cov(\varepsilon_1, \varepsilon_2) + \big(\gamma_{11}\gamma_{22} + \gamma_{12}\gamma_{21}\big)cov(z_1^*, z_2^*) + \big(\gamma_{11}\gamma_{23} + \gamma_{13}\gamma_{21}\big)cov(z_1^*, z_3^*) + \big(\gamma_{12}\gamma_{23} + \gamma_{13}\gamma_{22}\big)cov(z_2^*, z_3^*)$

28). $cov(R_{1t}, R_{3t}) = \gamma_{11}\gamma_{31}\sigma_{z_1^*}^2 + \gamma_{12}\gamma_{32}\sigma_{z_2^*}^2 + \gamma_{13}\gamma_{33}\sigma_{z_3^*}^2 + cov(\varepsilon_1, \varepsilon_3) + \big(\gamma_{11}\gamma_{32} + \gamma_{12}\gamma_{31}\big)cov(z_1^*, z_2^*) + \big(\gamma_{11}\gamma_{33} + \gamma_{13}\gamma_{31}\big)cov(z_1^*, z_3^*) + \big(\gamma_{12}\gamma_{33} + \gamma_{13}\gamma_{32}\big)cov(z_2^*, z_3^*)$

29). $cov(R_{1t}, R_{4t}) = \gamma_{11}\gamma_{41}\sigma_{z_1^*}^2 + \gamma_{12}\gamma_{42}\sigma_{z_2^*}^2 + \gamma_{13}\gamma_{43}\sigma_{z_3^*}^2 + cov(\varepsilon_1, \varepsilon_4) + \big(\gamma_{11}\gamma_{42} + \gamma_{12}\gamma_{41}\big)cov(z_1^*, z_2^*) + \big(\gamma_{11}\gamma_{43} + \gamma_{13}\gamma_{41}\big)cov(z_1^*, z_3^*) + \big(\gamma_{12}\gamma_{43} + \gamma_{13}\gamma_{42}\big)cov(z_2^*, z_3^*)$

30). $cov(R_{2t}, R_{3t}) = \gamma_{21}\gamma_{31}\sigma_{z_1^*}^2 + \gamma_{22}\gamma_{32}\sigma_{z_2^*}^2 + \gamma_{23}\gamma_{33}\sigma_{z_3^*}^2 + cov(\varepsilon_2, \varepsilon_3) + \big(\gamma_{21}\gamma_{32} + \gamma_{22}\gamma_{31}\big)cov(z_1^*, z_2^*) + \big(\gamma_{21}\gamma_{33} + \gamma_{23}\gamma_{31}\big)cov(z_1^*, z_3^*) + \big(\gamma_{22}\gamma_{33} + \gamma_{23}\gamma_{32}\big)cov(z_2^*, z_3^*)$

31). $cov(R_{2t}, R_{4t}) = \gamma_{21}\gamma_{41}\sigma_{z_1^*}^2 + \gamma_{22}\gamma_{42}\sigma_{z_2^*}^2 + \gamma_{23}\gamma_{43}\sigma_{z_3^*}^2 + cov(\varepsilon_2, \varepsilon_4) + \big(\gamma_{21}\gamma_{42} + \gamma_{22}\gamma_{41}\big)cov(z_1^*, z_2^*) + \big(\gamma_{21}\gamma_{43} + \gamma_{23}\gamma_{41}\big)cov(z_1^*, z_3^*) + \big(\gamma_{22}\gamma_{43} + \gamma_{23}\gamma_{42}\big)cov(z_2^*, z_3^*)$

32). $cov(R_{3t}, R_{4t}) = \gamma_{31}\gamma_{41}\sigma_{z_1^*}^2 + \gamma_{32}\gamma_{42}\sigma_{z_2^*}^2 + \gamma_{33}\gamma_{43}\sigma_{z_3^*}^2 + cov(\varepsilon_2, \varepsilon_4) + \big(\gamma_{31}\gamma_{42} + \gamma_{32}\gamma_{41}\big)cov(z_1^*, z_2^*) + \big(\gamma_{31}\gamma_{43} + \gamma_{33}\gamma_{41}\big)cov(z_1^*, z_3^*) + \big(\gamma_{32}\gamma_{43} + \gamma_{33}\gamma_{42}\big)cov(z_2^*, z_3^*)$

33). $cov(R_{1t-1}, R_{2t-1}) = cov(\varepsilon_1, \varepsilon_2)$

34). $cov(R_{1t-1}, R_{3t-1}) = cov(\varepsilon_1, \varepsilon_3)$

35). $cov(R_{1t-1}, R_{4t-1}) = cov(\varepsilon_1, \varepsilon_4)$

36). $cov(R_{2t-1}, R_{3t-1}) = cov(\varepsilon_2, \varepsilon_3)$

37). $cov(R_{2t-1}, R_{4t-1}) = cov(\varepsilon_2, \varepsilon_4)$

38). $cov(R_{3t-1}, R_{4t-1}) = cov(\varepsilon_3, \varepsilon_4)$

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Table I
Summary Statistics for Inventory Surprise and Futures Returns

Panel A. Inventory Surprises (%)

	Mean	Median	St. deviation	Minimum	Maximum
Petroleum Status Report					
Crude Oil	-0.03	0.01	0.94	-2.79	2.82
Gasoline	-0.02	-0.02	1.03	-3.04	3.33
Distillates	-0.01	0	1.19	-3.46	5.45
Natural Gas Storage Report	0.03	0	0.42	-1.86	1.36

Panel B. Futures Returns (%)

	Announcement Days			Non-announcement Days		
	Mean	Median	St. deviation	Mean	Median	St. deviation
Petroleum Status Report						
Crude Oil	-0.09	-0.08	0.94	-0.02	0	0.43
Gasoline	-0.13	-0.07	1.16	-0.03	-0.01	0.53
Heating Oil	-0.12	-0.12	0.93	-0.02	0	0.41
Natural Gas	-0.03	-0.02	0.70	-0.03	0	0.54
Natural Gas Storage Report						
Natural Gas	-0.26	-0.32	2.02	-0.03	0	0.55
Crude Oil	-0.03	-0.01	0.44	-0.04	0	0.44
Gasoline	-0.01	-0.02	0.47	-0.04	-0.01	0.55
Heating Oil	-0.01	-0.004	0.44	-0.03	0	0.41

The inventory surprises are computed as the difference between the actual and expected change in inventory, divided by the inventory level. The continuously compounded futures returns are computed in the intraday event window surrounding the inventory announcement. The event window is from 5 minutes before to 10 minutes after the announcement time. Non-announcement day returns are computed in the same time interval one day before the Petroleum Status Report announcements and two days before the Natural Gas Storage Report announcements. The sample period is from July 16, 2003 through June 27, 2012. The number of observations is 435.

Table II
Response of Energy Futures Prices to Petroleum Status Report Announcements

	OLS Estimates				ITC Estimates				
	Crude Oil Surprise	Gasoline Surprise	Distillate Surprise	R^2	Crude Oil Surprise	Gasoline Surprise	Distillate Surprise	Pseudo-R^2	Average Ratio ITC/OLS
Crude Oil	-0.48***	-0.31***	-0.17***	0.410	-1.06***	-0.55***	-0.31***	0.809	1.92
	(0.04)	(0.04)	(0.03)		(0.15)	(0.09)	(0.09)		
Gasoline	-0.29***	-0.66***	-0.13***	0.438	-0.52***	-1.25***	-0.23***	0.820	1.83
	(0.05)	(0.05)	(0.05)		(0.12)	(0.13)	(0.09)		
Heating Oil	-0.34***	-0.23***	-0.35***	0.423	-0.68***	-0.41***	-0.72***	0.817	1.94
	(0.04)	(0.04)	(0.04)		(0.10)	(0.08)	(0.11)		
Natural Gas	-0.17***	-0.16***	-0.13***	0.184	-0.33**	-0.24***	-0.23***	0.440	1.68
	(0.03)	(0.03)	(0.03)		(0.09)	(0.06)	(0.07)		
Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2 / \sigma_z^2\right)$					59%	49%	55%		

The table shows the estimated responses of energy futures returns to Petroleum Status Report announcements. The sample period is from July 16, 2003 through June 27, 2012. The number of observations is 435. The response coefficients are estimated using (1) equation-by-equation OLS with the White (1980) heteroskedasticity consistent covariance matrix and (2) identification-through-censoring (ITC) approach. All variables are demeaned prior to estimation. The null hypothesis of the Hansen (1982) test that the over-identifying restrictions of the ITC model are valid is not rejected at the 5% level. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table III
Response of Energy Futures Prices to Natural Gas Storage Report Announcements

	OLS Estimates		ITC Estimates			
	Response Coefficient	R^2	Response Coefficient	Pseudo-R^2	Ratio ITC/OLS	Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2/\sigma_z^2\right)$
Panel A. Full Sample (N=435)						
Natural Gas	-2.40 (0.25)***	0.244	-9.56 (0.94)***	0.929	3.98	73%
Crude Oil	-0.14 (0.08)*	0.017	-0.46 (0.12)***	0.203	3.28	
Gasoline	-0.13 (0.07)**	0.014	-0.33 (0.13)**	0.080	2.47	
Heating Oil	-0.15 (0.07)**	0.021	-0.48 (0.12)***	0.223	3.19	
Panel B. Injection Season (N=255)						
Natural Gas	-3.17 (0.43)***	0.266	-10.75 (0.99)***	0.918	3.38	69%
Crude Oil	-0.22 (0.08)***	0.021	-0.64 (0.14)***	0.062	2.99	
Gasoline	-0.24 (0.10)**	0.025	-0.54 (0.15)***	0.087	2.31	
Heating Oil	-0.24 (0.09)***	0.029	-0.64 (0.13)***	0.134	2.63	
Panel C. Withdrawal Season (N=180)						
Natural Gas	-2.05 (0.31)***	0.228	-8.07 (1.39)***	0.938	3.94	73%
Crude Oil	-0.11 (0.11)	0.012	-0.30 (0.15)**	0.348	2.83	
Gasoline	-0.08 (0.09)	0.008	-0.12 (0.17)	0.122	1.40	
Heating Oil	-0.11 (0.10)	0.011	-0.35 (0.15)**	0.358	3.36	
Panel D. Low Dispersion of Analyst Forecasts (N=218)						
Natural Gas	-4.99 (0.45)***	0.422	-10.80 (1.04)***	0.922	2.16	52%
Crude Oil	-0.20 (0.09)**	0.020	-0.50 (0.15)***	0.077	2.49	
Gasoline	-0.06 (0.10)	0.002	-0.32 (0.14)**	0.110	4.91	
Heating Oil	-0.21 (0.09)**	0.026	-0.48 (0.12)***	0.086	2.23	
Panel E. High Dispersion of Analyst Forecasts (N=217)						
Natural Gas	-1.76 (0.24)***	0.210	-7.77 (1.44)***	0.933	4.41	77%
Crude Oil	-0.12 (0.09)	0.017	-0.35 (0.15)**	0.244	2.83	
Gasoline	-0.15 (0.08)*	0.023	-0.27 (0.17)	0.027	1.81	
Heating Oil	-0.14 (0.09)	0.019	-0.46 (0.17)***	0.259	3.35	

The table shows the estimated responses of energy futures returns to unexpected changes in natural gas inventory. The sample period is from July 16, 2003 through June 27, 2012. The response coefficients are estimated using (1) equation-by-equation OLS with the White (1980) heteroskedasticity consistent covariance matrix and (2) identification-through-censoring (ITC) approach. All variables are demeaned prior to estimation. The null hypothesis of the Hansen (1982) test that the over-identifying restrictions of the ITC model are valid is not rejected at the 5% level. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table IV
Event-Window Correlations of Energy Futures Returns Before and After December 11, 2009

	Natural Gas Storage Report Announcements			Petroleum Status Report Announcements		
	Natural Gas	Crude Oil	Gasoline	Natural Gas	Crude Oil	Gasoline
Panel A. July 16, 2003 – December 11, 2009 (N=304)						
Crude Oil	**0.48*** **			**0.64*** **		
Gasoline	**0.39*** **	0.84***		**0.58*** **	0.84***	
Heating Oil	**0.50*** **	0.87***	0.83***	**0.65*** **	0.89***	0.79***
Panel B. December 12, 2009 – June 27, 2012 (N=131)						
Crude Oil	**0.07**			**0.15***		
Gasoline	**0.03**	0.84***		**0.19****	0.81***	
Heating Oil	**0.03**	0.88***	0.91***	**0.14**	0.88***	0.81***

The table shows Pearson correlations of energy futures returns in the event window from 5 minutes before to 10 minutes after the inventory announcement. The correlations of primary interest are shown in bold. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table V
Response of Energy Futures Prices to Natural Gas Storage Report Announcements Before and After December 11, 2009

	OLS Estimates		ITC Estimates			
	Response Coefficient	R^2	Response Coefficient	Pseudo-R^2	Ratio ITC/OLS	Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2/\sigma_z^2\right)$
Panel A. July 16, 2003 – December 11, 2009 (N=304)						
Natural Gas	-2.03 (0.26)***	0.209	-9.54 (1.29)***	0.912	4.71	78%
Crude Oil	-0.15 (0.09)*	0.019	-0.60 (0.16)***	0.261	3.95	
Gasoline	-0.16 (0.08)*	0.018	-0.46 (0.18)**	0.060	2.93	
Heating Oil	-0.18 (0.09)**	0.026	-0.72 (0.16)***	0.237	4.04	
Panel B. December 12, 2009 – June 27, 2012 (N=131)						
Natural Gas	-4.44 (0.54)***	0.445	-9.98 (0.98)***	0.965	2.25	53%
Crude Oil	-0.07 (0.08)	0.006	-0.07 (0.09)	0.006	0.98	
Gasoline	-0.02 (0.07)	0.0004	-0.01 (0.09)	0.051	0.42	
Heating Oil	-0.01 (0.08)	0.0003	-0.02 (0.08)	0.118	1.57	

The table shows the estimated responses of energy futures returns to unexpected changes in natural gas inventory. The response coefficients are estimated using (1) equation-by-equation OLS with the White (1980) heteroskedasticity consistent covariance matrix and (2) identification-through-censoring (ITC) approach. All variables are demeaned prior to estimation. The null hypothesis of the Hansen (1982) test that the over-identifying restrictions of the ITC model are valid is not rejected at the 5% level. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

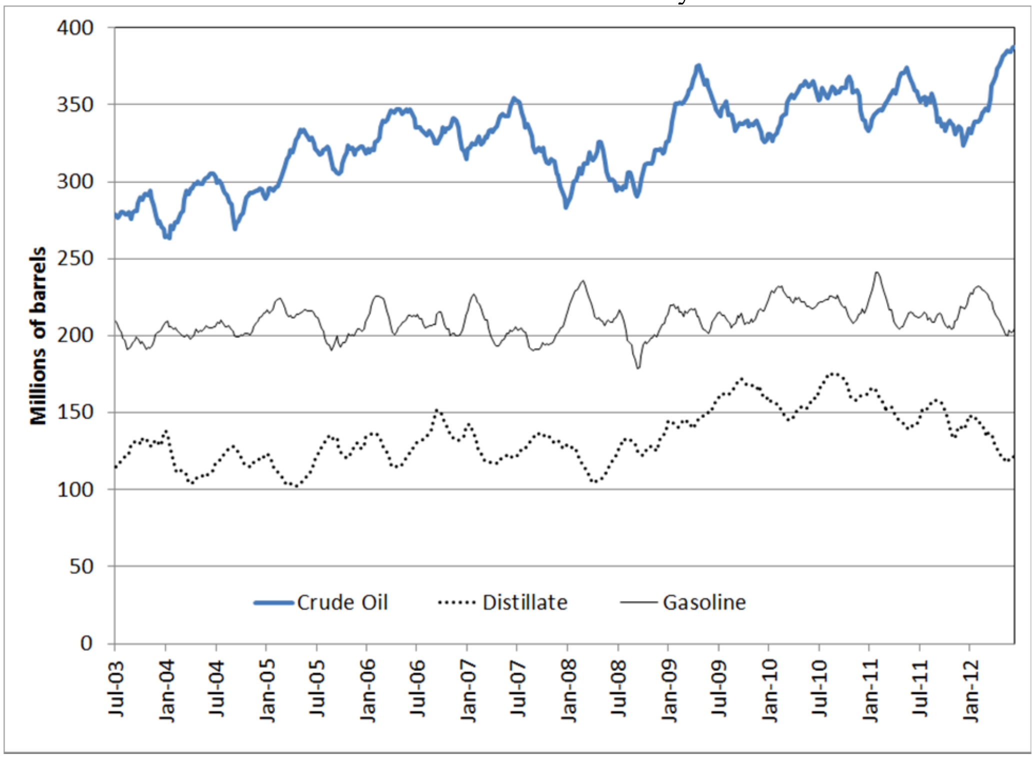
Table VI
Response of Energy Futures Prices to Petroleum Status Report Announcements Before and After December 11, 2009

	OLS Estimates				ITC Estimates				
	Crude Oil Surprise	Gasoline Surprise	Distillate Surprise	R^2	Crude Oil Surprise	Gasoline Surprise	Distillate Surprise	Pseudo-R^2	Average Ratio ITC/OLS
Panel A. July 16, 2003 – December 11, 2009 (N=304)									
Crude Oil	-0.59***	-0.36***	-0.24***	0.477	-1.18***	-0.59***	-0.34***	0.824	1.67
	(0.05)	(0.05)	(0.04)		(0.16)	(0.10)	(0.11)		
Gasoline	-0.37***	-0.77***	-0.20***	0.498	-0.60***	-1.35***	-0.26**	0.822	1.56
	(0.06)	(0.07)	(0.06)		(0.13)	(0.14)	(0.11)		
Heating Oil	-0.44***	-0.27***	-0.47***	0.502	-0.80***	-0.44***	-0.77***	0.820	1.71
	(0.04)	(0.04)	(0.04)		(0.12)	(0.09)	(0.12)		
Natural Gas	-0.23***	-0.20***	-0.21***	0.259	-0.43**	-0.27***	-0.29***	0.493	1.53
	(0.04)	(0.04)	(0.04)		(0.11)	(0.07)	(0.09)		
Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2/\sigma_z^2\right)$					54%	44%	44%		
Panel B. December 12, 2009 – June 27, 2012 (N=131)									
Crude Oil	-0.23***	-0.17***	-0.07*	0.303	-0.62***	-0.39***	-0.14	0.658	2.30
	(0.04)	(0.05)	(0.04)		(0.19)	(0.11)	(0.09)		
Gasoline	-0.13***	-0.34***	-0.02	0.358	-0.24	-0.84***	-0.09	0.773	3.06
	(0.04)	(0.05)	(0.04)		(0.18)	(0.18)	(0.10)		
Heating Oil	-0.16***	-0.13***	-0.14***	0.336	-0.33**	-0.31***	-0.41 ***	0.739	2.49
	(0.04)	(0.04)	(0.03)		(0.16)	(0.10)	(0.11)		
Natural Gas	-0.06	-0.07**	0.01	0.051	-0.11	-0.14**	-0.02	0.048	1.87
	(0.04)	(0.03)	(0.02)		(0.08)	(0.07)	(0.07)		
Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2/\sigma_z^2\right)$					64%	58%	65%		

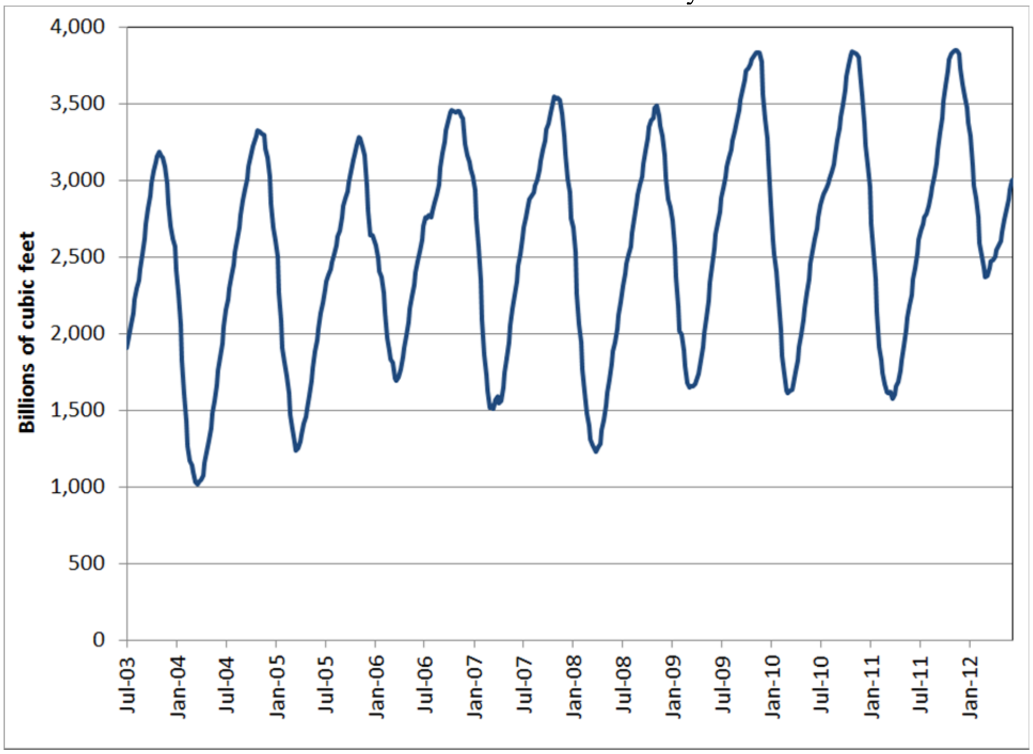
The table shows the estimated responses of energy futures returns to Petroleum Status Report announcements. The response coefficients are estimated using (1) equation-by-equation OLS with the White (1980) heteroskedasticity consistent covariance matrix and (2) identification-through-censoring (ITC) approach. All variables are demeaned prior to estimation. The null hypothesis of the Hansen (1982) test that the over-identifying restrictions of the ITC model are valid is not rejected at the 5% level. Standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Figure 1
Petroleum and Natural Gas Inventory

Panel A. Petroleum Inventory



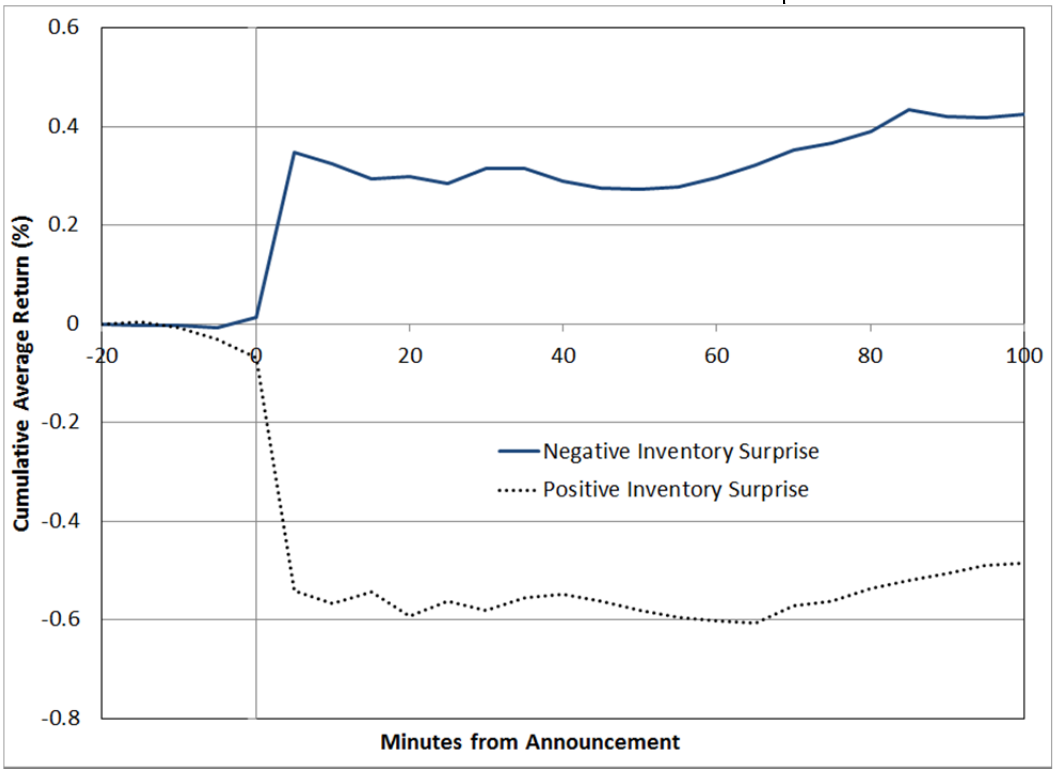
Panel B. Natural Gas Inventory



Source: http://www.eia.gov/

Figure 2
Futures Returns around Inventory Announcements

Panel A. Crude Oil Futures Returns around Petroleum Status Report Announcements



Panel B. Natural Gas Futures Returns around Natural Gas Storage Report Announcements

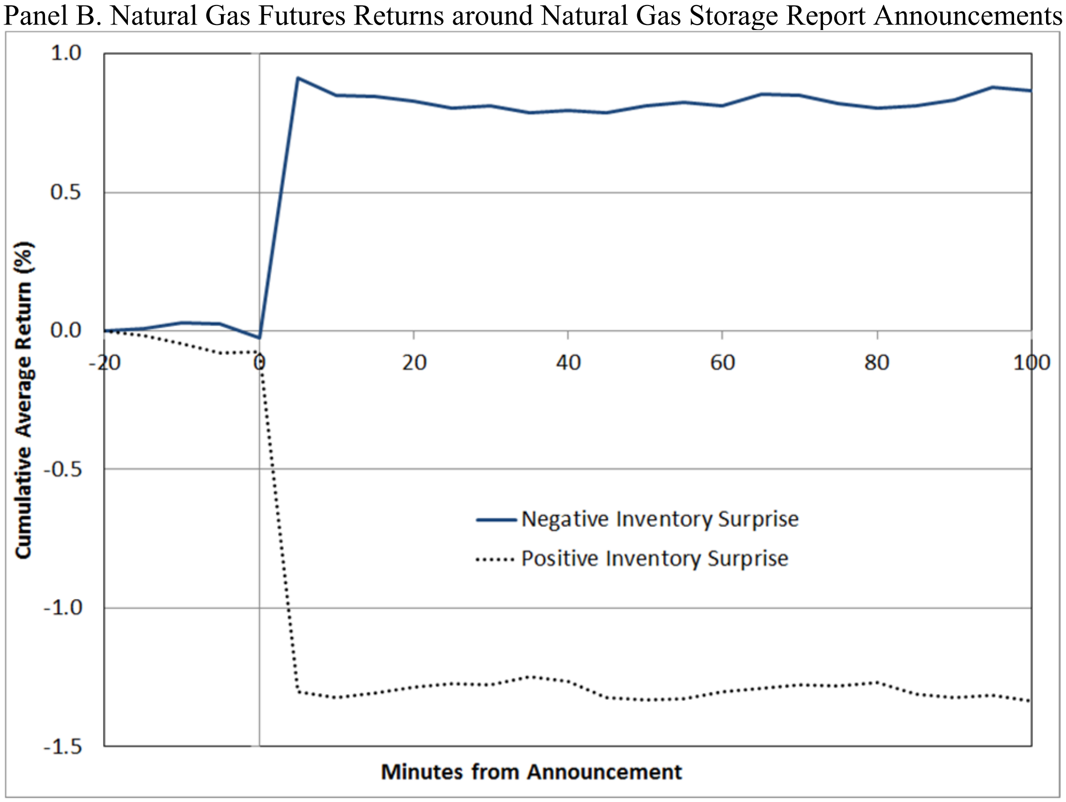
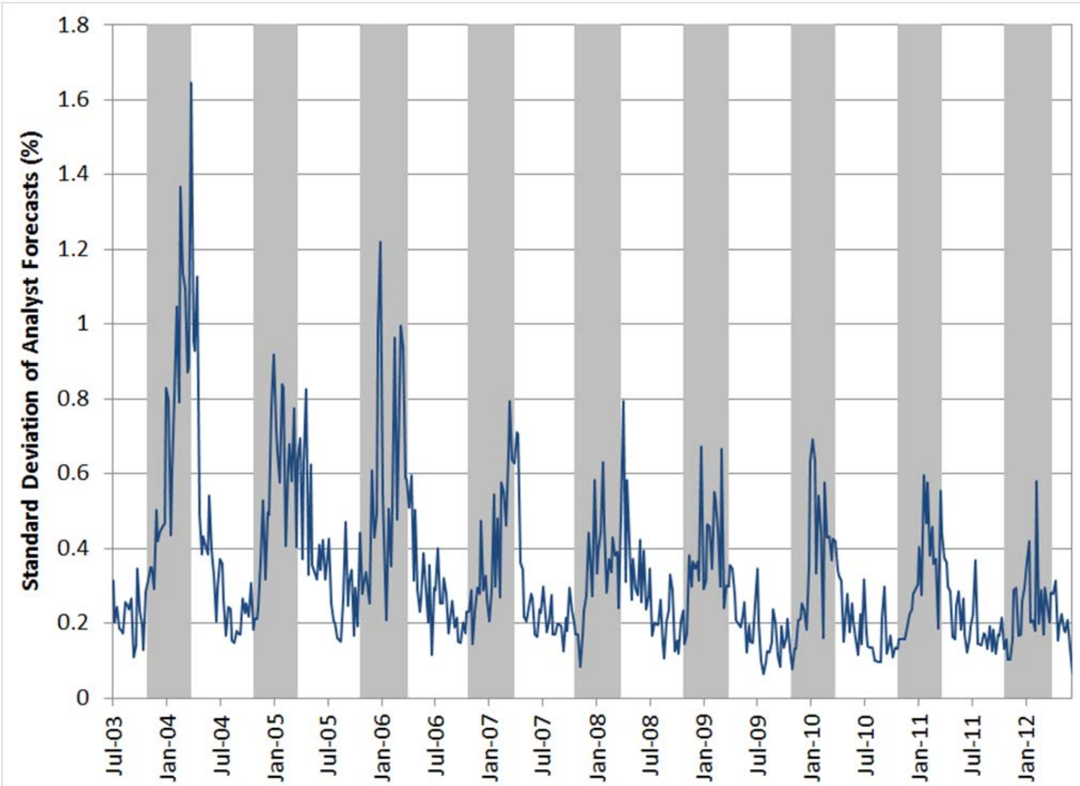
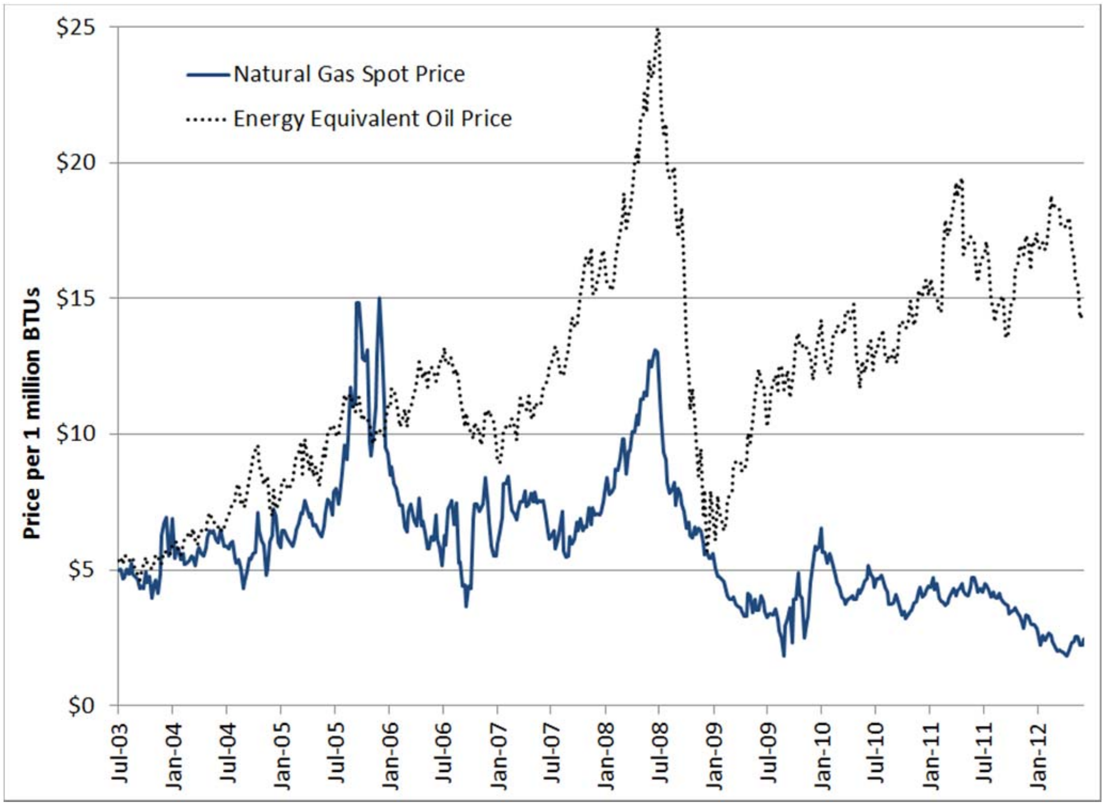


Figure 3
Standard Deviation of Analyst Forecasts for Natural Gas Inventory Changes



Shaded areas represent the withdrawal season (November through March).

Figure 4
Weekly Spot Natural Gas and Crude Oil Prices



Source: http://www.eia.gov/.

Energy equivalent price of crude oil is computed by dividing the WTI crude oil price per barrel by 5.825.

Figure 5
Realized Correlation Between Crude Oil and Natural Gas Futures Returns