**DETERMINANTS OF NATURAL GAS PRICES IN THE UNITED STATES – A STRUCTURAL VAR APPROACH**

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**Abstract**

*This study examines the dynamic economic relationships between the fundamental variables that influence natural gas prices within the U.S. market. I utilize a structural vector autoregressive (VAR) and Markov switching models to investigate the impact and stability of regime switches between the main drivers of natural gas prices. The results reveal that the U.S. gas market is sensitive to temperature deviations in the short term. Crude oil and coal prices have long-run effects on natural gas prices, emphasizing energy-specific demand shocks. Mainly, coal prices determine about 73% of gas price variability for the sample period with three discernable regime switches.*

Keywords: Natural gas, Structural VAR, Markov Switching, Weather, Storage.

JEL Classifications: C32, E32, G13, Q40

# Introduction

I aim to examine the dynamic interactions between the fundamental drivers of natural gas prices. The price of natural gas is relevant to various stakeholders due to its crucial role in the heating and cooling market and its input in electricity production. Therefore, understanding the price formation of natural gas is relevant from a macro-and microeconomic perspective. However, the price development is complex since markets are faced with a variety of specific supply and demand characteristics such as weather conditions, cross-commodity substitution effects, storage shocks, and business cycles.

In this research, I identify five fundamental drivers of natural gas prices in the U.S. gas market. The supply and demand interactions of temperature and storage deviations, short-term interest rate, coal, and crude oil prices are analyzed as variables that affect natural gas prices. I develop a structural vector autoregressive model (VAR) and a Markov Switching process to investigate the phenomena. The models yield insights into the dynamic relationship between the variables under study. The impulse response simulations from the VAR model are consistent with economic reasoning, implying that natural gas prices react to underlying supply and demand shocks. Natural gas prices rise in reaction to abnormal temperatures, which increases heating and cooling demands in the short term. The response of gas prices to structural shocks of storage is insignificant from this study. However, the empirical results reveal that storage level depletes through withdrawals in response to extraordinary temperatures, which increases demand for heating or cooling. Coal and crude oil price shocks show long-term effects on the natural gas price formation.

A significant contribution of this research is identifying the distinct contributive effects of the different variables on natural gas prices. I find coal prices to determine about 73% of gas price variability for the sample period, unambiguously making it a systematic determinant of natural gas prices. A three-state Markov switching process between coal and gas prices has been identified with discernable regime switches.

The finding that coal price is the primary influencer of natural gas prices may challenge the existing idea of crude oil being the only explanatory variable in gas price formation. For example, Hartley and Medlock (2014), Brown and Yücel (2008) argue that gas and crude oil prices are cointegrated in the short and long run. However, the stability of this cointegration dynamics is not stable over time. Ramberg and Parsons (2012) and Wang et al. (2019) bring to bear that the cointegration relationship between oil and gas in the U.S. market decouples over time. Particularly, Wang et al. (2019) demonstrate the declining role of oil prices in natural gas pricing mechanism with time-series data between 2001 and 2018. This is due to the demise of crude oil indexation of natural gas prices.

Historically, crude oil prices have been thought to be the most critical factor affecting natural gas prices in the long run. One simple rule of thumb – the 10-to-1 rule under which natural gas price was one-tenth the price of crude oil prevailed in the 1990s (Brown and Yücel, 2008). This oil-indexation trend has changed in recent years, specifically in the U.S., due to the shale gas revolution that began in 2005. With the successful application of horizontal drilling and fracking technologies, shale gas production has increased exponentially, accounting for about 79% of total gas supplies in the U.S.

The description of the data used are discussed in Section II. Section III outlines the empirical methodologies employed in previous research on the natural gas market, definition, and identification of the structural VAR model. Empirical results in the form of impulse responses and Markov switching processes are explained in Section IV. A summary and conclusion are presented in Section V.

# Data Description

The dataset used in this research consists of 471 observations of weekly data within the period from January 2, 2010, to December 29, 2018.[[1]](#footnote-1)It comprises the Henry Hub natural gas spot price, West Texas Intermediate (WTI) crude oil spot price, average U.S. spot coal price, U.S. natural gas storage, the annual yield on 3-month U.S. Treasury Bill, and the consumption-weighted temperature deviations from historical averages for the top 5 natural gas consumption states in the U.S.[[2]](#footnote-2) Figure 1 displays all the time series of the variables and Table 1 provides a summary definition of the variables used in this study.

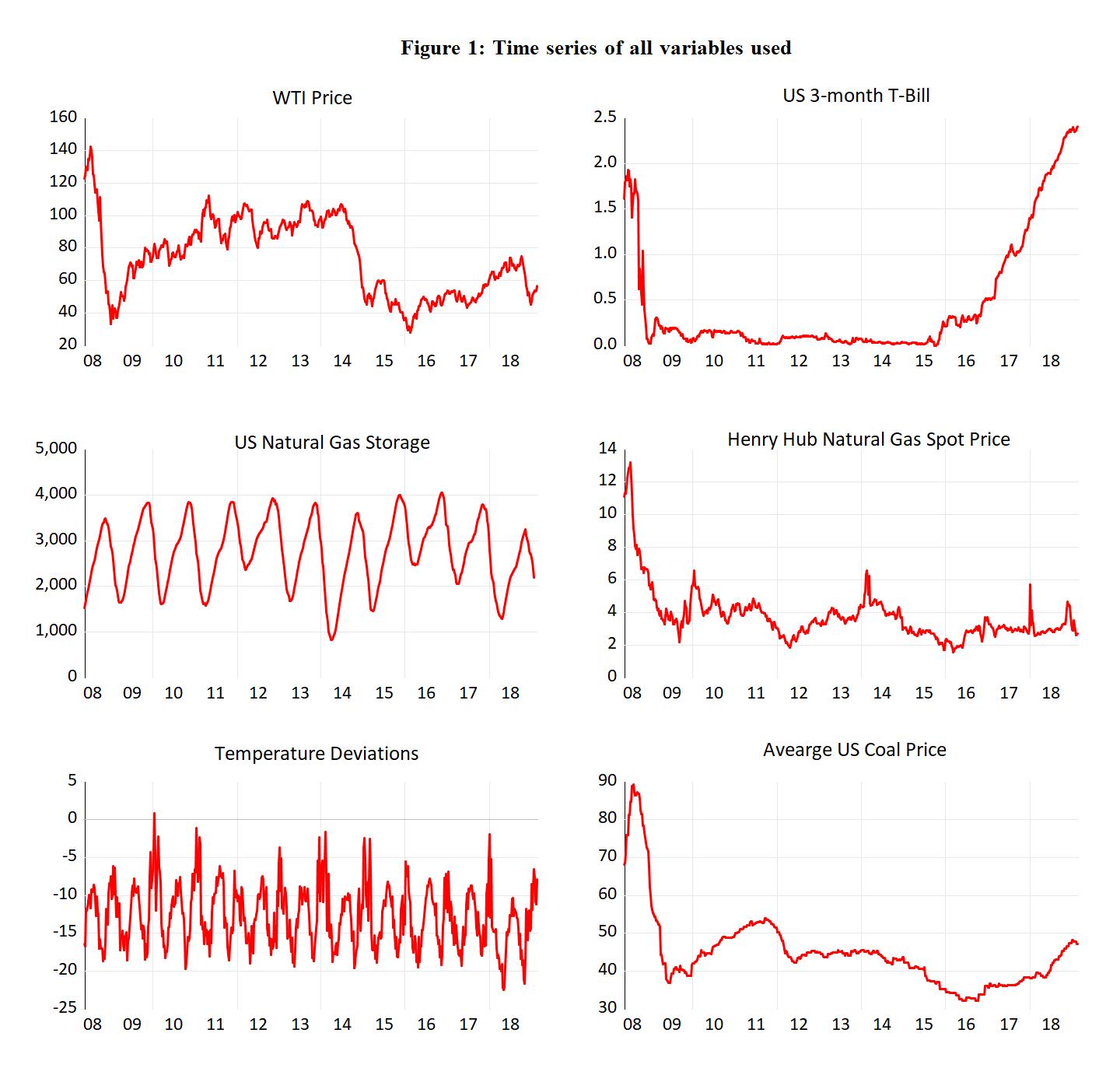


Table 1: Summary description of variables used

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Description | Unit | Source |
| Temperature Deviations | measured as the Degrees Day (D.D.) deviations from historical averages. DD= CDD + HDD. Where CDD is Cooling Degrees Day and HDD is Heating Degrees Day | Degrees Fahrenheit | National Weather Service (NWS) |
| WTI Price | West Texas Intermediate spot price for U.S. crude oil | USD per barrel | Bloomberg |
| Coal Price | The average spot price of U.S. coal from the five producing regions (Central Appalachian, N. Appalachian, Illinois Basin, Powder River Basin, Uinta Basin) | USD per ton | Quandl |
| Natural Gas Price | Henry Hub spot price | USD per million Btu (British thermal unit) | Bloomberg |
| Storage | Working gas in underground storage | Bcf (Billion cubic feet) | U.S. Energy Information Administration |
| Treasury Bill | Three months U.S. treasury bill | Percent | Federal Reserve Bank of St. Louis |

The choice of variables for this econometric analysis is comprehensive as it encompasses the diverse fundamental drivers of natural gas prices. I rely on spot prices because it allows me to capture some short-term impacts of interest, such as temperature-induced demand spikes. I used the Henry Hub spot price because its price movement is considerably affected by the temperature conditions of the top 5 natural gas consumption states considered in this study.

I specify the model using weekly data to allow for the inclusion of coal price data, which is only available in weekly frequency while capturing short-term meteorological conditions. Prices of crude oil and coal are used as proxies for energy-specific demand. The spot price of crude oil is incorporated to capture the substitution relationship of oil and gas in the domestic heating and cooling market. Coal prices placed in the model will capture the interaction of gas and coal in the electricity generation sector and therefore represents the cross-commodity effects related to fuel substitution (see, for example, Sebastian & Stefan, 2013). Natural gas, coal, and crude oil price time series are transformed to their natural logarithms. This approach is consistent with macroeconomic literature (see, for example, Ghyssels & Marcellino, 2018). I estimate the structural VAR (vector autoregressive) equation with log-level prices because I am only interested in the dynamic economic relationships between the selected variables with the natural gas market and not any possible cointegration or stationarity.

The natural gas demand in the residential heating market is susceptible to temperature. As such, in a liberalized market, it is expected that storage operators will exploit predictable seasonal demand variations. Therefore, extraordinary short-term weather conditions that cause a shift in demand are expected to be relevant to gas price formation and not predictable seasonal patterns. Consequently, I construct degree day deviations (D.D.) from normal historical averages to determine gas prices. Temperature expressed in degree days is a quantitative index that reflects a demand for energy to heat or cool houses and businesses. Degree days (D.D.) is the sum of heating degree days (HDD) in the winter and cooling degree days (CDD) in the summer. [[3]](#footnote-3)

DDt = CDDt+ HDDt (1)

CDDt= Max (0, Tavet – 65o F) (1.a)

HDDt = Max (0, 65oF – Tavet) (1.b)

where Tavet is the average daily temperature of date *t.*

The weather shock is defined as the deviation of D.D.s from the normal level over the period

*Wt*= (2)

where *m* is the weather period, is the degree days on day *t+i*, is the normal degree days which is the average degree days of the previous 30 years on day *t+i.* The use of deviations of the observed D.D. from their historical averages estimates the effect of unexpected conditions on gas prices.

I include storage data because storage operators are both supply-side (withdrawal phase) and demand-side (injection phase). I consider the change in utilization rate instead of absolute volumes as a measure of changes in total storage capacity. As a proxy for flexible storage levels that can respond to storage shocks, I utilize the difference between average seasonal changes in utilization and its corresponding actual change each week. The deep reasoning for this approach is to capture deviations from the seasonal storage utilization pattern. I do not include natural gas production since the U.S. has been a net exporter of LNG and crude oil since the shale gas boom in 2006. I fit three months treasury bills as a control variable. Treasury bills may affect natural gas prices because the short-term interest rate is a significant component of the cost of carrying inventories (Arango, Arias, & Florez, 2012, Frankel, 2006).

# Empirical Methodology

There has been enormous empirical research on the natural gas market in recent years. A common thematic approach underlying these findings is the relationship between natural gas and crude oil prices rather than exploring how the natural gas market works. These approaches ignore the possibility of structural dynamics within the market. For example, Pindyck (2004), Brigida (2014), Hartley and Medlock (2014), Brown and Yücel (2008), and Jadidzadeh and Serletis (2017) find movements in oil prices to influence natural gas prices. Brown and Yücel’s (2008) analysis involved testing for a cointegrating relationship using a vector error correction model (VECM). In contrast, other studies conclude that there is a weak link in the so-called oil-gas relationship (see, for example Ramberg and Parsons (2012), Zhang and Ji (2018).

Other complex and comprehensive frameworks have been used to explore and disentangle the supply and demand shocks driving natural gas prices using various structural or reduced-form models. Sebastian and Stefan (2013) analyze the German gas market using a structural VAR and find that weather, supply, storage, coal, and oil price shocks have a significant effect on natural gas price formation. Hou and Nguyen (2018) employ a Markov switching structural VAR model to investigate the regime-dependent responses to its fundamental shocks. They find that the impact of oil on natural gas prices is relatively small and regime-dependent. My attempt to use a structural VAR to model the fundamental drivers of weather, supply, interest rate, crude oil, and coal prices is a novel approach in U.S. gas market research.

## **Model Definition**

I employ a structural vector autoregression (SVAR) for modeling the interactions between the main gas market fundamentals in an attempt to examine the transmission channels affecting natural gas prices explicitly. To constrain the feedback effects of exogeneity of some of the variables used in this analysis, I restrict their coefficients to zero. The VAR model in its reduced form can be represented as

(3)

where is a vector of *m* endogenous variables, *p* is the number of lags of each variable, and is an *m ×*1 vector ofintercepts.

The error terms are grouped into such that the error term in each equation has a zero mean and is uncorrelated over time and homoskedastic. However, the error terms can be contemporaneously correlated with errors in other equations. Therefore, is a multivariate white noise process, , where is an *m* × *m* variance-covariance matrix. I specify the VAR model with a length of six lags as identified by the Akaike Information Criterion. The SIC indicates a lag length of one; however, there is a strong autocorrelation in the error terms with one lag.

The instantaneous causality among the variables represented byin the reduced-form model does not allow for an economic interpretation of the error term. To remedy the situation, a structural model has to be identified as

(4)

where represents the identity matrix of order *m*, A is an *m* × *m* matrix of instantaneous interaction among the variables and is equal to for *i =* 0, …, *p.* Additionally, is a row vector of *m* dimension which represents the structural errors with a variance-covariance matrix . As the instantaneous causality is captured by A, is diagonal. In this way, the errors of the structural representation are assigned to a single variable and can therefore be interpreted in terms of economic theory.

## **Model Identification**

To identify the model, I place restrictions on the instantaneous coefficient matrix A. The structural representation can be achieved by imposing *m*(*m*+1)/2 restrictions. The instantaneous restrictions imposed for identification of the structural VAR is summarized in Table 2.

Table 2: Identification of the contemporaneous matrix

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Temperature | Interest Rate |  | Storage | Crude Price | Coal Price | Gas Price |
| Degree days deviation | ✶ | 0 |  | 0 | 0 | 0 | 0 |
| Change in 3-month  T-bill | 0 | ✶ |  | 0 | 0 | 0 | 0 |
| Storage deviation | ✶ | ✶ |  | ✶ | ✶ | ✶ | ✶ |
| Price of WTI | ✶ | ✶ |  | 0 | ✶ | 0 | 0 |
| Price of coal | ✶ | ✶ |  | 0 | ✶ | ✶ | ✶ |
| Natural gas price | ✶ | ✶ |  | ✶ | ✶ | ✶ | ✶ |

*Notes*: Each row represents an equation in the VAR model with the independent variables ordered in columns. The ✶ denotes the parameters estimated from the data and allow for instantaneous interaction between the variables, whereas 0 indicates that the parameter has been restricted to zero.

Since weather and interest rate are exogenous to the other variables in this analysis, they are ordered first within the matrix of contemporaneous interactions. Temperature deviations are expected to affect storage levels (via withdrawal from underground working gas) for cooling or heating purposes. Consequently, I leave the instantaneous influence of temperature on storage unrestricted.

Storage of a commodity like natural gas is expected to be affected by the prevailing interest rate due to the cost of carrying inventory. In a high-interest rate environment, storage cost increases; therefore, I leave the interaction between interest rate and storage also unrestricted. Gas storage is expected to be affected by gas price changes since inter-temporal price arbitrage is the primary economic rationale for storage operators. Additionally, gas storage is used to balance temporary divergence in supply due to unexpected market conditions such as extreme weather conditions and cross-commodity effects. Thus, contemporaneous impact of oil, coal, natural gas prices on storage is left unrestricted.

It is intuitive to allow instantaneous interaction between crude oil, coal, gas prices, and temperature deviations. Extreme cold temperatures increase the demand for heating oil and can raise the price of WTI through this channel. The price of coal may be affected by oil and gas prices since coal serves as a substitute for electricity production. Therefore, I leave the contemporaneous interaction between coal, gas, oil prices, and temperature unrestricted.

The effect of interest rate across all three commodity prices (i.e., crude oil, coal, and natural gas) is unrestricted as it has significant explanatory power on the price variability. The overshooting model of Dornbusch hypothesizes that monetary changes have real short-run effects on commodity prices (Frankel, 1986). Whenever markets adjust in response to monetary changes, those sectors of the economy that are free to move (i.e., commodities and financial assets) must bear the burden of the sluggishness of the sticky sectors (i.e., manufacturing and services).

Finally, since the price of natural gas is the main variable of interest in this research, no restriction is placed on the variables in this equation. These specifications allow for a comprehensive analysis of the immediate impacts of all variables considered in the model on natural gas prices.

# Empirical Results

## **Impulse Response Function**

The application of the VAR model concerns the evaluation of the impact of structural shocks, which can be done using the moving average (M.A.) representation. Figure 2 presents the estimated impulse response functions for the natural gas price.



Figure 2: Responses of natural gas prices to shock from the other variables

*Notes*: response is to Cholesky one s. d. innovations 2 s. e.

The impulse response of gas prices to innovations in temperature is consistent with economic reasoning. The extreme temperature has an immediate and substantial impact on the price of natural gas through demand for heating or cooling in residential and business buildings. The effect is significant and declines over time but can last for as long as ten weeks, which indicates that temperature shocks have a short-term impact on natural gas prices. Short-term interest rate innovation has no significant effect on gas prices and crude oil and coal prices, which is contrary to my a priori assumption.

Innovations from storage do not also affect gas price movement. This finding is consistent with the results of another empirical research by Wang et al. (2019), who find that the influence of storage on natural gas prices proves to be marginal.

The derived structural response of natural gas prices to crude oil and coal prices reveals significant interdependencies among energy commodities. The price of gas responds positively to innovations in both oil and coal prices. However, the pattern with which oil and coal influence gas prices is fundamentally different. Oil price shocks impact natural gas prices instantly, causing the cyclical price movement in natural gas in the short-term, but later establish a long-run relationship after that. This long-run relationship between natural gas and oil prices is plausible as there exists a physical link in their direct substitution relation in the residential heating sector.

In contrast, coal prices only affect natural gas prices with a delay, but its effect is substantial and remains stable over time and gradually declines. The strong interdependency between coal and natural gas can be attributed to the energy mix of the U.S. electricity generation industry. According to the U.S. Energy Information Administration (EIA), about 35.1% and 27.4% of total electricity generation output were from coal and natural gas, respectively in 2018. This brings about fuel competition among energy producers, which may induce a positive cross-price elasticity of these two commodities. Consequently, a rise in the price of coal implies an increase in the demand for natural gas and, therefore a resulting price increase.

Although this research focuses on the determinants of natural gas price variability, it is worth discussing the structural response of storage, as shown in Appendix 1A. The impulse response function reveals that extraordinary temperatures lead to storage withdrawals. This phenomenon is caused by the demand for temperature-sensitive natural gas in the heating and cooling of residential and commercial facilities. The response of storage flows to natural gas price shocks is insignificant, and it’s inconsistent with economic expectations. This is because an increase in natural gas prices should incentivize storage holders to withdrawal from their inventory. However, storage withdrawals occur in response to shocks in coal prices. It could be explained by the cross-commodity relationship emphasized earlier. An increase in coal prices implies high demand; therefore, electricity producers who can switch their input move to natural gas, which affects storage levels through withdrawals.

## **Forecast Error Variance Decomposition**

After identifying the structural dynamics in the natural gas market, it is appropriate to investigate the fundamental influences of each variable on natural gas price movement. I perform a forecast error variance decomposition using the results of the estimated structural VAR model. The variance decomposition splits the forecast error variance of each endogenous variable, at different forecast horizons, into the components due to each of the shocks. This provides information on their relative importance. The contributions of innovations in variables calculated through the moving average representation of the VAR model are presented in Table 3.

Table 3: Forecast error variance decomposition for natural gas price

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Period | Temperature | Interest Rate | Storage | Crude Oil Price | Coal Price | Natural Gas Price |
| 1 | 0.00 | 0.37 | 0.02 | 16.88 | 72.60 | 10.13 |
| 2 | 0.00 | 0.18 | 0.02 | 16.99 | 72.79 | 10.03 |
| 4 | 0.00 | 0.14 | 0.02 | 17.04 | 72.84 | 9.97 |
| 12 | 0.00 | 0.32 | 0.01 | 17.00 | 72.83 | 9.84 |
| 26 | 0.00 | 0.37 | 0.01 | 17.19 | 72.68 | 9.75 |
| 52 | 0.00 | 0.40 | 0.01 | 17.37 | 72.50 | 9.72 |

*Notes*: values are expressed in percentages

Temperature and storage deviations unexpectedly have no explanatory power on the price formulation of natural gas. However, the forecast errors of gas prices can be explained more precisely by developments related to coal and oil markets. Coal price variations have the most impact on natural gas price variability, with maximum explanatory power in short-term horizons (4 to 12 weeks). Long-term natural gas price development (up to 52 weeks) is heavily affected by variations in oil prices. Coal and crude oil prices account for about 90% of the gas price variance with a forecast horizon of half a year.

## **Markov Switching**

Having identified coal prices to have the most explanatory power on natural gas price development, I run a Markov process to ascertain gas price regime changes as explained by coal price variability. Coal prices are the first difference to obtain stationarity, while natural gas price series are stationary at the level.[[4]](#footnote-4) I identify a three-state Markov switching process for the interaction between natural gas and coal prices, as presented in Table 4.

Table 4: Three state Markov switching regression for gas and coal price interactions

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Coefficient | Std. Error | z-Statistic | Probability |
| Regime 1 |  |  |  |  |
| C | 2.72055 | 0.03006 | 90.50647 | 0.00000 |
| D(COALPR) | 0.20023 | 0.06242 | 3.20756 | 0.00130 |
| Regime 2 |  |  |  |  |
| C | 3.85925 | 0.04661 | 82.80654 | 0.00000 |
| D(COALPR) | 0.20015 | 0.10493 | 1.90754 | 0.05650 |
| Regime 3 |  |  |  |  |
| C | 4.96656 | 0.10550 | 47.07560 | 0.00000 |
| D(COALPR) | 0.09762 | 0.18518 | 0.52716 | 0.59810 |
| Common |  |  |  |  |
| LOG(SIGMA) | -0.90061 | 0.03500 | -25.73061 | 0.00000 |

*Notes*: Dependent variable is the natural gas price

As shown in Table 4, Regime 1 shows a robust positive co-movement between gas and coal prices. Regime 2 (with a relatively moderate co-movement) does show a discernable switch from Regime 1 as observed in the coefficients. Regime 3, however, shows a weak co-movement. Explicitly, Regime 1 dominates the Markov process with a constantly expected duration of 56 weeks which is longer than the 24 weeks duration for Regime 2. The probability of remaining in that regime on any given day of 0.982 is the highest. See Appendix A3 for a detailed summary. The results mean that when there is a strong co-movement between natural gas and coal prices, one can expect it to last for a long as a year which is a high probability. Displayed in Figure 3 are the filtered switching probabilities for the Dominant Regime 1.



Figure 3: Markov switching probabilities for Regime 1

# Conclusion

Thus far, this paper has investigated the dynamic interaction between the fundamental variables within the U.S. natural gas market. The analysis is conducted with structural VAR and Markov switching models. This approach allows me to disentangle the effects of different fundamental influences on natural gas prices. The empirical results reveal that abnormal temperatures affect natural gas prices in the short term. However, the price development of natural gas is closely tied to crude oil and coal prices in the long term, indicating the high importance of cross-commodity effects. I explicitly analyze the specific contribution of the main fundamental drivers of gas price formation within the period under study. I find that coal prices account for about 73% of the price variability of natural gas prices with a persistently strong regime switch.

The results of this research are relevant to storage operators, electricity producers, and speculative investors in strategy formation and operations. As the results of this research are compelling, it cannot be generalized as natural gas prices are mainly determined by regional supply, demand, and temperature variations (see, for example, Zhang and Ji, 2018). The approach provides an innovative framework for further research on more specific economic mechanisms within the U.S. gas market. Additionally, this model can be used to study other regions within the U.S. The current application is still restricted by the limited data on certain variables used in this research. A future attempt will be made to generalize the findings for the entire U.S. gas market when more data become available.

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Appendix A1: Impulse response functions for all variables

Appendix A2: Markov switching regression results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Dependent Variable: NATI | | | |  |
| Method: Markov Switching Regression (BFGS / Marquardt steps) | | | | |
| Date: 04/21/19 Time: 00:52 | | | | |
| Sample (adjusted): 1/02/2010 12/29/2018 | | | | |
| Included observations: 470 after adjustments | | | | |
| Number of states: 3 | | | |  |
| Initial probabilities obtained from ergodic solution | | | | |
| Standard errors & covariance computed using observed Hessian | | | | |
| Random search: 25 starting values with 10 iterations using 1 standard | | | | |
| deviation (rng=kn, seed=1891994368) | | | | |
| Failure to improve objective (non-zero gradients) after 30 iterations | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|  |  |  |  |  |
|  |  |  |  |  |
| Regime 1 | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| C | 2.720548 | 0.030059 | 90.50647 | 0.0000 |
| D(AVCOALPR) | 0.200226 | 0.062423 | 3.207557 | 0.0013 |
|  |  |  |  |  |
|  |  |  |  |  |
| Regime 2 | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| C | 3.859252 | 0.046606 | 82.80654 | 0.0000 |
| D(AVCOALPR) | 0.200152 | 0.104927 | 1.907536 | 0.0565 |
|  |  |  |  |  |
|  |  |  |  |  |
| Regime 3 | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| C | 4.966557 | 0.105502 | 47.07560 | 0.0000 |
| D(AVCOALPR) | 0.097618 | 0.185178 | 0.527158 | 0.5981 |
|  |  |  |  |  |
|  |  |  |  |  |
| Common | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| LOG(SIGMA) | -0.900607 | 0.035001 | -25.73061 | 0.0000 |
|  |  |  |  |  |
|  |  |  |  |  |
| Transition Matrix Parameters | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| P11-C | 5.228732 | 0.961162 | 5.440012 | 0.0000 |
| P12-C | 0.870704 | 1.194852 | 0.728713 | 0.4662 |
| P21-C | -0.045753 | 0.823046 | -0.055590 | 0.9557 |
| P22-C | 3.823105 | 0.614132 | 6.225220 | 0.0000 |
| P31-C | -11.52074 | 42.31433 | -0.272266 | 0.7854 |
| P32-C | -2.379374 | 0.536109 | -4.438227 | 0.0000 |
|  |  |  |  |  |
|  |  |  |  |  |
| Mean dependent var | 3.398661 | S.D. dependent var | | 0.871952 |
| S.E. of regression | 0.459022 | Sum squared resid | | 97.55474 |
| Durbin-Watson stat | 0.654502 | Log likelihood | | -297.1593 |
| Akaike info criterion | 1.319827 | Schwarz criterion | | 1.434690 |
| Hannan-Quinn criter. | 1.365017 |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

Appendix A3: Markov switching summary on the three regimes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Equation: UNTITLED | | | |  |
| Date: 04/21/19 Time: 10:25 | | | | |
| Transition summary: Constant Markov transition probabilities and | | | | |
| expected durations | | | |  |
| Sample (adjusted): 1/02/2010 12/29/2018 | | | | |
| Included observations: 470 after adjustments | | | | |
|  |  |  |  |  |
|  |  |  |  |  |
| Constant transition probabilities: | | | | |
| P(i, k) = P(s(t) = k | s(t-1) = i) | | | | |
| (row = i / column = j) | | | |  |
|  |  | 1 | 2 | 3 |
|  | 1 | 0.982160 | 0.012575 | 0.005265 |
|  | 2 | 0.020026 | 0.959010 | 0.020964 |
|  | 3 | 9.08E-06 | 0.084758 | 0.915233 |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
| Constant expected durations: | | | | |
|  |  |  |  |  |
|  |  | 1 | 2 | 3 |
|  |  | 56.05415 | 24.39618 | 11.79699 |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |

1. The observations are averages for each week ending on Friday. [↑](#footnote-ref-1)
2. The top 5 natural gas consumption states are Pennsylvania, Florida, Texas, Louisiana and California. The weights are as follows: California, 0.20; Florida, 0.13; Louisiana, 0.15; Pennsylvania, 0.12; Texas, 0.37 [↑](#footnote-ref-2)
3. HDD and CDD are widely used weather derivatives in the energy industry which are traded at the Chicago Mercantile Exchange (CME). [↑](#footnote-ref-3)
4. T- stat (gas price) = -3.546417; T- stat (difference coal price) = -20.81579 [↑](#footnote-ref-4)