Essays on Commodity Market Uncertainties

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To my parents

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Abstract

This dissertation presents three essays on commodity market uncertainties. Fundamentally, uncertainty relates to a decrease in investment and reduction in the production of goods and services that causes a momentary decline in aggregate output as well as employment. Hence, the increase in uncertainty has a pervasive impact on the aggregate income received by all the factors of production in an economy.

In the first study, we measure the daily price uncertainty of 22 commodities and analyze the time and frequency connectedness among them. Applying spillover analysis and network graphs, we find that overall connectedness among commodity uncertainties increase during the global financial crisis (GFC) and the oil price collapse of 2014-16. Network analysis shows more spillover within a specific commodity class, and that precious metals due to less spillover with other commodities may serve as safe-haven during the crisis. The decomposition of the spillover index reveals that commodity markets are more connected in the long-run.

The second study builds on the energy – stock nexus by investigating the impact of energy commodity uncertainties on the systematic risk of twelve industries in the US. The dynamic betas indicate that real estate, financials, and basic materials are the high-risk industries. Notably, the systematic risk of the oil and gas sector was significantly affected during the Global Financial Crisis (GFC) and the Shale Oil Revolution (SOR) sub-periods. Our results provide convincing evidence of the positive impact of energy uncertainties on basic material, basic resources, financials, oil and gas, and real estate. On the other hand, we identify the negative impact on consumer goods, consumer services, health care, industrials, and technology industries.

Finally, our third study investigates the causal impact of global factors as drivers of transmission between oil and other commodity markets using the commodity uncertainty

indexes. We estimate strong bi-directional transmission between oil and metal (agriculture) markets. Our analysis also suggests that oil is a net transmitter to other commodity uncertainties, and this transmission significantly increased during the period of the global financial crisis. The use of linear and nonlinear causality tests indicates that the global factors have a causal effect on the overall connectedness, especially on the total transmission from oil to other commodity uncertainties. Further segregation of transmissions between oil to individual commodity markets indicates VIX, TED spread, and EPU as the most influential drivers of connectedness among commodity markets.

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CHAPTER ONE: Introduction

This chapter provides an overview of the three essays presented in this dissertation. The chapter, in particular, outlines the significant contribution and motivation that each essay provides to the present body of knowledge on commodities market uncertainties. The chapter concludes by outlining a structure for the remainder of the thesis.

1.1. Background of the Study

In the real world, things are always uncertain to some extent, particularly in the commodities markets where industrial actions, unexpected outages, misfortune events may disrupt the supply chain process. Commodities are highly homogeneous products, and their volatility is a significant source of uncertainty for the economic agents. Over the past two decades, there have been two major developments in commodity markets. First, commodity exports arise as an engine of global economic growth. From 1998 to 2017, developing countries have experienced a significant increase in Gross Domestic Product (GDP), in turn increasing the share of commodity exports and commodity prices. Second, relative to equity and bond prices, the volatility of commodity prices has increased substantially, which leads to the overall economic fluctuations. These two phenomena give rise to the importance of understanding the intra-commodity and inter-commodity relation with other financial markets, along with the global factors that are capable of driving commodity prices.

Understanding of commodity markets and their role in the global economy have become fundamental because industrial metals, precious metals, energy commodities, and agricultural commodities are now classified as financial assets. The inflow of funds has tripled into the commodity futures due to the sharp increase of investment in the commodity markets – termed as commodity "financialization" (Basak & Pavlova, 2016). The increased flow of capital between countries and substantial technological development are the key reasons contributing to globalization. This financialization, along with increased integration of global markets, has augmented the transmission between different markets (Aloui, Hammoudeh & Nguyen, 2011).

Brennan and Schwartz (1985) coined the theory of investment under uncertainty and argued that because of the irreversible nature of investment decisions, organizations postpone their capital-intensive investment decisions and use their real options to wait to invest in highly uncertain times. These real options approach raises the organization's option value (Aguerrevere, 2009). Besides, uncertainty also results in the reduction of employment and consumption due to a precautionary savings effect by economic agents (Caggiano, Castelnuovo & Groshenny, 2014), thus leading to a drop in aggregate investment and economic recessions (Schaal, 2017).

Previous literature suggests that there has been a negative impact of rising uncertainty on the macro-economy by proxying economic uncertainty using the VIX index, stock-market volatility or future economic policy uncertainty indexes (Drechsel & Tenreyro 2018; Basu & Bundick, 2017; Baker, Bloom & Davis, 2016; Carruth, Dickerson & Henley, 2000). A large and growing body in the literature also explores the volatility spillovers among the stock markets and energy commodities especially oil or natural gas (Arouri, Lahiani & Nguyen, 2015), while another strand of literature examines the volatility spillovers between commodity markets and energy commodities (Gozgor & Memis, 2015). The literature also explicitly explored whether the econometric methodologies that have been employed to analyze volatility spillovers are robust to the different time horizons (Gozgor, Lau & Bilgin, 2016), to the frequency of the data (Yarovaya, Brzeszczynski & Lau, 2016), and to the asymmetric effects presence across different commodity markets (Chang, McAleer & Tansuchat, 2013).

Additionally, empirical researches have been done to explain the possible channels of connectedness between the oil prices and commodity markets (Hunt, 2006; Jain & Ghosh, 2013; Bellemare, 2015; Zhang & Qu, 2015; Shahzad et al., 2017; Malik & Umar, 2019). An increase in oil prices leads to inclination in commodities prices, which is a vital channel to affect gold prices (Hunt, 2006). Hooker (2002) proposed that due to expansion in economic activities, there is seen an increase in global demand for oil, which enhances the oil prices that result in more usage of precious and industrial metals, say Tin and Copper. Moreover, the increase in global oil price also leads to an upward trend in metal or commodity prices due to their impact on production and transportation costs, which eventually hurts consumers and therefore increases market volatility that lower corporate earnings (Shahzad et al., 2017). Furthermore, this hike in agricultural commodities prices is related to the causative factors of social unrest and political instability (Bellemare, 2015).

The rest of the chapter is divided into the following sections. Section 1.2 to Section 1.4 provides an overview of essays one, two, and three and how each essay, in particular, contributes to the present body of knowledge. The research outputs are listed in section 1.5. Lastly, Section 1.6 outlines the sequence of the remainder of the thesis.

1.2. Essay One

In the thesis, the first essay examines the time and frequency connectedness of twenty-two uncertainties of individual commodities and different commodity classes by applying the spillover analysis and network graphs framework. More specifically, the essay provides evidence that how spillovers within a specific commodity class during the crisis period serve as a safe-haven for the investors.

Commodities are related to energy, metals, or food and are considered to be an essential component of everyday life. In the world market, the prices of these commodities are set by market forces – demand and supply or buyers and sellers. Thus, commodities can be a vital way to diversify a portfolio either for the long term or as a place to park cash during unusually volatile beyond traditional securities. The prices of commodities significantly impact the imports and exports of an economy, which further affects the overall external position of the country with the rest of the world. Therefore, policymakers, analysts, and businesses should keep a closer look on the price movements of the commodities in the daily activities due to their uncertain, volatile, and moving up or down movement over the short periods. According to Shahzad et al. (2018)**,** spiky movements in the prices of commodities often result from two main factors: (a) future demand and supply expectations, and (b) demand and supply changes.

In the short-term periods, expectations are particularly essential as on some day's commodities prices (say oil and precious metals) may vary quite sharply despite there is no change in the underlying demand and supply for the commodities. This is because people expect in the future some price changes, so they buy or sell today in anticipation of making returns or limiting the losses to overcome from the expected changes. On the contrary, more fundamental supply and demand effects tend to dominate in the long-term periods. Furthermore, fluctuations in exchange rates, interest rate changes, and returns associated with various types of equities, bonds, and other financial assets also impact the prices of commodities as these represent alternative investment options. Similarly, government policies and weather conditions affect the agricultural commodities supply (Kang et al., 2017). More broadly, these price movements of the commodity also affect the profitability of the business, livelihoods of people and macro-economic policies (de Nicola et al. 2016). Given the large size of commodity markets, it is important to examine whether commodities present a good hedge against global uncertainty factors and how they are connected to global factors over the short and long-run periods.

Unlike traditional asset classes, the commodities pricing behavior is different where demand and supply shocks determine the commodities prices. In financial risk management literature, Deibold et al. (2017) argued that the idea of connectedness is central and appears significant particularly in relation to commodities. Since the global financial crisis (GFC), there has been seen growing scholarly work on the connectedness among commodities to investigate its role in the reduction of risks and to explore different commodities class/groups investment potential. Industrial metals (say aluminum and copper) and energy commodities (say natural gas, gasoline, and crude oil) are used as inputs for industries and therefore their price movements are highly correlated to demand-side shocks, whereas precious metals (say gold and silver) serve as alternative investment vehicles to hedge against uncertainty (Diebold et al., 2017).

The financialization of commodity markets has significantly increased the integration of different commodity markets (such as agriculture, precious metals, energy, and industrial metal commodity). Kat & Oomen (2007) advocated that in order to hedge the risk in traditional financial assets (like stocks or bonds), commodity investment has become an attractive tool with financialization and ease of trading. In normal and crisis times, precious metals and energy commodities are recognized for their hedging abilities. However, high price movements in commodities have renewed interest regarding how uncertainty transmits from a specific commodity market to other commodity markets. Therefore, these changes in the connectedness dynamic of commodity price uncertainties require attention for portfolio allocation decisions and have become more critical for the economies (Barunik & Krehlik, 2018).

Given the importance of the commodity markets and their uncertain nature, the essay is different from earlier literature as this essay develops commodity uncertainty indexes after decomposing the total connectedness in short- and long-term connectedness, instead of simply employing volatility as a proxy for uncertainty. As the literature highlighted the differences between unexpected variation (uncertainty) and expected variation (risk), therefore, based on the facts mentioned above, the motivation arises to use uncertainty in this essay instead of total variations in the time series. Moreover, earlier work usually focused on volatility without differentiating ‘known’ and ‘unknown’ parts, this essay focus on only unknown parts due to the fact as highlighted by Chulia et al. (2017) that known part comprises of a small fraction of what decision-makers face while making investment-related decisions.

The essay compares total connectedness for the full sample and GFC and how the connectedness increases during the GFC. Finally, the time-frequency connectedness methodology recently developed by Barunik and Krehlik (2018) is applied, rather than the spillover index approach of Diebold and Yilmaz (2014) as it allows the assessment of the magnitude and direction of spillovers over time and across frequencies simultaneously. The essay uses daily spots and future prices of 22 commodities related to four distinct groups (agricultural commodities, precious metals, industrial metals commodities, and energy commodities) over the period January 2007 to December 2016 which are traded globally for the creation of uncertainty indexes obtained from Thomson Reuter's data stream.

In application, the study finds the importance of energy commodities and precious metals in the existing literature for investment management and risk analysis. The study provides new empirical evidence about the connectedness dynamics in the commodity markets by analyzing the total and frequency connectedness of commodities price uncertainty. Therefore, to develop efficient hedging strategies and to make sound investment decisions, investors must be better informed about the connectedness of commodity markets. Future researchers could use our uncertainty indexes in order to examine the commodity price uncertainties impact on other asset classes and uncertainties such as stock market uncertainty, geopolitical uncertainty, and economic policy uncertainty.

1.3. Essay Two

A fundamental opinion is that an increase in uncertainty has an invasive impact on the aggregate income level received by all the factors of production and results into decrease in investment, the decline in aggregate output and employment and reduction in the production of goods and services (Bachmann & Bayer, 2013). The second essay in the thesis examines the energy commodity uncertainties that influence the systematic risk of twelve industries within the US. Particularly, the essay measures the extent of how the future energy market price uncertainty impacts the riskiness of industries.

Several researchers and policy papers have examined different sources of uncertainty, such as macro-economic uncertainty (Jurado Ludvigson & Ng, 2015), future commodities prices uncertainty (Balli, Naeem, Shahzad & de Bruin, 2019), economic policy uncertainty (Baker et al., 2016) and stock market uncertainty (Chulia et al., 2017). Bams et al. (2017), Bekaert et al. (2009), and Anderson et al. (2009) proposed that uncertainty is crucial to the investment decisions and has a distinctive role to play in the financial markets. The review of these studies suggests mixed evidence. Drechsler & Yaron (2010) find a positive and statistically significant relationship between commodity price uncertainties and expected stock returns. Driesprong et al. (2008) argued that uncertainty in energy commodities has a significant influence on the economy as they are essential for different sectors of the economy. Bams et al. (2017) highlighted that uncertainty in energy commodities leads to lower investments, aggregate output, and durable consumptions.

According to Scholes and Williams (1977), one of the adequate measures of systematic risk is industry betas. Earlier research, such as Fama and French (1992) assumed betas remain constant over the estimation period. Contrarily, recent work by Yu et al. (2017), Bali, Engle and Tang (2017) and other scholars suggested that industry betas also changes over time since riskiness of the firm's cash flow and its correlation with the systematic shocks fluctuate over time, thus it is not a reasonable hypothesis to coin that betas remain stable over the period. Besides, some groups of commodities say gasoline and crude oil are vital inputs in the production process, and thus commodities uncertainty may be relevant to the systematic risk of industries. Therefore, uncertainty in the price of such commodities affects financial performance of the firms, which further leads to influence their retained earnings, dividend payments, and equity prices (Arouri et al., 2012; Park & Ratti, 2008).

The impact of uncertainty of energy commodities on the systematic risk of industries is studied for the two main reasons. Firstly, the performance of one specific industry is not identified by the market index especially during the turmoil periods, such as the recent oil market crisis of 2014-2016 and the GFC. Secondly, there is an asymmetric sensitivity of industries towards commodity price changes. For example, the impact of energy commodities on industry depends upon the nature of the relationship, that is, whether the relation between energy commodities and the industry is as a direct or indirect factor of production. Narayan and Sharma (2011) proposed that organizations related to transportation, industrials, and oil and gas are more dependent on energy commodities. Thus, there may be asymmetric sensitivities of industries to changes in commodity prices.

The study contributes that investors should be vigilant of the uncertainties of energy commodities to be able to forecast stock market returns and to make informed investment decisions. The essay suggests that there is a need to focus on financial stability measures by the policymakers and regulators that are usually being affected by the commodities uncertain behaviors such as oil and natural gas. These economic policies by the policy-makers will be able to help financial investors to identify the commodities uncertainties or demand shocks in these commodities. Moreover, there is a need to consider the effect of commodities' on the riskiness of industries by the policy-makers and regulators while developing economic growth policies for the country as this enables them to put a suitable value on essential commodities that are important for the booming growth of an economy.

1.4. Essay Three

The role of commodity markets and their understanding is vital because agricultural commodities, energy, industrial, and precious metals are now considered to be financial assets within the global economy. There has been seen a sharp upsurge of investment in commodity markets, which has tripled funds inflow during the past decade (Basak & Pavlova, 2016) into the commodity futures, known as 'financialization' of commodities (Chari & Christiano, 2017). This financialization has increased than before due to the integration of global markets (Cheng & Xiong, 2014). Thus, it is essential for financial institutions to understand the extent and nature of linkages among different financial markets (Shahzad et al., 2019). This essay examines the transmission between oil and other commodity uncertainties and investigates the impact of global factors on the transmission measures between oil and other commodity uncertainties using linear and nonlinear causality tests.

Various scholarly papers anticipated possible channels of connectedness between the crude oil and commodity markets, such as 1) an increase in oil prices leads to inclination in commodity prices (Malik & Umar, 2019), 2) the economies that rely on oil imports usually face inflation shock and exchange rate fluctuations when global oil prices increases, thereby allowing investors to invest in precious metals to hedge their portfolios (Jain & Ghosh, 2013), 3) oil price shocks result in commodity market inflationary pressure which craft policymakers to tighten the monetary policy that impacts significantly on consumer demand for durable goods (Hammoudeh & Yuan, 2008), 4) expansion in economic activities increases the oil prices that further upsurge usage of industrial and precious metals (Hooker, 2002) the cost of essential agricultural inputs also increases due to global oil prices upshot which further raises the agricultural products production costs (Zhang & Qu, 2015).

The empirical literature has also analyzed the transmission mechanism between the oil and commodity markets (Balli et al., 2019; Diebold et al., 2017; Rehman et al., 2018; Tiwari et al., 2019). Diebold et al. (2017) find that there is a high connectedness between energy, precious metals, industrial metals, and agricultural commodities. Sari et al. (2007) find a short-term relationship between precious metals and crude oil in the context of developed countries.

Along with the increased interest in the transmission dynamics, there has been considerable attention given by researchers to explore the influence of global factors on commodity markets (Albulescu et al., 2019; ; Badshah et al., 2019; De Boyrie & Pavlova, 2018; Kanjilal & Ghosh, 2017; Poncela, Senra & Sierra, 2014; Jebabli, Arouri & Teulon, 2014).

Despite a multitude of research concerning the impact of global factors on commodities and other financial markets in separate settings, however, the literature is silent on the effect of global factors on the transmission relationship between oil and commodity markets. Owning to the fact that the financialization of commodities has increased both the intra-commodity connectedness and the connectedness of commodities with other financial markets at a global level, one can assume that commodity markets are exposed to the risks associated with stock markets, currency markets, and uncertainty regarding economic policies. In light of the recent literature providing evidence of causal impact of economic policy uncertainty on the connectedness across oil and financial markets (Fang et al., 2018; Albulescu et al., 2019; Badshah et al., 2019), this essay contributes to the literature by (i) examining the transmission between oil and other commodity uncertainties using the Diebold & Yilmaz (2014) framework, and (ii) providing evidence on the causal impact of global factors on the intra-commodity transmission using linear and nonlinear causality frameworks proposed by Granger (1969) and Péguin-Feissolle & Teräsvirta (1999).

1.5. Research Outputs from the Thesis

Essay one

The first essay contained in this thesis is published in *Energy Economics*:

- Balli, F., Naeem, M. A., Shahzad, S. J. H., & de Bruin, A. (2019). Spillover network of commodity uncertainties. *Energy Economics, 81*, 914-927.

Essay two

The first essay contained in this thesis is published in *Energy Economics*:

- Naeem, M. A., Balli, F., Shahzad, S. J. H., & de Bruin, A. (2019). Energy commodity uncertainties and the systematic risk of US industries. *Forthcoming in Energy Economics,*

To this date, the essay has been presented at the following forums:

- Muhammad Abubakr Naeem (2019), “Can energy commodity uncertainties lead the systematic risk of industries?” 32nd Australasian Finance & Banking Conference (AFBC), Sydney, December 2019.

1.6. The sequence of the Thesis

The remainder of this thesis is structured as follows. Chapter 2 presents the first essay, which examines the spillover network of commodities uncertainties. The second essay, which examines the relationship between the energy commodities uncertainties and the systematic risk of US industries is presented in Chapter 3, while the third essay, which examines the impact of global factors on the transmission between the oil and other commodity uncertainties, is presented in Chapter 4. Finally, the key findings and implications of the three essays is outlined in Chapter 5, along with the potential areas of future research.

CHAPTER TWO: Spillover network of commodity uncertainties

2.1. Introduction

The understanding of commodity markets, in general, and their role in the global economy[1], in particular, is essential because energy, precious and industrial metals, and agricultural commodities are now categorized as financial assets. The sharp upsurge of investment in commodity markets over the past decades has tripled the inflow of funds into commodity futures, termed the “financialization” of commodities (Basak and Pavlova, 2016). Global market integration has augmented this financialization.

The pricing behavior of commodities is different from that of traditional asset classes such as stocks and bonds. Unlike stocks and bonds, traditional demand and supply shocks determine the prices of commodities. The demand for commodities closely links to global aggregate demand but not for precious metals such as gold and silver. This is because precious metals serve to hedge against uncertainty and are therefore alternative investment vehicles. On the contrary, energy commodities (like crude oil, gasoline, and natural gas) and industrial metals (like copper and aluminum) are used as raw material or inputs for industries. Hence, the prices of such commodities are subject to demand-side shocks that are highly correlated (Diebold et al., 2017). This was evident during the global financial crisis (henceforth GFC) when a sharp decrease in commodity prices followed the collapse of financial markets in 2007-09.

However, contrary to the demand for commodities, more idiosyncratic behavior is expressed by commodity supply. Various factors influence the supply of different commodity classes/groups (precious metals, energy, industrial metals, and agricultural commodities). For instance, government decisions in exporting countries affect the supply of precious and

[1] For an extensive synopsis from an empirical standpoint, see Chevallier and Ielpo (2013).

industrial metals and oil share in the world. Similarly, weather conditions and government policies affect the supply of agricultural commodities in short- and long-run, respectively (Kang et al., 2017). Hence, different processes influence the supply side of commodities, and therefore various price movements are observed in diverse commodity markets. It is also observed that even the unrelated commodity prices (demand and supply cross-price elasticities close to zero) tend to move together after controlling for market and macro-economic conditions (de Nicola et al. 2016).

Nevertheless, commodity markets financialization increases the integrations of different commodity markets; precious metal, industrial metal, energy, and agriculture. The energy sector is however more efficient in sending shocks to other commodities and thereby indicating a strong link with agricultural commodities, precious and industry metal (Diebold et al. 2017). For example, increase in oil prices increases the cost of essential agricultural inputs such as fertilizer, which in turn increases the production costs of agricultural commodities (Ji et al., 2018; Shahzad et al., 2018).

Commodity investment, with financialization and ease of trading, has now become an attractive tool to hedge the risk in traditional financial assets (Kat & Oomen, 2007a, 2007b). In particular, energy commodities and precious metals are known for their hedging abilities in normal and crisis times. However, large price swings in commodity prices have renewed interest regarding how uncertainty in a specific commodity market transmits to other commodity markets and vice versa. This change in connectedness dynamics of commodity price uncertainties requires attention for business cycle analysis, risk management, and portfolio allocation decisions (Barunik & Krehlik, 2018). This understanding becomes even more critical for the economies that rely heavily on commodity production.

Given its importance, we examine the connectedness between the uncertainties of individual commodities and different commodity classes. Our motivation to use uncertainty instead of total variations in the time series arises due to the fact that the literature emphasizes the difference between risk (expected variation) and uncertainty (unexpected variation). While most of the previous studies have focused on volatility without distinguishing the 'known' and the 'unknown' parts, we particularly focus on the later because the 'known' part constitutes only a very small fraction of what we see and face while making daily investment decisions (Chuliá et al. 2017).

In doing so, we first measure the daily price uncertainty of 22 commodities using the methodology recently proposed by Chuliá et al. (2017). The method is unique as it first removes the forecastable component of the variations before calculating the uncertainty. Chuliá et al. (2017) calculate the daily uncertainty measure for the real-time monitoring of the stock market. In similar fashion, we estimate a commodity uncertainty index as a non-latent variable. Moreover, the estimation process in this study uses an atheoretical approach similar to Jurado et al. (2015). This method provides a daily measure of aggregate commodity price uncertainty from the price variations in spot and futures markets, which is not the case when other measures of uncertainty based on macroeconomic considerations are formulated. The aggregation of unknown variations in spot and future (of different maturities) prices provides a complete picture about commodity uncertainties.

Secondly, we examine the connectedness between the uncertainties of individual commodities and different commodity classes by combining the forecast-error variance decomposition (FEVD) framework of Diebold and Yilmaz (2014) and network theory. Finally, the time-frequency connectedness methodology recently developed by Barunik and Krehlik (2018) is applied. This framework can be thought of as the time-frequency version of the spillover index approach of Diebold and Yilmaz (2014). While the Diebold-Yilmaz model focuses on the time domain only, the approach of Barunik and Krehlik (2018) allows the assessment of the magnitude and direction of spillovers over time and across frequencies simultaneously. Thus, apart from including the time-varying information of the method of Diebold and Yilmaz (2014), the Barunik-Krehlik framework decomposes aggregate connectedness into different frequency domains, enabling determination of the specific frequencies that most contribute to the connectedness of a system. The key reason for exploring the connectedness in the short- and long-run (employing various frequencies) is that economic agents operate on diverse investment horizons. These investment time horizons, presenting different trading frequencies, are associated with various trading tools, investment and investor types and diverse risk management strategies (Conlon, Cotter & Gençay, 2016).

In application, we find that the connectedness among commodity uncertainties increases during the period of the GFC. Full-sample network analysis indicates high, within commodity class connectedness. During the GFC, the connectedness among commodity uncertainties of different commodity classes also increases. Rolling window estimation among commodity uncertainty indicates the increase in total connectedness during the GFC and the oil price collapse of 2014-2016. Collectively, we find the importance of precious metals as safe-haven assets and the contagion effect of energy commodities. Additionally, the analysis of frequency connectedness among commodity uncertainties indicate high long-run connectedness.

The remainder of the study is structured as follows. In Section 2, we provide a review of related literature. Section 3 describes the methodology used to calculate the uncertainty indexes and the connectedness analysis. The data description and empirical results follow in Section 4. Finally, we conclude in Section 5.

2.2. Brief review of the literature

The idea of connectedness is central to financial risk management and appears particularly significant in relation to commodities (Diebold et al., 2017). Harri and Hudson (2009) and Nazlioglu et al., (2013) using Granger causality on variances find no relationship between daily agricultural and energy commodities, the only exception was wheat and crude oil. However, for the period after 2006, volatility spillovers from crude oil to corn and bidirectional causalities were found between soybeans-crude oil and wheat-crude oil pairs (Nazlioglu et al., 2013).

Beckmann & Czudaj (2014) using vector autoregressive (VAR) – generalized autoregressive conditional heteroskedasticity (GARCH) explored volatility spillovers between agricultural commodities (namely wheat, corn, and cotton) and conclude that speculation results in contagion effect among agricultural commodities. Mensi et al., (2014) investigate volatility spillovers between energy commodities (namely West Texas Intermediate (WTI) crude oil, gasoline, Brent crude, and heating oil) and cereals (namely wheat, barley, sorghum and corn). They use VAR- dynamic conditional correlation (DCC)-GARCH and VAR-BEKK-GARCH models to examine connectedness among commodities while accounting for Organization of the Petroleum Exporting Countries (OPEC) announcements. They find that correlations between cereals and energy commodities are time-varying and have increased since the global financial crisis. Lin & Li (2015) study the price and volatility spillovers between oil and natural gas markets for US, Japan, and Europe using vector error correction model (VECM) and show that the natural gas and crude oil decoupled after the GFC.

The literature on connectedness among commodities is growing since the GFC, to explore the risk reduction and investment potential of different commodity classes. The most recent and relevant study of Diebold & Yilmaz (2017) examines the connectedness among 19 commodities while considering their return volatilities. This study use variance decompositions in a high dimensional vector autoregressive process for estimating both static and dynamic connectedness. The results reveal the clustering of commodities while indicating the energy sector to be an important shock transmitter.

Table 1 provides the summaries of other related studies, where it is evident that most previous studies focus on connectedness among the commodities of a particular class/group or their inter-dependence with traditional (equity and fixed income) assets. Our study is different because we develop commodity uncertainty indexes, instead of simply using volatility as a proxy for uncertainty and decompose the total connectedness into short- and long-run connectedness. We also make a comparison of total connectedness for the full sample and GFC and compare how the connectedness increases during the GFC.

Table 2. 1. Summaries of studies on the connectedness between commodities.

Study Reference	Study Period	Methods	Commodity Class / Type	Summary
Nazlioglu (2011)	1994-2010	Toda–Yamamoto; Nonparametric causality	Oil and agriculture commodities	Nonlinear feedback relationship between the oil and the agricultural prices
Ewing & Malik (2013)	1993-2010	GARCH	Oil and gold	Significant volatility transmission between gold and oil
Wang, Wu & Yang (2014)	1980-2012	VAR; SVAR	Oil and agriculture commodities	Agricultural commodities do not respond to structural oil shocks
Zhang & Qu (2015)	2004-2014	ARMA-GARCH	Energy and agriculture commodities	Cash crops are more vulnerable to the effect of oil price shocks than food crops
Koirala, Mishra, D'Antoni & Mehlhorn (2015)	2011-2012	Copula model	Oil and agricultural commodities	Agricultural commodity and oil prices are highly positively correlated
Antonakakis & Kizys (2015)	1987-2014	VAR; FEVD	Oil and precious metals	Gold is net transmitter of return and volatility spillover
de Nicola, De Pace & Hernandez (2016)	1970-2013	VAR	Energy, agricultural and food commodities	Price returns of energy and agricultural commodities are highly correlated
Awartani, Aktham & Cherif (2016)	2012-2015	VAR	crude oil, precious metals and agricultural commodities	Little volatility transmission from oil to agricultural commodities; risk spillover from oil to precious metals is moderate
Chen & Wu (2016)	1995-2015	DCC; VAR	Energy, grains, soft, livestock commodities and precious metals	Co-movements and connectedness between commodities dramatically increased during 2007-2009 financial distress

Cabrera & Schulz (2016)	2003-2012	VECM; GARCH	Energy and agriculture commodities	Volatility of biodiesel is only weakly linked to the volatility of crude oil and rapeseed; the volatilities of rapeseed and biodiesel react asymmetrically to market shocks
Fowowe (2016)	2003-2014	Nonlinear causality	Oil and agriculture commodities	No effects oil prices on agricultural prices
Ahmadi, Behmiri & Manera (2016)	1983-2014	SVAR	Energy and agriculture commodities	Impact of oil shocks on agri-commodity volatilities is short-lived
Kang, McIver & Yoon (2017)	2002-2016	DECO-GARCH	Oil and agricultural commodities and precious metals	Strong spillover during crisis; Gold and silver are transmitters to other commodities
Diebold, Liu, & Yilmaz (2017)	2011-2016	VAR; FEVD; Network Analysis	Energy, livestock and agricultural commodities, precious and industrial metals,	Clustering of commodities into groups; high overall connectedness and energy sector sends shocks to other commodities
Śmiech, & Papież (2017)	1995-2015	ARMA-EGARCH	Oil, gold, S&P500, 10-year US government bond, US Dollar	Gold can act as a hedge for stocks for normal market conditions; Oil is negatively correlated with bonds, whereas the correlation with gold is positive
Rehman et al. (2018)	1989-2015	SVAR	Crude oil, precious and industrial metals	Structural oil shocks impact precious metal returns tails except gold
Zhang & Broadstock (2018)	1982-2017	VAR; FEVD	Crude oil, beverage, fertilizers, food, precious metals and raw materials	Codependence in price-changes among seven major commodity classes; the spillover from food commodities increases after GFC
Uddin et al. (2018)	1990-2017	VAR; MRS	Crude oil, copper, palladium, silver, platinum and gold	Asymmetric impact of oil price shocks on precious metals; influence of oil price risk shocks' on precious metals is regime dependent
Ferrer et al. (2018)	2003-2017	VAR; FEVD	Crude oil, US renewable energy stocks, high technology stocks,	Most of return and volatility connectedness is found in the short-term; Crude oil prices are not

conventional energy stocks, US 10-year Treasury bond yields	the key driver of renewable energy companies' performance

Note. VAR = Vector Auto-Regression; FEVD = Forecast Error Variance Decomposition; GVD = Generalized Variance Decomposition; GARCH = Generalized Autoregressive Conditional Heteroskedasticity; EGARCH = Exponential Generalized Autoregressive Conditional Heteroskedasticity; DCC = Dynamic Conditional Correlation; VECM = Vector Error Correction Model; SVAR = Structural Vector Auto-Regression; ARMA = Auto- Regressive Moving Average; ARJI = Auto-Regressive Conditional Jump Intensity; DECO = Dynamic Equi-correlation; MRS = Markov Regime Switching.

2.3. Methodology

2.3.1. Measuring commodity uncertainty

Most recently, using a generalized dynamic factor model, Chuliá et al. (2017) developed an approach to measure time-varying uncertainty. The construction of the uncertainty indexes involves two phases. In the first step, using the generalized dynamic factor model (GDFM)[2], the idiosyncratic components are extracted by filtering the time series. In this step, before the calculation of uncertainty, the forecastable component of variation is removed. The second step involves the computation of stochastic volatility of obtained residuals, i.e., the idiosyncratic variation, using Markov chain Monte Carlo (MCMC) framework. Finally, the estimated stochastic volatilities of commodity futures contracts, with different maturities, are averaged to obtain the individual commodity uncertainty Index.

Previous literatures (e.g., Chan & Grant, 2016; Yang & Hamori, 2018) employ models that use historical or implied volatility measures. We highlight that volatility of commodities is a stochastic process and thus use SV models as they perform better than these alternative volatility models.

2.3.1.1. Extraction of the idiosyncratic element

According to Bai & Ng (2008), considering the number of cross-sectional units to be N while T to be the number of observations taken for time series. The dynamic factor model for $i = 1, \ldots, N$ and $t = 1, \ldots, T$ is defined as follows;

$$z_{it} = \beta_i(L) f_t + \mu_{it} \tag{1}$$

Where f_t is a common factor vector and lag operator is L. β_i is a factor loading vector linked with f_t while $\beta_i(L) = (1 - \beta_{i1}L -, \ldots, - \beta_{is}L^S)$ indicates the dynamic factor loadings vector

[2] For a comprehensive understanding of the estimation and empirics, see Forni, Hallin, Lippi, & Reichlin (2000).

linked with the order s. μ_{it} indicates the idiosyncratic element of z_{it}. When the order of factor loadings, s, is finite, it indicates a dynamic factor model (DFM). Stock & Watson (2002, 2010) presented the examples of DFM model. Whereas, in the GDFM model proposed by Forni & Reichlin (1998) and Forni, Hallin, Lippi, & Reichlin (2000), the order s is allowed to be infinite. However, the factors f_t in DFM/GDFM evolve according to the following expression;

$$f_t = A(L)\xi_t \tag{2}$$

Where ξ_t indicates iid errors. q denotes the dimensions of f_t, which are similar to that of ξ_t and according to Bai and Ng (2007), it specifies the number of primitive or dynamic factors[3].

The model stated in (2) can be written in static form by simply redefining the factors' vector as well as their lags and accordingly the load matrix to contain dynamic factor, as;

$$\underset{(N\,x\,T)}{Z} = \underset{(N\,x\,r)}{B}\underset{(r\,x\,T)}{F} + \underset{(N\,x\,T)}{\mu} \tag{3}$$

Where $Z = Z_1, \dots, Z_N$ and $F = F_1, \dots, F_T$. Moreover, it is clear that B and F cannot be identified separately. In case of any arbitrary $(r\,x\,r)$ invertible matrix J, $FB' = FJJ^{-1}B' = F^{*}B'^{*}$, $F^{*} = FB$ and $B^{*} = BJ^{-1}$, hence through observation, the factor model is equal to $Z = F^{*}B'^{*} + \mu$. Therefore, F and B can be fixed uniquely through r^2restrictions (Bai & Wang, 2012). It is noted that the estimation of factors enforces the normalization that $\frac{B'B}{N} = I_r$ and $F'F$ is diagonal whenever they are estimated by singular value decomposition (SVD) or principal components (PC). This normalization is sufficient to assure the identification.

The GDFM is the generalization of the dynamic factor model (DFM) as it permits a better dynamic configuration to the factors. GDFM gives the variables with higher uncertainty elements smaller weights in order to minimize the idiosyncratic error of the linear combination.

[3] For a comprehensive derivation of the dynamic factor models, see Bai and Ng (2007).

In this manner, it is ensured that the idiosyncratic or uncertainty element is eradicated from the variations of risk.

Nevertheless, the first phase of the research enables the estimation of idiosyncratic elements of time series $\mu_{it}^{u} = Z_{it} - \hat{A}_{it}$ where $\hat{A}_{it} = \beta_i(L)f_t$. μ_{it}^{u} is principally linked with uncertainty while the variation in $\hat{A}_{it}$ is stated as risk.

2.3.1.2. Stochastic volatility estimation

Once the series of filtered returns μ_{it}^{u} are recovered, for each $i = 1, \dots, N$ a stochastic volatility (SV) model is identified on an individual level as[4];

$$\mu_t^u = \mu^{h_t/2}\,\epsilon_t \tag{4}$$

$$h_t = \partial + \varphi(h_{t-1} - \partial) + \sigma \eta_t \tag{5}$$

In the above equations, ϵ_t and η_t are independent standard normal innovations for all *t* and *s* relevant to $[1, \dots, T]$. The time varying volatility $h_t = (h_0, h_1, \dots, h_T)$ expressed in the above equation, is an unobservable process having initial state distribution, $h_0 |\, \mu, \varphi, \sigma \sim N\left(\mu, \sigma^2 / (1 - \varphi^2)\right)$. This is the model's centered parameterization and it should be compared with un-centered re-parameterization given by Kastner & Frühwirth-Schnatter (2014) as:

$$\mu_t^u \sim N\left(0, \mu^{\partial + \sigma \hat{h}_{ht}}\right) \tag{6}$$

$$\hat{h}_{ht} = \varphi \hat{h}_{ht-1} + \eta_t, \qquad \eta_t \sim N(0,1) \tag{7}$$

Whether any of the parameterizations mentioned above is preferred for estimation depends on the assessment of 'true' parameters (Kastner & FrühwirthSchnatter, 2014).

[4] For simplification, the subscript related to cross-section is omitted in the following section.

However, the sampling techniques of Markov chain Monte Carlo are needed for Bayesian estimation as both these parameters have an intractable likelihood.

The efficiency loss problem is overcome using the proposed strategy of Kastner & Frühwirth-Schnatter (2014). They propose interweaving (4) - (5) and (6) - (7) implementing the strategy of ASIS (ancillarity-sufficiency interweaving strategy) presented by Yu & Meng (2011). The findings of their study indicated that the strategy provides a robustly efficient sampler. Moreover, it always outperforms more effective parameterization with respect to all factors at low additional cost in terms of calculation or design. Therefore, our study follows the propositions of Kastner & Frühwirth-Schnatter (2014) to estimate the volatilities of idiosyncratic shocks.

Once the idiosyncratic stochastic volatilities (h_{it}) are estimated, we are able to calculate the individual commodity uncertainty index (V_t) as the simple average of individual volatilities:

$$V_t = \frac{\sum_{i=1}^{N} h_{it}}{N} \tag{8}$$

Equally, the weighted average is shown with this scheme, having $\sum_{i=1}^{N} w_i h_{it} \xrightarrow{p} E(V_t)$, where $w = \frac{1}{N}$. For the development of individual commodity indices, we use information from the daily returns of spot and future contracts of commodities.

2.3.2. Connectedness approach

Following the framework of Diebold & Yilmaz (2014), we use different connectedness measures build from the variance decomposition matrix derived from a vector-autoregressive (VAR) model. Consider a variance stationary N-variable, VAR (p), $y_t = \sum_{i=1}^{p} \omega_i y_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim N(0, \sum)$. The moving average is represented as $y_t = \sum_{i=0}^{\infty} \emptyset_i \varepsilon_{t-i}$, where $\emptyset_i$ represents $N \times N$ coefficient matrices and it obeys the recursion $\emptyset_i = \omega_1 \emptyset_{i-1} + \omega_2 \emptyset_{i-2} + \cdots + \omega_p \emptyset_{i-p}$, with $\emptyset_0$ representing identity matrix and $\emptyset_i = 0$ for $i < 0$. In these situations, the moving average coefficients assist in understanding the dynamics. Therefore, we use variance decompositions that are modern transformations of moving average coefficients. It permits the splitting of *H*-step-ahead forecast of each variable's error variances into parts. These parts are attributed to various shocks in the system.

Achieving orthogonality using Cholesky factor is dependent upon the ordering of variables. Therefore, the generalized approach of Koop, Pesaran, & Potter (1996) and Pesaran & Shin (1998) is used which permit the correlated shocks but appropriately accounts for them. We denote the entries of the connectedness table as $c_{ij}^{g(H)}$, which estimates the contribution of variable *j* to the *H*-step-ahead generalized forecast error variance of variable *i* as:

$$c_{ij}^{g(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \emptyset_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' \emptyset_h \Sigma \emptyset_h' e_i)^2} \tag{9}$$

where the covariance matrix of errors in the non-orthogonalized VAR is represented by Σ. σ_{jj} is the *j-th* diagonal component of the standard deviation. The selection vector e_i has a value 1 for *i-th* component and 0 otherwise. Finally, $\emptyset_h$ is the coefficient matrix that multiplies *h*-lagged error in the infinite moving-average representation of non-orthogonalized VAR.

In our connectedness table, $c_{ij}^{g(H)}$ measures the pairwise directional connectedness from *j* to *i* as:

$$C_{i \leftarrow j}^{H} = c_{ij}^{g(H)} \tag{10}$$

The off-diagonal sum of rows represents the total directional connectedness from others to *i* as:

$$C_{i \leftarrow \bullet}^{H} = \sum_{\substack{j=1 \\ j \neq i}}^{N} c_{ij}^{g(H)} \tag{11}$$

And off-diagonal sums of columns represent the total directional connectedness to others from j as:

$$C^{H}_{\bullet\leftarrow j} = \sum_{\substack{i=1 \\ i\neq j}}^{N} c^{g(H)}_{ij} \tag{12}$$

Finally, the total connectedness (system-wide) connectedness is the ratio of the sum of the to-others (from-others) elements of the variance decomposition matrix to the sum of all its elements:

$$C^{H} = \frac{1}{N}\sum\nolimits_{\substack{i,j=1 \\ i\neq j}}^{N} c^{g(H)}_{ij} \tag{13}$$

The mathematical structure of the connectedness table is graphically visualized where individual commodity uncertainties are represented as nodes. The arrows represent the pairwise connectedness among the commodity uncertainties.

2.3.3. Frequency decompositions of connectedness measures

The frequency dynamics of connectedness in the form of short- and long-term frequencies are described by considering the spectral representation of variance decompositions. Instead of impulse responses to shocks, these decompositions are based on frequency responses to shocks. Therefore, the building block of current theory considers the frequency response function, $\aleph\left(e^{-i\omega g}\right) = \sum_{g} e^{-iwg}\, \aleph_{g}$, and it can be obtained as the Fourier transform of the coefficients $\aleph_{g}$, having $i = \sqrt{-1}$. The spectral density of UV_t at frequency ω can therefore be defined as Fourier Transform for MA(∞) filtered series as:

$$S_{UV}(\omega) = \sum_{g=-\infty}^{\infty} E\left(UV_t {UV'}_{t-g}\right) e^{-iwg} = \aleph(e^{-iw}) \sum \aleph'(e^{+iw}) \tag{14}$$

Understanding the frequency dynamics depends upon the key quantity power spectrum $S_{UV}(\omega)$ because it describes how the variance of UV_t is distributed over the frequency components ω. Nevertheless, frequency domain as counterparts of variance decompositions are explained by the spectral decomposition for covariance, i.e. $E\left(UV_{t,}UV'_{t-g}\right) = \int_{-\varphi}^{\varphi} S_\gamma(\omega)e^{i\omega g}d\omega$.

Barunik & Krehlik (2018) describe the comprehensive derivation of quantities, while the current study describes the estimation of connectedness measures at varying frequencies. Hence, the standard Fourier transforms estimates the spectral quantities. The interval's cross-spectral density $d = (a, b) : a, b \in (-\varphi, \varphi), a < b$ is estimated as:

$$\sum_{\omega} \widehat{\aleph}(\omega)\widehat{\Sigma}\widehat{\aleph}'(\omega) \tag{15}$$

for $\omega \in \left\{\left\lfloor {}^{aG}/_{2\pi}\right\rfloor, \dots, \left\lfloor {}^{bG}/_{2\pi}\right\rfloor\right\}$ where

$$\widehat{\aleph}(\omega) = \sum_{g=0}^{G-1} \widehat{\aleph}_g e^{-2i\varphi\omega/G} \tag{16}$$

and $\widehat{\Sigma} = {}^{\hat{\varepsilon}'\hat{\varepsilon}}/_{(T-x)}$, where x indicates the correction for loss of degrees of freedom and it exclusively depends on the specification of VAR.

The decomposition of impulse response function is estimated at given frequency band as $\widehat{\aleph}(d) = \sum_\omega \widehat{\aleph}(\omega)$. Hence, the generalized decompositions of variance are estimated at desired frequency band as:

$$\left(\hat{\partial}_d\right)_{j,l} = \sum_{\omega} \hat{\rho}_j(\omega)\left(\hat{f}(\omega)\right)_{j,l} \tag{17}$$

where, $\left(\hat{f}(\omega)\right)_{j,l} = \hat{\delta}_{ll}^{-1}\left(\left(\widehat{\aleph}(\omega)\widehat{\sum}\right)_{j,l}\right)^2 \Big/ \left(\widehat{\aleph}(\omega)\widehat{\sum}\widehat{\aleph}'(\omega)\right)_{j,j}$ is the estimated generalized causation spectrum, and $\hat{\rho}_j(\omega) = \left(\widehat{\aleph}(\omega)\widehat{\sum}\widehat{\aleph}'(\omega)\right)_{j,j} \big/ (\emptyset)_{j,j}$ is the estimate of weighted fraction and $\emptyset = \sum_\omega \widehat{\aleph}(\omega)\widehat{\sum}\widehat{\aleph}'(\omega)$. Hence, at given desired frequency band, the measures of connectedness can be derived by substituting the estimate, $\left(\hat{\partial}_k\right)_{j,l}$ into the traditional measures.

2.4. Data and findings

For the creation of uncertainty indexes, we use the daily spots and futures price of 22 commodities which are traded globally, namely WTI crude oil, Brent crude oil, gasoline, heating oil, gas oil, natural gas, gold, silver, platinum, palladium, aluminium, copper, zinc, lead, nickel, wheat, corn, soybean, coffee, sugar, cocoa, and cotton. These commodities are related to four distinct groups, i.e., energy commodities, precious and industrial metals, and agricultural commodities. Data of spot and futures (future contracts with maturity from one to nine months) from January 2007 and December 2016 is obtained from Thomson Reuters Datastream.

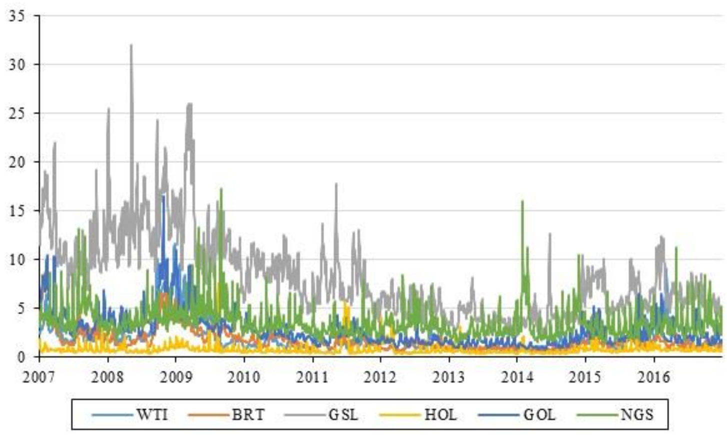
Figure 1 presents the commodity uncertainty indexes. Analyzing the graphs of these commodity uncertainty indexes, we observe that the uncertainties of energy and precious metal commodities peaked during the GFC. Although energy and precious metal commodities are considered to have a negative relationship with the financial markets (Raza, Shahzad, Tiwari, & Shahbaz, 2016), the uncertainties of these commodities were also at their peak during the GFC. This particular phenomenon can be associated with the fact that demand for commodities is linked to the income of consumers globally. The collapse of financial markets during the GFC negatively affected purchasing power, which subsequently decreased the demand for these commodities.

The uncertainty graphs of most of the industrial metals show peak uncertainties between 2007 and 2009. The price of aluminum rose to US $1.40 per lb in December 2007 and collapsed down to 60 cents per lb in November 2008. The price of nickel also boomed in the 1990s and imploded by the end of 2008 after experiencing two years of high uncertainty. Similarly, during this time, prices of other industrial metals nearly collapsed, increasing the uncertainty of industrial metals. Likewise, the graphs related to agricultural commodities show peaks during two main time frames, i.e., 2007-2008 and 2010-2012. These time frames are associated with world food crises, which created economic and political instability in both developed and underdeveloped nations.

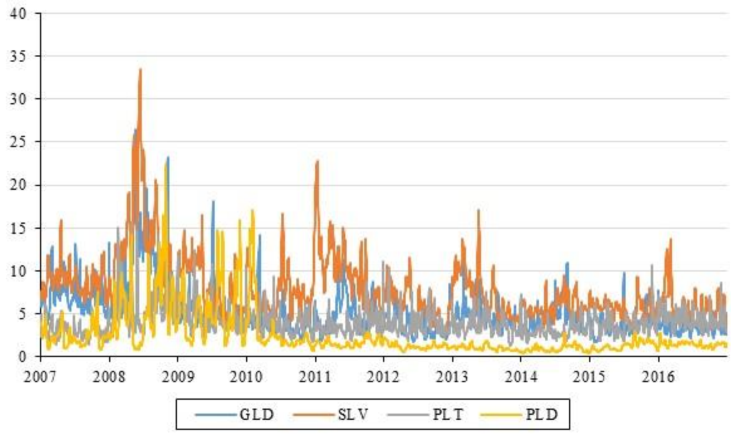
The descriptive statistics of the commodity uncertainty indexes are reported in Table 2. The summary statistics show that gasoline and silver have the highest average uncertainty, whereas copper, nickel, and coffee have the lowest uncertainty. Applying the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) on the logarithmic uncertainty series indicates all the series are stationary and appropriate for the use of a vector autoregressive model.

Figure 2. 1. Commodity Uncertainty Indexes

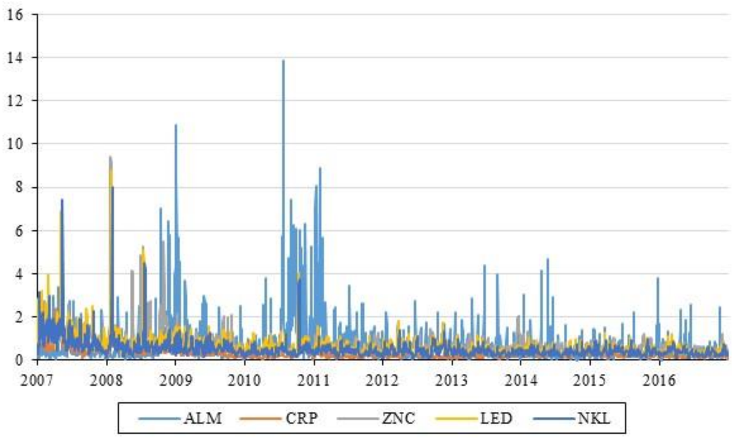
a) Energy



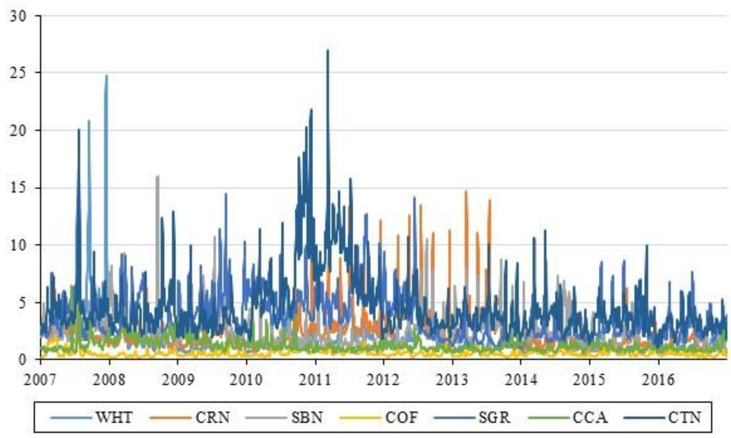
b) Precious Metals



c) Industrial Metals



d) Agriculture



Note. The symbols represent the following commodities: Crude Oil WTI (WTI), Crude Oil Brent (BRT), Gasoline (GSL), Heating Oil (HOL), Gas Oil (GOL), Natural Gas (NGS), Gold (GLD), Silver (SLV), Platinum (PLT), Palladium (PLD), Aluminium (ALM), Copper (CPR), Zinc (ZNC), Lead (LED), Nickel (NKL), Wheat (WHT), Corn (CRN), Soybean (SBN), Coffee (COF), Sugar (SGR), Cocoa (CCA) and Cotton (CTN).

Table 2. 2. Descriptive statistics of commodity uncertainties

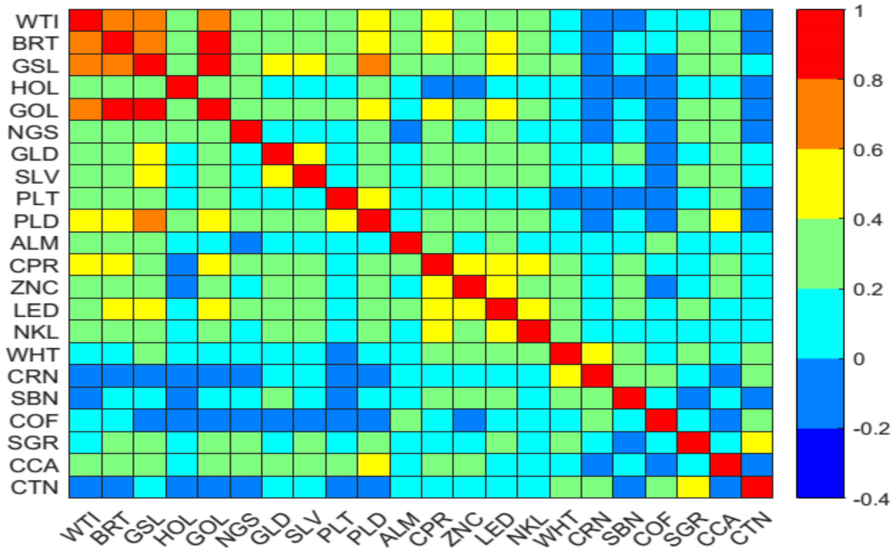
		Symbol	Average	Minimum	Median	Maximum	ADF	PP
Energy	WTI	WTI	1.87	0.52	1.47	11.58	-4.23***	-4.69***
	Brent	BRT	1.76	0.53	1.40	8.76	-4.43***	-5.11***
	Gasoline	GSL	8.07	2.15	6.95	31.97	-3.55***	-2.92***
	Heating Oil	HOL	0.81	0.35	0.67	7.63	-5.97***	-8.50***
	Gas Oil	GOL	2.71	0.81	2.24	16.48	-3.53***	-3.96***
	Natural Gas	NGS	3.59	1.45	3.20	17.28	-5.31***	-9.37***
Precious metals	Gold	GLD	5.15	1.76	4.37	26.43	-6.60***	-5.15***
	Silver	SLV	7.88	2.78	6.92	33.52	-4.98***	-4.57***
	Platinum	PLT	4.00	1.25	3.64	20.91	-12.02***	-9.42***
	Palladium	PLD	2.41	0.38	1.51	22.42	-5.93***	-5.59***
Industrial metals	Aluminum	ALM	0.63	0.02	0.31	13.87	-4.99***	-16.66***
	Copper	CPR	0.31	0.06	0.24	5.47	-4.38***	-4.46***
	Zinc	ZNC	0.72	0.15	0.60	9.38	-9.15***	-9.75***
	Lead	LED	0.66	0.15	0.55	8.76	-9.52***	-11.39***
	Nickel	NKL	0.52	0.09	0.42	8.00	-11.32***	-11.78***
Agricultural	Wheat	WHT	2.02	0.45	1.46	24.80	-5.56***	-3.91***
	Corn	CRN	2.42	0.56	1.99	14.70	-6.56***	-4.47***
	Soybean	SBN	2.33	0.61	1.97	15.96	-7.04***	-5.57***
	Coffee	COF	0.58	0.18	0.49	6.02	-8.87***	-8.69***
	Sugar	SGR	3.67	0.94	3.08	19.83	-5.81***	-4.30***
	Cocoa	CCA	1.27	0.48	1.09	10.63	-7.67***	-5.70***
	Cotton	CTN	4.50	1.09	3.71	26.99	-7.22***	-5.44***

Note. This table reports some basic statistics of uncertainty series estimated using method proposed by Chuliá et al. (2017). ADF and PP are the empirical statistics of the Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests, applied on logarithmic uncertainty series, respectively. As usual, *** denotes rejection of null hypothesis at 1% level of significance.

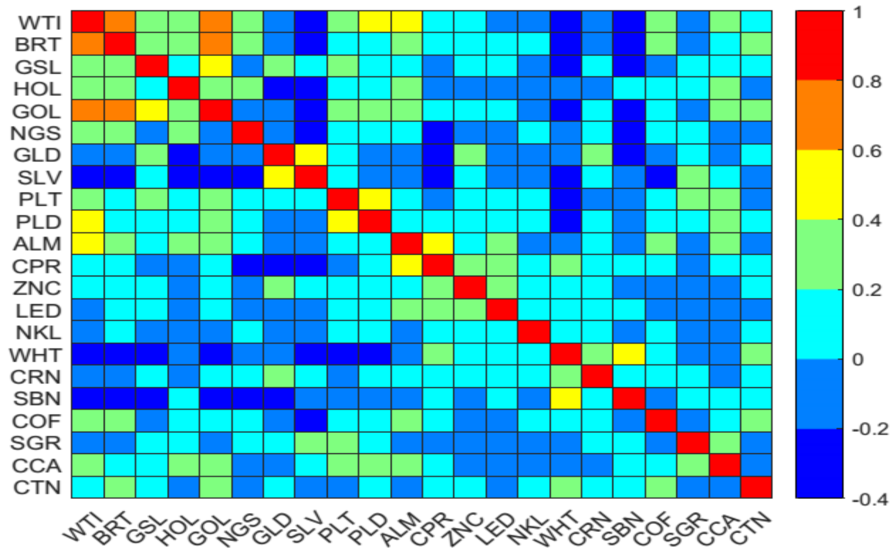
The correlation heatmaps in Figures 2 (a) and (b) display the visualization of the correlation matrix among the commodity uncertainty indexes for the full sample and the GFC sub-sample. Note that red and blue colors indicate the positive and negative correlations among the commodity uncertainty indexes. In the first instance, both correlation heatmaps (a) and (b) indicate high/positive correlation among the uncertainty indexes of energy commodities. Second, we see low/negative correlation among energy and agriculture commodities even more so during the period of GFC. Finally, the correlation among commodity uncertainty indexes decreased significantly during the GFC, indicating a possible diversification for commodity investors.

Figure 2. 2. Correlation heatmaps

a). Full sample



b). Global financial crisis sub-sample (Aug 2007 – Jun 2009)

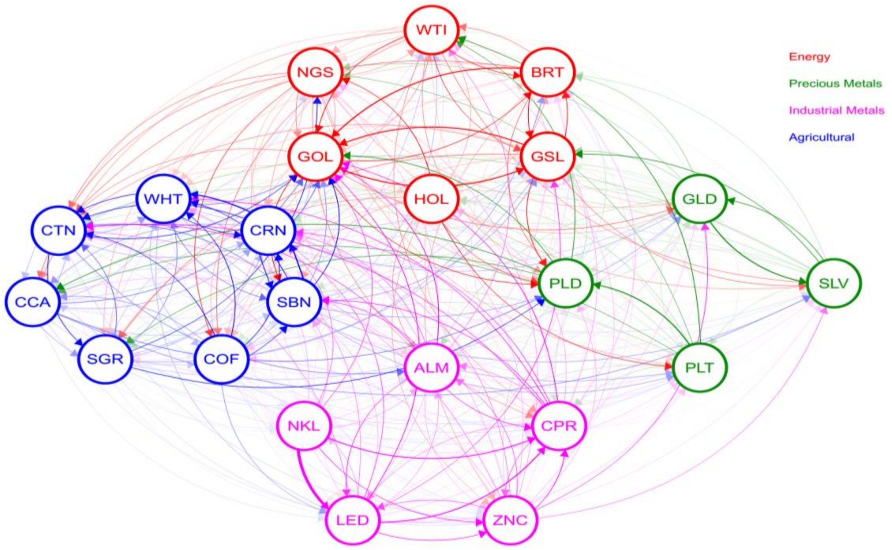


Note. These heatmaps show the pair-wise correlation between commodity uncertainties for full and GFC sample periods. Strength of correlation is show through color bar which is show on the right of each figure. The symbols represent the following commodities: Crude Oil WTI (WTI), Crude Oil Brent (BRT), Gasoline (GSL), Heating Oil (HOL), Gas Oil (GOL), Natural Gas (NGS), Gold (GLD), Silver (SLV), Platinum (PLT), Palladium (PLD), Aluminium (ALM), Copper (CPR), Zinc (ZNC), Lead (LED), Nickel (NKL), Wheat (WHT), Corn (CRN), Soybean (SBN), Coffee (COF), Sugar (SGR), Cocoa (CCA) and Cotton (CTN).

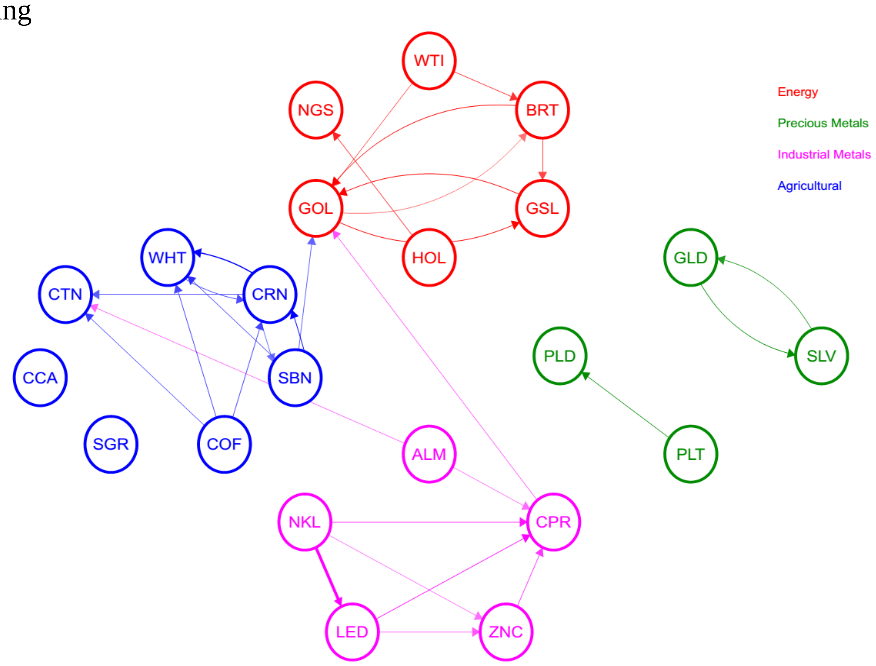
Figure 3a shows the spillover network of full sample pairwise connectedness of commodity uncertainties. This figure shows an elliptical network representation of a weighted adjacency matrix obtained using the estimates of VAR (3) model using Schwarz Criterion and examines the contribution to the variance decomposition of 12-days ahead forecast error of commodity uncertainty. Figure 3a is however less clear due to large pair-wise connections. To visualize the major connections, we apply hard thresholding (the values smaller than the average of first 100 largest partial derivatives are set to be 0s) to omit the smaller values. Figure 3b shows the spillover network after the thresholding. We can see that most of the connections are within the commodity classes, i.e., energy, precious metals, industrial metals, and agriculture. The strongest connection is between nickel and lead (the industrial metals). In the top red ellipse, gas oil is linked within group with WTI, Brent, and gasoline, whereas it is also linked with soybean and copper. Similarly, we see a few mutual connections between Brent/gas oil and gas oil/gasoline in the energy commodities, gold/silver in the precious metals, and between wheat/corn and corn/soybean pairs. Furthermore, the disconnection of precious metals from the other commodities points out to their safe-haven properties.

Figure 2. 3. Spillover network of commodity uncertainties – full sample

a). All connections



b). Thresholding

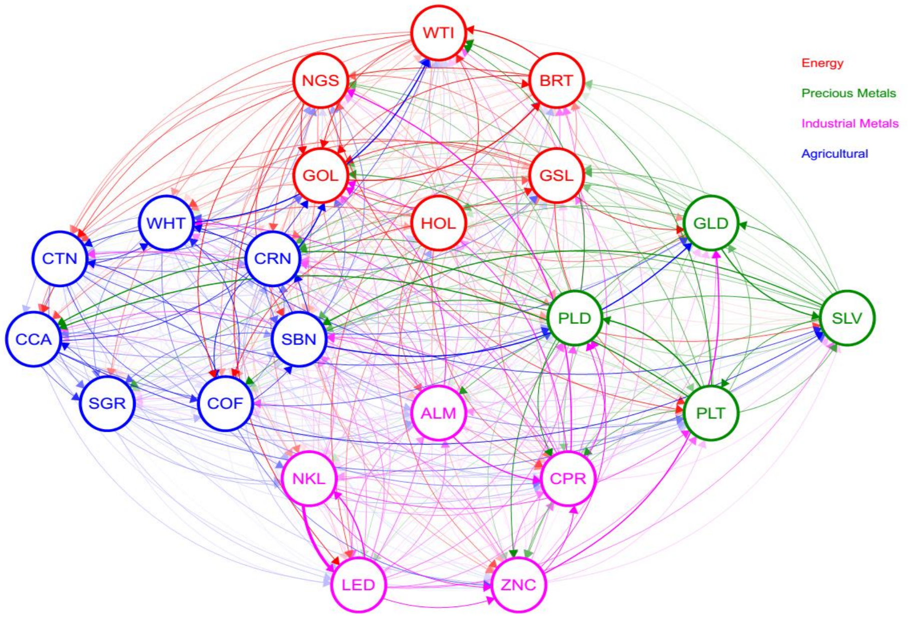


Note. The upper figure shows an elliptical network representation of a weighted adjacency matrix without the thresholding, obtained using the estimates of VAR (3) model using Schwarz Criterion, and examines the contribution to the variance decomposition of 12-days ahead forecast error of commodity uncertainty. The lower elliptical network represents the same weighted adjacency matrix after the thresholding (the values smaller than average of first 100 largest partial derivatives are set to be 0s). Energy commodities: 6 (upper red), Precious metals: 4 (right green), Industrial commodities: 5 (lower magenta), Agricultural commodities: 7 (left blue). The sample period is from January 2007 till December 2016, a total of 2610 daily observations.

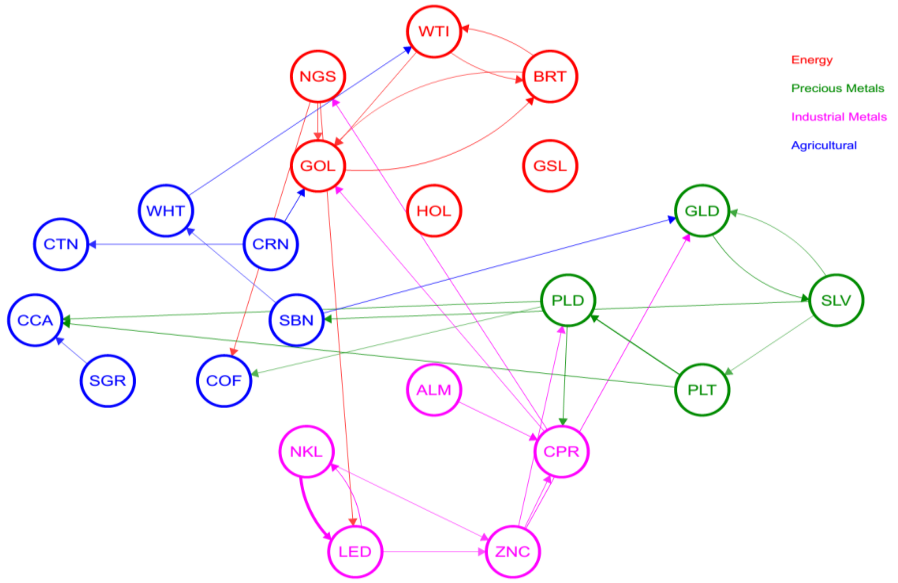
We further analyze the spillover network of commodity uncertainties during the period of the GFC (from August 2007 until June 2009) in Figure 4. Figure 4a represents all connections among the commodity uncertainties. We see a rise in the connectedness of commodity uncertainties during the period of the GFC. Besides the previous visible connections received by gas oil, cotton and copper, we see significant increase in the connections received by WTI in the upper red (Energy) ellipse, gold and platinum in the right green (Precious Metals) ellipse, zinc in the lower magenta (Industrial Metals) ellipse, and soybean and cocoa in the left blue (Agriculture) ellipse. A possible reason is that during the crisis period, uncertainty about the future prices of commodities increased which in turn increased the spillovers. We apply hard thresholding in Figure 4b to visualize the strong connections among commodity uncertainties. We see that the within commodity class connectedness is high among uncertainties. The strongest connection is still from nickel to lead, whereas we also see a mutual connection from lead to nickel indicating the two-way information spillover during the crisis period. Similarly, we also see mutual connection between WTI/Brent and gas oil/Brent in the energy ellipse, and between gold/silver in the precious metal ellipse. We also see an increase in the connections among commodity uncertainties from different classes. Coffee and lead are receiving connections from natural gas, WTI from wheat, whereas gas oil is receiving from corn. Cocoa is receiving connections from two precious metals, i.e., platinum and palladium and finally, gold is receiving connections from zinc and soybeans. Even though the connections among commodities from other markets increased during the GFC, we still see a disconnection between precious metals and energy commodities. This low connectedness among precious metals and energy commodities is again intuitive and points to their safe-haven properties. Possibly, investors and portfolio managers most concerned with energy commodities can mitigate the risk by adding precious metals to their portfolios.

Figure 2. 4. Spillover network of commodity uncertainties – global financial crisis

a). All connections



b). Thresholding



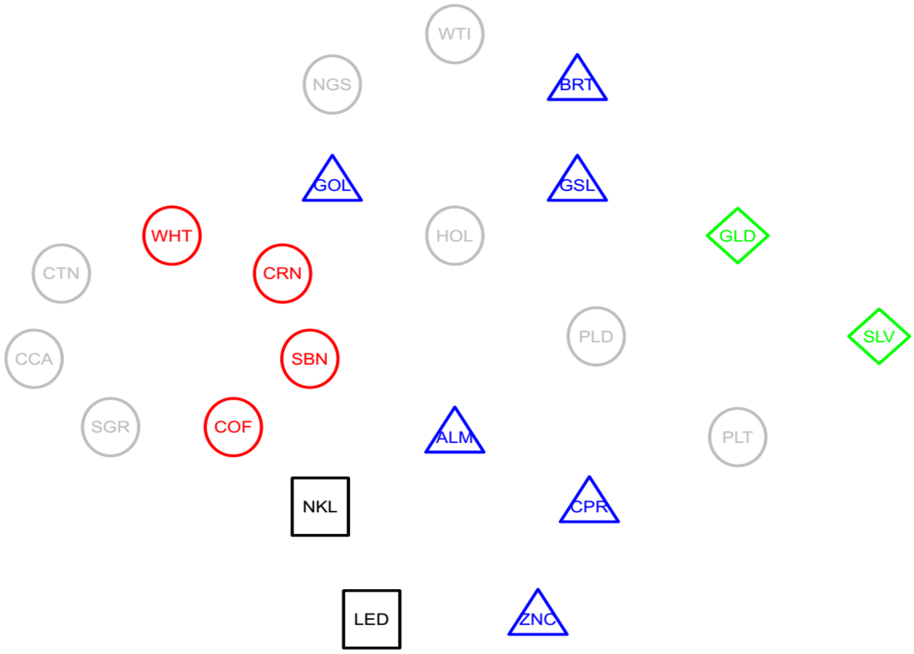
Note. The upper figure shows an elliptical network representation of a weighted adjacency matrix without the thresholding, obtained using the estimates of VAR (2) model using Schwarz Criterion, and examines the contribution to the variance decomposition of 12-days ahead forecast error of commodity uncertainty. The lower elliptical network represents the same weighted adjacency matrix after the thresholding (the values smaller than average of first 100 largest partial derivatives are set to be 0s). Energy commodities: 6 (upper red), Precious metals: 4 (right green), Industrial metals: 5 (lower magenta), Agricultural commodities: 7 (left blue). The sample period is from August 2007 till June 2009, a total of 500 daily observations.

In the previous step, we detected the connectedness among commodity uncertainties by applying the VAR model, in the next step we classify the risk clusters using hierarchical clustering. Figure 5a-b show the risk clusters for the full sample and the period of the GFC. In

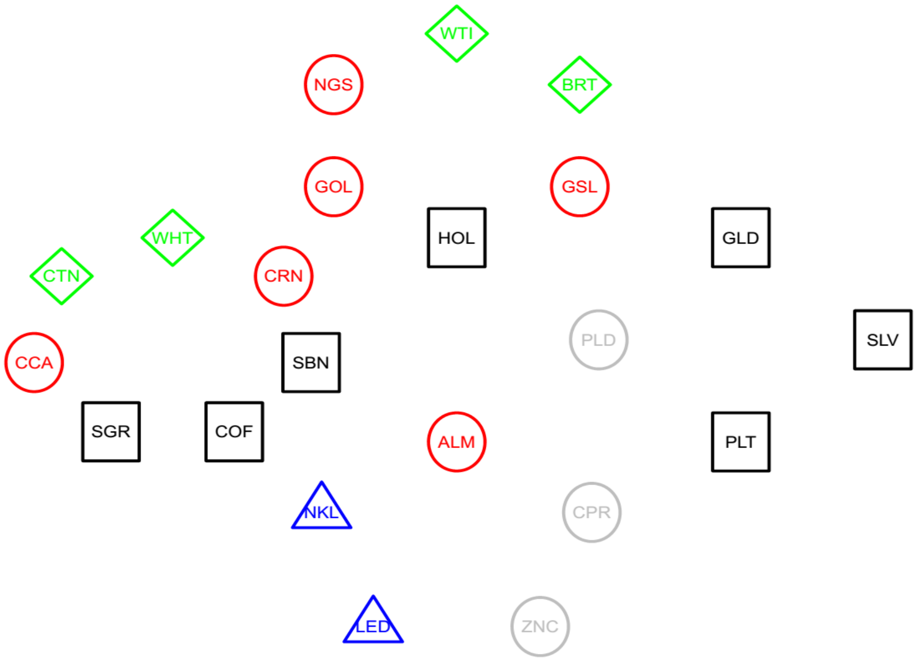
Figure 5a, the biggest cluster with blue triangle includes some energy commodities, like Brent, gasoline, gas oil, and some industrial metals, like aluminum, copper, and zinc. For Figure 5b, we see that the clusters are more widely spread across commodity classes. The biggest cluster is the Black Square and includes energy commodity heating oil, precious metals like gold, silver, platinum, and agriculture commodities, like soybean, coffee, and sugar. The second biggest cluster is the Red Circle, with energy commodities, like natural gas, gas oil and gasoline, agriculture commodities like cocoa and corn, and industrial metals such as aluminum.

Figure 2. 5. Spillover network of commodity uncertainties – cluster analysis

a). Full sample



b). Global financial crisis



Note. The upper figure shows an elliptical network representation of an unweighted adjacency matrix (1 and 0 representation) without thresholding for the full sample (details reported in notes to Fig. 2). The lower shows similar for GFC sub-sample (details reported in notes to Fig. 3). Green, blue, red, black represent four different risk clusters, and grey represents unconnected commodities.

In Figure 6a, we present the total time-varying connectedness among commodity uncertainties. Compared to the commodity volatility connectedness reported by Diebold et al. (2017), commodity price uncertainties tend to generate higher connectedness. Examining the total connectedness, we observe a surge during the 2008-2009 period. The financial crisis that started in the US in 2008 affected global income, prompting a rise in the uncertainty of commodity prices.

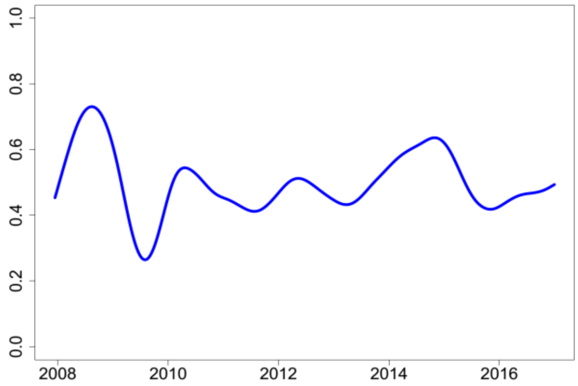
Accordingly, the total connectedness increased at the start of 2008 and following the bankruptcy of Lehman Brothers, peaked at the end of 2008. At this point, shocks to the system created a large portion of future uncertainty and the overall insecure economic situation globally attributed to the peak in connectedness. This finding complements the findings of Grosche & Heckelei (2016) and Kang, McIver, & Yoon (2017), who reported that commodities displayed higher spillovers (connectedness) during the GFC. After the financial system started to recover from the GFC, connectedness started to decrease and by mid-2009 dropped to its lowest. After hitting the lowest point, the total connectedness bounced back and started to increase from mid-2009 and reached 0.5 at the start of 2010. From the third quarter of 2011, we see a rise in the connectedness of commodity uncertainties. At one end, this increase can be associated with the European debt crisis of 2011-2012, when countries like Greece, Portugal, and Ireland were unable to bail out over-indebted financial institutions or even worse were unable to refinance their government debt. At the same time, there were serious concerns about political upheavals in the Middle East and North Africa, especially in countries like Libya and Egypt, which might boost the increase in total connectedness.

Analyzing the final phases of total connectedness of commodity uncertainties, we see a rise in early 2014. This rise in the total connectedness was due to the increased conflict between Russia, on the one side, and the U.S and the EU, on the other side. Another contributor to this increase was Saudi Arabia, who decided to change its policy of playing the marginal supplier in order to fight against the high-cost shale frackers. Hence, the oil market was the main contributor to the increase in connectedness during this period. After stabilization of the oil price at $50 per barrel, the commodity markets settled, and we see a decrease in the total connectedness. However, in mid-2015, the Chinese stock market bubble popped when a third of the value of A-shares on the Shanghai Stock Exchange was lost within a month. The disruption of the Chinese financial market increased uncertainty not only in the commodity markets but also in financial markets globally and increased the total connectedness. Hence, our analysis of total connectedness of commodity uncertainties indicates that commodity prices are highly susceptible to both economic and political global shocks.

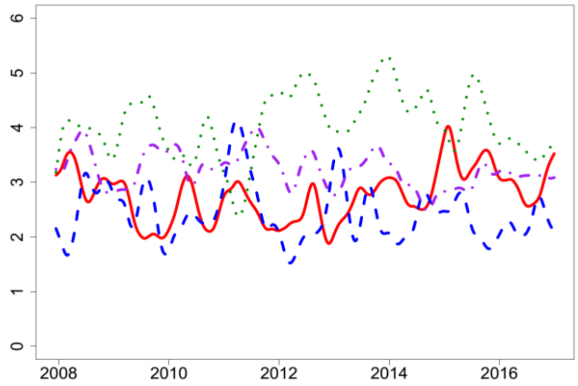
Figure 6b shows the connectedness of commodity uncertainties within commodity classes, Energy (solid red line), Precious metals (dashed blue line), Industrial Metals (dotted green line), Agriculture (dash-dot violet line). The patterns of these four commodity classes are almost identical. The most noticeable difference is the higher total connectedness of industrial metals commodity uncertainties, as compared to energy, precious metals, and agriculture. Figure 5c-f shows spillover from a specific commodity class to remaining classes; for example, Figure 5c shows the overall spillover from energy commodities to precious metals, industrial metals, and agriculture commodities.

Figure 2. 6. Rolling window spillover among commodity uncertainties

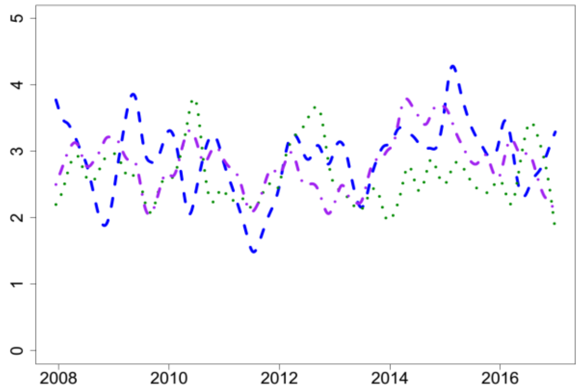
a). Total connectedness



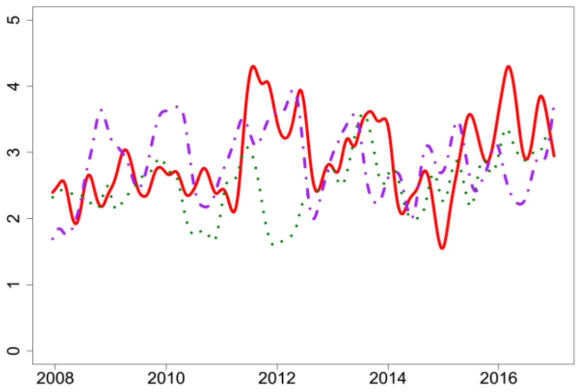
b). Within commodity class



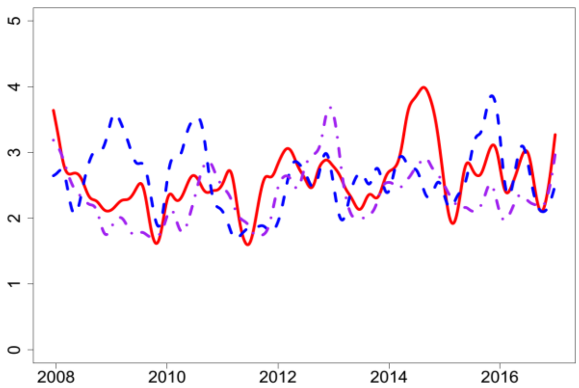
c). From energy to others



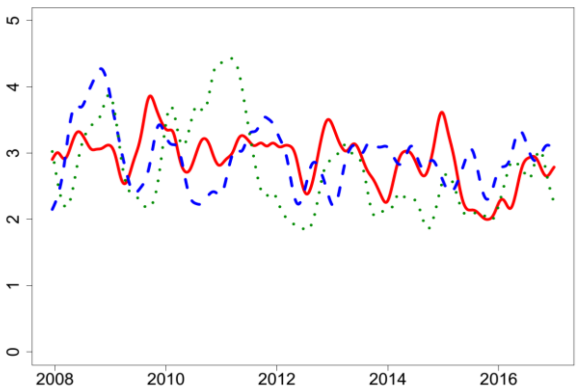
d). From precious metals to others



e). From industrial metals to others



f). From agricultural to others



Note. Top left figure shows total connectedness (solid blue line) of 22 commodities from 2007 to 2016, lag = 3, window size n = 250. Top right figure shows connectedness within four commodity classes. Energy: solid red line, Precious metals: dashed blue line, Industrial metals: dotted green line, Agricultural commodities: dash–dot violet line. Figures from c-f show spillover from a specific commodity class to remaining class, for example, figure c shows the overall spillover from energy commodities to precious metals, industrial metals and agricultural commodities.

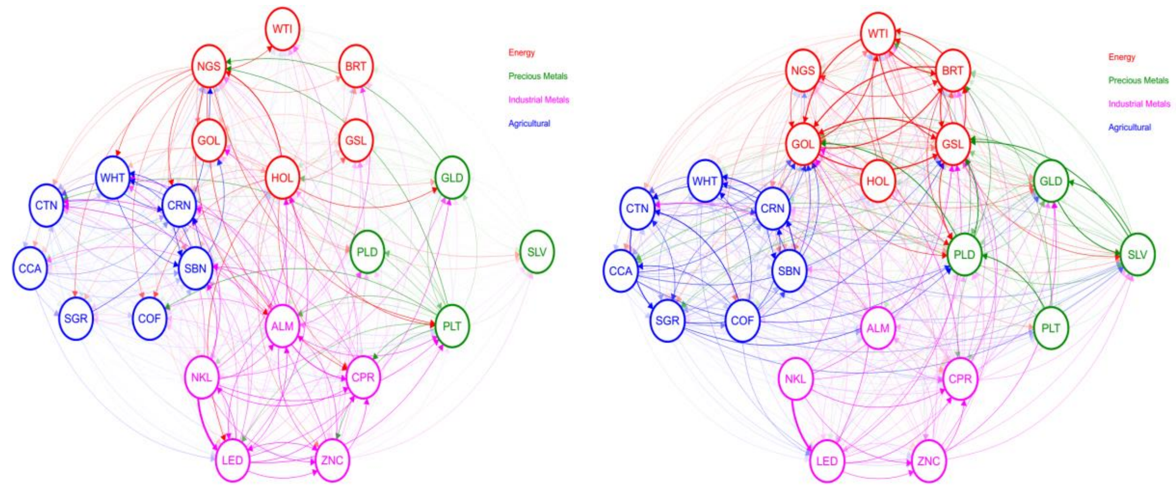
Finally, we decompose the total connectedness among commodity uncertainties into short-run and long-run frequencies using the method proposed by Barunik and Krehlik (2018). Figure 7a-b shows the elliptical network representation of adjacency matrices for higher frequency band (corresponding to movement up to five days/one week) and lower frequency band (corresponding to movement from six days or more). It presents the network analysis. Figure 7a-b displays the connectedness, in both the short-run and long-run, among four important commodity classes: energy commodities (red color), precious metals (green color), industrial metals (magenta color) and agricultural metals (blue color). It is evident from the analysis of short- and long-run networks that commodity uncertainties are more connected in the long-run. After applying hard thresholding, we can barely see a few connections in the short-run, except for the industrial metals, whereas we see strong within-group connectedness among the commodity uncertainties in the long-run.

Additionally, it is evident that in the short-run all commodity uncertainties tend to show connectedness with energy commodities. While in the long-run a similar pattern is observed, energy commodities also show heightened connectedness with other commodity groups. From an economic standpoint, in the long-run commodities would be affected by the imbalance between supply and demand shocks, thus translating into an increase in commodity price uncertainties. This is also intuitive as uncertainty in the price of one commodity might not have an effect on another commodity within a week's time, but depending upon the nature of commodity, it could have an impact in the long-run, confirming the findings of Ji et al. (2018) and Shahzad et al. (2018). Hence, in long-run, the increase in the price of energy commodities can increase the cost of inputs thereby ultimately increasing the production cost of other commodities.

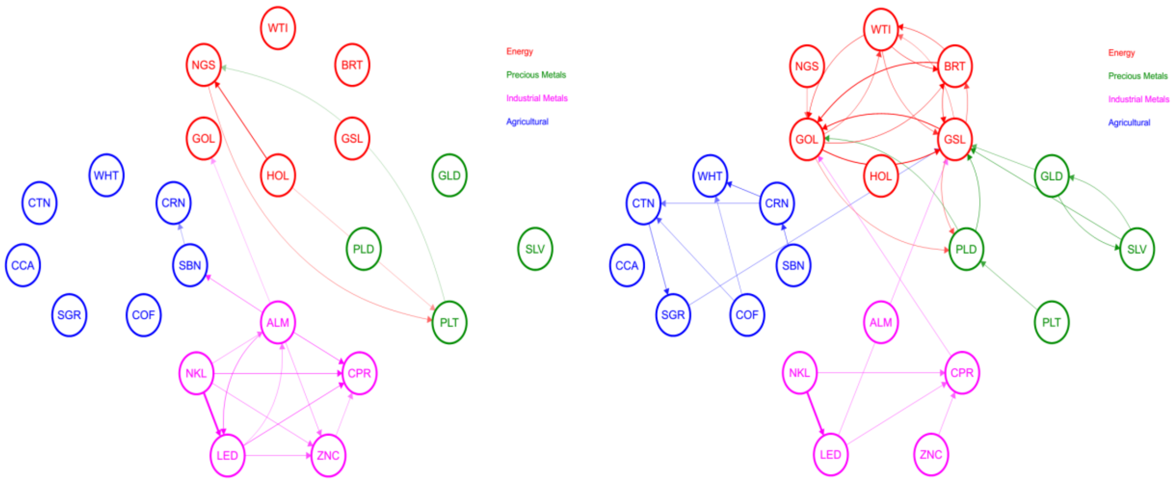
Figure 2. 7. Frequency decomposition-based spillover network of commodity uncertainties

Panel A: Short-run (upto 5 days) **Panel B:** Long-run (from 6 days onwards)

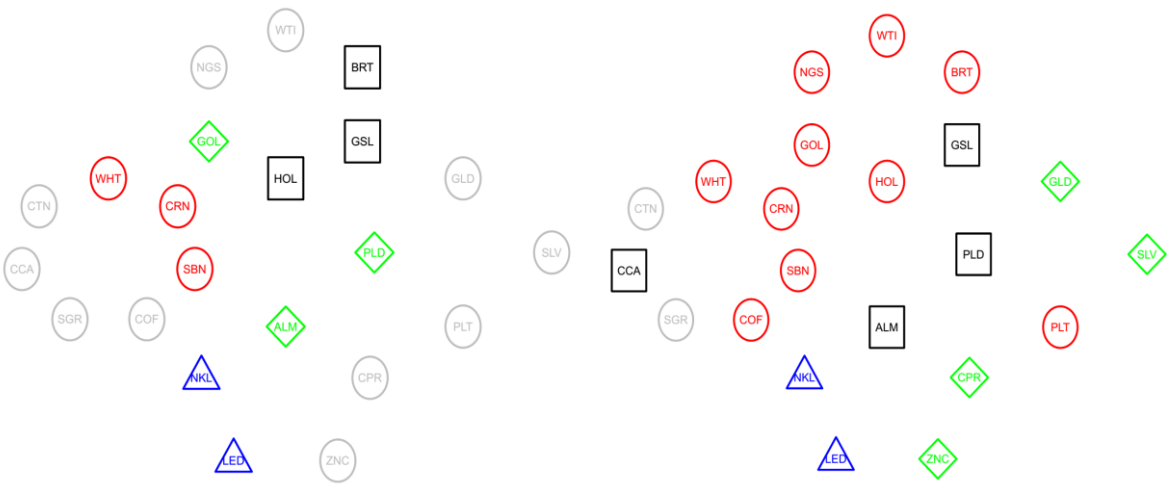
a). All connections



b). Thresholding



c). Clustering



Note. These figures show elliptical network representation of a adjacency matrices computed using the method of Barunik and Krehlik (2018). The left panel show results for the higher frequency band, which corresponds to movements up to five days (one week). The right panel show results for the lower frequency band, which corresponds to movements from more than six days (approximately up to two years). Figure (a) shows the elliptical network representation of a weighted adjacency matrix without the thresholding, obtained using the estimates of VAR (2) model using Schwarz Criterion, and examines the contribution to the variance decomposition of 100-days ahead forecast error of commodity uncertainty. Figure (b) shows the elliptical network represents the same weighted adjacency matrix after the thresholding (the values smaller than average of first 100 largest partial derivatives are set to be 0s). Energy commodities: 6 (upper red), Precious metals: 4 (right green), Industrial commodities: 5 (lower magenta), Agricultural commodities: 7 (left blue). The figure (c) shows elliptical network representation of an unweighted adjacency matrix (1 and 0 representation) without thresholding. Green, blue, red, black represent four different risk clusters, and grey represents unconnected commodities. The sample period is from January 2007 till December 2016, a total of 2610 daily observations.

2.5. Conclusion

In this study, we contribute to the understanding of uncertainty in prices of commodities by first estimating time-varying uncertainty indexes for 22 commodities. Our indexes provide a better understanding of uncertainty in the prices of commodities, as previous studies gauge the uncertainty in commodity markets by only using the variation/volatility in the prices of commodities. Second, to investigate how total connectedness evolves through time we deploy the connectedness model of Diebold & Yilmaz (2014). The analysis of total connectedness reveals that connectedness tends to increase during the period of crisis and that the global economic situation influences the connectedness of commodity uncertainty indexes. Analyzing the full sample directional connectedness, we find high connectedness within a specific commodity class. The connectedness among commodity uncertainties of different classes increased during the period of the GFC. We also find the disconnection of precious metals with other commodity classes giving proof to their safe-haven properties. Additionally, the analysis of time-varying connectedness indicates the increase among commodity uncertainties during the GFC and the oil price collapse of 2014-2016.

Finally, we employ the frequency connectedness framework of Barunik & Krehlik (2018) to assess the impact of uncertainty shocks on commodities at different frequency bands, i.e., short- and long-term investment horizons. The analysis of frequency connectedness reveals that the dynamics of short- and long-run connectedness differ and that the commodity uncertainties are highly connected in the long-run.

The analysis of total and frequency connectedness provides new evidence about the dynamics of connectedness among commodity markets and points out to the importance of precious metals and energy commodities in the literature related to risk analysis and investment management. Thus, investors can be better informed about connectedness in commodity markets in order to make sound investment decisions and develop efficient hedging strategies. The analysis of connectedness using graphical tools is particularly valuable for policymakers as it gives a clear picture to enable protection against the contagion effect and fostering of market stability.

Future research could investigate the impact of commodity price uncertainty on other asset classes using our uncertainty indexes. Furthermore, these uncertainty measures may also be used to assess the connectedness with other uncertainties such as economic policy uncertainty, stock market uncertainty, and geopolitical uncertainty. This would provide a better understanding of how other uncertainties interact with commodity price uncertainty.

CHAPTER THREE: Energy commodity uncertainties and the systematic risk of US industries

3.1. Introduction

A fundamental precept of uncertainty relates to a decrease in investment and reduction in the production of goods and services that causes a momentary decline in aggregate output as well as employment (Bachmann and Bayer, 2013; Bloom, 2009; Bloom et al., 2007). Hence, the increase in uncertainty has a pervasive impact on the aggregate income received by all the factors of production in an economy. The question then arises, what are the different sources of uncertainty? Previous studies identify different sources of uncertainty, such as economic policy uncertainty (Baker et al., 2016), macroeconomic uncertainty (Jurado et al., 2015), uncertainty in the stock market (Chuliá et al., 2017), and uncertainty in the future price of commodities (Balli et al., 2019).

Recent literature addressing the effect of uncertainty on asset prices indicates that uncertainty plays a distinctive role in financial markets and is crucial to the investment decisions (Anderson et al., 2009; Bams et al., 2017; Bansal and Yaron, 2004; Bekaert et al., 2009). Another strand of literature highlights the positive relationship between uncertainties in prices and expected stock returns (Bali and Zhou, 2016; Drechsler and Yaron, 2010). However, uncertainty in energy commodities, according to Driesprong et al. (2008), has significant impacts on the economy since energy commodities are essential for different sectors of economy. Uncertainty in energy commodities result in changes in interest rates, downstream inflationary pressures and changes in wealth transfers across oil-exporting and oil-importing countries, causing exchange rate fluctuations in return (Albulescu et al., 2019; Chen and Chen, 2007; Lizardo and Mollick, 2010). Moreover, energy commodity uncertainties also decrease aggregate output, investment and durable consumptions (Bams et al., 2017; Elder and Serletis, 2010). Additionally, sudden energy price shocks result in changes in demand for money and rebalancing of the industrial structural mix due to changes in the cost of production (supply-side effects). Consequently, uncertainty in energy commodities manifests in fluctuations in financial markets and various sectors of the economy (Broadstock et al., 2016).

A strand of literature indicates that industry betas are an adequate measure of systematic risk. Fund managers and investors with long-term concerns about the riskiness of their investment, use industry betas because many asset allocation models employ industry portfolios as base assets. Earlier studies estimate the static or unconditional betas (Dimson, 1979; Fama and French, 1992; Lintner, 1965; Scholes and Williams, 1977; Sharpe, 1964) and empirically assume that betas remain constant over the estimation period. However, recent studies contend that this is not a reasonable hypothesis. Since riskiness of a firm's cash flow and its correlation with systematic shocks are likely to fluctuate over time, industry betas also change over time (Baele and Londono, 2013; Bali et al., 2017; Engle, 2016; Yu et al., 2017).

Commodity uncertainty may be relevant to systematic risk of industries because some groups of commodities, such as crude oil and gasoline, are vital inputs in the production process. Therefore, uncertainty in the price of oil and gasoline affects firms' financial performance or cash flows, in turn, influencing their dividend payments, retained earnings and equity prices (Apergis and Miller, 2009; Arouri et al., 2012; Huang et al., 1996; Park and Ratti, 2008). In addition to the impact of energy commodity uncertainty on the market fundamentals, another channel that finds support in the literature relates to speculative dynamics and market contagion (i.e. investor sentiment, fads, overreaction to news, and investor attention to extreme price changes) (Du and He, 2015). However, a better understanding of the relationship between commodity and financial markets is required to benefit from the new horizons of investment opportunities (Diebold and Yilmaz, 2012).

Concurrently, researchers have also put a great deal of effort to evaluate how uncertainty in commodity markets impacts equity markets. The widely studied market in this regard is the crude oil market. The impact of oil prices on stock returns is a popular area of interest in energy and financial economics (see for example, Bams et al., 2017; Driesprong, Jacobsen and Maat, 2008; Elyasiani et al., 2011; Fan and Jahan-Parvar, 2012; Kilian and Park, 2009; Narayan and Sharma, 2011). However, Feng et al. (2017) identify the importance of other commodities apart from oil for their perceived economic significance. Similarly, besides crude oil, recent research has also highlighted the impact of gasoline and natural gas on stock markets (Broadstock et al., 2016; Galvani and Plourde, 2010; Zhang et al., 2017).

There are two main reasons why we study the impact of energy commodity uncertainties on the systematic risk of industries. First, the market index does not identify the performance of one specific industry, particularly during the turmoil periods, such as the Global Financial Crisis (GFC) and the recent oil market crisis during the Shale Oil Revolution (SOR). Second, industries have asymmetric sensitivity towards changes in commodity prices; for example, the impact of energy commodities on industry would depend on whether the relationship is as a direct or indirect factor of production. Since, firms related to oil and gas, transportation, and industrials are more dependent on energy commodities, as compared to health care and telecommunication, there may be asymmetric sensitivities of industries to changes in commodity prices (Narayan and Sharma, 2011).

Previous literature that examined the energy-stock nexus focused mostly on return and volatility estimations. We extend and contribute to this literature, by estimating the dynamic conditional betas for twelve industry portfolios using the DCC model of Engle (2002), which uses the GARCH process to estimate the conditional co-movement between assets, i.e., industry and market. Next, we use the predictive factor lagged model to find the answer to our question: Can uncertainty about the future price of energy markets lead the riskiness of industries? Additionally, we add several control variables to test whether our model is robust to different specifications. Empirically, our analysis of industry betas indicates the less risky nature of healthcare, consumer goods, and consumer services. Conversely, real estate, financials, and basic materials consistently remain high. Collectively, we find that energy commodity uncertainties can predict the systematic risk of industries, though we find heterogeneity due to different levels of exposure to energy uncertainties. Utilizing control variables in our models points out that our model is robust to different specifications. Finally, the sub-sample analysis of the GFC and SOR periods indicates the impact of oil uncertainty for oil-relevant industry investors is undiversifiable during the period of crisis.

The rest of the paper is structured as follows. In Section 2, we provide a brief review of the literature. Section 3 describes the data and empirical methodology. In Section 4, we discuss our empirical findings and perform robustness checks. Finally, we conclude in Section 5.

3.2. Literature review

Existing studies document the consequences of energy commodity uncertainty on various parts of the economy. However, the increasing body of literature particularly considers the US stock market in this regard. A large number of studies highlight the significant negative impact of oil price uncertainty or shocks on stock markets (Alsalman, 2016; Jones and Kaul, 1996; Driesprong et al., 2008; Narayan and Sharma, 2011). By contrast, Mohanty et al. (2011) argue that the impact of oil price shocks or uncertainty on stock markets of particular countries can be both negative and positive depending upon if the country is net consumer or net producer of oil resources. Hence, the documented negative relation in previous studies does not hold for the stock markets that are operating in oil-exporting countries. Instead, these countries show a positive impact on stock returns (Arouri and Rault, 2012; Bjornland, 2009; Wang, Wu and Yang, 2013). Tsai (2015) and Zhang (2017) also document similar positive results.

According to Narayan and Sharma (2011) and Phan et al. (2015), there is reasonable evidence of positive and negative impacts of energy commodity price uncertainty on sector returns. There are various reasons for such impacts, namely trade-offs between risk and return, inflationary uncertainty, the ability to hedge futures and spot contracts and effects of broader general equilibrium. Similarly, gasoline is also a valuable energy commodity for industry because of its importance for transportation services. Industries require gasoline for supply chain production or manufacturing of goods or services. It implies that gasoline uncertainty is more prevalent for companies rather than reactions to oil. Therefore, gasoline is another valuable energy commodity investigated in a few studies in terms of its impact on stock returns (Broadstock et al., 2016; Galvani and Plourde, 2010; Kang, de Gracia and Ratti, 2019; Shahid, Mahmood and Usman, 2017). Other important energy commodities, such as natural gas and gas oil are also investigated in terms of their uncertainty impact on stock prices (Acaravci, Ozturk and Kandir, 2012; Galvani and Plourde, 2010; Gatfaoui, 2016; Zhang, Chevallier and Guesmi, 2017). The table below presents the important energy commodities research in the case of U.S. stock market and industry markets.

Table 3. 1. Summary of main studies related to energy commodities and stocks

Study Reference	Study Period	Journal	Methods	Commodity Class / Type	Additional control variables	Summary
Acaravci, Ozturk, and Kandir (2012)	1990-2008	Economic Modeling	Johansen and Juselius cointegration test and error–correction-based Granger causality models	Natural gas	Nil	A significant long-run relationship exists between stock prices and natural gas prices. There is a unique long-term equilibrium relationship between natural gas prices, industrial production and stock prices in Austria, Denmark, Finland, Germany and Luxembourg
Mollick and Assefa (2013)	1999-2011	Energy Economics	GARCH and DCC-GARCH	WTI Crude oil and gold price	S&P 500, Dow Jones, NASDAQ, Russell 2000, VIX volatility	Before the financial crisis, stock returns are slightly (negatively) affected by oil prices and by the USD/Euro. For the subsample of mid-2009 onwards, stock returns are positively affected by oil prices and a weaker USD/Euro. Hence, U.S. stocks responding positively to expectations of recovery worldwide.
Tsai (2015)	1990-2012	Energy Economics	OLS with panel-corrected standard errors.	WTI crude oil	Nil	U.S. stock returns respond positively to the changes in oil prices during and after such a crisis. Big oil intensive firms are the most strongly and negatively influenced by an oil price shock before the crisis. On the other hand, our results indicate that an oil price shock in the post-financial crisis period is positively amplified in the case of medium-sized firms.
Kang, Ratti, and Yoon (2015)	1968-2012	Energy Economics	VAR	Crude oil	NYSE, AMEX and Nasdaq	The structural oil shocks account for 25.7% of the long-run variation in real stock returns overall, with substantial change in levels and sources of contribution over time. The contribution of oil supply shocks has trended downward from 17% to 5% over 1973–2012.
Narayan and Gupta (2015)	1859-2013	Energy Economics	Time - Series Predictive regression model	WTI spot crude oil	S&P 500	Both positive and negative oil price changes are important predictors of US stock returns, with negative changes relatively more important.
Balcilar, Gupta, and Miller (2015)	1859-2013	Energy Economics	MS-VEC model.	WTI crude oil	S&P 500	The high-volatility regime more frequently exists prior to the Great Depression and after the 1973 oil price shock caused by the Organization of Petroleum Exporting Countries. The low-volatility regime occurs more frequently when the oil markets fell largely under the control of the major international oil companies from the end of the Great Depression to the first oil price shock in 1973.
Salisu and Oloko (2015)	2002-2014	Energy Economics	VARMA–AGARCH	WTI crude oil and Brent crude oil	S&P 500	There is significant own asymmetric shock effect in both markets while volatility spillover from oil market to stock market became pronounced after the break which coincides with the period of global economic slowdown
Inchauspe, Ripple, and Trück (2015)	2001-2014	Energy Economics	Multi-factor CAPM	WTI crude oil	New Energy Global Innovation Index (NEX), MSCI, Pacific Stock Exchange	There is a strong influence of the MSCI World index and technology stocks throughout the sample period. The influence of changes in the oil price is significantly lower, although oil has become more influential from 2007 onwards.

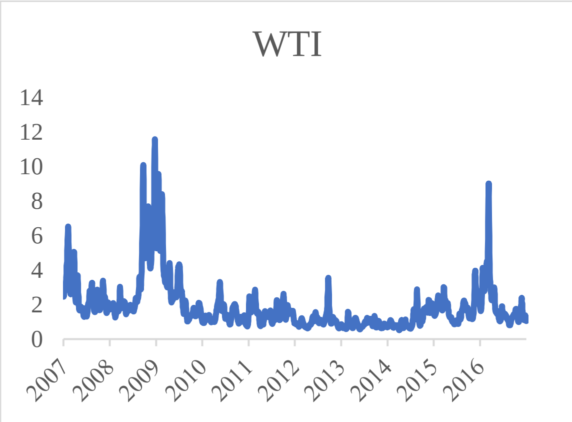
					Technology Index (PSE)	
Pana, Wang, and Liu (2016)	2000-2015	Energy Economics	ADECO	Petroleum	NYMEX	ADECO provides portfolios with better performances than existing popular DECO, DCC and ADCC models in the minimum-variance framework. Moreover, energy price risk can be better hedged by stocks in oil-exporting countries than stocks in oil-importing countries
Broadstock, Fan, Ji, and Zhang (2016)	2005-2012	The Energy Journal	CAPM and GARCH	WTI crude oil and gasoline	Shanghai composite stock index	89.2% of firms are susceptible to oil shocks, with positive and negative reactions observed even for firms within the same industry. Gasoline price shocks are more pervasive, affecting 95.7% of firms.
Gatfaoui (2016)	1997-2013	Energy Economics	Structural break test and Copula technique	Henry Hub Gulf Coast Natural Gas and WTI crude oil FOB	S&P 500	The linkages between the U.S. crude oil, natural gas and stock markets are unstable over time, which renders forecasts difficult.
Bouri, Awartani, and Maghyereh (2016)	2004-2013	Energy Economics	CCF, Granger-causality-in-variance and GARCH	Brent crude oil	Amman stock exchange	The influence is not uniform across the equity sectors. The oil return shocks significantly impact the Financials and the Services sectors, while its effect is insignificant on the Industrials sector. oil is a negligible risk factor. There is a significant evidence of risk transmission to the Industrials sector particularly during the Arab Uprisings period.
Zhang, Chevallier, and Guesmi (2017)	1999-2015	Energy Economics	VT-DCC	WTI crude oil, Henry Hub natural gas, NBP gas, Brent crude oil	VIX, VSTOXX	U.S. Henry Hub gas seems to be associated with the stock market volatility indexes, contrary to the European NBP gas, which is linked to the Brent. The four energy variables violate their thresholds at similar moments, and the stock market VIX and VSTOXX exhibit logically similarities.
Kang, de Gracia, and Ratti (2019)	1985-2016	Energy Economics	VAR	Crude oil and gasoline	EPU, CPI	The effect of oil price shocks on the real price of gasoline is interrelated with economic policy uncertainty. Economic policy shocks are linked with increased real price of gasoline and reduced consumption of gasoline. Positive shocks to economic policy uncertainty have relatively larger effects on gasoline prices than do negative shocks to economic policy uncertainty. Economic policy uncertainty responds asymmetrically to increases and decreases in real oil price.
Xu, Ma, Chen, and Zhang (2019)	2007-2016	Energy Economics	AG-DCC	WTI crude oil	S&P 500 and Shanghai stock market (SSM) composite	There exists an asymmetric spillover effect between the oil market and stock markets and that bad volatility spillovers dominate good volatility spillovers for most of the sampling period. Asymmetries exist in volatility shocks between the oil and stock markets due to bad volatility

Note: GARCH = Generalized autoregressive conditional heteroskedasticity; DCC = Dynamic conditional correlation; VAR = Vector autoregressive; MS-VEC = Markov-switching vector error correction; VARMA– AGARCH = Vector ARMA-Asymmetric GARCH; CAPM = Capital asset pricing model; ADECO = Asymmetric dynamic equi-correlation; CCF = Cross correlation function; VT-DCC = Volatility Threshold DCC; AG-DCC = Asymmetric generalized DCC

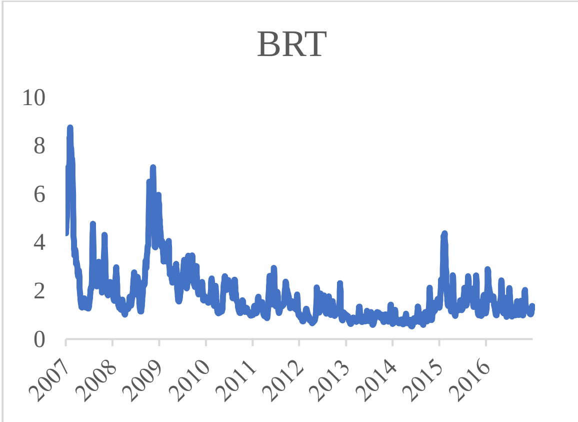
3.3. Data and empirical methodology

Given the importance of energy commodities, as highlighted in the previous section, we use daily data from January 2007 – December 2016 to study the predictive ability of energy commodity uncertainties (WTI crude oil, Brent crude oil, Gas oil, Gasoline, Heating oil, and Natural gas) for the U.S. industry betas. For energy commodity uncertainties, we use the indices developed in Balli et al. (2019). Briefly, their uncertainty index development constitutes of a two-step process. First, utilizing the generalized dynamic factor model (GDFM) of Forni et al. (2000), the authors separate the risk (variation) and uncertainty (idiosyncratic) components. Second, a stochastic volatility model, proposed by Kastner & Frühwirth-Schnatter (2014), is used to estimate the individual volatility of idiosyncratic series and averaged to formulate the uncertainty index. The selected period also covers several uncertainty periods for both the energy commodities and the industry sector of the U.S., for example, the Global Financial Crisis (GFC) and the Shale Oil Revolution (SOR). We were also motivated to select energy commodity uncertainties, as they are the most actively traded among the commodities. Secondly, despite much extensive literature on the energy – stock nexus (see, for example, Bams et al., 2017; Driesprong et al., 2008; Liu et al., 2015; Mensi et al., 2017; Narayan and Gupta, 2015), there is no clear consensus on the relationship between energy commodity uncertainty and the riskiness of stock markets. Also, the justification for using the Balli et al. (2019) uncertainty indices is that the authors utilize the unknown variations in the spot and futures prices (of different maturities) to provide real-time monitoring of the price uncertainty in energy commodity markets. Hence, we believe that these uncertainties would be able to predict the riskiness of industries. We plot the energy commodity uncertainty indices in Fig. 1.

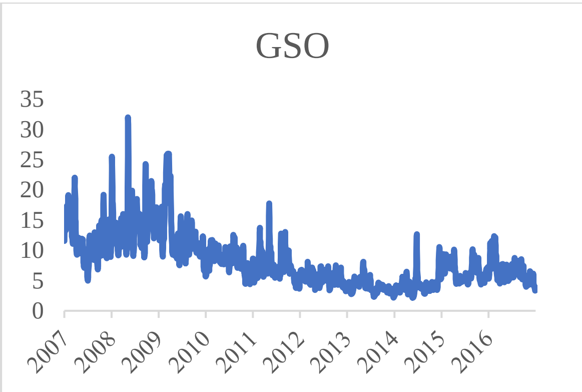
a) Crude oil WTI



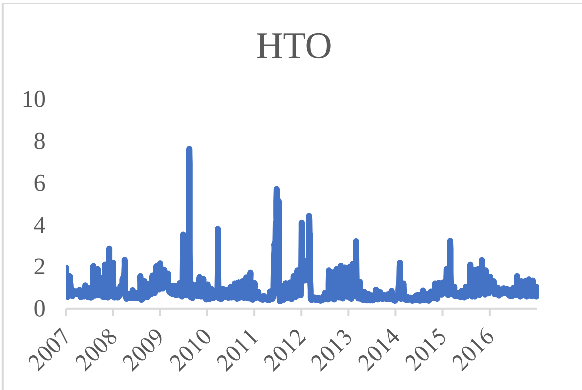
b) Crude oil Brent



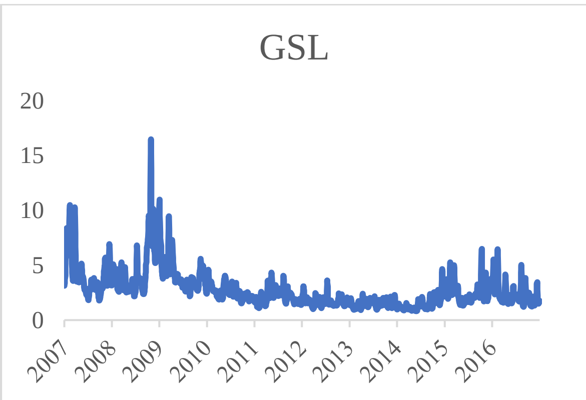
c) Gas oil



d) Heating oil



e) Gasoline



f) Natural gas

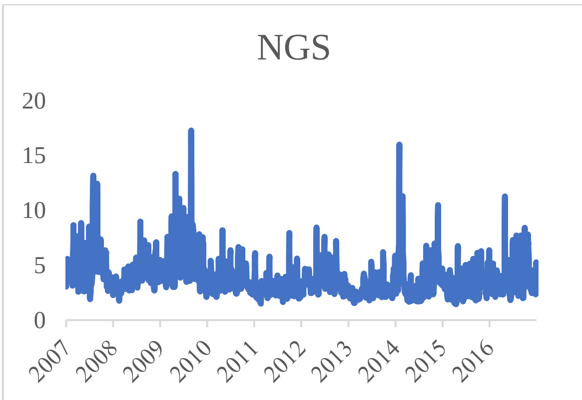


Figure 3. 1. Energy commodity uncertainties.

The Datastream U.S. industrial equity indices are utilized for the development of industry betas. Datastream's industrial indices are broken down into five levels. Level 1 is the total market index for each industry and covers all the sub-sectors in each relevant country. Hence, we use 12 industries from Level 1. Since we are interested in estimating the betas for the respective industries, we use the S&P 500 index as the benchmark market index for the U.S. Table 2 reports the summary statistics for industry-level returns, S&P 500 index, and energy commodity uncertainties. We use the returns (log difference) for the industry-level prices and S&P 500 index.

Table 3. 2. Summary statistics for industry returns and energy commodity uncertainties

	Symbol	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF
Basic Materials	BMT	0.02	1.88	-0.57	11.21	7468.62***	-52.78***
Basic Resources	BRS	-0.02	2.38	-0.39	11.89	8655.13***	-51.73***
Consumer Goods	CNG	0.02	1.00	-0.19	12.45	9717.04***	-40.30***
Consumer Services	CNS	0.03	1.24	-0.15	11.34	7566.75***	-53.84***
Financials	FIN	0.00	1.98	-0.17	14.67	14821.79***	-58.33***
Health Care	HLT	0.03	1.10	-0.16	12.07	8948.04***	-39.81***
Industrials	IND	0.02	1.41	-0.45	9.19	4251.10***	-53.35***
Oil and Gas	OGS	0.01	1.78	-0.39	15.34	16631.71***	-40.79***
Real Estate	RLS	0.00	2.22	-0.10	16.64	20238.77***	-62.80***
Technology	TEC	0.03	1.39	-0.10	9.75	4959.02***	-54.65***
Telecommunication	TEL	0.01	1.30	0.27	15.88	18063.13***	-40.55***
Utilities	UTL	0.01	1.19	0.23	16.71	20466.07***	-40.44***
S&P 500 Index		0.02	1.30	-0.33	13.39	11779.91***	-56.88***
WTI crude oil	WTI	1.87	1.42	2.80	12.83	13915.90***	-3.66***
Brent crude oil	BRT	1.76	1.15	2.49	11.06	9757.91***	-4.55***
Gas oil	GSO	2.71	1.69	2.38	11.55	10400.59***	-5.48***
Gasoline	GSL	8.07	4.20	1.32	5.23	1294.37***	-3.77***
Heating oil	HTO	0.81	0.53	4.98	40.38	162758.70***	-13.29***
Natural gas	NGS	3.59	1.51	2.26	12.20	11432.75***	-5.67***

Note: JB test indicates the test statistics for Jarque-Bera test of normality.
ADF test indicates the test statistics for Augmented Dickey-Fuller test for unit root.
*** indicates 1% significance level.

3.3.1. Dynamic conditional beta

We estimate the industry betas using the DCC model of Engle (2002), which uses the GARCH process to estimate the conditional co-movement between assets, i.e., industry and market.

$$r_d = \mu + \omega_d,\ \omega_d | \mathbb{I}_{d-1} \sim N(0, H_d) \quad (1)$$

where $r_d = (r_{1,d},\ r_{2,d},\ r_{3,d}, \dots, r_{n,d})'$ is a vector of returns of n assets at time d, vector of the expected value of conditional r_d is given by $\mu_d = (\mu_{1,d},\ \mu_{2,d},\ \mu_{3,d}, \dots, \mu_{n,d})'$, $\omega_d = (\omega_{1,d},\ \omega_{2,d},\ \omega_{3,d}, \dots, \omega_{n,d})'$, such that, $E[\omega_d] = 0$, $Cov[\omega_d] = H_d$ and H_d is the conditional covariance matrix. For estimation of time-varying conditional covariance, we use the standardized residuals $\mathcal{r}_{i,d} = \omega_{i,d} / \sqrt{\sigma_{i,d}^2}$.

We decompose conditional covariance matrix as

$$H_d = D_d \rho_d D_d, \text{ where } D_d = diag(\sqrt{\sigma_{i,d}^2}) \quad (2)$$

where ρ_d is the conditional correlation matrix of $\mathcal{r}_d$ at time *d*, and D_d is the diagonal matrix of conditional standard deviations for each series at time d. The standard deviations are estimated using a univariate GARCH (1, 1) process

$$\sigma_{i,d}^2 = \psi + \alpha_i \omega_{i,d-1}^2 + \beta_i \sigma_{i,d-1}^2 \quad (3)$$

We define the DCC-GARCH model in the next step as

$$Q_d = (1 - \alpha - \beta)\ \bar{Q} + \alpha \mathcal{r}_{d-1} \mathcal{r}_{d-1}' + \beta Q_{d-1} \quad (4)$$

$$\rho_d = \left(diag(Q_d)\right)^{-\frac{1}{2}} Q_d \left(diag(Q_d)\right)^{-\frac{1}{2}} \quad (5)$$

Where $Q_d = (q_{im,d})$ is the time-varying covariance matrix of standardised residuals r_d and $\bar{Q} = E[r_d r'_d]$ is the conditional correlation of r_d. α and β are unknown parameters, and should satisfy the condition $\alpha + \beta < 1$.

The dynamic conditional correlation between industry (*i*) and market (*m*) is given by

$$\rho_{im,d} = \frac{q_{im,d}}{\sqrt{q_{ii,d}q_{mm,d}}}, \quad i, m = 1, 2, \dots, n \; and \; i \neq m \tag{6}$$

where $\rho_{im,d}$ is the coefficient in the DCC-GARCH model. Finally, the dynamic conditional beta for the industry is defined as[5]

$$BETA_{i,d}^{DCC} = \frac{\sigma_{im,d}}{\sigma_{i,d}^2} \tag{7}$$

3.3.2. Predictive model

Ever since the inception of financial market analysis, factor models have laid the foundations for typical predictive regressions. These models are usually of the form $DV_t = \propto + \sum_i^N \lambda_i \mathcal{F}_{t-k}^i + \mathcal{E}_t$, where $\mathcal{F}_{t-k}^i$ is a factor with k-lags[6]. Among many others, Campbell (1987), Campbell and Shiller (1988), Campbell and Thompson (2008), Driesprong et al. (2008), Fama and French (1988) provide some important examples of predictive financial models. Our questions are relatively straightforward. Can uncertainty about the future price of energy markets lead the systematic risk of industries? If yes, how do the industries respond to energy commodity uncertainties? We answer these questions by first using the simple predictive regression model:

$$BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i \tag{8}$$

[5] Following Engle (2002), we estimate the dynamic conditional beta of each industry using maximum-likelihood function.
[6] For an exhaustive list of such models, see Welch and Goyal (2008).

where $BETA_d^i$ represents the estimated DCC-Beta of industry stock (i) at time (d), $\propto_i$ is the constant, U_d^{EN} represents the energy commodity uncertainties for WTI, BRT, GSO, GSL, HTO, and NGS. $\mathcal{E}_d^i$ are the idiosyncratic error terms for each industry. In order to answer our questions, we test whether λ_i is significantly different from zero. When λ_i is significant, we reject the null hypothesis of no effect of energy uncertainties. We further analyze the predictability of energy uncertainties on the riskiness of industries by performing Eq (8) for two sub-periods, i.e., GFC and SOR.

For robustness, we explore the ability of energy commodity uncertainties to predict the systematic risk of industries by extending the above equation and performing analysis for full-sample, and GFC, SOR sub-periods. Since our analysis is based on U.S. industry betas, we estimate the following specification separately for each of the 12 industry betas:

$$BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i \quad (9)$$

where CV_d represent the additional market predictors as control variables. We use a number of well-known market predictors as CV_d to address whether energy commodity uncertainties predict riskiness of industries even after applying these control variables. The four variables included in CV_d are: (1) r_d^{VIX} (returns of CBOE volatility index (VIX)), which represents the real-time expectation of the coming 30 days volatility of S&P 500 index options; (2) r_d^{B} (returns of U.S. benchmark 10-year government bond index); (3) ln_EPU_d (natural log of U.S. Economic Policy Uncertainty index developed by Baker et al. (2016)); (4) ln_GPR_d (natural log of U.S. Geopolitical Risk index developed by Caldara and Iacoviello (2018)).

Additionally, we assume that the ability of energy commodity uncertainties to predict the riskiness of industries might be impacted in the face of a shock, such as GFC or SOR because it had a significant impact on the energy commodities and other financial markets. Hence, we estimate the following regression model:

$$BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \eta_1 D(GFC) + \eta_2 D(SOR) + \mathcal{E}_d^i \quad (10)$$

where D (dummy variable) is equal to one during GFC and SOR, and zero otherwise.

We estimate Eq (8), (9) and (10) for each industry beta separately, using OLS (ordinary least square) regression, since we are interested in predicting the riskiness of industries using energy commodity uncertainties, we find they have leptokurtic distributions. Hence, we use Newey-West heteroscedasticity and HAC (autocorrelation consistent) covariance matrix estimators.

3.4. Empirical evidence

3.4.1. Analysis of industry betas

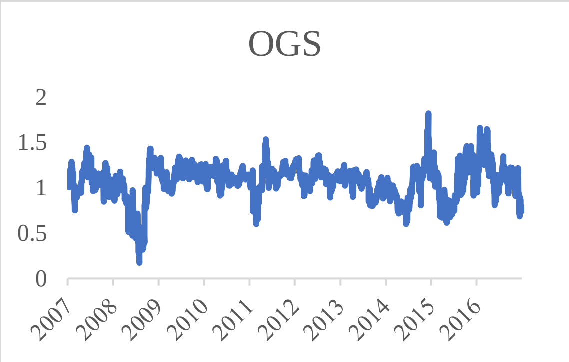
We present the summary statistics for the estimated industry betas in Table 3. The industries related to finance (FIN), basic resources (BRS), and basic materials (BMT) show the highest means, whereas utilities (UTL) has the lowest average. When analyzing the standard deviations of the betas; we find real estate (RLS), finance (FIN), and basic resources (BRS) are substantially more volatile as compared to other industries. The analyses of energy commodity uncertainties indicate high mean uncertainty among gasoline (GSL), natural gas (NGS), and gas oil (GSO). The standard deviation implies that the uncertainty of these commodity uncertainties is more volatile than the other energy commodities.

Table 3. 3. Descriptive Statistics for Industry Betas

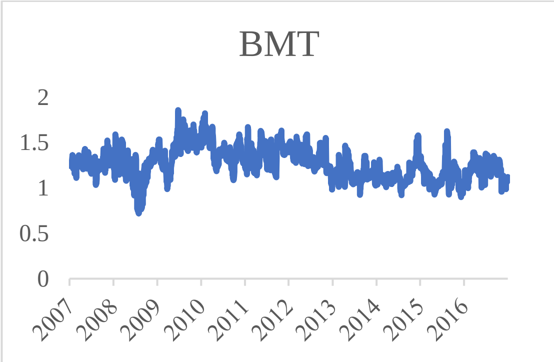
	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF
BMT	1.26	0.17	0.21	2.93	18.95***	-7.39***
BRS	1.40	0.25	0.25	3.15	28.84***	-6.86***
CNG	0.77	0.11	0.07	3.29	10.87***	-6.52***
CNS	0.93	0.08	0.13	3.52	36.95***	-7.80***
FIN	1.27	0.29	1.97	8.19	4623.33***	-4.91***
HLT	0.81	0.16	0.05	3.07	1.80	-6.10***
IND	1.08	0.12	-0.05	3.18	4.38	-7.62***
OGS	1.08	0.20	-0.82	5.03	740.89***	-5.84***
RLS	1.08	0.41	1.41	5.67	1635.99***	-4.68***
TEC	1.05	0.14	-0.11	2.75	12.30***	-7.75***
TEL	0.76	0.12	0.24	3.15	26.75***	-7.92***
UTL	0.65	0.17	0.40	4.19	221.95***	-6.48

Note: JB test indicates the test statistics for Jarque-Bera test of normality.
ADF test indicates the test statistics for Augmented Dickey-Fuller test for unit root.
*** indicates 1% significance level.
The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

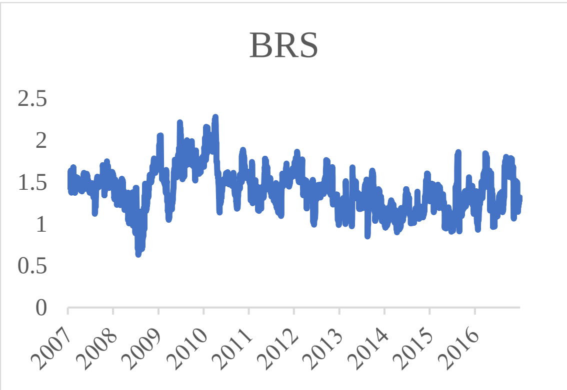
a) Oil and Gas



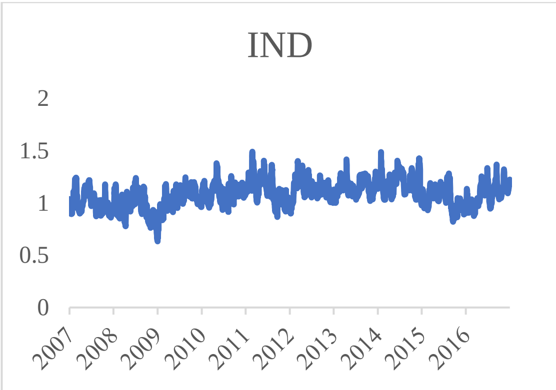
b) Basic Material



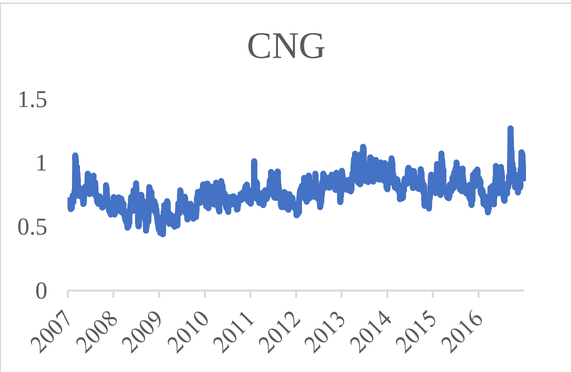
c) Basic Resources



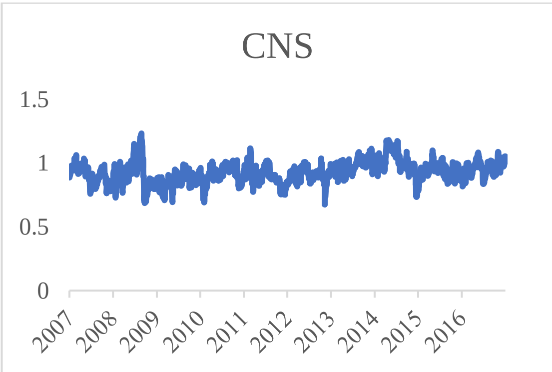
d) Industrials



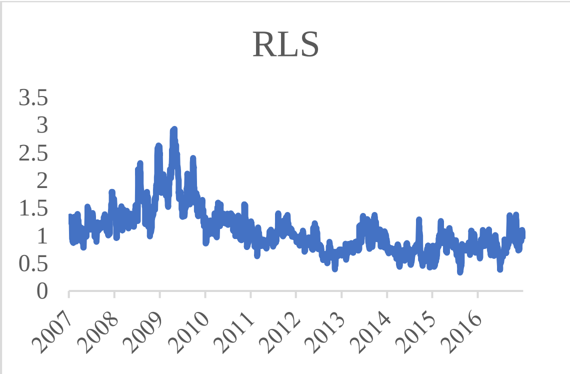
e) Consumer Goods



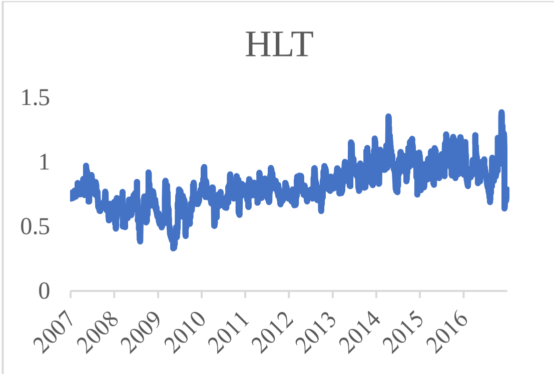
f) Consumer Services



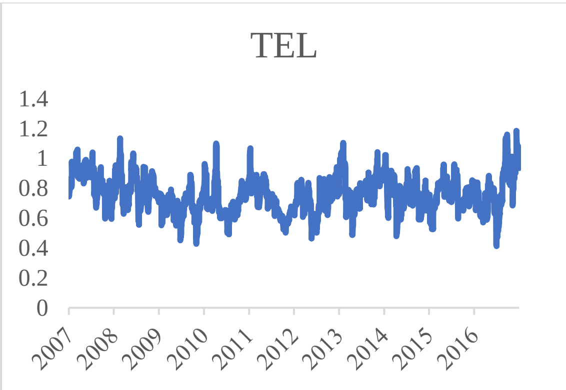
g) Real Estate



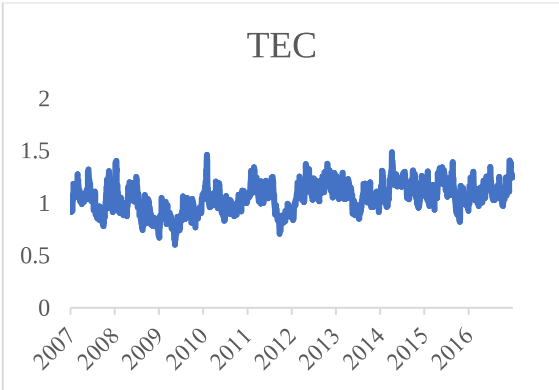
h) Health Care



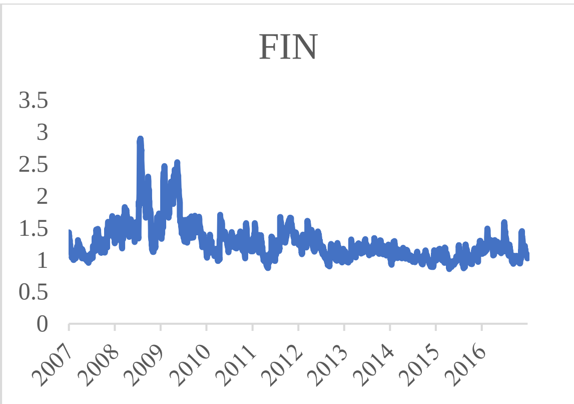
i) Telecommunication



j) Technology



k) Financials



l) Utilities

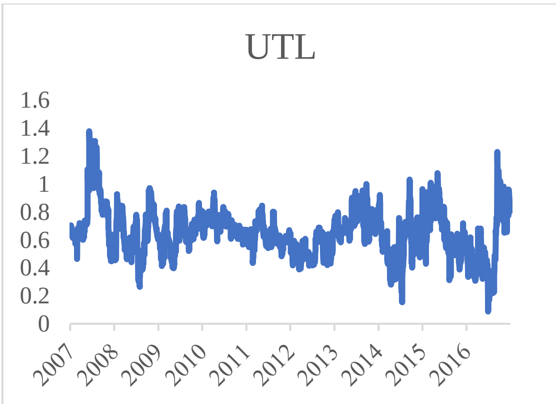
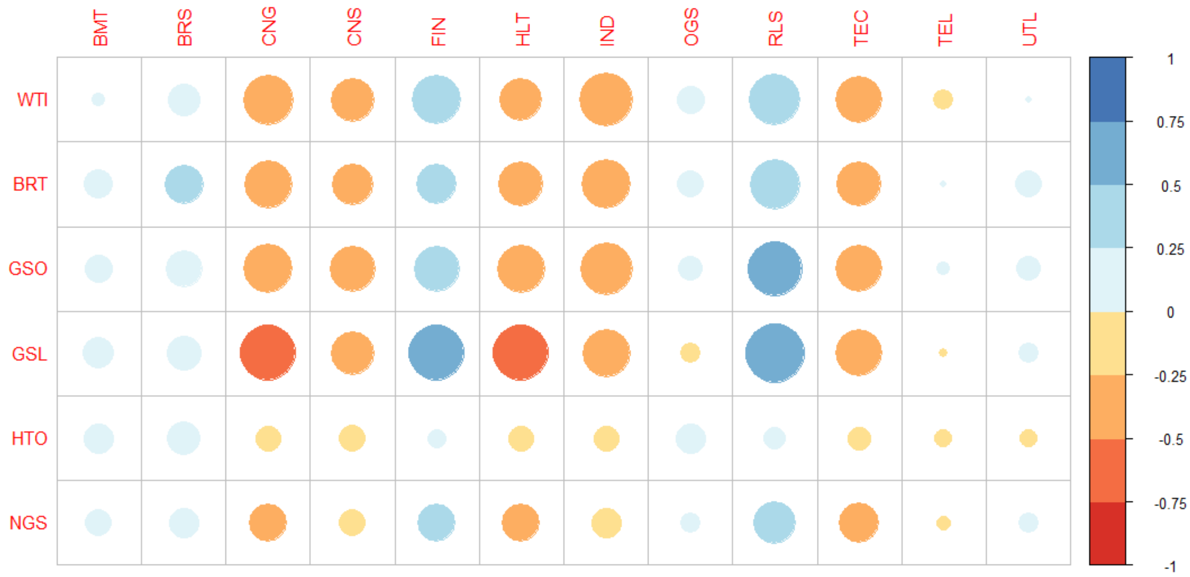


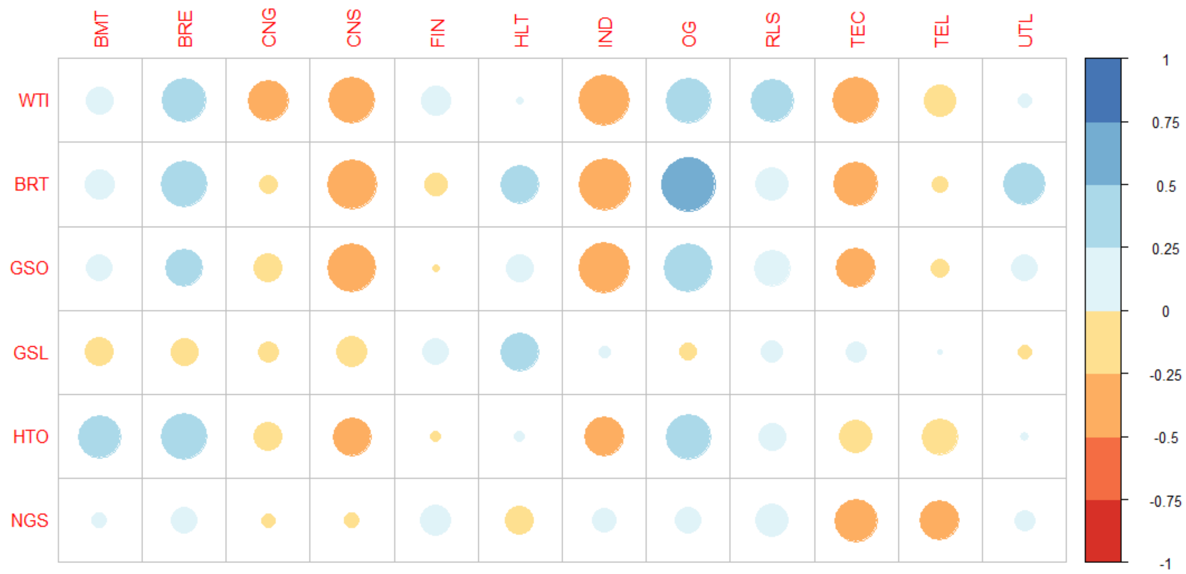
Figure 3. 2. Dynamic conditional betas of U.S. Industries.

In Fig. 2, we plot the dynamic conditional betas for 12 industries. Analysis of industry betas points out to the less risky nature of HLT, CNG, and CNS, as these industries provide everyday goods and services to the consumers and their supply and demand tend to remain consistent over time. Conversely, the betas for RLT, FIN, and BMT consistently remain high and fluctuate more, as the supply and demand for these industries tend to oscillate the most. Upon close analysis of the industry betas in Fig. 2, it is found that the betas for RLT, FIN, and OGS were significantly affected during the 2007–2009 GFC. Unsurprisingly, we also see a sharp rise in the riskiness of OGS, and related industries, such as BMT, BRS, and UTL during the 2014–2016 SOR.

a) Full sample (Jan 2007 – Dec 2016)



b) Global financial crisis sub-sample (GFC) (Aug 2007 – Jun 2009)



c) Shale oil revolution sub-sample (SOR) (Jan 2014 – Dec 2016)

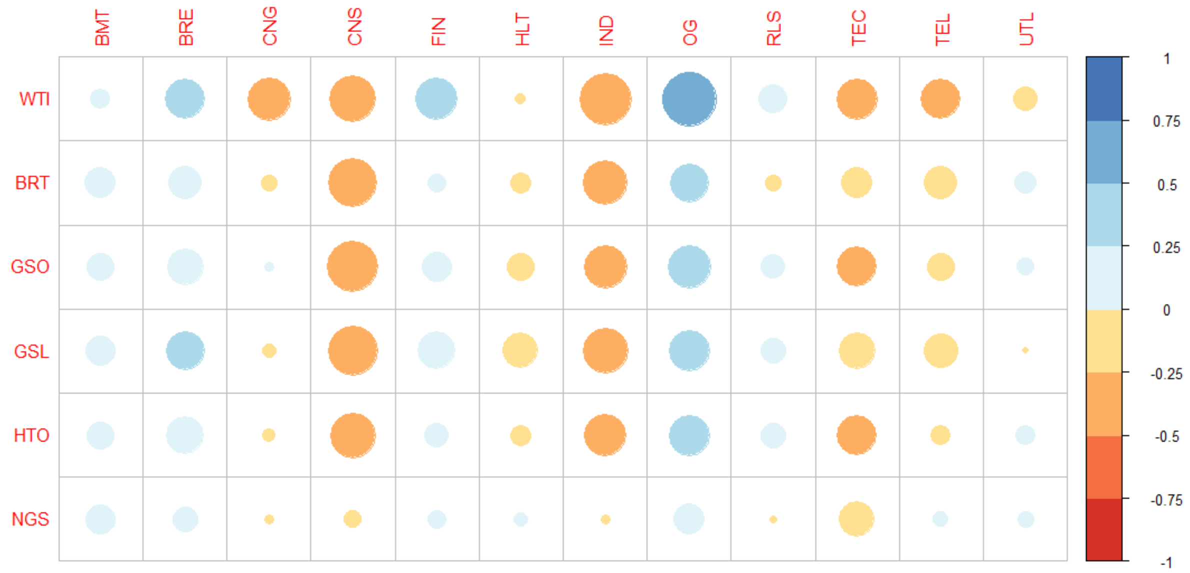


Figure 3. 3. Correlation heat-maps. a) Full sample b) Global financial crisis c) Shale oil revolution

Note. The correlation plot shows a pairwise correlation for industry betas and energy commodity uncertainties. The color bar on the right of the figures shows the strength of the correlation. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

We visualize the correlation matrix among the industry betas and energy commodity uncertainties using correlation heat-maps in Fig. 3 (a), (b) and (c) for full-sample, GFC sub-sample, and SOR sub-sample. Given the undeniable significance of energy commodities in the global economy, we perform GFC and SOR sub-sample analysis. Both the GFC and the SOR were catastrophic events for energy commodities, especially for the crude oil market. During the GFC, oil prices fell from a high of US$147 per barrel to as low as US$ 31 per barrel in the course of five months. Similarly, before SOR, the oil price was relatively stable between US$90 per barrel to US$120 per barrel, but increased production in the US coupled with the declining demand from emerging economies decreased the price to US$30 per barrel. During the GFC and SOR, similar patterns emerged for other energy commodities, such as Brent and Gas markets. This dramatic drop in the price of energy commodities along with heightened uncertainty (as presented in Fig. 1) about the future price of energy commodities, tempted the analysis of the impact of energy commodity uncertainties on the systematic risk of industries. Notice that blue and red colors indicate positive and negative correlation, respectively. An overview of the full-sample correlation heat-maps in (a) indicates the positive correlation of BMT, BRS, FIN, OGS, and RLS with the energy commodity uncertainties, whereas we find a negative correlation of CNG, CNS, HLT, IND, and TEC with energy commodity uncertainties. Second, although we find a similar correlation pattern in (b) and (c), the strength of the correlations is higher in (b) during the GFC, indicating to the impact of GFC on all the financial markets. These findings are in line with Kim et al. (2019), who reported the increased impact of energy prices on future U.S. stock returns, after the GFC.

3.4.2. Energy commodity uncertainties and industry betas

In this section, we report the estimated values of λ_i parameters in Eq (8), (9) and (10). For brevity, we draw the statistically significant values of λ_i in the form of a bar-chart, and also report the R^2 in the form of bar-chart alongside (complete tables are provided in the appendix). The positive(negative) values of λ_i indicate the increase(decrease) in the riskiness of industries due to the escalation of uncertainty in energy commodities. As expected, different sources of energy commodity uncertainties have a distinctive effect on the riskiness of industries. We notice that besides TEL, the null hypothesis of λ_i statististically different from zero is rejected for all other industries at 10% or less significance level. The lack of a significant impact of energy commodity uncertainty on the systematic risk of the Telecommunication industry seems reasonable taking into account that the activity of this industry does not depend at all on energy prices. Similarly, the limited effect of energy commodity uncertainty on the beta of the Utilities industry can also be related to the fact that Utilities provide basic services at regulated prices, so their main source of recurring income is not affected by energy price fluctuations.

Previous analysis of the correlation heat-maps indicated a high positive correlation among the energy commodity uncertainties. The graphical presentation of λ_i in Fig. 4 shows the impact of energy commodity uncertainties on the riskiness of industries. Consequently, we find a positive impact of uncertainties on BMT, BRS, FIN, OGS, and RLS. Whereas, the impact is negative for CNG, CNS, HLT, IND, and TEC. This result is in line with the finding of Elyasiani et al. (2011), and Narayan and Sharma (2011), who show that due to the heterogeneity of industries, they have different levels of exposure to oil price or volatility of oil price shocks.

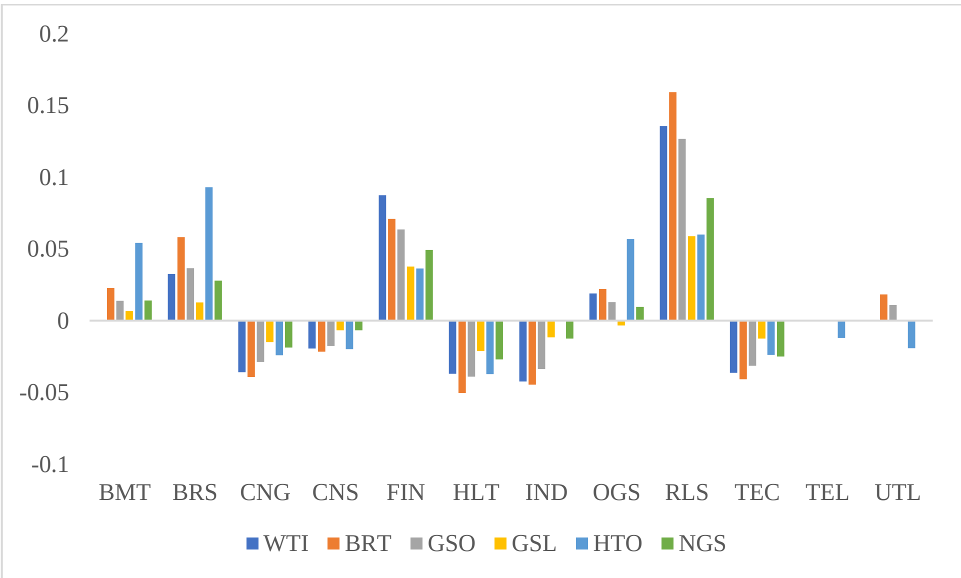


Figure 3. 4. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ using full sample.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

As indicated earlier, except TEL, all the industries are significantly predicted by the energy uncertainties. However, the strength of our models, represented with R^2 in Fig. 7 (Full sample) are typically high for CNG, FIN, HLT, and RLS. All of these industries are one way or the other, less dependent or not dependent on energy prices. This significance of our model parameters and the high strength of predictability of our models complement the finding of Driesprong et al. (2008), who find similar results about the high predictability of less energy dependent industries by oil returns. Another justification to the negative impact of energy market uncertainties can be that these industries provide goods and services for daily use and their demand is subject to the everyday needs of consumers. Hence, the riskiness of these industries is inelastic to uncertainty in energy markets.

From an economic standpoint, we find counter-evidence to the delayed reaction hypothesis of Hong et al. (2007), who provide an extension to the underreaction hypothesis of Hong and Stein (1996). In a nutshell, the primary assumption of the underreaction hypothesis is the bounded rationality of investors, which implies the gradual diffusion of information across investors who cannot process all the information related to an asset instantly. Since Balli et al. (2019) use the spot and futures (with maturity one to nine months) prices to develop the energy commodity uncertainties, they contain information regarding the uncertainty about the future price of energy commodities. That might also be a reason we find high predictability of riskiness of industries using energy uncertainties.

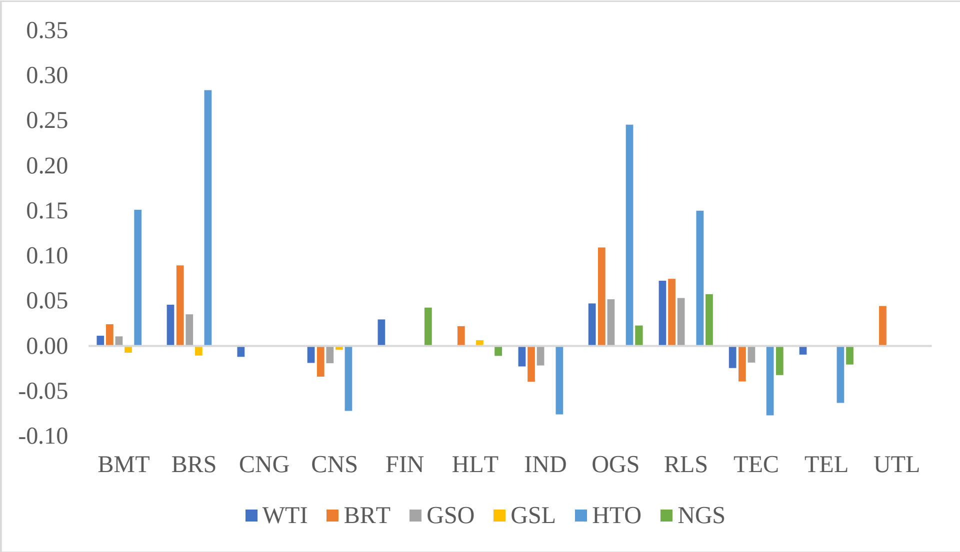


Figure 3. 5. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ during the Global financial crisis (GFC) sub-period.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

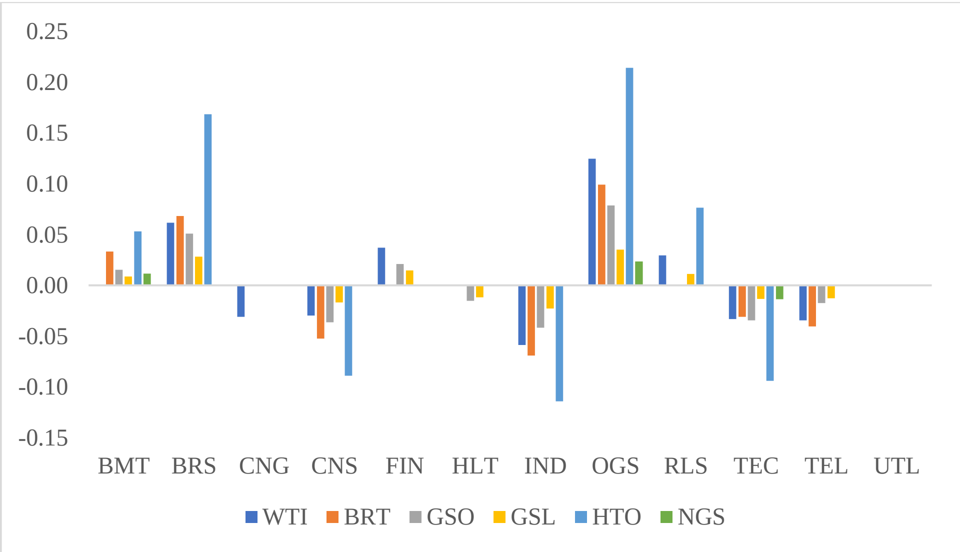


Figure 3. 6. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ during the Shale oil revolution (SOR) sub-period.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

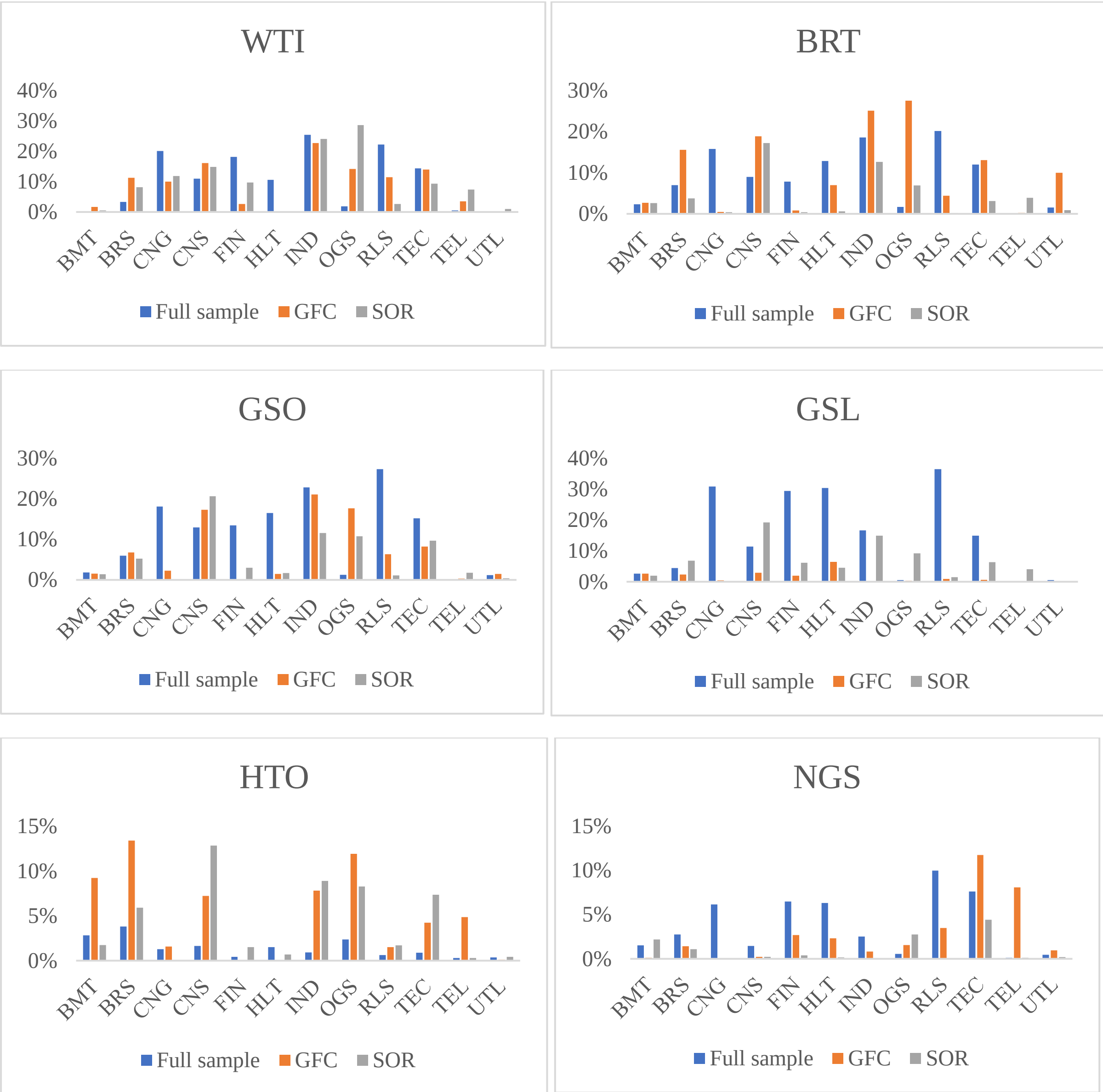


Figure 3. 7. Strength of the model. Above figures presents the R^2 for the models estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ for full sample, Global Financial Crisis (GFC) sub-period, Shale oil revolution (SOR) sub-period.

Note. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

For comparison purposes, we perform sub-sample analysis during the period of the GFC and SOR. We do this by performing Eq (8) during the GFC and SOR periods. Analyzing the results for the sub-period of the GFC in Fig. 5 and SOR in Fig. 6, we find that energy uncertainties had a significant impact on the industries which are more dependent on energy commodities. The impact of energy uncertainties on CNG, FIN, and HLT reduced significantly. The decrease in the impact of energy uncertainties on FIN industry is intuitive since the U.S. financial industry was mostly responsible for the GFC because of excessive risk-taking by investment institutions and banks such as Lehman Brothers. The impact later translated to other financial markets. Hence the high uncertainty in the energy sector was mostly due to the overall economic uncertainty. These findings are also in line with Elyasiani et al. (2011), who suggest the relationship between energy and stocks returns are sensitive to business cycles and that in the periods of high uncertainty, such as GFC, energy prices might follow, rather than lead the changes in stock markets.

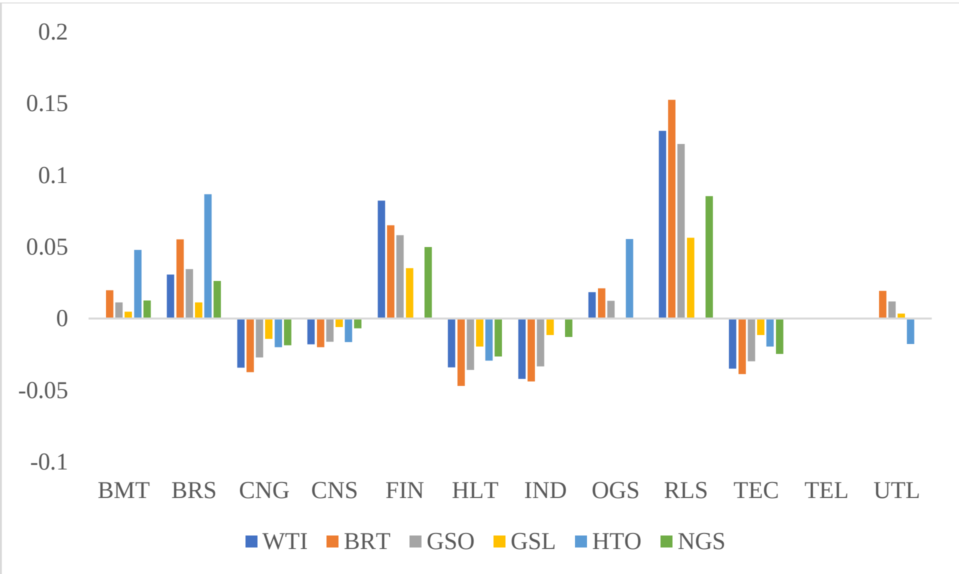


Figure 3. 8. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using full sample.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

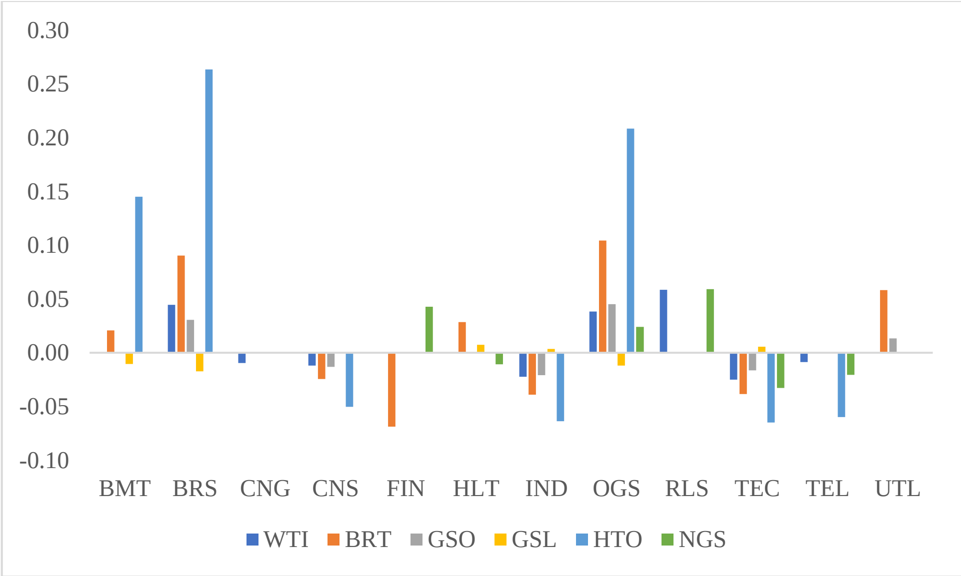


Figure 3. 9. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using Global Financial Crisis (GFC) sub-period.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

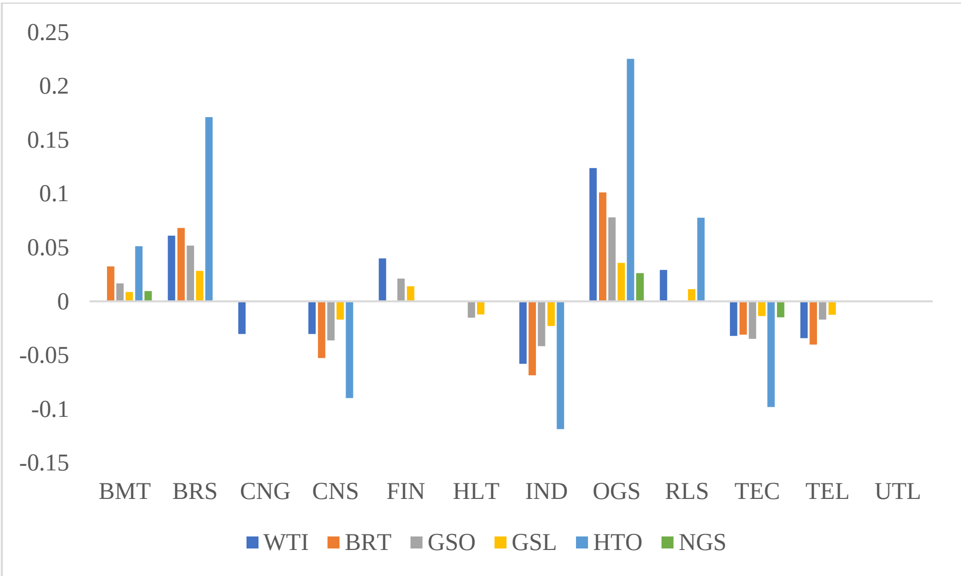
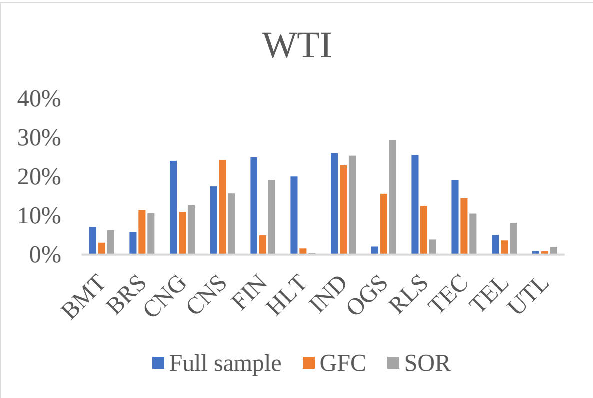
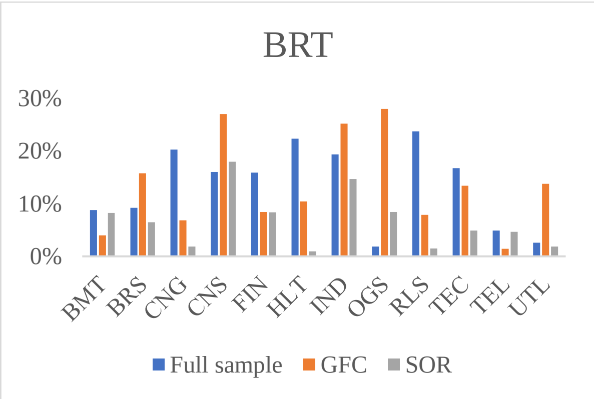


Figure 3. 10. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using Shale oil revolution (SOR) sub-period.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

Unsurprisingly, the energy-related and energy-substitute industries such as BMT, BRS, and OGS are profoundly impacted by energy uncertainties during the periods of GFC and SOR. As all these industries benefit from the increase in energy prices, hence increase in energy market uncertainties positively impacts these industries. These findings are also in line with Bams et al. (2017) and Scholtens and Yurtsevers (2012), who specify that investors specialized in oil-relevant industries cannot diversify the impact of oil uncertainty in their portfolios. Previously, we found the negligible impact of energy uncertainties on TEL industry, but we find a high negative impact during the period of SOR. Surprisingly, there is little to no impact of energy uncertainties on UTL industry during the GFC, and SOR period. Since the constituents of UTL consist of electricity and other utilities, these findings are also in line with Tsai (2015) and You et al. (2017), who do not find a relationship between energy commodities and electricity industry. Interestingly, compared with crude oil and other energy uncertainties, the impact of heating oil is the highest, especially during the periods of GFC and SOR. Hammoudeh et al. (2003) and Kaufmann and Laskowski (2005) explain the economic interpretation of these results by suggesting price asymmetries between crude oil and heating oil prices.





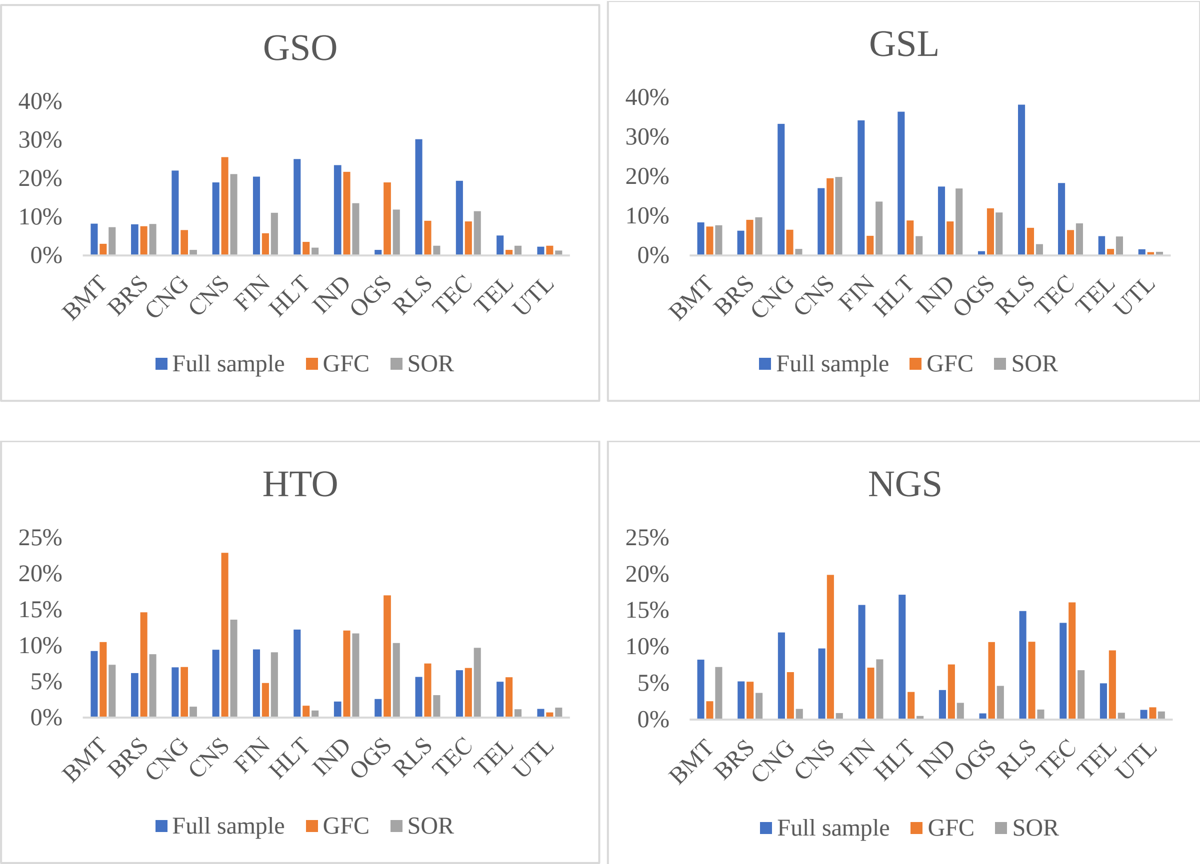


Figure 3. 11. Strength of the model. Above figures present the R^2 for the models estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ for full sample, the Global Financial Crisis (GFC) sub-period, the Shale oil revolution (SOR) sub-period.

Note. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

We further analyze whether the results presented in Fig. 4, 5, 6, and 7 are robust to different specifications. For the full sample, as indicated in Eq (9), we add control variables to test the impact of energy uncertainties on the systematic risk of industries. Additionally, we perform a similar analysis during the GFC and SOR sub-periods.

The analysis of Fig. 8, 9, and 10 shows that our results do not change due to the inclusion of additional control variables. Although the strength of our model increases significantly, we find little to no change in the overall significance and impact energy uncertainties on the riskiness of industries. Analyzing the above figures, although the energy uncertainties positively predict the real estate (RLS) and financial (FIN) industry, we notice that a decrease in the overall impact. The GFC was initially associated with the subprime mortgage market in the U.S., which later translated into a full-blown financial crisis, with the collapse of Lehman Brothers. As indicated in our univariate analysis above, the high uncertainty in the global financial system was mostly due to the overall economic uncertainty during the GFC period. Our analysis of Eq (9) for the sub-period of GFC confirms that EPU significantly and positively impacted the FIN and RLS industries. These results corroborate with the findings of Yu et al. (2017), who also find positive significant impact of EPU on the FIN industry systematic risk.

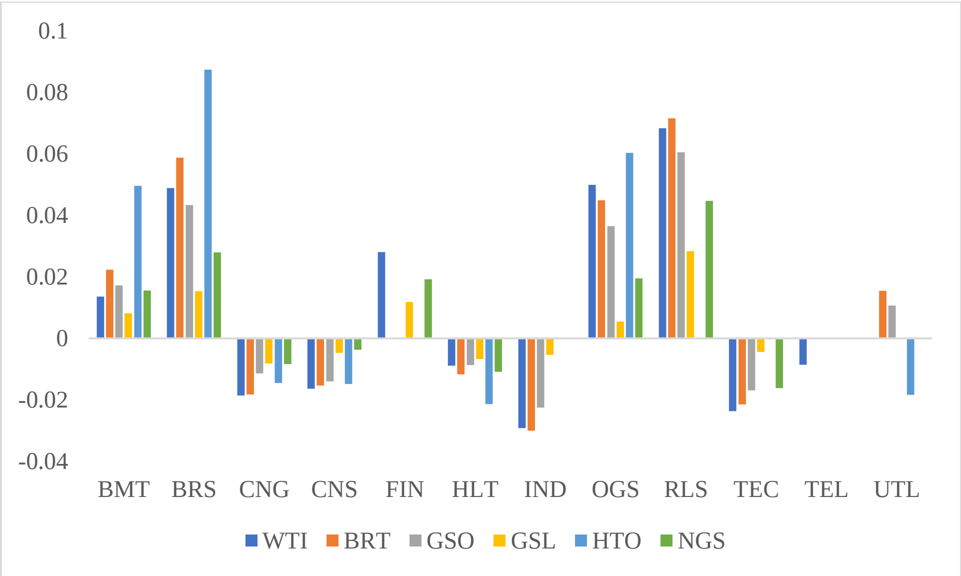


Figure 3. 12. Coefficient of energy commodity uncertainties estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \eta_1 D(GFC) + \eta_2 D(SOR) + \mathcal{E}_d^i$.

Note. The insignificant coefficients are set to zero. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

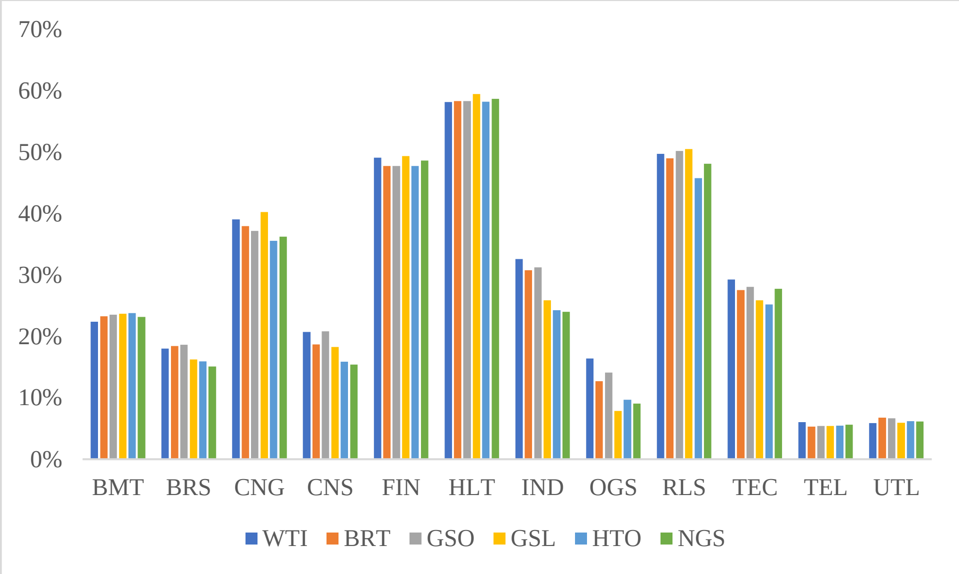


Figure 3. 13. Strength of the model. Above figure presents the R^2 for the models estimated using $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \eta_1 D(GFC) + \eta_2 D(SOR) + \mathcal{E}_d^i$ for full sample.

Note. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

Finally, instead of running separate regression for the periods of the GFC and SOR, we add the dummy variables for GFC and SOR to control for the extreme shocks associated with financial and energy markets in Eq (10). Although, the analysis of R^2 in Fig. 13 indicates a significant increase in the overall strength of the model, the estimated coefficients of energy uncertainties in Fig. 12 remain more or less the same indicating our results are robust to various alternative specifications.

3.5. Conclusion

This study investigates the impact of energy commodity uncertainties on the dynamic conditional betas of U.S. industry portfolios from Jan 2007 – Dec 2016. For this purpose, we first estimate the betas for U.S. industry portfolios using the DCC-GARCH model. Moreover, to determine the implications of our results to investors and policymakers, we use different specifications to test whether energy commodity uncertainties impact the U.S. industry betas.

The evidence from the outcomes is of great significance for various economic agents, particularly investors, regulators, and researchers who are interested in variations in stock prices.

Our results, on the one hand, provide convincing evidence of the positive impact of energy uncertainties on BMT, BRS, FIN, OGS, and RLS. On the other hand, we identify the negative impact on CNG, CNS, HLT, IND, and TEC. We derive two explanations about the difference in the impact of energy uncertainties and the high predictability of industry betas. First, the heterogeneous impact of energy uncertainties relates to the exposure of industries to energy price/volatility shocks confirming the findings of Elyasiani et al. (2011) and Narayan and Sharma (2011). Second is a more economic reason relating to the segmentation of markets. Since the uncertainty indices contain information regarding the uncertainty in the future price of commodities, our results counter-evidence to the delayed reaction hypothesis of Hong et al. (2007). Additional sub-sample analysis of GFC and SOR confirms the findings of Bams et al. (2017) about the undiversifiable impact of oil uncertainty for oil-relevant industry investors.

Consequently, to make informed investment decisions and to better forecast stock market returns, investors should be watchful of the energy commodity uncertainties. Investors specialized in energy-relevant industries can diversify their risk by investing in stocks that are inelastic to the uncertainty in energy markets. The evidence suggests that regulators or policymakers must focus on financial stability measures that might be affected by the uncertainty of commodities like oil or natural gas. Policymakers must focus on the effect of commodities on the riskiness of industries when formulating policies for the economic growth of countries. This will help them place appropriate value on essential commodities that are imperative for successful economic growth. Ultimately, such economic policies will help financial investors identify the demand shocks in commodities or their uncertainties. Moreover, global investors will be able to identify the effects of commodity uncertainties on their portfolios, consequently affecting international oil and related markets and the economy at a global level.

Future research can focus on the further segregation of industries or use firm-level data, which can provide an in-depth perspective on the impact of energy uncertainties. Subsequently, since the financialization of commodities, investors use other commodities for hedging purposes. Therefore, the impact of other commodity uncertainties on stock returns and out-of-sample forecasting can provide additional hedging opportunities for investors.

CHAPTER FOUR: Global factors and the transmission between Oil and other commodity uncertainties

4.1. Introduction

In this study, we provide novel insight to the emerging literature on the role of global factors as drivers of information transmission between oil and other commodity markets by examining their linear and nonlinear causal impact on the connectedness between oil and other commodity uncertainties. Amidst the financialization of commodities, understanding the dynamics of commodity markets, such as energy, precious metals, industrial metals, and agriculture, has become an important topic for investors, policymakers, and risk managers. This financialization, along with increased integration of global markets, has augmented the transmission between different markets (Aloui et al., 2011; Cheng & Xiong, 2014; Mensi et al., 2013). The increased flow of capital between countries and substantial technological development are the key reasons contributing to globalization. Thus, it is essential to understand the extent and nature of linkages among different financial markets (Shahzad et al., 2019).

In global financial markets, oil is considered to be an important commodity (Rehman, 2018). Despite being an underlying asset, oil is also considered as life support for profuse economies (Shahzad et al., 2017). The focus of researchers is now moved more towards the transmission among commodities, especially with oil markets, after an increase in general trend for investment in commodity markets (Baumeister & Kilian, 2013). Empirical researchers have proposed several possible channels of connectedness between the oil and other commodity markets. Accordingly, an increase in the price of oil leads to inclination in commodity prices (Malik & Umar, 2019). According to Jain and Ghosh (2013), the exchange rate and inflation shock in countries that rely heavily on oil imports results due to the increase in global oil prices.

Thereby, investors prefer to collect precious metals against inflation and currency risk in such a situation to hedge their portfolios. Hooker (2002) proposed that due to expansion in economic activities, there is seen an increase in global demand for oil, which enhances the oil prices that result in more usage of precious and industrial metals, say Tin and Copper.

Furthermore, oil price shocks result in commodity market inflationary pressure. Because of this inflationary pressure, policymakers tighten the monetary policy, thereby increasing the interest rates, which in turn impact the consumer demand for durable goods (Hammoudeh & Yuan, 2008). Likewise, the increase in global oil prices also leads to an upward trend in metal or commodity prices due to their impact on production and transportation costs (Shahzad et al., 2017). Additionally, oil prices also have an impact on the growth of an economy - a key driver of demand for agricultural commodities (Pal & Mitra, 2017). Recent studies suggested a bi-directional causal relation between agricultural commodity prices and global oil prices (Lucotte, 2016; Nazlioglu, 2011; Pal & Mitra, 2018). The increase in oil prices upshot the cost of essential agricultural inputs, which in turn increases the production costs of agricultural products, thus, affecting the cost of oil substitutes, such as bio-fuels (Zhang & Qu, 2015).

Recently, various studies have analyzed the transmission mechanism between the oil and commodity markets (for example, Ahmadi et al., 2016a; Balli et al., 2019; Diebold et al., 2017; Kang et al., 2017, 2019; Rehman et al., 2018; Tiwari et al., 2019; Umer et al., 2019). Hammoudeh & Yuan (2008) argued that oil prices act as a determinant of univariate volatilities of precious metals (gold, silver, and copper) in the US metals market. According to Huang et al. (2012), there is a positive effect of exchange rates and the US dollar on precious metals. Sari et al. (2007) find a short-term relationship between precious metals and crude oil in context of developed countries. Diebold et al. (2017) find that there is a high connectedness between energy, precious metals, industrial metals, and agricultural commodities.

Along with the increased interest in the transmission dynamics, there has been considerable attention given by researchers to explore the influence of global factors on commodity markets (Albulescu et al., 2019; Fang et al., 2018; De Boyrie & Pavlova, 2018; Badshah et al., 2019; Kanjilal & Ghosh, 2017; Poncela, Senra & Sierra, 2014; Jebabli, Arouri & Teulon, 2014). Batten, Szilagyi & Wagner (2015) argued that returns are time-varying, that is, risk-adjusted returns were negative during the Asian financial crisis period, whereas the returns were positive during the GFC of 2008-09. Poncela, Senra & Sierra (2014) explore the role of uncertainty in determining co-movements among non-energy prices in the short-run. The study finds increased spillovers among raw materials. Prokopczuk, Stancu & Symeonidis (2019) find that there is bidirectional relationship between volatility of commodity market with financial and economic uncertainty during recession period.

Despite a multitude of research concerning the impact of global factors on commodities and other financial markets in separate settings, however, the literature is silent on the effect of global factors on the transmission relationship between oil and commodity markets. Owning to the fact that the financialization of commodities has increased both the intra-commodity connectedness and the connectedness of commodities with other financial markets at a global level, one can assume that commodity markets are exposed to the risks associated with stock markets, currency markets, and uncertainty regarding economic policies. In light of the recent literature providing evidence of causal impact of economic policy uncertainty on the connectedness across oil and financial markets (Fang et al., 2018; Albulescu et al., 2019; Badshah et al., 2019), this paper contributes to the literature by (i) examining the transmission between oil and other commodity uncertainties using the Diebold & Yilmaz (2014) framework, and (ii) providing evidence on the causal impact of global factors on the intra-commodity transmission using linear and nonlinear causality frameworks proposed by Granger (1969) and Péguin-Feissolle & Teräsvirta (1999).

In application, our results indicate strong bi-directional transmission between oil and metal (agriculture) markets, and this transmission became significantly more pronounced during the turmoil period, i.e., the global financial crisis. Our analysis also suggests that oil is a net transmitter to other commodity uncertainties, and this transmission significantly increased during the period of the global financial crisis. Additionally, our results indicate that the global factors in some way have a causal effect on the overall connectedness, especially on the spillovers from oil to other commodity uncertainties. Further segregation of transmissions from oil to individual commodity markets and vice versa indicate VIX, and to some extent, TED spread and EPU as the most influential drivers of connectedness among commodity markets.

The remainder of this paper is divided into five sections. Section 2 provides a review of previous literature. Section 3 outlines the methodology used to analyze the transmission between oil and other commodity uncertainties and examination of the impact of global factors on the transmission across commodity markets. Section 4 provides details of the data and summary statistics. The empirical findings are discussed in Section 5. Finally, Section 6 makes concluding remarks.

4.2. Literature Review

4.2.1. Oil and Commodity markets

As indicated earlier, the empirical finance literature is rich in studies focusing on the linkage between the precious metals, industrial metals, agricultural commodities with oil markets (such as, Ahmadi et al., 2016b; Balli et al., 2019; Baumeister & Kilian, 2013; Beahm, 2008; Campiche et al., 2007; Cha & Bae, 2011; Ciner et al., 2013; Diebold et al., 2017; Hammoudeh & Yuan, 2008; Hammoudeh et al., 2009; Juvenal & Petrella, 2015; Kang et al., 2017, 2019; Kristoufek et al., 2012; Nazlioglu et al., 2013; Rehman et al., 2018; Tiwari et al., 2019; Umer et al., 2019; Zhang & Broadstock, 2018). Sari et al. (2007) find a short-term relationship between precious metals and crude oil in the context of developed countries.

According to Hammoudeh & Yuan (2008), indicate that lagged oil prices act as a determinant of univariate volatilities of precious metals (gold, silver, and copper) in the US metals market. Similarly, Zhang & Wei (2010) reported high correlation values between international oil and gold prices in the presence of long-term equilibrium. Bildirici & Turkmen (2015) reported long run non-linear relationship between international oil and precious metal markets. They also found the long run significant impact of oil market on gold and copper returns, which is in line with the findings by Kanjilal & Ghosh (2017). Diebold et al. (2017) characterize connectedness in 19 key commodity volatilities over the period 2011 to 2016 using high-dimensional VAR and network analysis. The study finds apparent clustering of commodities into groups, and the energy sector is most important in sending shocks to other commodities. Moreover, there is high connectedness between energy commodities, precious metals, industrial metals, agricultural commodities, and soft commodities. Balli et al. (2019) find that connectedness among 22 commodity uncertainty indexes increases during the GFC and the oil price collapse of 2014-2016 using spillover analysis. Furthermore, network graphs analysis shows that precious metals may serve as safe-haven due to less spillover with other commodities during the crisis period.

4.2.2. Global factors and Commodity markets

Various studies has witnessed more synchronization in the oil prices movement with commodity returns including precious metals, agricultural commodities, commodity futures for the current decade due to the increased financialization and inclusion of alternative investments within portfolio of investors (Ahmadi et al., 2016b; Aloui et al., 2016; Degiannakis et al., 2018; Pástor & Veronesi, 2012; Sari et al., 2013). The crude oil and commodity market risk and return interactions are profoundly investigated in the earlier studies from both directions (say Hammoudeh et al., 2013; Reboredo & Uddin, 2016; Wang & Wu, 2012). However, studies examining the possible causal effect of different global factors on the connectedness of oil and commodities are scarce. Thus, one can make an argument that global factors can have direct economy-wide effects, which eventually sweep into financial markets. Increased uncertainty regarding government economic policies can lead lenders to adopt a more conservative approach in government lending practices, eventually driving interest rates higher (Handley & Limao, 2015). Rogoff (2006) argues that higher oil consumption countries are less vulnerable to shocks than they were in the past due in part to increased energy efficiency. Bouiyour et al. (2019) characterizes the oil market as a nonlinear-switching phenomenon and examines its dynamics in response to changes in geopolitical risks over low- and high-risk scenarios.

Using VAR, VECM, and pairwise Granger causality test, Labuschagne & Le Roux (n.d.) find that there exists a relationship between the USD index (taken as a proxy for Cuban Peso) and three soft commodities, namely sugar, ethanol, and corn. Prokopczuk et al. (2019) explore the association between volatility of commodity markets and economic and financial uncertainty. They conclude that there is a bidirectional relationship between volatility of commodity market with financial and economic uncertainty during recession period. Ordu-Akkaya & Soytas (2018) finds that spillover from stocks to commodities during period of financialization increased for all commodities. Moreover, one of the underlying reasons for increasing spillover between markets was quantitative easing including default spread, current factors or interest rate.

Several other factors have shown to affect the commodity markets, such as, financial stress or TED spread (Buyuksahin & Robe, 2014; Cardarelli et al., 2009; Hakkio & Keeton, 2009; Sandahl et al., 2011), MSCI World index, USD index, and financial stress, among others (say Poncela, Senra & Sierra, 2014; Robe & Wallen, 2015; Roboredo & Uddin, 2016). Huang et al. (2012) analyze the impact of US oil prices and exchange rates on Chinese gold, silver, and copper, and concluded that the linkage between silver, gold, and oil have explanatory power in determining Chinese silver and gold pricing. Le Roux (n.d.) examines the relationship between four soft commodities (tobacco, coffee, sugar, and cocoa), MSCI Frontier markets, and Herzfeld Caribbean basin Fund (HCBF) against the USD Index. Accordingly, Jebabli, Arouri & Teulon (2014) find that shocks to MSCI markets or crude oil have short-term and immediate impacts on food markets during the GFC of 2008-09. De Boyrie & Pavlova (2018) find that increase in the CBOE volatility index (VIX) is related to higher agriculture commodities correlations.

Murray (2017) finds evidence of Granger causality from commodity prices to the geopolitical risk (GPR) index in the years preceding the GFC but not afterward. Liu et al. (2019) find that GPR and serious GPRS lead to oil market fluctuations within in-sample results, while strongly confirm that the GARCH-MIDAS-GPRS model with serious GPR significantly outperforms the GARCH-MIDAS model in the out-of-sample results. Robe & Wallen (2015) reveal that VIX and the constraints affecting oil output have economically significant explanatory power for the short-dated oil implied volatilities and for the WTI implied volatilities term structure. The other global factors about which the authors argue is an inflation channel, where increased oil prices not only infer higher costs in energy and production but also leads towards an interest rate hike. Badshah et al. (2019) findings point to a positive and significant effect of economic policy uncertainty (EPU) on stock-commodity correlations with notably stronger effects in the case of energy and industrial metals. On a similar note, Kanjilal & Ghosh (2017) present linkages between oil and gold in two different ways, either through an inflation channel for oil-importing countries or through a revenue channel for oil exporters.

4.3. Methodology

The empirical analysis of this paper is divided into two parts. First, we follow the connectedness framework of Diebold & Yilmaz (2014) to estimate the transmission between oil and other commodity uncertainties. After estimating the transmission measures, we then test the impact of global factors on the transmission measures between oil and other commodity uncertainties using linear and nonlinear causality tests.

4.3.1. Diebold and Yilmaz transmission approach

We follow the connectedness framework of Diebold & Yilmaz (2014) to estimate the different transmission measures built from the forecast-error variance decomposition (FEVD) matrix centered on the generalized vector-autoregressive (VAR) model. Consider an n-variate covariance stationary VAR(p) model,

$$x_t = \sum_{i=1}^{p} \gamma_i \, x_{t-i} + \epsilon_t \qquad (1)$$

where $\epsilon_t \sim N(0, \Sigma)$. The moving average component of the VAR process is represented by the following MA(∞) process

$$x_t = \sum_{i=0}^{\infty} \omega_i \, \epsilon_{t-i},$$

where ω_i is a $n \times n$ coefficient matrix and calculated recursively using $\omega_i = \gamma_1 \omega_{i-1} + \gamma_2 \omega_{i-2} + \cdots + \gamma_p \omega_{i-p}$, and ω_0 represents the identity matrix. Taking help from the MA coefficient, we utilize the generalized FEVD, which permits splitting the H-step-ahead forecast error of each variable and attributed to various shocks in the system.

We favour the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998) to achieve orthogonality since the Cholesky factor depends upon the ordering of the variables. The contribution of variable j to the *H*-step-ahead generalized variance of forecast error of variable *i* is denoted as τ_{ij}(H) and computed as:

$$\tau_{ij}(\mathrm{H}) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \omega_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \omega_h \Sigma \omega_h' e_i\right)^2} \qquad (2)$$

where the j^{th} diagonal component of the standard deviation is represented by σ_{jj}. $\sum$ represents the covariance matrix of errors. e_i has a value 1 for i^{th} component and 0 otherwise. Finally, the coefficient matrix that multiplies h-lagged error in the infinite moving-average representation of non-orthogonalized VAR is represented by ω_h.

We measure the pairwise directional transmission, $\tau_{ij}(\mathrm{H})$, from *j* to *i* as:

$$\mathrm{T}_{i\leftarrow j}^{H} = \tau_{ij}(\mathrm{H}) \tag{3}$$

The ratio of the off-diagonal sum of rows to the sum of all the elements represents the total directional transmission from others to *i* as:

$$\mathrm{T}_{i\leftarrow \bullet}^{H} = \frac{1}{N}\sum_{\substack{j=1\\ j\neq i}}^{N} \tau_{ij}(\mathrm{H}) \tag{4}$$

Furthermore, the ratio of the off-diagonal sums of columns to the sum of all the elements represents the total directional transmission to others from *j* as:

$$\mathrm{T}_{\bullet\leftarrow j}^{H} = \frac{1}{N}\sum_{\substack{i=1\\ i\neq j}}^{N} \tau_{ij}(\mathrm{H}) \tag{5}$$

Finally, the total system-wide transmission is the ratio of the sum of the from-others (to-others) elements of the variance decomposition matrix to the sum of all its elements:

$$\mathrm{T}^{H} = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N} \tau_{ij}(\mathrm{H}) \tag{6}$$

4.3.2. Causality tests

In the second part of our analysis, we empirically examine the impact of global factors on the transmission relationship between oil and other commodity uncertainties utilizing the linear and nonlinear causality tests.

4.3.2.1. Linear causality test

Based on the vector autoregressive (VAR) framework, we employ the linear causality test following Granger (1969). The test can be expressed as:

$$x_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} x_{t-i} + \sum_{i=1}^{m} \alpha_{2i} y_{t-i} + \varepsilon_{1t}$$

(7)

$$y_t = \beta_0 + \sum_{i=1}^{m} \beta_{1i} y_{t-i} + \sum_{i=1}^{n} \beta_{2i} x_{t-i} + \varepsilon_{2t}$$

where x_t and y_t represent global factors and transmission between oil and other commodity uncertainties, respectively. ε_{1t} and ε_{2t} are uncorrelated idiosyncratic terms. The null hypothesis tested using Granger (1969) causality test is "x_t does not granger cause y_t". If the lags of x_t can predict y_t, we can reject the hypothesis and x_t "Granger causes" y_t.

4.3.2.2. Nonlinear causality tests

The pioneering work by Granger (1969) paved the way for other researchers to look deeply into the causal relationship between economic and financial time series. Péguin-Feissolle & Teräsvirta (1999) proposed two nonlinear causality tests: (1) Taylor series approximation and (2) Artificial Neural Network (ANN) based.

The Taylor series approximation causality test is based on the Taylor expansion of the nonlinear function:

$$x_t = f^*\left(x_{t-1}, \dots, x_{t-q}, y_{t-1}, \dots, y_{t-n}, \vartheta^*\right) + \varepsilon_t \tag{8}$$

where ϑ^* is a vector, x_t and y_t are weakly stationary series, and f^* is an unknown function but assumed to represent the causal relationship between y_t and x_t. Moreover, for every point of the sample (parameter) space $\vartheta^* \in \Theta$, f^* has a convergent Taylor expansion. In order to examine the non-causality hypothesis, i.e., y_t does not cause x_t, we have:

$$x_t = f^*\left(x_{t-1}, \dots, x_{t-q}, \vartheta\right) + \varepsilon_t \tag{9}$$

To test Eq. (9) against Eq. (8), following Péguin-Feissolle & Teräsvirta (1999) and later Péguin-Feissolle et al. (2013) we linearize f^* and increase the function form into a k^{th} order

Taylor series around an arbitrary sample space. After the approximation and re-parametrization of f^*, we obtain:

$$x_t = \theta_0 + \sum_{j=1}^{q} \theta_j x_{t-j} + \sum_{j=1}^{n} \gamma_j y_{t-j} + \sum_{j_1=1}^{q} \sum_{j_2=j1}^{q} \theta_{j_1 j_2} x_{t-j_1} x_{t-j_2} +$$
$$\sum_{j_1=1}^{q} \sum_{j_2=1}^{n} \varphi_{j_1 j_2} x_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^{n} \sum_{j_2=j1}^{n} \gamma_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \cdots +$$
$$\sum_{j_1-1}^{q} \sum_{j_2=j_1}^{q} \dots \sum_{j_k=j_k-1}^{q} \theta_{j_1 \dots j_k} x_{t-j_1} \dots x_{t-j_k} + \cdots + \theta_{j_1 j_2} x_{t-j_1} x_{t-j_2} +$$
$$\sum_{j_1=1}^{n} \sum_{j_2=j1}^{n} \dots \sum_{j_k=j_k-1}^{n} \gamma_{j_1 \dots j_k} y_{t-j_1} \dots y_{t-j_k} + \varepsilon_t^* \tag{10}$$

where $\varepsilon_t^* = \varepsilon_t + {R_t}^{(k)}(y,x), {R_t}^{(k)}$ represents the remainder with $n \leq k$ and $q \leq k$.

Péguin-Feissolle & Teräsvirta (1999) indicate two possible difficulties related to Eq. (10). One being multicollinearity due to large k, q, and n, and second is the small number of degrees of freedom, due to the rapid increase in the number of regressors with k. By replacing some observation matrices with their principal components, we can tackle both problems. Hence, we use the first principal component and test the null hypothesis of zero coefficients of principal components, tested as:

$$General = \frac{(SSR_0 - SSR_1)/p^*}{SSR_1/(T-1-2p^*)} \tag{11}$$

where we obtain SSR_0 and SSR_1 using the following methods. For SSR_0, we regress x_t on 1 and the first principal components p^* of the matrix of lags of x_t only, to estimate the residuals $\hat{\varepsilon}_t, t = 1, \dots,$ T. The squared residuals are summed to obtain SSR_0. SSR_1 are obtained by regressing $\hat{\varepsilon}_t$ on 1 and all the terms of the two principal component matrices. The problem of degree of freedom can be tackled by assuming that the general model is “semi-additive”:

$$x_t = f\big(x_{t-1}, \dots, x_{t-q}, \vartheta_f) + g(y_{t-1}, \dots, y_{t-n}, \vartheta_g\big) + \varepsilon_t \tag{12}$$

where $\vartheta' = (\vartheta'_f, \vartheta'_g)'$ is the parameter vector. If $g(y_{t-1}, \ldots, y_{t-n}, \vartheta_g) = constant$, then y_t does not cause x_t. In order to obtain the static called *Additive*, we linearize both functions into $k^{th} - order$ Taylor series.

The artificial neural network causality test uses a logistic function. The approximation of the equation $g(y_{t-1}, \ldots, y_{t-n}, \vartheta_g)$ is obtained using:

$$\vartheta_0 + \tilde{\mu}_t' \alpha + \sum_{j=1}^{p} B_j \frac{1}{1+e^{-\gamma_j' \mu_t}} \tag{13}$$

where $\vartheta_0 \in R$, $\mu_t = (1, \tilde{\mu}_t')'$ is a $(n+1) \times 1$ vector, $\tilde{\mu}_t = (y_{t-1}, \ldots, y_{t-n})'$, $\alpha = (\alpha_1, \ldots, \alpha_n)'$ are $(n \times 1)$ vectors, and $\gamma_j = (\gamma_{j0}, \ldots, \gamma_{jn})'$ for $j = 1, \ldots, p$, are $(n+1) \times 1$ vectors. The null hypothesis of the test is $\{y_t\}$ does not cause $\{x_t\}$. The estimation of the ANN-based causality test serves as (1) comparative analysis for the Taylor-based nonlinear causality test, and (2) serves as a robustness check. Finally, it must be noted that since we use the estimated connectedness measures in our causality tests, an estimation error exists. In order to minimize possible estimation errors, we perform VAR stability tests and ensure that forecast error variance decompositions used for the spillover analysis are stable and the residuals are stationary. Furthermore, the use of nonlinear causality tests in the analysis also helps minimize possible estimation errors associated with nonlinearity in the data.

4.4. Data and summary statistics

In order to estimate the transmission between crude oil and other commodities, we use daily data of commodity uncertainties, namely crude oil WTI (WTI), gold (GLD), silver (SLV), platinum (PLT), palladium (PLD), aluminum (ALM), copper (CPR), zinc (ZNC), lead (LED), nickel (NKL), wheat (WHT), corn (CRN), soybean (SBN), coffee (COF), sugar (SGR), cocoa (COC), and cotton (COT) from January 2007 to December 2016. The sample period of commodity uncertainties developed by Balli et al. (2019) covers several periods of uncertainty for commodities, including the global financial crisis (GFC).

Table 4. 1. Descriptive statistics for commodity uncertainties and global factors

	Abbreviation	Mean	Standard deviation	JB	ADF	PP
CRUDE OIL WTI	WTI	1.87	1.42	13915.90***	-3.66***	-4.31***
GOLD	GLD	5.15	2.85	10078.38***	-5.47***	-5.61***
SILVER	SLV	7.88	3.69	8085.54***	-5.12***	-4.45***
PLATINUM	PLT	4.00	1.65	16150.18***	-14.35***	-12.29***
PALLADIUM	PLD	2.41	2.59	17149.21***	-6.37***	-5.06***
ALUMINIUM	ALM	0.63	0.94	147332.80***	-6.36***	-22.20***
COPPER	CPR	0.31	0.28	1282594.00***	-5.04***	-8.32***
ZINC	ZNC	0.72	0.52	741914.00***	-7.49***	-14.49***
LEAD	LED	0.66	0.51	589331.20***	-14.79***	-15.00***
NICKEL	NKL	0.52	0.45	1130079.00***	-14.40***	-15.91***
WHEAT	WHT	2.02	1.83	153832.00***	-7.20***	-5.58***
CORN	CRN	2.42	1.69	15834.98***	-8.89***	-8.73***
SOYBEAN	SBN	2.33	1.43	14194.39***	-9.93***	-9.65***
COFFEE	COF	0.58	0.37	302365.70***	-12.50***	-6.71***
SUGAR	SGR	3.67	2.11	4089.68***	-7.54***	-5.07***
COCOA	COC	1.27	0.63	212745.00***	-4.37***	-9.40***
COTTON	COT	4.50	2.68	12522.60***	-5.83***	-7.52***
US EPU	EPU	115.3	71.04	3810.31***	-7.96***	-35.98***
US GPR	GPR	85.19	60.89	14001.98***	-9.86***	-39.30***
VIX	VIX	21.05	9.98	6251.38***	-2.92**	-3.87***
MSCI World	MSCI	0.004	1.15	6912.08***	-34.90***	-43.06***
TED Spread	TED	0.448	0.50	36716.87***	-2.97**	-3.27**
USD index	USD	0.012	0.54	444.18***	-47.65***	-47.65***

Note. This table reports some basic statistics of uncertainty series of Balli et al. (2019). ADF and PP are the empirical statistics of the Augmented Dickey-Fuller (1979), and the Phillips-Perron (1988) unit root tests. JB is the Jarque-Bera test of normality.
** and *** denotes rejection of null hypothesis at 5% and 1% level of significance.

Table 1 reports the descriptive statistics for crude oil WTI and other commodity uncertainty indices. The summary statistics of uncertainty indices indicate that silver and gold have the highest mean uncertainty along with the highest standard deviation indicating the presence of extreme fluctuations. This can be related to the fact that investors use precious metals, such as gold, as a hedge against the inflationary and monetary policy uncertainty (Bams et al., 2017). The results of the Jarque Bera test rejects the null of normality for all uncertainty indices. Furthermore, the results of Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) indicate stationarity in all the uncertainty indices and hence, appropriate for the use of the DY framework. Following Balli et al. (2019), we analyze the uncertainty transmission between crude oil WTI and other commodity uncertainties using log-transformed uncertainty indices.

For our objective to analyze whether global factors impact the transmission between crude oil WTI and other commodity uncertainties, we employ a battery of six potential global factors, widely used in the literature. These include: (1) the U.S. economic policy uncertainty index (EPU) developed by Baker et al. (2016), (2) the U.S. geopolitical risk index (GPR) developed by Caldara and Iacoviello (2018), (3) the S&P 500 volatility index (VIX), developed by the Chicago Board Options Exchange (CBOE), (4) MSCI world index (MSCI) as a representative of the world stock market index, (5) TED spread (TED), which is the difference between the yield on 90-day Treasury Bill and LIBOR, and (6) the trade-weighted U.S. Dollar Index (USD). The summary statistics for six global factors indicate that EPU, GPR, VIX, and TED are stationary; hence, they are not transformed. Whereas, MSCI and USD are transformed using the logarithmic first difference in order to achieve stationarity.

4.5. Empirical findings

The empirical findings consist of two sections. First, we employ the DY framework to analyze the transmission between crude oil WTI and other commodities uncertainties and provide evidence of significant transmission between them. Second, we apply linear and nonlinear GC models to analyze the impact of six global factors on the transmission between crude oil WTI and other commodity uncertainties.

4.5.1. Transmission between oil and other commodity uncertainties

Table 2 reports the transmission estimates between oil and other commodity uncertainties. Panel A and B report the estimates of the DY framework for full-sample and the global financial crisis (GFC). Analyzing panel A, we find that metals, such as palladium, platinum, copper, aluminum, and lead are the highest receivers of uncertainty from oil, whereas silver, palladium, and copper are the highest transmitters. Strikingly, most of the metals are the highest transmitters and receivers of uncertainty from oil. These findings indicate the strong bi-directional transmission between oil and metal markets, which are in line with the findings evidenced by Kang et al. (2017) and Reboredo & Ugolini (2016). Additionally, we also find significant bi-directional transmission between oil and agricultural commodity uncertainties, consistent with the findings of Ji et al. (2018) and Nazlioglu et al. (2013). Although the analysis of overall net spillovers (Net spillover all uncertainties) between oil and other commodity uncertainties indicates that oil is mostly a net transmitter, additional examination of net pairwise spillovers between oil and other commodity uncertainties suggest oil is a net receiver from gold, silver, palladium, soybean, and cocoa. Similar to the findings of Albulescu et al. (2019) about the heterogeneity in the relationship between oil and commodity currencies, we find additional evidence of heterogeneity in the relationship between oil and other commodities.

Table 4. 2. Spillover tables

Panel A: DY spillover results - Full sample

	From WTI	From all uncertainties	To WTI	To all uncertainties	Net spillover WTI	Net spillover all uncertainties
WTI	68.767	1.952	68.767	2.128	0.000	0.176
GLD	0.901	2.333	1.343	2.694	-0.441	0.361
SLV	0.854	1.361	8.237	5.198	-7.383	3.836
PLT	4.743	1.843	0.324	0.651	4.419	-1.192
PLD	5.214	2.105	8.292	3.081	-3.078	0.976
ALM	3.117	2.110	0.067	1.541	3.049	-0.568
CPR	3.825	2.249	3.674	3.847	0.151	1.598
ZNC	1.112	2.418	0.372	1.493	0.740	-0.925
LED	2.947	2.830	0.270	4.167	2.677	1.337
NKL	2.040	5.801	0.783	0.409	1.257	-5.391
WHT	0.660	2.084	0.628	2.459	0.032	0.375
CRN	1.528	2.590	2.389	2.518	-0.860	-0.072
SBN	2.275	2.430	0.645	2.035	1.630	-0.395
COF	1.259	2.429	1.116	0.914	0.144	-1.514
SGR	0.731	1.699	0.246	2.490	0.486	0.791
COC	2.088	1.784	2.742	1.987	-0.654	0.204
COT	0.756	1.952	0.106	2.357	0.650	0.404

Panel B: DY spillover results - Global financial crisis (GFC) (January 2008 - June 2009)

	From WTI	From all uncertainties	To WTI	To all uncertainties	Net spillover WTI	Net spillover all uncertainties
WTI	51.759	3.015	51.759	3.709	0.000	0.694
GLD	0.240	2.549	0.439	2.192	-0.199	-0.357
SLV	0.625	2.828	1.908	2.879	-1.283	0.051
PLT	6.723	3.816	0.105	1.538	6.618	-2.279
PLD	4.820	2.197	7.294	3.753	-2.474	1.556
ALM	5.900	2.547	0.332	1.291	5.568	-1.255
CPR	0.221	2.623	0.811	2.699	-0.591	0.076
ZNC	0.281	2.099	0.190	2.118	0.091	0.019
LED	0.332	3.158	0.509	4.405	-0.177	1.247
NKL	0.481	4.447	1.810	3.586	-1.329	-0.861
WHT	24.671	3.760	6.656	2.870	18.015	-0.890
CRN	4.305	3.467	4.058	2.559	0.247	-0.908
SBN	5.537	2.859	3.435	2.581	2.102	-0.278
COF	1.077	2.433	6.606	3.035	-5.529	0.603

SGR	0.208	1.880	0.875	1.829	-0.667	-0.052
COC	2.578	2.757	9.109	6.788	-6.531	4.031
COT	1.340	3.007	4.104	1.612	-2.764	-1.396

Note. This table estimates the contribution to the variance of 100-day forecast error of asset *i* due to innovations in asset *j*. Panel A and B reports the spillover results of Diebold & Yilmaz (2014) for full sample and global financial crisis (GFC).

We further analyze the transmission between oil and other commodity uncertainties during the period of the global financial crisis (GFC) (from January 2008 until June 2009) in Table 2 panel B and find a substantial increase in the bi-directional transmission between oil and agricultural commodity uncertainties during the GFC. These results corroborate the findings of Shahzad et al. (2018), who find symmetry in the upside and downside spillover impact between oil and agricultural commodities. We also find a significant increase in the overall net spillovers of oil uncertainty, indicating an increase in the overall transmission from oil to other commodity uncertainties. Using visual aid in Fig. 1 provides additional support to the argument of a significant increase in the net spillovers of oil during the GFC period. Although we do not report the overall spillovers, the findings indicate a significant increase in the overall spillovers implying a more pronounced dependence between oil and other commodities during GFC.

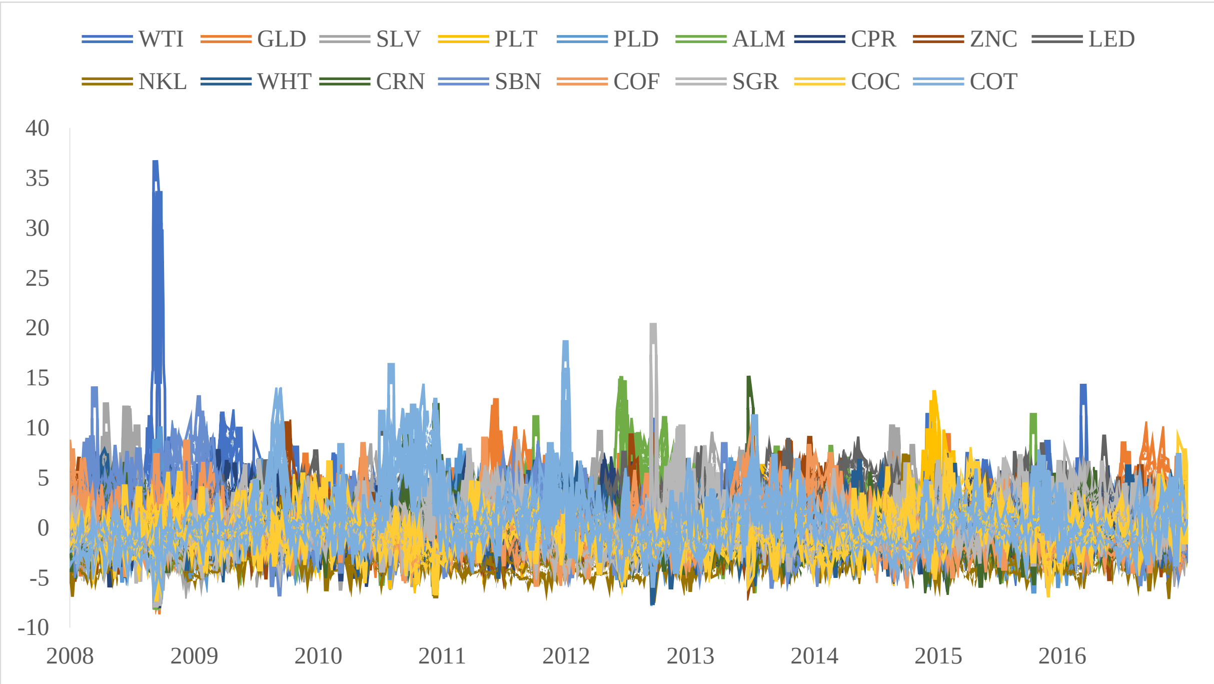


Figure 4. 1. Dynamics of net directional connectedness of oil and other commodity uncertainties

4.5.2. Impact of global factors

In the previous section, we observed bi-directional transmission between oil and other commodity uncertainties, with an increase in the overall transmission during the global financial crisis. Our analysis also points out the role of oil as a net transmitter of uncertainty shocks to the other commodities. In this section, we explore the impact of global factors on the connectedness of commodity markets. Indeed, with the world becoming a global village, stakeholders throughout the world have investments across different markets. Just as markets are open to investment opportunities, they also become prone to the risks associated with globalization, i.e., global liquidity conditions and the risk appetite of investors' (Albulescu et al., 2019; Tang & Xiong, 2012), the most notable example being the 2008 sub-prime mortgage crisis, which triggered a global financial meltdown.

Table 4. 3. Linear and nonlinear causality tests for overall and unidirectional spillovers

	EPU		GPR		VIX		MSCI World		TED		USD	
	Stat	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**
Panel A: Whole sample												
A1: H0: Global factor does not Granger cause overall spillovers												
Linear	3.5477	0.4707	4.7576	0.4462	4.5276	0.2098	0.5812	0.7478	**2.3654**	0.0509	2.5673	0.2770
Taylor-based	1.6579	0.1908	1.2495	0.2869	1.2478	0.2885	**2.3481**	0.0708	1.1532	0.2830	**1.6840**	0.0710
ANN-based	1.0184	0.4159	0.7018	0.6706	0.5621	0.7292	1.1202	0.3478	1.0622	0.3794	1.1660	0.3235
A2: H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO the other markets												
Linear	5.5983	0.3473	3.8061	0.5777	**5.5512**	0.0623	0.6598	0.8826	**19.7149**	0.0006	**9.7011**	0.0458
Taylor-based	**2.3048**	0.0986	**3.7839**	0.0229	**59.8155**	0.0000	**13.4252**	0.0000	**15.7838**	0.0001	**39.6647**	0.0000
ANN-based	0.2405	0.9752	1.1624	0.3212	**28.7543**	0.0000	**5.3966**	0.0000	**46.4748**	0.0000	**6.8233**	0.0000
A3: H0: Global factor does not Granger cause spillover FROM other markets TO Crude oil WTI market												
Linear	**9.1587**	0.0573	7.1653	0.2086	3.0813	0.2142	1.0881	0.5804	1.3590	0.7152	0.4477	0.5034
Taylor-based	**2.2803**	0.0585	**12.9045**	0.0000	1.8653	0.1138	0.9563	0.4686	0.9021	0.3423	**2.2701**	0.0595
ANN-based	0.9870	0.4388	**2.3820**	0.0199	0.8297	0.5284	1.3938	0.2132	**6.6518**	0.0000	**3.3619**	0.0050
Panel B: Global financial crisis (GFC) (January 2008 - June 2009)												
B1: H0: Global factor does not Granger cause overall spillovers												
Linear	1.6207	0.1841	1.3578	0.2554	1.0625	0.3649	0.9882	0.3208	0.0313	0.8596	0.1472	0.7015
Taylor-based	**2.4224**	0.0905	0.5475	0.5790	0.0825	0.7741	1.9579	0.1628	1.4666	0.2269	1.5912	0.2082
ANN-based	**2.7466**	0.0287	1.3996	0.2342	0.5213	0.7202	**5.3718**	0.0013	**5.8258**	0.0033	0.4788	0.6201
B2: H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO the other markets												
Linear	**2.3023**	0.0767	1.7942	0.1477	1.5400	0.2037	0.4954	0.6857	2.2322	0.1360	1.0346	0.3772
Taylor-based	0.4639	0.6293	0.3813	0.6833	**2.7720**	0.0970	**2.9639**	0.0325	**28.1361**	0.0000	**8.4097**	0.0000
ANN-based	1.1195	0.3475	**2.4767**	0.0445	1.1649	0.3265	0.5222	0.7594	0.3314	0.7182	0.5033	0.7334
B3: H0: Global factor does not Granger cause spillover FROM other markets TO Crude oil WTI market												
Linear	0.6159	0.4330	**2.3182**	0.0998	1.2820	0.2802	**3.4551**	0.0638	0.7287	0.3938	0.3681	0.5444

Taylor-based	0.5880	0.4438	2.0656	0.1286	0.4847	0.4869	2.2490	0.1074	1.3217	0.2515	0.0032	0.9549
ANN-based	1.1663	0.3130	**2.2859**	0.0790	**2.0375**	0.0893	1.6793	0.1716	**2.3566**	0.0966	0.0016	0.9984

Note. The table reports the causality test results for linear and nonlinear (Taylor- and ANN-based) causality tests. Panel A and B reports the findings for full sample and global financial crisis (GFC). Each panel reports the causality tests for the null hypothesis that global factor does not Granger cause overall spillover, spillover from oil to other commodity uncertainties, and from other commodity uncertainties to oil.

We test the impact of global factors on the transmission between oil and other commodity uncertainties using three distinct methods of causality tests, i.e., a linear Granger causality test proposed by Granger (1969), along with two nonlinear (Taylor- and ANN-based) causality tests proposed by Péguin-Feissolle & Teräsvirta (1999) and Péguin-Feissolle et al. (2013) in Table 3. Panel A and B report the findings for the whole sample and global financial crisis (GFC) period, respectively. The null hypothesis of Global factor does not granger cause (a) overall transmission (b) transmission from oil uncertainty to other commodity uncertainties and (c) transmission from other commodity uncertainties to oil uncertainty are tested.

Table 4. 4. Linear and nonlinear causality tests for spillovers FROM oil TO individual commodity uncertainties (Full sample)

	EPU		**GPR**		**VIX**		**MSCI World**		**TED**		**USD**	
	Stat	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Gold market												
Linear	0.8710	0.4996	**5.9034**	0.0000	0.4699	0.7990	**2.6677**	0.0461	**2.6953**	0.0444	**4.2863**	0.0000
Taylor-based	1.0077	0.3883	**2.8133**	0.0602	**14.7280**	0.0001	**2.0662**	0.0440	2.3609	0.1245	**11.8387**	0.0000
ANN-based	1.8283	0.1206	**2.4489**	0.0168	**14.3010**	0.0000	**5.3515**	0.0000	**29.6800**	0.0000	1.7658	0.1166
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Silver market												
Linear	0.4969	0.7788	**5.0657**	0.0001	0.5336	0.7510	**17.7453**	0.0000	**6.2423**	0.0003	0.3372	0.7984
Taylor-based	1.5600	0.2104	**17.2247**	0.0000	**94.1650**	0.0000	**4.3676**	0.0001	0.4990	0.4800	**16.5499**	0.0000
ANN-based	**6.3265**	0.0000	0.6425	0.7209	**43.7637**	0.0000	**11.1924**	0.0000	**16.2032**	0.0000	**9.2562**	0.0000
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Platinum market												
Linear	**1.9520**	0.0577	1.3830	0.1896	1.4211	0.1918	**2.0527**	0.0452	0.7224	0.6530	1.9196	0.1045
Taylor-based	1.7888	0.1472	**51.0005**	0.0000	**13.2123**	0.0003	**2.3438**	0.0293	**24.3331**	0.0000	**15.7756**	0.0000
ANN-based	0.9138	0.4549	**14.6384**	0.0000	**6.7743**	0.0000	1.7125	0.1141	**29.6308**	0.0000	**1.9994**	0.0758
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Palladium market												
Linear	0.2511	0.9091	0.3723	0.8679	1.7082	0.1291	**3.8372**	0.0093	**4.5799**	0.0033	**7.5449**	0.0000
Taylor-based	1.5862	0.2049	**3.5119**	0.0300	**11.0566**	0.0009	**4.2593**	0.0003	0.2601	0.6101	**10.4737**	0.0000
ANN-based	0.3651	0.9227	1.0353	0.4040	**20.6270**	0.0224	1.4707	0.1843	**15.1390**	0.0000	1.1743	0.3193
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Aluminum market												
Linear	0.2244	0.9249	1.7043	0.1300	0.8615	0.5061	1.1713	0.3213	1.7553	0.1350	1.6876	0.1501
Taylor-based	**5.8399**	0.0030	**7.7639**	0.0054	**66.5353**	0.0000	**1.9649**	0.0673	**4.6179**	0.0317	**6.9828**	0.0000
ANN-based	**11.0410**	0.0000	**10.4251**	0.0000	**22.0219**	0.0000	**6.7283**	0.0000	**28.7855**	0.0000	**6.7615**	0.0000
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Copper market												
Linear	1.3666	0.2059	0.9077	0.5249	0.3165	0.9287	**2.7122**	0.0056	1.0560	0.3912	**8.9293**	0.0000
Taylor-based	0.1401	0.8693	1.2701	0.2810	**27.8830**	0.0000	**3.0288**	0.0060	**17.0333**	0.0000	**8.9347**	0.0000
ANN-based	0.3411	0.9352	0.5291	0.8131	**9.7717**	0.0000	**3.2895**	0.0032	**16.6486**	0.0000	2.4563	0.0314
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Zinc market												
Linear	1.2261	0.2939	1.5267	0.1779	0.2293	0.9499	0.5766	0.6796	0.4732	0.7554	0.9708	0.4506
Taylor-based	**3.5515**	0.0288	0.0449	0.9561	**21.1715**	0.0000	1.8860	0.3667	0.0202	0.8871	**8.4231**	0.0000
ANN-based	3.8907	0.0087	0.6393	0.6344	**11.6719**	0.0000	**3.4005**	0.0024	**28.0229**	0.0000	**3.1977**	0.0070

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Lead market												
Linear	1.5391	0.1381	0.9741	0.4481	1.0533	0.3913	**3.5789**	0.0008	1.2507	0.2649	**9.0142**	0.0000
Taylor-based	**7.3626**	0.0007	0.1307	0.7178	**13.4060**	0.0003	**1.8092**	0.0935	1.3220	0.2504	0.4673	0.9431
ANN-based	**2.7422**	0.0272	1.0137	0.3855	**2.1832**	0.0535	0.6743	0.6705	**25.6573**	0.0000	0.2808	0.9238
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Nickel market												
Linear	**3.1023**	0.0029	**1.8810**	0.0684	0.5805	0.7724	**5.5338**	0.0000	**2.8659**	0.0055	**2.4901**	0.0414
Taylor-based	0.4995	0.6069	**2.7478**	0.0975	**4.3340**	0.0017	1.7599	0.1035	0.6584	0.4176	**2.5119**	0.0015
ANN-based	0.5692	0.6353	**16.5900**	0.0000	**12.4093**	0.0000	**6.9391**	0.0000	**33.3496**	0.0000	**3.4895**	0.0038
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Wheat market												
Linear	0.9868	0.4322	1.7429	0.1069	0.1421	0.9906	0.7651	0.5749	0.6987	0.6244	**5.4851**	0.0000
Taylor-based	**3.1870**	0.0744	0.2953	0.7443	**25.0459**	0.0000	0.6512	0.6893	0.1733	0.6772	**23.5971**	0.0000
ANN-based	0.4808	0.6183	0.7006	0.5915	**15.0613**	0.0000	**3.6814**	0.0012	**54.6548**	0.0000	**8.2629**	0.0000
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Corn market												
Linear	1.4560	0.2009	1.3021	0.2599	0.4638	0.8034	0.0887	0.7658	1.4749	0.2289	0.9274	0.4469
Taylor-based	**3.5315**	0.0294	0.6393	0.4240	**25.6121**	0.0000	0.8283	0.5478	**20.4587**	0.0000	**15.2950**	0.0000
ANN-based	**6.1555**	0.0004	0.3717	0.7734	**8.6047**	0.0000	0.7207	0.6329	**7.8646**	0.0000	**6.2589**	0.0000
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Soybean market												
Linear	1.3427	0.2343	**2.0056**	0.0747	**4.2398**	0.0003	**2.3241**	0.0304	1.2152	0.2950	**2.7128**	0.0038
Taylor-based	**13.8969**	0.0000	**56.4882**	0.0000	**16.4555**	0.0001	**2.6895**	0.0297	**18.4894**	0.0000	**8.3412**	0.0000
ANN-based	**17.6759**	0.0000	**28.4296**	0.0000	0.8032	0.5473	1.2743	0.2657	**16.1131**	0.0000	0.3351	0.8919
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Coffee market												
Linear	1.1418	0.3351	1.7509	0.1052	**2.0131**	0.0605	1.1059	0.3310	1.8247	0.1211	**5.8454**	0.0000
Taylor-based	0.3265	0.7215	**18.0011**	0.0000	**2.7338**	0.0984	**13.2656**	0.0000	**2.7315**	0.0985	**13.0944**	0.0000
ANN-based	0.1419	0.9349	1.3030	0.2718	1.8020	0.1092	**2.2906**	0.0330	**28.7761**	0.0000	**4.2095**	0.0008
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Sugar market												
Linear	1.4452	0.1932	0.4330	0.6486	0.3649	0.9015	0.1485	0.7000	1.8081	0.1434	**2.2569**	0.0210
Taylor-based	1.0333	0.3560	**7.4875**	0.0063	2.4626	0.1167	1.4398	0.1955	**17.5637**	0.0000	**5.5602**	0.0000
ANN-based	0.4111	0.7451	**2.6129**	0.0497	**2.0800**	0.0651	0.5306	0.7854	**5.8831**	0.0000	0.9720	0.4334
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Cocoa market												
Linear	1.5819	0.1762	3.6625	0.0026	**2.9011**	0.0128	1.6173	0.2035	1.5922	0.2036	**5.3742**	0.0000
Taylor-based	0.2980	0.7423	**89.8838**	0.0000	**12.0045**	0.0005	0.6071	0.7249	2.2374	0.1348	**8.8683**	0.0000
ANN-based	**3.2166**	0.0220	**21.6909**	0.0000	**10.1997**	0.0000	**4.7777**	0.0001	**13.5966**	0.0000	**3.3364**	0.0053

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Cotton market												
Linear	**2.0676**	0.0436	**2.0425**	0.0464	0.6190	0.7407	**2.8635**	0.0055	**1.1970**	0.3006	**9.9179**	0.0000
Taylor-based	**5.0514**	0.0065	**6.3274**	0.0120	**223.8052**	0.0000	**8.8553**	0.0000	**128.4767**	0.0000	**18.7563**	0.0000
ANN-based	**6.8771**	0.0001	1.4842	0.2169	**94.0210**	0.0000	**7.9605**	0.0000	**58.8682**	0.0000	**7.3980**	0.0000

Note. The table reports the causality test results for linear and nonlinear (Taylor- and ANN-based) causality tests reporting the findings for full sample. Each panel reports the causality tests for the null hypothesis that global factor does not Granger cause spillover from oil to individual commodity uncertainties.

The results from panel A indicate the impact of MSCI World, TED spread, and USD index on the overall connectedness of oil and other commodity uncertainties. We do not find the impact of EPU, GPR, and VIX on the overall connectedness. Interestingly, the results in sub-panel A2 indicate a substantial impact of the global factors on the transmission from oil to other commodity uncertainties, especially VIX, TED spread, and USD index, where linear and nonlinear tests show consistent evidence of causality. Consequently, we find evidence of the nonlinear causal impact of EPU, GPR, and MSCI World. The evidence from panel A3 further indicates the bi-directional impact of EPU, GPR, TED spread, and USD index. The above findings provide evidence that nearly all the global factors in some way tend to drive the bi-directional connectedness of commodity markets. The evidence also suggests the intermediary role of oil to transfer the impact of global factors on other commodity markets. The above evidence can be related to the findings provided by Ciner et al. (2013), and more recently, by Batten et al. (2019) about the feasibility of oil as a hedge against market shocks. Indeed, if oil can be used as a hedge against market shocks, it is safe to assume that oil acts as a buffer against the impact of global factors on other commodity markets.

Table 4. 5. Linear and nonlinear causality tests for spillovers FROM oil TO individual commodity uncertainties (GFC sub-sample)

	EPU		GPR		VIX		MSCI World		TED		USD	
	Stat	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Gold market												
Linear	**4.4579**	0.0354	0.0248	0.8748	1.5567	0.2129	**3.5815**	0.0592	**4.9691**	0.0264	0.1937	0.6601
Taylor-based	0.1232	0.7258	0.3159	0.5745	2.3378	0.1274	1.4502	0.2295	**4.7641**	0.0299	0.3339	0.7164
ANN-based	0.2373	0.7889	0.9207	0.3994	**6.6471**	0.0015	2.0564	0.1062	**4.1544**	0.0167	0.0185	0.9817
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Silver market												
Linear	**3.3127**	0.0695	1.0051	0.3167	0.8032	0.3707	**7.9639**	0.0050	2.0013	0.1580	0.9704	0.3252
Taylor-based	1.7354	0.1888	0.2433	0.6222	0.3360	0.5626	**4.1434**	0.0427	1.9444	0.1643	2.2424	0.1081
ANN-based	2.1174	0.1222	0.9729	0.3793	**14.4260**	0.0000	**4.7816**	0.0029	3.1676	0.0248	0.3190	0.7271
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Platinum market												
Linear	1.1630	0.2815	0.0331	0.8558	0.9920	0.3199	5.7417	0.0170	0.2809	0.5964	0.9070	0.3415
Taylor-based	0.2885	0.5916	0.2016	0.6538	2.0944	0.1489	0.0770	0.7816	0.5691	0.4513	0.5036	0.6049
ANN-based	1.1515	0.3176	0.6518	0.5219	**3.5038**	0.0314	0.1728	0.9147	**2.9054**	0.0563	0.2601	0.7712
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Palladium market												
Linear	0.0013	0.9711	**4.2638**	0.0396	**2.3240**	0.0993	0.7904	0.3745	1.8784	0.1542	0.5071	0.6027
Taylor-based	0.6660	0.4151	**5.4104**	0.0207	1.0176	0.3139	**3.5006**	0.0624	0.2558	0.6134	0.8411	0.5000
ANN-based	0.0749	0.9279	**3.7166**	0.0255	0.6453	0.5865	1.1465	0.3307	**5.0888**	0.0019	0.8479	0.4687
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Aluminum market												
Linear	1.1744	0.3101	**3.5215**	0.0305	0.8762	0.4172	0.7334	0.4810	0.1741	0.8403	0.4021	0.6692
Taylor-based	0.1152	0.8912	0.8317	0.4364	1.0421	0.3082	0.9555	0.3859	0.0002	0.9894	1.1176	0.3484
ANN-based	2.0870	0.1021	2.0881	0.1020	**3.8217**	0.0104	1.3113	0.2659	0.3463	0.7918	1.5545	0.2007
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Copper market												
Linear	0.1889	0.8279	0.9894	0.3728	**2.5380**	0.0803	**3.3991**	0.0660	0.5871	0.5564	2.4518	0.0875
Taylor-based	0.2542	0.7757	0.5865	0.5569	0.1972	0.6573	1.2961	0.2559	1.9775	0.1607	0.3123	0.8696
ANN-based	1.2786	0.2819	1.9588	0.1204	0.8161	0.4858	1.9088	0.1283	0.4726	0.7016	0.2778	0.8414
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Zinc market												
Linear	**2.9735**	0.0523	0.7906	0.4543	**2.9779**	0.0521	1.0800	0.3406	2.0918	0.1249	0.3088	0.7345
Taylor-based	1.9094	0.1501	0.0836	0.9198	**27.0131**	0.0000	0.3987	0.6716	**15.0899**	0.0001	0.3293	0.8582
ANN-based	**7.7015**	0.0001	1.4391	0.2316	**14.9703**	0.0000	1.0547	0.3793	**15.5111**	0.0000	0.0397	0.9894
H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Lead market												

Linear	0.9604	0.3837	1.8877	0.1528	**2.7977**	0.0622	0.4284	0.6519	0.5804	0.5601	0.8206	0.4409
Taylor-based	1.6344	0.1969	1.1500	0.3181	**20.6166**	0.0000	1.0624	0.3470	1.3575	0.2449	0.6314	0.5953
ANN-based	**3.0892**	0.0275	1.4262	0.2353	**11.6298**	0.0000	0.1239	0.9738	2.0109	0.1126	0.3142	0.8151

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Nickel market

Linear	0.5950	0.5521	1.0394	0.3547	1.0425	0.3536	1.7596	0.1735	1.3775	0.2534	0.1764	0.8383
Taylor-based	0.1266	0.8811	0.1267	0.8810	**6.9483**	0.0088	1.6785	0.1885	0.0448	0.8326	0.1095	0.9545
ANN-based	0.3130	0.8160	0.2319	0.8741	**2.1721**	0.0915	1.0371	0.3883	1.4059	0.2413	1.0813	0.3574

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Wheat market

Linear	2.1073	0.1230	0.4236	0.6550	0.5032	0.6803	0.1343	0.8744	1.3753	0.2540	0.1110	0.8950
Taylor-based	0.1436	0.8663	0.6182	0.5397	**7.2289**	0.0076	0.6362	0.5300	7.9758	0.0051	1.0394	0.3947
ANN-based	0.9423	0.4206	0.3033	0.8230	**2.1252**	0.0778	0.3164	0.8669	9.4944	0.0000	0.3717	0.7735

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Corn market

Linear	2.2643	0.1053	0.7066	0.4939	1.5678	0.2098	1.1141	0.3293	2.8131	0.0613	1.0090	0.3655
Taylor-based	0.1390	0.8703	0.0573	0.9443	**3.9452**	0.0480	0.3415	0.7110	0.1936	0.6602	1.1388	0.3384
ANN-based	**2.3449**	0.0731	0.5699	0.6353	**4.9415**	0.0023	0.2803	0.8906	6.2476	0.0004	1.1939	0.3123

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Soybean market

Linear	2.1177	0.1217	**2.758**	0.0647	**2.3294**	0.0987	0.2983	0.7423	2.1196	0.1215	1.1597	0.3147
Taylor-based	2.2474	0.1075	1.7454	0.1764	**25.7614**	0.0000	0.4707	0.6251	**6.3435**	0.0123	1.5713	0.1820
ANN-based	**3.8891**	0.0095	**2.2871**	0.0788	**9.8874**	0.0000	0.4177	0.7958	**4.1339**	0.0069	0.4854	0.6927

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Coffee market

Linear	0.5948	0.5522	1.1347	0.3226	0.3914	0.5319	0.2807	0.7554	3.6825	0.0260	**2.7715**	0.0638
Taylor-based	0.1268	0.8810	0.6092	0.5445	0.2305	0.6316	1.0686	0.3448	14.6356	0.0002	**2.8780**	0.0232
ANN-based	0.4277	0.7333	0.6272	0.5980	**8.5501**	0.0002	0.1777	0.9498	5.5274	0.0011	1.2700	0.2849

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Sugar market

Linear	**2.8093**	0.0615	0.3586	0.6989	1.5528	0.2130	0.2193	0.8032	1.5069	0.2229	1.6879	0.1863
Taylor-based	1.6930	0.1858	1.2182	0.2973	**24.7171**	0.0000	0.0105	0.9895	**11.7511**	0.0007	**5.6850**	0.0001
ANN-based	**4.7279**	0.0031	1.5323	0.2063	**12.7856**	0.0000	0.2252	0.9242	**9.6734**	0.0000	2.0541	0.1065

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Cocoa market

Linear	**3.8810**	0.0214	**2.3738**	0.0945	**4.9707**	0.0074	**2.6543**	0.0716	**6.8363**	0.0012	1.3764	0.2537
Taylor-based	0.2158	0.8060	**6.2279**	0.0023	**6.0169**	0.0148	0.1717	0.8423	1.2591	0.2628	1.2514	0.2853
ANN-based	0.1607	0.9227	**6.4393**	0.0003	**3.1426**	0.0257	0.1923	0.9423	**15.0651**	0.0000	1.4380	0.2319

H0: Global factor does not Granger cause spillover FROM Crude oil WTI market TO Cotton market

Linear	1.4136	0.2445	**2.3660**	0.0952	0.1440	0.8659	1.9120	0.1492	1.4759	0.2298	0.2480	0.7805
Taylor-based	**2.9424**	0.0543	1.3251	0.2674	**14.6169**	0.0002	0.7717	0.4632	**21.7886**	0.0000	1.8506	0.1031
ANN-based	**8.6847**	0.0000	1.3205	0.2679	**8.9606**	0.0000	1.0227	0.3958	**10.7312**	0.0000	1.2016	0.3095

Note. The table reports the causality test results for linear and nonlinear (Taylor- and ANN-based) causality tests reporting the findings for GFC sub- sample. Each panel reports the causality tests for the null hypothesis that global factor does not Granger cause spillover from oil to individual commodity uncertainties.

We further test the impact of global factors on the transmission between oil and individual commodity uncertainties. In Table 4, we present the results of linear and nonlinear causality tests for the spillovers running from oil to other commodity uncertainties for the whole sample. Although we generally find a significant impact of global factors, the results indicate a stronger impact of VIX, TED spread, and USD index on the transmissions running from oil to other commodity uncertainties. Additionally, a comparison of the linear and nonlinear causality tests yields that the relationship between the spillovers and the global factors is mostly nonlinear. In order to provide further insight into the impact of global factors on the transmission from oil to individual commodity uncertainties, we perform a sub-sample analysis during the period of the global financial crisis (GFC). We report the results of the causality tests in Table 5. Compared with other global factors, the analysis indicates the significant impact of VIX, and to some extent, the nonlinear impact of TED spread and EPU on the transmission from oil to individual commodity uncertainties during the GFC period.

Table 4. 6. Linear and nonlinear causality tests for spillovers FROM individual commodity uncertainties TO oil (Full sample)

	EPU		**GPR**		**VIX**		**MSCI World**		**TED**		**USD**	
	Stat	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**
H0: Global factor does not Granger cause spillover FROM Gold market TO Crude oil WTI market												
Linear	**2.5463**	0.0376	1.2626	0.2771	1.2216	0.2960	1.1192	0.3266	**2.4369**	0.0875	0.4159	0.7416
Taylor-based	**3.6286**	0.0267	0.8308	0.3621	**6.4024**	0.0115	0.4488	0.8462	**9.0302**	0.0027	1.0979	0.3556
ANN-based	**2.5192**	0.0564	0.4024	0.7513	**2.8510**	0.0143	0.8978	0.4955	**3.9610**	0.0014	0.3678	0.8709
H0: Global factor does not Granger cause spillover FROM Silver market TO Crude oil WTI market												
Linear	0.7789	0.5648	1.7541	0.1188	0.6988	0.6506	0.2830	0.5948	**4.4819**	0.0114	**0.3974**	0.7549
Taylor-based	**2.7037**	0.0672	1.5391	0.2149	**14.6086**	0.0001	0.4105	0.8725	**2.7730**	0.0960	**1.6356**	0.0754
ANN-based	**2.3208**	0.0734	1.9355	0.1217	**7.9589**	0.0000	**2.0167**	0.0602	1.4527	0.2022	**2.9420**	0.0119
H0: Global factor does not Granger cause spillover FROM Platinum market TO Crude oil WTI market												
Linear	0.7078	0.6175	1.4582	0.2001	1.4059	0.2187	0.6327	0.4264	0.3246	0.8617	0.2408	0.9153
Taylor-based	0.3349	0.7154	1.4555	0.2278	**2.8752**	0.0901	0.0446	0.7756	1.7180	0.1901	0.3453	0.9806
ANN-based	1.0272	0.3794	**2.1926**	0.0870	1.1101	0.3528	0.5376	0.7800	**2.0508**	0.0688	0.4528	0.8115
H0: Global factor does not Granger cause spillover FROM Palladium market TO Crude oil WTI market												
Linear	0.7236	0.5757	**3.5128**	0.0036	1.6055	0.1550	0.5220	0.4700	0.5014	0.4789	0.2229	0.9695
Taylor-based	**7.2218**	0.0007	**4.6478**	0.0312	0.0020	0.9646	1.0360	0.3997	0.2323	0.6299	**1.8908**	0.0268
ANN-based	1.4444	0.2280	1.8862	0.1298	**2.9725**	0.0111	1.0107	0.4164	1.7862	0.1123	**2.3967**	0.0353
H0: Global factor does not Granger cause spillover FROM Aluminum market TO Crude oil WTI market												
Linear	0.5298	0.7539	0.4175	0.8369	0.4439	0.8180	1.3064	0.2709	1.7434	0.1750	0.1824	0.9084
Taylor-based	1.8429	0.1747	0.8167	0.3662	**5.0610**	0.0246	0.5378	0.7798	**5.9429**	0.0149	0.2138	0.9986
ANN-based	0.3483	0.7060	0.5521	0.6467	0.6926	0.6291	0.6287	0.7074	**4.0515**	0.0012	0.7231	0.6061
H0: Global factor does not Granger cause spillover FROM Copper market TO Crude oil WTI market												
Linear	0.8401	0.4995	0.3255	0.8979	2.8305	0.0148	0.9063	0.3412	0.9703	0.3790	0.4408	0.7238
Taylor-based	0.0645	0.7996	**3.0005**	0.0834	**24.9853**	0.0000	0.0256	0.8730	**11.2288**	0.0008	**2.7059**	0.0670
ANN-based	**5.0885**	0.0062	**2.7896**	0.0617	**24.1857**	0.0000	**2.6963**	0.0677	**28.8469**	0.0000	**3.0171**	0.0491
H0: Global factor does not Granger cause spillover FROM Zinc market TO Crude oil WTI market												
Linear	0.5857	0.7110	0.4593	0.8067	0.2659	0.9319	0.5594	0.5716	0.5590	0.5718	1.9098	0.1257
Taylor-based	0.4094	0.5223	0.1434	0.7050	**14.7733**	0.0000	0.0001	0.9912	**6.3992**	0.0115	0.9289	0.3951

ANN-based	1.5976	0.2026	0.1820	0.8336	**11.0464**	0.0000	**3.1605**	0.0426	**25.4532**	0.0000	1.3158	0.2685
H0: Global factor does not Granger cause spillover FROM Lead market TO Crude oil WTI market												
Linear	0.3251	0.8613	0.1421	0.9824	1.4028	0.2400	0.2741	0.6006	0.1933	0.8243	0.5681	0.6360
Taylor-based	1.0661	0.3019	**2.9192**	0.0877	**15.8192**	0.0001	0.8060	0.3694	2.0017	0.1573	0.6943	0.4995
ANN-based	1.6191	0.1983	0.2438	0.7836	**10.7244**	0.0000	2.1816	0.1131	1.2114	0.2980	0.9628	0.3820
H0: Global factor does not Granger cause spillover FROM Nickel market TO Crude oil WTI market												
Linear	0.7725	0.5429	0.8914	0.4858	1.6156	0.1522	1.2158	0.2966	2.0001	0.1354	0.4759	0.6991
Taylor-based	0.1222	0.7267	0.0130	0.9094	0.1454	0.7030	1.3066	0.2531	0.0499	0.8233	1.1939	0.3032
ANN-based	0.8022	0.4485	0.4846	0.6160	**7.4321**	0.0006	1.0629	0.3456	0.2938	0.7455	1.7040	0.1822
H0: Global factor does not Granger cause spillover FROM Wheat market TO Crude oil WTI market												
Linear	**2.2945**	0.0570	3.9294	0.0015	1.1774	0.3176	0.0112	0.9159	2.0341	0.1309	0.3019	0.8240
Taylor-based	0.0509	0.8215	**5.1311**	0.0236	0.4847	0.4864	**8.4515**	0.0000	**10.1655**	0.0015	**2.1873**	0.0082
ANN-based	0.9839	0.3740	**5.0694**	0.0064	1.7740	0.1699	0.8199	0.5543	**9.5223**	0.0000	**2.0154**	0.0735
H0: Global factor does not Granger cause spillover FROM Corn market TO Crude oil WTI market												
Linear	1.4668	0.2095	0.4252	0.8314	0.4319	0.8266	**2.5221**	0.0804	1.0694	0.3433	0.5874	0.6232
Taylor-based	1.2311	0.2673	0.5975	0.4396	**14.2624**	0.0002	**3.9372**	0.0473	**5.4339**	0.0198	**6.7727**	0.0012
ANN-based	**2.8177**	0.0600	0.0336	0.9669	**8.8246**	0.0002	1.8167	0.1628	**5.2883**	0.0051	**7.2035**	0.0008
H0: Global factor does not Granger cause spillover FROM Soybean market TO Crude oil WTI market												
Linear	0.1230	0.9873	**2.5602**	0.0255	0.7850	0.5603	0.0000	0.9952	0.8804	0.3482	0.7356	0.5306
Taylor-based	1.4787	0.2241	**4.1616**	0.0415	**3.1446**	0.0763	**2.0225**	0.0595	0.0921	0.7615	**1.6979**	0.0551
ANN-based	0.3691	0.6914	**5.3245**	0.0012	**1.8706**	0.0963	**2.6492**	0.0146	1.1160	0.3496	**1.8952**	0.0920
H0: Global factor does not Granger cause spillover FROM Coffee market TO Crude oil WTI market												
Linear	1.3738	0.2403	1.0921	0.3625	0.2994	0.9134	0.2563	0.6127	0.1107	0.9539	1.0771	0.3574
Taylor-based	0.0849	0.7708	0.3653	0.6941	2.3349	0.1266	0.5752	0.7504	0.0005	0.9815	0.8890	0.5577
ANN-based	0.1296	0.8784	0.3762	0.9166	0.3557	0.8788	1.4022	0.2099	1.1146	0.3504	0.4008	0.8485
H0: Global factor does not Granger cause spillover FROM Sugar market TO Crude oil WTI market												
Linear	0.5325	0.7519	0.4831	0.7891	1.2370	0.2888	**6.1503**	0.0022	0.3019	0.7394	0.5316	0.6606
Taylor-based	0.5101	0.4752	1.6402	0.2004	**3.4481**	0.0081	**7.9170**	0.0000	**11.1397**	0.0009	0.9147	0.5368
ANN-based	0.0966	0.9079	1.2609	0.2836	**4.1431**	0.0009	**4.3244**	0.0002	**4.5370**	0.0004	0.1373	0.9837

H0: Global factor does not Granger cause spillover FROM Cocoa market TO Crude oil WTI market												
Linear	0.4491	0.7732	0.2735	0.9278	0.8575	0.5089	0.0021	0.9636	0.5331	0.5868	0.1782	0.9112
Taylor-based	0.0805	0.7766	1.2954	0.2740	**13.9516**	0.0002	0.4328	0.8574	**14.1409**	0.0002	**2.5138**	0.0015
ANN-based	0.1527	0.8584	0.5708	0.7802	1.6207	0.1511	0.9953	0.4266	**14.1446**	0.0000	0.2949	0.9159
H0: Global factor does not Granger cause spillover FROM Cotton market TO Crude oil WTI market												
Linear	1.3833	0.2370	0.4944	0.7807	0.8120	0.5408	**4.5693**	0.0104	1.1853	0.3057	0.3463	0.7919
Taylor-based	0.5274	0.4678	1.4633	0.2265	**16.7058**	0.0000	**4.6880**	0.0093	**14.5232**	0.0001	1.3881	0.2355
ANN-based	1.8427	0.1586	**11.0690**	0.0000	**7.3390**	0.0007	1.7160	0.1616	**10.8483**	0.0000	1.1197	0.3398

Note. The table reports the causality test results for linear and nonlinear (Taylor- and ANN-based) causality tests reporting the findings for full sample. Each panel reports the causality tests for the null hypothesis that global factor does not Granger cause spillover from individual commodity to oil uncertainties.

Finally, we report the results of linear and nonlinear causality tests for the transmissions running from individual commodity uncertainties to oil in Table 6. Comparing the results to Table 4, we find VIX and TED spread as the significant drivers of connectedness from individual commodity uncertainties to oil. We also find the nonlinear impact of the USD index across all commodity markets. Nevertheless, the analysis reported in Table 7 related to the transmission of individual commodity uncertainty to oil during the GFC sub-period points out to the importance of VIX, and to a lesser extent, TED spread and EPU, as the drivers to cross-commodity connectedness.

Interestingly, we find a heterogeneous impact of global factors across different commodity markets. Our findings provide further evidence in support of the idea of the 'financialization' of commodity markets (Aboura, & Chevallier, 2015; Bouri et al., 2017; Tang & Xiong, 2012) through various channels. First, our analysis of inter-connectedness between oil and other commodity uncertainties provides evidence of the increase in connectedness, especially during the global financial crisis. These findings are consistent with previous literature on the bi-directional inter-connectedness among commodity markets (such as Balli et al., 2019; Ji et al., 2018; Kang et al., 2017; Nazlioglu et al. 2013 and Shahzad et al., 2018). Second, the results related to VIX as the most influential driver of transmission between oil and other commodity uncertainties corroborate the finding of Silvennoinen, & Thorp (2013) and Yoon et al. (2019), indicating the importance of US stock market as the most significant contributor of spillovers across different asset classes. Finally, the relatively significant causal impact of TED spread, and EPU provides support to the evidence provided by Buyuksahin & Robe (2011) and Albulescu et al. (2019) for financial market stress (TED spread) and US monetary policy (EPU) as the drivers of financial market connectedness.

Table 4. 7. Linear and nonlinear causality tests for spillovers FROM individual commodity uncertainties TO oil (GFC sub-sample)

	EPU		**GPR**		**VIX**		**MSCI World**		**TED**		**USD**	
	Stat	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**	**Stat**	**p-Value**
H0: Global factor does not Granger cause spillover FROM Gold market TO Crude oil WTI market												
Linear	**6.6873**	0.0014	0.0247	0.9756	0.2400	0.7868	1.8050	0.1659	0.5736	0.5640	**4.8294**	0.0085
Taylor-based	0.1286	0.8793	0.2749	0.7599	1.6639	0.1981	0.3293	0.7197	0.4903	0.4844	**2.6751**	0.0475
ANN-based	0.8151	0.4864	0.2228	0.8805	0.2954	0.8287	1.1327	0.3413	0.4107	0.7455	**2.8753**	0.0365
H0: Global factor does not Granger cause spillover FROM Silver market TO Crude oil WTI market												
Linear	2.6290	0.1057	0.9477	0.3309	**3.3334**	0.0687	0.1356	0.8732	0.2525	0.7770	0.3792	0.6847
Taylor-based	0.6202	0.4316	1.2191	0.2705	1.9467	0.1640	0.2889	0.7493	0.3641	0.5467	0.2170	0.8846
ANN-based	1.1167	0.3288	0.4303	0.6507	1.2893	0.2771	1.4085	0.2312	0.1389	0.9367	0.4174	0.7406
H0: Global factor does not Granger cause spillover FROM Platinum market TO Crude oil WTI market												
Linear	0.3482	0.7062	1.6547	0.1991	**3.2449**	0.0724	1.2931	0.2562	0.0294	0.8638	0.1801	0.6715
Taylor-based	0.3748	0.6878	0.3281	0.5672	1.1185	0.2911	0.0369	0.8478	0.0492	0.8247	0.0285	0.8660
ANN-based	0.4594	0.7109	0.6075	0.5454	0.9215	0.3991	1.6897	0.1694	0.0537	0.9478	0.1460	0.8641
H0: Global factor does not Granger cause spillover FROM Palladium market TO Crude oil WTI market												
Linear	**7.2474**	0.0074	0.3978	0.5286	1.8911	0.1699	1.5476	0.2142	**9.9311**	0.0018	0.2689	0.6044
Taylor-based	**14.6447**	0.0002	0.3344	0.5635	1.1237	0.2900	1.5659	0.2118	1.8037	0.1803	0.4062	0.5244
ANN-based	**2.8239**	0.0610	**2.5265**	0.0817	1.1371	0.3222	**2.3562**	0.0721	**3.3952**	0.0349	0.3290	0.7199
H0: Global factor does not Granger cause spillover FROM Aluminum market TO Crude oil WTI market												
Linear	0.1509	0.6979	0.3782	0.5389	2.0756	0.1505	0.1627	0.6869	0.6246	0.4298	0.3378	0.5614
Taylor-based	0.3149	0.5751	0.0935	0.7600	0.8588	0.3548	0.0054	0.9414	0.2392	0.6252	0.0800	0.7775
ANN-based	0.3807	0.6837	0.8067	0.4474	2.3810	0.0943	1.5627	0.1986	0.2801	0.7559	0.2642	0.7680
H0: Global factor does not Granger cause spillover FROM Copper market TO Crude oil WTI market												
Linear	**5.1042**	0.0244	0.2301	0.6318	**10.2814**	0.0015	0.2774	0.5987	1.6092	0.2054	0.4268	0.5140
Taylor-based	0.3529	0.5530	0.4680	0.4945	2.6273	0.1061	0.0225	0.8809	0.6680	0.4144	0.0332	0.8555
ANN-based	**3.9242**	0.0208	0.0975	0.9071	**2.7403**	0.0662	1.3369	0.2626	0.4576	0.6333	0.5546	0.5749
H0: Global factor does not Granger cause spillover FROM Zinc market TO Crude oil WTI market												
Linear	0.0289	0.8651	0.1891	0.6639	0.6399	0.5279	0.1286	0.8794	1.1737	0.3103	0.4065	0.6663
Taylor-based	0.0552	0.8145	0.0225	0.8808	0.7578	0.3847	0.2044	0.8153	0.0045	0.9466	0.2369	0.8706
ANN-based	0.0179	0.9822	0.0813	0.9219	0.5549	0.6452	0.5052	0.7319	0.9641	0.4100	0.9860	0.3997

H0: Global factor does not Granger cause spillover FROM Lead market TO Crude oil WTI market												
Linear	**2.3690**	0.0949	**2.9176**	0.0553	1.8486	0.1588	0.3329	0.7170	**4.1145**	0.0171	0.6111	0.5433
Taylor-based	1.4634	0.2332	0.3759	0.6870	**8.2337**	0.0044	0.6839	0.5055	1.1119	0.2925	1.9047	0.1290
ANN-based	**2.1089**	0.0993	0.8872	0.4481	**3.3878**	0.0185	**4.1859**	0.0026	**3.9248**	0.0091	1.6112	0.1869
H0: Global factor does not Granger cause spillover FROM Nickel market TO Crude oil WTI market												
Linear	0.2796	0.5972	0.0959	0.7570	1.7964	0.1673	1.2845	0.2780	0.1098	0.8960	**2.4834**	0.0848
Taylor-based	0.0211	0.8845	**6.5693**	0.0109	1.1743	0.2794	**2.4563**	0.0876	0.0201	0.8874	1.0595	0.3667
ANN-based	0.0313	0.9692	1.2095	0.2999	0.4496	0.7178	1.8882	0.1126	2.0077	0.1130	0.6990	0.5533
H0: EPU does not Granger cause spillover FROM Wheat market TO Crude oil WTI market												
Linear	**7.9421**	0.0004	0.1987	0.8199	**3.6339**	0.0273	**5.9703**	0.0028	**6.7822**	0.0013	1.9061	0.1501
Taylor-based	**8.4740**	0.0003	0.1377	0.8714	**21.2606**	0.0000	**2.5399**	0.0807	**34.8651**	0.0000	**5.9021**	0.0006
ANN-based	**3.7853**	0.0109	0.5091	0.6763	**6.2896**	0.0004	0.8162	0.5157	**14.4067**	0.0000	0.7274	0.5364
H0: Global factor does not Granger cause spillover FROM Corn market TO Crude oil WTI market												
Linear	0.2648	0.6071	0.5532	0.4575	2.4653	0.1172	0.0150	0.9851	0.4998	0.6071	1.7389	0.1771
Taylor-based	0.0856	0.7700	0.0788	0.7791	1.0193	0.3135	0.0133	0.9869	0.2400	0.6246	0.5134	0.6733
ANN-based	0.4800	0.6193	0.0079	0.9922	0.8873	0.4129	0.5566	0.6944	0.7599	0.5174	1.6821	0.1710
H0: Global factor does not Granger cause spillover FROM Soybean market TO Crude oil WTI market												
Linear	0.4129	0.5209	0.5817	0.4461	0.6305	0.4277	0.0245	0.8757	0.1987	0.6560	**5.4783**	0.0198
Taylor-based	0.0214	0.8838	0.3379	0.5615	2.0935	0.1490	0.6002	0.4391	0.0611	0.8049	**3.1554**	0.0767
ANN-based	0.0224	0.9778	1.4816	0.2290	**3.0569**	0.0486	0.9054	0.4389	**3.6536**	0.0271	2.1741	0.1156
H0: Global factor does not Granger cause spillover FROM Coffee market TO Crude oil WTI market												
Linear	**6.5146**	0.0111	0.2425	0.6227	1.8421	0.1755	2.4073	0.1216	0.2300	0.6318	0.4226	0.5160
Taylor-based	**2.7819**	0.0965	0.1289	0.7198	2.2772	0.1324	0.1551	0.6940	0.0804	0.7770	0.2366	0.6271
ANN-based	**4.6430**	0.0104	0.2977	0.7428	1.7828	0.1700	1.5496	0.2019	1.9644	0.1420	0.1717	0.8423
H0: Global factor does not Granger cause spillover FROM Sugar market TO Crude oil WTI market												
Linear	0.7557	0.3852	**6.1963**	0.0132	0.8153	0.3671	**6.3019**	0.0125	**3.4366**	0.0645	0.6683	0.4142
Taylor-based	0.0858	0.7697	1.3323	0.2494	**4.0137**	0.0461	**14.9712**	0.0001	**11.5562**	0.0000	0.3172	0.5737
ANN-based	0.2788	0.7569	1.6590	0.1922	1.1815	0.3083	**4.3115**	0.0054	**28.5011**	0.0000	0.0586	0.9431
H0: Global factor does not Granger cause spillover FROM Cocoa market TO Crude oil WTI market												
Linear	0.0727	0.7876	0.2634	0.6081	0.0244	0.8760	0.5758	0.4484	1.0869	0.2978	0.7312	0.3930

Taylor-based	0.0964	0.7565	0.0368	0.8480	1.4858	0.2239	0.0778	0.7805	1.5105	0.2201	0.0005	0.9814
ANN-based	0.4809	0.6187	0.0175	0.9827	1.9466	0.1446	0.4400	0.7245	**9.2613**	0.0001	1.5288	0.2186
H0: Global factor does not Granger cause spillover FROM Cotton market TO Crude oil WTI market												
Linear	2.2028	0.1386	1.1079	0.2932	**4.7976**	0.0291	0.3255	0.5686	1.1729	0.2795	1.0565	0.3047
Taylor-based	0.2793	0.5976	0.2568	0.6127	1.6092	0.2056	0.0048	0.9451	0.4275	0.5138	0.0003	0.9869
ANN-based	0.8714	0.4195	0.5370	0.5851	1.6214	0.1994	1.0831	0.3566	0.4615	0.6308	0.2908	0.7479

Note. The table reports the causality test results for linear and nonlinear (Taylor- and ANN-based) causality tests reporting the findings for GFC sub-sample. Each panel reports the causality tests for the null hypothesis that global factor does not Granger cause spillover from individual commodity to oil uncertainties.

4.6. Conclusion

In this study, we investigate the impact of global factors on the connectedness of commodity uncertainties from January 2007 – December 2016. To this end, we first employ the methodology proposed by Diebold & Yilmaz (2014) to estimate the transmission between oil and other commodity uncertainties. Moreover, we make use of the linear and nonlinear (Taylor- and ANN-based) causality tests to estimate the impact of global factors on the connectedness of commodity uncertainties. Performing additional sub-sample analysis, during the global financial crisis, helps us obtain an in-depth insight into the relationship among commodity markets and their interaction with the global factors.

In our study, we find strong bi-directional transmission between oil and metal (agriculture) markets, and this transmission became significantly more pronounced during the turmoil period, i.e., the global financial crisis. Our analysis suggests that oil is a net transmitter to other commodity uncertainties, and this transmission of oil significantly increased during the period of the global financial crisis (2008 – 2009), which originated as the sub-prime mortgage crisis in the U.S. and consequently resulted in the meltdown of financial markets globally. Additionally, our results indicate that the global factors in some way have a causal effect on the overall connectedness, especially on the spillovers from oil to other commodity uncertainties. Further segregation of transmissions from oil to other commodity markets and vice versa indicate VIX, and to some extent, TED spread and EPU as the most influential drivers of connectedness among commodity markets.

Amidst the ‘financialization’ of commodities, resulting in a sharp upsurge in the connectedness of commodity markets and their interaction with other financial and macroeconomic determinants, we find that the price of commodities is not only dependent on the supply and demand channel but also determined by the risk appetite of stakeholders. Thus investors can be watchful of the global factors, such as VIX, which considered a proxy for investor sentiment and risk aversion (Bekaert et al., 2011) and also regarded as a good predictor of commodity and equity markets (Cheng et al. 2014; Coudert & Gex, 2008) to better forecast the price changes in commodity markets. Additionally, policymakers and regulators should carefully asses the risk associated with financial stress and economic policy. This way, they would be able to provide better avenues of risk-sharing for the producers and will be able to incentivize the commodity markets to provide relief to the consumers against the inflationary effects. A possible direction for future research can be the further segregation of total connectedness into frequencies (i.e., short-, medium-, and long-term). This would provide a more in-depth insight into the causal impact of global factors on different frequency scales.

CHAPTER FIVE: Conclusion

Commodity market uncertainty is the possibility that commodity prices will change and causes financial losses to the investors in the future. The uncertainty in commodity prices has direct input in financial risk management, hedging decisions and commodity contingent claim valuations, while the idea of connectedness is central to risk management that appears particularly significant concerning commodities. Thus, it is vital to understand the sources of its variations and connectedness with other commodity markets. Since market commodities are part of the real asset, therefore, investors have been taking an interest in these assets in recent years, particularly those with heavy exposures to assets. Moreover, the literature on connectedness among commodities is growing since the GFC to explore the investment potential of different commodity classes.

On the other hand, commodity market financialization increases the integrations of different commodity markets; however, the energy sector is more efficient in sending shocks to other commodities and thereby indicating a strong link with agricultural commodities, precious and industrial metals. The fluctuation in energy commodities prices not only has a tremendous influence on the company's profit margin but also greatly impacts the other commodity markets or industries. Besides, price shocks in energy commodities result in the rebalancing of industrial structural mix and changes in money demand due to changes in production costs. Accordingly, volatility in energy commodities buffeted in variation in financial markets and contributes significantly to the industries and economies due to speculative dynamics and market contagion as energy commodities are essential for different industrial sectors. Industry betas are an adequate measure of systematic risk and some groups of commodities say gasoline and crude oil are vital inputs in the production process and thus, commodities uncertainty may be relevant to the systematic risk of industries. Therefore, uncertainty in the price of such commodities affects the financial performance of the firms which further leads to influence their profit margins.

There have been heated debates among central banks, economists, and investors in the wake of GFC that what are the factors leading to risks or uncertainties faced by the developed and under-developed economies. Although precious metals have been a long-standing favorite for investors, they are also prone to volatility when things are not running smoothly globally. There are several factors, including the US interest rate, economic policy uncertainty, commodity-specific disruptions, financial uncertainty, and political uncertainty, which buffeted the prices of commodities over the last few years. The combination of these factors makes commodity markets as unpredictable as they were during the GFC.

This thesis concluded that the price of commodities is endogenous with respect to the global business cycle, where supply shocks have small transitory effects and demand shocks have sustained and delayed price movements. The thesis findings reveal high connectedness and spillovers within specific commodity groups. The thesis also finds that energy commodities uncertainties tend to be highly correlated during periods of crisis and unexpected inflation and tend to establish the positive impact of the energy commodities uncertainties on other US markets. Furthermore, various global factors affect the transmission measures between oil and other commodity uncertainties and the result is more important for commodities that are strongly related to the global business cycle and financialization of commodities has increased both the intra-commodity connectedness and the connectedness of commodities with other financial markets at a global level.

5.1. Essay One

The first essay determines the role of time and frequency connectedness of commodities prices uncertainty by deploying the connectedness model of Diebold & Yilmaz (2014) and by applying the estimating time-varying uncertainty indexes for 22 commodities related to four distinct groups (agricultural commodities, precious metals, industrial metals commodities, and energy commodities) which are traded globally for the creation of uncertainty indexes obtained from Thomson Reuter's data stream over the period January 2007 to December 2016. The essay also tried to compare total connectedness for the full sample and GFC and how the connectedness increases during the GFC.

Earlier studies used only the volatility/variation is commodity prices to gauge the uncertainty in the commodity markets, but our essay proposed indexes for 22 commodities prices thus presents a better understanding of commodities price uncertainty. The essay finds that the connectedness of commodity uncertainty indexes tends to increase over the period of crisis and that the global economic situation affects the connectedness of uncertainty in the commodity prices. The essay comparison of total connectedness for the full sample finds high connectedness within specific classes of commodities, which increases during the period of the GFC and the oil price collapse of 2014-2016 by analyzing the time-varying connectedness approach. The essay also finds the disconnection of precious metals with other commodity classes giving proof to their safe-haven properties.

The essay highlights the importance of energy commodities and precious metals in the existing literature with respect to investment management and risk analysis. The study provides new empirical evidence about the connectedness dynamics in the commodity markets by analyzing the total and frequency connectedness of commodities price uncertainty. Therefore, to develop efficient hedging strategies and to make sound investment decisions, investors must be better informed about the connectedness of commodity markets. The study depicts a clear picture of the policymakers to enable protection against the contagion effect and fostering of market stability. Future researchers could use our uncertainty indexes in order to examine the commodity price uncertainties impact on other asset classes and uncertainties such as stock market uncertainty, geopolitical uncertainty, and economic policy uncertainty. This would provide a better understanding of how other uncertainties interact with commodity price uncertainty.

5.2. Essay Two

Motivated by the real options approach of the theory of investment under uncertainty, we empirically examine the impact of energy commodity price uncertainty on US industries indices. The second essay investigates the energy commodity uncertainties that influence the systematic risk betas of twelve US industry portfolios over the period from January 2007 to December 2016. The essay measures the energy commodity uncertainties influence on the dynamic conditional betas of US industry portfolios by using the dynamic conditional correlation – generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model for the two major bases: a) there is an asymmetric sensitivity of industries towards the commodity prices changes, and b) the performance of one specific sector is not identified by the market index especially during the turmoil periods. This is because the impact of energy commodities on industry depends upon whether there is a direct or indirect factor of production between the relation between energy commodities and industry.

This study establishes positive impact of the energy commodities uncertainties on real estate (RLS), financials (FIN), oil and gas (OGS), basic material (BMT) and basic resources (BRS) sectors, while negative impact on technology (TEC), industrials (IND), consumer services (CNS), consumer goods (CNG) and health care (HLT) industries. The study also derives two explanations about the difference in the high predictability of industry betas and the impact of uncertainties of energy commodities. First is related to the market segmentation as the information regarding the uncertainty in the commodities futures price is contained in the uncertainty indices, the study results counter-evidence to the delayed reaction hypothesis, proposed by Hong et al. (2007). Second is the heterogeneous impact of energy commodities uncertainties related to the exposure of industries to the energy volatility/price shocks, thus consistent with the previous work of Narayan and Sharma (2011) and Elyasiani et al. (2011). The findings of the undiversifiable impact of oil uncertainty for oil-relevant industry investors for the sub-sample analysis of the Shale Oil Revolution (SOR) and global financial crisis (GFC) were also similar to the work of Bams et al. (2017).

This essay makes several important contributions to the literature in the context of the US. The study extends and contributes to earlier literature by estimating the dynamic conditional betas for twelve industry portfolios to estimate the conditional co-movement between assets, that is, markets and industry. The study contributes that investors should be watchful of the uncertainties of energy commodities to be able to forecast stock market returns better and to make informed investment decisions. The essay suggests that there is a need to focus on financial stability measures by the policymakers and regulators that are usually being affected by the commodities uncertain behaviors such as oil and natural gas. These economic policies by the policy-makers will able to help financial investors to identify the commodities uncertainties or demand shocks in these commodities.

Moreover, there is a need to consider the commodity's effect on the riskiness of industries by the policymakers and regulators while developing economic growth policies for the country as this enables them to put a suitable value on essential commodities that are important for the booming growth of an economy. The essay further contributes to identifying the commodities uncertainties effect on investor’s portfolio, thus allowing global investors to measure connectedness between global oil prices and related markets and the economy growth at the global level. Researchers could consider firm-level data or further segregation of industries for future research that might allow researchers an in-depth perspective on the impact of energy commodities uncertainties. Consequently, researchers could use other commodities uncertainties for hedging purpose for the financialization of commodities as out-of-sample forecasting can provide additional hedging opportunities for investors.

5.3. Essay Three

The third essay examines the transmission between oil and other commodity uncertainties by employing the proposed methodology by Diebold and Yilmaz (2014) and investigates the impact of global factors on the transmission measures between oil and other commodity uncertainties using linear and nonlinear (Taylor- and ANN-based) causality tests from January 2007 to December 2016. The essay also obtains an in-depth insight into the relationship between commodity markets and their interaction with the global factors during the GFC is achieved by performing additional sub-sample analysis.

The empirical findings suggest that there exists a strong bi-directional transmission between agriculture (metal) markets and crude oil; that is, oil is a net transmitter to other commodities uncertainties which became significantly more evident during the GFC or oil market crisis of 2014-2016. Moreover, our results indicate that the global factors in some way have a causal effect on the overall connectedness, especially on the spillovers from oil to other commodity uncertainties. Further segregation of transmissions from oil to other commodity markets and vice versa indicate VIX, and to some extent, TED spread and EPU as the most influential drivers of connectedness among commodity markets. The recent empirical findings of Elder and Serletis (2010), Jo (2014) and Elder (2018) provide further insights into the significant forecasting power of oil price uncertainty on economic activity.

Amidst the ‘financialization’ of commodities, resulting in a sharp upsurge in the connectedness of commodity markets and their interaction with other financial and macroeconomic determinants, we find that the price of commodities is not only dependent on the supply and demand channel but also determined by the risk appetite of stakeholders. Thus, investors can be watchful of the global factors, such as VIX, which considered a proxy for investor sentiment and risk aversion (Bekaert et al., 2011) and also regarded as a good predictor of commodity and equity markets (Coudert & Gex, 2008) to better forecast the price changes in commodity markets.

The essay makes several contributions. The policy implication behind our empirical findings is that policy-makers should turn their attention to perceiving oil uncertainty shocks as the commodity-related threat for the macro-economy. Additionally, policymakers and regulators should carefully assess the risk associated with financial stress and economic policy. This way, they would be able to provide better avenues of risk-sharing for the producers and will be able to incentivize the commodity markets to provide relief to the consumers against the inflationary effects. A possible direction for future research can be the further segregation of total connectedness into frequencies (i.e., short-, medium-, and long-term). This would provide a more in-depth insight into the causal impact of global factors on different frequency scales.

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Appendices

Table A.1. 1: U.S. industry betas and energy commodity uncertainties (Full sample)

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ using full sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

	BMT	**BRS**	**CNG**	**CNS**	**FIN**	**HLT**	**IND**	**OGS**	**RLS**	**TEC**	**TEL**	**UTL**
WTI	0.004	0.033[a]	-0.036[a]	-0.019[a]	0.087[a]	-0.037[a]	-0.042[a]	0.019[a]	0.136[a]	-0.036[a]	-0.006	0.001
	(0.005)	(0.009)	(0.003)	(0.003)	(0.014)	(0.005)	(0.004)	(0.007)	(0.017)	(0.004)	(0.004)	(0.006)
R^2	0.107%	3.334%	20.071%	10.976%	18.098%	10.565%	25.416%	1.875%	22.173%	14.333%	0.501%	0.005%
BRT	0.023[a]	0.058[a]	-0.039[a]	-0.022[a]	0.071[a]	-0.050[a]	-0.045[a]	0.022[a]	0.159[a]	-0.041[a]	0.001	0.018[b]
	(0.006)	(0.010)	(0.007)	(0.006)	(0.021)	(0.008)	(0.009)	(0.007)	(0.032)	(0.009)	(0.006)	(0.007)
R^2	2.351%	6.995%	15.800%	8.974%	7.863%	12.833%	18.564%	1.653%	20.135%	11.990%	0.007%	1.505%
GSO	0.014[a]	0.037[a]	-0.029[a]	-0.018[a]	0.064[a]	-0.039[a]	-0.034[a]	0.013[a]	0.127[a]	-0.031[a]	0.002	0.011[b]
	(0.004)	(0.007)	(0.004)	(0.003)	(0.014)	(0.006)	(0.004)	(0.005)	(0.020)	(0.004)	(0.003)	(0.004)
R^2	1.856%	5.940%	18.087%	12.905%	13.451%	16.473%	22.789%	1.234%	27.284%	15.182%	0.087%	1.152%
GSL	0.007[a]	0.013[a]	-0.015[a]	-0.007[a]	0.038[a]	-0.021[a]	-0.012[a]	-0.003	0.059[a]	-0.013[a]	0.000	0.003
	(0.002)	(0.004)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.003)	(0.005)	(0.002)	(0.001)	(0.002)
R^2	2.606%	4.462%	30.873%	11.425%	29.427%	30.355%	16.632%	0.489%	36.512%	14.953%	0.018%	0.545%
HTO	0.054[a]	0.093[a]	-0.024[b]	-0.020[b]	0.036[c]	-0.037[a]	-0.021	0.057[a]	0.060[b]	-0.024[b]	-0.012[b]	-0.019[b]
	(0.011)	(0.020)	(0.010)	(0.008)	(0.020)	(0.010)	(0.014)	(0.014)	(0.030)	(0.011)	(0.006)	(0.009)
R^2	2.817%	3.795%	1.277%	1.626%	0.440%	1.494%	0.911%	2.350%	0.610%	0.872%	0.285%	0.347%
NGS	0.014[a]	0.028[a]	-0.019[a]	-0.007[b]	0.049[a]	-0.027[a]	-0.013[a]	0.010[c]	0.086[a]	-0.025[a]	-0.003	0.008
	(0.005)	(0.008)	(0.004)	(0.003)	(0.011)	(0.006)	(0.004)	(0.006)	(0.016)	(0.004)	(0.003)	(0.006)
R^2	1.528%	2.751%	6.135%	1.450%	6.486%	6.316%	2.537%	0.548%	9.979%	7.626%	0.112%	0.452%

Table A.1. 2: U.S. industry betas and energy commodity uncertainties (Global financial crisis sub-sample 1/8/2007 - 30/6/2009)

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ using GFC sub-sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

	BMT	**BRS**	**CNG**	**CNS**	**FIN**	**HLT**	**IND**	**OGS**	**RLS**	**TEC**	**TEL**	**UTL**
WTI	0.0114[c]	0.0457[a]	-0.0122[a]	-0.0188[a]	0.0293[c]	0.0001	-0.0227[a]	0.0470[a]	0.0722[a]	-0.0245[a]	-0.0094[b]	0.0030
	(0.0064)	(0.0113)	(0.0037)	(0.0029)	(0.0174)	(0.0044)	(0.0045)	(0.0105)	(0.0202)	(0.0049)	(0.0042)	(0.0074)
R^2	1.704%	11.274%	9.967%	16.120%	2.667%	0.000%	22.680%	14.174%	11.433%	14.001%	3.496%	0.128%
BRT	0.0240[b]	0.0895[a]	-0.0044	-0.0339[a]	-0.0267	0.0220[a]	-0.0398[a]	0.1092[a]	0.0746[c]	-0.0394[a]	-0.0040	0.0444[a]
	(0.0106)	(0.0171)	(0.0075)	(0.0062)	(0.0258)	(0.0073)	(0.0073)	(0.0144)	(0.0396)	(0.0086)	(0.0079)	(0.0112)
R^2	2.709%	15.569%	0.462%	18.852%	0.794%	6.947%	25.038%	27.520%	4.391%	13.022%	0.226%	9.958%
GSO	0.0107[c]	0.0351[a]	-0.0058	-0.0193[a]	-0.0023	0.0060	-0.0217[a]	0.0519[a]	0.0531[c]	-0.0186[a]	-0.0029	0.0102
	(0.0059)	(0.0106)	(0.0050)	(0.0043)	(0.0172)	(0.0046)	(0.0045)	(0.0085)	(0.0288)	(0.0048)	(0.0048)	(0.0076)
R^2	1.542%	6.798%	2.273%	17.274%	0.017%	1.462%	21.064%	17.638%	6.333%	8.243%	0.337%	1.489%
GSL	-0.0073[b]	-0.0105[b]	-0.0014	-0.0041[b]	0.0127	0.0065a	0.0011	-0.0037	0.0104	0.0027	0.0001	-0.0018
	(0.0031)	(0.0050)	(0.0015)	(0.0018)	(0.0085)	(0.0024)	(0.0020)	(0.0051)	(0.0093)	(0.0031)	(0.0022)	(0.0038)
R^2	2.648%	2.301%	0.475%	2.916%	1.916%	6.407%	0.185%	0.340%	0.902%	0.657%	0.001%	0.181%
HTO	0.1510[a]	0.2837[a]	-0.0277	-0.0718[a]	-0.0229	0.0059	-0.0760[a]	0.2455[a]	0.1501[c]	-0.0768[b]	-0.0632[a]	0.0160
	(0.0356)	(0.0594)	(0.0182)	(0.0246)	(0.0731)	(0.0219)	(0.0284)	(0.0586)	(0.0904)	(0.0300)	(0.0213)	(0.0367)
R^2	9.208%	13.399%	1.578%	7.231%	0.050%	0.042%	7.802%	11.900%	1.521%	4.244%	4.842%	0.110%
NGS	0.0046	0.0235	-0.0013	-0.0033	0.0425[c]	-0.0110[c]	0.0062	0.0226[c]	0.0575[b]	-0.0324[a]	-0.0207[a]	0.0119
	(0.0100)	(0.0155)	(0.0043)	(0.0041)	(0.0226)	(0.0061)	(0.0042)	(0.0135)	(0.0282)	(0.0071)	(0.0064)	(0.0120)
R^2	0.132%	1.437%	0.053%	0.239%	2.693%	2.315%	0.816%	1.564%	3.477%	11.730%	8.078%	0.950%

Table A.1. 3: U.S. industry betas and energy commodity uncertainties (Shale oil revolution sub-sample 1/1/2014 - 31/12/2016)

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \mathcal{E}_d^i$ using SOR sub-sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), and Natural Gas (NGS).

	BMT	**BRS**	**CNG**	**CNS**	**FIN**	**HLT**	**IND**	**OGS**	**RLS**	**TEC**	**TEL**	**UTL**
WTI	0.0093	0.0618[a]	-0.0311[a]	-0.0299[a]	0.0371[a]	-0.0032	-0.0587[a]	0.1246[a]	0.0295[a]	-0.0331[a]	-0.0343[a]	-0.0211
	(0.0078)	(0.0151)	(0.0052)	(0.0078)	(0.0072)	(0.0062)	(0.0095)	(0.0224)	(0.0099)	(0.0081)	(0.0065)	(0.0145)
R^2	0.5436%	8.1095%	11.8545%	14.7823%	9.6658%	0.0809%	24.0651%	28.6073%	2.5922%	9.3397%	7.3673%	1.0317%
BRT	0.0332[b]	0.0681[a]	-0.0093	-0.0524[a]	0.0120	-0.0144	-0.0691[a]	0.0993[a]	-0.0112	-0.0311[a]	-0.0405[a]	0.0321
	(0.0148)	(0.0255)	(0.0113)	(0.0104)	(0.0135)	(0.0111)	(0.0139)	(0.0280)	(0.0216)	(0.0119)	(0.0125)	(0.0241)
R^2	2.6228%	3.7382%	0.4022%	17.2255%	0.3844%	0.6172%	12.6067%	6.8663%	0.1425%	3.1328%	3.8878%	0.9019%
GSO	0.0155[c]	0.0510[a]	0.0013	-0.0362[a]	0.0211[b]	-0.0152[c]	-0.0417[a]	0.0785[a]	0.0195	-0.0346[a]	-0.0174[b]	0.0133
	(0.0089)	(0.0137)	(0.0080)	(0.0072)	(0.0105)	(0.0090)	(0.0087)	(0.0176)	(0.0133)	(0.0093)	(0.0079)	(0.0164)
R^2	1.4216%	5.2466%	0.0212%	20.6294%	2.9600%	1.7124%	11.5287%	10.7607%	1.0757%	9.6979%	1.7948%	0.3852%
GSL	0.0088[b]	0.0282[a]	-0.0019	-0.0169[a]	0.0146[a]	-0.0119[a]	-0.0229[a]	0.0350[a]	0.0112[c]	-0.0135[a]	-0.0127[a]	0.0002
	(0.0045)	(0.0074)	(0.0037)	(0.0032)	(0.0045)	(0.0037)	(0.0044)	(0.0094)	(0.0068)	(0.0038)	(0.0044)	(0.0081)
R^2	1.9710%	6.8631%	0.1851%	19.1834%	6.1053%	4.5074%	14.9120%	9.1990%	1.5150%	6.3458%	4.0718%	0.0004%
HTO	0.0533[b]	0.1685[a]	-0.0049	-0.0889[a]	0.0468	-0.0299	-0.1142[a]	0.2142[a]	0.0763[b]	-0.0939[a]	-0.0225	0.0434
	(0.0260)	(0.0448)	(0.0188)	(0.0261)	(0.0304)	(0.0231)	(0.0302)	(0.0642)	(0.0347)	(0.0210)	(0.0195)	(0.0426)
R^2	1.7413%	5.9084%	0.0290%	12.8349%	1.5047%	0.6832%	8.9096%	8.2687%	1.6972%	7.3623%	0.3104%	0.4263%
NGS	0.0114[b]	0.0138	-0.0007	-0.0022	0.0045	0.0028	-0.0015	0.0235[b]	0.0001	-0.0138[a]	0.0029	0.0056
	(0.0051)	(0.0100)	(0.0048)	(0.0035)	(0.0061)	(0.0037)	(0.0063)	(0.0113)	(0.0064)	(0.0043)	(0.0052)	(0.0073)
R^2	2.2025%	1.0920%	0.0164%	0.2105%	0.3922%	0.1607%	0.0450%	2.7482%	0.0001%	4.4124%	0.1379%	0.1965%

Table A.1. 4: U.S. industry betas and energy commodity uncertainties (Full sample with control variables)

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using full sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), Natural Gas (NGS), CBOE SPX Volatility Index (VIX), U.S. 10-year treasury bond index (BOND), U.S. Economic Policy Uncertainty Index (EPU), and U.S. Geopolitical Risk Index (GPR).

	BMT		**BRE**		**CNG**		**CNS**		**FIN**		**HLT**	
WTI	**0.0014**	**(0.0052)**	**0.0307[a]**	**(0.0086)**	**-0.0343[a]**	**(0.0034)**	**-0.0179[a]**	**(0.0023)**	**0.0823[a]**	**(0.0130)**	**-0.0341[a]**	**(0.0049)**
VIX	0.0002	(0.0004)	0.0004	(0.0006)	0.0005[b]	(0.0003)	0.0000	(0.0002)	0.0003	(0.0005)	-0.0002	(0.0004)
BOND	0.0082	(0.0063)	0.0030	(0.0094)	-0.0016	(0.0043)	0.0003	(0.0026)	-0.0138	(0.0110)	0.0001	(0.0063)
EPU	0.0385[a]	(0.0097)	0.0229	(0.0150)	-0.0263[a]	(0.0062)	-0.0294[a]	(0.0053)	0.0997[a]	(0.0145)	-0.0558[a]	(0.0092)
GPR	-0.0486[a]	(0.0080)	-0.0506a	(0.0110)	0.0194[a]	(0.0044)	0.0113[a]	(0.0032)	-0.0505[a]	(0.0095)	0.0427[a]	(0.0067)
R^2	7.061%		5.777%		24.053%		17.449%		24.947%		20.020%	
BRT	**0.0198[a]**	**(0.0057)**	**0.0553[a]**	**(0.0095)**	**-0.0373[a]**	**(0.0062)**	**-0.0200[a]**	**(0.0049)**	**0.0651[a]**	**(0.0188)**	**-0.0469[a]**	**(0.0073)**
VIX	0.0002	(0.0004)	0.0005	(0.0006)	0.0005[c]	(0.0003)	-0.0001	(0.0002)	0.0004	(0.0006)	-0.0003	(0.0004)
BOND	0.0067	(0.0063)	0.0002	(0.0091)	-0.0004	(0.0044)	0.0010	(0.0027)	-0.0148	(0.0125)	0.0020	(0.0063)
EPU	0.0368[a]	(0.0097)	0.0243	(0.0148)	-0.0304[a]	(0.0067)	-0.0315[a]	(0.0056)	0.1120[a]	(0.0172)	-0.0588[a]	(0.0090)
GPR	-0.0474[a]	(0.0078)	-0.0470a	(0.0106)	0.0170[a]	(0.0043)	0.0100[a]	(0.0032)	-0.0462[a]	(0.0097)	0.0397[a]	(0.0063)
R^2	8.794%		9.169%		20.265%		16.004%		15.849%		22.323%	
GSO	**0.0112[a]**	**(0.0043)**	**0.0346[a]**	**(0.0068)**	**-0.0271[a]**	**(0.0042)**	**-0.0162[a]**	**(0.0026)**	**0.0582[a]**	**(0.0135)**	**-0.0359[a]**	**(0.0059)**
VIX	0.0002	(0.0004)	0.0003	(0.0006)	0.0006[b]	(0.0003)	0.0000	(0.0002)	0.0002	(0.0006)	-0.0001	(0.0004)
BOND	0.0079	(0.0064)	0.0034	(0.0093)	-0.0025	(0.0045)	-0.0001	(0.0027)	-0.0115	(0.0124)	-0.0005	(0.0064)
EPU	0.0357[a]	(0.0096)	0.0204	(0.0145)	-0.0267[a]	(0.0067)	-0.0290[a]	(0.0055)	0.1026[a]	(0.0165)	-0.0537[a]	(0.0090)
GPR	-0.0477[a]	(0.0079)	-0.0477a	(0.0108)	0.0171[a]	(0.0043)	0.0099[a]	(0.0032)	-0.0456[a]	(0.0093)	0.0397[a]	(0.0062)
R^2	8.245%		8.094%		21.994%		18.985%		20.415%		25.044%	
GSL	**0.0048[b]**	**(0.0023)**	**0.0112[a]**	**(0.0037)**	**-0.0143[a]**	**(0.0012)**	**-0.0059[a]**	**(0.0010)**	**0.0351[a]**	**(0.0041)**	**-0.0196[a]**	**(0.0020)**
VIX	0.0002	(0.0004)	0.0004	(0.0006)	0.0006[b]	(0.0003)	0.0000	(0.0002)	0.0002	(0.0005)	-0.0002	(0.0003)
BOND	0.0072	(0.0064)	0.0019	(0.0096)	0.0000	(0.0041)	0.0008	(0.0027)	-0.0178[c]	(0.0108)	0.0029	(0.0058)
EPU	0.0352[a]	(0.0098)	0.0215	(0.0152)	-0.0235[a]	(0.0064)	-0.0291[a]	(0.0054)	0.0923[a]	(0.0148)	-0.0489[a]	(0.0083)
GPR	-0.0456[a]	(0.0078)	-0.0435a	(0.0108)	0.0103[a]	(0.0037)	0.0075[b]	(0.0034)	-0.0282[a]	(0.0087)	0.0303[a]	(0.0055)
R^2	8.387%		6.236%		33.243%		16.979%		34.164%		36.345%	
HTO	**0.0478[a]**	**(0.0106)**	**0.0866[a]**	**(0.0192)**	**-0.0200[b]**	**(0.0098)**	**-0.0165[b]**	**(0.0078)**	**0.0234**	**(0.0195)**	**-0.0293[a]**	**(0.0094)**
VIX	0.0002	(0.0004)	0.0004	(0.0006)	0.0005[b]	(0.0003)	0.0000	(0.0002)	0.0003	(0.0006)	-0.0002	(0.0004)
BOND	0.0072	(0.0062)	0.0025	(0.0094)	-0.0029	(0.0051)	-0.0002	(0.0031)	-0.0102	(0.0134)	-0.0010	(0.0067)

EPU	0.0362[a]	(0.0096)	0.0253[c]	(0.0151)	-0.0331[a]	(0.0074)	-0.0326[a]	(0.0059)	0.1174[a]	(0.0185)	-0.0620[a]	(0.0099)
GPR	-0.0475[a]	(0.0079)	-0.0484[a]	(0.0108)	0.0189[a]	(0.0047)	0.0108[a]	(0.0033)	-0.0498[a]	(0.0102)	0.0420[a]	(0.0067)
R^2	9.229%		6.176%		6.957%		9.432%		9.468%		12.233%	
NGS	**0.0126[b]**	**(0.0054)**	**0.0263[a]**	**(0.0086)**	**-0.0186[a]**	**(0.0042)**	**-0.0067[b]**	**(0.0026)**	**0.0498[a]**	**(0.0102)**	**-0.0264[a]**	**(0.0062)**
VIX	0.0002	(0.0004)	0.0004	(0.0006)	0.0006[c]	(0.0003)	0.0000	(0.0002)	0.0003	(0.0006)	-0.0002	(0.0004)
BOND	0.0077	(0.0063)	0.0033	(0.0095)	-0.0025	(0.0048)	-0.0003	(0.0030)	-0.0119	(0.0126)	-0.0005	(0.0064)
EPU	0.0399[a]	(0.0097)	0.0322[b]	(0.0153)	-0.0358[a]	(0.0071)	-0.0341[a]	(0.0059)	0.1230[a]	(0.0176)	-0.0659[a]	(0.0093)
GPR	-0.0465[a]	(0.0078)	-0.0460[a]	(0.0109)	0.0162[a]	(0.0046)	0.0101[a]	(0.0034)	-0.0418[a]	(0.0096)	0.0381[a]	(0.0063)
R^2	8.231%		5.259%		11.963%		9.778%		15.713%		17.154%	

Table A.1.4: Continue …

	IND		OGS		RLT		TEC		TEL		UTL	
WTI	**-0.0421[a]**	**(0.0036)**	**0.0185[b]**	**(0.0075)**	**0.1308[a]**	**(0.0172)**	**-0.0350[a]**	**(0.0040)**	**-0.0039**	**(0.0040)**	**0.0022**	**(0.0065)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0004	(0.0008)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0020	(0.0043)	0.0087	(0.0069)	-0.0105	(0.0159)	-0.0045	(0.0049)	-0.0038	(0.0045)	-0.0024	(0.0068)
EPU	-0.0032	(0.0066)	0.0071	(0.0121)	0.0695[a]	(0.0226)	-0.0226[a]	(0.0080)	-0.0382[a]	(0.0081)	-0.0253[c]	(0.0142)
GPR	0.0061	(0.0047)	-0.0101	(0.0096)	-0.0834[a]	(0.0141)	0.0324[a]	(0.0052)	0.0084	(0.0054)	-0.0138	(0.0082)
R^2	26.006%		2.100%		25.483%		19.005%		5.053%		0.944%	
BRT	**-0.0439[a]**	**(0.0086)**	**0.0211[a]**	**(0.0065)**	**0.1526[a]**	**(0.0295)**	**-0.0388[a]**	**(0.0085)**	**0.0028**	**(0.0053)**	**0.0194[b]**	**(0.0078)**
VIX	0.0014[a]	(0.0003)	-0.0004	(0.0005)	-0.0002	(0.0009)	0.0010[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0007	(0.0041)	0.0080	(0.0067)	-0.0160	(0.0167)	-0.0032	(0.0048)	-0.0042	(0.0045)	-0.0038	(0.0067)
EPU	-0.0084	(0.0073)	0.0092	(0.0120)	0.0840[a]	(0.0236)	-0.0267[a]	(0.0083)	-0.0394[a]	(0.0079)	-0.0268[c]	(0.0140)
GPR	0.0033	(0.0051)	-0.0088	(0.0098)	-0.0735[a]	(0.0138)	0.0299[a]	(0.0054)	0.0086	(0.0054)	-0.0125	(0.0081)
R^2	19.327%		1.878%		23.676%		16.697%		4.917%		2.565%	
GSO	**-0.0334[a]**	**(0.0036)**	**0.0124[b]**	**(0.0050)**	**0.1217[a]**	**(0.0197)**	**-0.0297[a]**	**(0.0041)**	**0.0041**	**(0.0032)**	**0.0120[a]**	**(0.0046)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0007	(0.0008)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0030	(0.0041)	0.0092	(0.0068)	-0.0079	(0.0164)	-0.0053	(0.0047)	-0.0041	(0.0045)	-0.0027	(0.0067)
EPU	-0.0037	(0.0070)	0.0079	(0.0120)	0.0660[a]	(0.0220)	-0.0225[a]	(0.0081)	-0.0402[a]	(0.0080)	-0.0281[b]	(0.0139)
GPR	0.0033	(0.0049)	-0.0091	(0.0098)	-0.0732[a]	(0.0134)	0.0299[a]	(0.0054)	0.0088	(0.0054)	-0.0128	(0.0082)
R^2	23.450%		1.469%		30.137%		19.336%		5.167%		2.254%	
GSL	**-0.0115[a]**	**(0.0015)**	**-0.0039**	**(0.0030)**	**0.0564[a]**	**(0.0048)**	**-0.0115[a]**	**(0.0017)**	**0.0007**	**(0.0014)**	**0.0034[c]**	**(0.0019)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0006	(0.0008)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0015	(0.0046)	0.0105	(0.0070)	-0.0171	(0.0160)	-0.0036	(0.0049)	-0.0041	(0.0045)	-0.0031	(0.0067)
EPU	-0.0043	(0.0073)	0.0143	(0.0123)	0.0573[a]	(0.0200)	-0.0220[a]	(0.0079)	-0.0396[a]	(0.0081)	-0.0273[c]	(0.0140)
GPR	-0.0012	(0.0053)	-0.0126	(0.0097)	0.0476[a]	(0.0130)	0.0251[a]	(0.0057)	0.0089	(0.0053)	-0.0116	(0.0082)
R^2	17.398%		1.057%		38.089%		18.280%		4.900%		1.570%	

HTO	**-0.0199**	**(0.0134)**	**0.0555[a]**	**(0.0134)**	**0.0462**	**(0.0293)**	**-0.0195[c]**	**(0.0110)**	**-0.0082**	**(0.0058)**	**-0.0177[c]**	**(0.0091)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0005	(0.0009)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0037	(0.0054)	0.0083	(0.0069)	-0.0050	(0.0202)	-0.0058	(0.0057)	-0.0038	(0.0045)	-0.0019	(0.0068)
EPU	-0.0118	(0.0087)	0.0084	(0.0120)	0.0972[a]	(0.0264)	-0.0296[a]	(0.0090)	-0.0386[a]	(0.0080)	-0.0238[c]	(0.0142)
GPR	0.0056	(0.0056)	-0.0088	(0.0097)	-0.0821[a]	(0.0155)	0.0319[a]	(0.0057)	0.0082	(0.0054)	-0.0142	(0.0082)
R^2	2.248%		2.591%		5.644%		6.588%		4.977%		1.208%	
NGS	**-0.0129[a]**	**(0.0038)**	**0.0094**	**(0.0058)**	**0.0852[a]**	**(0.0161)**	**-0.0247[a]**	**(0.0040)**	**-0.0028**	**(0.0032)**	**0.0075**	**(0.0057)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0054	(0.0010)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0005)
BOND	-0.0035	(0.0053)	0.0092	(0.0069)	-0.0078	(0.0191)	-0.0051	(0.0054)	-0.0039	(0.0045)	-0.0026	(0.0068)
EPU	-0.0140	(0.0085)	0.0122	(0.0122)	0.1071[a]	(0.0251)	-0.0329[a]	(0.0087)	-0.0393[a]	(0.0079)	-0.0241[c]	(0.0141)
GPR	0.0039	(0.0055)	-0.0085	(0.0098)	-0.0686[a]	(0.0144)	0.0281[a]	(0.0054)	0.0079	(0.0053)	-0.0125	(0.0080)
R^2	4.059%		0.871%		14.890%		13.268%		4.963%		1.328%	

Table A.1. 5: U.S. industry betas and energy commodity uncertainties with control variables (GFC) 1/8/2007 - 30/6/2009

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using GFC sub-sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), Natural Gas (NGS), CBOE SPX Volatility Index (VIX), U.S. 10-year treasury bond index (BOND), U.S. Economic Policy Uncertainty Index (EPU), and U.S. Geopolitical Risk Index (GPR).

	BMT		**BRE**		**CNG**		**CNS**		**FIN**		**HLT**	
WTI	**0.0082**	**(0.0069)**	**0.0446^a**	**(0.0114)**	**-0.0096^b**	**(0.0039)**	**-0.0119^a**	**(0.0029)**	**0.0160**	**(0.0167)**	**0.0002**	**(0.0046)**
VIX	-0.0004	(0.0009)	-0.0012	(0.0013)	0.0002	(0.0004)	-0.0009^b	(0.0004)	0.0005	(0.0017)	-0.0001	(0.0005)
BOND	0.0128	(0.0109)	0.0266	(0.0174)	0.0089^c	(0.0050)	0.0011	(0.0038)	-0.0492^b	(0.0229)	0.0195^a	(0.0067)
EPU	0.0181	(0.0238)	0.0033	(0.0349)	-0.0147	(0.0099)	-0.0472^a	(0.0125)	0.0911^b	(0.0465)	0.0010	(0.0133)
GPR	-0.0291	(0.0199)	-0.0176	(0.0297)	0.0053	(0.0073)	0.0224^b	(0.0108)	-0.0098	(0.0335)	0.0024	(0.0092)
R^2	3.0304%		11.4267%		10.9478%		24.1728%		4.9736%		1.6270%	
BRT	**0.0209^b**	**(0.0101)**	**0.0905^a**	**(0.0163)**	**0.0044**	**(0.0082)**	**-0.0244^a**	**(0.0056)**	**-0.0688^a**	**(0.0254)**	**0.0285^a**	**(0.0078)**
VIX	-0.0003	(0.0009)	-0.0009	(0.0013)	0.0001	(0.0005)	-0.0010^b	(0.0004)	0.0007	(0.0017)	-0.0001	(0.0005)
BOND	0.0107	(0.0111)	0.0185	(0.0172)	0.0074	(0.0053)	0.0033	(0.0043)	-0.0384^c	(0.0221)	0.0157^b	(0.0062)
EPU	0.0113	(0.0205)	-0.0093	(0.0297)	-0.0369^a	(0.0111)	-0.0435^a	(0.0110)	0.1929^a	(0.0434)	-0.0284^b	(0.0114)
GPR	-0.0306	(0.0195)	-0.0246	(0.0279)	0.0056	(0.0074)	0.0242^b	(0.0103)	-0.0071	(0.0334)	0.0009	(0.0091)
R^2	3.9508%		15.7360%		6.8108%		26.9599%		8.4225%		10.4117%	
GSO	**0.0080**	**(0.0059)**	**0.0307^a**	**(0.0105)**	**-0.0015**	**(0.0055)**	**-0.0131a**	**(0.0043)**	**-0.0239**	**(0.0170)**	**0.0079**	**(0.0050)**
VIX	-0.0004	(0.0009)	-0.0012	(0.0014)	0.0001	(0.0005)	-0.0009^b	(0.0004)	0.0009	(0.0017)	-0.0002	(0.0005)
BOND	0.0132	(0.0111)	0.0295^c	(0.0178)	0.0080	(0.0051)	0.0005	(0.0044)	-0.0467^b	(0.0221)	0.0192^a	(0.0064)
EPU	0.0188	(0.0229)	0.0298	(0.0362)	-0.0295^a	(0.0113)	-0.0454^a	(0.0125)	0.1643^a	(0.0492)	-0.0129	(0.0129)
GPR	-0.0298	(0.0198)	-0.0211	(0.0299)	0.0059	(0.0074)	0.0235^b	(0.0107)	-0.0097	(0.0333)	0.0020	(0.0091)
R^2	3.0275%		7.5704%		6.5818%		25.4979%		5.7705%		3.5307%	
GSL	**-0.0105^a**	**(0.0033)**	**-0.0172^a**	**(0.0050)**	**0.0003**	**(0.0015)**	**-0.0005**	**(0.0015)**	**0.0076**	**(0.0089)**	**0.0074^a**	**(0.0023)**
VIX	-0.0001	(0.0009)	-0.0004	(0.0014)	0.0001	(0.0005)	-0.0010^b	(0.0004)	0.0005	(0.0018)	-0.0003	(0.0005)
BOND	0.0148	(0.0100)	0.0327^b	(0.0167)	0.0079	(0.0051)	0.0000	(0.0043)	-0.0485^b	(0.0226)	0.0187^a	(0.0064)
EPU	0.0596^b	(0.0236)	0.1286^a	(0.0398)	-0.0332^a	(0.0112)	-0.0679^a	(0.0109)	0.1018^c	(0.0552)	-0.0169	(0.0128)
GPR	-0.0322	(0.0197)	-0.0244	(0.0303)	0.0059	(0.0074)	0.0228^b	(0.0109)	-0.0087	(0.0341)	0.0043	(0.0084)
R^2	7.2867%		8.9970%		6.4845%		19.5574%		4.9948%		8.8545%	
HTO	**0.1453^a**	**(0.0337)**	**0.2637^a**	**(0.0555)**	**-0.0171**	**(0.0165)**	**-0.0502^a**	**(0.0194)**	**-0.0666**	**(0.0676)**	**0.0040**	**(0.0222)**
VIX	-0.0002	(0.0008)	-0.0006	(0.0013)	0.0001	(0.0005)	-0.0011^b	(0.0004)	0.0006	(0.0018)	-0.0001	(0.0005)
BOND	0.0076	(0.0099)	0.0199	(0.0161)	0.0087^c	(0.0051)	0.0020	(0.0045)	-0.0449^c	(0.0232)	0.0194^a	(0.0066)

EPU	0.0124	(0.0206)	0.0479	(0.0327)	-0.0299[a]	(0.0111)	-0.0619[a]	(0.0111)	0.1302[a]	(0.0503)	0.0009	(0.0139)
GPR	-0.0301	(0.0189)	-0.0210	(0.0285)	0.0059	(0.0073)	0.0232[b]	(0.0105)	-0.0104	(0.0336)	0.0023	(0.0092)
R^2	10.4598%		14.6295%		7.0397%		22.8775%		4.7992%		1.6444%	
NGS	**0.0047**	**(0.0100)**	**0.0245**	**(0.0155)**	**-0.0012**	**(0.0039)**	**-0.0040**	**(0.0035)**	**0.0429[b]**	**(0.0207)**	**-0.0106[c]**	**(0.0059)**
VIX	-0.0003	(0.0009)	-0.0006	(0.0014)	0.0001	(0.0005)	-0.0010[b]	(0.0005)	0.0009	(0.0018)	-0.0002	(0.0005)
BOND	0.0138	(0.0110)	0.0319[c]	(0.0180)	0.0079	(0.0051)	-0.0002	(0.0043)	-0.0457[b]	(0.0226)	0.0191[a]	(0.0066)
EPU	0.0337	(0.0227)	0.0881[b]	(0.0381)	-0.0324[a]	(0.0109)	-0.0695[a]	(0.0114)	0.1250[b]	(0.0508)	0.0004	(0.0135)
GPR	-0.0291	(0.0197)	-0.0178	(0.0298)	0.0057	(0.0075)	0.0226[b]	(0.0109)	-0.0070	(0.0335)	0.0014	(0.0091)
R^2	2.5276%		5.1966%		6.5067%		19.8740%		7.1411%		3.7769%	

Table A.1.5: Continue…

	IND		**OGS**		**RLT**		**TEC**		**TEL**		**UTL**	
WTI	**-0.0224[a]**	**(0.0048)**	**0.0383[a]**	**(0.0103)**	**0.0587[b]**	**(0.0241)**	**-0.0249[a]**	**(0.0055)**	**-0.0088[b]**	**(0.0046)**	**0.0046**	**(0.0075)**
VIX	0.0015a	(0.0005)	-0.0009	(0.0011)	-0.0037	(0.0023)	0.0011[c]	(0.0006)	0.0000	(0.0005)	0.0006	(0.0009)
BOND	-0.0053	(0.0063)	0.0180	(0.0136)	-0.0196	(0.0289)	-0.0027	(0.0074)	0.0076	(0.0066)	0.0162c	(0.0094)
EPU	-0.0006	(0.0111)	0.0610[b]	(0.0323)	0.0893	(0.0613)	0.0019	(0.0180)	-0.0015	(0.0136)	-0.0067	(0.0283)
GPR	-0.0052	(0.0079)	-0.0164	(0.0273)	0.0281	(0.0351)	0.0081	(0.0138)	0.0070	(0.0100)	-0.0061	(0.0169)
R^2	22.9117%		15.6296%		12.4968%		14.4573%		3.6497%		0.8411%	
BRT	**-0.0389[a]**	**(0.0080)**	**0.1044[a]**	**(0.0138)**	**0.0376**	**(0.0444)**	**-0.0384[a]**	**(0.0099)**	**0.0003**	**(0.0087)**	**0.0584[a]**	**(0.0134)**
VIX	0.0014[a]	(0.0005)	-0.0007	(0.0010)	-0.0033	(0.0024)	0.0009	(0.0006)	0.0000	(0.0005)	0.0005	(0.0008)
BOND	-0.0021	(0.0053)	0.0075	(0.0122)	-0.0192	(0.0293)	0.0001	(0.0071)	0.0067	(0.0067)	0.0087	(0.0092)
EPU	-0.0011	(0.0104)	0.0220	(0.0256)	0.1581[b]	(0.0612)	-0.0038	(0.0172)	-0.0180	(0.0133)	-0.0595[b]	(0.0288)
GPR	-0.0020	(0.0079)	-0.0238	(0.0242)	0.0232	(0.0369)	0.0114	(0.0145)	0.0074	(0.0103)	-0.0093	(0.0159)
R^2	25.1588%		27.9210%		7.8602%		13.3854%		1.4534%		13.7600%	
GSO	**-0.0209[a]**	**(0.0049)**	**0.0452[a]**	**(0.0078)**	**0.0342**	**(0.0313)**	**-0.0163[a]**	**(0.0052)**	**-0.0006**	**(0.0053)**	**0.0133[c]**	**(0.0075)**
VIX	0.0016[a]	(0.0005)	-0.0012	(0.0011)	-0.0037	(0.0025)	0.0011[c]	(0.0006)	0.0000	(0.0005)	0.0004	(0.0009)
BOND	-0.0065	(0.0054)	0.0197	(0.0129)	-0.0156	(0.0305)	-0.0044	(0.0070)	0.0068	(0.0067)	0.0160[c]	(0.0092)
EPU	-0.0039	(0.0108)	0.0493	(0.0310)	0.1354[b]	(0.0614)	-0.0143	(0.0170)	-0.0167	(0.0130)	-0.0225	(0.0273)
GPR	-0.0032	(0.0083)	-0.0202	(0.0266)	0.0237	(0.0371)	0.0101	(0.0148)	0.0074	(0.0102)	-0.0068	(0.0167)
R^2	21.7119%		18.9319%		8.9927%		8.7890%		1.4617%		2.5516%	
GSL	**0.0035[c]**	**(0.0020)**	**-0.0119[a]**	**(0.0045)**	**0.0012**	**(0.0096)**	**0.0056[c]**	**(0.0030)**	**0.0012**	**(0.0022)**	**-0.0023**	**(0.0037)**
VIX	0.0013[b]	(0.0006)	-0.0004	(0.0012)	-0.0033	(0.0024)	0.0008	(0.0006)	-0.0001	(0.0005)	0.0006	(0.0009)
BOND	-0.0078	(0.0068)	0.0230[c]	(0.0134)	-0.0143	(0.0306)	-0.0057	(0.0075)	0.0066	(0.0066)	0.0169[c]	(0.0096)
EPU	-0.0505[a]	(0.0109)	0.1613[a]	(0.0360)	0.1946[a]	(0.0592)	-0.0580[a]	(0.0166)	-0.0207[c]	(0.0125)	0.0075	(0.0273)
GPR	-0.0031	(0.0093)	-0.0215	(0.0279)	0.0254	(0.0383)	0.0109	(0.0150)	0.0077	(0.0102)	-0.0069	(0.0171)
R^2	8.5898%		11.8852%		7.0197%		6.4577%		1.6377%		0.8725%	

HTO	**-0.0637[b]**	**(0.0269)**	**0.2084[a]**	**(0.0515)**	**0.0860**	**(0.0799)**	**-0.0650[b]**	**(0.0286)**	**-0.0598[a]**	**(0.0212)**	**0.0160**	**(0.0383)**
VIX	0.0013b	(0.0005)	-0.0004	(0.0011)	-0.0032	(0.0023)	0.0008	(0.0006)	-0.0001	(0.0005)	0.0006	(0.0009)
BOND	-0.0047	(0.0065)	0.0131	(0.0131)	-0.0177	(0.0302)	-0.0024	(0.0075)	0.0092	(0.0062)	0.0159	(0.0098)
EPU	-0.0327[a]	(0.0114)	0.1017[a]	(0.0324)	0.1852[a]	(0.0536)	-0.0347[b]	(0.0149)	-0.0092	(0.0121)	-0.0005	(0.0294)
GPR	-0.0038	(0.0087)	-0.0193	(0.0264)	0.0247	(0.0376)	0.0097	(0.0147)	0.0077	(0.0101)	-0.0064	(0.0169)
R^2	12.0715%		16.9775%		7.4868%		6.8675%		5.5833%		0.7304%	
NGS	**0.0060**	**(0.0041)**	**0.0241[c]**	**(0.0132)**	**0.0591[b]**	**(0.0247)**	**-0.0329[a]**	**(0.0068)**	**-0.0206[a]**	**(0.0062)**	**0.0126**	**(0.0118)**
VIX	0.0014[b]	(0.0006)	-0.0005	(0.0012)	-0.0028	(0.0025)	0.0006	(0.0006)	-0.0002	(0.0005)	0.0007	(0.0009)
BOND	-0.0071	(0.0067)	0.0227	(0.0138)	-0.0114	(0.0300)	-0.0066	(0.0071)	0.0058	(0.0064)	0.0172[c]	(0.0097)
EPU	-0.0413[a]	(0.0118)	0.1340[a]	(0.0350)	0.2034[a]	(0.0539)	-0.0473[a]	(0.0151)	-0.0198	(0.0124)	0.0030	(0.0273)
GPR	-0.0035	(0.0094)	-0.0163	(0.0274)	0.0301	(0.0378)	0.0066	(0.0138)	0.0057	(0.0096)	-0.0052	(0.0163)
R^2	7.5604%		10.6277%		10.6956%		16.0964%		9.4856%		1.6916%	

Table A.1. 6: U.S. industry betas and energy commodity uncertainties with control variables (SOR) 1/1/2014 - 31/12/2016

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \mathcal{E}_d^i$ using SOR sub-sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), Natural Gas (NGS), CBOE SPX Volatility Index (VIX), U.S. 10-year treasury bond index (BOND), U.S. Economic Policy Uncertainty Index (EPU), and U.S. Geopolitical Risk Index (GPR).

	BMT		BRE		CNG		CNS		FIN		HLT	
WTI	**0.009**	**(0.007)**	**0.061[a]**	**(0.016)**	**-0.030[a]**	**(0.005)**	**-0.030[a]**	**(0.008)**	**0.040[a]**	**(0.007)**	**-0.004**	**(0.006)**
VIX	0.000	(0.001)	0.002[c]	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	0.000	(0.000)
BOND	0.019[c]	(0.011)	-0.015	(0.018)	-0.003	(0.009)	-0.002	(0.006)	0.009	(0.012)	-0.009	(0.012)
EPU	-0.027[b]	(0.013)	-0.042[b]	(0.021)	0.016[c]	(0.009)	-0.013[c]	(0.007)	0.072[a]	(0.018)	-0.005	(0.018)
GPR	-0.041[a]	(0.011)	-0.037[b]	(0.016)	0.002	(0.007)	-0.005	(0.005)	-0.001	(0.009)	-0.002	(0.007)
R^2	6.253%		10.583%		12.685%		15.701%		19.104%		0.426%	
BRT	**0.032[b]**	**(0.014)**	**0.068[a]**	**(0.025)**	**-0.009**	**(0.011)**	**-0.053[a]**	**(0.010)**	**0.010**	**(0.012)**	**-0.015**	**(0.011)**
VIX	0.000	(0.001)	0.002[c]	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	0.000	(0.000)
BOND	0.018[c]	(0.011)	-0.017	(0.018)	-0.002	(0.009)	-0.001	(0.006)	0.008	(0.013)	-0.009	(0.012)
EPU	-0.030[b]	(0.012)	-0.054[b]	(0.021)	0.020[b]	(0.010)	-0.007	(0.007)	0.066[a]	(0.018)	-0.004	(0.017)
GPR	-0.039[a]	(0.010)	-0.032[c]	(0.017)	0.000	(0.006)	-0.009[c]	(0.005)	0.001	(0.009)	-0.003	(0.007)
R^2	8.222%		6.475%		1.851%		17.930%		8.352%		0.968%	
GSO	**0.017[b]**	**(0.009)**	**0.052[a]**	**(0.013)**	**0.001**	**(0.008)**	**-0.036[a]**	**(0.007)**	**0.021[b]**	**(0.010)**	**-0.015[c]**	**(0.009)**
VIX	0.000	(0.001)	0.001	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	0.000	(0.000)
BOND	0.018[c]	(0.011)	-0.017	(0.018)	-0.002	(0.009)	-0.001	(0.006)	0.008	(0.013)	-0.009	(0.012)
EPU	-0.029[b]	(0.012)	-0.051[b]	(0.021)	0.020[b]	(0.010)	-0.009	(0.007)	0.066[a]	(0.018)	-0.005	(0.017)
GPR	-0.042[a]	(0.011)	-0.038[b]	(0.017)	0.000	(0.007)	-0.004	(0.005)	-0.001	(0.009)	-0.001	(0.007)
R^2	7.374%		8.162%		1.459%		21.078%		11.052%		2.012%	
GSL	**0.009[b]**	**(0.004)**	**0.028[a]**	**(0.007)**	**-0.002**	**(0.004)**	**-0.017[a]**	**(0.003)**	**0.014[a]**	**(0.004)**	**-0.012[a]**	**(0.004)**
VIX	0.000	(0.001)	0.002[c]	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	-0.001	(0.000)
BOND	0.018[c]	(0.011)	-0.017	(0.017)	-0.002	(0.009)	-0.002	(0.006)	0.008	(0.013)	-0.009	(0.012)
EPU	-0.030[b]	(0.012)	-0.056[a]	(0.020)	0.020[b]	(0.010)	-0.006	(0.007)	0.064[a]	(0.018)	-0.003	(0.017)
GPR	-0.039[a]	(0.011)	-0.031[c]	(0.017)	0.000	(0.006)	-0.009[c]	(0.005)	0.002	(0.009)	-0.004	(0.007)
R^2	7.650%		9.691%		1.640%		19.833%		13.603%		4.910%	
HTO	**0.051[b]**	**(0.024)**	**0.171[a]**	**(0.043)**	**-0.008**	**(0.019)**	**-0.090[a]**	**(0.027)**	**0.038**	**(0.031)**	**-0.030**	**(0.023)**
VIX	0.000	(0.001)	0.002	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	0.000	(0.000)
BOND	0.019[c]	(0.011)	-0.017	(0.018)	-0.002	(0.009)	-0.002	(0.006)	0.008	(0.013)	-0.009	(0.012)

EPU	-0.031^{b}	(0.013)	-0.060^{a}	(0.021)	0.021^{b}	(0.010)	-0.004	(0.007)	0.064^{a}	(0.019)	-0.003	(0.017)
GPR	-0.038^{a}	(0.011)	-0.028^{c}	(0.017)	0.000	(0.006)	-0.010^{c}	(0.005)	0.002	(0.009)	-0.003	(0.007)
R^2	7.322%		8.777%		1.505%		13.591%		9.071%		1.002%	
NGS	**0.009^{c}**	**(0.005)**	**0.013**	**(0.010)**	**-0.001**	**(0.005)**	**-0.003**	**(0.004)**	**0.003**	**(0.006)**	**0.003**	**(0.004)**
VIX	0.000	(0.001)	0.002	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)	0.000	(0.000)
BOND	0.017	(0.011)	-0.018	(0.018)	-0.002	(0.009)	-0.001	(0.007)	0.008	(0.013)	-0.009	(0.012)
EPU	-0.030^{b}	(0.013)	-0.054^{b}	(0.022)	0.020^{b}	(0.010)	-0.008	(0.007)	0.065^{a}	(0.018)	-0.005	(0.017)
GPR	-0.036^{a}	(0.011)	-0.028	(0.018)	0.000	(0.007)	-0.008	(0.006)	0.003	(0.008)	-0.001	(0.007)
R^2	7.197%		3.671%		1.478%		0.910%		8.292%		0.497%	

Table A.1. 6: Continue…

	IND		**OGS**		**RLT**		**TEC**		**TEL**		**UTL**	
WTI	**-0.058^{a}**	**(0.009)**	**0.124^{a}**	**(0.022)**	**0.029^{a}**	**(0.010)**	**-0.032^{a}**	**(0.008)**	**-0.034^{a}**	**(0.006)**	**-0.022**	**(0.015)**
VIX	0.002^{a}	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001b	(0.001)	0.001	(0.001)	0.001	(0.001)
BOND	-0.001	(0.009)	0.021	(0.018)	-0.049^{a}	(0.018)	0.000	(0.009)	-0.020	(0.013)	-0.040^{c}	(0.021)
EPU	0.004	(0.012)	-0.026	(0.016)	-0.010	(0.020)	0.013	(0.012)	-0.011	(0.018)	-0.027	(0.025)
GPR	-0.007	(0.009)	0.012	(0.015)	-0.010	(0.014)	-0.001	(0.009)	-0.009	(0.009)	-0.001	(0.016)
R^2	25.352%		29.244%		3.867%		10.508%		8.141%		2.002%	
BRT	**-0.069^{a}**	**(0.014)**	**0.101^{a}**	**(0.028)**	**-0.011**	**(0.022)**	**-0.031^{a}**	**(0.012)**	**-0.040^{a}**	**(0.012)**	**0.033**	**(0.024)**
VIX	0.002^{a}	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001^{b}	(0.001)	0.001	(0.001)	0.001	(0.001)
BOND	0.001	(0.010)	0.018	(0.020)	-0.050^{a}	(0.018)	0.001	(0.009)	-0.019	(0.013)	-0.040^{c}	(0.021)
EPU	0.014	(0.013)	-0.047a	(0.018)	-0.014	(0.019)	0.019	(0.012)	-0.005	(0.018)	-0.024	(0.026)
GPR	-0.012	(0.010)	0.021	(0.018)	-0.009	(0.014)	-0.004	(0.009)	-0.012	(0.009)	-0.001	(0.017)
R^2	14.663%		8.406%		1.513%		4.864%		4.658%		1.858%	
GSO	**-0.042^{a}**	**(0.009)**	**0.078^{a}**	**(0.018)**	**0.020**	**(0.013)**	**-0.035^{a}**	**(0.009)**	**-0.017^{b}**	**(0.008)**	**0.014**	**(0.016)**
VIX	0.002^{a}	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001^{a}	(0.001)	0.001	(0.001)	0.001	(0.001)
BOND	0.001	(0.010)	0.018	(0.020)	-0.050^{a}	(0.017)	0.001	(0.009)	-0.019	(0.013)	-0.040^{c}	(0.021)
EPU	0.012	(0.012)	-0.044b	(0.018)	-0.014	(0.020)	0.018	(0.012)	-0.006	(0.019)	-0.023	(0.025)
GPR	-0.006	(0.010)	0.011	(0.018)	-0.010	(0.014)	0.000	(0.009)	-0.009	(0.009)	-0.003	(0.016)
R^2	13.598%		11.881%		2.486%		11.478%		2.516%		1.298%	
GSL	**-0.023^{a}**	**(0.004)**	**0.036^{a}**	**(0.009)**	**0.011^{c}**	**(0.007)**	**-0.014^{a}**	**(0.004)**	**-0.012^{a}**	**(0.004)**	**0.001**	**(0.008)**
VIX	0.002a	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001^{b}	(0.001)	0.001	(0.001)	0.001	(0.001)
BOND	0.000	(0.010)	0.018	(0.020)	-0.050^{a}	(0.017)	0.001	(0.009)	-0.019	(0.013)	-0.040^{c}	(0.022)
EPU	0.016	(0.012)	-0.050^{a}	(0.018)	-0.016	(0.020)	0.020	(0.012)	-0.004	(0.018)	-0.024	(0.025)
GPR	-0.012	(0.010)	0.021	(0.018)	-0.007	(0.014)	-0.004	(0.009)	-0.012	(0.009)	-0.002	(0.016)
R^2	16.965%		10.848%		2.886%		8.107%		4.801%		0.893%	

HTO	**-0.119^{a}**	**(0.029)**	**0.225a**	**(0.064)**	**0.078^{b}**	**(0.035)**	**-0.098^{a}**	**(0.021)**	**-0.023**	**(0.020)**	**0.048**	**(0.043)**
VIX	0.002a	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001^{a}	(0.000)	0.001	(0.001)	0.001	(0.001)
BOND	0.000	(0.009)	0.018	(0.020)	-0.050^{a}	(0.017)	0.001	(0.009)	-0.019	(0.013)	-0.040^{c}	(0.021)
EPU	0.018	(0.012)	-0.056^{a}	(0.018)	-0.018	(0.020)	0.023^{c}	(0.012)	-0.005	(0.019)	-0.026	(0.025)
GPR	-0.014	(0.010)	0.025	(0.018)	-0.006	(0.014)	-0.006	(0.009)	-0.012	(0.009)	0.000	(0.017)
R^2	11.684%		10.336%		3.110%		9.695%		1.151%		1.400%	
NGS	**-0.003**	**(0.006)**	**0.026b**	**(0.011)**	**0.000**	**(0.006)**	**-0.015^{a}**	**(0.004)**	**0.002**	**(0.005)**	**0.006**	**(0.007)**
VIX	0.002^{a}	(0.001)	0.000	(0.001)	0.001	(0.001)	0.001^{a}	(0.001)	0.001	(0.001)	0.001	(0.001)
BOND	0.001	(0.010)	0.015	(0.021)	-0.050^{a}	(0.018)	0.002	(0.010)	-0.019	(0.013)	-0.040^{c}	(0.022)
EPU	0.013	(0.013)	-0.050^{a}	(0.019)	-0.014	(0.019)	0.021^{c}	(0.012)	-0.006	(0.018)	-0.025	(0.025)
GPR	-0.011	(0.011)	0.029	(0.018)	-0.008	(0.015)	-0.010	(0.009)	-0.010	(0.009)	0.001	(0.017)
R^2	2.302%		4.612%		1.368%		6.782%		0.932%		1.136%	

Table A.1. 7: U.S. industry betas and energy commodity uncertainties (Full sample with control variables, GFC and SOR dummy)

For each industry beta, the estimated parameters are obtained by applying the OLS regression $BETA_d^i = \propto_i + \lambda_i U_{d-1}^{EN} + \theta_i CV_{d-1} + \eta_1 D(GFC) + \eta_2 D(SOR) + \mathcal{E}_d^i$ using full sample. Newey-West HAC consistent standard errors appear in parentheses. a, b, and c denote rejection of null hypothesis at 1%, 5%, and 10% significance levels, respectively. The symbols represent the following: Basic Material (BMT), Basic Resources (BRS), Consumer Goods (CNG), Consumer Services (CNS), Finance (FIN), Health Care (HLT), Industrials (IND), Oil and Gas (OGS), Real Estate (RLS), Technology (TEC), Telecommunication (TEL), Utilities (UTL), WTI Crude Oil (WTI), Brent Crude Oil (BRT), Gas Oil (GSO), Gasoline (GSL), Heating Oil (HTO), Natural Gas (NGS), CBOE SPX Volatility Index (VIX), U.S. 10-year treasury bond index (BOND), U.S. Economic Policy Uncertainty Index (EPU), and U.S. Geopolitical Risk Index (GPR).

	BMT		**BRE**		**CNG**		**CNS**		**FIN**		**HLT**	
WTI	**0.0136^{b}**	**(0.0054)**	**0.0489^{a}**	**(0.0091)**	**-0.0186^{a}**	**(0.0035)**	**-0.0164^{a}**	**(0.0027)**	**0.0280^{b}**	**(0.0122)**	**-0.0089^{b}**	**(0.0036)**
VIX	0.0001	(0.0004)	0.0003	(0.0006)	0.0006^{b}	(0.0002)	0.0000	(0.0002)	0.0002	(0.0004)	-0.0001	(0.0003)
BOND	0.0086	(0.0060)	0.0035	(0.0092)	-0.0012	(0.0037)	0.0003	(0.0025)	-0.0152	(0.0096)	0.0007	(0.0045)
EPU	0.0025	(0.0099)	-0.0226	(0.0149)	-0.0091	(0.0062)	-0.0200^{a}	(0.0056)	0.0512^{a}	(0.0144)	-0.0013	(0.0072)
GPR	-0.0226^{a}	(0.0077)	-0.0177	(0.0108)	0.0075^{c}	(0.0039)	0.0046	(0.0036)	-0.0170^{b}	(0.0085)	0.0043	(0.0041)
D_GFC	-0.1128^{a}	(0.0278)	-0.1633^{a}	(0.0420)	-0.1061^{a}	(0.0125)	-0.0049	(0.0142)	0.3728^{a}	(0.0547)	-0.1538^{a}	(0.0160)
D_SOH	-0.1682^{a}	(0.0175)	-0.2170^{a}	(0.0275)	0.0445^{a}	(0.0119)	0.0361^{a}	(0.0101)	-0.1090^{a}	(0.0187)	0.1818^{a}	(0.0142)
R^2	22.376%		18.036%		39.039%		20.706%		49.084%		58.178%	
BRT	**0.0223^{b}**	**(0.0088)**	**0.0588^{a}**	**(0.0138)**	**-0.0183^{a}**	**(0.0048)**	**-0.0153^{a}**	**(0.0053)**	**-0.0003**	**(0.0119)**	**-0.0117^{b}**	**(0.0048)**
VIX	0.0002	(0.0004)	0.0004	(0.0006)	0.0006^{b}	(0.0003)	0.0000	(0.0002)	0.0002	(0.0005)	-0.0001	(0.0003)
BOND	0.0075	(0.0059)	0.0010	(0.0090)	-0.0006	(0.0037)	0.0009	(0.0026)	-0.0143	(0.0099)	0.0012	(0.0045)
EPU	0.0061	(0.0099)	-0.0114	(0.0151)	-0.0130^{b}	(0.0063)	-0.0234^{a}	(0.0058)	0.0548^{a}	(0.0157)	-0.0034	(0.0074)
GPR	-0.0232^{a}	(0.0075)	-0.0188^{c}	(0.0106)	0.0077^{b}	(0.0038)	0.0048	(0.0037)	-0.0163^{c}	(0.0088)	0.0046	(0.0041)
D_GFC	-0.1110^{a}	(0.0288)	-0.1336^{a}	(0.0430)	-0.1217^{a}	(0.0123)	-0.0196	(0.0145)	0.4263^{a}	(0.0511)	-0.1580^{a}	(0.0153)
D_SOH	-0.1567^{a}	(0.0179)	-0.1834^{a}	(0.0282)	0.0332^{a}	(0.0124)	0.0264^{a}	(0.0102)	-0.1020^{a}	(0.0207)	0.1753^{a}	(0.0144)
R^2	23.297%		18.457%		37.943%		18.694%		47.738%		58.312%	
GSO	**0.0173^{a}**	**(0.0053)**	**0.0434^{a}**	**(0.0080)**	**-0.0114^{a}**	**(0.0038)**	**-0.0139^{a}**	**(0.0032)**	**0.0038**	**(0.0104)**	**-0.0086^{b}**	**(0.0042)**
VIX	0.0001	(0.0004)	0.0002	(0.0006)	0.0006^{b}	(0.0003)	0.0000	(0.0002)	0.0002	(0.0005)	0.0000	(0.0003)
BOND	0.0088	(0.0060)	0.0045	(0.0092)	-0.0017	(0.0038)	0.0000	(0.0027)	-0.0144	(0.0099)	0.0005	(0.0046)
EPU	0.0042	(0.0100)	-0.0163	(0.0150)	-0.0115^{c}	(0.0063)	-0.0221^{a}	(0.0059)	0.0548^{a}	(0.0153)	-0.0024	(0.0074)
GPR	-0.0233^{a}	(0.0075)	-0.0190^{c}	(0.0106)	0.0077^{c}	(0.0039)	0.0050	(0.0037)	-0.0165^{c}	(0.0088)	0.0046	(0.0041)
D_GFC	-0.1228^{a}	(0.0293)	-0.1605^{a}	(0.0440)	-0.1177^{a}	(0.0127)	-0.0071	(0.0149)	0.4181^{a}	(0.0533)	-0.1527^{a}	(0.0153)
D_SOH	-0.1584^{a}	(0.0179)	-0.1887^{a}	(0.0277)	0.0356^{a}	(0.0126)	0.0268^{a}	(0.0101)	-0.1005^{a}	(0.0205)	0.1764^{a}	(0.0144)
R^2	23.536%		18.640%		37.198%		20.806%		47.773%		58.327%	
GSL	**0.0082^{a}**	**(0.0026)**	**0.0154^{a}**	**(0.0038)**	**-0.0081^{a}**	**(0.0015)**	**-0.0048^{a}**	**(0.0012)**	**0.0118^{a}**	**(0.0039)**	**-0.0067^{a}**	**(0.0019)**
VIX	0.0001	(0.0004)	0.0003	(0.0006)	0.0006^{b}	(0.0003)	0.0000	(0.0002)	0.0002	(0.0004)	-0.0001	(0.0003)
BOND	0.0076	(0.0061)	0.0025	(0.0098)	-0.0005	(0.0037)	0.0006	(0.0027)	-0.0163^{c}	(0.0096)	0.0016	(0.0045)
EPU	0.0061	(0.0100)	-0.0128	(0.0152)	-0.0134^{b}	(0.0061)	-0.0232^{a}	(0.0058)	0.0575^{a}	(0.0150)	-0.0040	(0.0074)

GPR	-0.0215[a]	(0.0076)	-0.0149	(0.0110)	0.0062[c]	(0.0037)	0.0037	(0.0037)	-0.0151[c]	(0.0085)	0.0034	(0.0040)
D_GFC	-0.1379[a]	(0.0303)	-0.1660[a]	(0.0466)	-0.0907[a]	(0.0146)	-0.0064	(0.0153)	0.3523[a]	(0.0549)	-0.1287[a]	(0.0185)
D_SOH	-0.1510[a]	(0.0180)	-0.1788[a]	(0.0275)	0.0262[b]	(0.0122)	0.0239[b]	(0.0102)	-0.0821[a]	(0.0200)	0.1683[a]	(0.0145)
R^2	23.718%		16.254%		40.239%		18.280%		49.374%		59.461%	
HTO	**0.0496[a]**	**(0.0110)**	**0.0874[a]**	**(0.0213)**	**-0.0145[c]**	**(0.0084)**	**-0.0149[b]**	**(0.0073)**	**0.0068**	**(0.0155)**	**-0.0213[a]**	**(0.0077)**
VIX	0.0001	(0.0004)	0.0003	(0.0006)	0.0006[b]	(0.0003)	0.0000	(0.0002)	0.0002	(0.0005)	-0.0001	(0.0003)
BOND	0.0079	(0.0059)	0.0030	(0.0092)	-0.0015	(0.0037)	0.0002	(0.0028)	-0.0145	(0.0099)	0.0009	(0.0045)
EPU	0.0018	(0.0095)	-0.0206	(0.0145)	-0.0108[c]	(0.0063)	-0.0214[a]	(0.0058)	0.0545[a]	(0.0152)	-0.0014	(0.0072)
GPR	-0.0212[a]	(0.0076)	-0.0145	(0.0108)	0.0067[c]	(0.0040)	0.0038	(0.0038)	-0.0161[c]	(0.0087)	0.0036	(0.0041)
D_GFC	-0.0904[a]	(0.0249)	-0.0765[c]	(0.0396)	-0.1404[a]	(0.0121)	-0.0350[a]	(0.0128)	0.4255[a]	(0.0498)	-0.1691[a]	(0.0151)
D_SOH	-0.1648[a]	(0.0173)	-0.2047[a]	(0.0276)	0.0398[a]	(0.0126)	0.0320[a]	(0.0103)	-0.1019[a]	(0.0193)	0.1796[a]	(0.0142)
R^2	23.797%		15.937%		35.585%		15.891%		47.753%		58.229%	
NGS	**0.0156[a]**	**(0.0043)**	**0.0280[a]**	**(0.0073)**	**-0.0084[b]**	**(0.0033)**	**-0.0037[c]**	**(0.0021)**	**0.0192[a]**	**(0.0063)**	**-0.0109[a]**	**(0.0035)**
VIX	0.0001	(0.0004)	0.0003	(0.0006)	0.0006[b]	(0.0003)	0.0000	(0.0002)	0.0002	(0.0005)	0.0000	(0.0003)
BOND	0.0084	(0.0059)	0.0040	(0.0094)	-0.0015	(0.0037)	0.0000	(0.0028)	-0.0150	(0.0098)	0.0008	(0.0044)
EPU	0.0072	(0.0097)	-0.0109	(0.0149)	-0.0131[b]	(0.0064)	-0.0228[a]	(0.0058)	0.0585[a]	(0.0149)	-0.0045	(0.0071)
GPR	-0.0204[a]	(0.0076)	-0.0130	(0.0110)	0.0060	(0.0040)	0.0037	(0.0038)	-0.0139	(0.0085)	0.0028	(0.0041)
D_GFC	-0.1024[a]	(0.0250)	-0.0982[b]	(0.0397)	-0.1331[a]	(0.0122)	-0.0324[b]	(0.0128)	0.4069[a]	(0.0479)	-0.1598[a]	(0.0149)
D_SOH	-0.1635[a]	(0.0175)	-0.2024[a]	(0.0281)	0.0392[a]	(0.0127)	0.0317[a]	(0.0104)	-0.1004[a]	(0.0191)	0.1787[a]	(0.0143)
R^2	23.146%		15.097%		36.246%		15.400%		48.626%		58.667%	

Table A.1. 7: Continue…

	IND		OGS		RLT		TEC		TEL		UTL	
WTI	**-0.0292[a]**	**(0.0040)**	**0.0500[a]**	**(0.0090)**	**0.0684[a]**	**(0.0154)**	**-0.0237[a]**	**(0.0042)**	**-0.0086[c]**	**(0.0049)**	**0.0020**	**(0.0073)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0007	(0.0007)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0004	(0.0004)
BOND	-0.0017	(0.0040)	0.0095	(0.0071)	-0.0122	(0.0130)	-0.0042	(0.0043)	-0.0039	(0.0045)	-0.0024	(0.0067)
EPU	0.0009	(0.0067)	0.0094	(0.0120)	-0.0261	(0.0197)	0.0008	(0.0078)	-0.0421[a]	(0.0088)	-0.0495[a]	(0.0154)
GPR	0.0035	(0.0048)	-0.0111	(0.0092)	-0.0164	(0.0110)	0.0159[a]	(0.0053)	0.0112[b]	(0.0051)	0.0035	(0.0076)
D_GFC	-0.0928[a]	(0.0145)	-0.2319[a]	(0.0402)	0.4044[a]	(0.0639)	-0.0699[a]	(0.0219)	0.0320[c]	(0.0193)	-0.0130	(0.0293)
D_SOH	-0.0043	(0.0140)	-0.0427[c]	(0.0250)	-0.2888[a]	(0.0307)	0.0772[a]	(0.0142)	-0.0086	(0.0169)	-0.0987[a]	(0.0270)
R^2	32.620%		16.405%		49.745%		29.259%		6.064%		5.902%	
BRT	**-0.0301[a]**	**(0.0069)**	**0.0450[a]**	**(0.0114)**	**0.0716[a]**	**(0.0209)**	**-0.0214[a]**	**(0.0075)**	**-0.0002**	**(0.0064)**	**0.0155c**	**(0.0089)**
VIX	0.0014[a]	(0.0003)	-0.0004	(0.0005)	-0.0006	(0.0007)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0005	(0.0004)
BOND	-0.0006	(0.0037)	0.0080	(0.0068)	-0.0149	(0.0133)	-0.0035	(0.0043)	-0.0042	(0.0045)	-0.0034	(0.0066)
EPU	-0.0054	(0.0069)	0.0196	(0.0123)	-0.0112	(0.0205)	-0.0041	(0.0078)	-0.0433[a]	(0.0085)	-0.0479[a]	(0.0155)

GPR	0.0039	(0.0050)	-0.0117	(0.0096)	-0.0176	(0.0113)	0.0162[a]	(0.0055)	0.0109[b]	(0.0051)	0.0029	(0.0076)
D_GFC	-0.1159[a]	(0.0150)	-0.1855[a]	(0.0379)	0.4571[a]	(0.0630)	-0.0917[a]	(0.0216)	0.0159	(0.0176)	-0.0259	(0.0260)
D_SOH	-0.0226	(0.0142)	-0.0138	(0.0266)	-0.2456[a]	(0.0306)	0.0634[a]	(0.0140)	-0.0108	(0.0166)	-0.0926[a]	(0.0272)
R^2	30.784%		12.730%		49.003%		27.562%		5.331%		6.761%	
GSO	**-0.0226[a]**	**(0.0035)**	**0.0365[a]**	**(0.0072)**	**0.0605[a]**	**(0.0165)**	**-0.0170[a]**	**(0.0042)**	**0.0023**	**(0.0041)**	**0.0106c**	**(0.0057)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0004)	-0.0008	(0.0007)	0.0012[a]	(0.0003)	0.0003	(0.0003)	0.0004	(0.0004)
BOND	-0.0023	(0.0038)	0.0107	(0.0069)	-0.0107	(0.0136)	-0.0048	(0.0042)	-0.0042	(0.0045)	-0.0024	(0.0066)
EPU	-0.0029	(0.0069)	0.0158	(0.0121)	-0.0172	(0.0205)	-0.0023	(0.0079)	-0.0432[a]	(0.0084)	-0.0492[a]	(0.0154)
GPR	0.0041	(0.0049)	-0.0120	(0.0096)	-0.0183[c]	(0.0111)	0.0163[a]	(0.0055)	0.0108[b]	(0.0051)	0.0029	(0.0076)
D_GFC	-0.1014[a]	(0.0142)	-0.2129[a]	(0.0405)	0.4084[a]	(0.0615)	-0.0795[a]	(0.0219)	0.0111	(0.0187)	-0.0314	(0.0284)
D_SOH	-0.0200	(0.0141)	-0.0167	(0.0260)	-0.2493[a]	(0.0312)	0.0649[a]	(0.0140)	-0.0099	(0.0166)	-0.0943[a]	(0.0272)
R^2	31.245%		14.105%		50.185%		28.056%		5.403%		6.665%	
GSL	**-0.0054[a]**	**(0.0017)**	**0.0055[c]**	**(0.0030)**	**0.0284[a]**	**(0.0054)**	**-0.0044[b]**	**(0.0018)**	**-0.0010**	**(0.0019)**	**0.0015**	**(0.0023)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0007	(0.0007)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0004	(0.0004)
BOND	-0.0017	(0.0041)	0.0102	(0.0074)	-0.0147	(0.0137)	-0.0042	(0.0044)	-0.0040	(0.0045)	-0.0026	(0.0067)
EPU	-0.0041	(0.0073)	0.0170	(0.0123)	-0.0107	(0.0187)	-0.0033	(0.0077)	-0.0435[a]	(0.0084)	-0.0489[a]	(0.0155)
GPR	0.0022	(0.0052)	-0.0093	(0.0099)	-0.0119	(0.0113)	0.0149[a]	(0.0057)	0.0108[b]	(0.0051)	0.0037	(0.0076)
D_GFC	-0.1147[a]	(0.0164)	-0.1713[a]	(0.0392)	0.3571[a]	(0.0767)	-0.0875[a]	(0.0224)	0.0220	(0.0201)	-0.0184	(0.0305)
D_SOH	-0.0208	(0.0147)	-0.0208	(0.0269)	-0.2238[a]	(0.0283)	0.0638[a]	(0.0141)	-0.0124	(0.0167)	-0.0958[a]	(0.0274)
R^2	25.887%		7.851%		50.485%		25.889%		5.400%		5.954%	
HTO	**-0.0145**	**(0.0103)**	**0.0604[a]**	**(0.0164)**	**0.0240**	**(0.0238)**	**-0.0146**	**(0.0097)**	**-0.0089**	**(0.0057)**	**-0.0184[c]**	**(0.0097)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0007	(0.0007)	0.0011[a]	(0.0003)	0.0003	(0.0003)	0.0004	(0.0004)
BOND	-0.0022	(0.0042)	0.0097	(0.0073)	-0.0106	(0.0140)	-0.0046	(0.0045)	-0.0040	(0.0045)	-0.0019	(0.0067)
EPU	-0.0021	(0.0075)	0.0129	(0.0119)	-0.0184	(0.0199)	-0.0016	(0.0078)	-0.0428[a]	(0.0085)	-0.0483[a]	(0.0154)
GPR	0.0024	(0.0052)	-0.0085	(0.0098)	-0.0141	(0.0119)	0.0150[a]	(0.0057)	0.0107[b]	(0.0051)	0.0031	(0.0076)
D_GFC	-0.1472[a]	(0.0137)	-0.1413[a]	(0.0347)	0.5324[a]	(0.0627)	-0.1137[a]	(0.0192)	0.0164	(0.0155)	-0.0080	(0.0252)
D_SOH	-0.0118	(0.0152)	-0.0301	(0.0262)	-0.2715[a]	(0.0309)	0.0712[a]	(0.0141)	-0.0107	(0.0166)	-0.0982[a]	(0.0270)
R^2	24.268%		9.705%		45.753%		25.189%		5.485%		6.201%	
NGS	**-0.0032**	**(0.0032)**	**0.0195[a]**	**(0.0057)**	**0.0447[a]**	**(0.0109)**	**-0.0162[a]**	**(0.0032)**	**-0.0045**	**(0.0033)**	**0.0061**	**(0.0050)**
VIX	0.0015[a]	(0.0003)	-0.0005	(0.0005)	-0.0007	(0.0007)	0.0012[a]	(0.0003)	0.0003	(0.0003)	0.0004	(0.0004)
BOND	-0.0025	(0.0042)	0.0104	(0.0073)	-0.0116	(0.0138)	-0.0044	(0.0044)	-0.0040	(0.0045)	-0.0025	(0.0067)
EPU	-0.0035	(0.0076)	0.0196	(0.0121)	-0.0086	(0.0197)	-0.0054	(0.0079)	-0.0441[a]	(0.0085)	-0.0480[a]	(0.0152)
GPR	0.0023	(0.0052)	-0.0074	(0.0099)	-0.0092	(0.0119)	0.0133[b]	(0.0056)	0.0104[b]	(0.0051)	0.0043	(0.0076)
D_GFC	-0.1451[a]	(0.0141)	-0.1564[a]	(0.0351)	0.4898[a]	(0.0604)	-0.0988[a]	(0.0189)	0.0202	(0.0158)	-0.0153	(0.0248)
D_SOH	-0.0120	(0.0153)	-0.0285	(0.0264)	-0.2680[a]	(0.0305)	0.0699[a]	(0.0138)	-0.0111	(0.0167)	-0.0978[a]	(0.0268)

R^2	23.998%	9.077%	48.114%	27.746%	5.611%	6.141%

A.2. 1: Statement of Contribution to Doctorate with Publications (Chapter 2)

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Muhammad Abubakr Naeem
Name/title of Primary Supervisor:	Dr. Faruk Balli (Associate Professor)
Name of Research Output and full reference:	
Spillover network of commodity uncertainties (Balli, F., Naeem, M. A., Shahzad, S. J. H., & de Bruin, A. (2019). Spillover network of commodity uncertainties. Energy Economics, 81, 914-927)	
In which Chapter is the Manuscript /Published work:	Chapter 2
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
This paper is chapter 2 in Muhammad Abubakr Naeem's Ph.D. Dissertation and while his supervisors have made contribution, which is reflected by co-authorship, the paper is essentially the work of Abubakr.	
For manuscripts intended for publication please indicate target journal:	
Candidate's Signature:	Muhammad Abubakr Naeem Digitally signed by Muhammad Abubakr Naeem DN: cn=Muhammad Abubakr Naeem, o=Massey University, ou=School of Economics and Finance, email=m.naeem@massey.ac.nz, c=NZ Date: 2019.12.22 14:10:04 +13'00'
Date:	22/12/2019
Primary Supervisor's Signature:	Faruk Balli Digitally signed by Faruk Balli Date: 2019.12.22 16:28:17 +13'00'
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A.2. 2: Statement of Contribution to Doctorate with Publications (Chapter 3)

DRC 16

MASSEY UNIVERSITY
GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Muhammad Abubakr Naeem
Name/title of Primary Supervisor:	Dr. Faruk Balli (Associate Professor)
Name of Research Output and full reference:	
"Energy commodity uncertainties and the systematic risk of US industries" (Naeem, M. A., Balli, F., Shahzad, S. J. H., & de Bruin, A. (2019). Energy commodity uncertainties and the systematic risk of US industries. Forthcoming in Energy Economics)	
In which Chapter is the Manuscript /Published work:	Chapter 3
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
Muhammad Abubakr Naeem is the main author of this paper and while his supervisors have made contribution, which is reflected by co-authorship, the paper is essentially the work of Abubakr.	
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Candidate's Signature:	Muhammad Abubakr Naeem Digitally signed by Muhammad Abubakr Naeem DN: cn=Muhammad Abubakr Naeem, o=Massey University, ou=School of Economics and Finance, email=m.naeem@massey.ac.nz, c=NZ Date: 2019.12.22 14:10:54 +13'00'
Date:	22/12/2019
Primary Supervisor's Signature:	Faruk Balli Digitally signed by Faruk Balli Date: 2019.12.22 19:41:43 +13'00'
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Essays on commodity market uncertainties : a thesis presented in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Finance at Massey University, Albany, New Zealand

Naeem, Muhammad Abubakr

2019