The Relationship between Crude Oil and Natural Gas Prices: The Role of the Exchange Rate

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The Relationship between Crude Oil and Natural Gas Prices: The Role of the Exchange Rate

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Several previous studies have found evidence that oil and natural gas prices in the United States are cointegrated. There is also evidence, however, that the relationship is unstable. One explanation is that technological changes alter the substitutability between natural gas and oil products. We reaffirm this finding, but also find evidence that the exchange rate influences the relative price of oil to natural gas in the United States. As in previous studies, we again find that short run departures from long run equilibrium are influenced by weather, product inventories, other seasonal factors and supply shocks such as severe tropical storms in the Gulf of Mexico.

Keywords: Oil/natural gas relative price, cointegration, exchange rate, nontraded and traded goods

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1. INTRODUCTION

A number of studies have documented that oil and natural gas prices in the United States are cointegrated. One might expect the prices to be linked because fuels can be substituted in some uses. Variability in the relative price, however, has raised doubts about the results. In the last few years in particular, the price of natural gas relative to crude oil has deviated dramatically from its recent historical norms, challenging yet again the notion that a stable long run relationship exists between the two prices.

Understanding the relationship between crude oil and natural gas prices, especially its permanence, is important to many stakeholders. Commercially, it is important when considering investments in gas-to-liquids or other technologies (such as compressed natural gas) enabling natural gas to penetrate the predominantly oil-using transportation sector. It is also important when considering LNG exports to consumers facing oil-indexed prices. Understanding the pricing relationship also can be important for evaluating policies to promote the use of one fuel over another, for example in the transportation sector.

We extend previous work in this area by providing an additional explanation for the recent drift in the crude oil-natural gas relative price. We begin with a theoretical analysis that builds on the observation that while the US trades crude oil internationally, natural gas predominantly trades in a continental market leaving little opportunity for direct arbitrage with European and Asian markets. As recently as the early 2000s, many were expecting increased North American LNG imports to facilitate arbitrage between continental gas markets. Growth in shale gas production has, however, kept the North American natural gas market largely isolated, and prevented spot natural gas prices in North America, Europe and Asia from reaching an equilibrium reflecting transport costs.[1] This implies, as will be shown, that the nominal value of the US dollar systematically affects the crude oil-natural gas relative price.

[1] Note this specifically refers to spot prices. Oil-indexed contract prices are of a different nature.

In the empirical analysis, we use monthly data from January 1995 through December 2011 to examine the relationship between oil and natural gas prices. We find evidence of a stable long run cointegrating relationship between the prices once we include a technology variable and the US dollar nominal exchange rate.

2. PREVIOUS RESEARCH

Several papers examining the cointegration of natural gas and oil prices are of particular relevance to the current study. Villar and Joutz (2006) were among the first to highlight the apparent decoupling of WTI crude oil and Henry Hub natural gas prices. They documented that the cointegrating relationship between the two prices exhibited a positive time trend, indicating an evolving rather than constant long run relationship. After allowing for the time trend, Villar and Joutz estimate an error correction model (ECM) that includes exogenous variables such as natural gas storage levels, seasonal dummy variables, and dummy variables for other transitory shocks.

Brown and Yücel (2008) used an ECM to analyze weekly prices from January 1994 through July 2006. They found a stable cointegrating relationship over this period, but also reported that a cointegrating relationship does *not* exist if they consider the shorter period of June 1997 through July 2006. Using the cointegrating relationship from the longer time period, they found that short run deviations could be explained by market fundamentals such as storage levels, weather, and production shut-in due to hurricanes.

Hartley, Medlock and Rosthal (2008) provide a technological explanation for the apparent change in the relationship between crude oil and natural gas prices for the period 1990 through 2006. Using monthly data, they estimate a vector error correction model (VECM) and find a stable cointegrating relationship between natural gas and crude oil prices after explicitly accounting for technological change. In particular, they assume that competition between fuels to generate electricity depends on costs per megawatt hour, so the heat rate (or thermal efficiency) of the plant, not just the fuel price, determines fuel use. Notably, the dramatic increase in high thermal efficiency combined-cycle power generation capacity in the early 2000s lowered the cost of producing electricity with natural gas. Since oil and natural gas often competed in the power sector from 1990 through 2006, technological change would have affected the long run relationship between natural gas and crude oil prices.

More recently, Ramberg and Parsons (2012) found that the cointegrating relationship was unstable. In particular, they show that while the prices may be tied together, substantial shifts in the underlying relationship can make the confidence interval for the price relationship very large. They also estimated an ECM to explain short run dynamic adjustment of natural gas and crude oil prices using variables similar to those introduced in Brown and Yücel (2008). They conclude that even if the long run pricing relationship changes, a relationship should eventually re-establish as new technologies introduce new margins of substitution between the fuels.

In this paper, we first introduce a simple model where oil is traded between a home and foreign market but natural gas is a non-traded good. If there are ample opportunities to substitute between crude oil and natural gas, the lack of direct arbitrage between the two natural gas markets is less important. Competition with oil will heavily influence natural gas prices, enabling *de facto* arbitrage through trade in crude oil. If the ability to switch fuels is constrained in one market, however, then the exchange rate will play an important and unambiguous role[2] in determining the relative price of natural gas to crude oil.

In the past several years, substitution between crude oil and natural gas has virtually disappeared in the US, as oil use for power generation has become almost entirely restricted to diesel and residual fuel oil peaking plants. The decline in substitution capability occurred after changes in heat rates and relative prices produced substantial grid-level switching from oil (largely residual fuel oil) to natural gas. The two fuels no longer experience a broad competitive margin. This has apparently left gas to

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[2] In an appendix available from the authors, we show that the assumption that natural gas is a non-traded good is critical to obtaining an unambiguous sign for the effect. In the more general case where the two countries trade both natural gas and crude oil, the nominal exchange rate still affects the relative price of the two commodities but the sign of the effect is ambiguous.

seek a new competitive margin, perhaps with coal. While this is a reasonable thesis, the role of the exchange rate is often ignored, a flaw which this paper highlights.

After estimating a cointegrating relationship that includes the exchange rate and a variable to capture technological change, we follow the previous literature in relating the dynamic adjustment process to deviations from the estimated long run relationship and to market fundamentals such as storage levels and weather shocks.

3. A SIMPLE TRADE MODEL

We assume two representative countries produce and consume both natural gas and crude oil. Moreover, each can switch between natural gas and crude oil in end-use. Crude oil is internationally traded, but natural gas is a non-traded good. We will show that this simple model implies that the exchange rate is an important systematic determinant of the relative price of natural gas to crude oil.

Assuming constant elasticity natural gas market supply and demand relationships in the "home" country the percentage changes[3] in supply $\hat{s}$ and demand $\hat{d}$ can be written

$$\hat{s}_{g,h} = \hat{z}_{s,h} + \beta_{1,h}\hat{p}_{g,h} \tag{1}$$

and

$$\hat{d}_{g,h} = \hat{z}_{d,h} - b_{1,h}\hat{p}_{g,h} + I_{sw,h}b_{2,h}\hat{p}_{o,h} \tag{2}$$

where $\hat{z}_{s,h}$ and $\hat{z}_{d,h}$ denote exogenous shocks to supply and demand growth respectively and $I_{sw,h}$ is an indicator variable equal to one when fuel switching capability exists and

[3] In the later empirical analysis, we will show that a linear combination of (the natural logarithms of) the prices and some exogenous variables produces a difference stationary error term. It follows that the first difference of the endogenous (natural logarithm of the) natural gas price can be written as a function of the lagged first differences of itself, (possibly lagged) first differences of the integrated variables that are assumed to be exogenous determinants of natural gas prices, and the lagged error term from the cointegrating regression. Accordingly, we develop the theoretical model to provide an explanation for the equilibrium *change* in the natural gas price as a result of various shocks to supply and demand, some of which are integrated of order 1.

zero otherwise. The variable $\hat{p}_{g,h}$ denotes the percentage change in the price of natural gas in the "home" country, *h*, and $\hat{p}_{o,h}$ denotes the percentage change in the price of oil.

If the home country does not trade natural gas, a necessary condition for market equilibrium is $\hat{d}_{g,h} = \hat{s}_{g,h}$, so that for a given oil price we have

$$\hat{p}_{g,h} = \hat{z}_h + \lambda_h \hat{p}_{o,h} \tag{3}$$

where $\hat{z}_h = \left(\hat{z}_{d,h} - \hat{z}_{s,h}\right) / \left(\beta_{1,h} + b_{1,h}\right)$ and $\lambda_h = \left[b_{2,h} / \left(\beta_{1,h} + b_{1,h}\right)\right] I_{sw,h}$. Hence, in this simple formulation, the relationship between crude oil and natural gas prices is primarily determined by the ability to switch between fuels. If $I_{sw,h} = 0$, so there is no fuel switching capability in the home country, (3) reduces to $\hat{p}_{g,h} = \hat{z}_h$ and the domestic natural gas price will respond only to exogenous variables affecting domestic supply and demand of *natural gas*.

For an autarkic equilibrium to persist, the cost of developing export (if the domestic price is below the foreign price) or import (if the domestic price is above the foreign price) capability must be prohibitive (or disallowed by policy). For example, if trade requires natural gas to be liquefied, the large capital costs of developing LNG liquefaction or regasification capabilities may allow domestic natural gas prices to fluctuate in a wide range for a long time without triggering international trade flows.

In contrast to natural gas, we assume that the "home" country trades oil as an importer. Assuming oil supply and demand curves analogous to (1) and (2), the percentage change in imports can be approximated by $\hat{m}_{o,h} = \theta_{o,h} \hat{d}_{o,h} + \left(1 - \theta_{o,h}\right) \hat{s}_{o,h}$ or

$$\hat{m}_{o,h} = \theta_{o,h} \left[\hat{w}_{d,h} - a_{1,h} \hat{p}_{o,h} + I_{sw,h} a_{2,h} \hat{p}_{g,h}\right] + \left(1 - \theta_{o,h}\right) \left[\hat{w}_{s,h} + \alpha_{1,h} \hat{p}_{o,h}\right] \tag{4}$$

where the exogenous shocks in the oil market are denoted by $\hat{w}$, and $\theta_{o,h} \equiv d_{o,h} / \left(d_{o,h} - s_{o,h}\right) > 1$ is the ratio of total domestic demand for oil to oil imports.

Aggregating the home country's trading partners into a "composite" foreign country, by analogy with (4), oil *exports* from the foreign country will be given by

$$\hat{x}_{f,h} = \theta_{o,f} \left[\hat{w}_{d,f} - a_{1,f} \hat{p}_{o,f} + I_{sw,f} a_{2,f} \hat{p}_{g,f}\right] + \left(1 - \theta_{o,f}\right) \left[\hat{w}_{s,f} + \alpha_{1,f} \hat{p}_{o,f}\right] \tag{5}$$

where the "h" has been replaced by "f" in the variable subscripts and, for a net exporter, $\theta_{o,f} \equiv d_{o,f} \big/ \left(d_{o,f} - s_{o,f}\right) < 0$. Although the foreign and home countries have access to the same technologies, there is no necessary reason for $I_{sw,f}$ to equal $I_{sw,h}$. In the absence of trade in natural gas between the home country and the rest of the world, the relative price of natural gas can remain higher abroad, allowing oil products to remain more competitive overseas.

In equilibrium, the percentage change in imports by the home country must equal the percentage change in exports from the rest of the world:

$$\hat{m}_{o,h} = \hat{x}_{o,f} \tag{6}$$

With no international trade in natural gas between the home country and the rest of the world, aggregate supply and demand for natural gas in the rest of the world also needs to equilibrate. This leads to an equation analogous to (3) for the composite foreign country

$$\hat{p}_{g,h} = \hat{z}_f + \lambda_f \hat{p}_{o,f} \tag{7}$$

where $\hat{z}_f = \left(\hat{z}_{d,f} - \hat{z}_{s,f}\right) \big/ \left(\beta_{1,f} + b_{1,f}\right)$ and $\lambda_f = \left[b_{2,f} \big/ \left(\beta_{1,f} + b_{1,f}\right)\right] I_{sw,f}$.

Although international transactions may be denominated in a particular currency, such as oil is in US dollars, oil sold in the foreign or home country is not denominated in the same currency units. To account for the relative value of the currencies in each market, we define the nominal exchange rate, e, as the value of the home currency relative to the value of the foreign currency. Then changes in the price of oil in the foreign country, when expressed in the home country units, will be $\hat{p}_{o,f} + \hat{e}$, and an equilibrium without arbitrage opportunities requires

$$\hat{p}_{o,h} = \hat{p}_{o,f} + \hat{e} \tag{8}$$

Combining equations (3), (4), (5), (6), (7) and (8), we can write the change in the price of oil denominated in the home currency in terms of the exogenous shocks and the change in the exchange rate:

$$\hat{p}_{o,h} = \hat{W} + \hat{Z} + \pi \hat{e} \tag{9}$$

where the exogenous shocks are[4]

$$\hat{W}=\frac{\theta_{o,h}\hat{w}_{d,h}-\theta_{o,f}\hat{w}_{d,f}+\left(1-\theta_{o,h}\right)\hat{w}_{s,h}-\left(1-\theta_{o,f}\right)\hat{w}_{s,f}}{\left(1-\theta_{o,f}\right)\alpha_{1,f}-\left(1-\theta_{o,h}\right)\alpha_{1,h}+\theta_{o,h}\left(a_{1,h}-I_{sw,h}a_{2,h}\lambda_h\right)-\theta_{o,f}\left(a_{1,f}-I_{sw,f}a_{2,f}\lambda_f\right)} \tag{10}$$

and[5]

$$\hat{Z}=\frac{\theta_{o,h}I_{sw,h}a_{2,h}\hat{z}_h-\theta_{o,f}I_{sw,f}a_{2,f}\hat{z}_f}{\left(1-\theta_{o,f}\right)\alpha_{1,f}-\left(1-\theta_{o,h}\right)\alpha_{1,h}+\theta_{o,h}\left(a_{1,h}-I_{sw,h}a_{2,h}\lambda_h\right)-\theta_{o,f}\left(a_{1,f}-I_{sw,f}a_{2,f}\lambda_f\right)} \tag{11}$$

and the coefficient on the exchange rate change is[6]

$$\pi=\frac{\left(1-\theta_{o,f}\right)\alpha_{1,f}-\theta_{o,f}\left(a_{1,f}-I_{sw,f}a_{2,f}\lambda_f\right)}{\left(1-\theta_{o,f}\right)\alpha_{1,f}-\left(1-\theta_{o,h}\right)\alpha_{1,h}+\theta_{o,h}\left(a_{1,h}-I_{sw,h}a_{2,h}\lambda_h\right)-\theta_{o,f}\left(a_{1,f}-I_{sw,f}a_{2,f}\lambda_f\right)}. \tag{12}$$

Notice that $\hat{W}$, $\hat{Z}$ and π each depend on the presence of substitution opportunities between oil and natural gas both at home and abroad. In particular, if there are no fuel switching possibilities both $I_{sw,f}$ and $I_{sw,h}$ are zero and the denominator in each of the above expressions must be positive. Even if $I_{sw,h}=0$, as long as there is fuel switching abroad exogenous shocks to the foreign natural gas market will affect the oil price.

Using (3) and (9), we see that changes in the *relative* price of crude oil to natural gas denominated in the home currency will be affected by exogenous shocks and changes in the exchange rate

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[4] Since $\theta_{o,f}<0$ and $\theta_{o,h}>1$ either type of oil market supply shock tends to reduce the price of oil, while either type of demand shock increases it so long as the denominator in $\hat{W}$ is positive. Note that $\hat{W}$ will certainly be positive if own price elasticities dominate cross price elasticities in oil demand.

[5] If the denominator in $\hat{Z}$ is positive, excess demand shocks in either the domestic or foreign natural gas markets will also drive up the price of oil as a result of fuel switching.

[6] A sufficient condition for the coefficient on the exchange rate to be positive is that the denominator is positive and in particular that the own-price elasticity dominates the cross-price elasticity in the foreign oil market, or $a_{1,f}>I_{sw,f}\alpha_{2,f}\lambda_f$.

$$\hat{p}_{o,h} - \hat{p}_{g,h} = (1 - \lambda_h)\left(\hat{W} + \hat{Z} + \pi\hat{e}\right) - \hat{z}_h \quad (13)$$

Assuming (a) own-price elasticities dominate cross-price elasticities in the home and foreign oil market, so that $\pi > 0$, and (b) own-price effects also dominate in the domestic gas market, so that $\beta_{1,h} + b_{1,h} > I_{sw,h} b_{2,h}$, or $\lambda_h < 1$, then depreciations of the home currency will have a positive effect on the relative price of oil to natural gas in the home currency. If fuel switching capabilities in the home country are diminished to the point that $I_{sw,h} = 0$, it is only necessary that own-price elasticities dominate cross-price elasticities in the home and foreign oil market for the result to hold.[7]

4. EMPIRICAL ANALYSIS

The empirical analysis follows Hartley, Medlock and Rosthal (2008), but we add the exchange rate as a variable affecting the price of crude oil relative to natural gas. Following Brown and Yücel (2008) and the other single equation studies mentioned above, we also simplify the analysis to a single equation error correction model rather than estimating a vector error correction model.[8] Specifically, we use the method of Engle and Granger (1987) to estimate an error correction model (ECM). The hypothesis

[7] As noted previously, in the more general case where trade can occur in both markets, the effect of the exchange rate on relative prices becomes indeterminate even if $I_{sw,h}$=0. Arbitrage opportunities induced by currency fluctuations are quickly monetized through commodity trades.

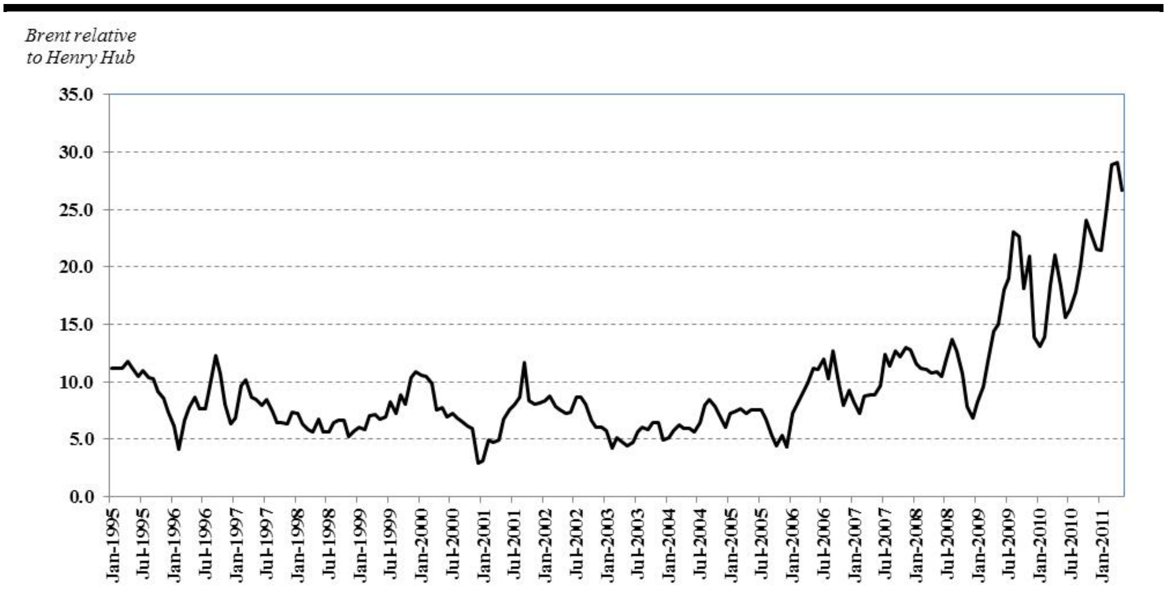
[8] For the single equation approach to yield unbiased parameter estimates, we need the integrated variables included in the cointegrating equation to be weakly exogenous. We expect the oil price, which is set in international markets, to be exogenous with respect to North American natural gas prices. Hartley, Medlock and Rosthal (2008) estimated a three variable vector error correction model (including US residual fuel oil prices along with WTI and the Henry Hub natural gas price) and found that the WTI oil price and the relative heat rate variable were weakly exogenous. They found that the WTI price influences the remaining prices mainly through its effect on the residual fuel oil price. While the heat rates of natural gas plants used to supply output at any time are likely to depend on the natural gas price, the evolving *minimum* heat rate variable constructed later should reflect exogenous technology changes. Finally, the nominal exchange rate should be influenced by many factors (especially monetary policy and potentially oil prices), but should also be exogenous with respect to US natural gas prices.

is that crude oil prices, natural gas prices technological change, and the exchange rate share unit root shocks that can be eliminated by a linear combination of these variables, called the cointegrating relationship. The Engle-Granger method first estimates the cointegrating relationship using ordinary least squares (OLS), then uses the resulting error, along with other predetermined variables, to estimate short run dynamic adjustments of the natural gas price to various shocks.

The cointegrating relationship

Taking the US as the home country, we use US Energy Information Administration (EIA) monthly data from January 1995 through December 2011 on the price of natural gas at the Henry Hub in US$/mcf and the price of Brent crude oil in US$/bbl. We use Brent crude rather than WTI in order to avoid potential problems associated with the recent disconnect between WTI and global crude oil prices resulting from a lack of takeaway capacity at Cushing.[9]

Figure 1. The Relative Price Of Crude Oil To Natural Gas (Jan 1995-Dec 2011)



Sources: US Energy Information Administration

[9] We also tried using WTI, and the results are not statistically significantly different.

Figure 1 plots the relative price measured as the Brent crude oil price divided by Henry Hub natural gas price. Clearly, the relationship between crude oil and natural gas prices has changed substantially in the last few years. After fluctuating between roughly 6:1 and 12:1 until 2008, the price ratio then climbed to values in excess of 25:1. Such extreme price ratios have not been seen since the 1970s, when, notably, the US dollar was also very weak. Of course other issues, such as wellhead price controls and import quotas, plagued pricing relationships in the 1970s.

Following Hartley, Medlock and Rosthal (2008), we include a relative heat rate variable in the cointegrating equation to allow for the effect of technological change.[10] The EPA NEEDS database that underlay the heat rate variable used in Hartley, Medlock and Rosthal (2008) is, however, not available for recent years that are the focus of this paper. Heat rate data were instead constructed using monthly fuel use and electric generation by type of plant as reported by the EIA. Specifically, a realized heat rate is first calculated by dividing monthly fuel use by the electricity generated by a specific type of plant. To control for variations resulting from different seasonal load requirements, we construct a "marginal" heat rate such that no rate in later months can be greater than a rate realized in a previous month. The result is a time series of marginal heat rates by type of generating facility that better captures technological progress.

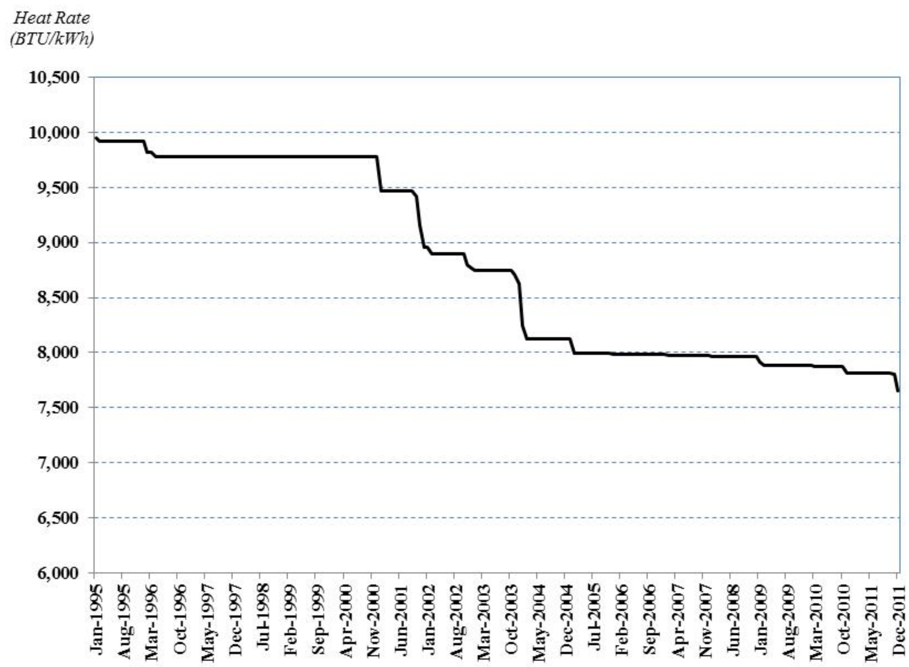
The resulting natural gas heat rate is shown in Figure 2, while the heat rate of natural gas relative to oil is depicted in Figure 3. The tremendous gain in the natural gas heat rate relative to oil made in the early 2000s coincides with the rapid build-up of the natural gas combined cycle fleet.

We also include, as a new variable in the cointegrating relationship, the foreign exchange value of the US dollar. Given that we are thinking of the rest of the world as all other countries that either export or import crude oil, we used the broadest possible index of the foreign exchange value of the US dollar, namely the Broad Trade Weighted

[10] The heat rate of a generating facility is inversely proportional to its thermal efficiency.

Exchange Rate Index compiled by the US Federal Reserve.[11] Another advantage of using a broad index is that changes in its value will primarily reflect movements in the US dollar rather than shocks affecting other economies.[12]

Figure 2. Estimated Heat Rate of Natural Gas Plants (Jan 1995 – Dec 2011)



[11] We used the nominal index available from the Board of Governors..

[12] We also conducted the analysis with the narrower Major Currencies Trade Weighted Exchange Rate also available from the Federal Reserve. The results are extremely similar to those reported herein, most likely because the two series are highly correlated. Indeed, the correlation between the changes in the logs of the two series is 0.9237.

Figure 3. Relative Heat Rate of Natural Gas to Oil (Jan 1995 – Dec 2011)

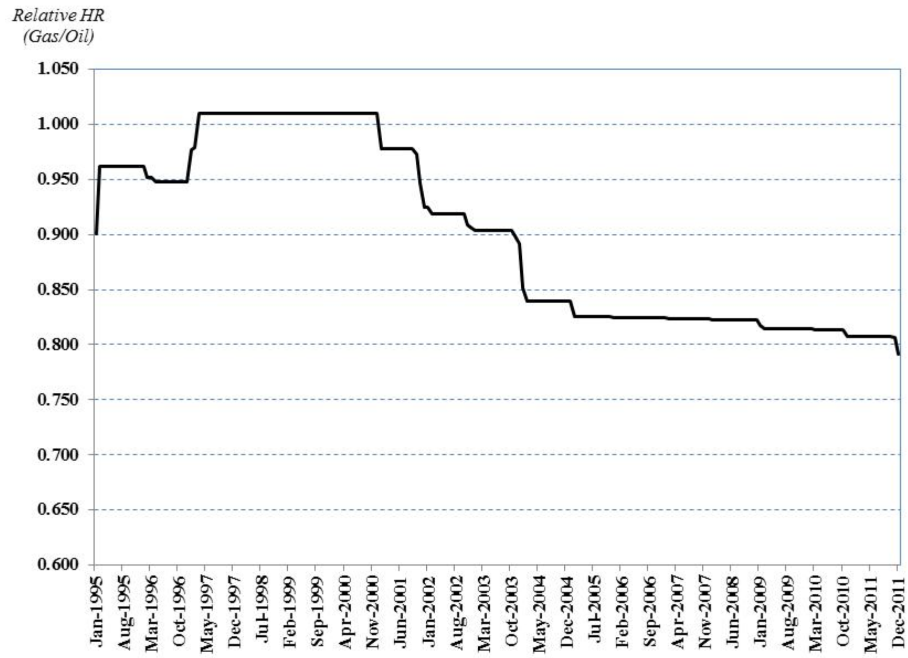


Table 1. Statistics testing for the presence of a unit root

Variable	$Z(\rho)$	$Z(\tau)$	*ADF*	*KPSS*
$\ln P^{ng}$	–10.210	–2.498	–2.427	0.932
$\Delta \ln P^{ng}$	–174.994	–13.002	–5.568	0.176
$\ln P^{oil}$	–2.049	–0.883	–0.937	1.35
$\Delta \ln P^{oil}$	–171.758	–11.851	–6.237	0.054
$\ln\left(HR^{ng}/HR^{oil}\right)$	–0.092	–0.063	–0.076	1.27
$\Delta \ln\left(HR^{ng}/HR^{oil}\right)$	–184.821	–14.513	–5.428	0.369
$\ln e$	–4.269	–1.631	–2.251	0.354
$\Delta \ln e$	–120.529	–9.309	–4.944	0.378

Note: In the levels tests, the interpolated 10% critical value for Z(ρ) is –11.137, and for Z(τ) is –2.573. The interpolated 10% critical value for the Dickey-Fuller statistic is also –2.573. The 1% critical value for the KPSS statistic is 0.739. For the differenced variables, the interpolated 1% critical value for Z(ρ) is –20.140, and for Z(τ) is –3.476. The interpolated 1% critical value for the Dickey-Fuller statistic is –3.478. The 10% critical value for the KPSS statistic is 0.347.

We first verified that each of the variables was integrated of order one $I(1)$. Table 1 presents a range of test statistics. The Phillips-Perron and ADF statistics test the null hypothesis that the variable is $I(1)$, while the KPSS statistic tests the null hypothesis that each variable is $I(0)$.[13] In each case, the Phillips-Perron and ADF statistics indicate that each of the variables is $I(1)$. Moreover, the KPSS statistics reject the hypothesis that the variables in levels are $I(0)$ at a better than 1% level for all variables but the exchange rate, for which the KPSS statistic implies we can reject the hypothesis that the variable is $I(0)$ at the 10% level. We conclude that each of the variables is $I(1)$.[14]

We then estimated (14) using OLS to obtain[15]

$$\ln P_t^{ng} = \underset{(1.1284)}{-10.2041} + \underset{(0.0775)}{0.5000} \ln P_t^{oil} + \underset{(0.2406)}{2.0568} \ln e_t \underset{(0.5508)}{-1.3712} \ln\left(\frac{HR_t^{ng}}{HR_t^{oil}}\right) + \varepsilon_t \qquad (14)$$

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[13] In calculating the Phillips-Perron statistics, we used 5 lags in calculating the Newey-West standard errors. Similarly, when calculating the ADF statistics, we allowed for 5 lagged difference terms in the covariate list. The KPSS statistic is reported for 14 lags, which was the lag length chosen by the Schwert criterion. The test outcomes were identical for other lags we tried, but 5 lags gave the strongest rejection of stationarity of the natural gas price level.

[14] For all variables except the exchange rate, the KPSS statistics do not reject the hypothesis that the first difference of the variable is *I(0)* at even the 10% level. For the exchange rate, the KPSS statistic implies we can reject at the 10%, but not the 5%, level the hypothesis that the variable and its first difference are $I(0)$.

[15] The estimated standard errors in parentheses below each estimated coefficient are robust sandwich-type estimators. The usual OLS estimators of the standard errors of the parameters in the cointegrating equation are asymptotically biased. Using bootstrap or jackknife methods to estimate the standard errors gave very similar values to the robust estimates, and the same inferences regarding statistical significance of the various parameters. We also estimated equation (14) using dynamic OLS (Stock and Watson, 1993). This involves augmenting the equation with leads and lags of changes in the right hand side variables to eliminate asymptotically possible bias due to endogeneity or serial correlation and using heteroskedasticity and autocorrelation-consistent (HAC) estimators of the covariance matrix. Specifically, we fit a general linear model to the equation augmented with 4 leads and lags of changes in the right hand side variables and using a HAC estimator based on the Newey-West kernel to estimate the covariance matrix. The resulting coefficient estimates and standard errors for the variables in the cointegrating relationship were –10.9144 (2.6749), 0.4405 (0.1085), 2.2319 (0.6085) and –2.4311 (0.7913).

Table 2. Statistics testing for the order of integration of the residuals to (14)

Variable	$Z(\rho)$	$Z(\tau)$	*ADF*	*KPSS*
$\hat{\varepsilon}$	–21.756	–3.156	–3.226	0.186
$\Delta\hat{\varepsilon}$	–170.929	–13.569	–5.782	0.158

Table 2 reports the test statistics for the order of integration of the residuals from (14).[16] Using the standard critical values for the test statistics, we see that at a minimum we can reject the null of $I(1)$ at the 5% critical value, and the KPSS statistic easily accepts the null that the residual is $I(0)$. However, the critical values need to be adjusted to account for the fact that a spurious regression could allow the residuals to appear to be stationary even if the variables are not truly cointegrated.[17] For the ADF statistic, using the modified critical values from MacKinnon (2010) we cannot reject the null that the residuals are $I(1)$. Similarly, Phillips and Ouliaris (1990) give modified critical values for the $Z(\rho)$ and $Z(\tau)$ statistics.[18] Again, we cannot reject the null that the residuals are $I(1)$.

We also can use the Johansen trace and maximum eigenvalue statistics to test for the number of cointegrating vectors in the system defined by $\ln P_t^{ng}$, $\ln P_t^{oil}$, $\ln e_t$ and $\ln\left(HR_t^{ng}/HR_t^{oil}\right)$. The resulting statistics are presented in Table 3.[19] Both the maximum

[16] In this case, we present test statistics using 1 lag in calculating the Newey-West standard errors and allowing for 1 lagged difference term in the covariate list in the ADF test. Estimating an AR(1) model for the residuals, we find the Portmanteau Q statistic for autocorrelation of the first N lags of the residuals from that AR is never significant at the 5% level and has a p-value greater than 0.50 after 6 lags and 0.15 after 12 lags. By contrast, the first difference of the estimated residuals from (14) has Portmanteau Q statistics that are significant at the 5% level for lags 13–18 and at the 10% level for lags 10–23. These results suggest that the residuals in (14) may be stationary.

[17] We thank a referee for raising this concern with our results.

[18] Phillips and Ouliaris (1990) also say that a suitably modified version of a test like KPSS with a null that the residuals are $I(0)$ is not available, since the critical values would need to be tailored to the distribution of the data used to estimate (14).

[19] We allow for 5 lags in the VAR model. Allowing 5 lags maximized the log likelihood values. Similar results were obtained for 6 lags, but allowing longer lags gave test statistics that were not quite significant

eigenvalue and the trace statistic suggest that there is one cointegrating vector among these variables at the 5% significance level, but at the 1% level the variables are not cointegrated.

Table 3. Johansen tests for cointegration

Max rank	eigenvalue	max statistic	5% critical value	1% critical value	trace statistic	5% critical value	1% critical value
0		31.164	27.07	32.24	52.269	47.21	54.46
1	0.145	13.940	20.97	25.52	21.106	29.68	35.65
2	0.068	6.765	14.07	18.63	7.165	15.41	20.04
3	0.033	0.400	3.76	6.65	0.400	3.76	6.65
4	0.002						

In summary, when allowing for the possibility that the relationship between the variables in (14) may be spurious, we conclude there is, at the very least, weak evidence that the variables are cointegrated. Furthermore, the alternative hypothesis that the estimated relationship between crude oil prices and natural gas prices is spurious does not fit with economic theory or evidence that relative price differentials between energy sources promote searches for new technologies or opportunities to profit from the gap. Indeed, this is the motivation for much of the literature that seeks to understand the structural, or long run, relationship between prices and the dynamic adjustment process in the event of shocks. A more plausible explanation for the results is that the adjustment process is sluggish.[20] Changes in end-use technology, or the large fixed capital

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at the 5% level.

[20] Assuming that the residuals are not integrated and estimating an ARMA model we find that a simple AR(1) model appears to yield white noise residuals (the Portmanteau Q statistics are given in a previous footnote). The estimated AR(1) coefficient is 0.9018, which is large, but since the estimated standard error is 0.0283 it would still be significantly different from 1. Such an AR(1) model for $\hat{\varepsilon}$ would imply that deviations in the cointegrating relationship are eliminated quite slowly, which is consistent with the results we report below. Another interpretation of the results, however, is that the residuals really are $I(1)$ and the estimated regression is unstable or omits some other $I(1)$ variable. For example, recall that the theoretical model implies the exchange rate may have an ambiguous effect on the crude oil-natural gas price relationship if natural gas is traded. From 2004-2007, North American LNG imports briefly expanded beyond the end-of-pipe markets traditionally served to become a more significant part of the core market.

investments needed to enable trade across markets, take time to implement. We return to this point below.

Further insight into the relationship between natural gas and crude oil prices can be gained from the residuals from two more regressions. In the first, the technology control and the exchange rate are omitted. In the second, only the exchange rate is omitted. More specifically, consider the residuals ω_t from the regression

$$\ln P_t^{ng} = \sigma_0 + \sigma_1 \ln P_t^{oil} + \omega_t \tag{15}$$

and ξ_t from the regression

$$\ln P_t^{ng} = \tau_0 + \tau_1 \ln P_t^{oil} + \tau_2 \ln\left(HR_t^{ng} / HR_t^{oil}\right) + \xi_t \tag{16}$$

Table 4 reports test statistics analogous to those presented in Table 2 for the residuals from (15) and (16). For ease of comparison, values from Table 2 have also been included in Table 4.

Table 4. Test for the order of integration of the residuals from (14)–(16)

Variable	$Z(\rho)$	$Z(\tau)$	*ADF*	*KPSS*
$\hat{\omega}$	–15.789	–2.714	–2.788	0.304
$\hat{\xi}$	–16.210	–2.792	–2.793	0.297
$\hat{\varepsilon}$	–21.756	–3.156	–3.226	0.186

Adding the relative heat rate then the exchange rate to (15) takes the residual closer to being $I(0)$. In particular, consistent with the findings of Ramberg and Parsons (2012), the oil price alone can account for a major part of the non-stationarity in natural gas prices, but not all of it. The results also suggest that the relative heat rate may be the least important variable for inducing stationarity in the residuals, but our measure of that variable is less satisfactory than was available in Hartley, Medlock and Rosthal (2008).

Alternatively, natural gas prices might also respond to an independent $I(1)$ shock in coal prices if the latter are not cointegrated with oil prices.

The parameter estimates in (14) also provide information on the relative importance of the different variables. The oil price coefficient is statistically significant at a better than 0.001 level, as is the exchange rate.[21] In particular, the hypothesis that a weaker US dollar has a positive influence on the spread between natural gas and crude oil prices cannot be rejected. This is consistent with prediction (13) of the trade model. The coefficient on the relative heat rate in (14) also is statistically significant, but at a lower level than the other two variables (p-value = 0.014).[22] The negative coefficient indicates that improvement in the relative thermal efficiency of natural gas generation technologies to oil generation technologies will tend to increase the price of natural gas relative to crude oil, as found in Hartley, Medlock and Rosthal (2008).

Figure 4. Influence of exchange rate changes on the cointegrating relationship

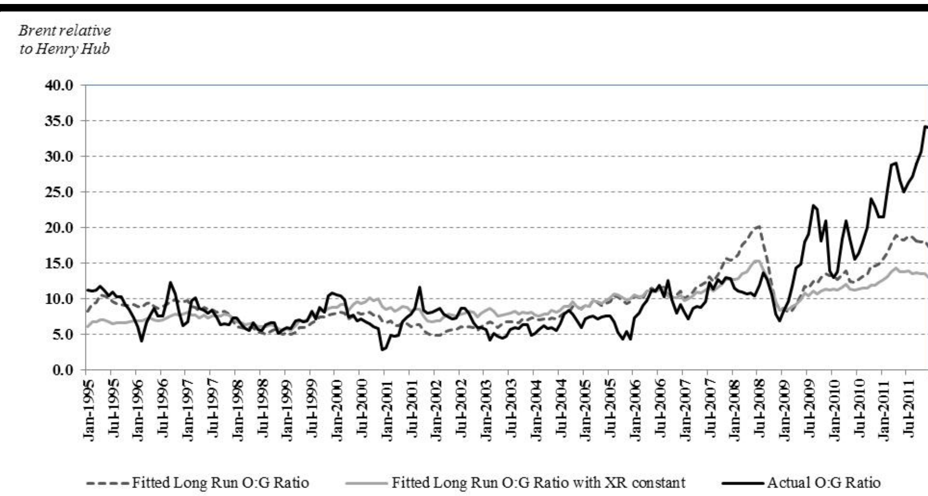

Figure 4 illustrates the effect of changes in the exchange rate on the cointegrating relationship. The light black line is the actual ratio of the price of Brent to the Henry Hub price. The dashed gray line shows the same relative price implied by the estimated cointegrating relationship and using the actual values of the right-hand side variables in

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[21] Both these coefficients also are statistically significant at the 0.001 level in the dynamic OLS specification.

[22] The coefficient on the relative heat rate variable is, however, statistically significant at better than the 1% level in the dynamic OLS estimation.

(14). It thus represents, at each month in the sample, the long-run relative price that would ultimately prevail absent any further shocks. The solid gray line shows the estimated cointegrating relationship if the exchange rate is held fixed at its average sample value. The actual exchange rate thus allows a better tracking of the long run relative price movement. In particular, the cointegrating relationship under-predicts the recent movement in the oil-gas price ratio by a wider margin if the exchange rate is held fixed. Figure 4 does not account for variations in factors such as inventories and weather that do not have unit roots. We include these influences in the estimated model in the next section of the paper.

Short-run dynamic adjustments

We next consider stationary variables likely to contribute to short-term fluctuations in natural gas prices by affecting natural gas supply or demand. We focused on: (1) inventory levels of natural gas as measured at the beginning of month; (2) heating and cooling degree-days; (3) an estimate of production losses in the Gulf of Mexico that have resulted from severe storms; and (4) a dummy variable to account for the winter of 1996.

Inventory data, inv_{ng}, reported as working gas in storage, were obtained from the EIA. These data are included as a measure of short run supply scarcity. High (low) inventories at the beginning of the month, all else equal, should mitigate (exacerbate) price changes in response to exogenous shocks over the month. We verified stationarity using Phillips-Perron tests.[23]

Instead of using actual inventory data, we divided the inventory changes into "anticipated" and "unanticipated" components. The hypothesis is that unanticipated changes may convey new information about near term supply-demand balance and exert

[23] The Phillips-Perron statistics for testing the stationarity of inv_{ng} are $Z(\rho) = -56.754$ and $Z(\tau) = -5.281$ and for $\ln inv_{ng}$ are $Z(\rho) = -56.820$ and $Z(\tau) = -5.340$ compared with interpolated 1% critical values of –20.143 for $Z(\rho)$, and –3.476 for $Z(\tau)$.

a different influence on current price movements. To obtain anticipated inventory levels, we regressed $\ln inv_{ng}$ on monthly indicator variables:

$$\ln inv_{ng,t} = \sum_{i=1}^{12} \beta_i I_{it} + u_t \tag{17}$$

where the variable I_{it} takes a value of 1 if period t is the i^{th} month of the year and zero otherwise, while u_t follows an ARMA process. Statistically significant coefficients on the monthly variables indicated that inventories display strong seasonality. The autocorrelation and partial autocorrelation functions of the resulting residuals indicated that the residual follows an AR(2) model $\left(1-\theta_1 L-\theta_2 L^2\right)u_t = v_t$ where v_t is a white noise process.[24] The predicted values from (17) estimated over rolling samples of 60 months were then used to define the *expected* values of natural gas in storage, denoted as $\widehat{inv}_{ng,t}$, while *unexpected* natural gas in storage is defined as the deviation from the expected value of inventories, $invdev_{ng,t} = inv_{ng,t} - \widehat{inv}_{ng,t}$.[25]

We also account for variations in heating and cooling degree-days (denoted HDD_t and CDD_t, respectively), as weather is a major factor influencing demand for natural gas. Increases in heating degree-days should, all else equal, increase the direct demand for natural gas for space heating. Increases in cooling degree-days should increase air conditioning and therefore raise the demand for electricity, and hence natural gas. Data on both variables, collected from the National Climatic Data Center (NCDC),

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[24] Consistent with the conclusion that the process was stationary, the estimated values for θ_1 and θ_2 (standard errors in parentheses) were 1.3584 (0.0538) and –0.4260 (0.0618). The autocorrelations and partial autocorrelations of the estimated residuals $\hat{v}_t$ also are consistent with that series being white noise. The Portmanteau Q statistics were 9.2527 (p-value of 0.6812) at lag 12, 29.571 (p-value of 0.1994) at lag 24 and 41.19 (p-value of 0.2539) at lag 36.

[25] We used rolling samples to estimate the parameters so the information used to produce anticipated inventories matches the information that would have been available to market participants at the time the forecasts would have been made. Using samples of 60 months corresponds to the common practice of taking the average of the past five years of storage as the "normal" level for a given month.

were used to calculate deviations from normal *HDD* and *CDD* in each month, denoted $HDDdev_t = HDD_t - HDDavg_t$ and $CDDdev_t = CDD_t - CDDavg_t$.[26] "Normal" is defined to be the 30-year average for each month ($HDDavg_t$ and $CDDavg_t$) over the period 1971-2000.[27]

We also included monthly dummy variables to allow for normal seasonal price changes. These result not only from normal monthly movements in *HDD* and *CDD*, but also from, for example, the number of days in a month and/or seasonal demand patterns in fuel consumption not captured by inventories or normal climate patterns.

We also follow Hartley, Medlock and Rosthal (2008) in allowing natural gas production losses associated with hurricanes in Gulf of Mexico to influence short run price movements. Natural gas production in the Gulf of Mexico region was regressed on a cubic time trend and a set of dummy variables representing periods when tropical weather, as reported by the National Hurricane Center (NHC), affected Gulf producing areas. Figure 5 plots production in the Gulf of Mexico. Darker shading identifies the months in which storms affected production.

To derive a value for lost production, we estimate

$$ng_t^{gulf} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_0 t^3 + \sum_j \sum_{t_j} \delta_{jt_j} D_{t_j} + \varpi_t \tag{18}$$

Where j indexes the storms that tracked through producing areas in the Gulf of Mexico within the sample period, t_j indexes months for which storm j had a statistically significantly negative effect on production (relative to trend), and $D_{t_j} = 1$ for $t = t_j$ and 0 otherwise. Production lost due to severe tropical storms and hurricanes is then defined as

$$GoMShutIn_t = -\sum_j \sum_{t_j} \delta_{jt_j} D_{t_j} \ . \tag{19}$$

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[26] The Phillips-Perron statistics for testing the stationarity of the weather variables are $Z(\rho) = -176.688$ and $Z(\tau) = -11.817$ for *HDDdev*, and $Z(\rho) = -125.316$ and $Z(\tau) = -9.509$ for *CDDdev*.

[27] We tested an extreme degree-day influence, defined to be observations in the top decile of all deviations, such as in Hartley, Medlock and Rosthal (2008), but the variables were not statistically significant.

Figure 5. Production and Storms in the Gulf of Mexico

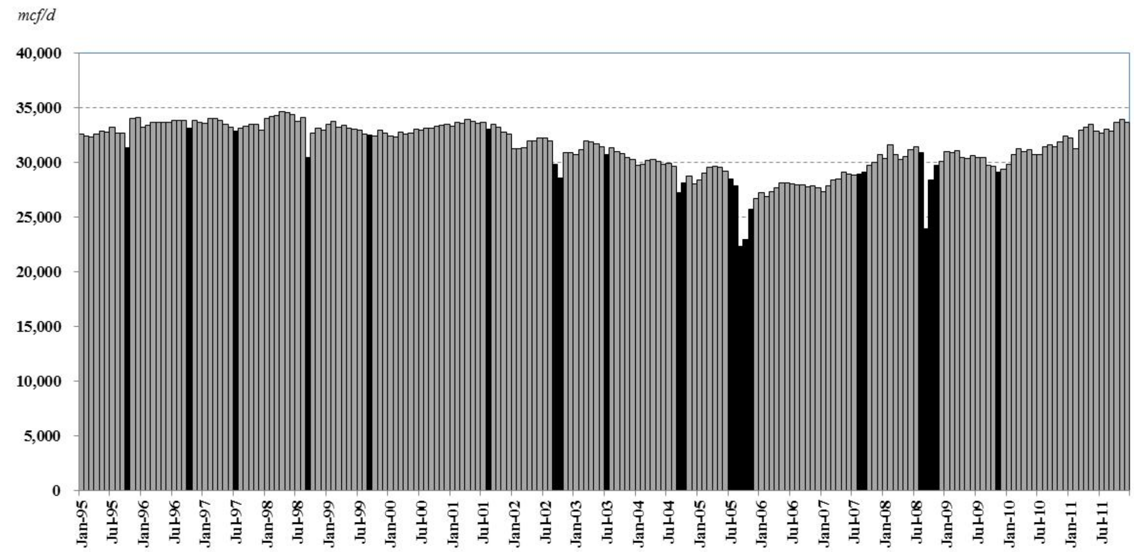
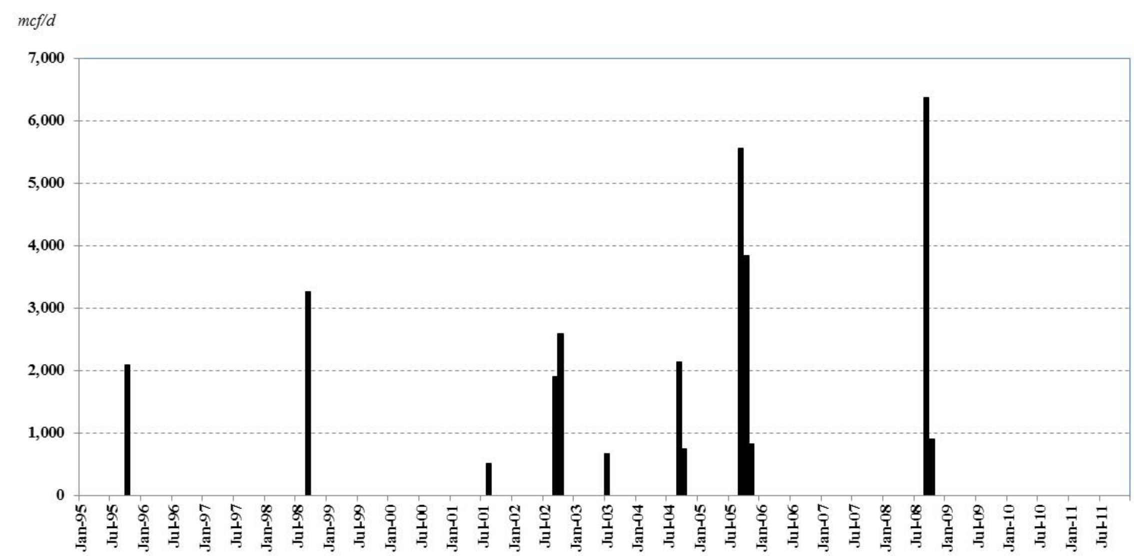


Figure 6. Shut-in production from Storms in the Gulf of Mexico



In contrast to using a simple dummy variable for the months of major storms, this method allows the effects on production to occur over an extended period and for the effects to vary by storm.[28] The results of the method are graphed in Figure 6, which

[28] We also examined using dummy-variables for lost production. The coefficient on the hurricane shut-in

indicates production was lost due to storms during October 1995, September 1998, August 2001, September-October 2002, August 2003, September-October 2004, September-December 2005 and September-October 2008.

Finally, we include an indicator variable ($Chicago$) for February 1996 to account for then unprecedented prices of natural gas associated with an extreme cold period coinciding with low inventory levels.[29]

We then estimate a dynamic adjustment of natural gas price to deviations from (14) allowing for shocks to weather, other seasonal factors and variations in inventory. Specifically, letting $\hat{\varepsilon}_t$ denote the cointegrating error from (14), the ECM for the change in natural gas prices can be written as

$$\begin{aligned}\Delta \ln P_t^{ng} = \sum_{i=1}^{12} \alpha_{0i} I_{it} + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 (L) \Delta \ln P_{t-1}^{ng} + \alpha_3 \widehat{inv}_{ng,t} + \alpha_4 invdev_{ng,t} \\ + \alpha_5 HDDdev_t + \alpha_6 CDDdev_t + \alpha_7 GoMShutIn_t + \alpha_8 Chicago_t + \mu_t\end{aligned} \quad . \tag{20}$$

The dynamic adjustment process is influenced by the error correction term $\hat{\varepsilon}_{t-1}$. If $\hat{\varepsilon}_{t-1} = 0$, so the relative price matches the relationship implied by (14), and all other variables remain unchanged, then the price of natural gas will change only according to normal seasonal influences. If $\hat{\varepsilon}_{t-1} \neq 0$ and $\alpha_1 < 0$ then the natural gas price will, absent further shocks, tend back to the *long-run* relationship implied by (14). The speed of adjustment is determined by the magnitude of α_1, but, absent other shocks, the dynamics of adjustment also depend on $\alpha_2(L)$ in (20).

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variable became less significant but none of the remaining coefficients were materially affected. The MMS also provides (www.gomr.mms.gov/homepg/whatsnew/hurricane/history.html) an estimate of shut-in production. However, these statistics are not consistent over the entire sample period, and do not generally track shut-in production for an extended period.

[29] The February 1996 episode is discussed in *Natural Gas 1996: Issues and Trends* which is available at www.eia.doe.gov/oil_gas/natural_gas/analysis_publications/natural_gas_issues_and_trends/it96.html Expansions of pipeline infrastructure (by Northern Border and Alliance) after the winter of 1996 increased access to Canadian supplies and storage and helped mitigate similar problems in subsequent years.

Column 1 of Table 2 presents the OLS estimates of the coefficients in (20).[30] Estimated coefficients have the expected signs, except for the coefficient on *invdev*, which is positive, but not statistically significantly different from zero.[31]

Since the estimated coefficient on the deviation from the cointegrating relationship is negative, we see that the cointegrating (or long run) relationship is stable. In other words, the natural gas price exhibits a tendency to return to the cointegrating relationship absent other shocks.

The estimated coefficients also indicate that weather plays a very important role in short run price movements. Deviations from normal weather, *HDDdev* and *CDDdev*, both tend to raise the natural gas price. In addition, the extremely cold weather in Chicago in February 1996 had an especially large effect on natural gas prices. Hurricanes also tend to have a significant positive impact on natural gas prices as supply is reduced. The estimated coefficient implies that for each billion cubic feet per day of production shut in by a hurricane in the Gulf of Mexico, natural gas prices at the Henry Hub increase by approximately $\$1.00/mcf\left(=e^{0.0000272}\right)$, holding all else constant.

Finally, the significance of the annual lagged price change (12 month lag) and the monthly dummy variables (the latter of which are not reported in Table 5) reveal seasonal effects in the price series that are not captured by the other variables. The monthly effects indicate price tends to increase the most in December and to decline the most (in absolute value) in March and July. The significance of the annual lagged price change suggests that the natural gas price also has an annual stochastic component that is not captured by the other variables.

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[30] The monthly dummy variables are not reported, but are available upon request.

[31] The coefficient should be negative since inventories represent readily available supply, and ample supply should reduce prices.

Table 5. Error Correction Model Estimation Results

Variable	Equation (20)	Equation (21)
$\hat{\varepsilon}_{t-1}$	-0.1409^{***} (0.0336)	-0.0611^{**} (0.0303)
$\Delta \ln P^{ng}_{t-1}$	0.1397^{**} (0.0629)	
$\Delta \ln P^{ng}_{t-12}$	-0.2418^{***} (0.0625)	-0.2015^{***} (0.0550)
$\widehat{inv}_{ng,t}$	$-1.74E\text{-}07^{***}$ $(4.66E\text{-}08)$	$-4.80E\text{-}07^{**}$ $(2.05E\text{-}07)$
$\widehat{inv}_{ng,t-1}$		$3.98E\text{-}07^{*}$ $(2.14E\text{-}07)$
$invdev_{ng,t}$	$1.61E\text{-}08$ $(3.89E\text{-}08)$	$-9.76E\text{-}07^{***}$ $(1.49E\text{-}07)$
$invdev_{ng,t-1}$		$9.37E\text{-}07^{***}$ $(1.39E\text{-}07)$
$HDDdev_t$	0.00124^{***} (0.00019)	0.00122^{***} (0.00017)
$HDDdev_{t-1}$		-0.00161^{***} (0.00030)
$CDDdev_t$	0.00187^{***} (0.00051)	0.00182^{***} (0.00046)
$CDDdev_{t-1}$		-0.00146^{***} (0.00052)
$GoMShutIn_t$	$2.72E\text{-}05^{**}$ $(1.33E\text{-}05)$	$3.47E\text{-}05^{***}$ $(1.20E\text{-}05)$
$GoMShutIn_{t-1}$		$-3.91E\text{-}05^{***}$ $(1.23E\text{-}05)$
$Chicago_t$	0.4852^{***} (0.1246)	0.5479^{***} (0.1096)
$Chicago_{t-1}$		-0.3740^{***} (0.1104)
N	191	191
R^2	0.4244	0.5807
Joint Sig	$F_{20,170} = 6.27^{***}$	$F_{25,165} = 9.14^{***}$
Q (1 lag)	$\chi^2_1 = 2.462$	$\chi^2_1 = 0.525$
Q (2 lags)	$\chi^2_2 = 4.272$	$\chi^2_2 = 2.194$
Q (3 lags)	$\chi^2_3 = 6.617^{*}$	$\chi^2_3 = 2.920$
Q (4 lags)	$\chi^2_4 = 7.957^{*}$	$\chi^2_4 = 3.167$
Breusch-Pagan	$\chi^2_1 = 8.30^{***}$	$\chi^2_1 = 1.30$

Statistically significant at the *** 1% level, ** 5% level, and * 10% level

While the estimated parameter values generally appear reasonable, diagnostic statistics applied to the estimated residuals reveal inadequacies in the model. In particular, the test for heteroskedasticity in the residuals is statistically significant at the 1% level. Portmanteau Q-statistics also suggest the residuals remain serially correlated, although additional lags of the dependent variable were not significant. This suggests it may be appropriate to include lagged values of one or more right-hand side variables among the regressors.

Accordingly, we estimated an alternative dynamic adjustment model that includes lags of the explanatory variables while dropping the lagged dependent variable $\Delta \ln P_{t-1}^{ng}$, which became insignificant once the additional lags of the remaining variables were included:[32]

$$\begin{aligned}\Delta \ln P_t^{ng} = \sum_{i=1}^{12} \alpha_{0i} I_{it} + \alpha_1 \hat{\varepsilon}_{t-1} + \alpha_2 \Delta \ln P_{t-12}^{ng} + \sum_{i=0}^{1} \Big[\alpha_{3i} \widehat{inv}_{ng,t-i} + \alpha_{4i} invdev_{ng,t-i} + \\ \alpha_{5i} HDDdev_{t-i} + \alpha_{6i} CDDdev_{t-i} + \alpha_{7i} GoMShutIn_{t-i} + \alpha_{8i} Chicago_{t-i} \Big] + \mu_t\end{aligned} \tag{21}$$

The estimated parameter values and standard errors for (21) are reported in column 2 of Table 5. Note there is now no evidence of heteroskedasticity or autocorrelation in the error term. The R^2 and F statistics in panel 2 of Table 5 also suggest that (21) is more consistent with the evidence than (20).

The coefficient on unexpected beginning of month storage that was insignificant and positive in column 1 now has the expected negative sign, and around twice the magnitude of the coefficient on expected inventory at the beginning of the month. The estimates in column 2 thus imply that both anticipated and unanticipated increases in beginning of month inventories tend to produce lower prices over the month, but the effects of unanticipated movements are about twice as large. This is consistent with the notion that unanticipated movements convey additional information to market participants.

[32] This effectively replaces the first-order autoregressive structure on the dependent variable by a first-order moving average structure on the explanatory variables. An ARIMA model with a combined autoregressive and moving average structure for the error term in (20) yielded similar results.

The remaining parameter estimates also have the expected signs. Extreme weather events (reflected in large values for *HDDdev* or *CDDdev*), the Chicago cold snap in February 1996, and significant Gulf Coast hurricanes all have significant positive impacts on natural gas prices. The opposite signs of the estimated coefficients on the lagged values of these variables suggest, however, that the effects of these shocks abate rapidly when the events pass. Indeed, suppose we express the lagged cointegrating error from (14) more compactly as $\varepsilon_t = \ln P_t^{ng} - \beta Z_t$, define X_t as the vector of short-run explanatory variables and δ_0 and δ_1 as the vectors of coefficients on X_t and X_{t-1}. We can then write (21) (ignoring the 12th order lagged endogenous variable and the monthly indicators) as:

$$\left(1-\left(1+\alpha_1\right)L\right)\ln P_t^{ng} = \left(\delta_0 - \delta_1 L\right)X_t - \alpha_1\hat{\beta}Z_{t-1} + \mu_t \tag{22}$$

Note that if

$$\delta_{i1} = \left(1+\alpha_1\right)\delta_{i0} \tag{23}$$

then the i^{th} component of X_t affects only the contemporaneous value of $\ln P_t^{ng}$. A weather shock, or beginning of month inventory shock, will affect prices over the subsequent month but the effect will disappear after just one month. We tested restriction (23) for each of the short-run explanatory variables, and found it could not be rejected in any case.[33]

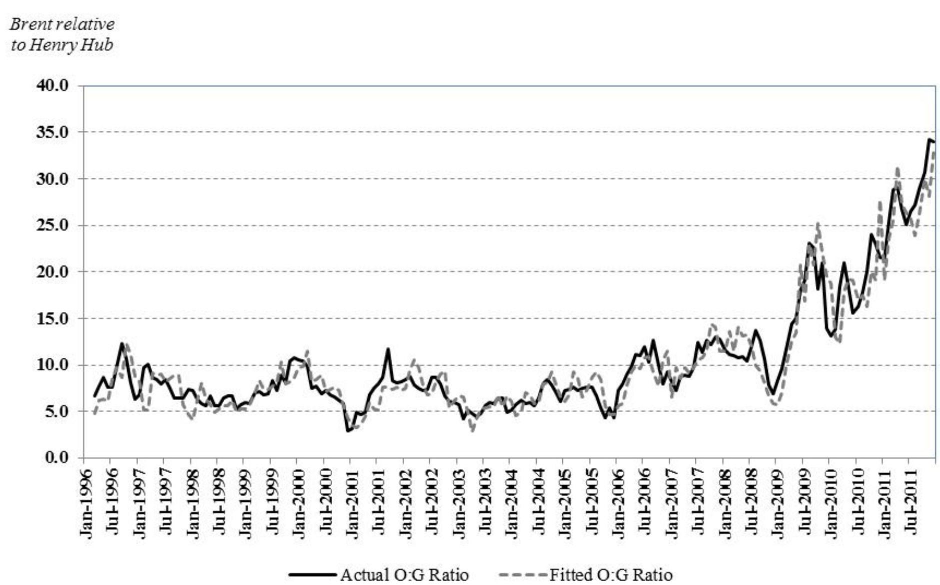
Recall that we can interpret the cointegrating error $\hat{\varepsilon}$ as the percentage deviation between the natural gas price and its long run level, which is given by βZ. Then α_1 is the fraction of that gap that is eliminated each period. Thus, the estimated value for α_1 in

[33] Wald-type tests based on the delta method yield $F_{1,165}$-statistics for testing the validity of the parameter restriction for one variable. The values, with corresponding *p*-values in parentheses, were 1.39 (0.2404) for $\widehat{inv}$, 0.26 (0.6088) for *invdev*, 1.88 (0.1720) for *HDDdev*, 0.18 (0.6736) for *CDDdev*, 0.21 (0.6451) for *GoMShotIn*, and 0.78 (0.3788) for *Chicago*. The statistic for testing all restrictions simultaneously is $F_{5,165} = 0.99$, which has a *p*-value of 0.4242.

(21) implies a sluggish adjustment of natural gas prices back toward the long run relationship.[34]

It is noteworthy that α_1 in (21) is about half what was estimated for (20). In (20), the speed of response of natural gas prices is the same regardless of what moves $\ln P_t^{ng}$ away from its long run value. The fact that α_1 has a smaller magnitude in (21) thus suggests that the larger adjustment speed estimated for (20) is reflecting rapid response to the transitory weather and inventory shocks. After the moving average specification allows prices to adjust quickly to these short-run shocks, the speed of adjustment to errors in the cointegrating relationship declines dramatically.

Figure 7. Within sample fit of the full model



Finally, Figure 7 shows the within sample fit of the ECM (21). The solid line is the *actual* ratio of the price of Brent crude oil to the price of Henry Hub natural gas over

[34] As remarked earlier, this result is consistent with the finding that $\hat{\varepsilon}$ apparently follows an autoregressive process with an AR(1) coefficient above 0.9.

the sample period, while the dashed line is the *fitted* ratio implied by both (14) and (21). The generally good fit reflects the R^2 and F statistics presented in Table 5.

Comparison of Figures 7 and 4 reveals the importance of the weather and inventory shocks in (21) for explaining persistent gaps between the actual and the long-term relative price ratio apparent in Figure 4. In particular, the large drift in the last few months of the sample can be attributed to mild winter weather and strong inventory build, both of which reflect a well-supplied North American natural gas market.

5. CONCLUDING REMARKS

This paper has demonstrated some important points regarding the relationship between crude oil prices and natural gas prices. First, our analysis is consistent with the findings in Hartley, Medlock and Rosthal (2008) that electricity generation technology has played an important role in establishing the crude oil-natural gas relative price.

Second, the analysis indicates that changes in the exchange rate can explain some longer-term movements in the crude oil-natural gas relative price. No other paper in the literature has considered the role of the exchange rate. Presenting evidence of an effect of exchange rate movements is important for highlighting a role that monetary and fiscal policies can play in determining relative energy prices.

Third, similar to previous studies, we find that weather-related events and changes in inventories significantly affect short run movements of the crude oil-natural gas relative price. In addition, we found evidence that the natural gas price responds rapidly to weather shocks and inventory changes, but much more slowly to departures from the long run cointegrating relationship. This result can explain the relatively high volatility of natural gas price as well as why deviations from the long-run cointegrating relationship can persist for some time. Both factors can give the impression that natural gas markets are not well connected with markets for other energy commodities, although the existence of a long-run cointegrating relationship suggests otherwise.

Finally, we emphasize that changes in the relationship between crude oil and natural gas prices are important to study for both commercial and policy reasons. For example, the crude oil-natural gas relative price affects the apparent profitability of technologies that allow direct switching between natural gas and other fuels, such as CNG vehicles, the profitability of indirect switching technologies, such as GTL, and perhaps even the profitability of LNG exports.

6. REFERENCES

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