Regime Switching in the Energy Market Volatility: The Role of Economic Policy Uncertainty

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Abstract

In this paper we analyze the volatility patterns of crude oil and natural gas markets in the United States, and how they have changed due to economic policy uncertainty in the pre- and post-shale era. Using Markov-Switching GARCH models, we find evidence of heterogeneous volatility regimes for both commodities (i.e., high vs. low volatility). While the volatility persistence for crude oil is similar during the two sub-periods, significant changes have occurred to the natural gas market. Natural gas during the post-2010 period is characterized by short-lived tranquil market conditions for the first regime, and periods with more persistent volatility and agitated movements in the second regime. Furthermore, using quantile regressions, we find that economic policy uncertainty indeed increases the probability of agitated market conditions of both energy markets, although this effect has dampened during the post-shale period, possibly due to the more flexible environment in producing and trading both commodities.

Keywords: Crude Oil, Natural Gas, Economic Policy Uncertainty, Volatility, Markov-Switching, Likelihood

JEL Classification: E31, E37, Q41, Q43

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1 Introduction

Recent changes in the U.S. energy sector have dramatically impacted the production and consumption of energy throughout the country. For instance, the deregulation of the natural gas market and the technological advances in the sector, of which horizontal drilling and hydraulic fracturing techniques are being utilized to produce more natural gas than ever, lowered natural gas prices throughout the country. The crude oil market is also experiencing lower prices due to the rise of shale oil production in the U.S. and the continued oversupply from major oil-producing countries, affecting the industry's financial capacity and creating a turmoil in the sector.[1] Many analysts, however, caution that the prices of non-renewable energies may experience the next bout of volatility due to U.S. economic policy uncertainty; of particular concern is the lack of clarity in trade policies and the country's unclear involvement in the international effort toward greenhouse gas mitigation.[2] Other economic policies, such as fiscal and monetary regulations, have long been found to influence energy market prices due to their vital role in inflation, economic development, and market supply and aggregate demand (Frankel, 2006; Calvo, 2008; Akram, 2009; Morana, 2013).

In this paper we analyze the volatility patterns of crude oil and natural gas market in the United States, and how they have changed due to economic policy uncertainty. Persistent changes in energy price volatility present risk to producers, industrial consumers, and investors, which in turn affects economic performance and inflation via consumption and production (Kilian, 2008, 2009; Kilian and Hicks, 2013; Baumeister and Kilian, 2016; Antonakakis et al., 2014). Hence, a better understanding of the effect of economic policy uncertainty on the energy market can provide information, and perhaps spawn actions to contain its propagation, decreasing turbulent moments in the economy.

There are at least three channels through which energy price fluctuations react to eco-

[1] See Deloitte: `https://www2.deloitte.com/content/dam/Deloitte/us/Documents/energy-resources/us-deloitte-marketPointOilPaper_09v5.pdf`, accessed on January 15, 2019.

[2] See Bloomberg: `https://www.bloomberg.com/news/articles/2017-02-06/u-s-oil-gas-prices-seen-falling-with-trump-energy-revolution`, accessed on January 15, 2019.

nomic policy uncertainty. Firstly, firm-level investment decisions are, in general, sensitive to uncertainties (Bernanke, 1983; Pindyck, 1991; Hoque and Zaidi, 2018). Bernanke (1983) introduced the concept of "option value to wait"— agents would be willing to forgo current returns to postpone irreversible investments that are of high risks. Uncertainties in macroeconomic policies, in particular, could discourage firms' investment as a result of dubious future energy demand and increased pressure on financing cost (Antonakakis et al., 2014; Kang et al., 2014; Wang et al., 2014). The resulting delayed response in quantity produced and consumed could lead to large price swings due to exogenous shocks as compared to an economy with less uncertainty (Van Robays, 2016).

Secondly, changes to energy-specific policies and regulations are expected to directly affect the supply and demand for energy products, causing price volatility in related sectors. Iledare (1995) notes that natural gas drilling activities respond significantly to economic incentives, effective tax rates, and market conditions. For instance, the possibility of including the fluids from unconventional gas and oil production under the Safe Drinking Water Act would curtail oil and gas production due to the resulting higher production cost, posing upward pressure on the supply-and-demand balance that could eventually lead to large price swings.

The third channel of how energy prices react to economic policy uncertainty is related to the trading behavior in the financial market. Behavioral finance has long outlined that "investor sentiment" significantly affects asset price fluctuations (Aboody et al., 2018; DeVault et al., 2018; Chiu et al., 2018; Qadan and Nama, 2018; Yang et al., 2018). An elevated economic policy uncertainty could lead to negative investment sentiment as risk-averse traders postpone trading activities, resulting in less speculation on financial products and consequently, affecting volatility in the energy market.[3] Zhang (2018) further notes that economic policy uncertainty may lead to inefficient capital allocation due to financial friction and exacerbated financial constraints, affecting investor sentiment and stock market returns. Qadan and Nama (2018) suggest that the economic policy uncertainty is a valid proxy for

[3]See https://www.govinfo.gov/content/pkg/CHRG-110shrg46015/pdf/CHRG-110shrg46015.pdf, accessed on March 18, 2019.

investor' sentiment in the energy market due to its predictability of crude oil returns and volatility.

While much empirical work has investigated the role of energy markets in economic development and vice versa, few have analyzed the effect of economic policy uncertainty on the volatility of crude oil and natural gas markets. The lack of recent empirical work on this aspect can be partially attributed to the absence of a reliable measure of policy uncertainty at the national level. Recently, Baker et al. (2016) proposed an index to measure economic policy uncertainty (EPU, hereinafter) at various data frequencies. Depending on the data frequency, the measure is derived from at least one of the three major metrics: newspaper coverage, federal tax provisions set to expire, and forecasters disagreement concerning policy-related macroeconomic variables. The EPU index has been shown to provide a good proxy for the uncertainties related to economic policies, presenting a high correlation with other uncertainty measures while unaffected by the political slant of newspapers (Antonakakis et al., 2014; Baker et al., 2016). Several recent papers examined the impact of economic policy uncertainty on various economic variables, including GDP growth, asset pricing, firm-level investment, inflation, and foreign direct investment, finding the EPU index to exert a significant effect on many aspects of the economy (Antonakakis et al., 2013, 2014; Wang et al., 2014; Kang et al., 2014; Wang et al., 2015; Ji et al., 2018; Kang et al., 2017a,b).

Energy markets have undergone tremendous volatility over the past several decades, directly affecting employment and investment in the economy, as well as contributing to fluctuations in the inflation and aggregate output (Ferderer, 1996). Volatility is also a key input to most of the risk management systems, for both short- and long-term business hedging strategies. A large body of literature has analyzed the volatility of energy prices, with the majority of studies focusing on the average market behavior over a long sample period using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type models (Wei et al., 2010; Hou and Suardi, 2012; Lv and Shan, 2013; Efimova and Serletis, 2014; Saltik et al., 2016). For instance, Narayan and Narayan (2007) use Exponential GARCH

(EGARCH) models and find that exogenous shocks have asymmetric and persistent effects on volatility, though the evidence is not consistent across various sub-periods.

Since GARCH models attribute shocks to the conditional variance that occurred many periods ago into the current period volatility (i.e., the so-called path-dependent problem), the estimated volatility persistence may be spurious if there are regime shifts or structural breaks in the volatility process (Lamoureux and Lastrapes, 1990; Choi and Hammoudeh, 2010). Indeed, Bauwens et al. (2014) and Ardia et al. (2018) note that many financial data present volatility breaks, and Danielsson (2019) goes so far as to argue that single-regime volatility forecasting models contributed to the 2008 global financial crisis: "*(s)tatistical pricing and risk-forecasting models played a significant role in the build-up to the crisis....the stochastic process governing market prices is very different during times of stress compared to normal times.*"

The purpose of this paper is therefore twofold: (1) to understand the volatility patterns of crude oil and natural gas markets in the United States under a regime-switching context; and (2) to investigate how the economic policy uncertainty impacts the presence of high and low volatility moments in the two markets. In particular, we seek to understand whether a high level of economic policy uncertainty increases the likelihood of volatile regimes in the two markets, and how this relationship has changed in light of the shale boom in the country. Since natural gas and oil market activities are directly related to economic performance through energy production (Kilian, 2009; Arora and Lieskovsky, 2014) as well as to policies that support the sector, we expect their volatility presents moments of high and low regimes that is adjusted according to major economic events, and consequently to economic policy uncertainty.

In the empirical analyses, we consider a two-step approach to tackle these research questions. First, we employ the Markov Switching Generalized Autoregressive Conditional Heteroscedasticity (MS-GARCH) models to capture the volatility behavior for the oil and natural gas markets in the U.S. during different regimes (i.e., high vs. low volatility). To allow the volatility regimes to differ before and after the shale boom, we consider a structural break and estimate separate MS-GARCH models for periods before and after 2010. Based on the results from the MS-GARCH models, we further investigate whether economic policy uncertainty affects the probability of a volatile regime in each energy market using quantile regressions.

We find evidence of heterogeneous volatility regimes for both commodities. In the oil market, the first regime best describes long-lived tranquil conditions and the second regime characterizes periods with less persistent volatility and agitated movements. The characteristics of the two regimes remained relatively stable in the pre- and post-2010 periods. For natural gas, the volatility regimes differ significantly across the two sub-periods, with the pre-2010 period regimes closely resemble those in the oil market. The post-2010 natural gas market, by contrast, is characterized by short-lived tranquil market conditions in the first regime, and more persistent, agitated movements in the second regime. However, the overall natural gas price volatility in both regimes has decreased drastically in the post-2010 period.

Our results further suggest that EPU significantly affects the volatility regimes of both energy markets. For crude oil, an elevated EPU is correlated with a higher likelihood of agitated market movements regardless of the initial conditions, both before and after 2010. In the natural gas market, during the pre-2010 period, EPU appears to positively affect the likelihood of agitated market conditions starting from quantile 0.6. For the post-2010 period, we only observe a significant effect of EPU when the natural gas market already presents a high likelihood of agitated movements. Moreover, after 2010, both markets appear to have become less sensitive to changes in the level of economic policy uncertainty, possibly due to the more flexible environment in producing and trading both commodities after the shale boom.

The remainder of the paper is structured as follows. Section two reviews the previous studies on economic policy uncertainty and energy market volatility. Section three and four discuss the methods and data used in the paper, respectively. Results are provided in section five. Section six concludes the paper.

2 Previous Literature on Economic Policy Uncertainty and Energy Markets Volatility

Baker et al. (2016) recently proposed an index to measure economic policy uncertainty at various data frequencies. The monthly index describes the uncertainty related to public views and economic policy-making, and is derived from three types of underlying components: (1) newspaper coverage, (2) federal tax provisions set to expire, and (3) forecasters disagreement concerning policy-related macroeconomic variables. For the daily EPU index, it is solely based on the number of articles containing at least one of the following up terms: economic (economy), uncertain (uncertainty), legislation, deficit, regulation, Congress, federal reserve or white house, from the Access World New's NewsBank service. As such, the daily index mainly reflects the public view of economic policy uncertainty. Both monthly and daily EPU indexes are found to be significantly correlated with real macroeconomic variables, and can be used to understand policy-related economic uncertainties.[4]

Since the development of the EPU index, several studies have examined how economic policy uncertainties affect various aspects of the economy. One strand of the literature analyzes the impact of the EPU on firm-level investment behavior. Using quarterly data for all companies publicly listed at the China Securities Regulatory Commission (CSRC), Wang et al. (2014) find that the level of corporate investment (capital expenditures divided by total assets at the beginning of the fiscal quarter) decreases (increases) when the policy uncertainty is high (low). However, they find that non-state owned firms respond less significantly to changes in economic policy uncertainty. Kang et al. (2014) further demonstrate that economic policy uncertainty, as well as its interaction with risks at the firm level, depresses firms' investment decisions.

[4] See `http://www.policyuncertainty.com/methodology.html` for the details on the EPU index.

A second strand of the literature examines the linkage between asset markets and the EPU. Antonakakis et al. (2013) find that except during the U.S. sub-prime crisis, EPU negatively correlates with stock market returns. This result is in direct contrast to those of Pástor and Veronesi (2013), who finds that under a general equilibrium model of government policy choices, stock market returns positively react to economic policy uncertainty. Arouri et al. (2014) examine the effect of the EPU from oil-importing countries on the stock markets in the Gulf Cooperation Council (GCC). Using panel regressions, they find that the level of the EPU in net-importing countries negatively affects stock market returns in the GCC countries, and that economic policy uncertainties in the U.S. and Europe present a higher risk on the GCC stock market than China. Given the importance of commodity markets to the overall economy, Wang et al. (2015) analyze the predictability of commodity prices on the EPU index. Their results show that including commodity prices in the forecasting model could significantly improve the forecast performance of the EPU models.

Another strand of the literature examines the interplay between the EPU and oil prices, often along with some other economic indicators. Kang and Ratti (2013) analyze the linkage between oil market shocks, stock market returns, and the EPU, finding that shocks to the oil market due to global aggregate demand not only increase real oil prices, but also decrease the level of economic policy uncertainty. The result is confirmed by Aloui et al. (2016) and Antonakakis et al. (2014), who find that on average, the EPU index negatively co-moves with crude oil market returns. Antonakakis et al. (2014) further note that while the EPU is a net transmitter of shocks in 1997-2009, after 2009 the oil sector is responsible for transmitting shocks within the system. Most recently, Ji et al. (2018) explore the impact of three different daily uncertainty measures, including the EPU, the CBOE implied volatility index (VIX), and the crude oil volatility index (OVX), on energy prices. Based on the Delta Conditional Value-at-Risk (ΔCoVar), they find that the volatility of clean energy and crude oil prices negatively responds to VIX and OVS, whereas the impact of the EPU is relatively weak, hovering around zero for the entire sample period.

The present paper contributes to the existing literature in a number of ways. Firstly, the majority of the previous studies only focus on analyzing the price behavior (or returns) of crude oil and their relations to the EPU, without considering the impact on the volatility. The importance of volatility in an investor's portfolio selection and market participants' risk management strategies has long been documented. For the energy market, price volatility also has considerable ramifications for large volume consumers that sometimes rely on short-term market purchases rather than fixed-price contracts, such as electric power plants and oil refineries. Understanding and continuously monitoring the volatility has become even more important in an era characterized by an increasingly connected global market and rising geopolitical risks.

Previous studies on energy market volatility tend to focus only on their long-term behavior. For example, Plourde and Watkins (1998) note that crude oil price volatility in 1985-1994 was higher than the volatility for nine other commodities. Regnier (2007) suggests that between 1945 and 2005 energy prices are more volatile than 95% of the products sold by domestic producers in the U.S. The literature investigating the relationship between energy market volatility and EPU is relatively limited, and presents mixed results. Shahzad et al. (2017) uncover a causal effect of EPU on crude oil volatility at its median distribution. Other suggest that the EPU index helps to forecast oil price volatility in the U.S. (Wei et al., 2017; Ma et al., 2018; Mei et al., 2019). By contrast, Bakas and Triantafyllou (2018) argue that EPU has a rather small and transitory effect on the volatility in energy markets.

Secondly, we incorporate the natural gas market into discussion due to its ever-increasing participation in the U.S. economy, especially after the shale boom. Natural gas production in the U.S. has increased roughly 50% over the past decade,[5] making it the second largest energy sector after crude oil and an integral component of the U.S. economy. Since February 2016, the U.S. has also begun exporting liquefied natural gas (LNG) from the lower 48 states, with its LNG export capacity continuing expanding at a rate that is poised to make

[5]See `https://www.csis.org/features/us-natural-gas-global-economy`, accessed December 5, 2018

the country the third largest exporter globally behind Australia and Qatar by the end of 2019. As a result, changes to the economic policy uncertainty should be aligned to both the crude oil and the natural gas markets, with the latter perhaps presenting an increasing linkage to EPU in recent years.

Thirdly, we allow the volatility to vary between high and low regimes in order to better characterize the volatility behavior under different market conditions. Previous studies have analyzed GARCH-type models' ability in characterizing oil market volatility, including the short- and long-term persistence (Pindyck, 2004; Narayan and Narayan, 2007; Salisu and Fasanya, 2013; Charles and Darné, 2017), predictive content (Sadorsky, 2006; Agnolucci, 2009; Chan and Grant, 2016; Kang et al., 2009), the presence of jumps (Chiou and Lee, 2009; Patton and Sheppard, 2015), etc. Zhang and Zhang (2015) stress the importance of considering different regimes when modeling oil price volatility, and caution that erroneous results may be generated if the regime-switching behavior is ignored in the empirical analysis. Indeed, volatility models excluding regime-switching behavior often generate unreliable forecasts of the underlying variable (Lin and Wesseh Jr, 2013; Choi and Hammoudeh, 2010; Charlot and Marimoutou, 2014; Nomikos and Pouliasis, 2011; Vo, 2009). This view is echoed by a recent empirical study of Hoque and Zaidi (2018) which suggests that global economic policy uncertainty has a greater impact on Malaysia's stock market when the volatility is high as compared to a tranquil period.

Finally, we explore the effect of the EPU on the likelihood of agitated market conditions in the oil and natural gas markets, based on the estimation results from MS-GARCH models. Using quantile regressions we measure how EPU increase/decrease the probability of volatile regimes across different initial market conditions. The combined use of the regime-switching volatility models and cross-sectional analysis allows us to shed further light on the interactions between economic policy uncertainty and energy price fluctuations.

3 Empirical Methods

GARCH models of Bollerslev (1986) have been shown an effective tool for volatility forecasting as compared to other more complex models (Hansen and Lunde, 2005). However, they tend to overestimate volatility persistence due to not considering the potential shifts in the unconditional variance of the underlying series (Dieobold, 1986; Haas et al., 2004). Here instead, we follow Haas et al. (2004) and consider Markov-Switching regimes GARCH (MS-GARCH) models to analyze the changing volatility of crude oil and natural gas prices.

Specifically, assuming y_t is the return series with $E(y_t) = 0$, the MS-GARCH model can be represented as:

$$h_{k,t} = \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 + \beta_k h_{k,t-1} \tag{1}$$

where $h_{k,t}$ is the volatility of y_t at volatility regime k. Assuming the volatility of y_t varies between low and high regimes (i.e., $K = 2$), each regime can be modeled as a first-order Markov-process with transition probabilities given by:

$$\mathbf{P} \equiv \begin{bmatrix} \mathrm{p}_{1,1} & \mathrm{p}_{1,2} \\ \mathrm{p}_{2,1} & \mathrm{p}_{2,2} \end{bmatrix}$$

where $p_{i,j} \equiv \mathbf{P}[s_t = j \mid s_{t-1} = i]$ is the probability of a transition from regime i to j. Additionally, the sum of the probabilities of being in the regime i and transit to other regimes equals one, i.e., $\sum_{j=1}^{K} p_{i,j} = 1, \forall i \in \{1, ..., K\}$. The specification in the MS-GARCH model permits a difference persistence in the conditional variance of each regime.

To estimate equation (1), we evaluate the following likelihood function:[6]

$$\mathscr{L}(\Lambda \mid \Psi_T) \equiv \prod_{t=1}^{T} f(y_t \mid \Lambda, \Psi_{t-1}) \tag{2}$$

[6] The Maximum Likelihood estimator is obtained by maximizing the logarithm form of equation (2). The implementation of MS-GARCH takes into account the K^T different volatility paths to solve the "path-dependency problem," where T is the sample size (Ardia et al., 2016).

where $\Lambda \equiv (\alpha_{0,k}, \alpha_{1,k}, \beta_k, P)$ is the vector of parameters to be estimated for different regimes k. The conditional density of y_t conditional on past information Ψ_{t-1} can be written as:

$$f(y_t \mid \Lambda, \Psi_{t-1}) \equiv \sum_{i=1}^{K} \sum_{j=1}^{K} p_{i,j} z_{i,t-1} f_D(y_t \mid s_t = j, \Lambda, \Psi_{t-1}) \tag{3}$$

where $f_D(y_t \mid s_t = j, \Lambda, \Psi_{t-1})$ represents the conditional density of y_t in regime j given past observations and model parameters, $z_{i,t-1} \equiv P[s_{t-1} = i \mid \Lambda, \Psi_{t-1}]$ is the filtered probability of state i at time $t-1$ obtained via Hamiltons filter. From the filtered probability, we estimate the probability based on the full-sample information, stable (smooth) probability of being in regime i, $sp_i \equiv P[s_{t-1} = i \mid \Lambda, \Psi_T]$.[7]

Due to the possible presence of non-homogeneous effects of positive and negative shocks, we next augment the MS-GARCH model with an asymmetric coefficient of Glosten et al. (1993). Let θ be a dummy variable related to negative returns in the sequence, the GJR Markov-Switching model (MS-GJR-GARCH) equation can be represented as follows:

$$h_t = \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 + \alpha_{2,k} y_{t-1}^2 \theta\{y_{t-1} < 0\} + \beta_k h_{t-1} \tag{4}$$

Our next step of the empirical analysis is to capture the effect of EPU on the volatility behavior of the two commodities, i.e., whether EPU affects the likelihood of crude oil and natural gas market experiencing a high-volatility regime. We consider the stable probability of a high-volatility regime estimated from the MS-GARCH models as the dependent variable. To obtain a complete picture of the relationship between EPU and volatility regimes, we rely on the quantile regression methodology developed by Koenker and Bassett Jr (1978). As compared to the conventional linear regression model, quantile regressions are more robust against outliers in the data, as well as when the data have a skewed distribution. The

[7] See Hamilton (1989, 1994) for further details.

quantile regression is described as follows:

$$sp_t = x_t^{'} \beta_q + e_t \tag{5}$$

where β_q is the vector of unknown parameters related to the quantile q^{th} of a given stable probability (sp_t).

As compared to the Ordinary Least Squares (OLS) that minimizes the sum of squared errors, the quantile regression minimizes the $\sum_t (q|e_t| + \sum_t (1-q)|e_t|)$ through linear programming methods. Using quantile regressions, we are able to capture how EPU impacts the stable probability of energy markets in different quantiles of its conditional distribution. Since the stable probability of a high-volatility regime reflects the likelihood of the market being in agitated market conditions, a non-significant β_q suggests that the probability of the energy market being in the volatile regime is not affected by variations on the level of EPU. A positively (negatively) significant β_q indicates that EPU increases (decreases) the likelihood of the market to be situated in an agitated market moment.

4 Data

We consider the nearby prices of Henry Hub (HH) and the West Texas Intermediate (WTI) futures contracts traded at the New York Mercantile Exchange (NYMEX) as a proxy for natural gas and oil prices in the U.S., respectively. Natural gas prices are calculated as the volume-weighted average price in dollars per MMBtu, and the crude oil prices are in dollars per barrel. Both price sequences are obtained from the Energy Information Administration (EIA). We deflate the two price series to 2016 U.S. dollar values to obtain their real prices. Data on the economic policy uncertainty in the U.S. are collected from the Economic Policy Uncertainty website first constructed by Baker et al. (2016). Taylor (2001) argues that high-frequency data should be considered in empirical financial market analysis to avoid possible underestimation of the speed of market adjustment common to low-frequency data. As such, we consider daily data for our analysis. It should be noted that the daily EPU is derived solely based on newspaper coverage of policy-related economic uncertainty, and, as such, primarily reflects the public's views and sentiments toward economic policy uncertainty.

The sample period of our analysis spans from January 1, 1994 to December 31, 2017. Since the primary goal of the present paper is to understand the dynamics between the energy market volatility and EPU, it is useful to first examine how the volatility has evolved in the two markets. Figure 1 plots the daily WTI crude oil and HH natural gas prices, along with their realized volatility, calculated as the squared logarithmic price returns.

As can be seen, there are several large spikes across the sample period for both volatility sequences, often coinciding with notable events in these markets. For instance, the natural gas prices were quite volatile at the beginning of the sample period, during which the market had just transitioned from regulated to deregulated trading and was still adjusting to a competitive pricing scheme. In 2001, after many years of declined production, the natural gas price went on a roller coaster ride due to increased demand and a subsequent economic downturn. The price for crude oil and natural gas both started to rise around 2002, possibly due to geopolitical factors such as the Middle East tension and increasing demand of oil from emerging countries such as China and India.

The two price sequences then peaked in mid-2008 before the financial crisis and plummeted in the second half of 2008. This pattern is reflected in the volatility sequences, both of which experienced large spikes during this period. Unlike oil prices which rebounded in 2010, natural gas prices have remained at a relatively low level since then. The low natural gas prices may largely be attributed to the popularization of the combined use of horizontal drilling and hydraulic fracturing techniques that can extract natural gas from shale and other lower-permeability formations in a cost-efficient manner. Meanwhile, due to rising shale oil production in the U.S. and an oversupply from major oil-exporting countries, starting from 2015 oil prices have been kept at a relatively low level. It is only until the end of the sample that oil prices began to rise slightly due to the OPEC oil production cut in 2014-2015.

Figure 1 further suggests the presence of volatility clustering in both markets, especially during the sub-prime crises in 2007-2009. Additionally, it appears that the volatility sequences may have undergone structural changes around 2010 as fewer spikes were observed in the latter sample period, reflecting the relative stability of both markets due to a boost in the U.S. production and a stagnating global economy. Figure 1 suggests that there might have been two distinct periods for the oil and natural gas volatility, i.e., pre- and post-2010. We therefore use the Chow test[8] to determine whether there had been a structural break around this period. Results confirm our prior expectations of different volatility behavior before and after 2010 as the Chow test rejects the null hypothesis of homogeneous coefficients across the two sub-periods. Hence, we divide our sample into two sub-periods: pre-2010 that ranges from 1994 to 2009, and post-2010 spanning from 2010 to 2017.

Table 1 presents the summary statistics of the EPU index, and crude oil and natural gas returns for sub-sample I (01/01/1994 to 12/31/2009) and sub-sample II (01/01/2010 to 12/31/2017). For both sub-samples, none of the sequences are normally distributed according to the Jarque-Bera (JB) normality test. Additionally, based on the Box-Pierce Q^2 statistic, we reject the null hypothesis of white noise, suggesting that all three series are auto-correlated. The ARCH test suggests the presence of autoregressive conditional heteroscedastic (ARCH) effects in all series. Lastly, the Augmented Dickey and Fuller (ADF) test suggests that the return series are stationary. For all three series, the post-2010 period presents less variability (standard deviation) with lower maximum values as compared to the pre-2010 period.

5 Results

Based on the statistical properties of the data and the proposed methods discussed in section 3, we first analyze the univariate behavior of each return series in the pre- and post-2010

[8]The Chow test is based on two linear regressions in non-overlapping sub-samples, before and after 2010, to determine whether the coefficients are statistically different across the samples.

periods and examine how their volatility has changed between high and low regimes across these two sub-periods. Based on the univariate results, we next estimate the relationship between the two markets' probabilities of experiencing a volatile regime and the EPU to shed light on the impact of policy uncertainty on the energy market volatility behavior.

5.1 Univariate GARCH modeling

Our baseline model is a GARCH (1,1) specification with a normally distributed error term. To account for the possibility of different volatility regimes, we next estimate an MS-GARCH model considering two possible regimes (i.e., low and high). We consider a model with normally distributed innovations as well as with Student-t distributed innovations. The latter specification captures "fat-tails" typical to the distributions of financial time series. We also allow positive and negative shocks to have different effects on volatility by estimating the GJR-MS-GARCH model developed by Glosten et al. (1993). Finally, we present the log-likelihood values and the diagnostic test statistics for the standardized residuals of the GARCH models ($\hat{\varepsilon} = \frac{\varepsilon}{\sqrt{h_t}}$). The results for the mean equation (Panel A), volatility equation (Panel B), and residual diagnostic test statistics (Panel C) for the two sub-samples, pre- and post-2010, are provided in the Appendix (Tables A1–A4).

For crude oil, model selection results based on the Akaike information criterion (AIC) suggest that the returns series should be modeled as an ARMA (1,5) and MA(1) for the pre-2010 and post-2010 periods, respectively. There is also a change on the mean equation for the natural gas series during the two sub-periods; before 2010, the AIC suggest an ARMA(1,1), while for the period after 2010, an MA(1). The coefficients for the autoregressive (AR) and moving-average (MA) terms for both energy commodities are all highly significant. For the volatility estimation, model diagnostic tests in Tables A1–A4 (panel C) suggest that the baseline GARCH specification present satisfactory performance across both commodities and sub-periods. However, the baseline specification may overestimate volatility persistence if there exist shifts in the unconditional variance of the underlying series (Dieobold, 1986;

Haas et al., 2004).

Of the two MS-GARCH specifications which account for regime-shifting, the one with Student t-distributed innovations performs better according to AIC, BIC and Log-Likelihood values, and it is also able to remove the remaining ARCH effects in the volatility sequence. Additionally, the MS-GARCH with Student-t distributed innovations is preferred over the MS-GJR-GARCH based on the diagnostic tests of standardized residuals. Overall, of the four univariate models presented, the MS-GARCH model with t-distributed innovations appears to present the most satisfactory overall performance for both energy markets. Results of the preferred models for crude oil and natural gas markets, i.e., the MS-GARCH models with t-distributed innovations, are presented in Tables 2 and 3, respectively.

Before delving into the details of the estimation results, it is useful to examine whether the preferred MS-GARCH models are able to efficiently classify the occurrence of different regimes in the sample period. We therefore test the quality of regime classification using the regime classification measure (RCM) of Ang and Bekaert (2002). Instead of focusing on the properties of the residuals, the RCM provides a point statistic based on the stable probability. To efficiently conduct inference regarding the regime, an MS-GARCH model should classify high and low regimes with high probability, in other words, sp_t closer to 0 or 1; and inferior models may provide sp_t closer to 0.5 (Ang and Bekaert, 2002). The RCM produces a range from 0 to 100, in which a value of 0 means a perfect regime classification, while 100 indicates that no information on the regimes is revealed. The RCM statistics can be computed as follows:

$$RCM = 400\frac{1}{T}\sum sp_t(1 - sp_t) \tag{6}$$

where sp_t is the stable probability of a given MS-GARCH model. Since the true regime is a Bernoulli variable, the RCM statistics is a sample estimate of the variance of a probability series. Table 4 reports the RCM statistics for the MS-GARCH model with t-distributed innovations for crude oil and natural gas. Our estimated RCM statistics are relatively low (ranging between 5 and 55), especially if compared to those found in Ang and Bekaert

(2002) and Basher et al. (2016), and similar to those reported in Choi and Hammoudeh (2010). Therefore, the MS-GARCH model with t-distributed innovations appears to classify the occurrence of different regimes over the two sample periods efficiently for both energy markets, with the MS-GARCH for crude oil presenting a higher efficiency.

Regarding the volatility behavior for the pre-2010 period, the parameters in panel B of Table 2 suggest rather distinct volatility patterns for crude oil during the two regimes, i.e., regime 1 (lower average volatility) vs. regime 2 (higher average volatility), with a high-to-low volatility ratio of 2.84. Natural gas, on the other hand, presents a less significant difference between regimes 1 and 2 — the high-to-low ratio is 1.15 with the volatility being 72.4 and 62.8, respectively (see Panel B of Table 3). The percentage of regime 2 (high volatility) for natural gas and oil during the pre-2010 period is 24.8%, 2.2%, respectively. Although the duration of the high volatility regime in both markets is close to 1 day, the low volatility regime lasts much longer in the oil ($\approx$ 46 days) than the natural gas ($\approx$ 4 days) market.

After 2010, both energy markets present less volatile behavior in the two regimes. Despite the decline in volatility, as can be seen in Tables 2 and 3, the probability of regime 2 (high volatility) for natural gas and crude oil upsurged, hitting 54.6% and 4.8%, respectively. The two regimes in the crude oil market remain rather distinguishable, with the high-to-low ratio reaching 4.06. For natural gas, the two regimes present more distinct unconditional volatilities as compared to the pre-2010 period—the high-to-low ratio is 2.09 (1.15 in sub sample I). For comparison, Choi and Hammoudeh (2010) find the high-to-low volatility ratio in the WTI crude oil market to be 2.21 between 1990 and 2006, the highest among all five commodities they investigated. Our results suggest that crude oil in 1994-2009 has a similar sensitivity to volatility switches as the pre-2006 period examined in Choi and Hammoudeh (2010), and after 2010 the market has become more sensitive to volatility switches. Natural gas prices present lower switch volatility compared to the oil market, but its sensitivity increased in recent years.

Turning next to the ARCH coefficient ($\alpha_{1,k}$). For all models, the first regime volatility is less sensitive to changes in past returns than the second regime. The volatility persistence ($\alpha_{1,k} + \beta_{1,k}$) for crude oil is similar across the two sub-samples: the low volatility regime (regime 1) is more persistent than the high volatility regime. Natural gas, on the other hand, presents higher volatility persistence in regime 1 for the pre-2010 period, while after 2010 regime 2 becomes more persistent.

Overall, the MS-GARCH results suggest that the crude oil market volatility can be summarized as follows: the first regime presents long-lived tranquil market conditions and the second regime portrays agitated movements with spikes on the volatility process; although the volatility has declined after 2010, the behavior of regime-switching volatility in terms of the high-to-low ratio and persistence remains similar across the two sub-periods. For natural gas, however, the volatility pattern differs significantly before and after 2010: in the post-2010 period regime 1 best describes short-lived tranquil market conditions and regime 2 characterizes periods with more persistent volatility and agitated movements; in the pre-2010 period the two regimes present rather comparable level of volatility, with the lower-volatility regime showing more persistence.

Figure 2 plots the probability of being in the high-volatility regime for crude oil and natural gas derived from the MS-GARCH models. The stable probability of crude oil being in a volatile regime is not as persistent as for natural gas, and it spikes in distressed economic moments such as the abrupt decline in oil consumption from Asian countries in 1996-1998, the U.S. financial crises in 2007-2008, the OPEC production cut in 2016-2017, to name just a few. Additionally, the dynamics of the stable probabilities for crude oil has not changed drastically during the sample period, as also suggested by Table 2. Despite the overall decline in volatility, the number of agitated moments in the crude oil market has increased after 2010. However, these moments remain rather short-lived. We also note that the majority of the stable probabilities for oil are close to either 0 or 1, corroborating the high efficiency of the MS-GARCH model in classifying different regimes for crude oil as suggested by the RCM statistics discussed earlier.

A similar analysis can be employed for the natural gas market. As can be seen in Figure 2, the natural gas market presents larger and more persistent swings in the stable probability of a volatile regime after 2010. Before 2010, the natural gas market was strongly linked to the crude oil market, and the probability of natural gas being in the volatile regime follows a similar pattern as the oil. After 2010, although the ever-increasing natural gas production has significantly decreased the overall market volatility, the likelihood of natural gas prices experiencing agitated market conditions has, in fact, increased. Scarcioffolo and Etienne (2018) show that the natural gas market in the U.S. has become less connected in the post-shale era due to transmission bottlenecks and an increasing level of speculation. These relative persistent agitated market moments may therefore be a reflection of declining market linkage that makes the Henry Hub prices more susceptible to exogenous shocks.

5.2 The Role of Economic Policy Uncertainty on Energy Market Volatility

The second step of our empirical analysis is to investigate whether economic policy uncertainty exerts an impact on the likelihood of crude oil and natural gas prices experiencing volatile moments. Understanding this relationship is important to both policy-makers and market participants; having the ability to predict moments of increased volatility due to changes in economic policy uncertainties can help them to adapt, and perhaps take actions towards the volatile scenario. To obtain a clearer picture of this relationship, we also consider several macroeconomic and financial variables that are linked to energy market volatility.

Firstly, under the classic theory of storage, storage plays a crucial role in stabilizing demand and supply shocks (Karali and Ramirez, 2014). Changes in the level of stocks above or below the expected level would affect commodity prices and volatility (Ng and Pirrong, 1994; Mu, 2007; Suenaga and Smith, 2011). Inventory data for crude oil and natural gas are obtained from the EIA. For crude oil, we use the "Weekly U.S. Ending Stocks of Crude Oil" series in thousand barrels, while for natural gas, we use "Weekly Lower 48 States Natural

Gas Working Underground Storage" in billion cubic feet. From the level series, we calculate the percentage changes in inventories from one period to the next ($\%\Delta Inventory$).

Following Behmiri et al. (2019) and Büyükşahin and Robe (2014), we consider the Aruoba-Diebold-Scotti (ADS) business conditions index (Aruoba et al., 2009) to represent business cycles in the U.S. The ADS was constructed to track real business conditions at high frequency. Positive (negative) indicates progressively better-than-average (worse-than-average) conditions. The index is measured on a weekly basis, and the data are obtained from the Federal Reserve Bank of Philadelphia.

Given the impact of exchange rates on commodity prices (Harri et al., 2009), we also consider the trade-weighted U.S. dollar index from the Federal Reserve Bank of St. Louis. Finally, we include a dummy variable to represent moments of recessions according to the National Bureau of Economic Research. Since the inventory levels and the ADS index are only available on a weekly basis, and our dependent variable, the probability of the market experiencing a volatile regime is defined on a daily basis, we follow Karali and Ramirez (2014) to interpolate the weekly series to daily data by assuming a step function.

Our main hypothesis is that EPU significantly affects the likelihood of a volatile regime occurring in the two markets. We do so by considering the daily EPU that reflects the public view regarding the economic policy uncertainty as constructed by Baker et al. (2016). We argue that the dynamics between EPU and energy market' stable probability presents a lead/lag relationship. An elevated level of EPU might deter physical and financial investments due to "option values to wait" and "investment sentiment", translating into higher market volatility as the demand and supply have to adjust to the new market conditions. Additionally, using the lagged EPU could help minimize the "reverse causality" problem that variations in energy market volatility may feed back into EPU.

Table 5 provides the correlation between EPU and the stable probability of being in regime 2, or the high-volatility regime for crude oil and natural gas. Consistent with our prior expectations, EPU is positively correlated with both stable probabilities, and the correlation is stronger in the pre-2010 period than the second sub-sample. Additionally, the correlation between the two stable probabilities has decreased after 2010, suggesting that the oil and natural gas volatilities have been driven more by market-specific fundamentals in recent years as compared to the pre-shale period.

We next use quantile regressions to estimate the effect of EPU on the probability of the market being in regime 2. The macroeconomic and financial variables described above are included as the control variables. Figures 3 and 4 plot the coefficients of lagged EPU across various quantiles of the stable probability for crude oil and natural gas, respectively.[9] For comparison, we also include the OLS regression coefficients in the graphs. As can be seen, with the exception of the natural gas market in the second sub-sample, the OLS regression results suggest that on average, the EPU has a positive and significant effect on the likelihood of agitated market conditions. However, results from quantile regressions point to rather heterogeneous effects of EPU across different quantiles of stable probability.

Focusing first on the crude oil market, Panel (a) of Figure 3 indicates that in the first sub-sample, EPU significantly increases the likelihood of agitated market conditions starting from quantile 0.3, with the magnitude of the effect increases sharply as we move to higher quantiles. The stable probability of agitated moments appears to become less sensitive to EPU in the post-2010 period, as we only observe a positive effect after quantile 0.6.

For natural gas, the EPU index exerts a positive and significant effect on the stable probability of agitated market conditions after quantile 0.6 in the pre-2010 period, and the magnitude of the effect increases at higher quantiles. This pattern appears to be rather similar to the pre-2010 oil market, perhaps due to the close linkage between the two commodities before the shale boom (Hartley et al., 2008; Brown and Yücel, 2008). The post-2010 natural gas market, on the other hand, is characterized by an inverse U-shaped relationship between EPU and the stable probability of agitated market conditions, as shown in Panel (b) of Figure 2. Except for the quantiles between 0.6 – 0.7 when the EPU has a positive significant

[9]The result for the other variables are available from the authors upon request.

effect on the volatility regimes, the estimated coefficients are not statistically significant.

Figures 3 and 4 suggest that the effect of EPU on the likelihood of volatile regimes differs before and after 2010 in both markets. As previously discussed, the energy production boom since 2010 due to the exploration of shale and low- permeability reserves across the country has transformed the energy industry. One of the main changes lies in the production efficiency; shale producers can react faster to price changes than conventional oil and gas producers, and the supply elasticity for shale oil and gas can be four times the conventional production (Bjørnland et al., 2017; Yücel, 2018). Moreover, the shale boom has lowered the U.S. dependence on foreign oil and gas, with crude oil imports declined from 51% of the total consumption in 2004 versus 30% today (Yücel, 2018). For natural gas the total reduction was around 41.8% during that period. The oversupply of natural gas has also changed how other sectors interact with the energy sector. The power generation, vehicle fuel, industrial, and commercial sectors have all increased the consumption of natural gas since 2010, and their demand is expected to continue to grow at a fast pace in the next decade.[10]

The relatively rigid production, along with a thinner market prior to 2010 (especially for natural gas), might have constrained how producers and investors adapt at increments on the economic policy uncertainty in the country. As a result, the EPU exerts a large effect on the probability of volatile regimes in both markets. After 2010, market participants might have more flexibility to trade and produce crude oil and natural gas, making both markets more independent from changes in the level of economic policy uncertainty.

Another implication of Figures 3 and 4 is that the effect of EPU on the likelihood of agitated market conditions differ between crude oil and natural gas. To interpret these results, it is useful to examine the distributional properties of the two stable probability sequences. As can be seen in Table 6, the distribution is highly positively-skewed for crude oil before 2010, with relatively few short-lived agitated moments (e.g., at 0.95 quantile the stable probability of volatile regime is only 6.42%). The probability of agitated market

[10]See `https://www.eia.gov/todayinenergy/detail.php?id=35792`, accessed November 10, 2018.

conditions for natural gas, on the other hand, is relatively more centered (at 0.95 quantile the probability of a volatile regime is 77.55%).

Combining Figures 3 and 4 along with Table 6, we can quantify the effects of EPU on the volatility regimes in the two markets. For example, in the pre-2010 crude oil market, at a stable probability of 6.42% (quantile 0.95), a one-standard-deviation increment on the level of EPU will increase, on average, the likelihood of agitated moments by 6.40 percentage point. At a similar likelihood, the effect of EPU on the natural gas probability is not significant. It is not until the 0.7 quantile when the likelihood of agitated market conditions is roughly 29% we observe a significant effect from EPU. After 2010, crude oil is still affected by the EPU at low levels of stable probability (although at higher quantiles), whereas the natural gas market is only affected by the EPU when faced with a relatively higher chance of turbulent moments.

The large differences in how the oil and gas volatility regimes respond to EPU might be attributed to the structure of the two markets. The crude oil and natural gas markets differ in many ways; while oil is one of the most economically mature commodity markets in the world, natural gas is still in a transition and developing stage.[11] The crude oil market is internationally integrated, with oil prices at different locations overall move in the same direction.[12] By contrast, the degree of market integration is significantly lower in the natural gas market (Li et al., 2014; Scarcioffolo and Etienne, 2018). It requires a complex pipeline system and/or LNG stations to transport natural gas across regions. Due to the large capital investment required to transport natural gas and the resulting transmission bottlenecks, the price of natural gas can differ substantially across regions, with price changes mainly reflect region-specific factors. Additionally, the open interest and trading volume in the crude oil futures market is much higher than for natural gas,[13] [14] as market participants across the

[11]See `https://www.iea.org/gas2018/`, accessed on June 28, 2019

[12]See `https://www.eia.gov/todayinenergy/detail.php?id=35792`, accessed on November 10, 2018.

[13]See `https://www.cmegroup.com/education/articles-and-reports/henry-hub-natural-gas-futures`, accessed on June 28, 2019

[14]See `https://www.cmegroup.com/trading/energy/light-sweet-crude-oil.html`, accessed on June 28, 2019

world seeking hedging and speculative positions. Consequently, crude oil prices tend to reflect geopolitical events across the world, while natural gas prices reflect more regional events such as weather, natural disasters, pipeline construction, etc.

Hence, we expect that oil and gas market participants to behave differently when faced with an increase in economic policy uncertainty. For oil, due to the large number of investors involved, changes in EPU might trigger larger and more significant changes in investment and trading behavior, even when the likelihood of agitated market conditions is low. As pointed out by Wei et al. (2017), EPU can simultaneously change the expectations of oil consumers, producers, and speculators, and hence affect the crude oil price volatility. For the natural gas market, since the market is less-integrated and relatively thinner, market participants may be less sensitive to aggregate economic policy uncertainties and are less likely to change their behavior when the likelihood of market turbulence is low.

After 2010, the EPU index appears to only affect the probability of volatile moments at higher likelihoods for both markets. However, as the likelihood of agitated market conditions in the natural gas market escalates quickly, the effect of EPU weakens. It is possible that when agitated market conditions are imminent, the majority of market participants have already modified their investment expectations, dampening the effect of EPU.

6 Conclusions

Energy markets play a key role in the U.S. economy at both the micro and macro scales. Understanding the dynamic volatility behavior in the energy markets are pertinent to both policy markets and market participants. In this paper, we evaluate the effect of economic policy uncertainty on the volatility pattern in the U.S. crude oil and natural gas markets, as well as how this relationship has changed in light of the new era of abundant market supply. We first estimate Markov-Switching Generalized Autoregressive Conditional Heteroskedasticity (MS-GARCH) models to capture regime switching in the volatility series before and after 2010. We then estimate the effect of economic policy uncertainty on the estimated stable probability of volatile regimes while accounting for important macroeconomic and financial variables.

Our results suggest that the MS-GARCH model that accounts for "fat-tails" in the distribution performs the best among the models considered. We identify two regimes in the volatility process, i.e., regime 1 (with lower average volatility) vs. regime 2 (with higher average volatility) in both markets. These models are able to efficiently classify the occurrence of different regimes. The volatility persistence for crude oil is similar during the two subperiods (i.e., before and after 2010), where regime 1 presents more persistent behavior. In other words, the crude oil markets first regime presents long-lived tranquil market conditions while the second regime portrays agitated movements with spikes on the volatility process. Natural gas, on the other hand, presents more persistence in regime 1 prior to 2010, while after 2010, regime 2 becomes more persistent. Natural gas during the post-2010 period can be characterized by short-lived tranquil market conditions for the first regime, and periods with more persistent volatility and agitated movements in the second regime. Although moments of high volatility have increased after the shale gas boom, the unconditional volatility of both regimes for natural gas has declined during this period.

We find that overall, EPU exerts a positive and significant effect on the likelihood of high-volatility regimes for both markets. However, the effect has declined in the second sub-sample, suggesting that the oil and gas markets have become less sensitive to economic policy uncertainty shocks after the shale boom. The upsurge and more efficient production allow market participants to respond faster to exogenous shocks, dampening the impact of EPU on volatility as compared to the pre-2010 period.

Quantile regression results further suggest that changes in EPU affect the oil and natural gas markets differently, and agents appear to change their investment expectations heterogeneously depending on the initial likelihood of agitated market conditions. For the pre-2010 crude oil market, EPU has a positive and significant effect on the likelihood of agitated regime except for quantiles below 0.3. The effect of EPU on oil volatility regimes is confined to quantiles above 0.7 in the post-2010 period. We also observe EPU affects the likelihood of agitated moments in the natural gas market differently before and after 2010. Prior to 2010, EPU exerts a positive impact on the likelihood of agitated moments in the natural gas market at higher quantiles (greater than 0.6). After 2010, the effect of EPU is only significant between the quantiles 0.6–0.7, corresponding to 83.08% - 97.71% probability to be in a high-volatility scenario.

Our results provide insights for both individual investors and policymakers on how economic policy uncertainty in the U.S. affect volatility dynamics in energy markets. For investors, it is important to understand how energy markets respond to abrupt changes in policy-related uncertainty since it affects their portfolio returns. Additionally, during periods of persistent turbulence attention should be drawn to the relationship between economic policy uncertainty and the nature of the markets since they present heterogeneous regime dependence. Moreover, policymakers should be cautious in formulating regime-dependent policies aimed to undermine the possible "wait to invest" effect in the sector since it might spillover to the energy futures market, impacting how private investors behave.

One limitation with the present paper is that the EPU index we used is constructed based on the overall uncertainty in the economy, and may not necessarily reflect the uncertainties specific to the energy markets. Deriving an energy-policy related uncertainty index similar to the EPU index of Baker et al. (2016) would shed further light on how the energy sector responds to changes in energy-specific uncertainties. The development of this new index could constitute potential avenues for further research as a way to better comprehend how investors and producers respond to specific policy changes, and thus providing insights on the regulations or market systems needed to combat extreme market volatility.

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Tables and Figures

Table 1: Summary Statistics

	Obs	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis	J-B Normality	ARCH (10)	ADF	Q^2
Sub-sample I - from 01/01/1994 to 12/31/2009											
EPU	4165	3.38	719.07	87.61	66.91	2.49	10.84	24732***	3204.2***	-13.48***	6315.7***
Return WTI	4165	-17.39	28.96	0.02	2.61	0.17	8.17	11611***	310.98***	-49.05***	55.09***
Return HH	4165	-37.58	35.77	0.00	3.96	0.35	8.09	11468***	153.62***	-47.485***	29.953***
Sub-sample II - from 01/01/2010 to 12/31/2017											
EPU	2086	3.32	548.47	107.03	64.01	1.61	4.05	2331.4***	3825.48***	-6.80***	5963.1***
Return WTI	2086	-11.76	15.70	-0.01	2.19	0.20	5.12	2302.8***	185.54***	-34.44***	25.56***
Return HH	2086	-18.64	20.67	-0.03	2.86	0.25	3.81	1288.8***	80.32***	-33.07***	17.03*

Note: Jarque-Berra (J-B) test is the Jarque and Bera (1980) normality test statistic. The test follows a χ^2 distribution with 2 degrees of freedom. $Q^2(10)$ is the BoxPierce Q-statistic of order 10 on the squared returns. ADF is the Augmented Dickey and Fuller (1979) unit root test statistic. ARCH test is the Lagrange multiplier test.

Table 2: Univariate GARCH with Student distributed innovations - Crude oil

	Sub-sample I (01/01/1994-12/31/2009)		Sub-sample II (01/01/2010-12/31/2017)	
Panel A - Mean Equation				
AR(1)	0.857***	(0.040)		
MA(1)	-0.876***	(0.042)	-0.092***	(0.022)
MA(2)	-0.061***	(0.021)		
MA(3)	0.055**	(0.022)		
MA(4)	0.004*	(0.021)		
MA(5)	-0.046**	(0.017)		
Panel B - Variance Equation				
μ_1	0.031***	(0.001)	0.015***	(0.001)
$\alpha_{1,1}$	0.021***	(0.001)	0.027***	(0.001)
β_1	0.972***	(0.001)	0.963***	(0.001)
μ_2	31.753***	(0.153)	18.611***	(0.124)
$\alpha_{2,1}$	0.054***	(0.003)	0.27***	(0.005)
β_2	0.003***	(0.002)	0.000	(0.000)
Stable Probability ($D = 1$)	0.978		0.952	
Stable Probability ($D = 2$)	0.022		0.048	
Duration ($D = 1$)	45.662		20.921	
Duration ($D = 2$)	1.022		1.05	
Unconditional Volatility ($D = 1$)	32.358		19.73	
Unconditional Volatility ($D = 2$)	92.096		80.032	
Panel C - Standardizde residual diagnostics				
$\hat{\varepsilon}$ Mean	0.015		-0.017	
$\hat{\varepsilon}$ Std. error	1.005		0.996	
$\hat{\varepsilon}$ Variance	1.01		0.993	
$\hat{\varepsilon}$ Skeness	-0.287		-0.344	
$\hat{\varepsilon}$ Kurtosis	4.032		4.331	
Jarque-Bera	2882.9***		1676.4***	
Arch Effect	10.209		2.927	
Ljung-Box (20)	19.253		15.252	
Log-Likelihood	-9336.761		-4270.08	
AIC	18693.522		8560.157	
BIC	18756.866		8616.587	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.

Table 3: Univariate GARCH with Student distributed innovations - Natural gas

	Sub-sample I (01/01/1994-12/31/2009)		Sub-sample II (01/01/2010-12/31/2017)	
Panel A - Mean Equation				
AR(1)	0.680***	(0.112)		
MA(1)	-0.732***	(0.103)	-0.058***	(0.022)
Panel B - Variance Equation				
μ_1	0.184***	(0.001)	0.015***	(0.001)
$\alpha_{1,1}$	0.074***	(0.001)	0.004***	(0.001)
β_1	0.914***	(0.001)	0.99***	(0.001)
μ_2	5.879***	(0.048)	0.914***	(0.012)
$\alpha_{2,1}$	0.078***	(0.001)	0.05***	(0.001)
β_2	0.658***	(0.002)	0.872***	(0.001)
Stable Probability ($D = 1$)	0.752		0.454	
Stable Probability ($D = 2$)	0.248		0.546	
Duration ($D = 1$)	4.039		1.83	
Duration ($D = 2$)	1.329		2.205	
Unconditional Volatility ($D = 1$)	62.762		25.949	
Unconditional Volatility ($D = 2$)	72.373		54.301	
Panel C - Standardizde residual diagnostics				
$\hat{\varepsilon}$ Mean	0.006		-0.012	
$\hat{\varepsilon}$ Std. error	0.972		1.001	
$\hat{\varepsilon}$ Variance	0.946		1.001	
$\hat{\varepsilon}$ Skeness	0.513		0.195	
$\hat{\varepsilon}$ Kurtosis	5.442		2.853	
Jarque-Bera	5328.9***		723.52***	
Arch Effect	11.459		8.343	
Ljung-Box (20)	22.357		24.130	
Log-Likelihood	-4000.776		-5001.611	
AIC	22151.25		10023.221	
BIC	22214.594		10079.651	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.

Table 4: Regime classification measure (RCM)

RCM	Crude oil	Natural gas
Sub-sample I (01/01/1994 - 12/31/2009)	5.197	55.275
Sub-sample II (01/01/2010 - 12/31/2017)	13.755	33.921

Note: $RCM = 400\frac{1}{T}\sum p_t(1 - p_t)$

Table 5: Correlation between EPU and energy market high volatility stable probability

Correlation	EPU	Crude oil	Natural gas
Sub-sample I (01/01/1994 - 12/31/2009)			
EPU	1.000		
Crude oil	0.203***	1.000	
Natural gas	0.189***	0.194***	1.000
n=	4165		
Sub-sample II (01/01/2010 - 12/31/2017)			
EPU	1.000		
Crude oil	0.045**	1.000	
Natural gas	0.057***	0.063***	1.000
n=	2086		

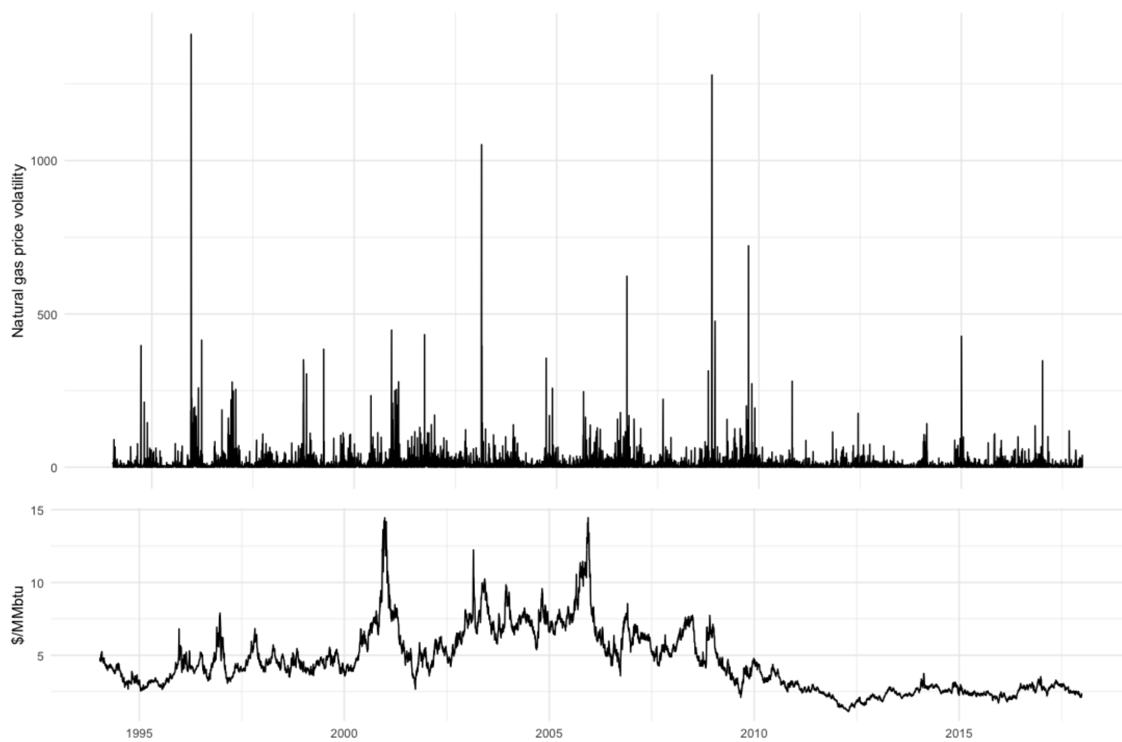
Note: Ordinary Pearson correlation method is used for calculating p-values.

Table 6: Distribution of the crude oil and natural gas stable probability of high volatility regimes

	Sub-sample I (01/01/1994 - 12/31/2009)		Sub-sample II (01/01/2010 - 12/31/2017)	
Quantile	Crude oil	Natural gas	Crude oil	Natural gas
0.1	0.07%	3.00%	0.65%	1.43%
0.2	0.10%	7.23%	0.86%	5.54%
0.3	0.13%	10.92%	1.08%	11.39%
0.4	0.17%	15.01%	1.38%	24.51%
0.5	0.22%	18.43%	1.74%	59.06%
0.6	0.32%	22.91%	2.33%	83.08%
0.7	0.48%	29.01%	3.18%	91.92%
0.8	0.92%	38.39%	4.85%	97.71%
0.9	2.72%	55.24%	9.04%	99.47%
0.95	6.42%	77.55%	17.14%	99.79%

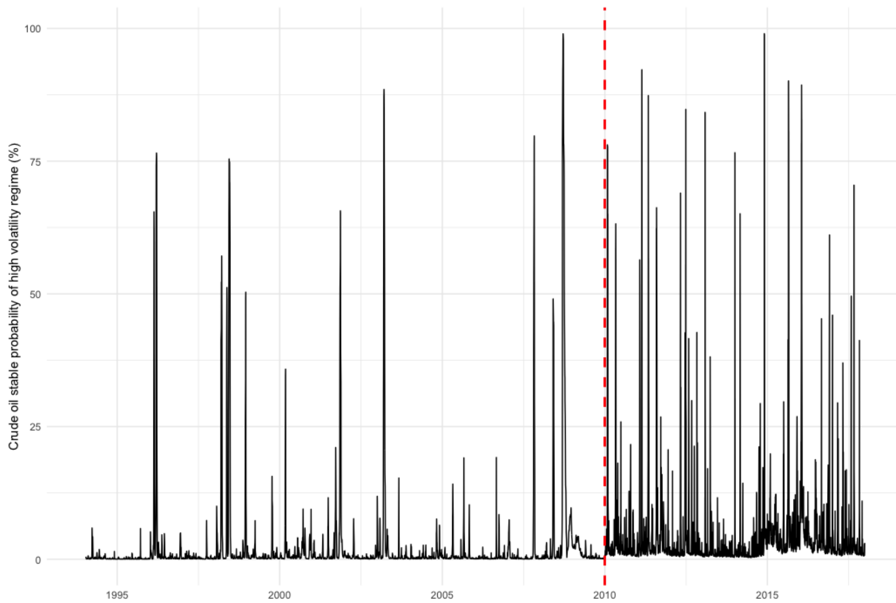
Figure 1: Daily volatility and price series of West Texas Intermediate (WTI) crude oil, and Henry Hub (HH) natural gas, January, 1994 - December, 2017

(a) Crude oil

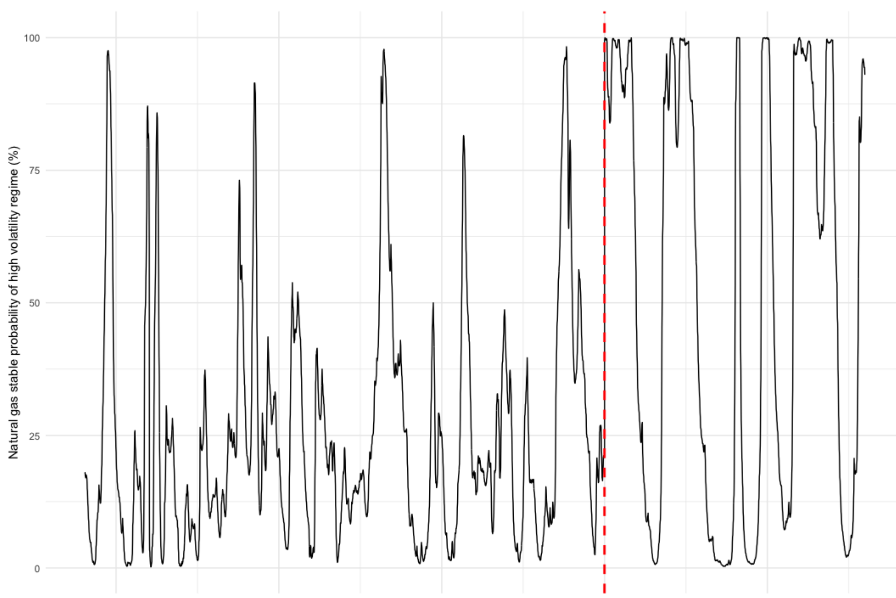


(b) Natural gas

Figure 2: Daily stable probability of high volatility regime of West Texas Intermediate (WTI) crude oil, and Henry Hub (HH) natural gas, January, 1994 - December, 2017



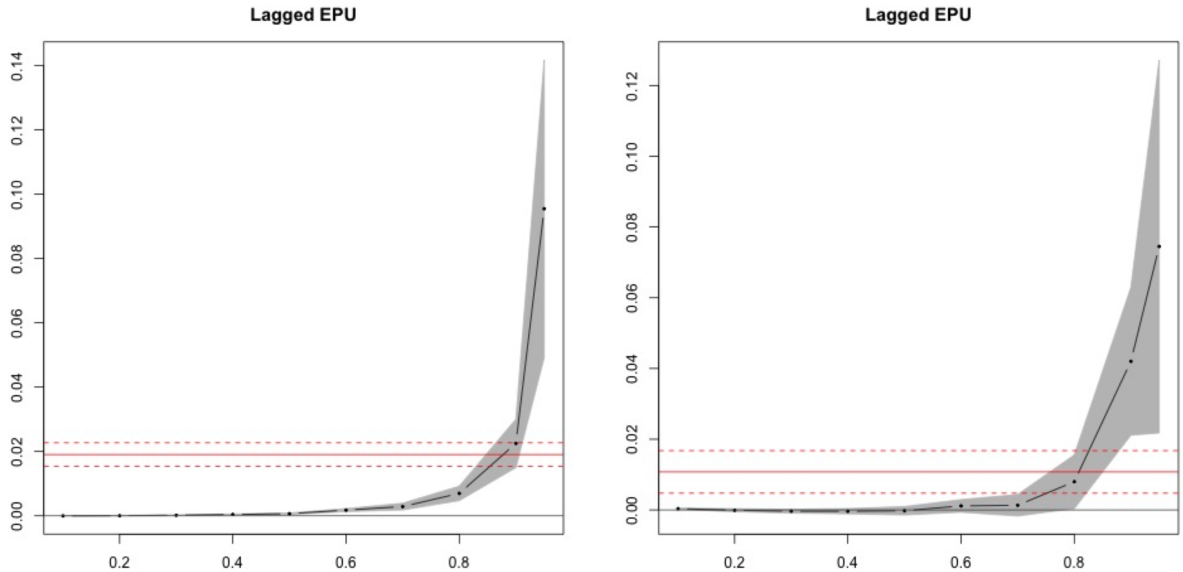
(a) Crude oil



(b) Natural gas

Note: The dashed-red line separate the two sub-samples. Sub-sample 1 (01/01/1994 – 31/12/2009) and Sub-sample II (01/01/2010 – 12/31/2017)

Figure 3: Quantile Regression using OLS for crude oil stable probability

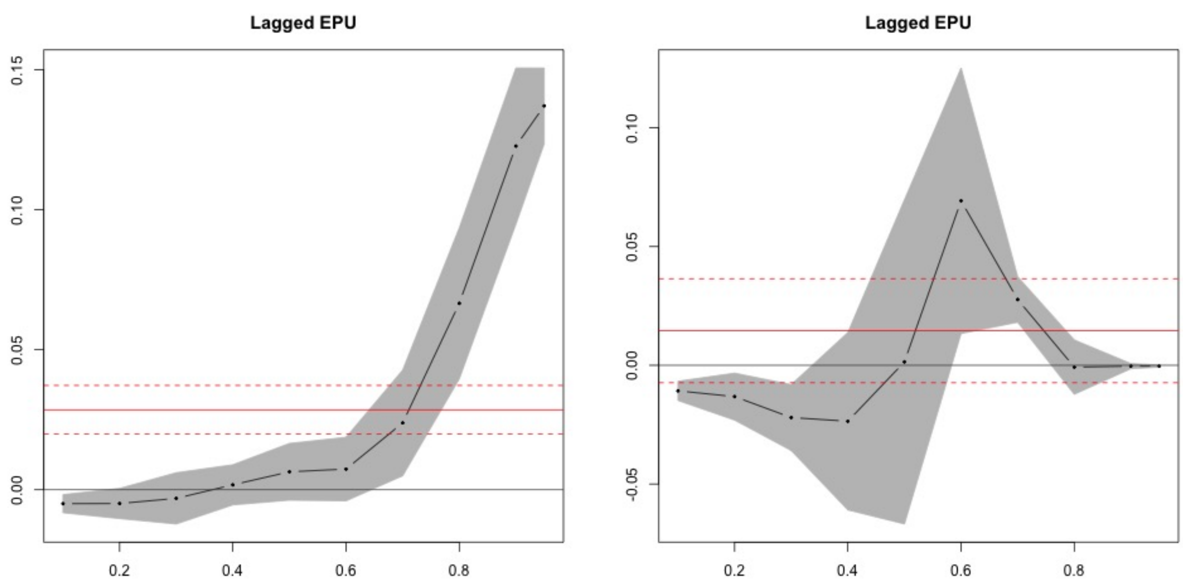


(a) Sub-sample I

(b) Sub-sample II

Note: Black dots are the slope coefficients for the each estimated quantile. The solid red line is the least squares estimate, and red dashed line is its confidence interval.

Figure 4: Quantile Regression using OLS for natural gas stable probability



(a) Sub-sample I

(b) sub-sample II

Note: Black dots are the slope coefficients for the each estimated quantile. The solid red line is the least squares estimate, and red dashed line is its confidence interval.

Appendix

Table A1: Univariate GARCH crude oil models - sub-sample I analysis (01/01/1994 - 12/31/2009)

	GARCH Model Normal distribution		MS-GARCH Normal distribution		MS-GARCH Student distribution		MS-GJR-GARCH Student distribution	
Panel A - Mean Equation								
AR(1)			0.857***	(0.040)				
MA(1)			-0.876***	(0.042)				
MA(2)			-0.061***	(0.021)				
MA(3)			0.055**	(0.022)				
MA(4)			0.004*	(0.021)				
MA(5)			-0.046**	(0.017)				
Panel B - Variance Equation								
μ_1	0.040***	(0.009)	0.028***	(0.001)	0.031***	(0.001)	0.031***	(0.000)
$\alpha_{1,1}$	0.033***	(0.002)	0.018***	(0.001)	0.021***	(0.001)	0.021***	(0.000)
$\alpha_{2,1}$							0.000***	(0.000)
β_1	0.961***	(0.001)	0.971***	(0.001)	0.972***	(0.001)	0.972***	(0.000)
μ_2			41.553***	(0.109)	31.753***	(0.153)	32.246***	(0.000)
$\alpha_{1,2}$			0.041***	(0.002)	0.054***	(0.003)	0.044***	(0.000)
$\alpha_{2,2}$							0.000***	(0.000)
β_2			0.001***	(0.000)	0.003***	(0.002)	0.000***	(0.000)
Stable Probability ($D = 0$)			0.955		0.978		0.978	
Stable Probability ($D = 1$)			0.045		0.022		0.022	
Duration ($D = 0$)			22.371		45.662		45.872	
Duration ($D = 1$)			1.047		1.022		1.022	
Unconditional Volatility ($D = 0$)			24.562		32.358		32.436	
Unconditional Volatility ($D = 1$)			104.359		92.096		92.107	
Panel C - Standardizde residual diagnostics								
$\hat{\varepsilon}$ mean	-0.006		2.502		0.015		0.015	
$\hat{\varepsilon}$ Std. error	0.999		0.6		1.005		1.005	
$\hat{\varepsilon}$ Variance	0.997		0.36		1.01		1.01	
$\hat{\varepsilon}$ Skeness	-0.336		2.36		-0.287		-0.287	
$\hat{\varepsilon}$ Kurtosis	3.94		6.863		4.032		4.03	
Jarque-Bera	2777.3***		12052***		2882.9***		2880.2***	
Arch Effect	9.824		29840.49***		10.209		10.154	
Ljung-Box (20)	37.178		80845***		19.253		38.162	
Log-Likelihood	-9524.722		-9361.519		-9336.761		-9336.773	
AIC	4.579		18739.038		18693.522		18697.546	
BIC	4.594		18789.714		18756.866		18773.56	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.

Table A2: Univariate GARCH natural gas models - sub-sample I analysis (01/01/1994 - 12/31/2009)

	GARCH Model Normal distribution		MS-GARCH Normal distribution		MS-GARCH Student distribution		MS-GJR-GARCH Student distribution	
Panel A - Mean Equation								
AR(1)			0.680***	(0.112)				
MA(1)			-0.732***	(0.103)				
Panel B - Variance Equation								
μ_1	0.306***	(0.061)	0.204***	(0.010)	0.184***	(0.001)	0.182***	(0.001)
$\alpha_{1,1}$	0.092***	(0.010)	0.041***	(0.001)	0.074***	(0.001)	0.074***	(0.001)
$\alpha_{2,1}$							0.000	(0.000)
β_1	0.896***	(0.010)	0.912***	(0.001)	0.914***	(0.001)	0.914***	(0.000)
μ_1			28.534***	(0.128)	5.879***	(0.048)	5.804***	(0.047)
$\alpha_{1,2}$			0.803***	(0.011)	0.078***	(0.001)	0.076***	(0.001)
$\alpha_{2,2}$							0.000	(0.000)
β_2			0.193***	(0.001)	0.658***	(0.002)	0.66***	(0.002)
Stable Probability ($D = 0$)			0.86		0.752		0.747	
Stable Probability ($D = 1$)			0.14		0.248		0.253	
Duration ($D = 0$)			7.148		4.039		3.954	
Duration ($D = 1$)			1.163		1.329		1.339	
Unconditional Volatility ($D = 0$)			32.85		62.762		63.393	
Unconditional Volatility ($D = 1$)			349.963		72.373		71.993	
Panel C - Standardizde residual diagnostics								
$\hat{\varepsilon}$ mean	0.007		0.003		0.006		0.006	
$\hat{\varepsilon}$ Std. error	1.000		0.997		0.972		0.973	
$\hat{\varepsilon}$ Variance	1.000		0.993		0.946		0.947	
$\hat{\varepsilon}$ Skeness	0.584		0.466		0.513		0.512	
$\hat{\varepsilon}$ Kurtosis	6.086		5.298		5.442		5.443	
Jarque-Bera	6674.1***		5028.5***		5328.9***		5331.6***	
Arch Effect	10.892		8.049		11.459		11.547	
Ljung-Box (20)	46.341**		45.535**		22.357		43.949**	
Log-Likelihood	-4057.81		-11109.97		-4000.776		-11065.64	
AIC	5.443		22235.942		22151.25		22155.273	
BIC	5.452		22286.618		22214.594		22231.286	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.

Table A3: Univariate GARCH crude oil models - sub-sample II analysis (01/01/2010 - 12/31/2017)

	GARCH Model Normal distribution		MS-GARCH Normal distribution		MS-GARCH Student distribution		MS-GJR-GARCH Student distribution	
Panel A - Mean Equation								
MA(1)			-0.092***	(0.022)				
Panel B - Variance Equation								
μ_1	0.024***	(0.011)	0.019***	(0.001)	0.015***	(0.001)	0.015***	(0.001)
$\alpha_{1,1}$	0.032***	(0.004)	0.029***	(0.001)	0.027***	(0.001)	0.025***	(0.001)
$\alpha_{2,1}$							0.011***	(0.001)
β_1	0.963***	(0.003)	0.951***	(0.001)	0.963***	(0.001)	0.96***	(0.001)
μ_2			18.131***	(0.164)	18.611***	(0.124)	6.978***	(0.282)
$\alpha_{1,2}$			0.261***	(0.005)	0.27***	(0.005)	0.054***	(0.009)
$\alpha_{2,2}$							0.383***	(0.013)
β_2			0.036	(0.008)	0.000	0.000	0.598***	(0.012)
Stable Probability ($D = 0$)			0.912		0.952		0.954	
Stable Probability ($D = 1$)			0.088		0.048		0.046	
Duration ($D = 0$)			11.416		20.921		21.692	
Duration ($D = 1$)			1.096		1.05		1.048	
Unconditional Volatility ($D = 0$)			15.144		19.73		19.029	
Unconditional Volatility ($D = 1$)			80.49		80.032		105.762	
Panel C - Standardizde residual diagnostics								
$\hat{\varepsilon}$ mean	-0.014		2.102		-0.017		-0.017	
$\hat{\varepsilon}$ Std. error	0.998		0.531		0.996		0.996	
$\hat{\varepsilon}$ Variance	0.997		0.282		0.993		0.992	
$\hat{\varepsilon}$ Skeness	-0.236		1.551		-0.344		-0.358	
$\hat{\varepsilon}$ Kurtosis	4.548		3.464		4.331		4.211	
Jarque-Bera	1822.9***		1883.9***		1676.4***		1591.2***	
Arch Effect	30.229***		9172.595***		2.927		3.656	
Ljung-Box (20)	21.936		27582***		15.252		21.673	
Log-Likelihood	-4412.456		-4275.798		-4270.078		-4269.538	
AIC	4.235		8567.597		8560.157		8563.075	
BIC	4.249		8612.741		8616.587		8630.791	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.

Table A4: Univariate GARCH natural gas models - sub-sample II analysis (01/01/2010 - 12/31/2017)

	GARCH Model Normal distribution		MS-GARCH Normal distribution		MS-GARCH Student distribution		MS-GJR-GARCH Student distribution	
Panel A - Mean Equation								
MA(1)			-0.058***	(0.022)				
Panel B - Variance Equation								
μ_1	0.240***	(0.072)	0.112***	(0.001)	0.015***	(0.001)	0.016***	(0.000)
$\alpha_{1,1}$	0.053***	(0.01)	0.020***	(0.001)	0.004***	(0.001)	0.004***	(0.000)
$\alpha_{2,1}$							0.000***	(0.000)
β_1	0.918***	(0.015)	0.953***	(0.001)	0.99***	(0.001)	0.990***	(0.000)
μ_2			1.522***	(0.067)	0.914***	(0.012)	0.919***	(0.000)
$\alpha_{1,2}$			0.004***	(0.001)	0.05***	(0.001)	0.050***	(0.000)
$\alpha_{2,2}$							0.000***	(0.000)
β_2			0.949***	(0.002)	0.872***	(0.001)	0.871***	(0.000)
Stable Probability ($D = 0$)			0.902		0.454		0.453	
Stable Probability ($D = 1$)			0.098		0.546		0.547	
Duration ($D = 0$)			10.215		1.83		1.827	
Duration ($D = 1$)			1.109		2.205		2.209	
Unconditional Volatility ($D = 0$)			32.357		25.949		26.12	
Unconditional Volatility ($D = 1$)			90.372		54.301		54.227	
Panel C - Standardizde residual diagnostics								
$\hat{\varepsilon}$ mean	-0.003		-0.011		-0.012		-0.012	
$\hat{\varepsilon}$ Std. error	1.001		1.006		1.001		1	
$\hat{\varepsilon}$ Variance	1.002		1.013		1.001		1.001	
$\hat{\varepsilon}$ Skeness	0.208		0.243		0.195		0.195	
$\hat{\varepsilon}$ Kurtosis	2.847		3.151		2.853		2.853	
Jarque-Bera	722.35***		886.78***		723.52***		723.42***	
Arch Effect	8.266		13.019		8.343		8.332	
Ljung-Box (20)	26.783		28.048		24.130		26.071	
Log-Likelihood	-4057.81		-5013.257		-5001.611		-5001.635	
AIC	4.875		10042.515		10023.221		10027.271	
BIC	4.889		10087.659		10079.651		10094.987	

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Number in parentheses are standard deviation.