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Three Essays on Energy Economics

Alexandre Ribeiro Scarcioffolo

Dissertation submitted to the
Davis College of Agriculture, Natural Resources, and Design
at West Virginia University
in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy
in
Natural Resource Economics

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Abstract

Three Essays on Energy Economics

Alexandre Ribeiro Scarcioffolo

This dissertation consists of three essays that explore empirical issues concerning energy prices in the United States. In particular, it analyzes the price transmission within and across different energy markets and their interactions with the overall economy. The first essay evaluates the dynamic spatial integration in the U.S. natural gas market and the relative importance of each location in the overall price discovery process. I show that the regional natural gas market is on average well-integrated in both the short- and long-runs, although market integration has declined over the past few years due to pipeline capacity constraints in an increasingly oversupplied market. In the second essay, I evaluate the effect of economic policy uncertainty on the volatility pattern in U.S. crude oil and natural gas markets, as well as how this relationship has changed in an era of abundant market supply. Natural gas and crude oil present heterogeneous volatility regimes (i.e., high vs. low volatility), in which the volatility persistence for crude oil is similar during the pre- and post-shale era, while natural gas presented significant regime changes. Economic policy uncertainty exerts a positive and significant effect on the likelihood of the high-volatility regime for both markets. However, the effect has declined after 2010, possibly reflecting the large and more efficient production of fossil fuels in the country which allows producers and investors to respond more rapidly to market shocks. Finally, the third essay revisits three important open questions in the energy economics literature, namely, the “decoupling” of crude oil and natural gas prices, the mixed relationship between natural gas and electricity prices, and the “rockets and feathers” effect between crude oil and petroleum product prices. Empirically, I analyze the directional price return predictability between various energy markets at different quantiles of their respective price return distributions. I find positive and significant spillover effects from crude oil to natural gas during bearish market conditions, which have weakened after 2013, suggesting a possible “delink” between the two markets in recent years. For the relationship between natural gas and electricity price returns, results suggest a bi-directional spillover at moderate and high return quantiles. In recent years, the two markets appear to have become more correlated during bearish market conditions, reflecting the increasing importance of natural gas as an input to produce electricity and the transition of natural gas from peak load to baseload power sources. Finally, no evidence is found for the “rockets and feathers” effect from crude oil to either gasoline or heating oil market.

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Chapter 1

Introduction

1.1 The Economy of Energy Markets

1.1.1 The Energy Market in the U.S.

The energy sector is an important component of the United States (U.S.) economy. Recent figures show that the total expenditure in the energy sector is responsible for 5.83% of the nation's gross domestic product (GDP). For states whose economy depends upon revenues from the energy sector, this number is much higher. For instance, 10.25% of West Virginia's GDP came from mining, quarrying, and oil and gas extraction in 2018. Further, the energy sector employs on average 4.6% of the nation's labor force, usually with salaries above the national average.¹ The production and consumption of primary fuel sources such as crude oil, natural gas, coal, nuclear, and renewable energy, and secondary sources (i.e., electricity, gasoline, heating oil) have been increasing over time. In particular, fossil fuels (crude oil, natural gas, and coal) have been dominating the U.S. energy mix for than a century.²

Several recent events in the energy market have been vital to push energy production to another whole level. For instance, the deregulation of the natural gas market that began in the early 1990s have eliminated excess regulations that prevented prices from reflecting market fundamentals, allowing demand and supply to determine prices more efficiently. More

¹See <https://www.usenergyjobs.org/>, accessed on March 27, 2020.

²See <https://www.eia.gov/energyexplained/us-energy-facts/>, accessed on March 27, 2020.

recently, the shale boom, which refers to the combination of hydraulic fracturing and horizontal drilling to explore shale and tight formations, has transformed the energy sector in the U.S., making the nation the world's top producer of petroleum and natural gas hydrocarbons.³ These events not only greatly impacted their respective market, but also have ripple effects on other energy markets due to the highly interconnected feature of the sector. For example, due to low prices, natural gas has been used more than ever as an input to produce electricity in recent years, overtaking coal as the largest fuel source for electricity generation in the U.S.

Given the importance of the energy sector on industrial production and economic growth, several studies contend that the U.S. economic activity is adversely affected by shocks from the energy sector, the crude oil market in particular (Antonakakis et al., 2014; Rahman and Serletis, 2011; Cologni and Manera, 2008; Kilian, 2009). Among these studies, the seminal paper by Hamilton (1983) suggests that crude oil market shocks may have contributed, at least in part, to several recessions in the U.S. prior to 1972. Though some empirical studies such as Kliesen (2006) finds a negligible impact of natural gas prices on total U.S. industrial output, Arora and Lieskovsky (2014) argue that since the shale revolution, the natural gas market is playing an increasingly important role in the U.S. economy. Other studies find that there exists a long-run relationship between economic growth in the U.S. and natural gas consumption (e.g., Apergis and Payne, 2010; Sari et al., 2008). On the other hand, there is a large literature investigating how macroeconomic factors can affect energy prices. Recent papers such as Kilian and Hicks (2013) and Baumeister and Kilian (2016) highlight the critical role of global economic activities on the oil market, finding that demand shocks not only drove up oil prices in 2008 but also partly contributed to the recent oil price decline. Karali and Ramirez (2014) find that macroeconomic events significantly impact oil price volatility, which subsequently affects natural gas and heating oil markets via cross-market spillovers.

The U.S. energy sector has entered a new era characterized by lower hydrocarbon imports, improved energy trade balance, and greater independence from fossil fuel exporting countries (Brown and Yücel, 2013). It presents a timeless opportunity to re-examine the intra- and

³See <https://www.eia.gov/todayinenergy/detail.php?id=36292>, accessed on March 27, 2020.

inter-market dynamics within the energy sector and how changes in macro-economic events affect these relationships. A more accurate understanding of these issues can help firms and investors establish more informed trading and investment strategies, and provide essential information to policymakers to design more effective energy policies that are conducive to the long-term economic growth.

1.2 Contribution and Outline

I study three topics that are of great importance to the U.S. energy sector, namely, the regional price integration in the natural gas market, the dynamics of the energy market volatility and its interplay with economic policy uncertainty, and the directional predictability between energy prices.

Chapter 2 studies the level of market integration in the regional natural gas market and the relative importance of each location in the overall price discovery process. To address this question, I use spot prices from seven natural gas spot markets in the U.S., as well as one Canadian spot market between 1994 and 2016. The main results show that the U.S. regional natural gas market is on average well-integrated in both the short- and long-runs. The connectedness price index I constructed ranges between 55% and 85% during the sample period. Though the market connectedness has generally improved over the years, a marked decline has occurred toward the end of the sample period, coinciding with the shale gas boom. This decline may be attributed to pipeline capacity constraints in an increasingly oversupplied market and the relatively small number of market participants voluntarily reporting transaction activities to price indexes. We find that the role of each regional market in the overall price discovery process has undergone several shifts during the sample period, depending on the specific market conditions at both the national and regional levels. Of the eight locations, Henry Hub and Oneok appear to be the two most active markets, both transmitting and receiving a substantial amount of information throughout most of the sample period.

Chapter 3 explores the volatility patterns of crude oil and natural gas prices in the U.S. and how they have changed due to economic policy uncertainty in the pre- (1994–2009) and

post- (2010–2019) shale era. Using Markov-Switching Generalized Autoregressive conditional heteroskedasticity (MS-GARCH) models to account for possible regime shifts in the volatility process, I find evidence of heterogeneous volatility regimes for the two markets (i.e., high vs. low volatility). Results show that the volatility persistence for crude oil is similar during the two sub-periods, while natural gas presented significant regime changes. In the pre-2010 period, the natural gas market is characterized by short-lived agitated conditions and persistent tranquil moments, while in the post-2010 period the agitated market conditions are more persistent. Using quantile regressions, I further show evidence that economic policy uncertainty positively affects the likelihood of high-volatility regimes in both markets. However, the two markets have become more independent from economic policy uncertainty shocks after 2010, possibly due to the upsurge and more flexible production of the two fossil fuels that allowed market participants to respond to market shocks more rapidly and more efficiently.

Chapter 4 examines three open questions in the energy literature, namely the “decoupling” of crude oil and natural gas markets, the mixed relationship between natural gas and electricity prices, and the “rockets and feathers” effect from crude oil to petroleum product prices. Based on directional predictability between daily returns from 2003 to 2019, my results support the decoupling between crude oil and natural gas markets; however, the decoupling appeared to have occurred in 2013, much later than commonly found in other studies. Regarding the directional predictability between natural gas and electricity prices, we find a stronger bi-directional spillover at moderate and high market conditions. More recently, both natural gas and electricity price returns have become more correlated at low quantiles, reflecting the large utilization of natural gas to produce electricity in the last few years. Finally, I fail to find evidence of the “rockets and feathers” effect from crude oil to two petroleum products (heating oil and gasoline). The directional predictability from crude oil to heating oil and gasoline appears to be more significant and persistent during low market conditions as compared to bullish moments, highlighting the possible lack of oligopolistic behavior in the wholesale market in comparison to the retail market.

This dissertation contributes to the literature in several ways. First, results from the three essays reinforce how the shale boom has impacted the energy market dynamics in the U.S.,

and their interplay with the macro-economic uncertainty. Second, Chapter 2 shows that the shale boom (a positive supply shock) appears to be an insufficient condition for improving the overall integration of the regional natural gas market, highlighting the importance of expanding pipeline capacity to connect production centers to the rest of the country. Thirdly, Chapter 3 highlights how crude oil and natural gas markets have become more independent from policy uncertainty shocks as producers can more efficiently adjust production and the trading of the two commodities after the shale boom. Lastly, Chapter 4 finds that investors and policymakers should consider the interrelationships between energy markets at different price/return quantiles, which tend to vary depending on the underlying market conditions.

Chapter 2

How Connected Are the U.S. Regional Natural Gas Markets in the Post-Deregulation Era? Evidence from Time-Varying Connectedness Analysis

2.1 Introduction

Historically, the natural gas industry has been one of the most heavily regulated commodity sectors in the United States (Park et al., 2008). Amid the natural gas shortages and the energy crises in the 1970s, the Federal Energy Regulatory Commission (FERC) started the deregulation process under the Natural Gas Policy Act of 1978 (NGPA), in part to promote a nationwide efficient natural gas market through competition (Cuddington and Wang, 2006; Park et al., 2008). The FERC further issued Order 436 in 1985 and Order 636 in 1992 to unbundle the gas from transportation services, allowing customers to ship their gas into the pipeline and mandate pipeline companies to only provide transportation services (Joskow, 2013; MacAvoy, 2008). Due to pervasive supply and demand imbalances throughout the 1980s, Congress passed the Natural Gas Wellhead Decontrol Act of 1989, formally eliminating all wellhead price ceilings that had prevented the prices from reflecting market fundamentals (Joskow, 2013; MacAvoy, 2008). It was not until 1993 that all

remaining NGPA price regulations were eliminated, allowing market supply and demand to completely determine natural gas wellhead prices.

During this progressive deregulation process, various natural gas spot markets were created and developed, most of which are located at the intersection of major pipeline systems and within the major producing regions. Given the homogeneous nature of natural gas, if the deregulation is achieving its intended goal, then these natural gas spot markets should be highly integrated, with the price differences between regional markets mainly reflecting transaction costs. This “law of one price” is ensured by spatial arbitrages as profit-maximizing traders exploiting price differences between locations, forcing prices at different markets to converge in the long-run. The level of price integration between regional markets has commonly been used as an indicator of market efficiency, determining the degree to which resources are allocated efficiently among market participants (King and Cuc, 1996; Park et al., 2008).

While it should be expected that the natural gas market in the U.S. becomes more efficient after the deregulation, there are at least three reasons to suspect that the level of market integration may be lower than commonly believed, and that the rate of improvement in market integration has not been uniform over the past few decades. Firstly, despite FERC’s continuing efforts to prevent market manipulation, market power remains a concern in the natural gas industry. The *Gas Daily* on June 10, 2004 (as cited in Murry and Zhu, 2008) noted that a group of 18 small cities filed a lawsuit against five major gas producers for driving up gas prices using market power. In 2015, FERC alleged that French firm Total SA manipulated natural gas prices in Southwestern U.S. on various occasions in 2009-2012 using leveraged trading strategies.¹ FERC made similar allegations to JP Morgan Chase and Barclays for manipulating energy markets, resulting in either fines or court settlements.² The problem of market manipulation may be further amplified due to the increasing popularity of high-frequency trading, which profits by driving up market volatility.³

¹See <https://www.reuters.com/article/us-total-ferc-manipulation/u-s-regulators-allege-total-rigged-natgas-market-for-three-years-idUSKCN0RM1VF20150922>, accessed on October 13, 2017.

²See <https://www.reuters.com/article/us-jpmorgan-ferc/jpmorgan-to-pay-410-million-to-settle-power-market-case-idUSBRE96T0NA20130730>, accessed on October 13, 2017.

³See <http://www.businessinsider.com/how-robots-manipulate-natural-gas-prices-2012-10>, accessed on October 13, 2017.

A second reason that may lead to natural gas market inefficiency is the thinning of physical markets. Murry and Zhu (2008) note that between 2000 and 2005, many less-used trading hubs were forced to drop out of the market due to illiquidity, with the number of trading hubs reported by The Gas Daily decreasing from 103 to 76 in this period.⁴ Concerns also arise as the trading volume used to construct spot price indices has plunged in many locations, in particular those along the U.S. Gulf Coast that have lost market shares to the northeast due to the rise in shale gas production.⁵ Throughout the post-deregulation era, the collapse of several large energy and energy-related companies raised additional concerns regarding the efficiency of physical natural gas markets. For instance, Murry and Zhu (2008) note that Enron's bankruptcy reduced trading volume, increased credit requirements demanded by counterparties, and diminished the number of market intermediaries in many regional markets. Other notable bankruptcies related to the natural gas industry include the Pacific Gas & Electric Company in 2001, the Calpine Corporation in 2005, the Energy Future Holdings in 2014, to name just a few.

Finally, unlike most of the commodities that can be moved across markets by a variety of transportation means (e.g., truck, rail, barge), natural gas can only be transmitted through pipelines, or transported via specially-designed tankers after being liquefied (liquefied natural gas, or LNG). Without an extensive pipeline system or sufficient LNG processing plants, the physical arbitrage between regional markets could be severely limited. In the presence of delivery constraints, one would expect shocks originated in one market to exert only a limited impact on other markets. Bottlenecks in regional markets for natural gas transmission services, if they exist, suggest that the level of market integration may be low when the production and consumption regions are highly separated.

The purposes of the present Chapter are to investigate dynamic price integration between regional U.S. natural gas markets and to determine how the relative importance of each location in the price discovery process has changed over time. Following previous studies, we consider daily prices from seven regional spot markets in the U.S., including (1) Chicago,

⁴The number of hubs with prices reported in The Gas Daily has rebounded in recent years. For instance, prices are reported for almost 100 locations in The Gas Daily in July 2016.

⁵See <https://www.risk.net/commodities/energy/2421660/fall-us-gas-hub-liquidity-hampers-derivatives-market>, accessed October 15, 2017.

Illinois; (2) Dominion South Point, Pennsylvania; (3) Henry Hub, Louisiana; (4) Malin, Oregon; (5) Oneok, Oklahoma; (6) Opal, Wyoming and (7) Waha Hub, Texas, as well as the AECO hub in Alberta, Canada from 1994 to 2016. AECO is included since it supplies much of the gas to the western U.S. Using a generalized vector autoregression framework that are invariant to the ordering of the variables, we follow Diebold and Yilmaz (2012, 2014) and construct both the total and directional spillover indexes from the forecast error variance decomposition matrix to determine the cross-market price spillovers and the role of each market in the price discovery process. In light of the changing production and consumption patterns across the U.S. over the past three decades, we further adopt a rolling-window approach to allow the spillover indexes to change over time and assess the time-varying market integration.

The level of spatial connectedness in the U.S. natural gas market has been under continual scrutiny in both the academic literature and the policy arena, resulting in a large number of papers investigating the price relationships between regional natural gas markets (e.g., Cuddington and Wang, 2006; De Vany and Walls, 1994a; Olsen et al., 2015) and a diverse set of policy reports on the effectiveness of market deregulation (e.g., GAO, 1993; 2002; 2006). This Chapter departs from these studies in a number of ways. First, with the exception of a few recent studies, most of the existing work has only focused on a rather short time period. Our long sample period, starting from 1994, allows us to investigate the time-varying market integration and identify cycles and patterns in the integration process. Second, unlike most of the previous studies that only investigate the qualitative aspect of the law of one price (i.e., whether the markets are integrated or not), we explicitly quantify the magnitude of market integration. This feature, combined with our time-varying approach, enables us to provide a direct comparison of the level of integration during different time periods. Finally, in addition to the overall market integration, we investigate the level of integration between pairs of regional markets, as well as the magnitude of total information spillovers to and from each market. Such analysis allows us not only to quantify the bi-directional effects of shocks between markets and the factors contribute to such pairwise spillovers, but also the role of each market in the overall natural gas price discovery in the U.S.

This Chapter produced some interesting insights. First, the U.S. regional natural gas

market is on average well-integrated in both the short- and long-runs, with the connectedness index we constructed ranges between 55% and 85% during the sample period. Second, though overall the market has become more connected over time, the total connectedness has declined over the past few years, perhaps due to pipeline capacity constraints in an increasingly oversupplied market and the relatively small number of market participants voluntarily reporting transaction activities to price indexes. Third, we identify three main cycles in the dynamic total price connectedness index, which are reflective of the market supply-and-demand conditions, as well as exogenous shocks such as natural disasters and technology improvement. Finally, we find that the role of each regional market in the overall price discovery process has undergone several shifts during our sample period. Henry Hub and Oneok appear to be the two most active markets, both transmitting and receiving most information throughout most of the sample period.

The remainder of the Chapter is organized as follows. Section two briefly reviews the literature. The model and data are presented in sections three and four, respectively. Section five discusses the main estimation results. Section six presents two robustness checks, and section seven concludes the Chapter.

2.2 A Brief Review of Literature

The literature on whether the law of one price holds in the U.S. natural gas markets is abundant, with the majority of the studies exploiting either the cointegration approach of Engle and Granger (1987) or the vector autoregression approach of Sims (1980), or modified models based on these two approaches. For instance, De Vany and Walls (1993) find that less than half of the market-pairs from 20 spot markets were cointegrated prior to 1991 but a year later, the integration level had already risen to 65%, an indication that the market had indeed become more competitive after the deregulation. Doane and Spulber (1994) consider monthly prices from five major gas producing regions from 1984 to 1991, finding that allowing open access to pipeline transportation for producers and customers had integrated the regional wellhead markets into a nationally competitive market. Similar conclusions were reached in Walls (1994a), who used daily prices from 20 nodes in 1989-1990,

De Vany and Walls (1994b) that used weekly prices of 25 regional markets from 1988 to 1990, De Vany and Walls (1996) that considered daily prices at city gates and hubs in 1990-1991, Serletis (1997) who investigated the monthly prices for eight producing regions in 1990-1996, and Olsen et al. (2015) that examined prices from 11 major gas markets in North America.

Recent studies investigating the spatial integration of the U.S. natural gas industry often account for structural breaks and non-linear adjustments between regional markets. Park et al. (2007), for instance, consider a three-regime threshold vector error correction model and find non-linear adjustments between seven regional natural gas markets, driven by location, season, and inventories. Apergis et al. (2015) test the cointegration between city gate and residential retail prices using state-level data from 1989 to 2012, finding a structural break between 1994 and 1995 in the integration process and more integrated market after the deregulation. Duangnate et al. (2015) investigated daily prices from eight regional markets, finding possible structural breaks in the long-run relationships between these markets in 2000 and 2009.

However, not all studies agree with the finding that the regional natural gas markets in the U.S. have been well-integrated since the deregulation took place in the 1980s. Earlier studies such as Walls (1994b) indicate that although natural gas markets were highly integrated within the production fields, the level of integration was quite weak between city markets and the field. King and Cuc (1996) find an east-west split in natural gas pricing due to capacity constraints in the transportation system that had limited producers in the western regions to transport gas to the east. A similar conclusion was found in Cuddington and Wang (2006) who investigated daily prices at 76 locations in the U.S. from 1993 to 1997, and noted that while markets in the East and Central U.S. regions are highly integrated, these markets are somewhat segregated from the western regions. Marmer et al. (2007) analyzed spot prices from 85 major hubs in the U.S. from 1988 to 2003, finding the natural gas pricing network in the U.S. to be divided into three local markets: Northeast, Midwest, and California.

Examples of recent studies supporting limited integration in the U.S. natural gas market include Brown and Yücel (2008); Murry and Zhu (2008); Avalos et al. (2016). Using daily data from 1997 to 2007, Brown and Yücel (2008) identify only limited arbitrage between

Henry Hub, the principal upstream natural gas market in the U.S., and two regional spot markets, one in the east and the other in the western U.S. They attribute the lack of integration between upstream and downstream markets to bottlenecks in the pipeline system resulting from physical limitations, regulatory inhibitions, or monopolization. Murry and Zhu (2008) investigated spot prices from 19 main hubs and futures prices from NYMEX, finding that the price responses to external shocks at some hubs were systematically asymmetric due to market power by either buyers or sellers. Avalos et al. (2016) find that pipeline congestion in Florida and Southern California prevented perfect arbitrage between these locations and the upstream markets, and inflated prices at the two markets by at least 6% and 11%, respectively, between 2006 and 2011.

Though informative, previous papers only examine the “average” level of integration for a given sample period, without considering the time-varying pricing relationships between regional markets. Apart from the progressive deregulation process, the natural gas market has undergone tremendous changes over the past few decades due to advances in technology. For instance, to facilitate price discovery, natural gas futures contracts were introduced by NYMEX in April 1990, which quickly became a popular risk management tool among market participants. Most recently, domestic production from shale and other lower-permeability formations has become economically profitable, sparked by the popularization of the combined use of horizontal drilling and hydraulic fracturing techniques. These new market developments have completely revolutionized the natural gas industry and could potentially impact the degree of regional integration within the U.S. These time-varying effects, if ignored, may lead to conflicting results regarding price integration as evidenced by previous studies and result in erroneous policy recommendations preventing further market integration.

Another important aspect relating to spatial integration is the degree to which each location contributes to the price discovery process, i.e., the impounding of information into prices. While a few papers have investigated the role of each regional market in determining the overall price of natural gas, these studies are rather limited as they only report the direction of contemporaneous causality between the markets, without specifying the relative magnitudes of their contributions. For instance, based on directed acyclic graphs (DAGs),

Olsen et al. (2015) report that the AECO hub, located in Alberta, Canada, is an “information sink” that receives information contemporaneously from various locations without passing information to other markets. A natural interpretation is then that AECO plays little role in the price discovery process. In fact, they conclude that for the 11 markets considered, no one market is a clear leader in the price discovery process. Such a conclusion should not be surprising since the DAGs only give directional causality between markets without calculating the exact magnitude of the effects. A similar critique applies to Park et al. (2008) who investigate the contemporaneous causality between seven regional markets in the U.S. and Canada using the DAG approach. Their results suggest that price discovery tends to reflect Canadian and U.S. regions of excess demand and supply, both of which are highly integrated. Additionally, Serletis and Rangel-Ruiz (2004) investigate the daily natural gas prices at Henry Hub and AECO Alberta, as well as West Texas Intermediate crude oil prices, finding that North America natural gas prices are largely defined by price trends at Henry Hub.

2.3 Econometric Methods

We use the recently-developed spillover index of Diebold and Yilmaz (2012, 2014) to evaluate the dynamic integration of regional natural gas market in the U.S., as well as the role of each regional market in the price discovery process. The method starts with a conventional Vector Autoregressive (VAR) model that estimates the interactions and lead/lag relationships between the prices of various markets, as in equation 2.1:

$$P_t = \sum_{i=1}^I \Phi_i P_{t-i} + \Psi W_t + \varepsilon_t \quad (2.1)$$

where $P_t = (P_{1t}, P_{2t}, \dots, P_{kt})'$ is an $K \times 1$ vector representing prices from K locations on day t , W_t is a $Q \times 1$ vector of exogenous variables consisting of Q predictors, $i = 1, \dots, I$ are the lag terms considered in the model, $\varepsilon_t \sim N(0, \Sigma)$ is a vector of independently and identically distributed disturbances, and Φ_i and Ψ are $K \times I$ and $K \times Q$ coefficient matrices, respectively.

A common property of time series variables is that they tend to be nonstationary, which may lead to “spurious regressions” and misleading parameter estimates. This is particularly evident in the case of commodity prices. In the event that the endogenous variables are nonstationary, we must test for cointegrating vectors, or long-run relationships between the price series. These long-run relationships, if they exist, can be modeled using a Vector Error Correction (VEC) model as in equation 2.2 assuming all prices (P_t) are stationary at the first difference:

$$\Delta P_t = \Pi P_{t-1} + \sum_{j=1}^{I-1} \Gamma \Delta P_{t-j} + \Psi W_t + \varepsilon_t \quad (2.2)$$

where $\Pi = -(I_k - \sum_{i=1}^I \Phi_i)$ are error correction terms; $\Gamma = -\sum_{i=j+1}^K \Phi_i$ are matrices of short-run parameters.

Direct interpretation of the VAR and VEC coefficients is often complicated due to the dynamics involved in the models. The most common innovation accounting methods used in the literature include impulse response functions and the forecast error variance decomposition (FEVD) that evaluates the contribution of an innovation in p_i to the forecast error variance of price sequence p_j various horizons. In the context of our analysis, the FEVD hence contains information regarding the effect of a shock originating from one regional market on another market at various horizons.

However, to calculate the FEVD it is required that we specify a structural VAR or VEC model that adequately accounts for the contemporaneous correlations between the endogenous variables. Though orthogonal white noise innovations can be achieved through Cholesky decomposition, the results of Cholesky factorization depend critically on the ordering of the endogenous variables. To obtain order-invariant FEVD that allows for correlated innovations, Koop et al. (1996) and Pesaran and Shin (1998), or KPSS, propose an alternative approach, namely the Generalized Forecast Error Variance Decomposition (GFEVD). The GFEVD utilizes the historically observed distribution of the errors to calculate the shocks, hence allowing uncorrelated shocks in the VAR model Diebold and Yilmaz (2012).

The H-step-ahead GFEVD is calculated as follows:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' C_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' C_h \sum C_h' e_j)} \quad (2.3)$$

where $\sum$ is the variance matrix of the vector of errors ε , σ_{jj} is the standard deviation of the error term of the j^{th} natural gas market, and e_i is a selection vector, with one on the i^{th} , zero otherwise.

Under the GFEVD, the sum of the contribution to the variance of the forecast error in each row is not necessarily one. To compare the relative importance of each shock in the overall forecast error variance, Diebold and Yilmaz (2012, 2014) propose to normalize each element of the variance decomposition matrix by the row sum, as in equation 2.4 :

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (2.4)$$

Therefore, by construction, the normalized variance share sums to 1 for any market i at a given horizon, or $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$, and the sum of the decomposition across all market equals N, or $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$. Under this framework, Diebold and Yilmaz (2012, 2014) define the own variance share as the contribution in forecasting p_i at the H-step ahead horizon attributable to shocks to its own price p_i and the spillover from p_j as the contribution in forecasting p_i at H-step ahead due to shocks in another location j . Under the context of our paper, $\theta_{ij}^g(H)$ therefore can be considered as the spillover from market j to i at the H-step ahead horizon, or $S_{i \leftarrow j}^g(H)$.

To measure the magnitude of all other markets jointly contributing to the forecast error variance of a single market at various horizons, Diebold and Yilmaz (2012, 2014) further define the directional spillover transmitted to market i ($S_{i \leftarrow o}^g(H)$) as the sum of spillover shares from all other locations, and the directional spillovers transmitted by market i to all other markets j , as in equations 2.5 and 2.6

$$S_{i \leftarrow o}^g(H) = \frac{\sum_{i \neq j=1} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i \neq j=1} \tilde{\theta}_{ij}^g(H)}{N} \times 100 \quad (2.5)$$

$$S_{o \leftarrow i}^g(H) = \frac{\sum_{i \neq j=1} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1} \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{i \neq j=1} \tilde{\theta}_{ji}^g(H)}{N} \times 100 \quad (2.6)$$

Diebold and Yilmaz (2012, 2014) next define the net directional spillover index for location i at H-step horizon ($S_i^g(H)$) as the difference between the share of total spillover transmitted by p_i to other locations ($S_{o \leftarrow i}^g(H)$) and the share of spillover transmitted to p_i from other locations ($S_{i \leftarrow o}^g(H)$) at the H-step horizon, the magnitude and sign of which can be used to evaluate the role of each market in the overall price discovery process. A positive (negative) $S_{i \leftarrow o}^g(H)$ would indicate that market i serves as a net transmitter (receiver) of shocks. Additionally, the greater the sum of the directional spillovers to and from other markets, the more significant role that p_i plays in the system.

We can construct a similar measure for pairwise relationships between two locations. Specifically, the net pairwise spillover from p_i to p_j at the H-step ahead horizon $S_{ij}^g(H)$ is the difference between the shocks transmitted from market i to j and those transmitted from j to i , as in equation 2.7:

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) \times 100 \quad (2.7)$$

Finally, to measure the level of overall connectedness within the entire system, Diebold and Yilmaz (2012, 2014) define the total spillover across all markets as the ratio of the sum of the off-diagonal elements of the GFEVD matrix by the sum of all its elements, as in equation 2.8:

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1} \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j} \tilde{\theta}_{ji}^g(H)}{N} \times 100 \quad (2.8)$$

The spillover index of Diebold and Yilmaz (2012, 2014) has been applied to a number of studies to evaluate the market connectedness in different contexts, including the equity market (e.g., Yilmaz, 2010), exchange rates (e.g., Antonakakis, 2012), oil prices (e.g., Awartani and Maghyreh, 2013), the policy uncertainty in different nations (e.g., Klößner and Sekkel, 2014), the stock market (e.g., Tsai, 2014), various commodities (e.g., Kang et al., 2017a, Diebold et al., 2017), electricity derivatives (e.g., Jaeck and Lautier, 2016), to name just a few.

2.4 Data

Following the previous literature (e.g., Olsen et al., 2015; Park et al., 2007, 2008; Duangnate et al., 2015) and considering data availability, we collect daily natural gas spot prices from eight locations in the U.S. and Canada, including (1) AECO Hub, Alberta, Canada (AEC); (2) Malin, Oregon (MAL); (3) Opal, Wyoming (OPA); (4) Waha Hub, Texas (WAH); (5) Henry Hub, Louisiana (HEN); (6) Oneok, Oklahoma (ONG); (7) Chicago, Illinois (CHI) and (8) Dominion South Point, Pennsylvania (DSO). Of these regions, Henry Hub has been commonly considered the benchmark for natural gas pricing, serving as the delivery point for natural gas futures contracts traded on the New York Mercantile Exchange (NYMEX). In recent years, however, the volume of gas flowing through Henry Hub has been challenged by other trading hubs, Dominion South Point in particular, due to the shale gas boom.⁶ We include AECO since it is located on the border between the U.S. and Canada, and it supplies much of the natural gas to the western U.S. Figure 2.1 plots the location of each spot market, as well as the major production and consumption regions in the U.S. As can be seen, Chicago and Malin are located in major consumption areas, while the remaining locations lie in production basins.

We consider a sample period of January 1, 1994–October 31, 2016, resulting in 5,870 daily observations for each location. Prices are obtained from Bloomberg and are calculated as the volume-weighted average price in dollars per MMBtu for gas delivered the next day. We prefer using the high-frequency daily data to avoid the potential underestimation of speeds of market adjustment when low-frequency data are used, as reported in Taylor (2001).

As can be seen in Figure 2.2, while all price sequences experienced similar boom-and-bust cycles during the sample period, i.e., high in 2005–2009 and low in other episodes, there exists considerable individual heterogeneity as prices differ substantially by location on several occasions. In particular, we note that most of these large price differentials between markets occurred in winter seasons when the demand of natural gas for heating is high. For instance, in December 2000 all eight locations experienced a price spike, but the

⁶See <http://powersource.post-gazette.com/powersource/companies/2014/12/07/Dominion-South-Point-could-be-candidate-for-regional-gas-hub/stories/201412070073>, accessed on October 28, 2017.

magnitude of the spike was particularly large for Chicago and Malin, both located in major consumption areas. Another episode standing out in Figure 2.2 is February 2014, during which almost all markets experienced a record-high price spike that followed by rapid price declines. Data from the U.S. Energy Information Administration (EIA) suggest that the low starting inventory for natural gas and the abrupt, persistent cold weather across the entire U.S. were at fault.⁷

We include lagged aggregate cooling degree-days (CDD) and heating degree-days (HDD) as exogenous variables to account for the weather effects on natural gas prices. As in Olsen et al. (2015), CDD and HDD are calculated as population-weighted averages of daily degree days for five major cities in the U.S., including Denver, Los Angeles, New York, Houston, and Seattle. Additionally, like all other tradable commodities, there may exist day-of-the-week effects in the natural gas market. We hence include four-weekday dummy variables in our estimation.

2.5 Results

Following common practices in commodity price literature, the natural logarithm of all prices is taken to reduce skewness and kurtosis before conducting the conventional unit root and cointegration tests. The first difference of logarithmic prices has a ready interpretation as daily returns. Using the augmented Dickey-Fuller (ADF) test with the number of lags selected using the Schwarz criteria, we find that all price sequences are non-stationary in levels but stationary in first differences (Table 2.1).

For non-stationary variables, there may exist linear combinations of these variables that are stationary. We next test for cointegrating relationships between the price sequences. Based on the Schwarz criteria, three lags are used in the VAR model. Using the Johansen maximum likelihood test, we find that there exist seven cointegrating vectors among the eight markets, i.e., the eight markets are linked through seven long-run equilibriums (Table 2.2). The large number of cointegrating vectors we found are consistent with Olsen et al. (2015), who determine that the 11 natural gas spot markets in their analysis are tied together

⁷See <https://www.eia.gov/naturalgas/review/winterlookback/2013/>, accessed on October 27, 2017.

by ten long-run equilibriums, as well as Park et al. (2008) that find five cointegrating vectors in the eight markets they analyzed. We hence include seven cointegrating vectors, as well as the lags of the price returns, weekday dummies, and the two weather variables in the VEC model, the results of which are available in Chapter 2 Appendix.

To shed further light on the behavior of each price sequence, we perform several tests on our short- and long-run parameters in the VEC model (Chapter 2 Appendix). The first is the exclusion test. Test results suggest that all price sequences should be included in the cointegrating vectors, or the long-run equilibriums estimated in the VEC model. Secondly, the highly significant p-value for the weak exogeneity test suggests that all prices are responsive in the short-run to deviations from the long-run relationships. Based on the cointegration framework, the regional natural gas market in the U.S. appears to be well-integrated.

2.5.1 Whole Sample Analysis

We first perform the whole sample analysis where a single VEC model is estimated for the entire sample period. Tables 2.3-2.4 present the total price spillover ($S^g(H)$), directional price spillover ($S_{i \leftarrow o}^g(H)$, $S_{o \leftarrow i}^g(H)$, $S_i^g(H)$), and pairwise price spillover ($S_{i \leftarrow j}^g(H)$, $S_{j \leftarrow i}^g(H)$, $S_{ij}^g(H)$) indices for each market at various forecast horizons. In the tables, the pairwise price spillover index is the ij^{th} entry representing the estimated contribution “to” the forecast error variance of market i “from” innovations to j . The off-diagonal column sums represent the total directional price spillover of market i “to” others, while the off-diagonal row sums represent the directional price spillover “from” other markets to i . Note that each shock’s contribution to other markets may exceed 100% since we do not place restrictions on column sums. The sum of other market’s contribution to market i (last column), on the other hand, cannot exceed 100%. Finally, the total price spillover index, which is the ratio of the sum of the off-diagonal elements of the variance decomposition matrix to the sum off all markets, provides information regarding the overall level of connectedness for all markets.

Several notable patterns emerge from the directional and total spillover index tables. First, as we move to the more distant forecasting horizons, an increasingly larger amount of

information is transmitted within the system. The total spillover index appears to be just over 50% at the most immediate horizon, but quickly rises to over 65% and 70% at the 5-day and 20-day horizons, respectively.⁸ Information appears to flow relatively quickly between regional gas markets in the U.S. during the post-deregulation period, most noticeably within the first week of the appearance of a shock. These numbers are higher than several recent papers using the Diebold and Yilmaz index to measure connectedness within a system. For instance, Antonakakis (2012) finds a total spillover of 46.0% and 31.3% among exchange rates before and after the introduction of Euro at the 10-day horizon. Awartani and Maghyreh (2013) show a total connectedness of 27.1% and 19.5% at the 10-week horizon for the return and volatility spillover of oil prices and equities in the Middle-East, respectively. Kang et al. (2017a) suggest that gold, silver, crude oil, wheat, and rice have a total connectedness of 33.3% at the 10-week horizon.⁹

Secondly, focusing on the directional spillovers from market i “to” other markets, Henry Hub (HEN) and Oneok (ONG) stand out as the largest information transmitters within the system. The two locations each transmits over 90% information to other locations at the 5-day ahead horizon (94.87 and 99.25, respectively), and at the 10-day horizon they both transmit over 100% information to other markets. At the most immediate horizon, Waha is also an important transmitter of shocks (76.28). By contrast, Opal transmits little information to other locations, with the spillover “to” index hovering around 20% at all horizons. It is also interesting to note that unlike other locations, the spillover “to” index for Chicago and Waha decline over time, suggesting that shocks from these two locations at longer horizons play an increasingly less important role in the price fluctuation of other markets.

Thirdly, Waha, Henry Hub, Oneok, which are located in the south and mid-continent producing basins, receive a considerable amount of information from other markets. In par-

⁸The rise in total connectedness at longer horizons is expected since a longer period allows more information to transmit between markets.

⁹A possible explanation for the higher total connectedness found in our study is that we focus on a homogeneous commodity (natural gas) within the U.S. Other studies have considered either different commodities (e.g., Kang et al., 2017a, Diebold et al., 2017), or the same commodity across different countries (e.g. Awartani and Maghyreh, 2013) that may present lower connectedness due to regulations, fundamental factors, and other market-specific drivers.

ticular, Waha consistently receives the most information from other markets at all horizons. At longer horizons, Chicago (located in the Midwest net importing area) quickly emerges as an influential information receiver, receiving the second most information (78.61%) after Waha at the 20-day horizon. On the other hand, the contribution of other markets to the forecast error variances of AECO and Opal are relatively low, with the spillover index “from” other locations reaching only 60% at the 20-day ahead horizon.

The difference between the spillover “to” and “from” other locations give rise to the net directional spillover index for each location, which is indicative of each market’s contribution in the overall natural gas price discovery process (i.e., how information is reflected in prices). To provide a direct depiction of the relative role played by each market, we plot the net spillover indices at various forecast horizons for each location in Figure 6.1. As can be seen, Henry Hub and Oneok are the largest net information transmitter at all horizons. Malin is also a net information transmitter, and its role increases at longer horizons. Opal appears to be the largest net information receiver in the system, with the net spillover index reaching over -40% at the 20-day ahead horizon. Dominion South remains a stable net information receiver at all forecast horizons, while Chicago becomes increasingly more of an information receiver at longer horizons. Additionally, AECO is first a net information receiver but becomes a net transmitter of shocks at longer forecasting period.

The importance of Henry Hub in the natural gas price discovery process can be largely attributed to its strategic location, expansive transportation network, and easy access to storage facilities. The hub is situated in one of the largest production areas in the U.S. that also presents one of the largest and oldest natural gas pipeline system in the country (see Table 2.5 for a summary of inflow and outflow pipeline capacity by state in 2016). It also has a direct connection to storage facilities that present high deliverability and high cycling rate, facilitating withdraw and injection of natural gas all year long.¹⁰ Besides its capacity to produce and transport natural gas throughout the country, Henry Hub is the delivery point for natural gas future market traded at NYMEX, hence its price is often served as the benchmark for the entire North American natural gas market. For Oneok, it is located on

¹⁰See <https://www.cmegroup.com/education/files/henry-hub-emerges-as-a-global-gas-benchmark.pdf>, accessed on June 4, 2018.

the Southwest region (Arkansas, Louisiana, New Mexico, Oklahoma, and Texas), where the major pipeline companies Oklahoma can be easily transported to both eastern and western markets, and is often sold to the market with the highest price (Park et al., 2008; Serletis, 1997). Data from EIA suggest that Oklahoma has been consistently equipped with a large pipeline outflow capacity, even in the early 1990s when the inflow and outflow capacities were low for many of the states.¹¹

Finally, the pairwise spillover index in Tables 2.3 and 2.4 confirms that prices in a given market are more affected by nearby locations than more distant one, a long-held hypothesis in the literature of price convergence (e.g., Olsen et al., 2015). For instance, AECO receives most of the information from Malin, and these two locations serve as the largest contributors to each other's forecast error variance at all periods. The price at Dominion South is most affected by Henry Hub and Oneok, and least influenced by Opal. Waha transmits most of the information to Oneok and Henry Hub, all of which are located in the south and mid-continent producing basins. Henry Hub receives the most information from Waha and Oneok, and less so from AECO and Opal. For Opal, the market that transmits the least information to other markets, its prices are also more influenced by innovations from nearby markets (AECO, Malin, and Oneok), and less by markets that are further away (e.g., Chicago and Dominion South Point).

All in all, our whole sample analysis presents interesting results regarding the overall level of integration in the U.S. natural gas market and the role each regional market plays in the price discovery process. As expected, the U.S. natural gas market is well-integrated, not only in the long-run (cointegrating relationship) but also in the short-run as demonstrated by the high level of total connectedness. Unlike Olsen et al. (2015) who are unable to identify a clear leader in the price discovery process, we find that Henry Hub and Oneok are the two most active markets in the system, both receiving and transmitting a substantial amount of information. Opal appears to be primarily an information receiver, transmitting little information to other markets. While we are hesitant to conclude from the whole sample analysis that there exists an east-west split as reported in King and Cuc (1996), we note that

¹¹See U.S. State-to-State pipeline capacity data from EIA: <https://www.eia.gov/naturalgas/data.phppipelines>, accessed on October 27, 2017.

the spillover indices appear to be lower in AECO, Malin, and Opal, all located in the west, than markets at the south and mid-continent producing basins. Our results also support the findings from Olsen et al. (2015) that prices at a given location are more affected by nearby markets than distant ones.

2.5.2 Rolling-sample Total Spillover Index

Massive changes have occurred to the natural gas market since deregulation began almost four decades ago (Wiggins and Etienne, 2017). Even during our sample period, the market has undergone tremendous volatility due to various structural or progressive changes. A reasonable assumption then, is that the level of spatial integration in the natural gas market may have not been constant but varied considerably depending on the specific market conditions. To account for such a time-varying relationship, we employ a rolling-window approach to re-estimate the connectedness between the eight markets, as well as their changing roles in the shock transmitting mechanism. Compared to the conventional approach in the literature that imposes a discrete structural break in the data, the rolling-window method not only accounts for abrupt, sudden changes occurred in the market, but also allows for progressive, slowly- evolving developments due to technology advances, changes in consumer preferences, etc. Additionally, by constructing a long-series of connectedness indices from the rolling-window analysis we can uncover patterns and cycles in the evolution of market integration, if they exist.

We set the fixed window in the rolling-window analysis to 786 days, or approximately three years.¹² After the initial window (1994-1996), the estimation period is rolled one day forward in each iteration until the end of the sample is reached. For each estimation window, we fit a VEC model and compute the corresponding spillover indices. In total, we obtain 5,084 sets of spillover indices. One complication with the rolling-window approach, however, is that the number of cointegrating vectors can vary depending on the specific estimation window considered. Indeed, we find that there exist five to seven cointegrating vectors for different estimation windows. For robustness, we conduct our analysis by considering five,

¹²We also consider using 252 days (approximately one year) as the window size. The results, available in Chapter 2 Appendix, are qualitatively similar.

six, and seven cointegrating relationships in the VEC model, and compute the corresponding spillover indices.

Figure 2.4 plots the time-varying total spillover indices during the sample period for 1, 5, 10, and 20-days ahead forecast horizons for each ending date, i.e. the last observation of the estimation window. For each horizon, the total spillover index appears to behave similarly regardless of the number of cointegrating vectors used in the VEC model, though the difference becomes more noteworthy at distant horizons. The results from the dynamic estimation corroborate findings from the whole-sample analysis that the eight markets are overall well-integrated, with the total connectedness index ranging between 55% and 85%, and that the total spillover within the system increases at longer-horizons. Clearly, the level of market integration has been neither constant nor uniformly increasing during the sample period. Three peaks stand out in the total connectedness indices: one in 2002, the second in 2006, and the last in 2012. Based on these peaks, we divide our sample into three episodes, the first from 1997 to 2004, corresponding to the period immediately after the natural gas market deregulation, the second in 2005- 2010, reflecting the boom-and-bust in the general economy and encompassing the “2008 Financial Crisis”, and the third from 2011 to 2016, more commonly known as the “shale boom.” One caveat is that since we use three-year of prices to construct each connectedness index, the numbers shown in Figure Figure 2.4 should be interpreted as a measure of connectedness during the preceding three-year window, rather than the ending date alone.

In the first sub-period (1997 -2004), the total level of connectedness rose rapidly before peaking in 2002. This period is marked by the rapid transition from regulated to unregulated prices, allowing ultimate gas buyers (the demand side) and the original producers (the supply side) to interact directly and quickly. Spillovers between spot markets increased dramatically, reflecting that information transmission has sped up and the overall market has become more efficient as contractual prices were increasingly linked to price indices. The total spillover index declined slightly, however, between 2001 and 2002, possibly reflecting the California crisis (2000-2001) in which California experienced a dramatic shortage of natural gas that resulted in elevated prices and large price swings. While fundamentals are the main culprits behind the large price movements, some volatility can be attributed to

market manipulation, which diverted gas away from California to other states.¹³ The crisis led to many subsequent commercial, legal and regulatory changes in the natural gas market, including the construction of new pipeline capacity and the investigation of gas price reporting system throughout the industry, among others (Smead, 2010). After the crisis, the total connectedness quickly recovered, eventually peaking in mid- 2002, perhaps reflecting the regulatory changes that took place at the end of 2001 and in the beginning of 2002. The total connectedness then declined slightly, and remained relatively stable afterwards.

During the second episode (2005-2010), the total spillovers between the eight markets were high, ranging between 70% and 85%, with the peak occurring in the first half of 2006 (corresponding to the 2003-2006 estimation window). A few events are worthy of attention during this episode. The first is the loss of offshore supply due to hurricanes Katrina and Rita in the summer of 2005. It is estimated that over 6 billion cubic feet per day of offshore natural gas supply were lost for an extended period and the equivalent of 10% of U.S. consumption remained shut-in due to problems with transportation and production in the months after the hurricanes (Kumins and Bamberger, 2005). The tightening supply-and-demand condition clearly made its way to other parts of the U.S., as natural gas prices hit elevated levels at almost all regional markets. The total spillover indices rose sharply during this period and eventually peaked at the beginning of 2006.

The second prominent event during this cycle is the unexpected run-ups in natural gas prices in 2007-2008. Though the market was apparently in oversupply as the domestic gas production increased at a faster rate than the consumption thanks to expanding shale production, natural gas prices almost doubled between 2007 and 2008. Some combination of factors such as high oil prices, weather conditions, and financial speculation may explain the natural gas price escalation in 2007-2008 (Wiggins and Etienne, 2017). Notably, the total spillover index in 2009-2010 (estimated using data from 2006 to 2010) had dropped to about 70% at 1- and 5-day horizons, possibly reflecting market distortions due to financial speculation. Additionally, during this cycle the Energy Policy Act of 2005 was passed, providing tax incentives and loan guarantees for various energy producers to combat the

¹³For a detailed discussion on the California Energy Crisis, refer to https://en.wikipedia.org/wiki/California_electricity_crisis, accessed on October 22, 2017.

growing energy security and environmental problems in the U.S. It also exempted fluids from unconventional gas extraction from the Underground Injection Control provisions of the Safe Drinking Water Act, increasing unconventional gas production that eventually led to the shale boom in the third cycle (2011-2016).

During the third cycle (2011-2016) the total connectedness peaked in mid-2012 (reflecting the estimation window of mid-2009 to mid-2012), and steadily declined afterwards. As the production of unconventional gas rose, the gap between natural gas consumption and domestic production narrowed and the competition between domestic producers intensified, resulting in faster and more efficient information transmission between regional markets. This pattern is justified by the behavior of the spot price series — as can be seen in Figure 2.2, the eight price sequences followed a similar path in 2009-2012. Figure 2.4 suggests that the total connectedness index had increased substantially in 2011-2013 for all forecast horizons. Except for the beginning of 2014 when natural gas prices spiked in almost all regions in the U.S. due to unexpected cold weather and low inventory, the total spillover index, however, has declined in the last few years of the sample period.

A few factors may explain the recent decline in the level of market integration. First and perhaps most importantly, the pipeline system in the U.S. may lack the capacity to support the arbitrage activities required to integrate regional natural gas markets. Despite the continued growth of natural gas supply and the rise of production in shale-rich areas, the major supply and consumption regions in the U.S. remain largely separate (Figure 2.1). Since the pipeline capacity essentially sets the upper limit on the amount of natural gas that can be transmitted between regions, shocks originated from one market can only have a limited effect on other regions when the pipeline capacity is binding, preventing prices at geographically-separated locations from converging. This problem has been reported widely, e.g., Brown and Yücel (2008); De Vany and Walls (1996); Marmer et al. (2007). Most recently, Avalos et al. (2016) report that realized citygate prices in Florida and Southern California would have been 11% and 6% lower without pipeline capacity constraints. The negative effect of pipeline capacity constraints on market integration could worsen in the shale boom era when the production growth outpaces the pipeline capacity expansion.

Second, during the shale boom era, many trading hubs along the Gulf Coast have suf-

ferred a plunge in liquidity as production in the Appalachian basin rises and fewer firms are voluntarily submitting trade data to indexes. DeFrancesco (2017) notes that only 132 out of 1,233 FERC-registered natural gas market participants were price reporters in 2016, and that ten of the 20 largest market participants by volume did not report prices. Since the spot prices at hubs are calculated as the volume-weighted prices for gas delivered the next day (based on fixed-price contracts), the decline in trading volumes reported to indexes could hamper the robustness of the price indexes, and in some instances, preventing spot prices to reflect the true market value.¹⁴ DeFrancesco (2017) discussed reasons behind the decline in reported trading volumes, including the weakened demand for fixed-price contracts by hedgers due to low natural gas prices, as well as the perceived regulatory risk comes with reporting, i.e. the FERC's lack of clarity in the safe-harbor policy regarding inadvertent errors in price reporting.¹⁵ The low liquidity in hubs could mean that the price calculated for each region does not accurately reflect the underlying supply-and-demand conditions, thus preventing spatially separated market prices from converging.

Finally, we explore the time-varying roles of the eight markets in the overall price discovery process by plotting their total price spillovers to and from other regions, as well as the net price spillovers from the rolling-window analysis. Figure 2.5 suggests all the market participants were either a net transmitter or receiver of shocks at one point during the sample period. Consistent with findings from the full-sample analysis (Tables 2.1 and 2.2, Figure 6.1), Henry Hub and Oneok are the most active markets, transmitting and receiving most shocks relative to other locations throughout most of the sample period. In contrast to Olsen et al. (2015) who identified AECO as an information sink that transmits little information to other markets, we find AECO switched from a net receiver of shocks to a net transmitter in 2005. This pattern might reflect the decrease of natural gas imports from Canada in light

¹⁴Under FERC's regulations, firms are not required to report their trading volumes and prices. The spot prices calculated by index providers rely on the volume and prices voluntarily reported by market participants.

¹⁵DeFrancesco (2017) states that the "FERC established a safe-harbor policy in 2003 that the agency 'does not intend' to prosecute or penalize firms for inadvertent errors as long as they follow its standards. However, the regulator also made it clear it could still pursue companies that violate its good faith standards and intentionally submit false, incomplete or misleading information to index companies." Many market analysts believe that the lack of clarity in this policy prevented firms from voluntarily reporting transaction activities.

of the expansion in production of fossil fuels in the U.S. From 2010 to 2016, imports of natural gas from Canada has decreased roughly 17%. Looking at Waha, we observe a reversed pattern; Waha switched from a net transmitter to receiver of shocks around 2005. Again, the decline in Waha's directional spillover to other markets may be driven by bottlenecks in transmission capacity, or the rise of shale production in the Appalachian basin. Similarly, Opal was once a large net information transmitter but had been a net receiver since 2000, though the information it transmitted and received both increased in 2005-2007, and again in 2010-2014.

For Malin, Oneok, and Chicago, their roles in the overall price discovery process all encountered several shifts during the sample period. In the past few years, Malin and Oneok had increasingly been a net transmitter of shocks, while Chicago has been increasingly a net receiver. In particular, the spillovers transmitted from and received by Chicago declined in the shale boom era. We also find that Dominion South Point started out as an information transmitter, but was a net receiver in 2006-2010, and again in 2014-2016. Finally, with few exceptions, Henry Hub consistently served as a net transmitter of shocks.

2.6 Additional Analyses

To provide further insights on the connectedness of the U.S. regional natural gas market, we next perform two simple variations of our analysis, namely (1) determining whether the connectedness patterns observed in section five hold for lower frequency data (i.e., weekly), and (2) examining the volatility transmissions between the eight spot markets.¹⁶ Since our raw data consists of daily volume-weighted average prices for each location, we use the standard deviation of returns during the week as a measure of volatility.¹⁷ In total, we

¹⁶We also conduct an additional analysis that accounts for the outliers in the price series (see Figure 2.1), and the results are rather similar to those from the raw daily data.

¹⁷In Diebold and Yilmaz (2009) and several subsequent studies, weekly volatility is measured as: $\tilde{\sigma}^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2$, where H is the Monday-Friday high, L is the Monday-Friday low, O is the Monday open and C is the Friday close. An alternative way is to use the intra-day data to calculate the daily realized volatility. However, our data only consists of one daily observation for each location (the volume-weighted average price), we cannot calculate the volatility using these two methods. We hence use the standard deviation of returns during each week to measure the volatility. In the estimation, the logarithmic transformation is used for both prices and volatility to reduce skewness.

obtain 1,172 weekly observations for both analyses. A VEC model with two lags and five cointegration factors (Table 6.2 available on Chapter 2 appendix), and a VAR model with four lags (Table 6.3 available on Chapter 2 appendix) are used to estimate the weekly total price and volatility connectedness, respectively. In both scenarios, weekly average HDD and CDD are included as exogenous variables. Additionally, 200 weeks are used as the window size.

Results suggest that using the weekly price data do not change our general conclusions regarding the connectedness between the U.S. regional natural gas markets.¹⁸ As can be seen in Panel A of Figure 2.6, the weekly total price connectedness presents similar peaks and troughs to those obtained from the daily data, though the magnitude of the total connectedness is slightly higher when the weekly prices are used, possibly because the weekly data contain less noise.

Panel B of Figure 2.6 presents the time-varying total volatility connectedness at various forecast horizons. From a bird's-eye perspective, we can see that the volatility connectedness behaves similarly to the price connectedness, ranging between 50% to 85% over the estimation period. The three main cycles reported for the price connectedness, namely 1997-2004, 2005-2010, and 2011-2016, are also present in the volatility spillover index. We similarly observe a decline in the total connectedness towards the end of the sample in the volatility connectedness. Comparing the volatility to the price spillover index, perhaps one of the most outstanding differences is that the volatility spillover index appears to contain more variability, in particular during the last cycle (2011-2016). There is an abrupt drop of the total volatility connectedness in the 2014-15, roughly corresponding to the severe winter that resulted in skyrocketing natural gas prices in many parts of the U.S. (see Figure 2.1). Unlike prices, the volatility of natural gas returns in each market in the winter of 2004-2005 may have been driven more by regional-specific factors as compared to other estimation periods.

¹⁸The weekly data also present less heteroskedasticity than the daily data as evidenced by the smaller ARCH test statistic following the VECM model.

2.7 Conclusions

The level of market integration is a critical indicator of resource allocation efficiency. In this paper, we evaluate the dynamic spatial integration in the U.S. natural gas market since deregulation and the relative importance of each location in the price discovery process. Using data from eight natural gas spot markets in the U.S and Canada from 1994 to 2016, we find that the eight markets are connected through seven long-run cointegrating relationships, and that each market is present in the long-run equilibriums. Following Diebold and Yilmaz (2012, 2014), we constructed the directional spillover “to” and “from” other markets, as well as the net spillover index for each location, and the total connectedness for the system. We find a high level of total spillover among the eight regional price sequences, suggesting that the natural gas market in the U.S. is overall well-connected and that shocks originating from one region quickly flow to other regions.

Analyzing the net directional spillover index for each market, we find that Henry Hub and Oneok are on average the two most active markets. The importance of Henry Hub may be explained largely by its strategic location, expansive transportation network, and easy access to storage facilities, as well as its role in the natural gas futures market. For Oneok, gas from southern Oklahoma can be easily transported to both eastern and western markets, and is often sold to the market with the highest price (Park et al., 2007; Serletis, 1997). By contrast, Opal appears to be separated from other markets. Although not all markets provide the same amount of information to price discovery, all markets appear to play a role: AECO, Malin, Henry Hub, and Oneok are net information transmitters, and Opal, Waha, Chicago, and Dominion South are net receivers of information.

Taking into consideration the time-varying relationships, we conduct rolling-sample analysis and identify three main cycles in the spillover index. The total dynamic connectedness spillover index has declined over the past few years, which we attribute in part to the lack of pipeline capacity to support the arbitrage activities necessary to integrate the regional markets. The problem may have worsened in the shale boom era as the gas becomes increasingly more abundant in the U.S., outpacing the speed of pipeline capacity expansion. The decline in the total connectedness may also be partly driven by the plunge in liquidity for

markets along the Gulf Coast as production shifted to the Appalachian basin, as well as a relatively small proportion of market participants voluntarily reporting transaction activities to indexes. These results are confirmed when we use the lower frequency data (i.e. weekly prices), as well as the weekly volatility. However, the volatility connectedness does appear to show more variability compared to the price spillover indices.

Regarding the dynamic role of each regional market, we find that each market is either a net transmitter or receiver of information over the rolling window horizon, highlighting the highly volatile nature of the market. The level of market integration, as well as the role of each regional market in the overall price discovery process, are apparently highly affected by the supply and demand conditions at both the national and regional levels. Unexpected supply shortfalls such as the hurricane season in 2005 increase the level of market integration, while demand shocks in a given region may not fully transmit to other markets due to pipeline congestion and market power, as evidenced by the 2001-2002 California natural gas crisis. Additionally, we find that AECO, Malin, and Oneok have increasingly become a net information transmitter, while Waha, Chicago, and Dominion South have increasingly become a net information receiver over the past few years.

While we do not find evidence supporting an east-west split in the U.S. natural gas market as in King and Cuc (1996), we note that the spillover indices appear to be lower in AECO, Malin, and Opal, all located in the west, than markets at the south and mid-continent producing basins. Our results point to the importance of expanding pipeline transmission capacity to increase arbitrage opportunities, improve market efficiency, and optimize resource allocation. Additionally, expanding export markets by constructing new pipelines to Mexico and expediting LNG exports may be an important step toward reducing excess domestic supply and improve the overall market integration. It is expected that the role of each regional market in the overall price may once again shift following these new developments.

Table 2.1: Unit root test statistic

Location	Price in level	First Difference
Texas (Waha)	25.81	-64.3553***
Wyoming (Opal)	19.7	-75.0438***
Alberta, Canada (AECO)	22.23	-67.0248***
Illinois (Chicago)	24.35	-66.9654***
Pennsylvania (Dominion south point)	18.69	-66.4307***
Oklahoma (Oneok)	2.014	-66.7805***
Oregon (Malin)	5.064	-61.4777***
Louisiana (Henry hub)	5.44	-62.5542***

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. Unit root test statistic is based on the Augmented Dickey and Fuller test (Dickey and Fuller, 1979).

Table 2.2: Cointegration rank test

Cointegration rank	Johansen Maximum Likelihood Test
$r \leq 7$	27.41***
$r \leq 6$	61.06***
$r \leq 5$	136.14***
$r \leq 4$	284.81***
$r \leq 3$	449.23***
$r \leq 2$	639.03***
$r \leq 1$	1052.53***
$r = 0$	1949.19***

Note: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. r corresponds to the number of cointegration rank. Cointegration test is based on Johansen maximum likelihood test. (Johansen, 1995).

Table 2.3: Whole sample analysis: directional and total spillover indices for the eight regional natural gas markets at 1- and 5-day ahead horizons (%)

Panel A. 1-day ahead horizon									
$i \ j$	AEC	MAL	OPA	WAH	HEN	ONG	CHI	DSO	Directional "FROM" others
AEC	<u>47.08</u>	11.17	2.28	7.20	9.98	10.53	6.14	5.63	52.92
MAL	10.07	<u>37.55</u>	3.95	11.06	11.41	13.34	6.97	5.65	62.45
OPA	4.80	9.18	<u>55.94</u>	7.34	5.93	10.26	3.83	2.71	44.06
WAH	6.21	10.47	3.17	<u>27.18</u>	15.91	19.7	10.31	7.05	72.82
HEN	7.24	9.82	2.26	13.86	<u>28.67</u>	15.92	10.75	11.5	71.33
ONG	7.11	10.55	3.41	15.78	15.35	<u>28.23</u>	12.05	7.53	71.77
CHI	5.54	7.58	1.99	11.75	14.42	15.6	<u>35.15</u>	7.97	64.85
DSO	6.00	6.94	1.50	9.29	16.53	11.89	9.73	<u>38.13</u>	61.87
Directional "TO" others	46.95	65.71	18.55	76.28	89.53	97.23	59.79	48.04	Total
Net directional	-5.97	3.26	-25.51	3.46	18.19	25.46	-5.07	-13.83	55.03
Panel B. 5-day ahead horizon									
$i \ j$	AEC	MAL	OPA	WAH	HEN	ONG	CHI	DSO	Directional "FROM" others
AEC	<u>44.78</u>	12.62	2.55	7.02	10.54	10.80	5.96	5.74	55.22
MAL	11.38	<u>37.9</u>	4.15	10.45	11.39	13.05	6.34	5.33	62.10
OPA	6.15	11.11	<u>49.8</u>	7.57	6.79	11.55	4.23	2.79	50.20
WAH	7.44	11.78	3.35	<u>22.56</u>	16.46	20.55	10.40	7.46	77.44
HEN	7.97	10.38	2.25	13.00	<u>27.87</u>	15.87	10.84	11.81	72.13
ONG	7.92	11.62	3.58	15.14	16.01	<u>26.58</u>	11.23	7.92	73.42
CHI	6.41	8.82	2.37	11.41	16.48	15.42	<u>30.32</u>	8.77	69.68
DSO	6.35	7.47	1.50	9.15	17.21	12.01	9.60	<u>36.71</u>	63.29
Directional "TO" others	53.62	73.8	19.76	73.75	94.87	99.25	58.61	49.83	Total
Net directional	-1.61	11.70	-30.45	-3.69	22.74	25.83	-11.07	-13.46	65.43

Notes: (1) AEC=AECO, Alberta. MAL=Malin, Oregon. OPA=Opal, Wyoming. WAH=Waha, Texas. HEN=Henry Hub, Louisiana. ONG=Oneok, Oklahoma. CHI=Chicago, Illinois. DSO=Dominion South Point, Pennsylvania. (2) All directional and total spillover indices are calculated based on the VEC model for the whole sample period (1994-2016). The predictive horizons are one and five days in panels A and B, respectively. (3) The j^{th} element in each panel (off-diagonal element) represents the pairwise directional spillover to market i from j . The diagonal element (with underline) suggests the own spillover index for each market. (4) The rightmost column ("FROM") shows the total spillover to market i from the remaining seven markets, while the "TO" row indicates the spillover from market i to other markets. The net spillover (last row of each panel) is the difference between the "TO" row and "FROM" column for each market. Finally, the "Total" spillover index at the bottom right (in boldface) for each panel shows the level of total connectedness, calculated as the mean of either directional "FROM" or directional "TO".

Table 2.4: Whole sample analysis: directional and total spillover indices for the eight regional natural gas markets at 10- and 20-day ahead horizons (%)

Panel A. 10-day ahead horizon									
$i \ j$	AEC	MAL	OPA	WAH	HEN	ONG	CHI	DSO	Directional "FROM" others
AEC	<u>43.03</u>	13.79	2.75	7.10	11.11	10.9	5.53	5.79	56.97
MAL	12.62	<u>36.3</u>	4.22	10.54	11.87	13.14	6.00	5.33	63.7
OPA	7.54	12.25	<u>45.54</u>	7.76	7.45	12.16	4.52	2.79	54.46
WAH	8.49	12.46	3.38	<u>19.57</u>	17.16	20.84	10.22	7.87	80.43
HEN	8.62	10.68	2.19	12.68	<u>27.3</u>	15.98	10.78	11.77	72.7
ONG	8.61	12.17	3.66	14.86	16.6	<u>25.44</u>	10.48	8.17	74.56
CHI	7.15	9.44	2.52	11.39	18.25	15.56	<u>26.28</u>	9.41	73.72
DSO	6.76	7.67	1.42	9.07	17.75	12.19	8.89	<u>36.24</u>	63.76
Directional "TO" others	59.79	78.48	20.14	73.41	100.2	100.8	56.4	51.12	Total
Net direc- tional	2.81	14.78	-34.32	-7.02	27.49	26.2	-17.32	-12.64	67.54
Panel B. 20-day ahead-horizon									
$i \ j$	AEC	MAL	OPA	WAH	HEN	ONG	CHI	DSO	Directional "FROM" others
AEC	<u>40.04</u>	15.48	3.01	7.44	11.97	11.12	5.14	5.80	59.96
MAL	14.67	<u>33.27</u>	4.24	10.6	12.71	13.38	5.76	5.37	66.73
OPA	10.04	13.84	<u>39.13</u>	8.14	8.49	12.78	4.86	2.72	60.87
WAH	10.01	13.24	3.39	<u>17.1</u>	17.98	20.37	9.64	8.26	82.9
HEN	9.76	11.18	2.12	12.42	<u>26.38</u>	16.07	10.5	11.56	73.62
ONG	9.86	12.92	3.68	14.35	17.35	<u>23.73</u>	9.64	8.47	76.27
CHI	8.39	10.22	2.59	11.5	20.17	15.7	<u>21.39</u>	10.04	78.61
DSO	7.49	7.99	1.29	9.16	18.38	12.52	8.05	<u>35.13</u>	64.87
Directional "TO" others	70.24	84.87	20.32	73.6	107	102	53.58	52.22	Total
Net direc- tional	10.28	18.14	-40.55	-9.29	33.43	25.68	-25.03	-12.65	70.48

Notes: (1) AEC=AECO, Alberta. MAL=Malin, Oregon. OPA=Opal, Wyoming. WAH=Waha, Texas. HEN=Henry Hub, Louisiana. ONG=Oneok, Oklahoma. CHI=Chicago, Illinois. DSO=Dominion South Point, Pennsylvania. (2) All directional and total spillover indices are calculated based on the VEC model for the whole sample period (1994-2016). The predictive horizons are ten and twenty days in panels A and B, respectively. (3) The j^{th} element in each panel (off-diagonal element) represents the pairwise directional spillover to market i from j . The diagonal element (with underline) suggests the own spillover index for each market. (4) The rightmost column ("FROM") shows the total spillover to market i from the remaining seven markets, while the "TO" row indicates the spillover from market i to other markets. The net spillover (last row of each panel) is the difference between the "TO" row and "FROM" column for each market. Finally, the "Total" spillover index at the bottom right (in boldface) for each panel shows the level of total connectedness, calculated as the mean of either directional "FROM" or directional "TO".

Table 2.5: Pipeline capacity by state in 2016 (capacity in million cubic feet per day)

Location	Outflow	Inflow
Illinois (Chicago)	15,886	18,002
Pennsylvania (Dominion south point)	25,290	15,780
Louisiana (Henry Hub)	29,839	40,413
Oregon (Malin)	3,619	5,549
Oklahoma (Oneok)	15,335	5,962
Wyoming (Opal)	14,644	6,525
Texas (Waha)	36,096	14,407
Alberta, Canada (AECO)	21,400*	21,400*

Notes: (1) In the parenthesis is the hub considered in our paper located in each state. (2) For Alberta, the Canada National Energy Board does not provide information regarding the natural gas pipeline capacity segregated by outflow and inflow. The numbers shown are for outflow and inflow combined. Source: US Energy Information Administration <https://www.eia.gov/naturalgas/data.phpppipelines>; Canada National Energy Board <https://www.neb-one.gc.ca/nrg/ntgrtd/trnsprtttn/2016/cnds-ppln-trnsprtttn-systm-eng.html>

Figure 2.1: Locations of the eight spot markets considered in the analysis, and the difference between the production and consumption of natural gas for each state in 2016

Note: Red (net exporter of natural gas); Green (net importer of natural gas). Source: Net production and consumption data are from the US Energy Information Administration <https://www.eia.gov/naturalgas/data.cfm> pipelines.

Figure 2.2: Daily prices of eight natural gas spot markets in the U.S. and Canada, January 1, 1994 - October 31, 2016

Figure 2.3: Whole sample analysis (1994-2016): net spillover index for each market at different forecast horizons

Figure 2.4: Rolling-sample analysis: total spillover index at various forecast horizons using vector error correction models with different number of cointegrating vectors (fixed window period = 786 days)

Figure 2.5: Rolling-sample analysis: net spillover index at 10-day ahead horizon for each location (fixed window period = 786 days, or approximately three years; number of cointegrating vector = 7)

Figure 2.6: Additional analyses: total price (Panel A) and volatility (Panel B) spillovers at the weekly frequency (fixed window period = 200 weeks)

Chapter 3

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

3.1 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 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

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

²See <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.

due to their vital role in inflation, economic development, market supply, and aggregate demand (Frankel, 2006; Calvo, 2019; Akram, 2009; Morana, 2013).

In this Chapter we analyze the volatility patterns of crude oil and natural gas markets in the U.S. and examine how they have changed due to economic policy uncertainty. Persistent changes in energy price volatility present risks 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, mitigating turbulent moments in the economy.

Energy prices react to economic policy uncertainties through at least three channels. Firstly, firm-level investment decisions are, in general, sensitive to uncertainties (Bernanke, 1983; Pindyck, 1991; Hoque and Zaidi, 2019). 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 due to increased pressure on financing cost and dubious future energy demand (Antonakakis et al., 2014; Kang et al., 2014; Wang et al., 2014). The resulting delayed response in quantity produced and consumed may lead to more pronounced price swings when exogenous shocks occur as compared to when the economy presents 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 by increasing the production cost, posing upward pressure on the supply-and-demand balance that may 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., 2019; Chiu et al., 2018; Qadan and Nama, 2018; Yang et al., 2019). An elevated economic policy uncertainty could lead to negative investment sentiment as risk-averse traders postpone trading activities, affecting volatility in the energy market.³ Zhang (2019) 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 economic policy uncertainty is a valid proxy for investor sentiment in the energy market due to its predictability of crude oil returns and volatility.

While much empirical work has investigated the effect of energy markets on economic development and vice versa, few have analyzed how economic policy uncertainty may affect 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., 2017b,c).

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

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

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; Degiannakis and Filis, 2017). 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 Chapter 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 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 first employ the Markov Switching Generalized Autoregres-

sive 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 moments in the first regime, and more persistent, agitated movements in the second regime. However, the overall natural gas 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 markets. For crude oil, an elevated EPU is linked to 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. In the post-2010 period, we observe a large and significant effect of EPU during low likelihood of agitated market conditions, followed by a decrease in the effect as we move to higher quantiles. 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 Chapter 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 Chapter, respectively. Results are provided in section five. Section six concludes the Chapter.

3.2 Existing Work on EPU and Energy Price Volatility

Baker et al. (2016) 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

Several recent 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. Wang et al. (2014) find that the level of corporate investment for companies listed at the China Securities Regulatory Commission decreases (increases) when the policy uncertainty is high (low). 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.

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. Aroui 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

⁴See <http://www.policyuncertainty.com/methodology.html> for the details on the EPU index.

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 markets. 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 Chapter 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. The few papers that investigated the relationship between energy volatility and EPU found rather mixed results. Shahzad et al. (2017) uncover a causal effect of EPU on crude oil volatility at its median distribution. Several other papers suggest that

the EPU index helps to forecast oil price volatility in the U.S. (Degiannakis and Filis, 2017; 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, and Ji et al. (2018) find that EPU has virtually zero effect on energy market volatility.

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 the country the third largest exporter globally behind Australia and Qatar. 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). This view is echoed by a recent empirical study of Hoque and Zaidi (2019) which suggests that global economic policy uncertainty has a greater impact

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

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. Unlike previous studies that only consider energy market volatility, we instead focus on volatility regimes as many of the investment portfolios and hedging strategies are regime-dependent. Using quantile regressions we measure how EPU affects 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.

3.3 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 (Diebold, 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:

$$h_{k,t} = \alpha_{0,k} + \alpha_{1,k}y_{t-1}^2 + \beta_k h_{k,t-1} \quad (3.1)$$

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:

$$\mathbf{P} \equiv \begin{bmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{bmatrix} \quad (3.2)$$

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., $\sum_{j=1}^K p_{i,j} = 1, \forall i \in \{1, \dots, K\}$. The specification in the MS-GARCH

model permits a difference persistence in the conditional variance of each regime.

To estimate equation (3.1), we evaluate the following likelihood function:⁶

$$L(\Lambda \mid \Psi_T) \equiv \prod_{t=1}^T f(y_t \mid \Lambda, \Psi_{t-1}) \quad (3.3)$$

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:

$$f(y_t \mid \Lambda, \Psi_{t-1}) \equiv \sum_{i=1}^K \sum_{j=1}^K p_{i,j} z_{i,t-1} f_D(y_t \mid s_t = j, \Lambda, \Psi_{t-1}) \quad (3.4)$$

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 Hamilton's filter. From the filtered probability, we estimate the probability based on the full-sample information, stable (smooth) probability of being in regime i , $sp_i \equiv P[s_t = i \mid \Lambda, \Psi_T]$.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:

$$h_t = \alpha_{0,k} + \alpha_{1,k} y_{t-1}^2 + \alpha_{2,k} y_{t-1}^2 \theta \{y_{t-1} < 0\} + \beta_k h_{t-1} \quad (3.5)$$

The 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 approach of Koenker and Bassett (1978). As compared to the conventional linear regression model, quantile regressions are more robust against outliers in

⁶The Maximum Likelihood estimator is obtained by maximizing the logarithm form of equation (3.3). 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., 2019).

⁷See Hamilton (1994) for further details.

the data, as well as when the data have a skewed distribution. The quantile regression is described as follows:

$$sp_t = \alpha_q + \beta_q EPU_{t-1} + \theta_q \mathbf{W}_{t-1} + \mathbf{e}_t \quad (3.6)$$

where β_q is the vector of unknown parameters related to the quantile q^{th} of a given stable probability (sp_t). $\mathbf{W}$ is a vector of financial and macroeconomic variables to help isolate the relationship between EPU and the likelihood of agitated market conditions.

As compared to the 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 likelihood of agitated market movements at different quantiles of its conditional distribution. A non-significant β_q suggests that the probability of the energy market being in the volatile regime is not affected by changes in 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.

3.4 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. 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 therefore reflects mostly the public's views and sentiments toward economic policy uncertainty.

The sample period of our analysis spans from January 1, 1994 to December 31, 2019. 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 3.1 plots the daily WTI crude oil and HH natural gas prices, along with their realized volatility, calculated as the squared logarithmic price returns.⁸

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. The two price sequences 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 2016-2017.

Figure 3.1 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 rise of domestic production in the U.S. and a stagnating global economy. We employ the ICSS method of Inclan and Tiao (1994) to test for a possible structural break in the two volatility sequences.⁹ Estimation results confirm our prior expectations of a structural break around 2010—for natural gas, a break was detected on 12/10/2009, while for crude oil the break

⁸We assume realized volatility as the squared price returns just for the sake of simplicity since its only purposes is to portray the dynamics of energy price fluctuation. Other methods such as the standard deviation of price returns as realized volatility used on Chapter 2 portrays similar dynamics. For discussion on more efficient methods to estimate realized volatility, please see Garman and Klass (1980); Martens and Van Dijk (2007).

⁹The ICSS is largely used in the literature to test structural break in the variance, especially in forecasting volatility in financial markets (Poon and Granger, 2003).

occurred on 06/04/2009. Similar break dates are also found by the Pruned Exact Linear Time (PELT) algorithm developed by Killick et al. (2012). Since the break dates identified are not far apart, for easier presentation we divide the sample periods into two sub-periods: pre-2010 and post-2010 for both markets.¹⁰

Table 3.1 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 12/31/2019). 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.

3.5 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 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.

3.5.1 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 both

¹⁰Results using the identified break dates of ICSS and PELT are qualitatively similar and are available from the authors upon request.

normally-distributed and t-distributed error terms. 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 of 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 for Chapter 3 (Tables 6.4–6.7).

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. The mean equation for natural gas is modeled as an ARMA(1,1) in sub-sample 1 and MA(1) for sub-sample 2. The coefficients for the autoregressive (AR) and moving-average (MA) terms are all highly significant in the mean equations. For the volatility estimation, model diagnostic tests in Tables 6.4–6.7 (panel C) suggest that the baseline GARCH specification presents satisfactory performance across sub-periods. However, the baseline specification may overestimate volatility persistence if there exist shifts in the unconditional variance of the underlying series (Diebold, 1986; Haas et al., 2004).

Of the two MS-GARCH specifications which account for regime-shifting, the one with 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 t-distributed errors is preferred over the MS-GJR-GARCH model 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 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 3.2 and 3.3, 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. 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 inferences, an MS-GARCH model should classify high and low regimes with high probability, in other words, sp_t closer to 0 or 1 (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:

$$RCM = 400 \frac{1}{T} \sum sp_t(1 - sp_t) \quad (3.7)$$

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 3.4 reports the RCM statistics for the preferred MS-GARCH models. The estimated RCM statistics are relatively low (ranging between 5 and 55) when 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 errors can efficiently classify the occurrence of different regimes over the two sample periods, with the MS-GARCH for crude oil presenting a higher efficiency.

Regarding the volatility behavior for the pre-2010 period, the parameters in Table 3.2 panel B 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 3.3). 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 oil (≈ 46 days) than natural gas (≈ 4 days).

After 2010, both markets present less volatile behavior in the two regimes. Despite the decline in volatility, as can be seen in Tables 3.2 and 3.3, the probability of regime 2 (high volatility) for natural gas and crude oil increased, hitting 78.5% and 2.9%, respectively. The two regimes in the crude oil market remain rather distinguishable, with the high-to-low

ratio reaching 3.12. For natural gas, the two regimes present more distinct unconditional volatilities as compared to the pre-2010 period—the high-to-low ratio is 2.01 (1.15 in sub sample 1). For comparison, Choi and Hammoudeh (2010) find the high-to-low volatility ratio in the WTI crude oil 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 3.4 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 did change drastically during the sample period, as also suggested by Table 3.2. Despite the overall decline in volatility, the number of agitated moments in crude oil 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.

For natural gas, as can be seen in Figure 3.4 it presents larger and more persistent swings in the probability of a volatile regime after 2010. Before 2010, the probability of natural gas being in the volatile regime follows a similar pattern as the oil. After 2010, although the rising natural gas production has significantly decreased the overall market volatility, the likelihood of natural gas prices experiencing agitated market moments has, in fact, increased. Scarcioffolo and Etienne (2019) 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.

3.5.2 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 for designing regime-specific hedging strategies and investment portfolios. We estimate Equation (3.6) considering 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. Changes in the level of stocks above or below the expected level would affect commodity prices and volatility. 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, and calculate the percentage changes in inventories from one period to the next ($\% \Delta Inventory$). To match the frequency of the dependent variable, we convert the weekly inventory data to the daily frequency by assuming a constant level throughout a week.

Following Behmiri et al. (2019), 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 daily basis, and the data are obtained from the Federal Reserve Bank of Philadelphia. Given the impact of exchange rates on commodity prices, 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 as defined by the National Bureau of Economic Research.

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 volatility as the demand and supply have to adjust to the new market conditions. Using the lagged EPU also help minimize the “reverse causality” problem that variations in energy market volatility may feed back into EPU. Additionally, the results based on the lagged EPU can be used to predict the likelihood of agitated movements in the following period. For similar reasons, we also consider the lagged values of the financial and macroeconomics variables to estimate Equation (3.6).

Table 3.5 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 each market being in regime 2. The macroeconomic and financial variables described above are included as the control variables. Figures 3.3 and 3.4 plot the coefficients of EPU across various quantiles of the dependent variables.¹¹ For comparison, we also include the OLS regression coefficients in the graphs. As can be seen, with the exception of natural gas in sub-sample 2, 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, Figure 3.3(a) indicates that in sub-sample 1, a higher EPU significantly increases the likelihood of agitated market conditions starting from quantile 0.3, with the magnitude of the effect increases sharply at higher quantiles. The stable probability of agitated moments becomes less sensitive to EPU in the post-2010 period, with the coefficients become smaller in sub-sample 2.

For natural gas, EPU exerts a positive and significant effect on the probability of agitated movements 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. The post-2010 natural gas market, on the other hand, is characterized by an inverse U-shaped relationship between EPU and the probability of agitated market conditions, as shown in Figure 3.4(b). Except for the quantiles between 0.8–0.95 when the EPU is not statistically significant, the estimated coefficients are positive, spiking at quantile 0.3, followed by a sharp decline as we move to higher quantiles.

Figures 3.3 and 3.4 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 markets in the U.S. has undergone tremendous changes over the past decade. One of the main

¹¹The result for the other variables are available from the authors upon request.

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) and around 41.8% for natural gas. The oversupply of natural gas has also changed how other sectors interact with the energy industry.

The relatively rigid production, along with a thinner market prior to 2010 (especially for natural gas), might have constrained how producers and investors adapt to economic policy uncertainties. As a result, EPU exerts a large effect on the probability of volatile regimes in both markets prior to 2010. 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 3.3 and 3.4 is that the effect of EPU on the likelihood of agitated market conditions differ between crude oil and natural gas. To understand these results, it is useful to examine the distributional properties of the two stable probability sequences. As can be seen in Table 3.6, 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 6.41%). The probability of agitated market 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%).

We next quantify the effects of EPU on the volatility regimes in the two markets at different quantiles. For example, in the pre-2010 crude oil market, at a probability of 6.41% (quantile 0.95), a one-standard-deviation increment on the level of EPU is associated with a increase, on average, by 6.40 percentage point on the likelihood of agitated moments. At a similar likelihood, the effect of EPU on the natural gas probability is not significant. It is not until quantile 0.7 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, whereas the natural gas market is only highly affected by the EPU when faced with a relatively lower likelihood 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.¹² The crude oil market is internationally integrated, with oil prices at different locations overall move in the same direction.¹³ By contrast, the degree of market integration is significantly lower in the natural gas market (Li et al., 2014; Scarcioffolo and Etienne, 2019). 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,^{14 15} as market participants across the 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 responses 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, significantly affecting 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 relative higher likelihoods for crude oil market, whereas for natural gas, we observe a larger

¹²See <https://www.iea.org/gas2018/>, accessed on June 28, 2019

¹³See <https://www.eia.gov/todayinenergy/detail.php?id=35792>, accessed on June 28, 2019

¹⁴See <https://www.cmegroup.com/education/articles-and-reports/henry-hub-natural-gas-futures>, accessed on June 28, 2019

¹⁵See <https://www.cmegroup.com/trading/energy/light-sweet-crude-oil.html>, accessed on June 28, 2019

impact at low quantiles. As the likelihood of agitated market conditions in the natural gas market escalates quickly (at quantile 0.3, the probability of a volatile regime is 79.25%) 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.¹⁶

3.6 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 is 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.

Estimation results suggest that MS-GARCH models that accounts for “fat-tails” 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). The volatility persistence for crude oil is similar during the two sub-periods (i.e., before and after 2010), where regime 1 presents more persistent behavior. In other words, crude oil regime 1 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

¹⁶We present the results between the two markets’ probabilities of experiencing a volatile regime and the EPU considering the whole sample in Appendix of Chapter 3 (Figures 6.2 and 6.3). EPU significantly increases the likelihood of agitated market conditions for crude oil at higher quantiles. For natural gas, the whole sample results closely follow those from sub-sample II analysis. At low probability of agitated moments EPU exerts a positive impact while at higher likelihood, EPU effects becomes insignificant.

tranquil market conditions for the first regime, and periods with more persistent volatility and agitated movements in regime 2. 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. These results are in direct contrast from those in Ji et al. (2018) and Bakas and Triantafyllou (2018) but corroborate those in Shahzad et al. (2017), although all those previous studies focus on volatility instead of volatility regimes. We further find that the effect has declined in the second sub-sample and 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 volatility regimes is confined to relative larger probability of volatile regimes in the post-2010 period.

Prior to 2010, EPU exerts a positive impact on the likelihood of agitated moments in the natural gas market at low likelihood (quantiles great than 0.6). After 2010, the effect of EPU presents a inverted U-shaped effect; increasing effect on low quantiles (quantile range 0.1–0.3 represents the range of probability of a volatile regime between 10.03%–79.25%), followed by sharp dampening effect at high likelihood of agitated market conditions (after quantile 0.3), as majority of market participants have already modified their investment expectations.

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 energy trading, impacting how private investors behave.

Interestingly, results from crude oil are key to understanding possible ramifications to the maturing natural gas market in the U.S. and its interaction with the EPU. With increasing exports of LNG, the natural gas market in the U.S. is likely to become integrated with other international markets; hence natural gas pricing might move from regional perspectives to reflect global fundamentals, similar to crude oil markets. Under this scenario in coming years, we might expect to see EPU exerting a more significant impact on the likelihood of agitated market conditions even when the market presents tranquil conditions as market participants across the world seek hedging and speculative positions at increments on the level of economic policy uncertainty.

One limitation with the present paper is that the EPU index used in the analysis 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.

Table 3.1: Summary statistics

	Sub-sample I - from 01/01/1994 to 12/31/2009			Sub-sample II - from 01/01/2010 to 12/31/2019		
	Return Crude oil	Return Natural gas	EPU	Return Crude oil	Return Natural gas	EPU
Obs	4,165	4,165	4,165	2,608	2,608	2,608
Min	-17.387	-37.575	3.380	-10.794	-18.055	3.320
Max	28.961	35.766	719.070	16.099	21.064	548.470
Mean	0.018	0.000	87.610	-0.011	-0.037	104.592
Std. Dev.	2.605	3.955	66.909	2.159	2.864	60.991
Skewness	0.174	0.354	2.489	0.246	0.197	1.643
Kurtosis	8.167	8.093	10.843	4.937	4.586	4.368
J-B Normality	11,611***	11,468***	24,732***	2,681.3***	2,308.2***	3253.3***
ARCH(10)	310.98***	153.62***	3,204.2***	222.32***	232.11***	4553.8***
ADF	-49.05***	-47.48***	-13.48***	-38.56***	-37.93***	-7.652***
Q^2	55.086***	29.953***	6315.7***	22.28***	19.56***	6602.9***

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 Box-Pierce 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 3.2: Univariate GARCH with Student distributed innovations - Crude oil

	Sub-sample I (01/01/1994-12/31/2009)		Sub-sample II (01/01/2010-12/31/2019)	
Panel A - Mean Equation				
AR(1)	0.857***	(0.040)		
MA(1)	-0.876***	(0.042)	-0.087***	(0.020)
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)	0.022***	(0.000)
$\alpha_{1,1}$	0.021***	(0.001)	0.038***	(0.001)
β_1	0.972***	(0.001)	0.954***	(0.000)
μ_2	31.753***	(0.153)	17.854***	(0.167)
$\alpha_{2,1}$	0.054***	(0.003)	0.291***	(0.006)
β_2	0.003***	(0.002)	0.006***	(0.003)
Stable Probability ($D = 1$)	0.978		0.971	
Stable Probability ($D = 2$)	0.022		0.029	
Duration ($D = 1$)	45.662		34.014	
Duration ($D = 2$)	1.022		1.03	
Unconditional Volatility ($D = 1$)	32.358		25.589	
Unconditional Volatility ($D = 2$)	92.096		79.969	
Panel C - Standardized residual diagnostics				
$\hat{\varepsilon}$ Mean	0.015		-0.016	
$\hat{\varepsilon}$ Std. error	1.005		0.991	
$\hat{\varepsilon}$ Variance	1.01		0.983	
$\hat{\varepsilon}$ Skeness	-0.287		-0.257	
$\hat{\varepsilon}$ Kurtosis	4.032		3.928	
Jarque-Bera	2882.9***		1709.9***	
Arch Effect	10.209		5.494	
Ljung-Box (20)	38.164		16.721	
Log-Likelihood	-9,336		-5,332	
AIC	18,693		10,684	
BIC	18,756		10,743	

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

Table 3.3: Univariate GARCH with Student distributed innovations - Natural gas

	Sub-sample I (01/01/1994-12/31/2009)		Sub-sample II (01/01/2010-12/31/2019)	
Panel A - Mean Equation				
AR(1)	0.680***	(0.112)		
MA(1)	-0.732***	(0.103)	-0.055***	(0.02)
Panel B - Variance Equation				
μ_1	0.184***	(0.001)	0.158***	(0.002)
$\alpha_{1,1}$	0.074***	(0.001)	0.007***	(0.000)
β_1	0.914***	(0.001)	0.935***	(0.001)
μ_2	5.879***	(0.048)	0.235***	(0.002)
$\alpha_{2,1}$	0.078***	(0.001)	0.045***	(0.001)
β_2	0.658***	(0.002)	0.934***	(0.000)
Stable Probability ($D = 1$)	0.752		0.215	
Stable Probability ($D = 2$)	0.248		0.785	
Duration ($D = 1$)	4.039		1.274	
Duration ($D = 2$)	1.329		4.653	
Unconditional Volatility ($D = 1$)	62.762		26.159	
Unconditional Volatility ($D = 2$)	72.373		52.727	
Panel C - Standardized residual diagnostics				
$\hat{\varepsilon}$ Mean	0.006		-0.01	
$\hat{\varepsilon}$ Std. error	0.972		0.995	
$\hat{\varepsilon}$ Variance	0.946		0.99	
$\hat{\varepsilon}$ Skeness	0.513		0.296	
$\hat{\varepsilon}$ Kurtosis	5.442		2.645	
Jarque-Bera	5328.9***		800.89***	
Arch Effect	11.459		13.458	
Ljung-Box (20)	22.357		21.383	
Log-Likelihood	-4001		-6181	
AIC	22,151		12,382	
BIC	22,215		12,441	

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

Table 3.4: 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 - 12/31/2019)	9.730	22.066

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

Table 3.5: Correlation between EPU and energy market high volatility stable probability

RCM	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 - 12/31/2019)			
EPU	1.000		
Crude oil	0.017*	1.000	
Natural gas	0.136***	0.096***	1.000
n=	2608		

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

Table 3.6: Distribution of the crude oil and natural gas stable probability of high volatility regimes

Quantile	Sub-sample I (01/01/1994 - 12/31/2009)		Sub-sample II (01/01/2010 - 12/31/2019)	
	Crude oil	Natural gas	Crude oil	Natural gas
0.1	0.07%	3.00%	0.54%	10.03%
0.2	0.10%	7.23%	0.68%	47.10%
0.3	0.13%	10.92%	0.83%	79.25%
0.4	0.17%	15.01%	1.01%	95.72%
0.5	0.22%	18.43%	1.27%	98.16%
0.6	0.32%	22.91%	1.61%	99.09%
0.7	0.48%	29.01%	2.13%	99.51%
0.8	0.92%	38.39%	3.06%	99.84%
0.9	2.72%	55.24%	5.26%	99.95%
0.95	6.41%	77.55%	9.73%	99.98%

Figure 3.1: Daily volatility and price series of West Texas Intermediate (WTI) crude oil, and Henry Hub (HH) natural gas, January, 1994 - December, 2019

(a) Crude oil

(b) Natural gas

Figure 3.2: Daily stable probability of high volatility regime of West Texas Intermediate (WTI) crude oil, and Henry Hub (HH) natural gas, January, 1994 - December, 2019

(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 – 12/31/2019)

Figure 3.3: Quantile regression using OLS for crude oil stable probability

(a) Sub-sample I (01/01/1994 - 12/31/2009)

(b) Sub-sample II ((01/01/2010 - 12/31/2019)

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 3.4: Quantile regression using OLS for natural gas stable probability

(a) Sub-sample I (01/01/1994 - 12/31/2009)

(b) Sub-sample II ((01/01/2010 - 12/31/2019)

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.

Chapter 4

Testing Directional Predictability Between Energy Prices: A Cross- quantilogram Analysis

4.1 Introduction

The energy system in the U.S. consists of a colossal interconnected network that produces and supplies a great variety of energy sources to attend an ever-increasing demand. The dynamics of the energy sector, including primary sources such as crude oil and natural gas as well as secondary sources such as electricity and fuels, depends on an array of complex and diversified factors that goes beyond the demand and supply framework (Ji et al., 2018). For instance, events such as turmoil in the Middle East, global financial crisis, natural disasters, economic uncertainty, and extreme weather events have been shown to greatly influence energy price volatility (Pindyck, 2001; Serletis and Rangel-Ruiz, 2004; Mu, 2007; Kilian, 2008; Aloui et al., 2014; Lin and Li, 2015; Shahzad et al., 2017; Ji et al., 2018). As a result, significant price fluctuations are an intrinsic aspect of the energy market. Under these circumstances, price dependence of energy commodities is likely to vary as well due to the complex nature of the interrelationships within the energy sector. For example, variation on natural gas prices is a key input into decisions on whether to generate electricity using natural gas, consequently impacting the price of electricity. Accurately understanding the

linkages between energy prices are essential to policymakers who wish to design effective energy policies that encourage the use of one resource over another and to assess the effect of energy regulations in one sector on the other. In addition, energy firms and downstream industries need to understand these linkages for their hedging strategies and investment in inventories or different types of energy-using equipment, as well as to private investors on their trading strategies.

The present Chapter examines three essential questions for the U.S. energy markets that remain unresolved due to conflicting results in the literature, namely 1) the “decoupling” of crude oil and natural gas prices; 2) the mixed relationship between natural gas and electricity prices, and 3) the “rockets and feathers” effect between crude oil and petroleum products prices. For instance, Woo et al. (2006) and Emery and Liu (2002) suggest that natural gas and electricity prices are cointegrated, presenting a bi-directional causal dependence, a hypothesis that was earlier rejected by Serletis and Herbert (1999). Regarding the crude oil and natural gas markets, Brown and Yücel (2008) and Hartley et al. (2008) advocate that crude oil has a prominent role in pricing natural gas, whereas Zhang and Ji (2018) suggest the two markets have decoupled since they do not share the same fundamentals. Borenstein et al. (1997) found that gasoline prices respond faster to increases than decreases in the crude oil prices, albeit Lahiani et al. (2017) indicate that crude oil price changes are more correlated with the gasoline market at low and medium price quantiles.

One possible explanation of these contradicting results is that most previous studies focus on the interrelationship between these markets at either their first (i.e., mean prices or returns) or second (i.e., volatility) moments of the distribution (Serletis and Herbert, 1999; Mjelde and Bessler, 2009; Woo et al., 2006; Emery and Liu, 2002; Erdős, 2012; Radchenko, 2005; Aloui et al., 2014). While energy sources are closely intertwined due to their multipurpose applications, the causal price dependence, as well as its duration, may vary significantly depending on the fluctuations in prices. For instance, shocks to one market when prices are low may not impact the prices of other energy sources. In contrast, innovations originated from the same market during a price boom period may exert significant effects. These changes in the causal patterns, in principle, could be highly non-linear and depend on the underlying market conditions. As is evident, analyses focusing on the average

price/volatility relationship may fail to capture the whole dynamics between two markets if the extremely negative and positive observations are not considered separately.

A growing strand of literature has highlighted the importance of examining the dependence structure at different quantiles. Recent quantile-based analyses in the energy markets include, among others, Lahiani et al. (2017); Aloui et al. (2014); Shen et al. (2018). However, these studies often rely on econometric methodologies with strong assumptions on the distributional properties of the variables and the autocorrelation structure of the error term. For instance, focusing on the extreme quantiles by employing Copula-GARCH models, Aloui et al. (2014) find that crude oil and natural gas markets tend to co-move closely during bullish periods, but not at all during bearish periods. The authors attribute the stronger linkage during boom periods to the increased use of natural gas by the industrial sector and the rising conversion capacity between oil and natural gas. During contracting periods, by contrast, the industrial use of natural gas shrinks, with major importers pushing natural gas prices to be delinked from oil-indexed long-term supply contracts. While informative, Aloui et al. (2014) only consider the marginal distributional properties of the underlying variables which may fail to depict the relationship when the distributional assumptions are invalid.¹

In this Chapter, we extend the literature by employing a recently developed semi-parametric methodology, namely, the cross-quantilogram of Han et al. (2016) to analyze the directional quantile dependence between energy prices. Compared to the existing methods, this approach offers two main advantages. First, it captures the interplay between energy price by analyzing all parts of the distribution, from extremely low to extremely high observations. Thus, it provides us with a tool to understand the complete picture of the relationship between two variables regardless of the distribution region. Second, it does not require distributional assumptions of the underlying variables to test causality (in the Granger sense). This is particularly useful in our case as the distribution of energy prices often exhibits heavy tails. Additionally, the method allows us to consider very long lags in the causality test, which is typically unfeasible in the conventional regression-based analysis due to the degree-of-freedom concern.

We analyze three commonly discussed questions that remain unresolved in the literature,

¹See <http://web.math.ku.dk/~mikosch/Preprint/Copula/s.pdf>, accessed on March 3, 2020.

namely, the “decoupling” of crude oil and natural gas prices, the mixed relationship between natural gas and electricity prices, and the “rockets and feathers” effect between crude oil and petroleum products prices. Using daily prices between 2003 and 2019, we find that there exists a positive and significant spillover from oil to natural gas during bearish market conditions vis-à-vis a lack of effect during bullish market conditions, and that the spillover during bearish moments have weakened since 2013, suggesting a possible “delink” between crude oil and natural gas after the rise of unconventional oil and gas production. However, the “delink” appears to have occurred at a much later time period than suggested by some previous studies. Regarding the directional predictability between natural gas and electricity markets, we find a bi-directional spillover at different quantiles and the effect is more pronounced during moderate and high market conditions. More recently, the two prices appear to be more correlated at lower quantiles, reflecting the decline of electricity generation from coal-fired power plants and the transition of natural gas power plants from peak to baseload facilities. Finally, our results do not support the “rockets and feathers” effect between oil and two refined products, i.e., heating oil and gasoline. The directional predictability from crude oil to the wholesale prices of the two refined products is more significant and persistent during low market conditions as compared to bullish market moments.

The remainder of the Chapter is structured as follows. Section two discusses the energy market causal dependencies, while section three describes the methodology employed. Section four presents the data, and the results are discussed in section five. Section six concludes the Chapter.

4.2 Energy Market Causal Dependencies

4.2.1 The Decoupling of Crude oil and Natural gas Prices

Crude oil and natural gas markets are linked through at least three channels: joint production, resource competition, and fuel substitution. With regard to the first, natural gas can be produced from either gas wells and condensate wells (for natural gas and natural gas liquids), or from oil wells as a byproduct (associated gas). The joint production na-

ture suggests that there exists a negative correlation between oil and gas prices—high oil prices will incentivize investment in the oil industry, leading to higher oil and associated gas production, which further results in lower natural gas prices.

The resource competition and fuel substitution channels, on the other hand, suggest a positive correlation between oil and natural gas prices. Fossil fuel companies often produce both oil and natural gas, and would have to allocate investment according to the returns to each commodity.² Higher natural gas prices would attract investment and resources away from the oil industry, resulting in lower oil production and higher oil prices. Meanwhile, natural gas and crude oil are close substitutes. Large fuel consumers, e.g., power plants, iron, steel, and paper mills, can switch between natural gas, petroleum products, and coal, depending on the cost of each fuel on a heat-equivalent basis. Hartley et al. (2008) find a strong plant-level substitution between residual fuel oil and natural gas in a few North American Electric Reliability (NREC) regions with strong system-wide switching capability, as well as a grid-level substitution in other regions where different types of plants can be operated for different lengths of time depending on relative fuel prices. Additionally, liquefied natural gas (LNG) is often priced outside of the US in oil-to-gas contract, tightening the positive link between natural gas and crude oil markets (Brown and Yücel, 2008).

The mixed effects of the three channels suggest that the price linkage between oil and natural gas can vary depending on which channel dominates the relationship. The majority of the existing literature indicates that at least as recent as 2008, the fuel substitution and resource competition channels play a more important role than the joint production channel—not only did oil and natural gas prices move together in both the short- or long-runs (Serletis and Herbert, 1999; Brown and Yücel, 2008; Hartley et al., 2008; Villar and Joutz, 2006), but oil prices also dominated natural gas pricing.

However, the shale boom that started in 2007-2009 has impacted the production of both commodities due to the combined use of hydraulic fracturing and horizontal drilling that enabled efficient production of oil and gas from lower and tight formations. As a result of the increased availability of natural gas in the country, lower natural gas prices relative

²See <https://www.cmegroup.com/education/articles-and-reports/are-crude-oil-natural-gas-prices-linked.html>, accessed November 21, 2019.

to other fuels, and the ability of natural gas to comply with environmental regulations, the US manufacturers' short-term capability to switch between fuels has declined, weakening the effect from the fuel substitution channel in the price relationship.³ Meanwhile, the electricity generating capacity from petroleum-fired plants has dramatically declined in the US due to high oil prices in the past few decades, with utilities switching to other fuel sources. In 2016, only 1% of the total electricity produced in the US came from oil-fired plants, further limiting the fuel substitution effect.

The rising joint production of natural gas due to the shale boom, on the other hand, has strengthened the negative price relationship between natural gas and crude oil. In 2018, associated gas accounted for 16% of the total US natural gas production, up from 8% in 2006. In the five major tight oil production regions (i.e., Permian, Bakken, Eagle Ford, Niobrara, and Anadarko), the share of associated gas in total natural gas production grew from 8% in 2006 to 37% in 2018.⁴ The rapid expansion of associated gas production suggests that oil and natural gas prices may become more negatively linked.

Spurred by the dramatic shift in the energy sector over the past two decades, a growing number of papers suggests that crude oil and natural gas markets have “delinked” (Serletis, 2007; Erdős, 2012; Zhang and Ji, 2018; Batten et al., 2017; Lin and Li, 2015). Indeed, as can be seen in Figure 4.1, prior to 2008 the two markets appear to have moved together, both peaking in 2008 and subsequently plummeting in the second half of 2008. While oil prices rebounded in 2010, natural gas prices have remained at a relatively low level since then. Serletis and Rangel-Ruiz (2004) attribute the decoupling of the two markets to the deregulation of the energy sector in the US. A similar result is found by Erdős (2012) and more recently, by Batten et al. (2017) and Zhang and Ji (2018), who argue that the US crude oil and natural gas markets no longer share the same fundamentals.

However, the decoupling of oil and gas prices is not a universal conclusion in the literature. A recent study suggests that the two markets in fact have temporarily shifted rather than permanently “delinked” (Brigida, 2014). Focusing on volatility and risk transmission, Karali

³See https://www.eia.gov/consumption/manufacturing/reports/2014/fuel_switching/index.php, accessed December 5, 2018.

⁴See <https://www.eia.gov/todayinenergy/detail.php?id=41873>, accessed March 5, 2020.

and Ramirez (2014), Aloui et al. (2014) and Shen et al. (2018) argue that oil and gas markets still present some level of integration. Karali and Ramirez (2014) suggest an indirect bi-directional volatility spillover through a covariance term between natural gas and the crude oil markets. Aloui et al. (2014) show evidence of asymmetric dependence between natural gas and crude oil markets—the two prices move closely during bullish periods, but not during bearish periods. Shen et al. (2018) estimate the risk transmission at different quantiles, finding that shocks on the crude oil market are easily transmitted to the natural gas market during high-risk conditions as compared to moderate-risk moments. Additionally, there exists little risk transmission from the natural gas to the crude oil market.

The existing evidence on whether the crude oil and natural gas markets have delinked in recent years appears to be mixed, and that even for the studies favoring a decoupling of the two markets, there is no consensus as to when the two markets have in fact become delinked. Our study aims to contribute to this discussion from a time-varying, cross-quantile perspective.

4.2.2 The Mixed of Electricity and Natural gas Price Dependence

The consumption of natural gas in the US is mainly dependent on the industrial and electricity sector, accounting for roughly 68% of the total consumption in the country.⁵ In recent years, natural gas has taken over coal as the largest fuel source for electricity generation. Apart from the input-output relationship, natural gas and electricity are substitutes during the heating process for commercial and residential purposes. It is expected that natural gas prices affect electricity prices and vice-versa. During cold weather, the demand for natural gas for heating increases, translating into higher natural gas prices. Consequently, the cost to produce electricity by open-cycle gas turbine (OCGT) and combined-cycle gas turbine (CCGT) plants would also increase, which in turn affects electricity prices. Meanwhile, an increment in the demand for electricity due to extremely hot weather can be translated into higher electricity prices due to inelastic electricity demand. High-peak generators such as OCGT are utilized to balance demand and supply, driving up natural gas prices (Uribe et al.,

⁵See <https://www.eia.gov/energyexplained/natural-gas/use-of-natural-gas.php>, accessed February 4, 2020.

2018).

Despite the apparent relationship between the two energy markets, results regarding the dynamics between the electricity and natural gas markets are surprisingly mixed. For instance, Woo et al. (2006) suggest only a short-run bi-directional Granger causality between natural gas and electricity prices, while Emery and Liu (2002) indicates that the two prices are cointegrated in the long-run. Looking at peak electricity prices, Mjelde and Bessler (2009) suggest that electricity prices influence natural gas prices in the short-run. Xia et al. (2020)'s results suggest a heterogeneous directional causality—in the short-run, there is a unidirectional Granger causality from electricity to natural gas prices, while in the long-run, natural gas and crude oil prices Granger cause the electricity market. Meanwhile, Nakajima and Hamori (2013) and Serletis and Herbert (1999) find no statistically significant causality in mean or variance between electricity and natural gas markets in the U.S.

The conflicting results regarding the relationship between the two markets may be due to the complex, yet evolving structure of the electricity industry. The decreasing natural gas prices over the past decade and the more stringent environmental regulations have boosted the utilization of OCGT and CCGT plants and accelerated the retirement of many aging coal-fired power plants. Natural gas-fired generators were usually employed for intermediate or peak load. With the increased efficiency and flexibility, CCGT plants have become more competitive with coal-fired plants for baseload operations. Alexopoulos (2017) argues that with the retirement of coal power plants, the average cost of natural gas will become the determinant factor setting average electricity prices in the near future.

Figure 4.2 portrays this evolution. In 2003, more than 50% of the average electricity produced in the US came from coal, while in 2018, it only represents 30%. Utilization of natural gas, on the other hand, has increased from 17% in 2003 to 38% in 2018, the largest share across all fuel sources. The PJM Interconnection⁶ presents the largest increment in the utilization of natural gas-fired generators in the country. Between 2013 and 2017, 19% of the region's coal capacity was retired, while increasing the region's natural gas capacity

⁶PJM Interconnection is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.

by 18% (11 GW). Importantly, 95% of the added natural gas capacity was CCGT plants.⁷

The present Chapter will reexamine the price relationship between electricity and natural gas markets in light of the evolving structure in the electricity industry. Two recent papers that attempt to account for these changes are Alexopoulos (2017) and Uribe et al. (2018). Alexopoulos (2017) applies a one-step-ahead rolling forecast to examine the performance of using the average natural gas cost to predict retail electricity prices, finding that after 2014, the impact of natural gas in electricity prices on retail electricity rates becomes stronger (i.e., higher forecast accuracy). Meanwhile, Uribe et al. (2018) measure the directional predictability of regional electricity and natural gas prices in the US, finding a bi-directional causality between natural gas and electricity which strengthens as prices increase. However, the authors do not consider how the directional predictability might have changed over time.

4.2.3 Crude oil and Petroleum Products – “Rockets and Feathers” Effect

Crude oil is commonly refined into different petroleum products such as gasoline, distillates (diesel fuel and heating oil), jet fuel, petrochemical feedstocks, asphalt, etc.⁸ Due to the importance of oil and its refined products in the economy, a large number of papers have examined their price relationships (Borenstein et al., 1997; Villar and Joutz, 2006; Lahiani et al., 2017; Joëts and Mignon, 2012; Atil et al., 2014; Chen et al., 2005). Since the seminal study of Bacon (1991), a consensus in the literature is that petroleum products, especially gasoline, respond faster and more significantly to crude oil price increases than to decreases. This relationship is usually described as “rockets and feathers”—petroleum product prices rise as fast as rockets when crude oil prices increase, but fall as slowly as feathers as the prices of oil decline. This effect is often explained by factors such as inventory levels, market competition, production lags, and the oligopolistic coordination theory, with firms combined acting faster when there is an increase in crude oil prices (Bacon, 1991; Borenstein et al., 1997; Brown and Yucel, 2000; Atil et al., 2014).

⁷See <https://www.power-eng.com/2019/04/11/eia-gas-fired-combined-cycle-now-generates-more-u-s-power-than-coal/gref>, accessed February 6, 2020.

⁸See <https://www.eia.gov/energyexplained/oil-and-petroleum-products>, accessed on February 11, 2020.

On average, 40% of a barrel of oil is designated to produce gasoline in the US, and crude oil reflects roughly 60% of the average cost per gallon of retail regular-grade gasoline and an even higher percentage at the wholesale level. Hence, it is expected that there exists a high level of spillover from crude oil to the gasoline market. Although the majority of studies have focused on retail gasoline prices, Borenstein et al. (1997) suggest that gasoline prices at various stages of production and distribution, from the refinery to the retail pump, all respond quickly to increases than decreases in crude oil prices, supporting the “rockets and feathers” hypothesis. Moreover, Radchenko (2005) present evidence that the degree of asymmetry between the two markets decreases when oil price volatility increases, which often corresponds to a more bearish market condition. The asymmetric responses between wholesale gasoline prices and crude oil may reflect the competitive market forces at the refinery level, bottleneck in distribution, inventory adjustment cost, and price expectation that affect energy markets differently depending on economic conditions (Balke et al., 1998; Brown and Yucel, 2000; Borenstein and Shepard, 2002; Atil et al., 2014).

Some studies also suggest the presence of asymmetric effects between crude oil and heating oil. Heating oil is used mainly in boilers, furnaces, and water heaters. About 5.7 million households in the US use heating oil as their main space heating fuel. The US Northeast region accounts for roughly 80% of the total population that use heating oil for space heating.⁹ Kaufmann and Laskowski (2005) argue that the asymmetric relationship between oil and heating oil is likely due to contractual arrangements between retailers and consumers. Karali and Ramirez (2014) find evidence of direct and indirect asymmetric spillovers between crude oil shocks and heating oil volatility, which they attribute to the fall in industrial production, decline of oil prices, and the highly volatile nature of heating oil prices.

Despite the overall consensus on the “rockets and feathers” relationship between the prices of oil and its refined products in the literature, there is reason to believe that the asymmetric response may not be static and even if the asymmetry does exist, the degree of price responses may vary depending on market conditions, especially at the wholesale level. Brown and Yucel (2000) argue that there is little evidence of monopolization in the US refinery and wholesale

⁹See <https://www.eia.gov/energyexplained/heating-oil/use-of-heating-oil.php>, accessed February 11, 2020.

gasoline markets, limiting the presence of the “rockets and feathers” relationship. Although Balke et al. (1998) show there exists asymmetric response from wholesale gasoline prices to crude oil prices, they find the degree of asymmetry is quite small and of short duration—the difference in response of wholesale gasoline to 1% increase and decrease in oil prices is only 0.35% and lasts only two weeks. Meanwhile, Atil et al. (2014) suggest that refineries may face very costly production and inventory adjustments in the short-term, leading to the delayed response of wholesale gasoline prices to oil price changes. They further find that exists a short-run asymmetric relationship between crude oil and wholesales gasoline prices, with crude oil price decreases affect wholesale gasoline prices more noticeably than price increases. Additionally, Lahiani et al. (2017) use a quantile autoregressive distributed lag model and find that crude oil prices dominate gasoline prices across low and medium quantiles, and across all quantiles for diesel and heating prices.

Figure 4.3 plots the price difference between (wholesale) gasoline and crude oil on a per-barrel basis. The spreads between oil and its refined products are often used to estimate the theoretical refining margins to guide refineries’ hedging strategies. As can be seen in the figure, the two prices appear to co-move with gasoline prices presenting larger fluctuations. There exist episodes when gasoline prices react faster and more significantly to crude oil price increases (e.g., 2008-2009, 2015-2016, 2019-2020), supporting the “rockets and feathers” hypothesis. However, in some other periods, such as 2007-2008, 2012-2013, and 2016-2017, gasoline prices appear to have responded more significantly when crude oil prices decline. This conflicting relationship between crude oil and petroleum products prices highlights the importance of re-examining the price dynamics from a time-varying, market-condition based perspective.

4.3 Econometric Method

We use the cross-quantilogram (CQ) method developed by Han et al. (2016) to analyze the lead-lag correlation between energy price returns for different lags and quantiles simultaneously. Compared to other econometric procedures, the CQ is a semi-parametric approach with only a key assumption that the series considered should be strictly stationary.

Sequences that present “heavy tails” such as energy price returns are suitable under the CQ methodology.

Define $x_{i,t}, t \in Z$ for $i = 1, 2$ as two strictly stationary series. For instance, $x_{1,t}$ and $x_{2,t}$ are the returns of oil and gasoline prices, respectively. From the strictly stationary energy price return series, we define the $F_i(\cdot)$ and $f_i(\cdot)$ as the distribution and density function, respectively. The quantile of each price return series is defined as $q_{i,t}(\alpha_i) = \inf(v : F_i(v) \geq \alpha_i) \forall i \in \{0, 1\}$, generating cutting points of the probability distribution into continuous intervals with probability equal to α_i . The CQ methodology is based in two steps: it first estimates the quantile-hit process (quantile-exceedance process), which is the serial dependence between two events $x_{1,t} \leq q_{1,t}(\alpha_1)$ and $x_{2,t-k} \leq q_{2,t-k}(\alpha_2)$, and the second step is defined as the cross-correlation of the different quantile-hit process (Han et al., 2016):

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t} - q_{1,t}(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - q_{2,t-k}(\alpha_2))]}{\sqrt{E[\psi_{\alpha_1}^2(x_{1,t} - q_{1,t}(\alpha_1))]} \sqrt{E[\psi_{\alpha_2}^2(x_{2,t-k} - q_{2,t-k}(\alpha_2))]}}. \quad (4.1)$$

where $\psi_{\alpha_i}(x_{i,t}) \equiv 1[x_{i,t} \leq q_{i,t}(\alpha_i)] - \alpha_i$ represents the quantile-hit and k the lead-lag periods to time t . The CQ captures the serial dependence between two energy price returns at different quantile levels, hence the presence of directional predictability between them. For $\alpha = (\alpha_{oil}, \alpha_{gasoline})$, $\rho_\alpha(1)$ represent the cross-correlation between the crude oil price return being above or below quantile $q_{oil}(\alpha_{oil})$ at time t and the gasoline price returns being above or below the quantile $q_{gasoline}(\alpha_{gasoline})$ at time $t - 1$. For $\rho_\alpha(1) = 0$, the CQ suggests no cross-dependence or directional predictability from gasoline to oil price return on the next trading day. In contrast, $\rho_\alpha(1) \neq 0$ indicates that there exists 1-day directional predictability from gasoline price returns to oil price returns at quantile α .

Additionally, Han et al. (2016) propose a quantile version of the Ljung-Box test with $H_0 : \rho_\alpha(K) = 0 \forall k \in 1, \dots, K$ against the alternative $H_1 : \rho_\alpha(K) \neq 0 \forall k \in 1, \dots, K$:

$$\hat{Q}_\alpha(K) = T(T+2) \sum_{k=1}^p \frac{\hat{\rho}^2(k)}{T-k} \quad (4.2)$$

The portmanteau test $\hat{Q}_\alpha(K)$ is used to test the directional predictability of price returns of one sequence series to another for events up to K lags at each pair of quantiles. Han et al. (2016) suggest using the stationary bootstrap (SB) of Politis and Romano (1994) to

calculate the confidence intervals since this procedure accounts for possible misspecifications under the null hypothesis of no directional predictability while guarantying the stationary property of each series for each block of the bootstrap procedure.¹⁰

The cross-quantilogram approach has been employed in different contexts. For instance, Uribe et al. (2018) measure the directional predictability between regional electricity and natural gas prices. Their results suggest that both New England and Pennsylvania-New Jersey-Maryland regions present a bidirectional causality, in which the effect becomes stronger when both price sets are at and above their median value. Analyzing the directional predictability between renewable energy stocks (RE), aggregate stock returns, exchange rates, crude oil and gold prices, Uddin et al. (2019) suggest that the relationship between RE stock returns and oil prices is not symmetric as previously believed, and this asymmetry increases at longer lags. Shahzad et al. (2019), on the other hand, focus on the debate on the oil-precious metal nexus. Their results suggest that silver, palladium, and platinum cannot act as perfect hedges against downturns in oil markets.

4.4 Data

We consider daily spot prices for crude oil, natural gas, electricity, heating oil and gasoline. The West Texas Intermediate (WTI) and the Henry hub prices are used for crude oil (\$/barrel) and natural gas (\$/MMbtu), respectively. The New York Harbor No. 2 is a proxy for heating oil (\$/gallon), while the reformulated blendstock for oxygenate blending (RBOB) is chosen to represent gasoline (\$/gallon). Finally, we consider the next-day wholesale PJM West weighted average price (\$/MWh) to be a proxy for electricity price. The PJM is the world's largest competitive wholesale company in the electricity market (Scarcioffolo et al., 2018). Crude oil, natural gas, heating oil, gasoline are obtained from the Energy Information Agency (EIA), while electricity prices are obtained from the PJM official website. The sample period considered is November 24, 2003–August, 12, 2019, resulting in a total of 4,101 observations. We consider high-frequency data (daily data) due to the likely presence of a short-term relationship between energy markets as shown in previous studies, as well as to

¹⁰Please, see Politis and Romano (1994) for further information.

avoid the possible underestimation of the speed of adjustment between energy prices.

Figure 4.4 plots the log-returns, $100 \cdot \ln(P_t/P_{t-1})$. Several volatility clusters exist in the return series, possibly representing events that occurred in the underlying market. For instance, in 2005 the hurricane season disrupted the supply of natural gas in the U.S., increasing price across the country. Such an effect might spillover to other markets including crude oil, heating oil and gasoline, the return series of which also present small volatility clusters during this period. The 2008/2009 financial crisis disrupted the entire U.S. economy and as can be seen, natural gas and electricity presents the largest fluctuations during this period. After 2010, all markets but the electricity present moments of tranquil conditions until 2014, possibly due to the rapid rise of unconventional oil and natural gas production in the U.S.

Table 4.1 sheds light on the distribution of each return series. The electricity market shows the highest volatility among the markets considered. Natural gas comes in second regarding dispersion (4.467), while crude oil, heating oil, and gasoline present similar standard deviations. The mean daily returns for natural gas and electricity are negative, while for the other markets the returns are positive. Except for electricity, all return series are positively skewed. Additionally, all return sequences present positive kurtosis (heavy tails) in their distributions. None of the markets considered are normally distributed nor homoskedastic according to the Jarque-Bera and ARCH-LM tests, respectively. Since the CQ method does not impose restrictions on the distributional properties of the series, the presence of heteroskedasticity and non-normality does not affect the results on directional predictability between the markets. Finally, we test for stationarity behavior using the Augmented Dickey-Fuller (Dickey and Fuller, 1979) and the Phillip-Perron (Phillips and Perron, 1988) tests. We find that all our variables are stationary, fulfilling the only CQ methodology restriction.

4.5 Results

To address the three questions previously discussed, namely 1) the “decoupling” of crude oil and natural gas prices, 2) the mixed relationship between natural gas and electricity prices, and 3) the “rockets and feathers” effect between crude oil and refined product markets, we

provide the estimation results in three different manners. First, we analyze the quantile spillovers between two return sequences when both markets present extreme low ($\alpha = 0.05$), low ($\alpha = 0.1$), medium ($\alpha = 0.5$), high ($\alpha = 0.9$), and extreme high ($\alpha = 0.95$) prices. We consider a lead-lag relationship up to 21 days in order to observe how the dynamics between the two energy markets change over a month. For statistical significance test, we use the 95% bootstrapped confidence interval with 1,000 repetitions.¹¹ These results are shown in Figures 4.5, 4.8, and 4.11 for the three hypotheses, respectively.

Second, we present heating maps for the lead-lag relationship at the one-day horizon to show different combinations of quantiles between two markets in Figures 4.6, 4.9, and 4.12. In each plot, the horizontal axis corresponds to the market in which the shock is originated from, and the vertical axis represents the market affected by this shock. The advantage of heating maps is that we can simultaneously capture several measurements of the dependence between two markets as well as the magnitude of the spillover effects. To simplify the plots, we set the dependence to zero when the CQ measure is not statistically significant based on the 95% bootstrapped confidence interval.

Lastly, we consider the one day-ahead rolling window cross-quantilogram (Figures 4.7, 4.10, and 4.13). The rolling window approach can uncover possible structural changes and show how events in the economy might have impacted the dependence structure. For each pair of markets, we use the first 1,260 observations (roughly five years) as the initial window to calculate the one-day cross-quantilogram. Then, we roll the window one day ahead and compute the cross-quantilogram until the end of the sample is reached.¹²

4.5.1 Crude oil and Natural gas Price Dependence

Panel A of Figure 4.5 shows that when crude oil presents low to moderate returns, i.e., $\alpha = 0.05, 0.1$, and 0.5 , the cross-quantilogram is positive and statistically significant after one day. For instance, the $CQ(\alpha_{0.05})$ is 0.05 , suggesting that when the crude oil market is presenting substantial losses, there is an increased likelihood for the natural gas market to

¹¹We did not include the portmanteau no directional predictability test $\hat{Q}_\alpha(20)$ here to save space. Results are available upon request.

¹²The results considering a window with 756 observations (3 years) is present in the Chapter 4 Appendix.

also present large to moderate losses on the next trading day. This relationship becomes more pronounced as the crude oil market returns move to higher quantiles. However, when the oil market experiences significant positive gains ($\alpha = 0.9$ and 0.95), the spillover effect to the natural gas market is non-significant in the short-term. For longer horizons, there exists directional predictability from crude oil to natural gas across all quantiles. However, at extreme high returns ($\alpha = 0.95$), we only observe significant directional predictability to the natural gas market after four weeks.

Consistent with previous studies such as Hartley et al. (2008), we find little directional predictability from natural gas to crude oil (Panel B of Figure 4.5). First, regardless of the natural gas return quantiles, there is no short-term spillover to the oil market (after one trading day). Secondly, at a relatively longer horizon, there exists a few negative directional predictability from natural gas to crude oil at moderate and extremely high returns. For instance, when the natural gas market return is at quantile 0.95, there is an increased likelihood of crude oil market to have relatively lower positive gains after six trading days, $CQ(\alpha_{0.95}) \cong -0.025$.

Figure 4.6 presents the cross-quantilogram after one trading day between crude oil and natural gas for different combinations of return quantiles. Panel A corroborates the short-run heterogeneous directional predictability from crude oil to natural gas found in Figure 4.5. Natural gas is more likely to present low to moderate performance when crude oil presents bearish moments. On the other hand, as the crude oil starts moving to bullish conditions, the short-run directional predictability to natural gas weakens and the effect disappears during extreme positive gains.

Panel B of Figure 4.6 shows the lack of directional predictability from natural gas to crude oil after one trading day. We observe a relatively small positive predictability when the natural gas market is at low to moderate returns, but these effects appear to be isolated. In other words, our results do not show relatively significant predictability from natural gas to crude oil returns up to 21 days (Figure 4.5) and also at different combinations of market conditions (Figure 4.6).

Consistent with Brown and Yücel (2008) and Hartley et al. (2008), our results suggest that crude oil has an essential role in predicting natural gas returns in the short-term. How-

ever, this effect appears to be heterogeneous depending on the initial market condition; during bearish markets, natural gas returns are more likely to present similar performance as in the oil market, while during moments of extreme positive gains, the directional predictability from crude oil to natural gas is weaker. During contracting economic periods, the resource competition becomes the prominent channel between the two market since the joint production effect is reduced due to decrease of industrial demand for natural gas and crude oil, while the industrial conversion capacity shrinks, burden the fuel substitution effect. At expanding market conditions, on the other hand, higher demand for both commodity escalates the joint production effect along with resource competition and the fuel substitution channels, possibly counterbalancing the channel effect between the two prices. Our results differ from Aloui et al. (2014), in which they find a strong tail dependence during bullish market conditions. It is important to highlight that their results are based on a sample that partially covers the shale boom (1997-2012), in which the resource competition and fuel substitution channel presented stronger effect.

Regarding the directional predictability from natural gas to the crude oil market, we do not observe a significant spillover effect regardless of the market conditions during the whole sample analysis. The lack of spillover from natural gas to oil possibly reflect the difference between the two energy markets; natural gas prices reflect regional events such as weather, natural disasters, the region's access to different supply basins, pipelines and storage facilities vis-à-vis the international dynamics for the crude oil market (e.g., economic recession, financial crises, geopolitical tension, and wars) that are likely to affect natural gas prices over the long-run (Atil et al., 2014).

To test the hypothesis whether the two markets have “decoupled” in recent years, we compute the rolling window directional predictability between crude oil and natural gas (Figure 4.7) when both markets are in bearish ($\alpha = 0.1$), moderate ($\alpha = 0.5$), and bullish ($\alpha = 0.9$) conditions.¹³ Based on panel A, during bearish moments, ($\alpha = 0.1$), there is a strong positive and significant directional predictability from crude oil to natural gas until 2009, followed by a sharp decline in the spillover effect. After 2011, the directional predictability bounced back, staying positively significant until 2013 but presented a negative

¹³Results for different quantiles are available upon request

trend afterwards until the end of the sample. Similarly, for moderate market conditions, the oil market presents significant directional predictability to natural gas until 2015. On the other hand, for bullish market conditions, the directional predictability is insignificant across the sample period.

Taken together, these results suggest that the crude oil market indeed has a strong one-day directional predictability for the natural gas market during bearish to moderate conditions, which has subsequently weakened in recent years. This new dynamics might suggest a new era of the fossil fuels price dependence in the U.S., in which the deregulated natural gas market, the financialization of the energy market, as well as the rise of unconventional oil and gas production, may have changed the fundamentals of both oil and natural gas. However, the decoupling between the two markets might have occurred much later than found in many previous studies, many of which suggest that the two markets have become “delinked” since 2008 (Serletis and Rangel-Ruiz, 2004; Erdős, 2012; Zhang and Ji, 2018). Our results, on the other hand, show that oil and natural gas did not permanently “decoupled” in 2008, but rather, drifted apart later in 2013 for bearish market conditions, and in 2015 for moderate conditions.

4.5.2 Price Dependence between Natural gas and Electricity

Panel A of Figure 4.8 shows that the electricity market affects natural gas in the very short-run (1 trading day), as well as at longer horizons depending on its initial market condition. For instance, when the electricity returns are low ($\alpha=0.1$), it is expected that the natural gas returns will perform similarly or better after one trading day, i.e., $CQ(\alpha_{0.1}) = 0.05$. On the other hand, at a longer horizon, shocks to the electricity market negatively spillovers onto the natural gas market regardless of the initial electricity market condition. For example, after 12 days, when the electricity market presents moderate returns ($\alpha=0.5$), the natural gas returns is expected to perform relatively worse.

We also observe directional predictability running from natural gas to the electricity market (panel B). Similarly, there is a transient positive spillover at moderate market conditions after one trading day. For other quantiles (low, high, and extremely high), natural gas ap-

pears to positively impact the electricity market at a longer horizon (19 days). Hence, the bi-directional dependence between electricity and natural gas returns is evident at longer horizons, and this effect is more pronounced during bullish market moments.

The one-day directional predictability from the electricity to the natural gas market is rather significant when the electricity market present moderate to high returns, as suggested by the darker-shaded area in panel A of Figure 4.9. Moreover, there is no evidence of spillover when the electricity market shows extremely high returns. Shocks to demand and supply in the electricity market are hard to mitigate due to the non-storable nature of the electricity market, generating volatile price behavior with short-term peaks (Scarcioffolo et al., 2018). Since those peaks are only short-lived, it does not affect natural gas returns after one day.

Regarding the directional predictability from natural gas to electricity (panel B of Figure 4.9), we observe significant spillover when the natural gas market present high returns. For instance, when natural gas exhibit extremely positive returns ($\alpha=0.95$), electricity is expected to present from low to moderate price returns. At extremely high natural gas prices, the utilization of natural gas-fired power plants might be replaced with other power plants that run on coal or residual fuel oil, dampening the high price effect from natural gas to the electricity market. Our results corroborate findings of Uribe et al. (2018), that there exists a bi-directional causality between natural gas and electricity when both prices were above their median.

Figure 4.10 shows how the one-day bi-directional predictability between natural gas and electricity has evolved over the sample period for low, moderate, and high market conditions. Panel A shows that for bearish and moderate market conditions, the directional predictability from electricity to natural gas has become positively significant after 2015. On the other hand, for bullish market conditions, the price dependence running from electricity to natural gas presents a negative trend, becoming insignificant in recent years.

The strong price dependence between electricity and natural gas markets at low to moderate quantiles in recent years is likely due to the transition in the power generating sector in which natural gas power plants have become baseload generators, compared to the peakload generators in the pre-shale era. As shown in Figure 4.2, the share of electricity produced by natural gas has upsurged, with an 18% increment in 2015. Specifically, in the PJM region,

investment on CCGT plants has increased sharply over recent years, and more than 29,000 MW of new natural gas plants are planned or under development in the region.¹⁴

The transformation of the electricity sector may also impact the directional predictability from natural gas to electricity price returns. It is clear that for low and high market conditions, there is a positive trend on the directional predictability (panel B of Figure 4.10). With a larger share of electricity produced using natural gas, fluctuations in natural gas prices are translated into volatility in the electricity market. At lower price levels, natural gas power plants produce cheaper electricity, whereas during high natural gas prices, baseload cost of production increases, impacting the overall price of electricity. Our results corroborate the findings on Alexopoulos (2017), in which after 2015, both energy commodities have become more relevant to each other.

4.5.3 Crude oil and Petroleum Products Price Dependence

As depicted in Figure 4.11, the directional predictability from crude oil to gasoline (panel A) and heating oil (panel B) present the most persistent effect among the pairs of markets considered in this study. Our results suggest a stronger correlation between these markets during bearish vis-à-vis bullish market conditions. For instance, when crude oil presents losses ($\alpha=0.1$), the gasoline market is more likely to present similar performance after one trading day. At longer horizons, the directional predictability appears to increase, peaking after 12 trading days. At higher quantiles, the spillover effect weakens relative to lower quantiles. Additionally, crude oil presents the weakest directional predictability power on gasoline returns during moderate market moments.

The directional predictability from crude oil to heating oil presents similar dynamics as in the relationship between crude oil and gasoline, i.e., more substantial and persistent positive spillover during low market conditions as compared to higher return quantiles. The asymmetric lead-lag correlation across the extreme quantiles from crude oil to heating oil returns corroborate the findings in Karali and Ramirez (2014). The asymmetric spillover from crude oil to the wholesale petroleum products prices might reflect the downward price

¹⁴See <https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/54111666>, access on February 4, 2020.

expectations that affect both markets during downward economic conditions, implying that the share of consumers' and producers' budget to purchase gasoline is larger when crude oil prices declines than when it rises (Atil et al., 2014).

Figure 4.12 presents the one-day directional predictability for different combinations of quantiles. In panel A, when crude oil presents low levels of returns, gasoline is more likely to present a similar performance. Additionally, the predictability is non-significant when gasoline returns are high (low) and crude oil presents bearish (bullish) market conditions on the previous trading day. The negative directional predictability between opposite market conditions is more evident for crude oil and heating oil (panel B). Shocks to the crude oil market appear to negatively spillover into heating oil. Additionally, we only observe positive and significant directional predictability at extremely low quantiles. Therefore, our results contradict the "rockets and feathers" hypothesis but are in line with Karali and Ramirez (2014); Atil et al. (2014); and Lahiani et al. (2017) that gasoline and heating oil markets present more persistent and quick responses during bearish than bullish conditions in the crude oil market.

Figure 4.13 sheds light on the evolution of the one-day directional predictability from crude oil to gasoline (panel A) and heating oil (panel B) at different market conditions. Panel A shows that at low quantiles, the cross quantilogram was quite stable during the sample period, except for 2014 when the dependence sharply plunged, possibly reflecting the crude oil price downturn in 2014 due to robust global production and sluggish demand. A similar decline, but of a smaller magnitude, is also observed at moderate and high quantiles after 2014. This result is largely consistent with Martínez et al. (2018) who use wavelet correlations to show that there exists a steady decay in the correlation between crude oil and gasoline prices between 2013 to 2015, possibly reflecting the overproduction of tight oil in the US and a slowdown in global demand for oil.

Regarding the spillover effect from crude oil to heating oil, at low quantiles the directional predictability was high, followed by a sharp drop in 2014. At moderate market conditions, the spillover effect appears to be negative at the beginning of the sample, becoming insignificant after 2010. On the other hand, the spillover effect from crude oil to heating oil during bullish market conditions has increased over time. These results highlight the importance

of accounting for the time-varying effects when analyzing the relationship between crude oil and petroleum product prices.

4.6 Conclusions

The U.S. energy market is composed of interrelated sectors that produce, transport and distribute an array of energy commodities, placing the country as a key player in producing and supplying various energy products, as well as one of the world's largest energy consumers. In this paper, we apply the cross-quantilogram and portmanteau test of Han et al. (2016) to gauge the directional predictability and the duration of the causal effect in different price regimes between various energy markets. We examine three important open questions, namely, the “decoupling” of crude oil and natural gas markets, the mixed relationship between natural gas and electricity prices, and the “rockets and feathers” effect from crude oil to petroleum product prices.

Our results overall support the decoupling between oil and natural gas markets; however, the decoupling appeared to have occurred at a later date (2013) than commonly found in other studies. Additionally, unlike previous studies show a higher spillover between the two markets when prices are high, we find there exists a positive spillover effect during bearish market conditions vis-à-vis the lack of effect during bullish moments. We further find that the spillover effect during bearish market conditions has weakened after 2013, and in 2015 for moderate returns. It possibly reflects a new era of fossil fuels in the US, where the fuel substitution effect weakens as a result of lower natural gas prices and less flexibility in substitution, and the joint production effect strengthens due to the shale boom that shifted the fundamentals of both markets. These two opposite effects combined have worked to “delink” the oil and natural gas markets. This finding implies that the weak relationship between the two commodities in recent years is unlikely to remake both fossil fuels as close substitutes in diversified portfolios to hedge against similar risks, even at low market conditions. Therefore, investment strategies for private and midstream industries should be considered the weak link between the two commodities to efficiently hold speculative and hedging positions according to changes in the energy market conditions.

Regarding the directional predictability between natural gas and electricity prices, we find a bi-directional spillover at different quantiles between both markets. This relationship is more pronounced during moderate and high market conditions, consistent with Uribe et al. (2018) who find a bi-directional causality between the two markets when both prices were above their medians. In light of the recent transformation of the electricity market—coal power plants retiring, and natural gas power plants transitioning from peak to baseload facilities—our results suggest that both natural gas and electricity returns are, in fact, more correlated at low return quantiles. Therefore, large electricity consumers may wish to design their investment strategies taking into account the strong relationship between these two energy commodities during bearish market conditions, but not at the bullish market conditions. Investment in new combined-cycle gas turbine plants to replace old natural- gas-fired generators should be incentivized as the new facilities are more efficient and produce fewer pollutants.

Finally, our results do not show evidence of the “rockets and feathers” effect for neither of the petroleum products (heating oil and gasoline). For both commodities, the directional predictability from crude oil appears to be more significant and persistent during low market conditions as compared to bullish moments. The asymmetric lead-lag correlation across the extreme quantiles from crude oil to heating oil returns corroborate those of Karali and Ramirez (2014) that there is a rapid, larger, and more persistent spillover effect during bearish markets than during bullish markets between the two markets. The discrepancy with the literature may highlight the lack of oligopolistic behavior in the wholesale markets in comparison to the retail market, in which the level of asymmetric in the wholesale market is most likely the result of competitive market forces, bottleneck in distribution, inventory adjustment cost, and price expectation that affect energy markets differently depending on economic conditions (Balke et al., 1998; Brown and Yucel, 2000; Borenstein and Shepard, 2002; Atil et al., 2014). This finding is particularly important for private traders and companies who hedges and trades the “crack spread”—conventional approaches based on the “rockets and feathers” may fail to be effective as crude oil appears to have a stronger and lasting effect on petroleum products during bearish market conditions.

Our empirical results also provide some necessary information for policymakers, as suc-

cessful energy policies depend upon an explicit recognition of the interaction between crude oil and natural gas, and secondary markets such as fuels and electricity. For instance, policies to keep low natural gas prices as well as a reliable supply is essential as we enter a new era where natural gas has become the bridge fuel to produce relatively cleaner and cheaper electricity. Additionally, a mature natural gas market has implications for developing a more independent market from fluctuations in the international crude oil market. Policies that favor the consumption or production of one commodity over another might have to take into account the actual market conditions for each sector since the existence of an interaction between energy markets is conditional on the performance of each market.

Table 4.1: Descriptive statistics

	Crude oil	Electricity	Natural gas	Heating oil	Gasoline
Min	-12.827	-153.024	-47.561	-12.708	-26.489
Max	16.414	111.734	52.535	14.862	48.38
Mean	0.002	-0.013	-0.027	0.006	0.002
St. Dev	2.346	17.756	4.338	2.162	3.402
Skewness	0.115	-0.242	0.567	0.179	0.727
Kurtosis	7.377	11.501	23.013	6.699	18.794
Jarque-Bera	3282***	12,389***	68,663***	2,360***	42,990***
ADF	-47.230***	-54.884***	-48.950***	-47.329***	-44.769***
PP	67.045***	-71.843***	64.175***	-68.039***	-64.024***
ARCH-LM(10)	406.10***	374.41***	425.349***	404.0.9***	251.67***

Note: Jarque-Berra test is the Jarque and Bera (1980) normality test statistic. The test follows a χ^2 distribution with 2 degrees of freedom. The ADF (Augmented Dickey-Fuller) and PP (Phillips–Perron) are test statistics to test the null Hypotheses of normality unit root. ARCH test is the Lagrange multiplier test to check for homokedasticity.

Figure 4.1: West Texas Intermediate (WTI) crude oil and Henry Hub natural spot price, November 24, 2003 to August, 12, 2019

Note: Dashed-red line divides the sample before and after 2009.

Figure 4.2: U.S. electricity generation by major energy source

Figure 4.3: Daily gasoline crack spread, November 24, 2003 to August, 12, 2019

Note: Crack spreads are differences between gasoline prices and crude oil prices.

Figure 4.4: Daily price returns of crude oil, electricity, natural gas, heating oil, and gasoline, November 24, 2003 to August, 12, 2019

Figure 4.5: Daily cross-quantilogram between crude oil and natural gas

Panel A - Cross-quantilogram from crude oil to natural gas

Panel B - Cross-quantilogram from natural gas to crude oil

Note: Cross-quantilogram of daily price returns spillovers between crude oil and natural gas when both markets take same quantiles. Results for extreme low quantile ($\alpha = 0.05$), low quantile ($\alpha = 0.1$), median quantile ($\alpha = 0.5$), high quantile ($\alpha = 0.9$), and extreme high quantile ($\alpha = 0.95$) with lag $k = 1, 2, \dots, 20$. Red-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 4.6: Cross-quantilogram between crude oil and natural gas after one trading day

Panel A - Cross-quantilogram from crude oil to natural gas

Panel B - Cross-quantilogram from natural gas to crude oil

Note: Cross-quantilogram of daily price returns spillovers between crude oil and natural gas at different quantiles. Results from extreme low ($\alpha = 0.05$) to extreme high ($\alpha = 0.95$) after one trading day. Cross-quantilogram statistics that are not significant at the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates are assumed to be zero.

Figure 4.7: Rolling daily cross-quantilogram between crude oil to natural gas

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from crude oil to natural gas at low ($\alpha = 0.1$) and high ($\alpha = 0.9$) quantiles. Panel B presents rolling cross-quantilogram from natural gas to crude oil market, respectively. The window has a fixed length of 1260 days (roughly 5 years). Ending year of the rolling window is marked on the horizontal axis. Solid black circles are the rolling window cross-quantilogram for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 4.8: Daily price return spillovers between electricity and natural gas

Panel A - Cross-quantilogram from electricity to natural gas

Panel B - Cross-quantilogram from natural gas to electricity

Note: Cross-quantilogram of daily price returns spillovers between electricity and natural gas when both markets take same quantiles. Results for extreme low quantile ($\alpha = 0.05$), low quantile ($\alpha = 0.1$), median quantile ($\alpha = 0.5$), high quantile ($\alpha = 0.9$), and extreme high quantile ($\alpha = 0.95$) with lag $k = 1, 2, \dots, 20$. Red-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 4.9: Daily price return spillovers between electricity and natural gas

Panel A - Cross-quantilogram from electricity to natural gas

Panel B - Cross-quantilogram from natural gas to electricity

Note: Cross-quantilogram of daily price returns spillovers between crude oil and natural gas at different quantiles. Results from extreme low ($\alpha = 0.05$) to extreme high ($\alpha = 0.95$) after one trading day. Cross-quantilogram statistics that are not significant at the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates are assumed to be zero.

Figure 4.10: Rolling daily cross-quantilogram between electricity and natural gas

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from electricity to natural gas at low ($\alpha = 0.1$), moderate ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles. Panel B presents rolling cross-quantilogram from natural gas to electricity, respectively. The window has a fixed length of 1260 days (roughly 5 years). Ending year of the rolling window is marked on the horizontal axis. Solid black circles are the rolling window cross-quantilogram for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 4.11: Daily price return spillovers between crude oil and petroleum products

Panel A - Cross-Quantilogram from crude oil to gasoline

Panel B - Cross-Quantilogram from crude oil to heating oil

Note: Cross-quantilogram of daily price returns spillovers between crude oil and petroleum products when both markets take same quantiles. Results for extreme low quantile ($\alpha = 0.05$), low quantile ($\alpha = 0.1$), median quantile ($\alpha = 0.5$), high quantile ($\alpha = 0.9$), and extreme high quantile ($\alpha = 0.95$) with lag $k = 1, 2, \dots, 20$. Red-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 4.12: Daily price return spillovers between crude oil and its byproducts

Panel A - Cross-Quantilogram from crude oil to gasoline

Panel B - Cross-Quantilogram from crude oil to heating oil

Note: Cross-quantilogram of daily price returns spillovers from crude oil to petroleum products at different quantiles. Results from extreme low ($\alpha = 0.05$) to extreme high ($\alpha = 0.95$) after one trading day. Cross-quantilogram statistics that are not significant at the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates are assumed to be zero.

Figure 4.13: Rolling daily cross-quantilogram between crude oil and its byproducts

Panel A - Cross-quantilogram from crude oil to gasoline

Panel B - Cross-quantilogram from crude oil to heating oil

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from crude oil to gasoline at low ($\alpha = 0.1$), moderate ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles. Panel B presents rolling cross-quantilogram from crude oil to heating oil, respectively. The window has a fixed length of 1260 days (roughly 5 years). Ending year of the rolling window is marked on the horizontal axis. Hollow black circles are the rolling window cross-quantilogram for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Chapter 5

Concluding Remarks

The energy sector is a vital part of the United States economy as it helps to boost economic growth, speed up job creation, spur new investment, revitalize manufacturing industries, and generate spillover and multiplier effects to other sectors of the economy. This dissertation focuses on the dynamics of several energy markets in the U.S. Specifically, Chapter 2 analyzes natural gas price integration in several regional spot markets, Chapter 3 investigates the effect of economic policy uncertainty on the likelihood of agitated market conditions in crude oil and natural gas markets, and Chapter 4 explores the directional price predictability across several energy markets.

In Chapter 2, I find that the regional natural gas market in the U.S. is on average well-integrated, and the level of integration has fluctuated over time due to developments in the underlying market. However, the market connectedness has declined in recent years, possibly due to the lack of pipeline capacity in an oversupplied market and the decline in market participants voluntarily reporting to price indexes. While results do not support an east-west split in the U.S. natural gas market, price integration appears to be stronger in producing regions (east) in comparison to the western region.

Chapter 3 shows that natural gas and crude oil present heterogeneous volatility regimes (i.e., high vs. low volatility), in which the volatility persistence for crude oil is similar during the pre- and post-shale era, while natural gas presented significant regime changes. Results further suggest that while economic policy uncertainty positively increases the likelihood of natural gas and crude oil experiencing agitated market conditions, this effect has dampened

after 2010. A possible contributing factor is that producers and investors are able to adjust production and investment strategies more efficiently and rapidly in the new era of rising shale gas and oil production.

Chapter 4 revisits three open questions in the energy economics literature by evaluating the directional predictability between several energy markets at different quantiles of their respective price return distributions. First, results suggest that crude oil and natural gas have “delinked” after 2013, later time period than suggested by some previous studies, echoing the change in fundamentals of both markets after the shale boom. Second, the relationship between natural gas and electricity price returns have strengthened during low market conditions, reflecting the transition of the natural gas power plants from peak to baseload facilities. Finally, I do not find evidence of the “rockets and feathers” effect from crude oil to two refined products (i.e., gasoline and heating oil). The correlation between crude oil and petroleum products is higher during bearish market conditions than in bullish periods.

Several implications can be drawn from the analyses conducted in the three essays. First, results highlight how the exploration of unconventional fossil fuels has revolutionized the energy industry in the U.S., affecting the dynamics between energy prices as well as their interplay with the overall macro-economy. Second, Chapter 2 suggests that pipeline capacity expansion is necessary to improve the overall natural gas market integration in the U.S. It is important to improve infrastructure and enable the transportation of natural gas from over-supplied production centers to major consumption regions. The increased arbitrage opportunities will help improve market efficiency and optimize resource allocation.

Thirdly, Chapter 3 shows that it is important for investors to understand how energy markets respond to abrupt changes in policy-related uncertainty since it impacts their portfolio returns. 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 energy trading, impacting how private investors behave. Lastly, Chapter 4 suggests that investment strategies and policy decisions should consider interrelationships between energy markets at different quantiles, which are likely to behave rather differently depending on the underlying market conditions.

Future work should expand on these issues and concentrate in gathering more detailed data. For instance, considering different economic policy uncertainty channels such as monetary and fiscal might be beneficial to understand specific impacts and draw appropriate responses in order to decrease turbulent moments in the energy market. Moreover, information transmission from natural gas players might be dependent on the withdraw and injection periods. By expanding this analysis considering both periods separately, this might be crucial to understand the overall dynamics of the natural gas market integration.

Chapter 6

Appendices

6.1 Chapter 2

Figure 6.1: Rolling-sample analysis: total spillover index at various forecast horizons using vector error correctional models with different number of cointegrating vectors (fixed window period = 252 days, or approximately one year)

Table 6.1: Vector error correction estimation results using daily prices, January 1994-October 2016

	AEC	MAL	OPA	WAH	HEN	ONG	CHI	DSO
ECT1	-0.028***	0.03***	0.039***	0.023***	0.013***	0.014**	0.009	0.009
ECT2	0.03***	-0.045***	0.03*	0.027***	0.005	0.014*	0.008	0.002
ECT3	0.002	0.002	-0.083***	0.000	-0.004	0.004	0.006	-0.005
ECT4	-0.041*	-0.026	-0.09*	-0.391***	-0.034*	-0.016	-0.057*	-0.045*
ECT5	0.041**	0.034**	0.028	0.089***	-0.029**	0.054***	0.163***	0.036**
ECT6	0.020	0.022	0.086**	0.240***	0.034**	-0.065***	0.033	0.044*
ECT7	-0.018.	-0.015	0.004	0.005	0.009	-0.017	-0.177***	-0.022*
AEC lag 1	-0.147***	0.134***	0.123***	0.095***	0.077***	0.081***	0.076***	0.072***
MAL lag 1	0.082***	-0.062***	0.142***	0.023	0.050***	0.039*	0.036	0.017
OPA lag 1	-0.015*	-0.020**	-0.381***	-0.014	-0.007	-0.012	-0.012	-0.013
WAH lag 1	-0.091***	-0.134***	-0.158***	-0.515***	-0.052***	-0.097***	-0.078**	-0.116***
HEN lag 1	0.068*	0.038	0.041	0.185***	-0.135***	0.113***	0.214***	0.136***
ONG lag 1	0.036	0.051*	0.306***	0.332***	0.084***	-0.136***	0.097**	0.151***
CHI lag 1	0.024	0.018	-0.049	0.029*	0.029**	0.066***	-0.275***	0.090***
DSO lag 1	-0.002	0.007	0.002	0.000	0.055***	0.037*	0.041*	-0.226***
AEC lag 2	-0.208***	0.008	0.000	0.005	-0.001	0.007	-0.003	-0.024
MAL lag 2	0.037	-0.082***	0.095**	0.064***	0.011	0.059***	0.068**	0.019
OPA lag 2	0.008	0.011	-0.289***	0.012	0.004	0.011	0.026**	0.002
WAH lag 2	-0.042	-0.044*	-0.050	-0.313***	-0.030	-0.023	-0.034	-0.002
HEN lag 2	0.011	-0.004	0.019	-0.004	-0.147***	0.044	0.166***	0.022
ONG lag 2	0.039	0.015	0.143**	0.082**	-0.008	-0.25***	-0.098**	-0.040
CHI lag 2	0.002	-0.022	-0.048	-0.020	-0.002	-0.022	-0.28***	0.030
DSO lag 2	-0.007	-0.026	-0.050	-0.012	0.020	0.003	-0.003	-0.187***
HDD lag 1	-0.001***	-0.001***	0.000	-0.001***	0.000***	-0.001***	0.000	-0.001***
CDD lag 1	-0.001***	-0.001***	-0.001*	0.000*	-0.001***	-0.001***	-0.001**	-0.002***
Monday	0.013***	0.033***	0.024***	0.033***	0.018***	0.026***	0.018***	0.035***
Tuesday	0.011***	0.017***	0.022***	0.022***	0.008***	0.015***	0.006*	0.024***
Wednesday	0.014***	0.020***	0.032***	0.022***	0.011***	0.017***	0.014***	0.021***
Thursday	0.003	0.010***	0.015***	0.013***	0.006***	0.006**	0.002	0.010***
Exclusion test	156.9***	107.68***	792.58***	284.71***	607.11***	323.51***	72.22***	70.91***
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak Exogeneity	1816.93***	1759.21***	1759.8***	1045.65***	1724.97***	1575.02***	1556.88***	1873.25***
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively. For the exclusion test, the is not in the cointegration space. The null hypothesis under the weak exogeneity test is that a market is weakly exogenous with respect to perturbations in the co-integrating vectors. Under the null hypothesis, both test statistics are distributed as a χ^2 with 49 degrees of freedom.

Table 6.2: Vector error correction estimation results using weekly prices, January 1994-October 2016

	AECO	MAL	OPA	WAH	HEN	ONG	CHI	DSO
ECT 1	-0.122***	-0.018	0.005	-0.001	-0.029*	-0.008	-0.016	-0.018
ECT 2	0.085	-0.292***	-0.075*	-0.073*	-0.138***	-0.047	0.01	-0.039
ECT 3	0.046	0.025	-0.109***	0.068**	-0.009	0.02	0.042*	0.005
ECT 4	0.071**	0.011	0.052**	-0.051**	0.026	0.023	0.035*	0.012
ECT 5	-0.043***	-0.015*	-0.010	0.003	-0.013*	0.000	-0.01*	-0.006
AECO Lag1	-0.222***	0.022	0.021	0.014	0.015	0.029*	0.047*	-0.006
MAL Lag1	0.036	-0.413*	0.048	0.011	-0.033	0.052	0.086*	0.062*
OPA Lag1	0.141*	0.048	-0.107*	0.146**	0.002	0.057	0.069	0.027**
WAH Lag1	0.150**	0.203	0.096*	-0.109**	0.115**	0.167***	0.177***	0.114
HEN Lag1	-0.028	-0.013	0.013	-0.026	-0.202***	-0.036	-0.037	-0.029
ONG Lag1	0.125	-0.059	-0.051	0.032	0.104	-0.269*	0.288***	0.086
CHI Lag1	-0.222*	-0.310***	-0.024	-0.114	-0.178*	-0.117	-0.786***	-0.083
DSO Lag1	0.097	0.697***	0.093	0.208*	0.364***	0.211*	0.261**	-0.023
AECO Lag2	-0.095*	0.046	-0.010	0.001	0.010	0.016*	0.016	-0.005
MAL Lag2	0.079	-0.398***	-0.045	-0.07	0.032	0.023	0.108*	0.062
OPA Lag2	0.06	0.095*	-0.071	0.084*	0.063	0.074*	0.087*	0.078*
WAH Lag2	0.149*	0.092*	0.096*	-0.144***	0.047	0.112**	0.120**	0.075*
HEN Lag2	0.103	0.224***	0.122*	0.087*	-0.009	0.124**	0.134**	0.078*
ONG Lag2	0.069	0.083	0.006	0.052	-0.106	-0.110	0.397***	0.053
CHI Lag2	-0.202	-0.131	-0.001	-0.068	0.079	-0.051	-0.662***	0.008
DSO Lag2	-0.201	-0.186*	-0.182*	-0.042	-0.190*	-0.290***	-0.324***	-0.417***
HDD Lag1	0.001*	0.001***	0.000	0.000	0.001***	0.001*	0.000	0.001
CDD Lag1	0.001	0.001*	0.000	0.000	0.000	0.001	0.001*	0.000

Notes: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively.

Table 6.3: Vector autoregressive estimation results using weekly volatility, January 1994-October 2016

	AECO	MAL	OPA	WAH	HEN	ONG	CHI	DSO
Constant	0.022***	0.000***	0.012**	0.018	0.005	0.01***	0.017***	0.008**
AECO Lag1	0.497***	-0.023***	0.006***	-0.003***	-0.002***	0.01***	0.038***	0.005***
MAL Lag1	0.269***	0.458	0.174***	0.107	0.088	0.235	0.161	0.072
OPA Lag1	-0.129	-0.024***	0.279***	-0.003***	-0.028**	-0.049***	-0.007***	-0.016***
WAH Lag1	0.087	0.129	0.109	0.276	0.088***	0.16	0.17*	0.105
HEN Lag1	-0.061	-0.048	-0.004	-0.016	0.355	0.026***	0.066***	0.005
ONG Lag1	-0.069	-0.008	-0.027	-0.058	0.023	0.172	0.211*	0.009
CHI Lag1	-0.125	-0.034	-0.052***	0.047	-0.046***	0.02***	-0.109***	-0.015***
DSO Lag1	-0.051	-0.049	-0.159	-0.028	-0.212	-0.291	-0.218	0.117
AECO Lag2	0.058***	0.056**	0.006**	-0.01	0.005***	0.040*	0.008***	0.000***
MAL Lag2	-0.204	0.053	-0.046	0.009	0.06	-0.035*	-0.054	0.067
OPA Lag2	0.050	-0.024	0.022	-0.023***	-0.017	-0.058	-0.046	0.003
WAH Lag2	-0.049	0.002	0.034	0.105	-0.058***	-0.006	-0.058	-0.013
HEN Lag2	0.005	0.029	0.021	-0.042	0.11	-0.008**	-0.028	0.022
ONG Lag2	0.099	0.009	0.048	0.028	-0.04	0.076	0.051	-0.041
CHI Lag2	-0.055	0.08	0.006	0.042	0.026*	-0.018***	-0.021***	-0.025***
DSO Lag2	0.106	0.062	0.026	-0.005	0.073	0.200	0.296	0.142
AECO Lag3	0.043***	-0.047	-0.01***	0.015	0.004***	-0.02***	0.017**	0.004***
MAL Lag3	-0.093	0.034	-0.1***	-0.028	-0.072	-0.153	-0.053	-0.072
OPA Lag3	0.03	0.047	0.152	-0.004**	0.014	0.003	0.037	-0.016
WAH Lag3	0.03	-0.055	0.024	0.085	0.043***	-0.046	-0.001	-0.007
HEN Lag3	-0.028**	0.015	-0.038	-0.001	0.092	-0.028	-0.038	-0.03
ONG Lag3	-0.121	-0.056	-0.05	-0.008	-0.033	0.047	0.031	0.012
CHI Lag3	0.045***	0.029***	-0.037***	-0.054	0.018	0.019***	0.000**	0.045***
DSO Lag3	0.204	0.154	0.211	0.038	0.012	0.262	0.092	0.209
AECO Lag4	0.164**	0.023***	0.016	-0.007	0.003	0.038	-0.017*	0.005*
MAL Lag4	0.068	0.158	0.007***	-0.005**	-0.03	0.006	0.037	-0.024
OPA Lag4	0.037	0.019	0.21***	0.072	-0.006	0.049	-0.014**	0.017
WAH Lag4	-0.065	-0.046	-0.106	0.041	0.027***	-0.054	-0.094	-0.038
HEN Lag4	0.041	-0.017	0.017	0.031	0.125	0.014***	0.059	0.009*
ONG Lag4	0.051**	0.059	0.031	0.054	-0.006*	0.146	0.014	0.041
CHI Lag4	-0.167	0.065***	0.001***	-0.018	0.094***	0.021***	0.046	0.02
DSO Lag4	0.101	-0.362	-0.116	-0.061	-0.106	-0.148	0.000	0.033
HDD Lag1	-0.001***	0.001***	0.000	0.000	0.001***	0.000	0.000	0.000
CDD Lag1	-0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.000

Notes: One, two, and three asterisks indicate statistical significance at 10%, 5%, and 1%, respectively.

6.2 Chapter 3

Table 6.4: Univariate GARCH crude oil models - sub-sample I analysis (01/01/1994 - 12/31/2009)

	GARCH Model		MS-GARCH		MS-GARCH		MS-GJR-GARCH	
	Normal distribution		Normal distribution		Student distribution		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 ($D = 1$)			0.955		0.978		0.978	
Stable Probability ($D = 2$)			0.045		0.022		0.022	
Duration ($D = 1$)			22.371		45.662		45.872	
Duration ($D = 2$)			1.047		1.022		1.022	
Unconditional Volatility ($D = 1$)			24.562		32.358		32.436	
Unconditional Volatility ($D = 2$)			104.359		92.096		92.107	
Panel C - Standardized 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 (30)	37.178		80845***		38.164		38.162	
Log-Likelihood	-9524.72		-9361.519		-9336.76		-9336.77	
AIC	4.579		18739.038		18693.52		18697.55	
BIC	4.594		18789.714		18756.87		18773.56	

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

Table 6.5: Univariate GARCH natural gas models - sub-sample I analysis (01/01/1994 - 12/31/2009)

	GARCH Model		MS-GARCH		MS-GARCH		MS-GJR-GARCH	
	Normal distribution		Normal distribution		Student distribution		Student distribution	
Panel A - Mean Equation								
AR(1)			0.68***	(0.112)				
MA(1)			-0.731***	(0.104)				
Panel B - Variance Equation								
μ_1	0.306***	(0.061)	0.204***	(0.001)	0.184***	(0.001)	0.182***	(0.001)
$\alpha_{1,1}$	0.092***	(0.01)	0.041***	(0.000)	0.074***	(0.001)	0.074***	(0.001)
$\alpha_{2,1}$							0.000***	(0.000)
β_1	0.896***	(0.01)	0.912***	(0.000)	0.914***	(0.000)	0.914***	(0.000)
μ_2			28.507***	(0.128)	5.864***	(0.048)	5.811***	(0.048)
$\alpha_{1,2}$			0.803***	(0.011)	0.078***	(0.001)	0.076***	(0.001)
$\alpha_{2,2}$							0.000***	(0.000)
β_2			0.193***	(0.000)	0.658***	(0.002)	0.660***	(0.002)
Stable Probability ($D = 1$)			0.86		0.753		0.748	
Stable Probability ($D = 2$)			0.14		0.248		0.252	
Duration ($D = 1$)			7.148		4.04		3.968	
Duration ($D = 2$)			1.163		1.329		1.337	
Unconditional Volatility ($D = 1$)			32.88		63.17		63.481	
Unconditional Volatility ($D = 2$)			413.636		72.944		72.208	
Panel C - Standardized residual diagnostics								
$\hat{\varepsilon}$ Mean	0.007		0.012		0.006		0.006	
$\hat{\varepsilon}$ Std. error	1.000		1.489		0.973		0.973	
$\hat{\varepsilon}$ Variance	1.000		2.218		0.946		0.947	
$\hat{\varepsilon}$ Skeness	0.584		0.147		0.513		5.448	
$\hat{\varepsilon}$ Kurtosis	6.086		15.804		5.445		0.512	
Jarque-Bera	6,674.1***		28,760***		5,335.7***		5335.7***	
Arch Effect	10.892		240.93***		11.456		11.527***	
Ljung-Box (20)	46.341**		37.78***		22.355		43.949**	
Log-Likelihood	-11329.4		-6633.651		-11,065.62		-11,065.64	
AIC	5.443		22,235.942		22,151.25		22,155.273	
BIC	5.452		22,286.618		22,214.595		22,231.287	

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

Table 6.6: Univariate GARCH crude oil models - sub-sample II analysis (01/01/2010 - 12/31/2019)

	GARCH Model		MS-GARCH		MS-GARCH		MS-GJR-GARCH	
	Normal distribution		Normal distribution		Student distribution		Student distribution	
Panel A - Mean Equation								
MA(1)			-0.087***	(0.020)				
Panel B - Variance Equation								
μ_1	0.035***	(0.009)	0.024***	(0.000)	0.022***	(0.000)	0.014***	(0.000)
$\alpha_{1,1}$	0.041***	(0.004)	0.031***	(0.000)	0.038***	(0.001)	0.01***	(0.000)
$\alpha_{2,1}$							0.059***	(0.001)
β_1	0.952***	(0.005)	0.943***	(0.000)	0.954***	(0.000)	0.957***	(0.000)
μ_2			1.309***	(0.016)	17.854***	(0.167)	0.036***	(0.000)
$\alpha_{1,2}$			0.09***	(0.002)	0.291***	(0.006)	0.019***	(0.000)
$\alpha_{2,2}$							0.043***	(0.001)
β_2			0.897***	(0.000)	0.006***	(0.003)	0.955***	(0.000)
Stable Probability ($D = 1$)			0.89		0.971		0.343	
Stable Probability ($D = 2$)			0.111		0.029		0.657	
Duration ($D = 1$)			9.05		34.014		1.522	
Duration ($D = 2$)			1.124		1.03		2.916	
Unconditional Volatility ($D = 1$)			15.226		25.589		31.265	
Unconditional Volatility ($D = 2$)			155.175		79.969		37.875	
Panel C - Standardized residual diagnostics								
$\hat{\varepsilon}$ Mean	-0.03		2.068		-0.016		-0.018	
$\hat{\varepsilon}$ Std. error	0.998		0.496		0.991		0.976	
$\hat{\varepsilon}$ Variance	0.997		0.247		0.983		0.952	
$\hat{\varepsilon}$ Skeness	-0.301		1.38		-0.257		-0.265	
$\hat{\varepsilon}$ Kurtosis	3.664		2.019		3.928		3.601	
Jarque-Bera	1502.2***		1273.1***		1709.9***		1443.4***	
Arch Effect	12.228		18806.26***		5.494		12.115	
Ljung-Box (30)	17.011		45035***		16.721		24.105	
Log-Likelihood	-5477.17		-5344.536		-5332.24		-5317.994	
AIC	4.208		10705.072		10684.48		10659.989	
BIC	4.23		10752.003		10743.14		10730.385	

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

Table 6.7: Univariate GARCH natural gas models - sub-sample II analysis (01/01/2010 - 12/31/2019)

	GARCH Model		MS-GARCH		MS-GARCH		MS-GJR-GARCH	
	Normal distribution		Normal distribution		Student distribution		Student distribution	
Panel A - Mean Equation								
MA(1)			-0.055***	(0.02)				
Panel B - Variance Equation								
μ_1	0.181***	(0.045)	0.143***	(0.001)	0.158***	(0.002)	0.158***	(0.000)
$\alpha_{1,1}$	0.076***	(0.01)	0.037***	(0.000)	0.007***	(0.000)	0.012***	(0.000)
$\alpha_{2,1}$							0.000***	(0.000)
β_1	0.904***	(0.011)	0.926***	(0.000)	0.935***	(0.001)	0.930***	(0.000)
μ_2			3.768***	(0.058)	0.235***	(0.002)	0.204***	(0.000)
$\alpha_{1,2}$			0.115***	(0.004)	0.045***	(0.001)	0.041***	(0.000)
$\alpha_{2,2}$							0.000***	(0.000)
β_2			0.865***	(0.001)	0.934***	(0.000)	0.940***	(0.000)
Stable Probability ($D = 1$)			0.932		0.215		0.218	
Stable Probability ($D = 2$)			0.068		0.785		0.782	
Duration ($D = 1$)			14.663		1.274		1.278	
Duration ($D = 2$)			1.073		4.653		4.591	
Unconditional Volatility ($D = 1$)			31.272		26.159		26.171	
Unconditional Volatility ($D = 2$)			218.892		52.727		51.246	
Panel C - Standardized residual diagnostics								
$\hat{\varepsilon}$ Mean	0.000		-0.01		-0.01		-0.01	
$\hat{\varepsilon}$ Std. error	1.001		0.994		0.995		1.000	
$\hat{\varepsilon}$ Variance	1.001		0.988		0.99		1.001	
$\hat{\varepsilon}$ Skeness	0.282		0.297		0.296		0.292	
$\hat{\varepsilon}$ Kurtosis	2.588		2.795		2.645		2.648	
Jarque-Bera	764.65***		889.71***		800.89***		801.410***	
Arch Effect	8.38		14.78		13.458		15.039	
Ljung-Box (30)	26.864		30.437		21.383		26.637	
Log-Likelihood	0		-6199.868		-6181.175		-6182.283	
AIC	4.818		12415.737		12382.351		12388.565	
BIC	4.829		12462.668		12441.014		12458.961	

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

Figure 6.2: Quantile regression using OLS for crude oil stable probability - January, 1994 - December, 2019

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 6.3: Quantile regression using OLS for natural gas stable probability - January, 1994
- December, 2019

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.

6.3 Chapter 4

Figure 6.4: Rolling daily cross-quantilogram between crude oil to natural gas

Panel A - Cross-quantilogram from crude oil to natural gas

(a) $\alpha = 0.1$

(b) $\alpha = 0.9$

Panel B - Cross-quantilogram from natural gas to crude oil

(c) $\alpha = 0.1$

(d) $\alpha = 0.9$

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from crude oil to natural gas at low ($\alpha = 0.1$) and high ($\alpha = 0.9$) quantiles, while Panel B from natural gas to crude oil market. The window has a fixed length of 756 days (roughly 3 years). Ending year of the rolling window is marked on the horizontal axis. Solid black circles are the rolling window spillover for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 6.5: Rolling daily cross-quantilogram between electricity and natural gas

Panel A - Cross-quantilogram from electricity to natural gas

Panel B - Cross-quantilogram from natural gas to electricity

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from electricity to natural gas at low ($\alpha = 0.1$) and high ($\alpha = 0.9$) quantiles. Panel B presents rolling cross-quantilogram from natural gas to electricity. The window has a fixed length of 756 days (roughly 3 years). Ending year of the rolling window is marked on the horizontal axis. Hollow black circles are the rolling window cross-quantilogram for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

Figure 6.6: Rolling daily cross-quantilogram between crude oil and petroleum products

Panel A - Cross-quantilogram from crude oil to gasoline

Panel B - Cross-quantilogram from crude oil to heating oil

Note: Panel A exhibits the 1 day ahead rolling cross-quantilogram from crude oil to gasoline at low ($\alpha = 0.1$) and high ($\alpha = 0.9$) quantiles. Panel B presents rolling cross-quantilogram from crude oil to heating oil. The window has a fixed length of 756 days (roughly 3 years). Ending year of the rolling window is marked on the horizontal axis. Solid black circles are the rolling window cross-quantilogram for 1 day, solid red squares are 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

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