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The switching relationship between natural gas and crude oil prices☆

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ABSTRACT

In this analysis we more accurately capture the cointegrating relationship between natural gas and crude oil prices by endogenously incorporating shifts in the cointegrating vector into the estimation of the cointegrating equation. Specifically, we allow the cointegrating equation to switch between *m* states, according to a first-order Markov process. First, we find evidence that regime-switching exists in the relative pricing relationship, and that two is the optimal number of states. Once we control for shifts in the cointegrating vector, we find that natural gas and crude oil prices are cointegrated, and an error correction model (ECM) of their long-term equilibrium relationship is properly specified. This finding broadens the ECM model of their relationship to longer and more varied sample periods. Also, in a direct comparison of the two and one state cointegrating equations, we found evidence of the potential superiority of the two-state equation, in that it may be robust to shifts in the cointegrating vector which are missed by standard tests for a unit root. Further, our analysis finds evidence that natural gas and crude oil prices did not permanently 'decouple' in the early 2000s, but rather experienced a temporary shift in regimes. We find that forecasts of the relative pricing of natural gas and crude oil should be conditioned on state probability.

1. Introduction

Many recent studies on the long-term relationship between natural gas and crude oil prices have found that the series are generally cointegrated (Bachmeier and Griffin, 2006; Brown and Yucel, 2008; Hartley et al., 2008; Ramberg and Parsons, 2012; Serletis and Herbert, 1999; Villar and Joutz, 2006).[1] However, noted in many of these analyses is the likely presence of structural breaks in the relationship.

This is prompted by the observation that over the last 30 years there has been a wide variation in the ratio of crude oil to natural gas prices. This ratio was above 10 for much of the 1985–1995 'gas bubble' period, and then below 10 until 2005. Since 2009 the ratio has spiked above 30. This marked change in the ratio since 2009 has renewed speculation of 'decoupling' between the price series. In addition, Ramberg and Parsons (2012) found evidence for structural breaks in 2006 and 2009 using the Gregory and Hansen (1996) test for a single structural break in a cointegrating relationship.[2]

Our present analysis builds on the prior literature by endogenously incorporating shifts in the cointegrating vector into the estimation of the cointegrating equation. That is, we model the structural breaks in the relative pricing relationship as switches between cointegrating regimes, and these switches are endogenously determined according to a first-order Markov process. This approach will afford a probability law over the entire data generating process which takes into account distinct changes in the cointegrating vector.

Once such regime changes are controlled for in this manner, one can model the long-term equilibrium relationship between natural gas and crude oil over wider and more varied sample periods. This affords a better measure of present energy market integration, possibly better forecasts of relative prices, and a more thorough understanding of how technological changes affect the natural gas and crude oil pricing relationship.

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[1] For more on the methodology employed in these cointegrating analyses see Hendry and Juselius (2000, 2001) and Engle and Granger (1987).

[2] They used the version of the test based on the augmented Dickey–Fuller test statistic. While the test is for a single structural break, Ramberg and Parsons (2012) used the test over the period 1997–2010 and found a break in February 2009. They then used the test again over the interval 1997 through February 2009 and found a break in March 2006. They did not choose to repeat this procedure over the sample period 1997 through March 2006.

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That the regime-switching is endogenous is an important point. In our model, changes in regime are determined solely by the underlying data generating process. This obviates biases an econometrician may have in determining whether regime changes exist, and the timing of such changes.

Some events which may induce regime switches in the relationship between natural gas and oil are technological changes and legislation, among others. For example, Hartley et al. (2008) found evidence that the marked increase in the use of the combined-cycle combustion turbines for electricity generation in the late 1990s made natural gas electricity generation more cost effective, thereby substantially increasing demand for natural gas and increasing prices. More recently, an increase in the supply of shale gas because of the introduction of hydrofracking has driven North American natural gas prices lower.

Including such structural breaks into any model of the relationship is important because, as Villar and Joutz (2006) note, structural changes in the cointegrating equation can cause forecast failure. The present analysis incorporates such structural changes into the cointegrating equation, and thereby the error correction model (ECM).

In this analysis we further offer an answer to the idea that the relative pricing relationship between natural gas and oil permanently 'decoupled'. Using the regime-switching model, and data though 2012, we will show that the parameters governing the relationship between natural gas and crude oil did indeed change from 2000 to 2009,[3] however the parameters have since reverted to their pre-2000 values. That is, the 'decoupling' was a temporary shift in regimes.

Throughout this paper we use a standard error correction model (ECM) analysis similar to prior literature, but with our regime-switching cointegrating equation. We first estimate an ECM over our entire sample and review the results. We then estimate an ECM over a subinterval for which we can also estimate a control (the standard nonswitching cointegrating equation), and compare our results to this control.

Lastly, understanding the relative pricing of natural gas and oil is important for both corporate managers and policymakers. Models of the pricing relationship are necessary to estimate cash flows in the long-term capital budgeting plans of both energy producers and consumers. For instance dynamics of the relationship may dictate whether an energy producer should drill wells to target natural gas or oil. Alternatively, the relative pricing may determine the type of fuel to use when building a power plant. For policymakers the relative pricing may affect decisions from permitting energy transportation infrastructure to setting royalty payments.

The paper is as follows: Section 2 presents the Markov-switching cointegration equation, the determination of the number of states, and results; Section 3 describes the ECM and results; Section 4 concludes.

2. Markov-switching cointegrating equation

The cointegrating equation with first-order, M-state, endogenous Markov-switching parameters may be written as:

$$P_{HH} = \beta_{0,S_t} + \beta_{1,S_t} P_{WTI} + e_t, \quad e_t \sim N\left(0, \sigma^2_{S_t}\right) \tag{1}$$

$$P(S_t = j | S_{t-1} = i) = p_{ij}, \quad \forall i, j \in 1, 2, \ldots M, \text{ and } \textstyle\sum_{j=1}^{M} p_{ij} = 1 \tag{2}$$

$$\beta_{0,S_t} = \beta_{0,1} S_{1t} + \beta_{0,2} S_{2t} + \ldots + \beta_{0,M} S_{Mt} \tag{3}$$

$$\beta_{1,S_t} = \beta_{1,1} S_{1t} + \beta_{1,2} S_{2t} + \ldots + \beta_{1,M} S_{Mt} \tag{4}$$

$$\sigma_{0,S_t} = \sigma_{0,1} S_{1t} + \sigma_{0,2} S_{2t} + \ldots + \sigma_{0,M} S_{Mt} \tag{5}$$

where for $m \in 1, 2, \ldots, M$, if $S_t = m$, then $S_{mt} = 1$, and $S_{mt} = 0$ otherwise. P_{HH} and P_{WTI} refer to the log of natural gas and crude oil prices respectively. $\beta_{0,St}$, $\beta_{1,St}$, and σ_{St} are parameters to be estimated for each state S_t, and p_{ij} is the transition probability from state i to state j.

Construction of the likelihood function for the above Markov switching cointegrating equation was done using the Hamilton filter (see Hamilton (1994) or Kim and Nelson (1999)). Minimization of the negative log-likelihood was done using the *optim* function in the R programming language. The minimization was unconstrained.

The residuals of the m-state model are weighted by *filtered* state probability, which is the probability that the relationship is in state S_t given information only through time $t-1$. This means probabilities in the residual are not biased by using information through time T, as would be the case if we used smoothed state probabilities.[4] The time t weighted residual in the m-state case is:

$$e_t = e_{S_t=1} P(S_t = 1 | \varphi_{t-1}) + \ldots + e_{S_t=m} P(S_t = m | \varphi_{t-1}) \tag{6}$$

where φ_{t-1} denotes the information available at time $t-1$, and $e_{S_t=m}$ denotes the time t residual of the state m model.

The data used to estimate the model are monthly and weekly logged prices for rolling front month NYMEX full-size natural gas and oil futures. The crude oil contract is for west Texas intermediate deliverable in Cushing Oklahoma, and the natural gas contract is for delivery at the Henry Hub in Louisiana. The data are available from the Energy Information Agency of the U.S. Department of Energy.

2.1. Determining the number of states

The prior literature has generally alluded to two regimes in the natural gas and crude oil relationship: one regime where crude oil prices are relatively high compared to natural gas (1985–1995 gas bubble and post-2009), and another regime where natural gas prices are relatively high (the interval from 1995–2005). Ramberg and Parsons (2012) also estimate two cointegrating equations over the interval 1997–2010.

However, to determine the appropriate number of states we estimated the cointegrating equation allowing for the number of states to range from one to three. Note, a one-state equation is the standard, non-switching, cointegrating equation. We compared the results of each model based on the behavior of the residuals, the estimated state probabilities, and Akaike's Information Criterion (AIC).[5] Ultimately, we concluded that two states best described the process.

Comparing the one and two state models, we cannot reject a unit root in the residuals of the one-state cointegrating equation using either monthly or weekly prices. This is evidence that the logs of natural gas and oil prices are not cointegrated in the one-state model. Importantly, this means an ECM of the relationship between crude oil and natural gas is internally inconsistent[6] with respect to the residuals in the one-state cointegrating equation.

[3] The relationship switched to a second state in August 2000, and stayed in this state until April 2009, with one interruption from September 2001 to October 2002 which coincides with the Enron collapse and its attendant effect on natural gas markets.

[4] Smoothed probabilities are $P(S_t = m | \varphi_T)$, which are the probabilities that the model is in state m at time t given information through time T.

[5] Given unresolved issues in implementing likelihood ratio tests (such as in Hansen (1992)) to determine the number of states, Psaradakis and Spagnolo (2003) employ a Monte Carlo analysis to test the performance of methods based on complexity-penalized likelihood criteria in Markov switching autoregressive models. They found that the AIC was generally successful in choosing the number of states, so long as (1) the sample size and (2) the parameter changes are both sufficiently large.

[6] Because the error correction term, and hence the right hand side, has a unit root.