Essays on the Impacts and Spillover Effects of Energy Prices and the Stock Market: Evidence from the United States and Its Main Trading Partners

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Summary

This thesis encompasses of three empirical chapters targeting energy prices, labour market outcomes and volatility of stock market returns. The first chapter employs a modern GARCH framework to investigate the association between crude oil prices, sectoral stock market returns, the macroeconomy, precious metals and cryptocurrency. Pre COVID-19, findings reveal that oil-exporting countries share the same significant positive correlation between oil prices and all sectoral stock returns (aside from Canadian energy and United States telecommunication sectors). A significant positive (negative) volatility correlation between Bitcoin (3-month deposit rate) and oil prices is also detected. Results are rather ambiguous for oil-importing countries. However, during the pandemic sectoral stock market returns of all countries share the same significant positive correlation (aside from Canadian energy sector) with oil prices. A transition from significant positive volatility correlation between Bitcoin and oil prices to an insignificant one was uncovered for all countries. Yet, no change was reported between oil prices and the 3-month deposit rate. Finally, gold and oil prices are found to be significantly positively correlated while it is ambiguous for the nominal effective exchange rate before and during the pandemic.

The second chapter uses multiple GARCH techniques to model returns volatility of the FTSE4Good USA (F4GU) index and eleven sectoral stock indices of United States' main trading partners. A VAR framework is then constructed to examine returns volatility spillover effect of the F4GU index on sectoral stock indices of Canada, the United Kingdom and Japan. All sectoral stock indices (aside from Canadian health care, British real estate, financials, information technology and consumer discretionary) reveal a positive response shock to a sudden increase in volatility of returns in the F4GU index. The spillover effect is greatly pronounced between 5 to 15 days for all three countries. In addition, returns volatility of the F4GU index explains more than 14%, 3.5% and 5% of the returns volatility in most Canadian, British, and Japanese sectoral stock indices respectively on the 25th day period. The explanation with the highest empirical support corresponds to the real estate sector of Canada and Japan at 18.6% and 28% while it's health care for the United Kingdom at 9% on that particular day.

The last chapter conducts an event study to evaluate impacts of the Regional Greenhouse Gas Initiative (RGGI) on the United States' labour market outcomes. It undertakes a comparison to account for differences between the effect on states which enforced the policy versus those that did not. Results show a noticeable decline in annual income from wages of unskilled workers (without a college or high school degree) in energy intensive sectors. On average, the decline in annual wages accounts for about 7% 4 years after the reform. However, no effect was detected for skilled workers in these sectors. Similarly, there weren't any significant impacts of RGGI on average weeks worked and probability of unemployment, nor on wages and employment status of workers in non-energy intensive sectors.

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List of Abbreviations

ADF	Augmented Dicky Fuller
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ASEC	Annual Social and Economic Supplement
BOE	Bank of England
BTC	Bitcoin
CAN	Canada
CAPM	Capital Asset Pricing Model
CCC-GARCH	Constant Conditional Correlation GARCH
CD	Consumer Discretionary
CPS	Current Population Survey
CS	Consumer Staples
CV	Coefficient of Variation
DCC-GARCH	Dynamic Conditional Correlation GARCH
DiD	Difference-in-Difference
ECB	European Central Bank
EGARCH	Exponential GARCH
EN	Energy
ESG	Environmental, Social and Governance
EPU	Economic Policy Uncertainty
EUETS	European Union Emissions Trading System
F4GU/ FTSEUS	FTSE4Good USA Index
FED	Federal Reserve
FIN	Financials
FRA	France
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
HC	Health
IEA	International Energy Agency
IGARCH	Integrated GARCH
IMF	International Monetary Fund
IND	Industrials
IR	3-Month Deposit Rate
IRF	Impulse Response Function
IT	Information Technology
JAP	Japan
KDD	Kernel Density Distribution
LL	Loglikelihood ratio
MA	Moving Average
MAT	Basic Materials
MGARCH	Multivariate GARCH
NEER	Nominal Effective Exchange Rate

OVX	Crude Oil Volatility Index
PP	Phillips Perron
RE	Real Estate
RGGI	Regional Greenhouse Gas Initiative
SD	Standard Deviation
SIC	Schwarz Information Criterion
SUTVA	Stable Unit Treatment Value Assumption
TARCH	Threshold GARCH
TEL	Telecommunication
UK	United Kingdom
USA / US	United States
UTI	Utilities
VAR	Vector Autoregressive
VEC-GARCH	Vector GARCH
VECM	Vector Error Correction Model
WDT	Wold Decomposition Theorem

Introduction

This thesis comprises of three empirical essays focusing on the uncertainty of future economic dynamics which has a great influence on the decision-making processes and overall market outcomes. The first chapter is devoted to modelling the impacts of oil price volatility on the macroeconomy, precious metals, cryptocurrency, and eleven sectoral stock indices of five major advanced economies (the United States (US), Canada (CAN), the United Kingdom (UK), France (FRA), and Japan (JAP)). The second, analyses the spillover effects of the FTSE4Good USA (F4GU) index on the sectoral stock indices of the US main international trade partners. While the third, examines impacts of the Regional Greenhouse Gas Initiate (RGGI) on labour market outcomes in the US.

The motivation behind selecting the US, CAN, FRA, UK, and JAP is because of their strong bilateral trade relations along with the vital roles that each country exemplifies in oil and financial markets[1]. According to the World Bank (2021), the US is classified as one of the world's largest trading nations with trade relations exceeding 200 countries. Its main trading partners are Canada, Mexico, China, Japan, and the United Kingdom with petroleum oils amongst the most exported and imported commodities. After the removal of the US ban on exports of crude oil in 2015, the country has become the world's largest exporter of refined petroleum products between 2016 and 2017 as per Sieminski et al. (2017) from the Centre for Strategic and International Studies. Even more compelling, according to the US Energy Information Administration (EIA) (2023), US oil exports reached a record high of 3.6 million barrels per day in 2022 due to a sharp rise in demand from European countries. As sanctions on Russia continued, US oil exports hit another record in March 2023 reaching 4.8 million barrels per day resulting from the reinvigoration of Chinese demand. When considering CAN, the country constantly ranks amongst the top oil-exporting countries in the world. Its oil reserves are also classified as one of the largest globally. According to Venkatachalam (2024) from the Canadian Energy Centre, a large portion of the country's oil exports goes to the US. It plays a crucial role in supporting North America's refineries which transform Canada's

[1] There are some other countries of equal importance, but our focus is on the top five US trading partners. We were also restricted by data access and availability where we had to drop China and Mexico from our study.

crude oil into products that are used on daily basis notably diesel, gasoline, and other essential chemicals. In 2024, this has been estimated to safeguard 1.6 million jobs and $1.6 trillion worth of goods and services produced by the industry. FRA, UK, and JAP have been repeatedly listed in the top 20 oil-importing countries in the world. Similarly, they rely heavily on refined crude oil into diesel, gasoline, and other essential chemicals which is then used in automobiles, aircrafts, ships, machines and heating buildings etc. According to the International Energy Agency (IEA), refined crude oil is also used by these countries for generating non-energy products such as raw materials for making plastic, engine lubricates, asphalt etc. Despite having a diversified energy mix comprising of liquified natural gas, nuclear, renewable energy etc, oil remains an important product for all three countries.

On that note, it is undoubtable that the US would have a major influence on world economies and financial markets let alone its main trading partners. Indeed, Kose et al. (2017) have shown that US financial markets are highly correlated with global ones. According to Credit Suisse (2024), the US accounted for approximately 60% of total world equity market value. Its main trading partners JAP (ranked second), UK (ranked third) and CAN (ranked sixth) followed suit at 6.2%, 3.7%, and 2.6% respectively. Investors are also looking to make a difference considering the existing paradigm shift towards sustainability. Given that countries are seeking to constrain carbon emissions, substantial investment in wind farms, solar energy and hydroelectric power is essential to achieve that goal. In the same light, constraining carbon emissions is often associated with the implementation of climate change mitigation policies. This is particularly crucial for the US because according to Friedrich (2023) from the World Resource Institute the country stands as the second most carbon dioxide emitter in the world. As a result, it would be useful for financial institutions, investors, and portfolio managers to understand the impacts of oil price volatility during extreme times of uncertainty such as a pandemic. Likewise, understand the returns volatility spillover effect of sustainable firms in the stock market to the sectoral stock indices of the US main trading partners. While policy makers would be interested in recognising the impact of climate change mitigation policies on labour market outcomes.

Noting these recent dramatic changes in oil and financial markets signifies that there exists ample uncertainty about future economic dynamics. There is a need to explore such topics in a greater depth and contribute towards enhancing decision-making processes. Consequently, the first chapter of this thesis examines the impacts of oil price volatility on two oil-exporting (US, and CAN) and three oil-importing (UK, FRA, and JAP) countries. Our aim is to answer the following research questions. (1) Can volatility of oil prices explain the volatility of returns in sectoral stock indices, exchange rates, interest rates, precious metals, and cryptocurrencies? (2) Does this explanation differ; (a) between oil-exporting and oil-importing countries (b) before and during the COVID-19 pandemic. Work in this area is quite limited and does not always cover all eleven sectors and other investment options resulting from restrictions imposed by the econometric methodologies employed. Never mind considering extreme times of uncertainty such as a pandemic or distinguishing between the impact on oil-exporting and importing countries. This yields an incomplete investigation of the impacts of oil price volatility. We overcome this limitation in existing literature by estimating the univariate GARCH model prescribed by Gibson et al. (2017) for all sixteen variables individually and for the summation of crude oil prices with each of the remaining fifteen variables. The time varying conditional correlation are then generated which are used to answer our research questions. To the best of our knowledge, this is the first study which conducts a comprehensive investigation of oil price volatility before and during the COVID-19 pandemic whilst distinguishing between the impact on oil-exporting and importing countries. We fill the gap in existing literature by providing a supplementary piece of information for investors, firms, and other economic agents to understand trends. Hence, contributing towards making better informed decisions during uncertain times. Pre COVID-19, our findings reveal that oil-exporting countries share the same significant positive correlation between oil prices and all sectoral stock returns (aside from Canadian energy and United States telecommunication sectors). A significant positive (negative) volatility correlation between Bitcoin (3-month deposit rate) and oil prices is also detected. Results are rather ambiguous for oil-importing countries. However, during the pandemic sectoral stock market returns of all countries share the same significant positive correlation (aside from Canadian energy sector) with oil prices. A transition from significant positive volatility correlation between Bitcoin and oil prices to an insignificant one was uncovered for all countries. Yet, no change was reported between oil prices and the 3-month deposit rate.

Finally, gold and oil prices are found to be significantly positively correlated while its contradictory for the nominal effective exchange rate before and during the pandemic.

The second chapter makes use of the F4GU index to examine its returns volatility spillover effect on the sectoral stock indices of CAN, JAP, and the UK. The F4GU index is a US stock market index specified to assess the performance of firms against a predetermined set of environmental, social and governance (ESG) criteria. It forms part of the FTSE4Good Index Series which accounts for several local and international indices that monitor firms' sustainability performance. Investors utilise the F4GU index as a benchmark for developing a sustainable investment portfolio by investing in firms that prioritise ESG. It is worth mentioning that firms should pass a stringent inspection process by the FTSE Russell to be included in the index. The overwhelming majority of existing research focuses on the traditional FTSE index which does not consider firms sustainability performance. Considering the existing paradigm shift towards sustainability, it would be useful for financial institutions, investors, and portfolio managers to understand the returns volatility spillover effect of firms which demonstrate good sustainability practice. This would contribute towards assisting the three participants when making investment decisions. To fill this gap, we make use of the F4GU Index to answer two key questions. (1) Do returns volatility of each sectoral stock index respond to shocks from the F4GU index? (2) What is the proportion of sectoral stock index returns volatility explained by that of the F4GU index? To answer these questions, we begin by estimating the GARCH family to obtain the optimum time varying conditional variances. The corresponding volatility series are then generated and assessed in a multivariate VAR model. Accordingly, we obtain the Impulse Response Functions (IRFs) assisting us in answering (1) as they illustrate the persistence, direction, and magnitude of the response of each sectoral stock index returns volatility to one standard deviation variation in the F4GU index. To answer (2), the variance decompositions are calculated to understand the proportion of sectoral stock index returns volatility explained by that of the F4GU index. To the best of our knowledge, this is the first piece of research which attempts to examine returns volatility spillover effects of the F4GU index to sectoral stock indices of the US main trading partners. We make use of the US as a benchmark in our research because the country has the largest total world equity market value and to extend the analysis presented by Kose et al. (2017). CAN, UK, JAP are selected because they are amongst the top five US trading partners and are also classified as countries with large total world equity market value. Our findings reveal that all sectoral stock indices (aside from Canadian health care, British real estate, financials, information technology and consumer discretionary) reveal a positive response shock to a sudden increase in volatility of returns in the F4GU index. The spillover effect is greatly pronounced between 5 to 15 days for all three countries. In addition, returns volatility of the F4GU index explains more than 14%, 3.5% and 5% of the returns volatility in most Canadian, British, and Japanese sectoral stock indices respectively on the 25th day period. The highest explanation corresponds to the real estate sector of Canada and Japan at 18.6% and 28% while it's health care for the United Kingdom at 9% on that particular day.

Lastly, the third chapter evaluates the impacts of RGGI (a cap-and-trade carbon emissions programme) on US labour market outcomes. RGGI is a collaborative agreement between eleven states to cap and minimise carbon dioxide emissions from the electricity generation sector. Purchase of allowances is necessary as they permit a regulated power plant to emit an extra ton of carbon dioxide. Because of this, the policy induces firms to invest in environmentally friendly production techniques to ensure that they adhere with pre-determined levels of emissions. RGGI states allocated allowances by conducting auctions on quarterly basis. These are purchased by electricity generating sectors, environmental and national governmental organisations. Revenue generated from these auctions is invested in renewable and energy efficient programmes. It is important to note that the cap to minimise overall carbon emissions produced by power plants decreases over time. This means that the price of permits are volatile resulting from changes in regulations which influences firms investment and operational decisions. The vast majority of existing literature that examined the impacts of RGGI focused on energy generation, consumption, switching, emissions, and leakages. None of which considered the link between RGGI and labour market outcomes. We contribute to the literature by evaluating the impacts of RGGI on average income, weeks worked and unemployment in the US by answering two research questions. (1) Does RGGI have an impact on average income, weeks worked and unemployment? (2) Is there a difference between the impact on employees working in energy and non-energy intensive sectors? To answer question (1), an event study is undertaken to estimate the impact of RGGI post its imposition on the three main outcomes. This also assists us in conducting a comparison between employees working in energy and non-energy intensive sectors thereby addressing question (2). Answers to these questions provides insights for policy makers when comparing the impacts of RGGI on labour market outcomes with other climate change mitigation policies. Our results show a noticeable decline in annual income from wages of unskilled workers (without a college or high school degree) in energy intensive sectors. On average, the decline in annual wages accounts for about 7% 4 years after the reform. However, no effect was detected for skilled workers in these sectors. Similarly, there weren't any significant impacts of RGGI on average weeks worked and probability of unemployment, nor on wages and employment status of workers in non-energy intensive sectors.

Chapter 1

COVID-19, Stock Market Returns and Crude Oil Price Volatility: A Comparative Study between Oil-Exporting and Oil-Importing Countries

Note: This essay was co-authored with Hussein Hassan, who is the Undergraduate Programme Director of Studies and Lecturer in Economics at the University of Reading; hussein.hassan@reading.ac.uk. Hussein acknowledges that I had a significant contribution to this paper and can therefore appear within this thesis.

1.1 Introduction

Research on the link between oil prices and stock market returns have been quite extensive for the last two decades[2]. A large fraction of these studies focused heavily on the general stock index in oil-exporting countries. Such studies are often vulnerable to stiff criticism because the relationship between oil prices and the general stock index is somewhat endogenous. One can find very little diversification among the nature of firms that account for the general stock index since the overwhelming majority are energy intensive. This means that, most of the volatility and returns of the general stock index in these countries is greatly driven by that of oil prices and energy intensive firms' decisions. Let alone, that stock markets of these countries are predominately thin (Bouri et al., 2016; Charfeddine and Ben Khediri, 2016).

To make the analysis of oil price volatility and stock market comprehensive, it is important to evaluate the former's relationship with the returns of sectoral stock indices. Work in this area is quite limited and does not always cover all eleven sectors resulting from

[2] See, Habib and Kalamova, 2007; Bjørnland, 2009; Arouri et al., 2011; Buetzer et al., 2012; Ramos and Veiga, 2013; Khandelwal et al., 2016; Kayalar et al., 2017; Maghyereh et al., 2017.

restrictions imposed by the econometric methodologies employed. For the same reason, studies often end up turning a blind eye to the impact on the macroeconomy[3]. There seems to be an absence in the literature of a study that performs a comparative analysis of oil price volatility and sectoral stock index returns of oil-exporting and oil-importing countries before, during or after a pandemic. Information on trends and comparative studies are very useful for investors in determining whether to enter the stock market or not or to buy more or sell shares. It also assists firms and other economic agents in deciding whether to alter or delay consumption or production.

Due to all of these reasons, we conduct a comprehensive comparative study to investigate whether volatility in oil prices can explain volatility of returns in the eleven sectoral stock indices of both oil-exporting and oil-importing countries, before and during one of the most prominent pandemics of all time, COVID-19. Given that investors have the option to invest their funds in foreign exchange currencies or short-term AAA rated government bonds, we incorporate the nominal effective exchange rate and 3-month deposit rate. These two variables will capture the impact on the macroeconomy, and they also fit within our daily data perspective. Finally, the study also accounts for gold to consider precious metals and Bitcoin to represent cryptocurrency, since both are two other lucrative choices for investors.

The rest of this chapter is structured in the following way. Section 1.2 offers an extensive review of existing literature. Section 1.3 analyses the data used, compares the utilised econometric methodology with other relevant ones and describes the theoretical link between sectoral stock indices and oil prices. Section 1.4 discusses the results generated. Section 1.5 confirms the accuracy of our findings by illustrating the necessary robust checks. Last of all, section 1.6 concludes the chapter and sheds light on relevant implications.

1.2 Closest Literature

The best place to start with is from the considerable amount of empirical literature which investigated the relationship between oil price volatility and the exchange rate. A

[3] See, Cong et al., 2008; Ratti and Hasan, 2008; Arouri, 2011; Bouri et al., 2016; Kayalar et al., 2017; Hamdi et al., 2019.

portion of these studies stated that there exists a positive relationship between the two variables. In particular, higher oil price volatility is associated with an appreciation in the exchange rate[4]. For instance, Habib and Kalamova (2007) revealed that the Russian Rouble can be classified as an “oil currency” (i.e., when oil prices are highly volatile, this leads to an appreciation of a particular country’s currency) because there appears to be a common stochastic trend between oil price volatility and the real exchange rate. These results were derived by employing VAR and VECM models using quarterly data. Likewise, using ARIMA, GARCH and several copula techniques, Kayalar et al. (2017) indicated that stock indices and exchange rates of nearly all oil-exporting countries reveal greater dependence on oil prices after using a mixture of monthly and daily data.

However, other studies indicated that there either exists a negative relationship between oil price volatility and the exchange rate[5] or that the relationship is weak[6]. On one hand there is, Ahmad et al. (2020) employing a GARCH (1, 1) for the period January 2013 – October 2019 to examine the effect on two oil-importing countries (China and India). They detected that oil jumps tends to have negative effects on the exchange rate conditional volatility. This goes in hand with the analysis made by Cifarelli and Paladino (2010). After using a multivariate constant conditional correlation (CCC) GARCH-in mean (GARCH-M) framework using weekly data, they concluded that oil price volatility is inversely linked to exchange rate variations.

While on the other, Buetzer et al. (2012) argued that there does not exist any evidence suggesting that exchange rates of oil-exporting countries experience an appreciation resulting from oil price volatility when compared to oil-importing countries. They employed an SVAR model for a sample of 44 countries (amongst which fourteen are oil-exporting) using monthly data. Indeed, Habib and Kalamova (2007) also found little to no relationship between the two variables for Saudi Arabia and Norway despite of finding a positive one for

[4] See, Golub, 1983; Krugman, 1983; Chen and Chen, 2007; Korhonen and Juurikkala, 2009; Coudert et al., 2011; Aloui et al., 2013; Dauvin, 2014.
[5] See, Basher et al., 2012; Reboredo and Castro, 2013; Jawadi et al., 2016; Yang et al., 2017; Wen, 2018; Tiwari et al., 2019.
[6] See, Reboredo, 2012; Bal and Rath, 2015.

Russia (in line with what was mentioned earlier). Truly, the relationship between oil price volatility and the exchange rate is ambiguous.

Second and even more importantly, is the analysis conducted to examine the link between oil price volatility and the stock market. The first strand of these studies concluded that higher oil price volatility is associated with a negative impact on the stock market[7]. For example, Ramos and Veiga (2013) revealed that an increase in oil price volatility tends to have an adverse effect on the stock market of oil-importing countries. It is worth mentioning that these findings were generated after incorporating a traditional GARCH (1, 1) model using monthly data. This piece of evidence is also consistent with the investigation conducted by Xiao et al. (2018). Although, they make use of a fascinating variable called crude oil volatility index (OVX) to account for investors' expectations of future oil prices, they still emphasised that OVX volatility fundamentally revealed significant negative impacts on sectoral and aggregate stock returns in bear markets of China. These results were obtained after employing a quantile regression technique using daily data.

The second strand of literature argues that there exists a positive relationship or co-movement between oil price volatility and the stock market[8]. With the help of a multivariate dynamic conditional correlation (DCC) GARCH model and monthly data set, Guesmi and Fattoum (2014) indicated that oil prices present a positive correlation with stock markets. Another indication of this, Bjørnland (2009) uncovered that for an oil-exporting country such as Norway, a 10% increase in oil price volatility yields a 2.5% rise in stock returns after employing an SVAR framework for monthly data from 1993 until 2005. The latter relationship is also compatible with Ramos and Veiga (2013) for oil-exporting countries but not for oil-importing ones.

The third and final strand of literature claims that oil price volatility either had a weak or no impact on the stock market[9]. In principle, Huang et al. (2017) has studied this topic by employing a VAR and wavelet transformation technique for a daily data set starting from

[7] See, Park and Ratti, 2008; Vo, 2011; Bouri, 2015; Diaz et al., 2016; Rahman, 2021; Joo and Park, 2021.
[8] See, Wang et al., 2013; Sukcharoen et al., 2014; Jiang and Yoon, 2020; Yang et al., 2021; Tian et al., 2021.
[9] See, Chen et al. 1986; Huang et al., 1996; Jones and Kaul; 1996; Henriques and Sadorsky 2008; Apergis and Miller 2009.

October 2006 until December 2014. They found that there is no effect from oil price volatility on the stock market across a multi scale. Confirming this, Sukcharoen et al. (2014) also found weak dependence between oil price volatility and the stock market for most scenarios (aside from large oil consuming and producing countries which tend to present strong dependence).

Moreover, few studies have gone a step further by conducting a more extensive investigation. They focused on the impact of oil price volatility on various sectors of the stock market showing that the effect is inconsistent[10]. After incorporating a GARCH framework for a daily data set based on two sub-samples, Bouri et al. (2016) emphasised that oil price volatility had an insignificant impact on industrials but a significant one on services and financials sectors in Jordan. This was also consistent with the study of Ratti and Hasan (2013) where they obtained significant impacts for most (but not all) stock market sectors of Australia. Here a multivariate GARCH (MGARCH) model was employed using daily data.

The last indication of oil price volatility is its relationship with gold prices. Many researchers have detected a positive relationship between the two variables[11]. Namely, Zhang and Wei (2010) employed a cointegration and Granger (linear and nonlinear) causality test using daily data to assess the price information spillover channel. They found that there exists a long-run equilibrium relationship between the two variables, where crude oil price volatility has a linear Granger causality on volatility of gold prices. There also exists consistent trends among the two variables with a significant positive correlation coefficient of 0.93. Such results were confirmed by Bonato et al. (2020) after revealing a causal chain in the realised volatility of oil prices to gold through a financial parlance. This was obtained by employing various Granger causality techniques for intraday data.

Clearly, numerous studies have examined the impact of oil price volatility on the stock market, gold, and exchange rate. However, we are providing a supplementary piece of information for investors, firms, and other economic agents to understand trends contributing towards making better informed decisions. With that said, none of the above

[10] See, Arouri, 2011; Kayalar et al., 2017; Yu et al., 2018, Hamdi et al., 2019.
[11] See, Hammoudeh and Yuan, 2008; Charlot and Marimoutou, 2014; Shahbaz et al., 2017; Singh et al., 2019; Dai et al., 2020; Umar et al., 2021; Yang et al., 2021.

literature attempts to examine or compare whether oil prices volatility can explain volatility in gold prices, cryptocurrency, interest rates and returns of sectoral stock index returns of oil-exporting and importing countries, before or during the COVID-19 pandemic. Indeed, there are some studies that have made a distinction between impacts of oil prices volatility on the exchange rate and stock market of oil-exporting and oil-importing countries, but they neither account for cryptocurrency nor returns of sectoral stock indices with the presence of a pandemic. Never mind distinguishing between the impact on oil-exporting or oil-importing countries.

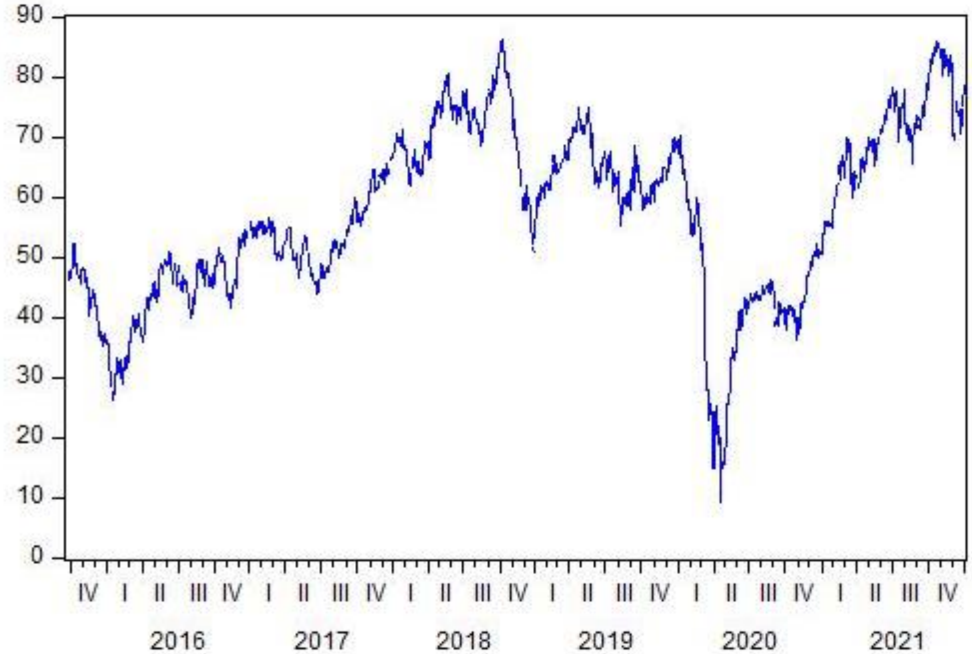
1.3 Data, Theory and Methodology

1.3.1 Data

Daily data for sixteen variables is employed in our empirical investigation obtained from Bloomberg, for a period between 24th of September 2015 – 31st of December 2021. The reason behind selecting the former starting date is data availability for the Japanese real estate sectoral stock index. We selected five OECD countries classified as two oil-exporting (i.e., the United States (USA) and Canada (CAN)) and three oil-importing (i.e., the United Kingdom (UK), France (FRA) and Japan (JAP)). These were selected solely based on their major roles in the oil and financial markets. In addition, the variables Bitcoin (BTC), gold price (GOLD), nominal effective exchange rate (NEER) and 3-month deposit rate (IR) were chosen to assess whether crude oil price volatility can translate the volatility of cryptocurrencies, precious metals, and the macroeconomy respectively.

According to figure 1.1, there are six major events that happened before and during the COVID-19 pandemic leading to changes to oil prices. Beginning with the three events that happened before the pandemic (i.e., between 24th of September 2015 – 30th of December 2019). On the 20th of January 2016, there was a decrease in oil prices reaching $26 per barrel. This was mainly due to the removal of sanctions imposed on Iran fuelling the prospects of a price war with Saudi Arabia. Next, towards the 4th of October 2018, there was an increase in oil prices reaching to a peak of $86 per barrel. During this time, US sanctions were imposed back on Iranian oil exports. Saudi Arabia and other leading oil producing countries started hinting of supply cuts for the upcoming year. These events have generated

Figure 1.1: Crude Oil Prices



Notes: The figure shows volatility of crude oil prices ($ per barrel) for the period 24th of September 2015 – 31st of December 2021.

more uncertainty in the oil market and thus higher volatility. Adding to those, on the 31st of December 2018, there was another severe drop in oil prices reaching $51 per barrel. The growth rate in demand for oil was stable while the growth rate in US crude output has exceeded expectations.

Over to the three notable events that happened during the pandemic. On the 21st of April 2020, there was a considerable decline in oil prices reaching a record of $9 per barrel. Global consumption and demand for oil dramatically decreased resulting from lockdowns, travel restrictions and business closure. Secondly, in the second half of 2020 oil prices recovered reaching $45.5 per barrel. With the introduction of various COVID-19 vaccines, ease of lockdown in certain countries and OPEC agreeing to reduce crude oil production, demand and supply for oil was gradually stabilising. Lastly, there was a sharp upward increase in oil prices reaching to the highest value in our sample period (again) of $86 per barrel on the 20th of October 2021. During this period, there were additional relaxation of COVID-19 and travel restrictions, a drastic increase in vaccination rates and stores of crude oil during the pandemic started running out. Hence, global demand for oil started increasing more quickly than the supply given the agreed cut in oil production by OPEC in 2020.

To examine whether oil price volatility can explain volatility of stock market returns, we incorporated eleven FTSE-100 sectoral stock indices. In particular, real estate (RE) which accounts for the performance of real estate investment trusts and firms that invest in real estate via ownership, development or management etc, health care (HC) which comprises of pharmaceutical companies, health care service providers and their equipment along with biotechnology, energy (EN) which takes into consideration businesses involved in oil and gas refining, developing, drilling and exploring, telecommunication (TEL) which is made up of organisations dealing with telecom services, internet, mobile communications and their equipment, materials (MAT) which includes firms that take part in refining, mining, processing and developing raw materials such as arboriculture, chemicals, metals etc, industrials (IND) comprises of firms that primarily produce capital goods (such as machinery, vehicles, tools etc) used in construction and manufacturing, consumer discretionary (CD) which contains firms that offer non-essential consumer goods (for example, jewellery, apparel, home furniture, electronics, automobiles etc), consumer staples (CS) which takes into consideration firms that sell essential consumer goods (such as, hygiene products, food and beverages etc), financials (FIN) which accounts for insurance companies, banks, and other financial institution, information technology (IT) which represents firms that are engaged in technology, research and development of computer software, electronics, mobile phones, televisions and any product related to information technology and finally utilities (UTI) which accounts for firms that provide basic services of infrastructure (i.e., water, electricity, gas etc).

All of the above variables (aside from gold, oil and Bitcoin since they are international) will have the country name as a subscript so that it corresponds to the country in question. Tables A1 – A5 in the appendix shed light on the descriptive statistics of all variables in question for the five selected OECD countries. The coefficient of variation (CV) shows the standard deviation (SD) as a percentage of the arithmetic mean. This equivalent to 24% for crude oil prices (oil) across all three countries. It indicates that the variable has a relatively higher volatility when compared to most variables within our dataset. The highest CV corresponds to Bitcoin (BTC) while the lowest is associated with the nominal effective exchange rate (NEER) of each country. All variables in question are not normally distributed as per the reported skewness. But most conclusive, they all have a kurtosis less than 3 (excluding HCCAN and IRJAP) which means that our data set has little to no outliers with lighter tails when compared to a normal distribution.

We now take the natural logarithm of all variables aside from IR to conduct the Phillips Perron (PP) and Augmented Dicky Fuller (ADF) unit root tests. These will guide us in understanding the integration order of variables in our model. Table 1.1 and 1.2 below presents the outcome of the two tests at level and first order difference respectively using a drift without a trend for each country. We reject the null hypothesis, that the series has a unit root for variables containing asterisks at the corresponding significance levels. For variables that are stationary at level, they are integrated at order 0 (i.e., I (0)). Whereas those which are stationary at first order difference are integrated at order 1 (i.e., I (1)).

Table 1.1: Unit Root Tests at Level

	USA		CAN		UK		FRA		JAP	
Variable	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF
LBTC	-1.43	-1.433	-1.433	-1.435	-1.443	-1.446	-1.442	-1.444	-1.721	-1.717
LCD	-0.143	-0.113	-1.531	-1.3	-2.863**	-2.976**	-1.546	-1.104	-2.351	-2.279
LCS	-0.142	-0.05	-0.648	-0.704	-2.903**	-2.913**	-1.09	-0.694	-2.15	-2.219
LEN	-1.914	-1.958	-2.605***	-2.42	-1.688	-1.681	-2.473	-2.18	-1.676	-1.696
LFIN	-1.084	-1.053	-1.51	-1.249	-2.26	-2.284	-2.146	-2.247	-2.686***	-2.591***
LGOLD	-0.806	-0.839	-0.802	-0.833	-0.807	-0.837	-0.804	-0.837	-0.955	-1.041
LHC	-0.201	-0.1	-4.562*	-4.456*	-1.886	-1.692	-1.097	-0.832	-1.737	-1.816
LIND	-1.008	-0.823	-0.885	-0.509	-1.243	-1.159	-1.632	-1.393	-1.534	-1.82
LIT	0.247	0.391	-0.363	-0.192	-2.249	-2.29	-0.515	-0.259	-0.598	-0.677
LMAT	-1.242	-0.977	-1.985	-1.947	-1.532	-1.267	-1.009	-0.818	-2.179	-2.411
LNEER	-2.302	-2.26	-2.999**	-2.928**	-3.030**	-2.979**	-1.533	-1.46	-2.951**	-3.020**
LOIL	-2.182	-2.703***	-2.199	-2.637***	-2.195	-2.632***	-2.2	-2.641***	-2.542	-2.752***
LRE	-2.347	-2.301	-2.418	-2.476	-2.986**	-3.042**	-2.032	-1.959	-3.304**	-3.094**
LTEL	-4.137*	-3.797*	-2.177	-1.722	-1.378	-1.389	-1.806	-1.526	-2.316	-2.085
LUTI	-1.749	-1.224	-1.081	-0.433	-2.113	-2.113	-2.714***	-2.958**	-1.083	-1.11
IR	-1.365	-0.686	-1.584	-0.822	-1.538	-1.215	-3.092**	-2.785***	-13.947*	-5.308*

1. **, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*
2. *The L indicates natural logarithm to distinguish it from level data.*
3. *The null hypothesis indicates that the series contains a unit root (non-stationary) compared with an alternative, it does not contain a unit root (stationary).*

Table 1.2: Unit Root Tests at First Order Difference

	USA		CAN		UK		FRA		JAP	
Variable	PP*	ADF*	PP*	ADF*	PP*	ADF*	PP*	ADF*	PP*	ADF*
D(LBTC)	-41.185	-21.338	-41.437	-21.645	-41.125	-21.548	-41.314	-21.611	-39.806	-20.119
D(LCD)	-45.982	-13.144	-42.844	-10.191	-36.571	-14.592	-38.965	-10.527	-40.58	-16.186
D(LCS)	-45.078	-11.831	-40.756	-12.285	-40.062	-10.286	-39.665	-15.927	-40.814	-20.642
D(LEN)	-42.525	-10.561	-42.057	-11.879	-36.186	-14.288	-36.145	-13.679	-38.135	-38.13
D(LFIN)	-46.533	-10.343	-42.307	-11.004	-38.008	-14.359	-36.796	-11.883	-38.755	-22.962
D(LGOLD)	-38.536	-38.529	-38.773	-38.77	-38.573	-38.571	-38.659	-38.657	-37.918	-37.778
D(LHC)	-46.004	-12.151	-38.494	-10.387	-40.718	-14.963	-39.662	-13.772	-39.033	-16.178
D(LIND)	-44.79	-10.672	-44.716	-12.289	-38.189	-14.637	-38.055	-14.845	-39.316	-22.673
D(LIT)	-49.252	-11.251	-40.51	-9.177	-39.762	-14.303	-39.54	-15.405	-39.437	-26.077
D(LMAT)	-42.796	-10.993	-39.079	-39.079	-40.06	-10.438	-42.943	-14.069	-38.84	-22.16
D(LNEER)	-39.316	-39.316	-38.71	-24.517	-38.622	-20.756	-43.144	-11.592	-39.328	-19.337
D(LOIL)	-41.419	-6.385	-41.795	-6.482	-41.599	-6.398	-41.703	-6.446	-38.872	-8.492
D(LRE)	-42.677	-10.453	-38.374	-13.64	-33.725	-14.402	-37.525	-10.749	-34.586	-11.437
D(LTEL)	-44.452	-11.528	-46.659	-9.366	-38.537	-14.68	-40.702	-14.021	-40.566	-10.915
D(LUTI)	-44.535	-10.304	-42.363	-13.396	-39.5	-12.211	-37.384	-13.26	-37.584	-16.526
D(IR)	-81.149	-9.268	-87.317	-8.834	-60.821	-19.571	-94.561	-10.474	-88.567	-10.731

1. **, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*
2. *The D corresponds to the first order difference of a variable.*
3. *The L indicates natural logarithm to distinguish it from level data.*
4. *The null hypothesis indicates that the series contains a unit root (non-stationary) compared with an alternative, it does not contain a unit root (stationary).*

1.3.2 Theoretical Application

The theoretical relationship between oil price volatility and sectoral stock market returns varies as it depends upon the sector in question. According to Hamilton, (1983) it is based on sensitivity to changes in the macroeconomic environment and firms' usage of oil as an input in the production process. In other words, oil price volatility contributes to the uncertainty in inflation and interest rates thereby affecting the stability of the macroeconomy. This makes it difficult for firms in sectors such as FIN, CD and RE to predict macroeconomic conditions which impacts their stock returns since they are all sensitive to changes in the macroeconomy. When oil prices are highly volatile, consumer confidence and spending on automotive, hospitability and retail sectors are also distorted. This creates uncertainty about future demand leading to an increase in volatility of returns in the CD sector. Hamilton (1983) states that oil price volatility is also affected by supply shocks and geopolitical events. This contributes to the significant cost uncertainties for sectors such as

EN, MAT, UTI and IND since they rely heavily on oil as an input factor. Thus, making it challenging for firms in these sectors to manage their costs efficiently. Let alone that these firms also face uncertain revenue streams during times of high oil price volatility. All of which impacts profitability and stock market returns volatility.

However, previous theoretical and empirical studies on the relationship between oil prices and stock market returns suffer from two major drawbacks. First, the assumption that it is possible to examine the impact of an increase in oil price volatility without understanding the underlying reasons behind such volatility. Second, volatility of oil prices is classified as exogenous with respect to the global economy where all other variables within the model are held constant (ceteris paribus)[12]. According to Kilian and Park (2009), these assumptions are flawed as the cause and effect are mis-specified in the regressions of stock returns on oil price volatility. This is because, results relating stock returns to innovations in oil prices will be biased towards finding relationships that are unstable overtime. Instead, Kilian and Park (2009) attribute the surge in global demand for all industrial commodities to be the main driving factor of oil price volatility. It stems from the rise in demand for automotive, hospitality and retail sectors as opposed to supply shocks and geopolitical tensions. Their findings also reveal that the input cost of oil is an insignificant factor when interpreting the differences in the response of stock market returns across manufacturing sector firms. All of which contradicts the conclusions made by Hamilton (1983).

Finally, according to Sadorsky (1999) several energy intensive firms make use of financial derivatives (such as options, forwards, futures etc) to hedge against oil price volatility. During times of high oil price volatility, the cost of hedging increases depressing firms' profits. To put differently, when energy intensive firms do not manage their exposure to oil price volatility successfully, their profits face higher degree of uncertainty. This leads to an increase in volatility of their stock market returns. It is worth noting that, energy intensive firms may postpone capital investment decisions during times of high oil price

[12] See, Hamilton, 1983; Jones and Kaul; 1996; Sadorsky, 1999; Wei, 2003.

volatility. The reason behind this is that it becomes difficult to predict future input costs and revenues causing ambiguity in investment returns.

1.3.3 Methodology and Econometric Framework

Initially, the Capital Asset Pricing Model (CAPM) was used to estimate expected returns of an investment based on the market risk.[13] A multifactor model was then developed by Ross (1976) to account for various sources of risk. Both models revealed a linear relationship between expected returns of the investment portfolio, risk factors and premiums. This is usually captured by using the Fama and MacBeth (1973) two step procedure. First, a CAPM would be employed to measure systematic risk. Second, cross section regressions of returns are estimated. Basher and Sadorsky (2006) employed the multifactor model and CAPM to investigate the impact of oil price volatility on emerging stock market returns. However, after conducting further examinations of the CAPM, it was reported that the association between systematic risk and return was meaningless.[14] Campbell et al. (1997) also criticised the technique as it ignores the estimation error at first stage regressions. Consequently, the standard errors of the coefficients at second stage regression will be excessively high.

Pettengill et al. (1995) suggested a rounded approach to the Fama and MacBeth (1973) which concentrates on the difference between expected and realised returns. They made use of a conditional technique which distinguishes positive market returns from negative ones. Bearing in mind, ex post (as opposed to ex ante) returns are the ones to be included when estimating the CAPM. The incorporation of realised returns generates a conditional association between risk and return. Investors will choose to hold a low beta portfolio if and only if there is a positive probability that the return on the low beta portfolio is higher than that of the high beta one. This happens when the return on the risk-free asset is greater than the market return. Moreover, a positive conditional association between beta and returns is present when the average excess returns in a market is positive and when the link between risk and return is uniform across positive and negative excess returns. Hence, a conditional relationship between beta and returns is valid relying on the sign and magnitude of market

[13] See, Sharpe, 1964; Lintner, 1965; Black, 1972.
[14] See, Fama and French, 1992; Jegadeesh, 1992; Harvey and Zhou, 1993; Ferson and Harvey, 1994.

returns. In other words, if market returns are negative (positive), then there must be a negative (positive) relationship between beta and asset returns. After employing this technique, Pettengill et al. (1995) showed strong evidence for beta as a measure of risk in the USA stock market.

In some evaluations of existing literature, the econometric methodologies employed to model oil price volatility were MGARCH models. For instance, the BEKK-GARCH technique has been classified as the most prominent MGARCH framework by Baba et al. (1987), Engle and Kroner (1995) to estimate the time varying conditional variances. This is because, it permits for highly sophisticated interactions amongst the covariances leading to greater functionality. Therefore, making it better than the Constant Conditional Correlation (CCC-GARCH) MGARCH technique where time varying conditional covariances are parametrised to be symmetrical to the product coinciding with the conditional standard deviations. It is also better than the Dynamic Conditional Correlation (DCC-GARCH) MGARCH model which forces a constant dynamic structure for every conditional correlation. The next reason, a BEKK-GARCH guarantees a positive semi-definiteness of the estimated conditional covariance matrices. This is achieved by imposing an automatic underlying restriction within the structure of the model. Such feature does not exist in the Vector (VEC-GARCH) MGARCH technique as it does not guarantee positive semi-definiteness. Of course, BEKK-GARCH provides higher time variation in covariances unlike Factor (FGARCH) MGARCH model. The latter also confines the number of corresponding factors for variables in question.

However, all of these MGARCH econometric methodologies (including BEKK-GARCH) have proven to be problematic when setting up large conditional covariance matrices resulting from the direct extension of univariate GARCH to MGARCH models. To put differently, the latter generates a massive number of parameters to be estimated as the number of equations increases. Consider for example, if the number of variables to be entered into an equation is B, then for a BEKK-GARCH (1,1) technique, the estimated number of parameters is going to be $2B^2 + \frac{B(B+1)}{2}$. This signifies that there is an exponential growth in the number of parameters as B increases. Hence, if the number of variables in question is sixteen (such as our case), BEKK-GARCH (1,1) would require estimating 648 parameters in the variance equation which is an incredibly high value. According to Caporin and McAleer, (2010) this model also tends to generate non-linearity in parameters making its convergence to be extremely challenging for high B.

There are techniques to overcome these dimensionality issues but they often involve either limiting the number of variables in question (which leads to an incomplete analysis of the impacts of oil price volatility) or simplifying the model (which is predominantly invalid). To overcome these limitations and achieve our aim of contributing to existing literature, we employ a modern GARCH technique suggested by Gibson et al. (2017). This econometric framework enables the construction of conditional covariance matrices with unlimited size. Accordingly, we construct a GARCH framework to assess whether volatility of crude oil prices can translate volatility of gold prices, Bitcoin, nominal effective exchange rate, 3-month deposit rate and the returns of eleven sectoral stock indices of two oil-exporting and three oil-importing OECD countries. We achieve this by estimating the daily time-varying conditional covariance and correlations through a noncomplex computational technique for establishing large conditional covariance matrices. As a result, we overcome all restrictions imposed in previous literature and bypass the dimensionality issue of traditional MGARCH models.

Another way to look at this, according to Morelli (2002) and Gibson et al. (2017), our GARCH model can estimate the time-varying conditional variances which is classified as the most accurate measure of risk. This differs greatly from constant unconditional variances that are estimated by other GARCH techniques. The link between the conditional variance of any two variables, such as "v" and "w" and their conditional variance summations can be formalised using equations (1.1) to (1.3) below:

$$E(v_t + w_t \mid \varepsilon_t)^2 = E({v_t}^2|\varepsilon_t) + E({w_t}^2|\varepsilon_t) + 2E(v_t w_t|\varepsilon_t) \quad (1.1)$$

$$Var(v_t + w_t \mid \varepsilon_t) = Var(v_t|\varepsilon_t) + Var(w_t|\varepsilon_t) + 2Cov(v_t w_t|\varepsilon_t) \quad (1.2)$$

$$Cov(v_t w_t|\varepsilon_t) = [Var(v_t + w_t|\varepsilon_t) - Var(v_t|\varepsilon_t) - Var(w_t|\varepsilon_t)]/2 \quad (1.3)$$

Equations (1.1) to (1.3), present the conditional variance and covariance of the two variables “v” and “w”. There is solely one assumption here where both variables have a zero-mean process. Furthermore, it is vital to estimate the conditional variance of each variable individually (in this case, “v” and “w”) along with the summation of their conditional variances to obtain the conditional covariance. We obtain this by employing a univariate GARCH (1,1) model. All conditional variances in equation (1.3) are expected to be consistent which is also reflected on the conditional covariance (since GARCH relies on maximum likelihood to estimate conditional variances).

It is worth mentioning however, if we estimate these conditional variances via a univariate GARCH technique, our model could potentially suffer from omitted variable bias (resulting from omitting covariance terms). According to Gibson et al. (2017), although the parameters of a univariate GARCH framework are inconsistent estimates for the parameter matrices of MGARCH ones, we are solely interested in obtaining a consistent estimate of the three conditional variances stated in equation (1.3). Thus, it is not essential to acquire consistent estimates for the parameter matrices of an MGARCH framework.

We can demonstrate the consistency of these conditional variances by relying on the Wold Decompostion Theorm (WDT). It indicates that any process can be symbolised by an infinite order Moving Average (MA) univariate paradigm which occurs for two reasons. First, a GARCH technique is a time-series illustration of the variance process. Second, it is due to the WDT assumption which states that a valid univariate characterisation exists despite the model in question being a multivariate one. Because of this, a univariate GARCH (1,1) framework that is identical to an infinite order MA technique guarantees conditional variance consistency subject to inserting sufficient number of lags in the univariate GARCH technique.

To employ this model, we need to estimate the daily time-varying conditional variances of all sixteen variables by using the conventional univariate GARCH model that is restricted to GARCH (1,1) specification. This yields the daily conditional variances that consequently stratifies equation (1.3) to obtain the conditional covariance. The mean equation of our univariate GARCH model will have the following error correction model[15]:

$$\Delta w_{it} = d_i + \sum_{i=1}^{16} \sum_{j=1}^{k} \theta_{ij} \, \Delta w_{it-j} + \sum_{i=1}^{16} \gamma_i \, w_{it-1} + \varepsilon_{it} \qquad \varepsilon_t \, \big| \, I_{t-1} \sim N(0, z_t) \qquad (1.4)$$

Where, Δw_{it-j} and Δw_{it} are the lagged and current return of the variable in question, respectively. k is the optimum lag length, while d_i corresponds to the deterministic component. ε_{it} is associated with present innovation of the variable in question conditional on a lagged set of information I_{t-1} which is normally distributed with zero mean and time-reliant variance z_t. On the other hand, the variance equation of a GARCH (1,1) is as follows:

$$z_{it} = h + \lambda \varepsilon_{it-1}^2 + \alpha z_{it-1}, \qquad h > 0, \qquad \big| \lambda + \alpha \big| < 1 \qquad (1.5)$$

Where, z_{it} represents the time-varying conditional variance of the variable in question. λ is the coefficient of the lagged residuals squared ε_{it-1}^2 with the latter obtained from equation (1.4). α, on the other hand is the coefficient of z_{it-1} which is the lagged conditional variance. The condition $\big| \lambda + \alpha \big| < 1$ is essential for a GARCH model to be stationary. Taking into consideration the residuals' conditional normality, our GARCH model demonstrated in equations (1.4) and (1.5) can be estimated using that maximum likelihood function below.

$$L = -\frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} log \, \big| z_t \big| - \frac{1}{2} \sum_{t=1}^{T} \varepsilon_t^2 \, / \, \big| z_t \big| \qquad (1.6)$$

With T being the total number of observations. We make use of the absolute value of z_t here to secure positive conditional variances in our log likelihood function.

[15] The mean equation of univariate GARCH techniques for the summation terms is represented as:

$$\Delta w_{(s+i)t} = d_{s+i} + \sum_{i=1}^{16} \sum_{j=1}^{k} \theta_{ij} \, \Delta w_{it-j} + \sum_{i=1}^{16} \gamma_i \, w_{it-1} + \varepsilon_{(s+i)t} \qquad \varepsilon_t \, \big| \, I_{t-1} \sim N(0, z_t)$$

Where, s and i corresponds to the natural logarithm of oil prices and all other fifteen variables in questions respectively.

1.4 Results and Interpretation

Our empirical analysis commences with estimating the univariate GARCH models prescribed in equations (1.4) and (1.5) for the sixteen variables individually and for the summation of crude oil prices with each of the remaining fifteen variables for each country. The findings are illustrated in tables (1.3) and (1.4) below.

Table 1.3: Individual GARCH Estimation Results

Variable		USA	CAN	UK	FRA	JAP
$\Delta LBTC_t$	h	0.000118*	0.000125*	0.000107*	0.000113*	0.000197*
	λ	0.147*	0.154*	0.134*	0.160*	0.144*
	α	0.817*	0.808*	0.833*	0.810*	0.793*
	λ+α	0.964	0.962	0.967	0.970	0.937
	LL	2669.258	2720.139	2691.121	2719.942	2339.906
	SIC	-3.248	-3.248	-3.241	-3.256	-3.092
ΔLCD_t	h	3.08E-06*	3.31E-06*	6.25E-06*	5.49E-06*	1.76E-05*
	λ	0.152*	0.149*	0.152*	0.117*	0.211*
	α	0.822*	0.820*	0.812*	0.851*	0.631*
	λ+α	0.975	0.970	0.963	0.968	0.843
	LL	5184.268	5294.566	4915.385	4845.227	4569.375
	SIC	-6.469	-6.481	-6.058	-5.931	-6.212
ΔLCS_t	h	4.18E-06*	6.46E-06*	8.33E-06*	4.96E-06*	1.27E-06*
	λ	0.233*	0.096*	0.181*	0.109*	0.044*
	α	0.729*	0.878*	0.752*	0.855*	0.942*
	λ+α	0.961	0.974	0.933	0.964	0.986
	LL	5385.825	4538.285	5080.697	4974.106	4589.335
	SIC	-6.727	-5.531	-6.267	-6.094	-6.240
ΔLEN_t	h	3.43E-06*	0.000233**	3.03E-06*	3.35E-06*	5.21E-06*
	λ	0.119*	0.150***	0.098*	0.119*	0.036*
	α	0.876*	0.600*	0.899*	0.878*	0.943*
	λ+α	0.995	0.750	0.997	0.997	0.979
	LL	4341.069	4022.297	4289.410	4446.409	3891.185
	SIC	-5.389	-4.883	-5.265	-5.429	-5.263
$\Delta LFIN_t$	h	8.42E-06*	3.05E-06*	5.93E-06*	7.68E-06*	1.09E-05*
	λ	0.230*	0.171*	0.150*	0.152*	0.265*
	α	0.714*	0.807*	0.836*	0.829*	0.715*
	λ+α	0.944	0.978	0.987	0.981	0.980
	LL	4983.961	5275.047	4581.062	4515.483	4279.588
	SIC	-6.212	-6.456	-5.635	-5.516	-5.807
$\Delta LGOLD_t$	h	1.07E-06*	1.25E-06*	5.16E-07*	4.71E-07*	2.01E-06*
	λ	0.044*	0.049*	0.031*	0.031*	0.070*
	α	0.941*	0.933*	0.962*	0.963*	0.908*
	λ+α	0.985	0.982	0.993	0.994	0.978

	LL	5287.106	5420.498	5352.921	5361.931	4741.959
	SIC	-6.600	-6.639	-6.612	-6.582	-6.454
ΔLHC_t	h	3.26E-06*	5.59E-05*	6.13E-06*	3.78E-06*	3.29E-06*
	λ	0.118*	0.169*	0.073*	0.084*	0.072*
	α	0.848*	0.823*	0.884*	0.885*	0.903*
	λ+α	0.966	0.992	0.957	0.970	0.976
	LL	5158.917	3011.035	4809.842	4983.474	4383.687
	SIC	-6.436	-3.614	-5.924	-6.105	-5.952
$\Delta LIND_t$	h	5.49E-06*	4.60E-06*	7.46E-06*	6.99E-06*	1.98E-06*
	λ	0.189*	0.082*	0.144*	0.164*	0.054*
	α	0.771*	0.889*	0.810*	0.803*	0.930*
	λ+α	0.960	0.971	0.955	0.967	0.984
	LL	5076.081	4843.977	4828.151	4833.511	4387.704
	SIC	-6.330	-5.915	-5.948	-5.917	-5.958
ΔLIT_t	h	7.78E-06*	2.36E-06*	5.39E-06*	8.85E-06*	3.33E-06*
	λ	0.210*	0.079*	0.100*	0.121*	0.076*
	α	0.758*	0.914*	0.900*	0.841*	0.901*
	λ+α	0.968	0.994	1.000	0.962	0.977
	LL	4758.048	4471.643	4129.185	4586.850	4375.376
	SIC	-5.923	-5.447	-5.062	-5.606	-5.941
ΔIR_t	h	2.88E-14*	9.80E-14*	3.07E-14*	2.80E-14*	3.28E-14*
	λ	0.366*	0.601*	0.146*	0.220*	0.381*
	α	0.750*	0.640*	0.828*	0.739*	0.718*
	λ+α	**1.116**	**1.241**	0.974	0.959	**1.099**
	LL	18706.520	19141.900	20051.700	20634.920	17708.770
	SIC	-23.783	-23.866	-25.230	-25.805	-24.602
$\Delta LMAT_t$	h	7.58E-06*	2.19E-06*	8.59E-06*	1.10E-05*	2.05E-06*
	λ	0.134*	0.055*	0.073*	0.139*	0.040*
	α	0.819*	0.936*	0.904*	0.792*	0.946*
	λ+α	0.953	0.991	0.977	0.930	0.986
	LL	4744.508	4471.119	4041.998	4850.194	4212.208
	SIC	-5.905	-5.447	-4.952	-5.938	-5.712
$\Delta LNEER_t$	h	2.02E-07*	6.82E-07*	1.39E-06*	6.42E-08*	3.51E-07*
	λ	0.063*	0.077*	0.136*	0.102*	0.040*
	α	0.914*	0.874*	0.810*	0.878*	0.945*
	λ+α	0.977	0.952	0.945	0.980	0.985
	LL	6966.260	6695.673	6325.607	7983.367	5575.888
	SIC	-8.750	-8.240	-7.844	-9.881	-7.621
$\Delta LOIL_t$	h	2.24E-05*	2.03E-05*	2.13E-05*	2.06E-05*	2.33E-05*
	λ	0.153*	0.140*	0.139*	0.141*	0.148*
	α	0.818*	0.835*	0.834*	0.832*	0.829*
	λ+α	0.971	0.974	0.973	0.973	0.977
	LL	3725.982	3789.721	3745.518	3775.847	3330.422
	SIC	-4.601	-4.591	-4.576	-4.585	-4.478
ΔLRE_t	h	3.94E-06*	1.99E-06*	5.34E-06*	3.60E-06*	4.41E-06*
	λ	0.142*	0.120*	0.227*	0.129*	0.113*

	α	0.830*	0.867*	0.774*	0.861*	0.843*
	λ+α	0.972	0.987	**1.001**	0.990	0.957
	LL	4957.606	5221.379	4769.984	4684.166	4625.989
	SIC	-6.178	-6.389	-5.874	-5.729	-6.291
$\Delta LTEL_t$	h	1.56E-05*	6.38E-06*	8.88E-06*	4.60E-06*	3.26E-05*
	λ	0.158*	0.160*	0.117*	0.095*	0.259*
	α	0.699*	0.785*	0.853*	0.880*	0.578*
	λ+α	0.856	0.945	0.971	0.975	0.837
	LL	4984.047	5233.181	4430.788	4772.213	4203.813
	SIC	-6.212	-6.404	-5.444	-5.840	-5.701
$\Delta LUTI_t$	h	2.88E-06*	2.18E-06*	1.28E-05*	6.00E-06*	1.08E-05*
	λ	0.094*	0.123*	0.159*	0.116*	0.080*
	α	0.877*	0.856*	0.775*	0.855*	0.849*
	λ+α	0.971	0.980	0.933	0.971	0.929
	LL	5099.476	5288.046	4723.319	4717.774	4275.873
	SIC	-6.360	-6.472	-5.815	-5.771	-5.801

1. *LL: Loglikelihood ratio.*
2. *SIC: Schwarz Information Criterion.*
3. **, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*
4. *Values in bold indicate non-stationarity.*

Table 1.4: Summations GARCH Estimation Results

Variable		USA	CAN	UK	FRA	JAP
$\Delta(LOIL + LBTC)_t$	h	0.000232*	0.000195*	0.000168*	0.000183*	0.000260*
	λ	0.130*	0.116*	0.112*	0.123*	0.135*
	α	0.801*	0.827*	0.840*	0.824*	0.798*
	λ+α	0.932	0.943	0.952	0.948	0.933
	LL	2379.410	2431.672	2406.418	2432.126	2103.378
	SIC	-2.877	-2.886	-2.880	-2.894	-2.761
$\Delta(LOIL + LCD)_t$	h	2.94E-05*	2.88E-05*	2.47E-05*	2.61E-05*	3.16E-05*
	λ	0.156*	0.155*	0.135*	0.125*	0.132*
	α	0.815*	0.819*	0.847*	0.852*	0.839*
	λ+α	0.972	0.973	0.982	0.977	0.971
	LL	3499.847	3570.715	3435.981	3440.991	3148.472
	SIC	-4.312	-4.316	-4.184	-4.164	-4.224
$\Delta(LOIL + LCS)_t$	h	2.30E-05*	2.90E-05*	2.53E-05*	2.29E-05*	2.52E-05*
	λ	0.150*	0.122*	0.124*	0.134*	0.133*
	α	0.826*	0.856*	0.850*	0.846*	0.845*
	λ+α	0.976	0.978	0.975	0.980	0.978
	LL	3573.551	3345.883	3514.148	3498.063	3167.646
	SIC	-4.406	-4.034	-4.283	-4.236	-4.250
$\Delta(LOIL + LEN)_t$	h	2.89E-05*	3.68E-05*	2.79E-05*	2.93E-05*	5.32E-05*
	λ	0.135*	0.138*	0.120*	0.127*	0.123*
	α	0.851*	0.843*	0.869*	0.858*	0.836*
	λ+α	0.986	0.981	0.989	0.986	0.959
	LL	3110.965	3168.911	3059.781	3160.462	2905.536
	SIC	-3.814	-3.812	-3.708	-3.811	-3.884
$\Delta(LOIL + LFIN)_t$	h	2.85E-05*	2.40E-05*	2.69E-05*	2.52E-05*	2.62E-05*
	λ	0.153*	0.133*	0.132*	0.143*	0.141*
	α	0.820*	0.848*	0.853*	0.844*	0.841*
	λ+α	0.974	0.981	0.984	0.987	0.982
	LL	3446.565	3482.564	3308.253	3322.741	3099.012
	SIC	-4.244	-4.206	-4.022	-4.015	-4.154
$\Delta(LOIL + LGOLD)_t$	h	2.77E-05*	2.57E-05*	2.62E-05*	2.43E-05*	3.34E-05*
	λ	0.128*	0.121*	0.113*	0.121*	0.135*
	α	0.836*	0.846*	0.852*	0.848*	0.828*
	λ+α	0.965	0.967	0.965	0.968	0.963
	LL	3591.804	3668.254	3620.408	3657.259	3214.130
	SIC	-4.429	-4.439	-4.418	-4.436	-4.315
$\Delta(LOIL + LHC)_t$	h	2.60E-05*	9.23E-05*	2.42E-05*	2.47E-05*	3.19E-05*
	λ	0.143*	0.170*	0.111*	0.117*	0.135*
	α	0.829*	0.817*	0.864*	0.856*	0.836*
	λ+α	0.972	0.987	0.975	0.973	0.971
	LL	3525.531	2612.010	3475.055	3519.095	3140.732
	SIC	-4.345	-3.113	-4.234	-4.262	-4.213
$\Delta(LOIL + LIND)_t$	h	3.05E-05*	2.17E-05*	2.80E-05*	2.54E-05*	3.03E-05*

	λ	0.153*	0.122*	0.125*	0.135*	0.134*
	α	0.817*	0.862*	0.851*	0.846*	0.840*
	λ+α	0.970	0.984	0.976	0.981	0.974
	LL	3461.878	3433.902	3393.620	3415.835	3096.927
	SIC	-4.263	-4.145	-4.131	-4.132	-4.151
$\Delta(LOIL + LIT)_t$	h	3.68E-05*	1.82E-05*	3.37E-05*	2.90E-05*	2.83E-05*
	λ	0.162*	0.114*	0.110*	0.121*	0.133*
	α	0.805*	0.875*	0.868*	0.853*	0.844*
	λ+α	0.967	0.989	0.978	0.975	0.976
	LL	3411.782	3362.910	3232.429	3393.213	3112.648
	SIC	-4.199	-4.055	-3.926	-4.104	-4.173
$\Delta(LOIL + IR)_t$	h	2.24E-05*	2.03E-05*	2.13E-05*	2.06E-05*	2.33E-05*
	λ	0.153*	0.140*	0.139*	0.141*	0.148*
	α	0.818*	0.835*	0.834*	0.832*	0.829*
	λ+α	0.971	0.974	0.973	0.973	0.977
	LL	3725.984	3789.724	3745.516	3775.847	3330.422
	SIC	-4.601	-4.591	-4.576	-4.585	-4.478
$\Delta(LOIL + LMAT)_t$	h	2.99E-05*	2.96E-05*	3.86E-05*	2.65E-05*	3.17E-05*
	λ	0.146*	0.109*	0.118*	0.124*	0.130*
	α	0.828*	0.866*	0.858*	0.851*	0.844*
	λ+α	0.975	0.975	0.976	0.975	0.974
	LL	3369.064	3342.925	3075.082	3454.821	3057.806
	SIC	-4.144	-4.030	-3.727	-4.181	-4.097
$\Delta(LOIL + LNEER)_t$	h	2.34E-05*	2.29E-05*	2.43E-05*	2.05E-05*	2.35E-05*
	λ	0.147*	0.143*	0.137*	0.142*	0.152*
	α	0.821*	0.830*	0.833*	0.831*	0.823*
	λ+α	0.967	0.974	0.970	0.973	0.975
	LL	3739.359	3710.255	3682.996	3779.435	3361.784
	SIC	-4.618	-4.492	-4.497	-4.590	-4.522
$\Delta(LOIL + LRE)_t$	h	3.02E-05*	2.51E-05*	3.06E-05*	2.21E-05*	2.72E-05*
	λ	0.149*	0.135*	0.159*	0.149*	0.134*
	α	0.819*	0.844*	0.820*	0.837*	0.842*
	λ+α	0.967	0.979	0.979	0.987	0.975
	LL	3500.610	3510.868	3430.859	3437.683	3163.340
	SIC	-4.313	-4.241	-4.178	-4.160	-4.244
$\Delta(LOIL + LTEL)_t$	h	3.20E-05*	2.38E-05*	2.02E-05*	2.31E-05*	2.80E-05*
	λ	0.143*	0.149*	0.129*	0.140*	0.135*
	α	0.821*	0.830*	0.862*	0.842*	0.846*
	λ+α	0.964	0.979	0.990	0.982	0.981
	LL	3498.673	3575.702	3320.456	3465.292	3064.196
	SIC	-4.310	-4.323	-4.038	-4.195	-4.106
$\Delta(LOIL + LUTI)_t$	h	2.92E-05*	2.72E-05*	2.62E-05*	2.32E-05*	2.83E-05*
	λ	0.141*	0.136*	0.121*	0.130*	0.129*
	α	0.821*	0.837*	0.856*	0.851*	0.847*
	λ+α	0.963	0.974	0.976	0.981	0.976
	LL	3577.316	3534.216	3446.806	3442.522	3103.491

	SIC	-4.411	-4.271	-4.198	-4.166	-4.161

1. *LL: Loglikelihood ratio.*
2. *SIC: Schwarz Information Criterion.*
3. **, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*

From table (1.3), it is clearly evident that the coefficients of the lagged conditional variance (α) and lagged squared residual (λ) are strongly statistically significant at 1% for all sixteen variables a side from the Canadian energy sub index where λ is significant at 10%. Whereas in table (1.4), the summation of crude oil prices with each variable reveal that both α and λ are strongly statistically significant at 1% for all variables and countries. In line with conditions stated in equation (1.5), both the non-negativity and stationarity conditions are satisfied most of the time.

Given these results, we then obtain the time-varying conditional variances which we use for calculating the conditional covariances by applying equations (1.2) and (1.3). Eventually, to make our interpretations more meaningful and overcome the scaling issue of conditional covariances, we generate the time-varying conditional correlations. These figures are demonstrated in the form of sets for each country from A1 – A5 in the appendix.

1.4.1 Impacts of Oil Prices Pre COVID-19

Following Xiao et al. (2018), we distinguish between the association of oil prices with energy intensive (i.e., CD, EN, IND, UTI and MAT) and non-energy intensive sectoral stock indices (i.e., FIN, CS, TEL, IT, RE and HC). Hamilton (1983) classifies the latter as defensive sectors since they are less vulnerable to oil price volatility. Although this relies on their energy cost structures and dependence on oil as a source of input in the production process. The same applies to UTI resulting from a stable demand for services. Supporting the interpretations of the time varying conditional correlations by the Granger causality test, we begin by analysing both sectors after which we explain the link between oil prices and all other variables.

When looking at oil-exporting countries such as the USA and CAN in figures A1 and A2 of the appendix respectively, we find that in most cases returns of all energy and non-energy intensive sectoral stock indices of both countries exhibit a significant positive correlation with oil prices. In other words, when oil prices are highly volatile, returns of both sets of sectoral stock indices will also experience high volatility. This goes in hand with our Granger causality test results in tables A6 and A7 of the appendix where volatility of returns in most sectoral stock indices of both countries reveal a unidirectional causality with volatility of oil prices. To put differently, returns volatility of sectoral stock indices Granger causes volatility in oil prices. Such findings are in line with the theoretical application of Kilian and Park (2009) where the surge in global demand for automotive, hospitality, retail sectors and all industrial commodities are the main driving factor of oil price volatility. Non-energy intensive sectors mimic the results on energy intensive ones as investors' apprehension about stock markets and economic uncertainty explain these findings which is consistent with evidence presented by Kilian and Park, 2009; Alsalman and Herrera, 2015; Hamdi et al., 2019. Uncertainty in transportation costs which is associated with importing or delivering health care products, mobile equipment, essential consumer goods could also explain these findings.

When looking at oil-importing countries namely UK, FRA, and JAP in figures A3 – A5 of the appendix respectively, all energy (excluding LCDUK, LUTIUK and LUTIJAP) and non-energy intensive sectoral stock index returns (apart from LCSUK, LITUK, LREUK, LTELUK) reveal a significant positive correlation with oil prices. For the UK and FRA, this is consistent with our Granger causality test results reported in tables A8 and A9 of the appendix where volatility of returns in most sectoral stock indices Granger causes volatility of oil prices. Such findings are in line with the theoretical application of Kilian and Park (2009) as indicated above. However, there are three notable differences in our findings when compared to those obtained for the USA and CAN. First, the existence of insignificant association between oil prices and returns of CD and UTI is explained by the theory presented by Sadorsky (1999). He argued that firms in both sectors use financial derivatives (such as options, forwards, futures etc) to hedge against the impact of oil price volatility on their profits and thus stock returns. Arouri (2011) have also shown that CD and UTI firms exercise periodic risk management strategies to hedge against oil price volatility. Second, the insignificant association between oil prices and non-energy intensive sectors mentioned earlier fall under Hamilton's (1983) classification of defensive sectors. Their energy cost structures and dependence on oil as a source of input in the production process is low which means that they are less vulnerable to oil price volatility. Both insignificant associations are confirmed by the Granger causality test results reported in tables A8 and A9 of the appendix labelled as independent. Third, in JAP the Granger causality test results reported in table A10 of the appendix reveals that volatility in oil prices Granger causes the volatility of returns in most sectoral stock indices. This direction of volatility relationship is in sharp contrast to what has been observed for other countries. According to Workman (2023), JAP is ranked as the fifth largest oil-importing country in the world which means that oil still plays a significant role in the Japanese economy. It also indicates that Japan's economy is less diversified when compared to other countries in question. These results are consistent with Hamilton (1983) theory where oil price volatility affects the stability of the macroeconomy making it difficult for non-energy intensive firms to predict macroeconomic conditions which impacts their stock returns. There also exists significant cost uncertainties for energy intensive firms since they rely heavily on oil as an input factor. As a result, it becomes challenging to manage costs efficiently which impacts profitability and stock market returns volatility.

Over to the relationship linking oil prices, macroeconomy, precious metals and cryptocurrency. Our time varying conditional correlations and Granger causality tests report ambiguous results for the relationship between oil price volatility and NEER of all countries in question. This goes in hand with existing literature (see for example, Chen and Chen, 2007; Habib and Kalamova, 2007; Cifarelli and Paladino, 2010; Basher et al., 2012; Reboredo, 2012). Similarly, the association between oil price volatility and IR is ambiguous for oil-importing countries while its negative for oil-exporting ones. This is plausible as according to Filis and Chatziantoniou (2014), the response of IR to an oil price shock (or vice versa) relies heavily on the monetary policy regime of each country. With regards to gold, all countries in question share the same significant positive correlation with oil prices. It is unidirectional from gold to oil prices (excluding JAP for the same reasons supported by Workman (2023) and Hamilton (1983) mentioned earlier) where volatility of gold Granger causes volatility of oil prices. This is explained by the theory of Kilian and Park (2009) where investors demand for precious metals increases during times of political tensions. Hence, leading to an increase in volatility of oil prices and a hike in the share prices of gold producing firms. Our findings are also compatible with existing literature on the relationship between gold and oil prices (see for example, Hammoudeh and Yuan, 2008; Zhang and Wei, 2010; Gkillas et al., 2022; Hazgui et al., 2022). Finally, our time varying conditional correlations reveal a significant positive association between BTC and oil prices for most countries. The relationship is unidirectional from volatility of oil prices to BTC as per the Granger causality tests results. Chancharat and Butda (2021) attributes this to investors sentiment and hedging against inflation to be main factors that explain these results.

1.4.2 Impacts of Oil Prices Intra COVID-19

As discussed in section 1.3.1, volatility of oil prices during the COVID-19 pandemic was quite erratic. We detect three key differences on the relationship between oil price volatility and variables in question when compared to the time before the pandemic. First, figures A1 – A5 of the appendix illustrate that the returns of most energy and non-energy intensive sectoral stock indices reveal a significant positive correlation with oil prices for all countries. This is in line with our Granger causality test results in tables A6 – A10 of the appendix where volatility of returns in most sectoral stock indices Granger causes volatility in oil prices. The foregoing reported unidirectional causality from oil prices to the returns of various Japanese sectoral stock indices have now been reversed. Second, sectors such as LTELUSA, LTELUK, LCDUK, LUTIUK, LUTIJAP, LCSUK, LITUK and LREUK which previously displayed an insignificant correlation with oil prices have now changed to report a significant positive one. Our Granger causality test results in tables A6 – A10 of the appendix confirm these transitions. They have now changed from independent to unidirectional causality from volatility of returns in these sectors to volatility of oil prices. All of this is consistent with Kilian and Park's (2009) theory which states that it is the surge in global demand for commodities which drives oil price volatility. We also attribute the pandemic to be a contributing factor behind these results.

With regards to the TEL sector, this is because of a sudden evolution towards work from home and e-learning practices. This would require importing or delivering equipment to be used for both, thereby explaining the significant positive correlation. When considering UTI, the transition is meaningful as during lockdowns households' consumption of electricity, water and gas have dramatically increased. For CD, CS and IT, the transition is explained by a sudden increase in the sale of hygiene products, food and beverages caused by panic buying, the requirement of immediate advancement to computer software and electronics to cope up with the new normal means that there is great uncertainty in returns of these sectoral stock indices resulting from the COVID-19 pandemic. Given that volatility of returns in these sectors Granger causes volatility in oil prices, this reinforces Kilian and Park's (2009) theory in relation to the surge in global demand for commodities which drives oil price volatility.

Third, we uncover a transition from significant positive correlation between BTC and oil prices to an insignificant one for all countries in question according to figures A1 – A5 of the appendix. This is also confirmed by our Granger causality test results in tables A6 – A10 of the appendix where the unidirectional causality among volatility of BTC and oil prices have now become independent. Recent studies find that BTC did not serve as a reliable hedge or safe haven for oil markets during the pandemic. Despite BTC's energy-intensive mining process being associated with energy prices, the relationship was inadequate to generate significant correlations with volatility of oil prices especially during times of extreme uncertainty caused by the pandemic.[16]

The relationship between oil price volatility and NEER of all countries remains ambiguous as per the time varying conditional correlations and Granger causality tests results. Similarly, the association between oil price volatility and IR is still ambiguous for oil-importing countries and negative for oil-exporting ones. With regards to gold, all countries in question share the same significant positive correlation with oil prices. It is unidirectional from gold to oil prices where volatility of gold Granger causes volatility of oil prices.

1.5 Robustness Checks and Summary of Results

Using the conditional variance from the GARCH equation (1.5) for each individual variable, we employed the Granger causality test in sections 1.4.1 and 1.4.2. to confirm results obtained in the time varying conditional correlations. The idea is to understand the

[16] See, Ibrahim et al., 2022; Maghyereh and Abdoh, 2022; Zha et al., 2023; Foroutan and Lahmiri, 2024

lag transmission between volatility of oil prices and all variables in our model. In simple terms, does volatility in oil prices causes volatility in the variable in question? If the answer is yes, then lags of oil prices must be significant in the equation of the variable in question. This would be classified as unidirectional causality or in other words volatility of oil prices Granger causes volatility of the variable in question. Additionally, if volatility of the variable in question also causes volatility in oil prices, then we have a case of bidirectional causality. As a result, lags of the variable in question will definitely be significant in the equation of oil. It is important to note however, detecting a Granger causality does not necessary mean that variation in one variable explicitly causes variation in the other. Instead, it merely refers to the historical or sequential ordering of variation in two time series. More specifically, one can say that variations in one variable seem to drive the variation of the other (for example, having a correlation among existing values of a variable and the previous values of the other). With that said, tables A6 – A10 (in the appendix) present the Granger causality test results pre and intra the COVID-19 pandemic with the inclusion of 2 lags for each combination. This is because, most the affect is captured within 2 days.

As an additional confirmation to our results, we assess the sign (whether positive or negative) of oil price volatility and volatility of all variables in question via the kernel density distribution (KDD). These are illustrated in figures A6 – A10 of the appendix for each country. The horizontal axis accounts for the time varying conditional correlation while the vertical presents its density. For variables that revealed significant positive (negative) correlation with oil prices, we can see that density is highest (lowest) for correlation values greater than or equal to 0.2 (-0.2). For variables that Granger cause volatility in oil prices, this indicates that 20% or more of volatility in oil prices is explained by that of corresponding variables. Conversely, when volatility in oil prices Granger cause volatility of variables in question, 20% or more of the latter is explained by that of the former. For variables which revealed insignificant correlation with oil prices, density is highest for correlation values between 0 and 0.1. Therefore, little to no volatility in variables in question is explained by that of oil prices and vice versa.

Table 1.5: Summary of Results

Volatility Relationship	Pre COVID-19 – (Oil-Exporting)	Pre COVID-19 – (Oil-Importing)	Intra COVID-19 – (Oil-Exporting)	Intra COVID-19 – (Oil-Importing)
Oil – Sectoral Stock Indices	Significant (+)	Ambiguous	Significant (+)	**Significant (+)**
Oil – Nominal Effective Exchange Rate	Ambiguous	Ambiguous	Ambiguous	Ambiguous
Oil – 3-month Deposit Rate	Significant (-)	Ambiguous	Significant (-)	Ambiguous
Oil – Bitcoin	Significant (+)	Ambiguous	**Insignificant**	**Insignificant**
Oil – Gold Price	Significant (+)	Significant (+)	Significant (+)	Significant (+)

Note: The table summarises results obtained in time varying conditional correlations, Granger causality tests and KDDs. Words in bold refer to the observed transitions in volatility relationship during the pandemic.

According to table 1.5, when considering oil-exporting countries, Bitcoin and gold exhibit a significant positive correlation with oil prices before the pandemic. Similarly, in most cases returns of all energy and non-energy intensive sectoral stock indices reveal a significant positive correlation with oil prices. However, the relationship is significantly negative for the 3-month deposit rate while its ambiguous for the nominal effective exchange rate. When looking at oil-importing countries, the relationship between oil prices and all variables in question (aside from gold prices) is ambiguous. During the pandemic, we uncover three transitions where both oil-exporting and importing countries now report an insignificant association between Bitcoin and oil prices. Finally, oil-importing countries now present a significant positive correlation between returns of most sectoral stock indices and oil prices. This confirms the conclusions made by Huang et al. (2018) where the relationship between returns of sectoral stock indices and oil prices differs over time.

1.6 Conclusion

To re-emphasise, this chapter conducts a comparative study between five OECD oil-exporting and importing countries. The aim was to investigate whether there exists a difference in the ability of oil price volatility to explain volatility of FTSE-100 sectoral stock index returns, macroeconomy, precious metals and cryptocurrency pre and intra the COVID-19 pandemic. To achieve this, we initially employ a technique proposed by Gibson et al. (2017) to estimate the daily time varying conditional covariance and correlations. Second, to understand whether volatility of oil prices causes volatility of an individual variable (or vice versa), we obtain the time varying conditional variance from the GARCH equation to test for Granger causality. Finally, to confirm whether the correlation relationship is positive or negative, we generate the KDDs.

Our empirical findings reveal that, the difference between the explanation of oil prices and all variables in question pre and intra the COVID-19 pandemic for oil-exporting and importing countries is quite ambiguous. In pre COVID-19 times, although oil-exporting countries produce the same results when looking at the relationship between oil prices and sectoral stock index returns, but we are unable to generate a solid conclusion for oil-importing countries given that the results are contradictory. Likewise, for the 3-month deposit rate, Bitcoin and oil prices, oil-exporting countries present a consistent outcome while it is again uncertain for oil-importing countries. Lastly, both oil-exporting and importing countries report conflicting results for the nominal effective exchange rate and oil prices while all countries reveal the same oil-gold relationship.

However, during the pandemic we see a transition from insignificant to significant (and vice versa) correlation between oil prices and variables in question for both set of countries. Oil-exporting and importing countries share the exact same significant correlation between returns of all sectoral stock indices and oil prices. We attribute the pandemic to be the driving factor of volatility for both oil and sectoral stock index returns. Investors and firms are also expected to take effective hedging strategies that would protect them from oil price volatility. When examining macroeconomic, gold and cryptocurrency, all countries share the same correlation relationship between Bitcoin, gold, and oil price. Yet, it is not a clear cut for the nominal effective exchange rate, 3-month deposit rate and oil price correlation when comparing oil exporting and importing countries. Therefore, during times of high oil price volatility risk loving investors could choose to invest in variables that share a significant positive relationship. Whereas risk averse investors could choose to invest in those variables that reveal insignificant or negative relationship with oil prices. In the same light, firms and other economic agents could alter or delay production and consumption decisions accordingly. Given the contradiction in our results and existing literature, financial institutions, investors, and portfolio managers should consider each country on a case-by-case basis.

Appendix A

Table A1: Descriptive Statistics - United States

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Min	Max	Count
BTC	12484.793	413.746	7122.400	236.700	16362.587	267734260.699	2.041	1.807	131.060	233.800	67527.900	1564
CDUSA	2643.298	19.387	2489.400	1814.770	766.710	587843.528	-0.500	0.774	29.006	1587.090	4558.690	1564
CSUSA	1222.256	6.037	1126.790	1129.810	238.740	56996.899	0.189	1.265	19.533	881.880	1875.610	1564
ENUSA	742.719	3.760	782.405	851.210	148.709	22114.459	0.026	-0.910	20.022	299.800	969.700	1564
FINUSA	846.191	4.395	843.210	629.520	173.829	30216.485	-0.139	0.533	20.543	517.960	1279.850	1564
GOLD	1442.383	6.480	1320.790	1107.900	256.273	65676.090	-1.047	0.639	17.767	1051.100	2063.540	1564
HCUSA	2210.363	11.938	2146.555	1724.660	472.130	222906.841	-0.361	0.719	21.360	1502.130	3408.440	1564
INDUSA	1598.203	9.947	1540.215	1194.380	393.365	154736.333	-0.269	0.749	24.613	976.420	2471.030	1564
ITUSA	1810.199	21.235	1569.555	910.290	839.774	705219.647	-0.068	0.980	46.391	798.050	4005.070	1564
IRUSA	1.238	0.022	1.240	0.195	0.882	0.777	-1.359	0.258	71.244	0.124	2.830	1564
MATUSA	720.937	3.508	698.440	561.770	138.715	19241.788	0.160	0.813	19.241	455.070	1076.590	1564
NEERUSA	120.720	0.087	120.565	118.880	3.448	11.891	0.809	0.470	2.856	112.830	132.550	1564
OIL	57.070	0.360	57.835	70.710	14.255	203.195	-0.342	-0.294	24.978	9.120	86.070	1564
REUSA	2966.799	7.597	2935.300	2715.710	300.439	90263.720	0.631	0.245	10.127	1870.510	3896.380	1564
TELUSA	443.640	0.635	440.560	444.560	25.109	630.468	-0.535	0.262	5.660	375.840	504.120	1564
UTIUSA	601.899	1.984	587.445	734.470	78.447	6153.903	-0.922	0.121	13.033	437.850	780.970	1564

Table A2: Descriptive Statistics - Canada

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Min	Max	Count
BTC	12418.910	407.376	7129.200	236.700	16269.546	264698124.709	2.090	1.817	131.006	233.800	67527.900	1595
CDCAN	1159.356	3.934	1122.220	969.810	157.127	24688.931	-0.769	0.341	13.553	809.850	1533.200	1595
CSCAN	721.568	4.761	666.160	598.880	190.151	36157.424	1.131	1.400	26.352	358.790	1259.140	1595
ENCAN	499.808	1.837	515.130	518.010	73.379	5384.406	0.301	-0.993	14.681	234.630	620.370	1595
FINCAN	772.312	3.104	773.940	627.390	123.947	15362.928	0.235	0.589	16.049	467.050	1090.790	1595
GOLD	1441.821	6.408	1321.430	1107.900	255.933	65501.706	-1.039	0.642	17.751	1051.100	2063.540	1595
HCCAN	599.140	13.116	486.400	458.350	523.835	274402.879	17.556	3.934	87.431	183.910	4530.580	1595
INDCAN	823.184	6.015	760.550	487.150	240.228	57709.409	-0.851	0.525	29.183	409.810	1369.890	1595
ITCAN	76.951	1.108	58.710	40.620	44.263	1959.170	0.003	1.139	57.521	29.360	196.160	1595
IRCAN	1.036	0.016	0.945	0.210	0.630	0.397	-1.413	0.072	60.811	0.120	2.335	1595
MATCAN	260.915	1.217	245.560	217.600	48.598	2361.766	-0.557	0.491	18.626	154.030	374.290	1595
NEERCAN	84.194	0.056	84.080	84.210	2.255	5.085	0.870	-0.034	2.678	75.340	90.480	1595
OIL	57.070	0.356	57.830	70.710	14.199	201.608	-0.331	-0.295	24.880	9.120	86.070	1595
RECAN	2114.239	6.183	2114.980	#N/A	246.930	60974.436	-0.243	-0.122	11.679	1231.322	2674.858	1595
TELCAN	1046.678	2.633	1040.510	1092.890	105.152	11056.900	-0.057	0.266	10.046	741.860	1297.390	1595
UTICAN	823.159	3.498	791.990	739.470	139.716	19520.438	-0.136	0.572	16.973	503.730	1180.890	1595

Table A3: Descriptive Statistics - United Kingdom

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Min	Max	Count
BTC	12482.221	410.320	7165.500	236.700	16315.053	266180961.794	2.049	1.808	130.706	233.800	67527.900	1581
CDUK	383.116	0.891	382.760	387.300	35.439	1255.906	0.769	-0.627	9.250	227.670	450.850	1581
CSUK	872.355	1.724	871.490	916.560	68.537	4697.319	0.234	-0.204	7.857	579.710	1047.140	1581
ENUK	532.959	3.082	554.460	587.210	122.554	15019.604	-0.779	-0.385	22.995	237.450	766.930	1581
FINUK	242.451	0.869	243.630	234.920	34.534	1192.566	0.114	-0.492	14.244	146.110	320.140	1581
GOLD	1442.758	6.445	1321.900	1107.900	256.279	65678.714	-1.051	0.635	17.763	1051.100	2063.540	1581
HCUK	535.173	1.512	519.710	608.230	60.117	3614.002	-1.011	0.396	11.233	430.820	679.040	1581
INDUK	399.156	1.668	385.130	349.020	66.315	4397.723	0.512	1.045	16.614	243.150	583.760	1581
ITUK	20.235	0.097	18.870	18.220	3.850	14.826	-0.572	0.643	19.026	11.150	30.400	1581
IRUK	0.495	0.007	0.530	0.575	0.259	0.067	-1.266	-0.151	52.323	0.027	0.969	1581
MATUK	298.968	2.015	300.060	277.380	80.121	6419.434	-0.258	0.241	26.799	121.050	501.470	1581
NEERUK	99.859	0.119	98.410	98.390	4.739	22.462	2.633	1.616	4.746	92.230	117.160	1581
OIL	57.084	0.358	57.860	70.710	14.219	202.173	-0.329	-0.299	24.909	9.120	86.070	1581
REUK	2300.153	7.038	2285.150	2424.760	279.860	78321.351	0.592	0.286	12.167	1397.370	3190.400	1581
TELUK	218.583	1.792	197.010	189.420	71.265	5078.723	-0.804	0.521	32.603	107.870	385.400	1581
UTIUK	832.525	2.696	822.460	1014.880	107.189	11489.516	-0.735	0.333	12.875	579.530	1091.560	1581

Table A4: Descriptive Statistics - France

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Min	Max	Count
BTC	12444.186	408.187	7129.600	236.700	16281.478	265086540.615	2.076	1.814	130.836	233.800	67527.900	1591
CDFRA	384.915	1.345	388.920	384.560	53.638	2877.017	-0.192	0.376	13.935	257.450	518.810	1591
CSFRA	2563.737	15.418	2550.150	1760.730	614.964	378180.932	-0.435	0.565	23.987	1585.120	3934.080	1591
ENFRA	965.540	3.767	985.310	895.590	150.259	22577.888	0.117	-0.466	15.562	440.510	1282.980	1591
FINFRA	249.794	1.092	250.970	262.900	43.556	1897.125	0.037	-0.103	17.437	130.300	356.710	1591
GOLD	1442.425	6.417	1321.600	1107.900	255.939	65504.559	-1.043	0.639	17.744	1051.100	2063.540	1591
HCFRA	1120.990	3.753	1089.090	1018.330	149.689	22406.753	-0.301	0.725	13.353	879.900	1509.550	1591
INDFRA	358.027	1.864	366.170	261.880	74.342	5526.701	-1.005	0.026	20.764	222.880	504.440	1591
ITFRA	364.481	2.788	346.570	242.670	111.187	12362.534	0.547	1.038	30.506	216.290	701.910	1591
IRFRA	-0.374	0.003	-0.373	-0.385	0.118	0.014	0.697	0.513	-31.551	-0.775	0.020	1591
MATFRA	1124.483	5.877	1098.320	868.430	234.428	54956.279	-0.891	0.421	20.848	735.120	1605.660	1591
NEERFRA	100.617	0.049	100.830	100.850	1.950	3.802	-0.831	-0.334	1.938	95.640	103.940	1591
OIL	57.087	0.356	57.840	70.710	14.189	201.331	-0.329	-0.295	24.855	9.120	86.070	1591
REFRA	1171.041	4.315	1195.390	1191.570	172.117	29624.215	-0.133	-0.671	14.698	678.830	1536.710	1591
TELFRA	187.716	0.525	191.020	185.340	20.939	438.424	-0.957	-0.401	11.155	137.190	228.960	1591
UTIFRA	177.580	0.466	178.380	174.290	18.605	346.153	0.401	-0.794	10.477	118.150	210.310	1591

Table A5: Descriptive Statistics - Japan

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Min	Max	Count
BTC	12905.189	431.896	7400.100	236.700	16337.985	266929767.360	1.870	1.763	126.600	233.800	67527.900	1431
CDJAP	226.261	0.507	228.370	227.460	19.175	367.664	-0.990	0.051	8.475	182.410	267.570	1431
CSJAP	319.214	0.890	314.310	308.620	33.659	1132.918	-0.817	0.118	10.544	236.700	397.920	1431
ENJAP	96.065	0.551	92.100	86.040	20.859	435.088	0.195	0.944	21.713	60.760	161.340	1431
FINJAP	43.150	0.117	43.010	41.910	4.434	19.656	-0.038	-0.135	10.276	29.740	55.810	1431
GOLD	1456.402	6.645	1326.840	1237.970	251.386	63195.058	-1.121	0.646	17.261	1061.100	2063.540	1431
HCJAP	342.583	1.555	329.110	326.600	58.814	3459.047	-0.986	0.439	17.168	232.130	476.350	1431
INDJAP	368.769	1.819	362.450	262.040	68.795	4732.710	-0.557	0.355	18.655	218.000	538.370	1431
ITJAP	94.145	0.648	88.260	104.540	24.528	601.625	-0.362	0.788	26.053	55.030	158.650	1431
IRJAP	-0.156	0.002	-0.130	-0.110	0.092	0.009	10.287	-2.064	-58.974	-1.050	0.125	1431
MATJAP	151.882	0.587	149.110	133.270	22.223	493.854	-0.879	-0.022	14.632	98.200	201.520	1431
NEERJAP	87.006	0.090	86.090	85.360	3.405	11.596	-0.301	0.099	3.914	76.720	95.200	1431
OIL	57.884	0.364	59.240	70.710	13.782	189.946	-0.146	-0.351	23.810	9.120	86.070	1431
REJAP	26.013	0.052	25.753	24.309	1.973	3.892	0.453	0.212	7.585	16.476	30.885	1431
TELJAP	363.647	1.728	344.050	332.290	65.352	4270.861	0.772	1.108	17.971	222.530	569.240	1431
UTIJAP	42.308	0.122	42.720	44.080	4.607	21.223	-0.290	-0.307	10.889	30.200	52.290	1431

Figure A1: Time Varying Conditional Correlation of Oil Prices and all Variables in Question – United States

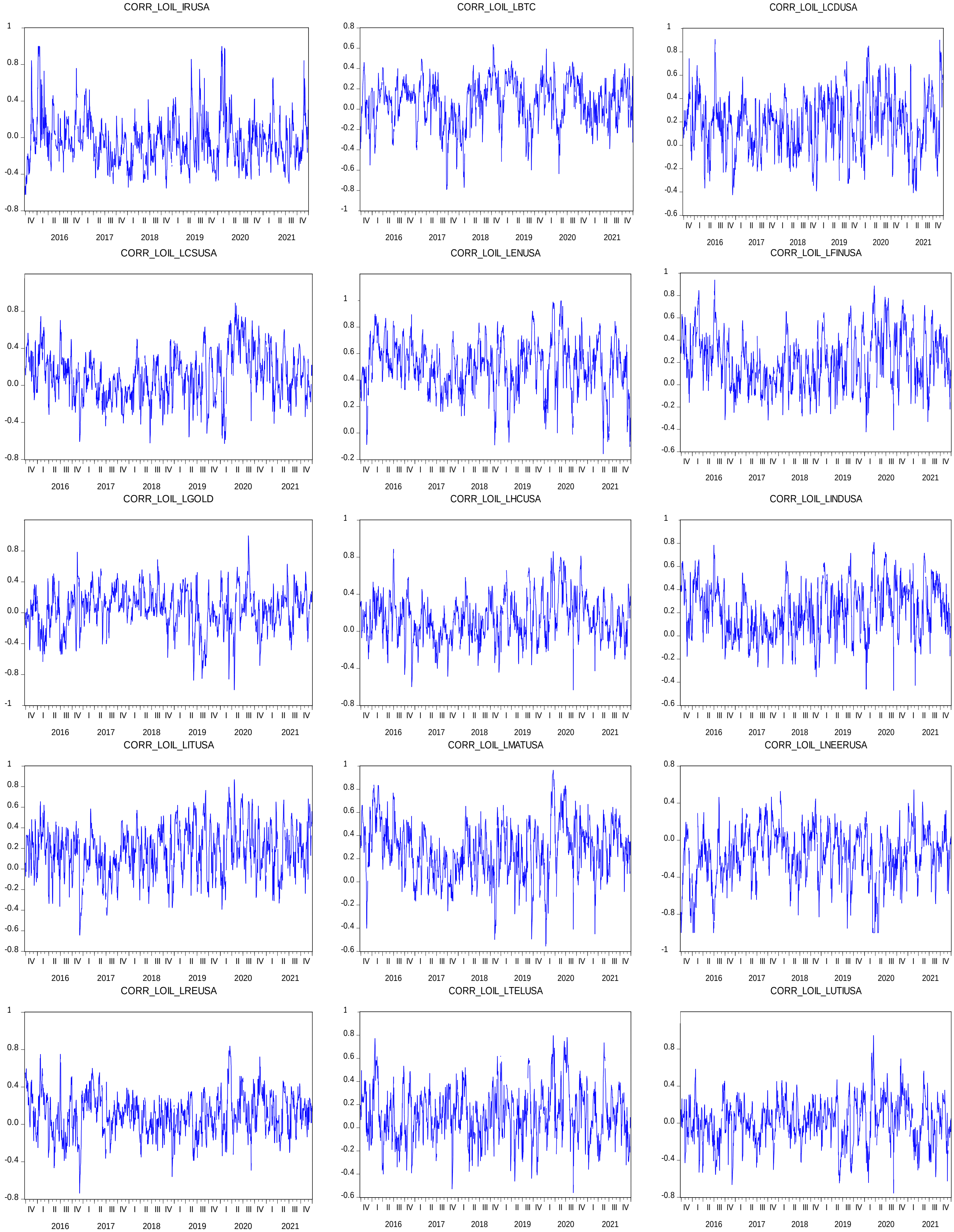


Figure A2: Time Varying Conditional Correlation of Oil Prices and all Variables in Question – Canada

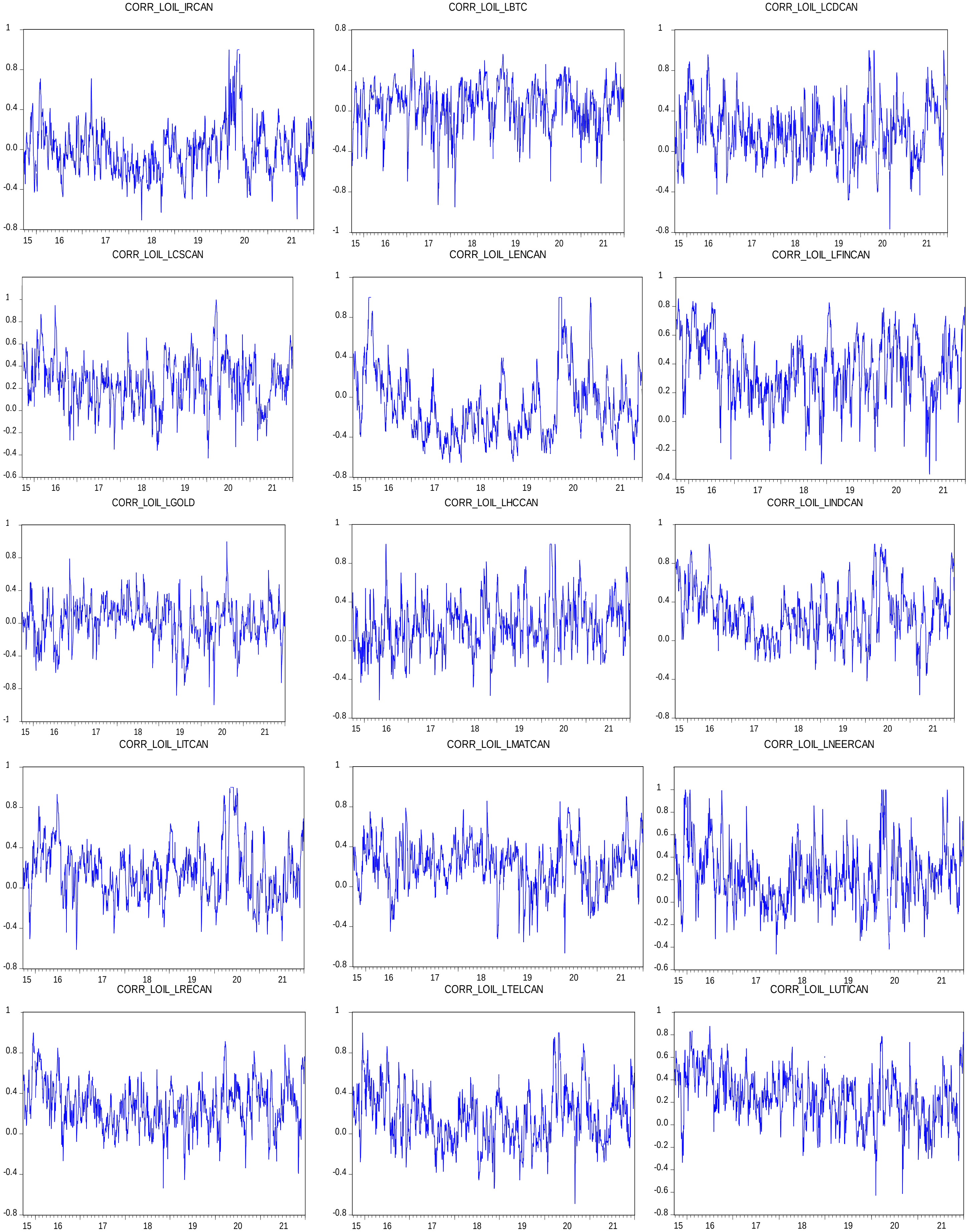


Figure A3: Time Varying Conditional Correlation of Oil Prices and all Variables in Question – United Kingdom

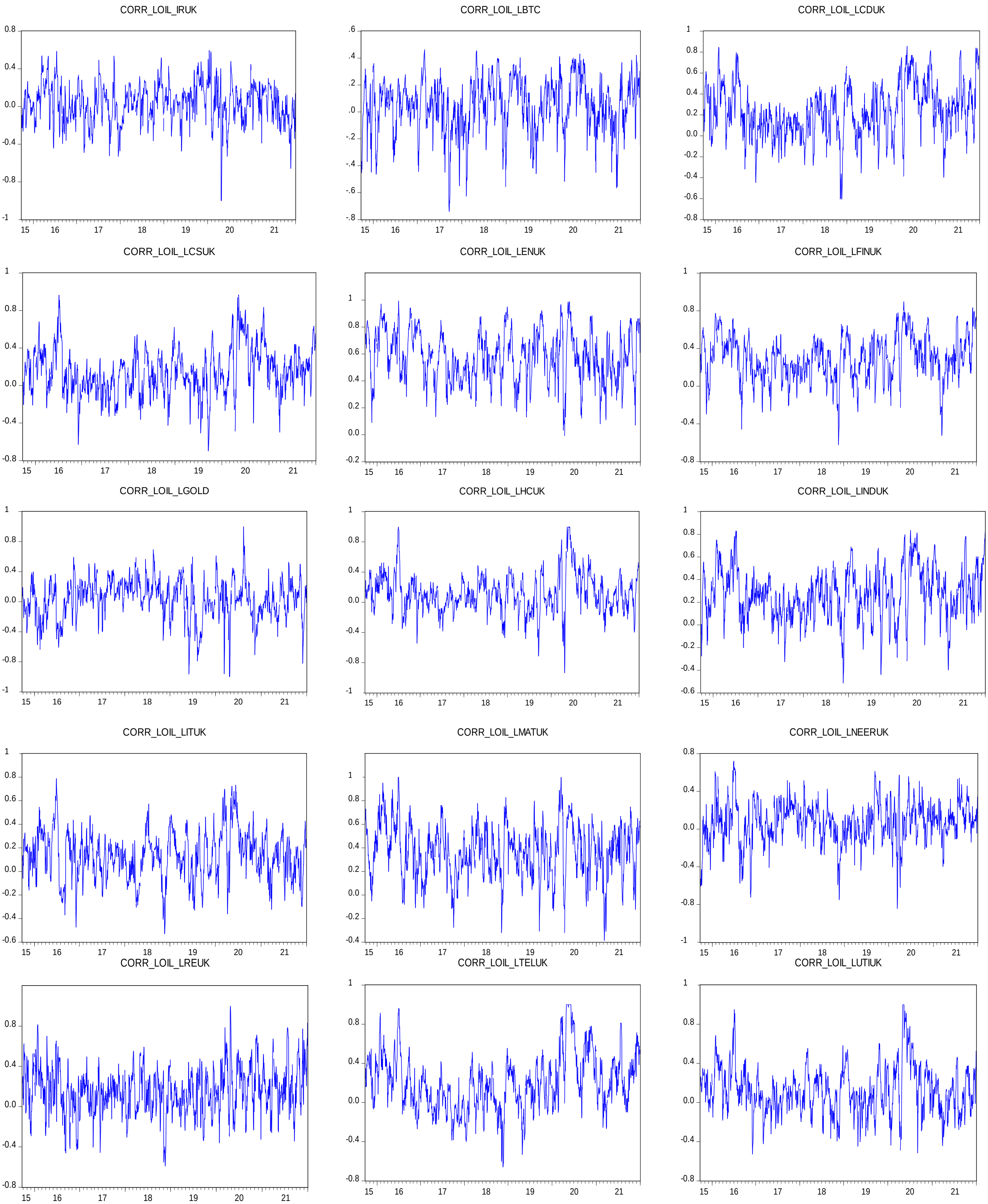


Figure A4: Time Varying Conditional Correlation of Oil Prices and all Variables in Question – France

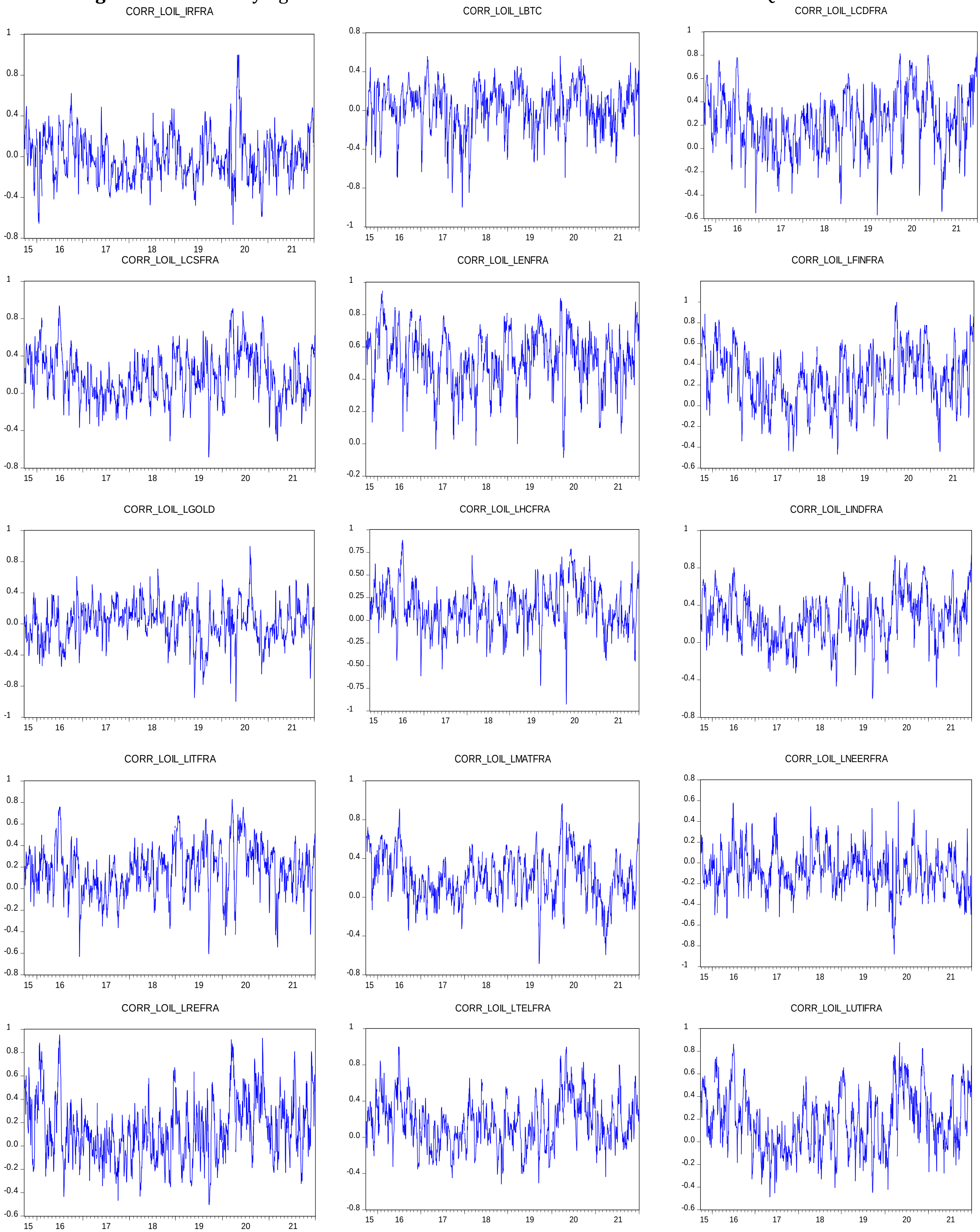


Figure A5: Time Varying Conditional Correlation of Oil Prices and all Variables in Question – Japan

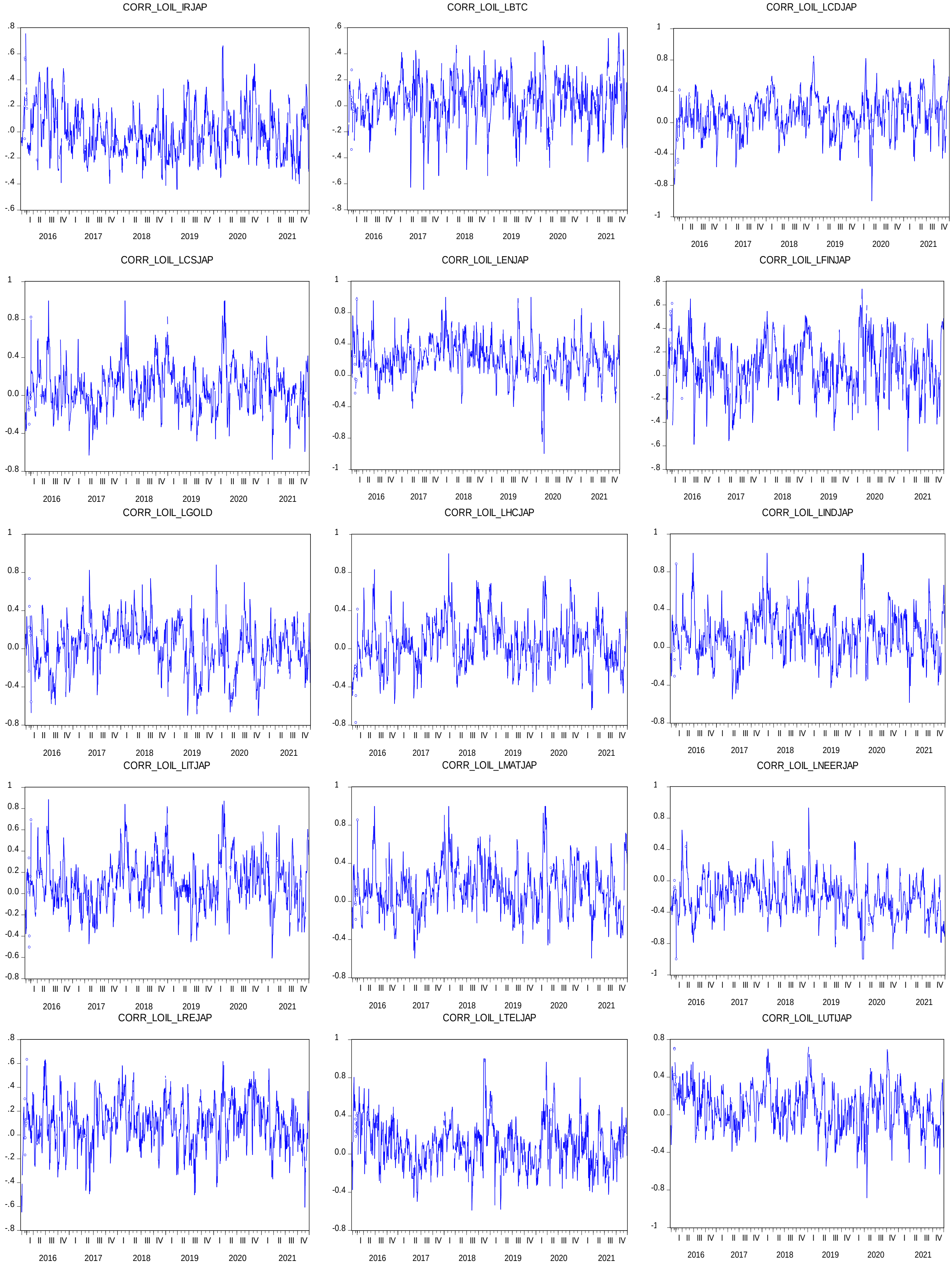


Table A6: Granger Causality Test Results - United States

Null Hypothesis	Pre COVID-19 F-Statistic (p-value)	Intra COVID-19 F-Statistic (p-value)	Causality Decision (Pre COVID-19)	Causality Decision (Intra COVID-19)
VAR_IRUSA does not Granger Cause VAR_LOIL	2.378***(0.093)	96.947* (3.0E-36)	VAR_IRUSA → VAR_LOIL	VAR_IRUSA ↔ VAR_LOIL
VAR_LOIL does not Granger Cause VAR_IRUSA	1.080 (0.340)	6.589* (0.002)		
VAR_LBTC does not Granger Cause VAR_LOIL	0.021 (0.980)	1.076(0.342)	VAR_LOIL → VAR_LBTC	Independent
VAR_LOIL does not Granger Cause VAR_LBTC	2.600*** (0.075)	0.437 (0.646)		
VAR_LCDUSA does not Granger Cause VAR_LOIL	5.081* (0.006)	5.861* (0.003)	VAR_LCDUSA → VAR_LOIL	VAR_LCDUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCDUSA	0.262 (0.770)	0.189 (0.828)		
VAR_LCSUSA does not Granger Cause VAR_LOIL	6.046* (0.003)	2.600*** (0.075)	VAR_LCSUSA → VAR_LOIL	VAR_LCSUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCSUSA	1.124 (0.325)	0.824 (0.439)		
VAR_LENUSA does not Granger Cause VAR_LOIL	10.550* (3.0E-05)	8.416* (0.000)	VAR_LENUSA → VAR_LOIL	VAR_LENUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LENUSA	1.337 (0.263)	1.087 (0.338)		
VAR_LFINUSA does not Granger Cause VAR_LOIL	8.437* (0.000)	5.304* (0.005)	VAR_LFINUSA ↔ VAR_LOIL	VAR_LFINUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LFINUSA	2.920*** (0.054)	0.593 (0.553)		
VAR_LGOLD does not Granger Cause VAR_LOIL	13.551* (2.E-06)	11.891* (9.0E-06)	VAR_LGOLD → VAR_LOIL	VAR_LGOLD → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LGOLD	1.035 (0.3555)	0.414 (0.661)		
VAR_LHCUSA does not Granger Cause VAR_LOIL	5.681* (0.004)	8.922* (0.000)	VAR_LHCUSA → VAR_LOIL	VAR_LHCUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LHCUSA	1.217(0.296)	1.711 (0.181)		
VAR_LINDUSA does not Granger Cause VAR_LOIL	5.886* (0.003)	6.058* (0.003)	VAR_LINDUSA → VAR_LOIL	VAR_LINDUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LINDUSA	1.239 (0.290)	1.216 (0.297)		
VAR_LITUSA does not Granger Cause VAR_LOIL	4.502** (0.011)	3.160** (0.043)	VAR_LITUSA → VAR_LOIL	VAR_LITUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LITUSA	0.926 (0.397)	0.060 (0.942)		
VAR_LMATUSA does not Granger Cause VAR_LOIL	8.695* (0.000)	7.795* (0.001)	VAR_LMATUSA → VAR_LOIL	VAR_LMATUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LMATUSA	1.845 (0.159)	1.114 (0.329)		
VAR_LNEERUSA does not Granger Cause VAR_LOIL	1.609 (0.201)	10.869* (2.0E-05)	Independent	VAR_LNEERUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LNEERUSA	0.053 (0.949)	1.288 (0.277)		
VAR_LREUSA does not Granger Cause VAR_LOIL	3.497** (0.031)	5.871* (0.003)	VAR_LREUSA ↔ VAR_LOIL	VAR_LREUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LREUSA	2.793*** (0.062)	0.631 (0.532)		
VAR_LTELUSA does not Granger Cause VAR_LOIL	1.110 (0.330)	4.267** (0.015)	Independent	VAR_LTELUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LTELUSA	0.239 (0.787)	0.716 (0.489)		
VAR_LUTIUSA does not Granger Cause VAR_LOIL	4.098** (0.017)	10.101*(5.0E-05)	VAR_LUTIUSA → VAR_LOIL	VAR_LUTIUSA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LUTIUSA	0.741 (0.477)	1.719 (0.180)		

, ** and * corresponds to significance level at 1%, 5% and 10% respectively*

Table A7: Granger Causality Test Results - Canada

Null Hypothesis	Pre COVID-19 F-Statistic (p-value)	Intra COVID-19 F-Statistic (p-value)	Causality Decision (Pre COVID-19)	Causality Decision (Intra COVID-19)
VAR_IRCAN does not Granger Cause VAR_LOIL	1.691 (0.185)	0.225 (0.799)	VAR_LOIL → VAR_IRCAN	VAR_LOIL → VAR_IRCAN
VAR_LOIL does not Granger Cause VAR_IRCAN	3.368** (0.035)	19.005* (1.0E-08)		
VAR_LBTC does not Granger Cause VAR_LOIL	0.075 (0.9275)	0.817 (0.442)	VAR_LOIL → VAR_LBTC	Independent
VAR_LOIL does not Granger Cause VAR_LBTC	2.459*** (0.086)	0.486 (0.616)		
VAR_LCDCAN does not Granger Cause VAR_LOIL	19.385* (5.0E-09)	5.884* (0.003)	VAR_LCDCAN ↔ VAR_LOIL	VAR_LCDCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCDCAN	4.296** (0.014)	0.541 (0.582)		
VAR_LCSCAN does not Granger Cause VAR_LOIL	5.640* (0.004)	8.327* (0.000)	VAR_LCSCAN ↔ VAR_LOIL	VAR_LCSCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCSCAN	2.913*** (0.055)	0.941 (0.391)		
VAR_LENCAN does not Granger Cause VAR_LOIL	6.883* (0.001)	3.568** (0.029)	VAR_LENCAN ↔ VAR_LOIL	VAR_LENCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LENCAN	6.136* (0.002)	0.086 (0.918)		
VAR_LFINCAN does not Granger Cause VAR_LOIL	11.467* (1.0E-05)	5.880* (0.003)	VAR_LFINCAN ↔ VAR_LOIL	VAR_LFINCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LFINCAN	2.833*** (0.059)	1.796 (0.167)		
VAR_LGOLD does not Granger Cause VAR_LOIL	16.309* (1.0E-07)	10.188* (5.0E-05)	VAR_LGOLD → VAR_LOIL	VAR_LGOLD → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LGOLD	0.657 (0.519)	0.574 (0.5639)		
VAR_LHCCAN does not Granger Cause VAR_LOIL	0.209 (0.811)	4.687** (0.010)	VAR_LOIL → VAR_LHCCAN	VAR_LHCCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LHCCAN	3.468** (0.031)	0.058 (0.944)		
VAR_LINDCAN does not Granger Cause VAR_LOIL	16.563* (8.0E-08)	8.920* (0.000)	VAR_LINDCAN ↔ VAR_LOIL	VAR_LINDCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LINDCAN	2.337*** (0.097)	2.113 (0.122)		
VAR_LITCAN does not Granger Cause VAR_LOIL	11.688* (1.0E-05)	13.958* (1.0E-06)	VAR_LITCAN → VAR_LOIL	VAR_LITCAN ↔ VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LITCAN	0.397 (0.673)	2.662*** (0.071)		
VAR_LMATCAN does not Granger Cause VAR_LOIL	5.294* (0.005)	13.981* (1.0E-06)	VAR_LMATCAN → VAR_LOIL	VAR_LMATCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LMATCAN	1.019 (0.361)	1.072 (0.343)		
VAR_LNEERCAN does not Granger Cause VAR_LOIL	3.976** (0.019)	6.603* (0.002)	VAR_LNEERCAN ↔ VAR_LOIL	VAR_LNEERCAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LNEERCAN	2.638*** (0.072)	2.156 (0.117)		
VAR_LRECAN does not Granger Cause VAR_LOIL	5.815* (0.003)	7.941* (0.000)	VAR_LRECAN → VAR_LOIL	VAR_LRECAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LRECAN	4.126** (0.016)	1.110 (0.330)		
VAR_LTELCAN does not Granger Cause VAR_LOIL	1.255 (0.286)	3.812** (0.023)	VAR_LOIL → VAR_LTELCAN	Independent
VAR_LOIL does not Granger Cause VAR_LTELCAN	5.392* (0.005)	0.940 (0.391)		
VAR_LUTICAN does not Granger Cause VAR_LOIL	10.347* (4.0E-05)	10.593* (3.0E-05)	VAR_LUTICAN → VAR_LOIL	VAR_LUTICAN → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LUTICAN	0.942 (0.390)	2.123 (0.121)		

, ** and * corresponds to significance level at 1%, 5% and 10% respectively*

Table A8: Granger Causality Test Results - United Kingdom

Null Hypothesis	Pre COVID-19 F-Statistic (p-value)	Intra COVID-19 F-Statistic (p-value)	Causality Decision (Pre COVID-19)	Causality Decision (Intra COVID-19)
VAR_IRUK does not Granger Cause VAR_LOIL	0.647(0.524)	1.087 (0.338)	Independent	Independent
VAR_LOIL does not Granger Cause VAR_IRUK	0.915 (0.401)	0.116 (0.890)		
VAR_LBTC does not Granger Cause VAR_LOIL	0.034(0.967)	0.719 (0.488)	VAR_LOIL → VAR_LBTC	Independent
VAR_LOIL does not Granger Cause VAR_LBTC	2.920*** (0.054)	0.374 (0.688)		
VAR_LCDUK does not Granger Cause VAR_LOIL	1.576 (0.207)	7.360* (0.001)	Independent	VAR_LCDUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCDUK	0.141 (0.869)	0.695 (0.500)		
VAR_LCSUK does not Granger Cause VAR_LOIL	1.747 (0.175)	3.646** (0.027)	Independent	VAR_LCSUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCSUK	0.003 (0.997)	0.051 (0.950)		
VAR_LENUK does not Granger Cause VAR_LOIL	13.926* (1.0E-06)	11.168* (2.0E-05)	VAR_LENUK → VAR_LOIL	VAR_LENUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LENUK	0.753 (0.471)	0.475 (0.622)		
VAR_LFINUK does not Granger Cause VAR_LOIL	2.446*** (0.087)	9.073* (0.000)	VAR_LFINUK → VAR_LOIL	VAR_LFINUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LFINUK	0.686 (0.504)	0.039 (0.962)		
VAR_LGOLD does not Granger Cause VAR_LOIL	15.542* (2.0E-07)	10.054* (5.0E-05)	VAR_LGOLD → VAR_LOIL	VAR_LGOLD → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LGOLD	0.486 (0.615)	0.565 (0.569)		
VAR_LHCUK does not Granger Cause VAR_LOIL	8.556* (0.000)	5.780* (0.003)	VAR_LHCUK → VAR_LOIL	VAR_LHCUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LHCUK	1.412 (0.244)	0.326 (0.722)		
VAR_LINDUK does not Granger Cause VAR_LOIL	2.706 *** (0.067)	8.776* (0.000)	VAR_LINDUK → VAR_LOIL	VAR_LINDUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LINDUK	0.314 (0.731)	1.176 (0.309)		
VAR_LITUK does not Granger Cause VAR_LOIL	0.197 (0.821)	8.540* (0.000)	Independent	VAR_LITUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LITUK	0.173 (0.841)	0.301 (0.740)		
VAR_LMATUK does not Granger Cause VAR_LOIL	7.250* (0.001)	9.351* (0.000)	VAR_LMATUK ↔ VAR_LOIL	VAR_LMATUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LMATUK	6.917* (0.001)	0.410 (0.664)		
VAR_LNEERUK does not Granger Cause VAR_LOIL	0.570 (0.566)	2.717*** (0.067)	Independent	VAR_LNEERUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LNEERUK	0.188 (0.828)	0.697 (0.498)		
VAR_LREUK does not Granger Cause VAR_LOIL	0.789 (0.454)	7.194* (0.001)	Independent	VAR_LREUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LREUK	0.191 (0.826)	0.904 (0.406)		
VAR_LTELUK does not Granger Cause VAR_LOIL	1.759 (0.173)	4.305** (0.014)	Independent	VAR_LTELUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LTELUK	0.027 (0.973)	0.078(0.925)		
VAR_LUTIUK does not Granger Cause VAR_LOIL	0.973 (0.378)	4.069** (0.017)	Independent	VAR_LUTIUK → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LUTIUK	0.027 (0.973)	0.359 (0.699)		

, ** and * corresponds to significance level at 1%, 5% and 10% respectively*

Table A9: Granger Causality Test Results - France

Null Hypothesis	Pre COVID-19 F-Statistic (p-value)	Intra COVID-19 F-Statistic (p-value)	Causality Decision (Pre COVID-19)	Causality Decision (Intra COVID-19)
VAR_IRFRA does not Granger Cause VAR_LOIL	7.231* (0.001)	1.229 (0.294)	VAR_IRFRA → VAR_LOIL	VAR_LOIL → VAR_IRFRA
VAR_LOIL does not Granger Cause VAR_IRFRA	0.553 (0.576)	2.415*** (0.090)		
VAR_LBTC does not Granger Cause VAR_LOIL	0.004 (0.996)	0.971 (0.379)	VAR_LOIL → VAR_LBTC	Independent
VAR_LOIL does not Granger Cause VAR_LBTC	3.116** (0.045)	0.362 (0.697)		
VAR_LCDFRA does not Granger Cause VAR_LOIL	3.159** (0.043)	7.451* (0.001)	VAR_LCDFRA → VAR_LOIL	VAR_LCDFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCDFRA	0.510 (0.601)	0.172 (0.842)		
VAR_LCSFRA does not Granger Cause VAR_LOIL	5.231* (0.006)	7.213* (0.001)	VAR_LCSFRA → VAR_LOIL	VAR_LCSFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCSFRA	0.242 (0.785)	0.437 (0.647)		
VAR_LENFRA does not Granger Cause VAR_LOIL	8.231* (0.000)	7.765* (0.001)	VAR_LENFRA → VAR_LOIL	VAR_LENFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LENFRA	0.013 (0.988)	0.284 (0.753)		
VAR_LFINFRA does not Granger Cause VAR_LOIL	2.488*** (0.084)	6.161* (0.002)	VAR_LFINFRA → VAR_LOIL	VAR_LFINFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LFINFRA	1.362 (0.257)	0.355 (0.702)		
VAR_LGOLD does not Granger Cause VAR_LOIL	14.298* (E.0E-07)	8.944* (0.000)	VAR_LGOLD → VAR_LOIL	VAR_LGOLD → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LGOLD	1.165(0.312)	0.176 (0.839)		
VAR_LHCFRA does not Granger Cause VAR_LOIL	4.930* (0.008)	7.317* (0.001)	VAR_LHCFRA → VAR_LOIL	VAR_LHCFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LHCFRA	1.260(0.284)	0.379 (0.685)		
VAR_LINDFRA does not Granger Cause VAR_LOIL	3.379** (0.035)	7.194* (0.001)	VAR_LINDFRA → VAR_LOIL	VAR_LINDFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LINDFRA	0.770 (0.464)	0.863 (0.422)		
VAR_LITFRA does not Granger Cause VAR_LOIL	3.001*** (0.050)	8.204* (0.000)	VAR_LITFRA → VAR_LOIL	VAR_LITFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LITFRA	0.178 (0.837)	0.407 (0.666)		
VAR_LMATFRA does not Granger Cause VAR_LOIL	2.717*** (0.067)	3.758** (0.024)	VAR_LMATFRA → VAR_LOIL	VAR_LMATFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LMATFRA	1.490 (0.226)	0.226 (0.798)		
VAR_LNEERFRA does not Granger Cause VAR_LOIL	1.652 (0.192)	2.913*** (0.055)	Independent	VAR_LNEERFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LNEERFRA	0.007 (0.993)	1.175 (0.310)		
VAR_LREFRA does not Granger Cause VAR_LOIL	4.035** (0.018)	6.408* (0.002)	VAR_LREFRA → VAR_LOIL	VAR_LREFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LREFRA	1.235 (0.291)	0.413 (0.662)		
VAR_LTELFRA does not Granger Cause VAR_LOIL	2.498*** (0.083)	4.039** (0.018)	VAR_LTELFRA → VAR_LOIL	VAR_LTELFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LTELFRA	1.059 (0.347)	0.166 (0.847)		
VAR_LUTIFRA does not Granger Cause VAR_LOIL	5.057* (0.007)	5.364* (0.005)	VAR_LUTIFRA → VAR_LOIL	VAR_LUTIFRA → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LUTIFRA	1.166 (0.312)	0.140 (0.870)		

, ** and * corresponds to significance level at 1%, 5% and 10% respectively*

Table A10: Granger Causality Test Results - Japan

Null Hypothesis	Pre COVID-19 F-Statistic (p-value)	Intra COVID-19 F-Statistic (p-value)	Causality Decision (Pre COVID-19)	Causality Decision (Intra COVID-19)
VAR_IRJAP does not Granger Cause VAR_LOIL	0.088 (0.916)	8.509* (0.000)	VAR_LOIL → VAR_IRJAP	VAR_IRJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_IRJAP	4.471** (0.012)	0.111 (0.895)		
VAR_LBTC does not Granger Cause VAR_LOIL	1.950 (0.143)	0.773 (0.462)	Independent	Independent
VAR_LOIL does not Granger Cause VAR_LBTC	0.728 (0.483)	0.437 (0.647)		
VAR_LCDJAP does not Granger Cause VAR_LOIL	0.207 (0.812)	1.141(0.320)	VAR_LOIL → VAR_LCDJAP	Independent
VAR_LOIL does not Granger Cause VAR_LCDJAP	17.423* (4.00E-08)	1.030(0.358)		
VAR_LCSJAP does not Granger Cause VAR_LOIL	3.995** (0.019)	15.627*(3.0E-07)	VAR_LCSJAP ↔ VAR_LOIL	VAR_LCSJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LCSJAP	127.882* (7E-50)	0.648 (0.524)		
VAR_LENJAP does not Granger Cause VAR_LOIL	2.151 (0.117)	7.326* (0.001)	VAR_LOIL → VAR_LENJAP	VAR_LENJAP ↔ VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LENJAP	2.721*** (0.066)	130.981* (7E-46)		
VAR_LFINJAP does not Granger Cause VAR_LOIL	7.712* (0.000)	3.127** (0.045)	VAR_LFINJAP ↔ VAR_LOIL	VAR_LFINJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LFINJAP	431.082 (7E-134)	1.406 (0.246)		
VAR_LGOLD does not Granger Cause VAR_LOIL	0.133 (0.875)	7.773* (0.001)	VAR_LOIL → VAR_LGOLD	VAR_LGOLD → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LGOLD	473.341 (3E-143)	0.297 (0.743)		
VAR_LHCJAP does not Granger Cause VAR_LOIL	5.568* (0.004)	13.391* (2.0E-06)	VAR_LHCJAP ↔ VAR_LOIL	VAR_LHCJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LHCJAP	7.746* (0.001)	0.599 (0.550)		
VAR_LINDJAP does not Granger Cause VAR_LOIL	3.746** (0.024)	13.626* (2.0E-06)	VAR_LINDJAP ↔ VAR_LOIL	VAR_LINDJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LINDJAP	180.181* (5E-67)	1.640 (0.195)		
VAR_LITJAP does not Granger Cause VAR_LOIL	2.070 (0.127)	9.003* (0.000)	VAR_LOIL → VAR_LITJAP	VAR_LITJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LITJAP	229.337* (6E-82)	1.008 (0.366)		
VAR_LMATJAP does not Granger Cause VAR_LOIL	3.709** (0.025)	13.766* (2.0E-06)	VAR_LMATJAP ↔ VAR_LOIL	VAR_LMATJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LMATJAP	187.219* (3E-69)	1.460 (0.233)		
VAR_LNEERJAP does not Granger Cause VAR_LOIL	0.171 (0.843)	10.947* (2.0E-05)	VAR_LOIL → VAR_LNEERJAP	VAR_LNEERJAP ↔ VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LNEERJAP	17.896* (2.00E-08)	13.298* (2.0E-06)		
VAR_LREJAP does not Granger Cause VAR_LOIL	1.019 (0.361)	4.597**(0.011)	VAR_LOIL → VAR_LREJAP	VAR_LREJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LREJAP	38.534* (8.00E-17)	0.483 (0.617)		
VAR_LTELJAP does not Granger Cause VAR_LOIL	0.573 (0.564)	0.840 (0.432)	VAR_LOIL → VAR_LTELJAP	Independent
VAR_LOIL does not Granger Cause VAR_LTELJAP	11.468* (1.00E-05)	0.584 (0.558)		
VAR_LUTIJAP does not Granger Cause VAR_LOIL	1.132 (0.323)	6.198* (0.002)	Independent	VAR_LUTIJAP → VAR_LOIL
VAR_LOIL does not Granger Cause VAR_LUTIJAP	2.023 (0.133)	0.126 (0.882)		

, ** and * corresponds to significance level at 1%, 5% and 10% respectively*

Figure A6: Kernel Density Distribution of Oil Prices and all Variables in Question – United States

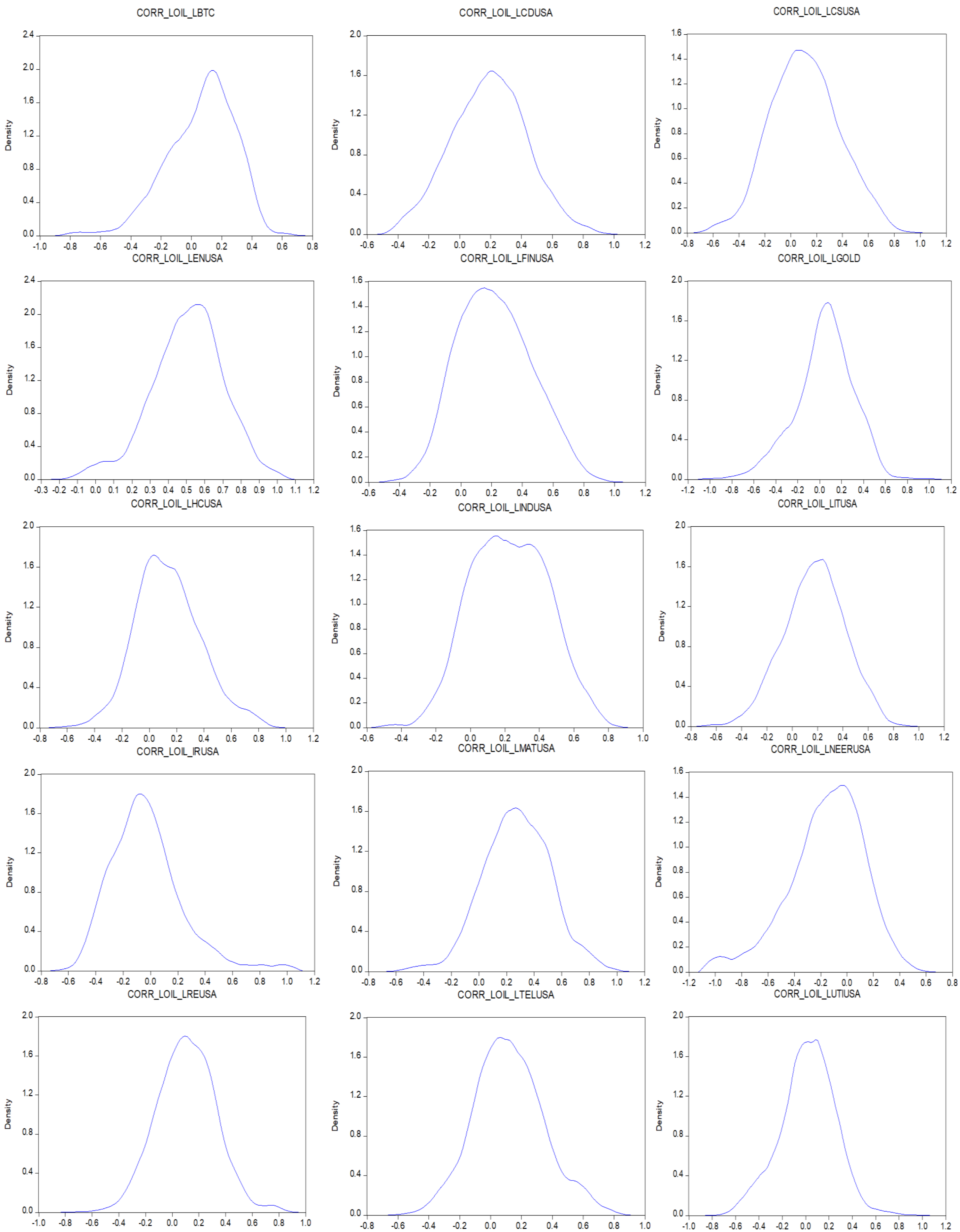


Figure A7: Kernel Density Distribution of Oil Prices and all Variables in Question – Canada

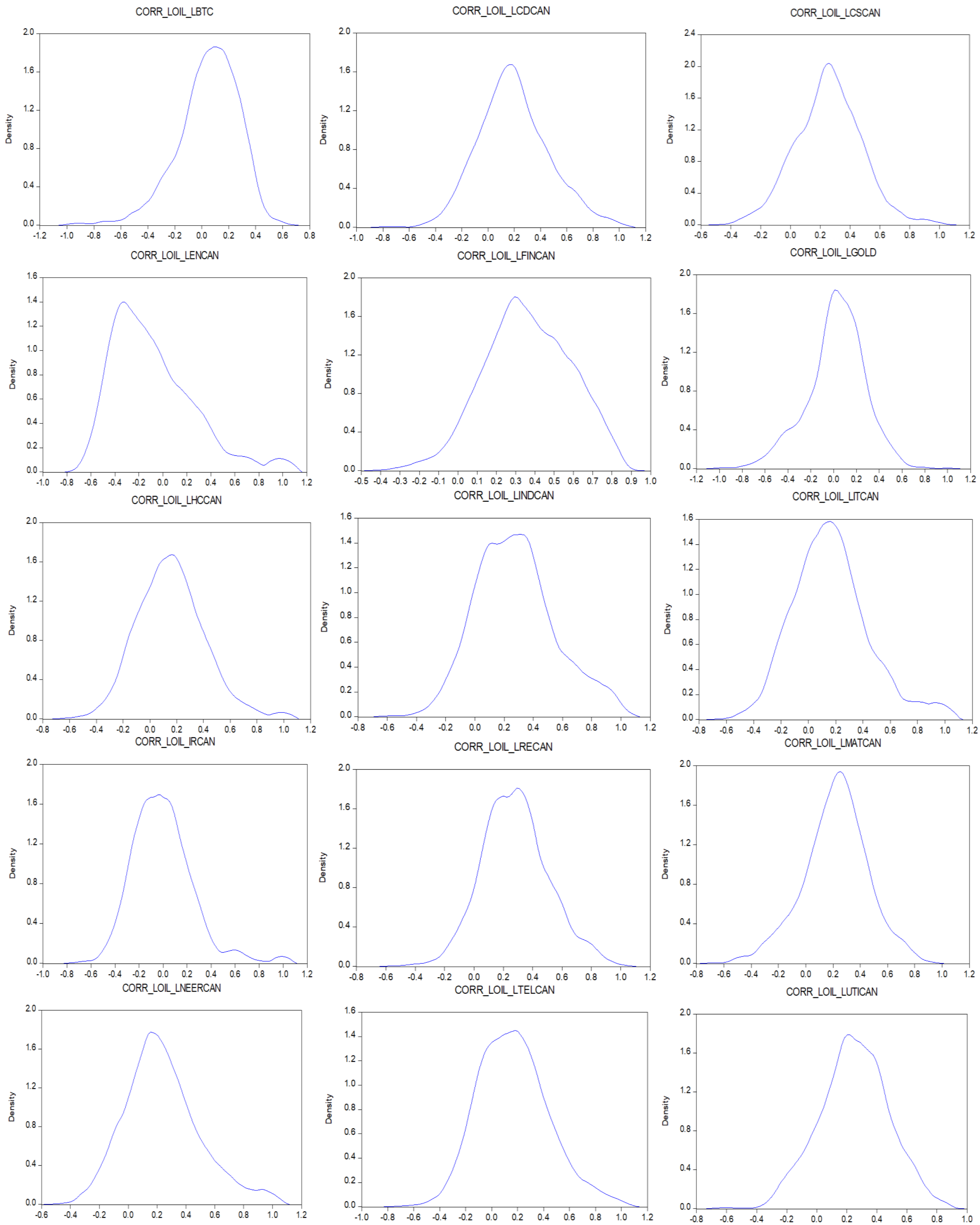


Figure A8: Kernel Density Distribution of Oil Prices and all Variables in Question – United Kingdom

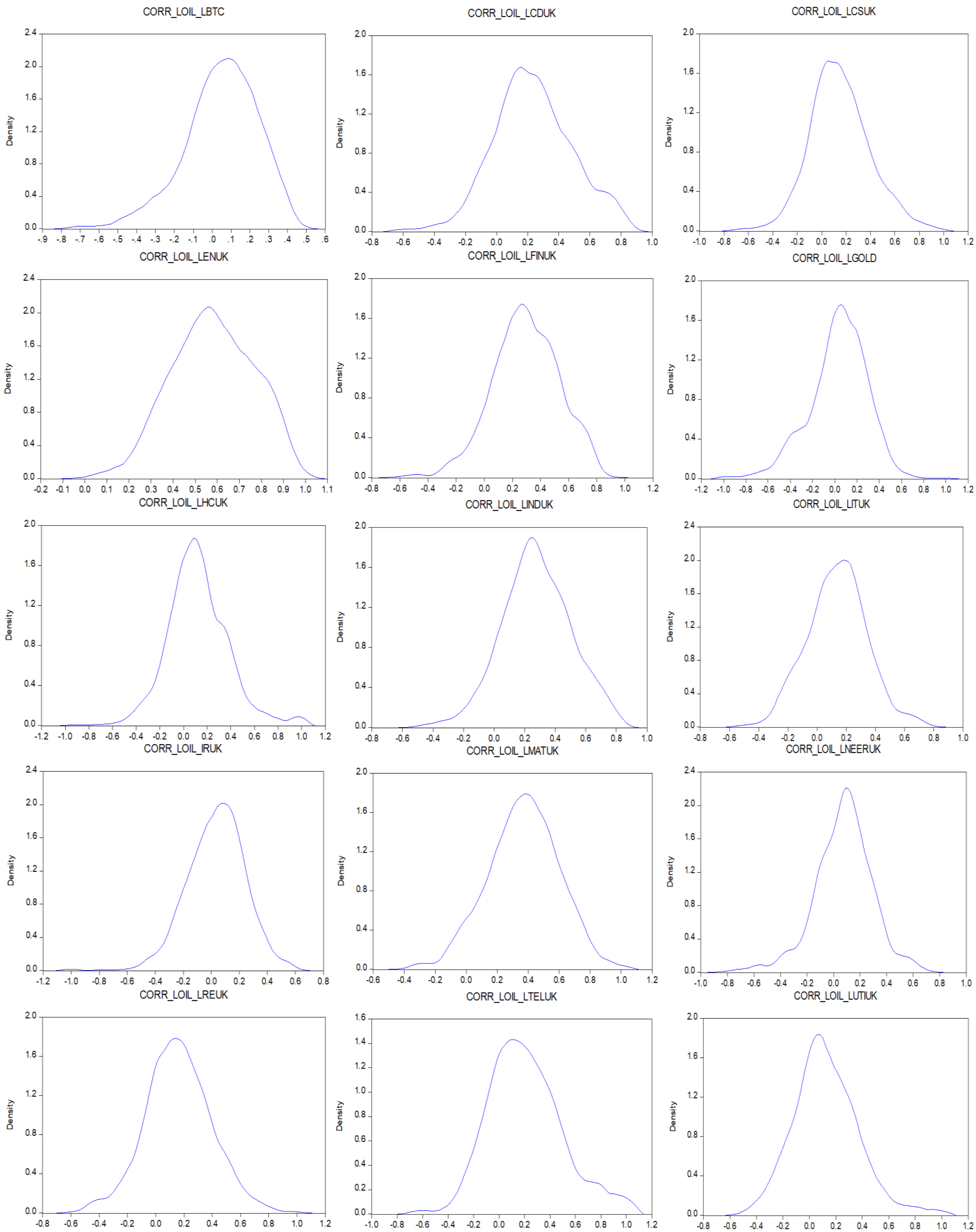


Figure A9: Kernel Density Distribution of Oil Prices and all Variables in Question – France

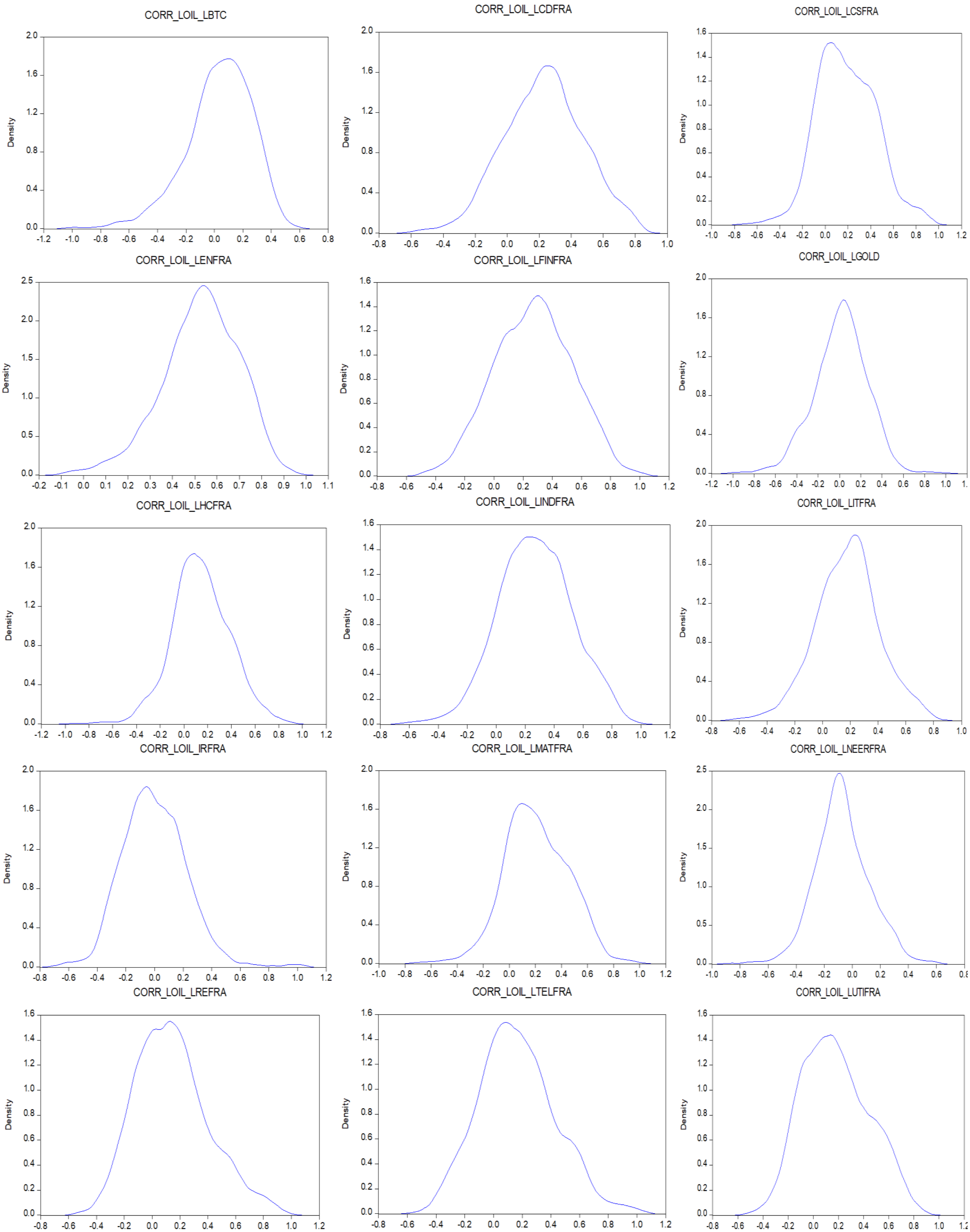
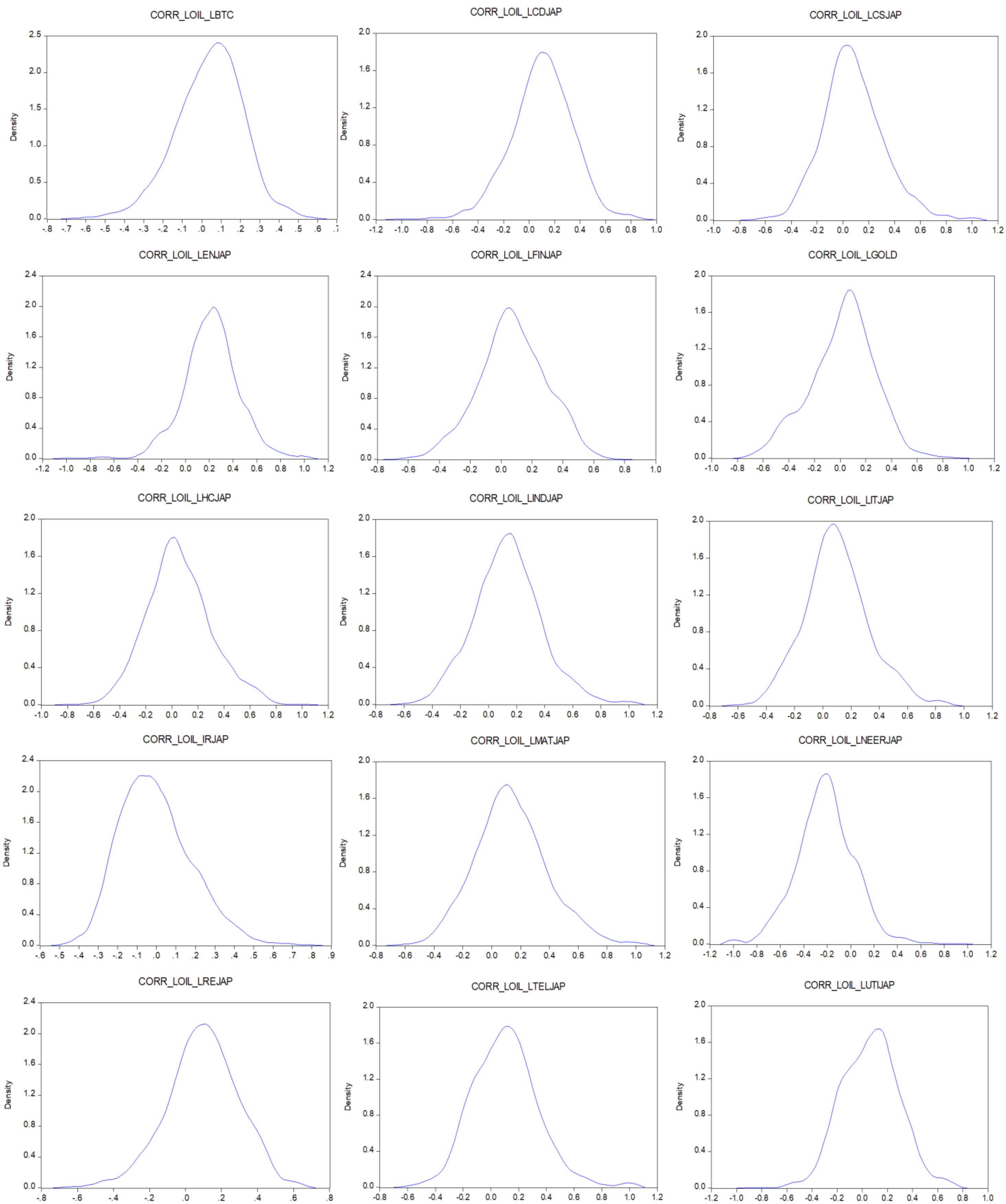


Figure A10: Kernel Density Distribution of Oil Prices and all Variables in Question – Japan



Chapter 2

Evaluating the Spillover Effects of FTSE4GoodUSA Index: A Sectoral Analysis of United States' International Trade Partners

2.1 Introduction

The growing economic integration of global stock markets has possessed a significant role over the past two decades. Researchers (e.g. Malik and Hammoudeh, 2007; Moore 2011; Balcilar et al., 2018; Gkillas et al., 2022) not only consider returns causality links but also estimate volatility spillover effects as returns volatility is predominantly used as an approximate measure of the risk of holding financial assets (Brooks, 2008). Existing studies focused on returns volatility spillover effect between the stock market of one country with that of others, exchange rates, economic policy uncertainty, gold, and oil prices. It is crucial for financial institutions, investors, and portfolio managers to apprehend the type and degree of association among these variables.

However, considering the existing paradigm shift towards sustainability, it would be useful for the three participants to understand returns volatility spillover effect of firms which demonstrate good sustainability practice. This would ensure that they obtain comprehensive analysis of stock market spillover effects, contributing towards making better informed decisions and recommendations. Unfortunately, the overwhelming majority of existing research have not paid attention to this area, never mind looking at the effect from a sectoral stock index point of view. To fill this gap, we make use of a unique variable called FTSE4Good USA (F4GU) index which differs from its conventional parent FTSE USA in several ways. According to El Ouadghiria et al. (2021), the F4GU comprises of one-sixth of the firms in the FTSE USA index. As the number of stocks in the FTSE USA index is approximately 600, the F4GU accounts for the biggest 100 firms measured by market valued. The F4GU is a United States (US) stock market index specified to assess the performance of firms against a predetermined set of environmental, social and governance (ESG) criteria. When looking at environmental, firms are inspected based on their operations and policies towards climate change, carbon emissions, minimisation of waste, energy efficiency etc. While social refers to firms' evaluation on labour policies, employee relations, diversity and inclusion, product safety etc. Finally, governance is associated with investigating firms' practices in relation to ethical business management, transparency, governance structure etc. As a result, firms should pass a stringent inspection process by the FTSE Russell to be included in the index.

Belghitar et al. (2014) also reported a difference between the F4GU and FTSE USA index when studying their corresponding mean-variance characterisation. The F4GU forms part of the FTSE4Good Index Series which accounts for several local and international indices that monitor firms' sustainability performance. It is set to expose investors to US firms that display robust ESG practices. Investors also utilise the F4GU index as a benchmark for developing a sustainable investment portfolio by investing in firms that prioritise ESG. The variable is of great relevance to our research question as it solely accounts for those firms which have established an excellent track record of sustainable performance. To the best of our knowledge, this is the first piece of research that attempts to examine returns volatility spillover effects of the F4GU index to sectoral stock indices of the US main trading partners. The reason behind selecting the US as a benchmark is because of its vital role in the international trade and finance market. According to the World Bank, the US is classified as one of the world's largest trading nations with trade relations exceeding 200 countries. Its main trading partners are Canada, Mexico, China, Japan, and the UK. Petroleum oils, monolithic integrated circuits, soya beans, transmission apparatus for radiotelephony, automobiles, storage units and medicaments account for the most exported and imported commodities.

The rest of this chapter will be divided into six sections. Section 2.2 presents a review of existing literature. Section 2.3 thoroughly analysis the econometric methodologies employed. Section 2.4 describes the data used. Section 2.5 discusses findings obtained after conducting the estimations and while section 2.6 demonstrates the necessary robust checks to confirm the accuracy of our results. Lastly, section 2.7 concludes our evaluation and summarises our findings.

2.2 Closest Literature

Initially, we analyse the empirical literature which focused on volatility spillover effects between exchange rates and stock market returns. Here, the impact has proven to be significant from the former to the latter variable and is even stronger during times of uncertainty[17]. Indeed, Sui and Sun (2016) found significant spillover effects from foreign exchange rates to stock market returns (but not vice versa) in the short run. They added that the effect is clearly visible during the financial crisis. These findings were obtained after employing a VECM and VAR techniques for a daily data set between 1993 and 2014. Similarly, Chen et al. (2022) showed significant volatility spillover effects from the US dollar per Chinese Renminbi exchange rate to the Chinese stock market returns during reform period of the country's exchange rate system. Copula and marginal distribution models along with daily data for a sample period from March 2011 until September 2019 was utilised to yield these results.

Along with that, there is substantial amount of evidence which explored the spillover effects connecting oil prices and stock market returns. They stated that there exist significant volatility spillover effects between oil prices and general stock index returns of multiple countries[18]. In essence, Basher and Sadorsky (2006) indicated that oil price volatility has a strong influence on stock market returns of emerging economies. An international multi-factor model which is related to the Capital Asset Pricing Model (CAPM) was applied to capture both conditional and unconditional risk factors. Their study was based on a daily data set covering the period 31st of December 1992 to 31st of October 2005. In line with these outcomes is the investigation conducted by Zhang and Ma (2019). They emphasised that the contemporaneous risk spillover effect among oil prices and stock market returns is fairly evident. Again, daily data was used but for the period 4th of January 2000 until 29th of March 2019. An EVaR framework based on CAR-ARCHE technique was used to uncover these findings.

In the same light however, a handful number of studies have gone a step further by examining the spillover effects among oil prices and returns of sectoral stock indices. The

[17] See, Apergis and Rezitis, 2001; Antonakakis, 2012; Grobys, 2015; Leung et al., 2017; Bajo-Rubio et al., 2017; Gokmenoglu et al., 2021.
[18] See, Ågren, 2006; Malik and Hammoudeh, 2007; Lin et al., 2014; Du and He, 2015; Li and Wei, 2018; Balcilar et al., 2018.

main of aim of these evaluations was to dismantle the potential override or shadow of aggregate stock market indices from the heterogeneity of various sectors when responding to oil price volatility. It was detected that the spillover effect from the latter variable is significant for the returns of most sectoral stock indices while its degree varies across sectors[19]. Li et al. (2022a) argued that spillover effects of oil price volatility and geopolitical risk are higher for industrials, health care, consumer discretionary, information technology, and basic materials when compared to other sectoral stock market indices. The Diebold and Yilmaz (2012, 2014) network connectedness technique was employed to estimate the spillover effect between variables in question for a monthly data set covering the period January 2009 to April 2022. Furthermore, Arouri et al. (2011) supplemented these results by stating that the spillover effect is predominantly bidirectional from the oil market to sectoral stock indices in the US while it is unidirectional in Europe. A multivariate VAR(k)-GARCH(p,q) framework was used for a weekly data set ranging from 1st of January 1998 to 31st of December 2009.

In addition to the first two, is the spillover effect linking gold prices and stock market returns. Empirical evidence suggests that there exist significant time varying spillover effects between the two variables[20]. Namely, He et al. (2020) claimed that the highest volatility spillover effect for the US and Chinese stock markets (S&P-500 & SSE) is transmitted via gold prices. More than half of the volatility spillover effect happens in the long run while most of the return spillover occurs in the short run. Daily data starting from 4th of January 2000 to 30th of November 2018 along with Diebold-Yilmaz and Barunik-Krehlik econometric techniques were used. Comprehending these outcomes from a sectoral stock index point of view were Mensi et al. (2021b). They found that gold and oil futures including all sectoral stock indices (excluding basic materials since it is a net contributor of spillovers) are net receivers of spillovers. These were greatly influenced by the COVID-19 pandemic, slump in oil prices, European and global financial crisis. The same econometric methodology (Diebold and Yilmaz, 2012) used in the former study was employed for a daily data set from 4th of January 2005 to 15th of May 2020.

Another strand of literature are the studies which evaluated the spillover effect between policy uncertainty and stock market returns. On one hand, a portion of these

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[19] See, Malik and Ewing, 2009; Arouri et al., 2012; Wang and Wang, 2019.

[20] See, Miyazaki et al., 2013; Mensi et al., 2013; Patel, 2013; Jiang et al., 2019; Mensi et al., 2021a; Civcir and Akkoc, 2021.

investigations focused on spillover effects of domestic economic policy uncertainty (EPU) and stock market returns of the country in question. They detected that spillover effects from EPU to stock market returns is time varying[21]. For instance, Li et al. (2016) employed a bootstrap rolling window causality test for a monthly data set starting from February 1995 to February 2013 to examine the causality relationship between China and India's EPU and their corresponding stock markets. They discovered bidirectional causality linking the two variables in several sub-periods but not across the entire sample. When looking at Chinese sectoral stock indices, Si et al. (2021) revealed extremely high association among information technology, utilities, energy, telecommunication, financials, and the country's EPU mostly in the medium and long run. Monthly data ranging from January 2001 to January 2020 along with time frequency connectedness technique established by Diebold and Yilmaz (2009, 2012) and Barunik and Krehlik (2018) were exerted to generate these conclusions.

While on the other, direction of analysis was devoted towards spillover effects of US EPU and returns of international stock markets. Results demonstrate that the impact is generally significant from the former to latter variable[22]. To be more specific, Hu et al. (2018) displayed that shocks in US EPU significantly translate the negative returns of Chinese A-shares by a lag of one week. Building on this, they also implied that information technology, media and manufacturing firms were highly vulnerable to US EPU shocks (unlike real estate and agriculture firms which exhibit lower responsiveness). GARCH and ARIMA (1,1) techniques for a weekly data set between March 2006 to April 2016 were used to obtain these results. Likewise, Yun et al. (2021) indicated that the Korean stock market is greatly susceptible to US EPU explaining lower future returns. They employed Fama and French (2015) five factor model for a combination of daily and monthly data set ranging from January 1992 to June 2017.

Equally as interesting is the spillover effect combining the general stock index of one country with that of others. Many researchers have shown that the relationship is significant between both variables[23]. In particular, Wang et al. (2018) revealed that there

[21] See, You et al., 2017; Huang et al., 2019; Li et al., 2019; Gao et al., 2020; Dai and Peng, 2022.
[22] See, Acemoglu et al., 2015; Ozdagli and Weber, 2017; Hua et al., 2020; Balli et al., 2021; Di Giovanni and Hale, 2022.
[23] See, Theodossiou and Lee, 1993; Li and Giles, 2015; Mensi et al., 2016; Chow, 2017; BenSaïda, 2018; Kahraman and Keser 2022.

exist high volatility spillover effects from the US S&P-500 to five major economies general stock index. The result was also stronger during times of uncertainty such as the business cycle recession. A HVS-GARCH framework was used for daily data between January 1991 to December 2015 were used in this study. This goes in hand with the analysis conducted by Uludag and Khurshid (2019) but using China's stock market as the benchmark. Significant volatility spillover effects were traced from the Shanghai composite index of China to the general stock index of G7 and E7 countries. It also illustrated explicit co-movement with the stock market of countries within the same geographical area. Daily data for the period 1st of September 1995 to 3rd of March 2015 accompanied by a VAR-GARCH (1,1) technique were used to obtain these findings.

All of this together means that, existing literature focuses primarily on volatility spillover effects of the general stock index of one country with that of others, exchange rates, policy uncertainty, gold and oil prices. Indeed, Moore (2011) evaluated volatility spillover of the US and United Kingdom (UK) markets to the returns of their corresponding sectoral stock indices. Despite providing a meaningful comparison between the two countries, the author was silent about the UK being one of the main trading partners of the US[24]. Let alone distinguishing between returns volatility spillover effect of firms which demonstrate good sustainability practice versus those that do not. However, El Ouadghiria et al. (2021) did compare returns on US sustainability stock indices (which includes F4GU Index) with their conventional parent indices (in this case FTSE USA). Yet, the idea was to assess the impact of public attention to climate change and pollution, not returns volatility spillover effect from a sectoral stock index point of view.

Thus, to fill the gap in existing literature we make use of the F4GU index to examine its returns volatility spillover effect on sectoral stock indices of the US's main trading partners. We also account for all other variables that were previously studied to make our analysis equally rigours and comprehensive.

2.3 Methodology

We initially begin by estimating the volatility series of all variables in question by using the GARCH family to obtain the optimum time varying conditional variances. After

[24] This was also ignored in papers which addressed the case of the US and China.

which a multivariate VAR technique is developed to understand returns volatility spillover effects of the F4GU index to sectoral stock indices of the US's main trading partners. The GARCH family comprises of four univariate (i.e., GARCH (1,1) specification) models. Namely, Integrated GARCH (IGARCH), Threshold ARCH (TARCH), Exponential GARCH (EGARCH) and finally the standard GARCH. They all share the same mean equation and have the following error correction model:

$$\Delta w_{it} = d_i + \sum_{i=1}^{17} \sum_{j=1}^{k} \theta_{ij}\, \Delta w_{it-j} + \sum_{i=1}^{17} \gamma_i\, w_{it-1} + \varepsilon_{it} \qquad \varepsilon_t \,\big|\, I_{t-1} \sim N(0, z_t) \quad (2.1)$$

Where, Δw_{it-j} and Δw_{it} are the lagged and present return of the variable in question respectively. k is optimum lag length, while d_i corresponds to the deterministic component. ε_{it} is associated with present innovation of the variable in question conditional on a lagged set of information I_{t-1} which is normally distributed with mean zero and time reliant variance z_t.

However, IGARCH, GARCH, TARCH, and EGARCH have different variance equations, and these are illustrated in (2.2) – (2.5) respectively below:

$$z_{it} = \lambda \varepsilon_{it-1}^2 + \alpha z_{it-1}, \qquad \lambda + \alpha = 1 \quad (2.2)$$

$$z_{it} = h + \lambda \varepsilon_{it-1}^2 + \alpha z_{it-1}, \qquad h > 0, \quad |\lambda + \alpha| < 1 \quad (2.3)$$

$$z_{it} = h + \lambda \varepsilon_{it-1}^2 + \beta \varepsilon_{it-1}^2 I_{it-1} + \alpha z_{it-1}, \qquad h > 0, \; |\lambda + \alpha| < 1 \quad (2.4)$$

$$\log(z_{it}) = h + \lambda \left(\left| \frac{\varepsilon_{it-1}}{\sqrt{z_{it-1}}} \right| - E \left| \frac{\varepsilon_{it-1}}{\sqrt{z_{it-1}}} \right| \right) + \beta \frac{\varepsilon_{it-1}}{\sqrt{z_{it-1}}} + \alpha \log(z_{it-1}), \; h > 0 \quad (2.5)$$

Where, z_{it} represents the time varying conditional variance of the variable in question. λ is the coefficient of the lagged residual square ε_{it-1}^2 with the latter obtained from equation (2.1). α, on the other hand is the coefficient of z_{it-1} which is the lagged conditional variance. h is a constant that needs to be positive to satisfy the variance non-negativity condition[25]. The condition $|\lambda + \alpha| < 1$ is essential for a GARCH model to be stationary[26].

TARCH and EGARCH techniques go a step further by accounting for asymmetric components having the coefficient β. This is I_{it-1} for the former taking the value 1 to

[25] This excludes IGARCH as the model assumes it to be equal to zero.
[26] This excludes IGARCH as the model assumes it to be equal to one.

capture the impact of bad news and 0 otherwise. β will be positive and statistically significant conditional on the presence of leverage effects. Therefore, the impact of bad news $\lambda + \beta$ tends to be greater than the impact of good news λ on the conditional variance. For the latter, the asymmetric component corresponds to $\frac{\varepsilon_{it-1}}{\sqrt{z_{it-1}}}$. Here if β is negative and statistically significant, then negative shocks generate larger subsequent period conditional variance than positive ones of the same magnitude (Brooks, 2008).

Taking into consideration the residuals conditional normality, equations (2.2) – (2.5) can be estimated by maximising the following likelihood function:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log\left| z_t \right| - \frac{1}{2}\sum_{t=1}^{T} \varepsilon_t^2 / \left| z_t \right| \tag{2.6}$$

With T being the total number of observations. We make use of the absolute value of z_t here to secure positive conditional variances in our log likelihood function.

Moreover, our VAR model can be presented in the following way:

$$z_t = c + \Sigma_{i=1}^{p} A_i z_{t-1} + \epsilon_t \tag{2.7}$$

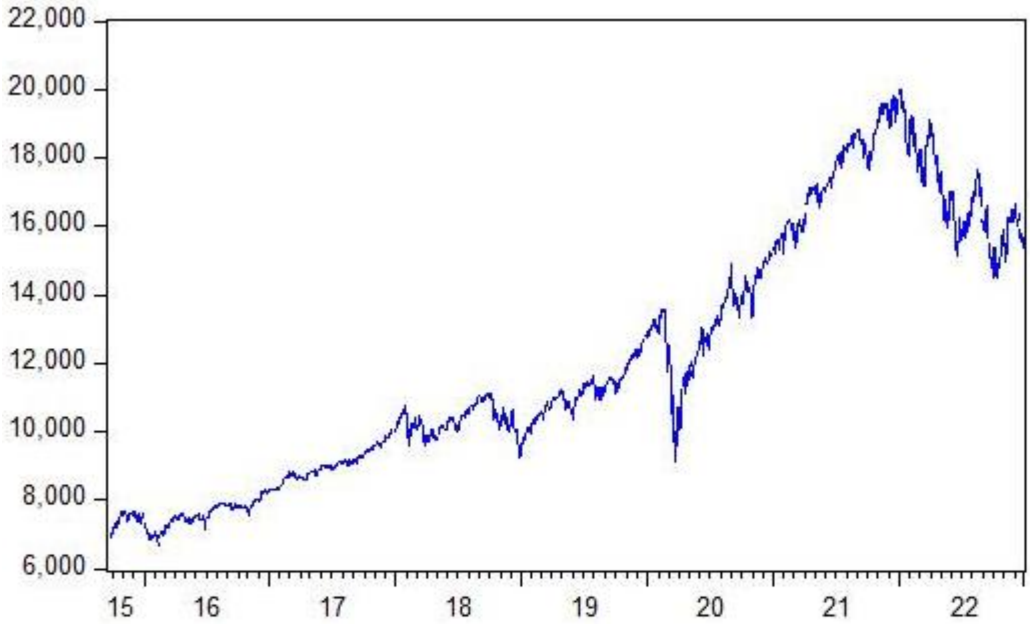
Where, z_t refers to the 15 x 1 column vector of the time varying conditional variance of the F4GU index returns, returns of eleven sectoral stock indices, along with the spot price of gold, oil, and Bitcoin. c corresponds to the 15 x 1 column vector of the deterministic elements representing the constant while A_i is the 15 x 15 coefficient matrix. p is the optimum lag length, ϵ_t is the 15 x 1 innovations column vector that is simultaneously independent from all z_{t-i}.

To explain VAR estimation results, we rely on the variance decompositions and Impulse Response Functions (IRF). The former divides volatility of one variable into synthetic shocks through the VAR framework. This yields the necessary information about relative importance of all variable's innovation included within our VAR. Hence, supporting us in understanding the impact of F4GU index returns volatility. The latter on the other hand, investigates response of all variables in question to Cholesky one standard deviation (SD) innovation in the F4GU index returns volatility incorporated within the VAR model. We generate this by apprehending the magnitude, sign, and persistence level of responses of the variable in question to shocks in the F4GU index.

2.4 Data

To understand the spillover effects between the F4GU index returns volatility and US's main trading partners (Canada, Mexico, China, Japan, and the UK) along with other variables of interest, daily data on seventeen variables was compiled from Bloomberg ranging from 24th of September 2015 to 30th of December 2022. We have the F4GU index, returns volatility of eleven sectoral stock indices, nominal effective exchange rates, 3-month deposit rates of the US main trading partners along with the spot price of gold, oil, and Bitcoin[27].

Figure 2.1: FTSE4Good USA Index



Notes: The figure shows volatility of FTSE4Good USA Index for the period 24th of September 2015 – 30st of December 2022.

According to figure 2.1, there are six episodes which initiated upward and downward volatility in the F4GU index returns. Three for the former and another three for the latter. We begin by analysing the events which initiated upward volatility. On the 26th of January 2018, the index has climbed to 10747. Low interest rates from the Federal Reserve (FED) and Bank of England (BOE) have contributed to asset price inflation (but a lower one for debt) by pumping money through financial institutions encouraging the purchase of bonds. Because of this, investors have flocked into risker assets such as equities to yield

[27] Due to certain data restriction and availability, we had to drop China and Mexico to preserve the extensiveness of our study in terms of variables. Likewise, the starting date 24th of September 2015 is due to the unavailability of data for the Japanese real estate sectoral stock index.

higher returns. At the same time Japanese shares have reached a 26-year record high according to the Guardian. Another piece of evidence, according to the ADP National Employment Report, they estimated that firms have created additional 250,000 jobs in the US economy. This was considerably greater than the initial projection made by economists justifying the upward volatility in the F4GU index returns.

Moreover, on the 19th of February 2020 there was an upward volatility in the index returns reaching 13575. This was attributed to hopes that central banks and governments will intervene in markets to alleviate the impact of COVID-19 on the national economy. According to the BBC News (2020), US President Donald Trump urged the FED to implement large interest rate cuts. While BOE and European Central Bank (ECB) were closely monitoring the situation and ready take necessary decisions. On the 29th of December 2021, there was an upward volatility in the index returns reaching a new record of 20000. During this time, governments and central banks introduced stimulus packages to support economic growth, COVID vaccines were rolled out and countries gradually eased lockdowns and restrictions. As a result, stock markets recovered from the severe shock caused in 2020 to pre-pandemic levels. According to Wearden (2021) from the Guardian, Richard Flax Chief Investment Officer of Moneyfarm said that the second half of 2021 has experienced higher volatility than the first mainly due to Omicron variant of the COVID-19. Nevertheless, there was an ease in investors' fears because it was proven that Omicron may cause less severe symptoms.

Turning to the events which initiated downward volatility in the F4GU index. On the 21st of December 2018, returns have plummet to 9212. According to Wearden and Partington (2018) from the Guardian, the index has fallen by 12.5% reaching its greatest decline since the financial crisis. Investors were deeply concerned about the FED's decision on increasing interest rates as it could decelerate growth in US economy. Adding to the negative sentiment were the US-China trade war and Brexit uncertainty. The US had imposed hefty tariffs on $250 billion worth of Chinese imports with further threats of introducing additional levies if China did not revise its trade policies. Next, there was a severe downward volatility in the F4GU index returns on the 23rd of March 2020 hitting 9140. It has experienced its biggest decline (25%) resulting from economic disruptions caused by the COVID-19 pandemic. This was the time when the virus was spreading too rapidly across the US, UK, and rest of the world. According to Partington (2020) from the

Guardian, Vicky Redwood a senior economic advisor at consultancy Capital Economics said that investor and consumer confidence could be restrained for some time especially if the virus persists. Lastly, the index experienced downward volatility in returns reaching to 14484 on the 12th of October 2022. According to Shankar and Kamdar (2022) from Thomson Reuters, geopolitical tensions between Russia and Ukraine were intensifying. Stock markets reacted to the catastrophic bombings that shook Kiev and other Ukrainian cities. The sale of British government bonds by investors also had a contributing factor since this would mean higher interest rates within the market.

For all of these reasons, one can see that interest rates, purchase or sale of government bonds, job creations, government spendings, geopolitical relationships, trade tensions, investors and consumers' confidence were the main driving factors of the F4GU index returns volatility across our sample period.

We are now able to analyse the descriptive statistics of all variables for the selected US trade partners. These are depicted in tables B1 – B3 of the appendix. The coefficient of variation (CV) shows the standard deviation (SD) as a percentage of the arithmetic mean. This equivalent to 30% for the F4GU index (FTSEUS) across all three countries. It indicates that the variable has a relatively higher risk when compared to most variables within our dataset. The highest CV corresponds to Bitcoin (BTC) while the lowest is associated with the nominal effective exchange rate (NEER) and 3-month deposit rate (IR) of each country. When looking at the skewness of FTSEUS, we can see that its fairly symmetrical as it lies between -0.5 and 0.5. BTC on the other hand is highly skewed to the right while the same applies to the 3-month deposit rate (IR) of all countries (excluding Japan since its highly skewed to the left given the negative value). Adding to those, all variables present a kurtosis which is less than 3 (excluding the healthcare subindex of Canada (HCCAN), IRUK and IRJAP). Accordingly, our data set has little to no outliers with lighter tails when matched with normal distribution.

Taking the natural logarithm of all variables (bypassing IR since its already in percentage points) to scale the data (they are now distinguished by an L) for implementing the Augmented Dicky Fuller (ADF) and Phillips Perron (PP) unit root tests. Here, the aim is to deduce the integration order of variables within our model. Table 2.1 and 2.2 below presents the outcome of the two tests at level and first order difference respectively using a drift without a trend for all three countries. The null hypothesis indicates that the series contains a unit root (non-stationary) compared with an alternative, it does not contain a unit root (stationary). We reject the null hypothesis for variables containing asterisks at the corresponding significance levels. For variables that are stationary at level, they are integrated at order 0 (i.e., I (0)). Whereas those which are stationary at first order difference are integrated at order 1 (i.e., I (1)).

Table 2.1: Unit Root Tests at Level

	CAN		UK		JAP	
Variable	PP	ADF	PP	ADF	PP	ADF
LFTSEUS	-1.301	-1.247	-1.306	-1.250	-1.456	-1.537
LBTC	-2.288	-2.322	-2.291	-2.327	-2.596***	-2.621***
LCD	-1.912	-1.936	-3.017**	-3.067**	-2.514	-2.775***
LCS	-0.700	-0.550	-2.838***	-2.824***	-2.386	-2.392
LEN	-2.578***	-2.846***	-1.978	-2.032	-1.941	-2.015
LFIN	-2.130	-2.091	-2.397	-2.421	-2.882**	-2.936**
LGOLD	-1.098	-1.124	-1.102	-1.128	-1.235	-1.313
LHC	-2.999**	-2.999**	-2.071	-2.120	-2.138	-2.267
LIND	-1.248	-1.152	-2.179	-2.179	-2.227	-2.260
LIT	-1.655	-1.654	-1.729	-1.626	-1.773	-1.779
IR	1.164	2.863	4.236	5.290	-15.910*	-6.877*
LMAT	-2.086	-2.100	-1.720	-1.731	-2.373	-2.395
LNEER	-3.150**	-3.241**	-3.311**	-3.311**	-1.466	-1.496
LOIL	-2.019	-2.120	-2.017	-2.117	-2.175	-2.200
LRE	-2.895**	-2.932**	-2.451	-2.666***	-2.475	-2.019
LTEL	-2.566	-2.515	-0.667	-0.681	-2.597***	-2.681***
LUTI	-1.586	-1.403	-2.652***	-2.645***	-1.092	-1.350

Table 2.2: Unit Root Tests a First Order Difference

	CAN		UK		JAP	
Variable	PP*	ADF*	PP*	ADF*	PP*	ADF*
D(LFTSEUS)	-51.585	-13.510	-51.418	-13.515	-50.224	-29.161
D(LBTC)	-44.197	-44.173	-43.944	-43.908	-42.700	-42.719
D(LCD)	-44.197	-44.215	-39.901	-39.891	-44.019	-43.532
D(LCS)	-43.631	-43.490	-43.731	-43.729	-44.546	-44.347
D(LEN)	-44.062	-14.062	-39.934	-39.997	-41.192	-41.131
D(LFIN)	-44.248	-14.325	-41.508	-41.516	-41.809	-41.766
D(LGOLD)	-42.059	-42.047	-41.789	-41.780	-41.270	-41.114
D(LHC)	-41.661	-41.674	-43.839	-43.839	-43.274	-42.738
D(LIND)	-46.465	-46.607	-41.229	-41.233	-42.680	-42.658
D(LIT)	-41.715	-41.729	-42.511	-42.485	-41.870	-41.870
D(IR)	-82.971	-37.799	-53.305	-37.609	-106.338	-25.597
D(LMAT)	-42.414	-42.411	-42.616	-42.616	-41.959	-41.957
D(LNEER)	-42.530	-42.478	-41.545	-41.560	-42.276	-42.279
D(LOIL)	-44.460	-33.220	-44.292	-33.090	-41.757	-31.086
D(LRE)	-40.211	-15.020	-37.691	-37.888	-37.856	-18.677
D(LTEL)	-48.545	-15.023	-41.898	-41.907	-44.409	-44.000
D(LUTI)	-44.354	-15.567	-42.102	-24.237	-41.717	-41.071

1. **, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*
2. *The D corresponds to the first difference of a variable.*

2.5 Results and Discussion

Using the maximum likelihood, we begin by estimating the GARCH family through equations (2.1 – 2.5) for all seventeen variables of interest individually. These results are demonstrated below in tables 2.3, 2.4 and 2.5 for Canada (CAN), UK, and Japan (JAP) respectively. We hand pick the optimum time varying conditional variance according to four essential characteristics. In particular, the valid model possessing lowest Schwarz Information Criterion (SIC). Next, the one that satisfies the stationarity condition (i.e., $|\lambda + \alpha| < 1$). Third, the one that satisfies the variance non-negativity condition (i.e., $h > 0$). Finally, the one that exhibits insignificant residuals ARCH effect (captured by F-LM).

Applying these requirements, for CAN the standard GARCH model of LBTC, LCS, LGOLD, LIND, LNEER and LTEL are selected to estimate their time varying conditional variances. Likewise, for the UK its LBTC, LFIN, LGOLD, LIT, LMAT, LNEER, and LTEL. When looking at JAP its LCD, LCS, LEN, LFIN, LGOLD, LHC, LIND, LNEER, and LTEL. Whilst TARCH is chosen for all remaining variables accordingly. It is worth mentioning that IGARCH was chosen for the Canadian LHC and IR of all three countries. Lastly, all of these models outperformed the EGARCH technique for all three countries.

From the optimum time varying conditional variances of each variable, we generate their corresponding volatility series. These are then assessed within a multivariate VAR framework as it is classified as one the most useful models in explaining the relationship amongst variables without enforcing any preceding restrictions. Given the aim of our study is to investigate the spillover effect of F4GU returns volatility on the volatility of sectoral stock index returns of CAN, UK, and JAP, we treat both sets of variables as endogenous. Whereas volatility of gold (VAR_LGOLD), oil (VAR_LOIL) and Bitcoin (VAR_LBTC) are classified as exogenous. We discard volatility of the 3-month deposit rate (VAR_IR) and nominal effective exchange rate (VAR_LNEER) because we are solely interested in accounting for their impact when estimating the time varying conditional variances.

Table 2.3: GARCH Estimation Results - Canada

		ΔIR_t	$\Delta LBTC_t$	ΔLCD_t	ΔLCS_t	ΔLEN_t	$\Delta LFIN_t$	$\Delta LFTSE_t$	$\Delta LGOLD_t$	ΔLHC_t	$\Delta LIND_t$	ΔLIT_t	$\Delta LMAT_t$	$\Delta LNEER_t$	$\Delta LOIL_t$	ΔLRE_t	$\Delta LTEL_t$	$\Delta LUTI_t$
GARCH	h	2E-08*	1E-04*	2E-06*	6E-06*	2E-04*	2E-06*	3E-06*	8E-07*	-1E-06*	4E-06*	2E-06*	2E-04**	7E-07*	2E-05*	2E-06*	6E-06*	2E-06*
	λ	1.079*	0.133*	0.130*	0.081*	0.150**	0.151*	0.213*	0.039*	0.167*	0.076*	0.072*	0.150**	0.073*	0.147*	0.128*	0.151*	0.122*
	α	-0.053	0.820*	0.853*	0.891*	0.600*	0.838*	0.778*	0.951*	0.891*	0.902*	0.927*	0.600*	0.875*	0.827*	0.867*	0.797*	0.855*
	α+λ	1.026	0.952	0.984	0.972	0.750	0.989	0.991	0.990	1.058	0.977	0.999	0.750	0.948	0.973	0.996	0.948	0.976
	F-LM	0.000*	0.555	0.800	0.733	0.146	0.526	0.973	0.295	0.965	0.820	0.333	0.159	0.437	0.069***	0.930	0.464	0.067
	LL	11213	3152	5978	5274	4637	5979	6015	6218	3336	5519	4939	4734	7736	4325	5947	6004	6083
	SIC	-12.026	-3.269	-6.339	-5.574	-4.883	-6.340	-6.380	-6.600	-3.468	-5.840	-5.210	-4.988	-8.249	-4.543	-6.306	-6.367	-6.454
EGARCH	h	-3.500*	-0.711*	-8.523	-0.278*	-0.242*	-0.378*	-0.666*	-0.199*	-6.197*	-0.425*	-7.737	-0.218*	-0.917*	-0.444*	-0.337*	-8.842***	-0.391*
	λ	0.996*	0.273*	0.010	0.129*	0.057*	0.168*	0.281*	0.075*	0.010	0.170*	0.010	0.139*	0.190*	0.254*	0.227*	0.010	0.197*
	α	0.895*	0.916*	0.010	0.979*	0.977*	0.973*	0.951*	0.985*	0.010	0.966*	0.010	0.987*	0.931*	0.967*	0.982*	0.010	0.975*
	β	0.126*	0.000	0.010	-0.060*	-0.148*	-0.136*	-0.127*	0.048*	0.010	-0.036*	0.010	-0.033*	-0.032**	-0.082*	-0.072*	0.010	-0.089*
	α+λ	1.891	1.189	0.020	1.108	1.034	1.141	1.233	1.060	0.020	1.136	0.020	1.126	1.122	1.221	1.209	0.020	1.172
	F-LM	0.524	0.812	0.000*	0.726	0.560	0.209	0.880	0.491	0.475	0.873	0.000*	0.915	0.716	0.187	0.995	0.000*	0.169
	LL	22044	3164	5232	5275	5160	6006	6028	6226	3090	5521	4510	5067	7736	4335	5945	5529	6087
	SIC	-23.788	-3.278	-5.525	-5.572	-5.447	-6.365	-6.389	-6.604	-3.198	-5.839	-4.741	-5.345	-8.245	-4.551	-6.299	-5.848	-6.453
TARCH	h	1E-13*	1E-04*	3E-06*	7E-06*	6E-06*	2E-06*	3E-06*	1E-06*	-2E-06***	4E-06*	2E-06*	2E-06*	8E-07*	3E-05*	2E-06*	9E-05*	2E-06*
	λ	0.615*	0.108*	0.019	0.045*	-0.004*	0.012	0.115*	0.072*	0.114*	0.068*	0.009	0.036*	0.058*	0.067*	0.057*	0.150	0.043*
	α	0.616*	0.817*	0.878*	0.895*	0.896	0.887*	0.778*	0.939*	0.909*	0.902*	0.941*	0.940*	0.867*	0.819*	0.883*	0.600*	0.881*
	β	0.012	0.046*	0.147*	0.053*	0.164*	0.157*	0.193*	-0.055*	0.042**	0.013	0.086*	0.033*	0.036***	0.144*	0.099*	0.050	0.103*
	α+λ	1.231	0.925	0.897	0.940	0.892	0.898	0.893	1.012	1.023	0.970	0.950	0.976	0.925	0.886	0.940	0.750	0.925
	F-LM	0.654	0.561	0.774	0.887	0.793	0.494	0.493	0.222	0.894	0.833	0.414	0.794	0.596	0.576	0.853	0.382	0.122
	LL	22046	3153	5994	5277	5143	6000	6029	6227	3353	5519	4951	5067	7737	4338	5954	5496	6092
	SIC	-23.790	-3.266	-6.353	-5.573	-5.428	-6.359	-6.391	-6.606	-3.484	-5.836	-5.220	-5.345	-8.246	-4.553	-6.309	-5.811	-6.459
IGARCH	λ	0.107*	0.043*	-0.003*	0.062*	-0.005*	-0.005*	-0.005*	0.000	0.096*	0.058*	0.057*	0.049*	0.039*	0.110*	-0.006*	0.092*	0.081*
	α	0.893*	0.957*	1.003*	0.938*	1.005*	1.005*	1.005*	1.000*	0.904*	0.942*	0.943*	0.951*	0.961*	0.890*	1.006*	0.908*	0.919*
	F-LM	0.013**	0.108	0.000*	0.473	0.000*	0.000*	0.000*	0.235	0.703	0.596	0.196	0.588	0.003*	0.201	0.000*	0.833	0.000*
	LL	22037	3067	5204	5251	4817	5506	5609	6085	3332	5497	4930	5055	7717	4283	5487	5947	6060
	SIC	-23.793	-3.185	-5.507	-5.557	-5.086	-5.835	-5.947	-6.464	-3.473	-5.824	-5.208	-5.344	-8.237	-4.506	-5.814	-6.313	-6.436

1. LL: Loglikelihood ratio.
2. SIC: Schwarz Information Criterion.
3. F-LM: ARCH Test, p-value for Heteroskedasticity.
*4. *, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*

Table 2.4: GARCH Estimation Results – United Kingdom

		ΔIR_t	$\Delta LBTC_t$	ΔLCD_t	ΔLCS_t	ΔLEN_t	$\Delta LFIN_t$	$\Delta LFTSE_t$	$\Delta LGOLD_t$	ΔLHC_t	$\Delta LIND_t$	ΔLIT_t	$\Delta LMAT_t$	$\Delta LNEER_t$	$\Delta LOIL_t$	ΔLRE_t	$\Delta LTEL_t$	$\Delta LUTI_t$
GARCH	h	4E-07*	1E-04*	4E-06*	8E-06*	2E-06*	4E-06*	3E-03	9E-07*	5E-06*	6E-06*	3E-04*	8E-06*	1E-06*	2E-05*	5E-06*	1E-05*	1E-05*
	λ	1.034*	0.133*	0.138*	0.150*	0.097*	0.127*	-0.188	0.040*	0.063*	0.140*	0.357*	0.071*	0.115*	0.140*	0.198*	0.104*	0.149*
	α	-0.073***	0.831*	0.843*	0.787*	0.904*	0.867*	0.315	0.948*	0.904*	0.830*	-0.016	0.908*	0.842*	0.832*	0.801*	0.862*	0.789*
	$\alpha+\lambda$	0.961	0.964	0.981	0.937	1.001	0.994	0.128	0.988	0.967	0.970	0.341	0.979	0.956	0.972	1.000	0.966	0.939
	F-LM	0.000*	0.703	0.892	0.857	0.627	0.913	0.000*	0.306	0.234	0.818	0.778	0.226	0.732	0.043**	0.401	0.669	0.537
	LL	8506	3131	5607	5838	4887	5239	3267	6170	5521	5525	4734	4643	7328	4285	5383	5101	5422
	SIC	-9.141	-3.266	-5.972	-6.224	-5.186	-5.570	-3.415	-6.587	-5.878	-5.882	-5.018	-4.918	-7.853	-4.527	-5.727	-5.418	-5.769
EGARCH	h	-0.976*	-0.693*	-0.493*	-0.770*	-0.189*	-0.362*	-0.698*	-0.193*	-0.206*	-0.483*	-4.357*	-0.228*	-0.619*	-0.449*	-0.479*	-0.453*	-0.560*
	λ	0.216*	0.271*	0.224*	0.257*	0.111*	0.196*	0.306*	0.068*	0.002	0.184*	0.297*	0.095*	0.236*	0.251*	0.319*	0.201*	0.210*
	α	0.970*	0.918*	0.964*	0.937*	0.987*	0.975*	-0.109*	0.985*	0.977*	0.962*	0.487*	0.981*	0.959*	0.965*	0.973*	0.964*	-0.078*
	β	0.041*	-0.015	-0.112*	-0.081*	-0.093*	-0.087*	0.950*	0.052*	-0.093*	-0.123*	-0.412*	-0.074*	0.002	-0.087*	-0.050*	-0.043*	0.954*
	$\alpha+\lambda$	1.186	1.189	1.188	1.195	1.099	1.171	0.196	1.053	0.979	1.146	0.785	1.075	1.195	1.216	1.292	1.165	0.133
	F-LM	0.193	0.707	0.647	0.406	0.494	0.567	0.88	0.689	0.059***	0.274	0.691	0.27	0.634	0.159	0.547	0.943	0.91
	LL	23029	3143	5621	5837	4923	5256	5986	6183	5548	5540	4811	4656	7305	4295	5385	5117	5433
	SIC	-25.008	-3.275	-5.983	-6.219	-5.220	-5.584	-6.382	-6.597	-5.904	-5.895	-5.098	-4.929	-7.823	-4.534	-5.725	-5.432	-5.778
TARCH	h	9E-13*	1E-04*	5E-06*	9E-06*	3E-04*	5E-06*	3E-06*	1E-06*	4E-06*	6E-06*	1E-04*	3E-04*	1E-06*	3E-05*	5E-06*	2E-04**	1E-05*
	λ	0.150*	0.115*	0.044*	0.093*	0.150**	0.053*	0.134*	0.074*	-0.009	0.039*	-0.006	0.150***	0.116*	0.067*	0.138*	0.150	0.064*
	α	0.600*	0.830*	0.849*	0.784*	0.600*	0.877*	0.773*	0.937*	0.944*	0.848*	0.588*	0.600*	0.841*	0.820*	0.803*	0.600*	0.807*
	β	0.050	0.028***	0.155*	0.100*	0.050	0.111*	0.165*	-0.059*	0.075***	0.151*	0.158*	0.050	-0.003	0.139*	0.112*	0.050	0.132*
	$\alpha+\lambda$	0.750	0.945	0.894	0.877	0.750	0.930	0.907	1.011	0.935	0.887	0.582	0.750	0.957	0.887	0.941	0.750	0.871
	F-LM	0.000*	0.646	0.844	0.763	0.172	0.948	0.604	0.36	0.088***	0.882	0.92	0.906	0.729	0.431	0.355	0.878	0.601
	LL	22339	3131	5620	5843	4400	5246	5989	6181	5530	5541	4735	4285	7328	4296	5388	4744	5431
	SIC	-24.254	-3.262	-5.982	-6.225	-4.649	-5.573	-6.385	-6.595	-5.884	-5.895	-5.015	-4.523	-7.849	-4.535	-5.729	-5.025	-5.776
IGARCH	λ	0.068*	0.058*	0.030*	0.084*	-0.005*	0.082*	-0.005*	-0.003*	-0.004*	-0.005*	-0.002*	0.044*	0.027*	0.099*	0.128*	-0.004*	-0.005
	α	0.932*	0.942*	0.970*	0.916*	1.005*	0.918*	1.005*	1.003*	1.004*	1.005*	1.002*	0.956*	0.973*	0.901*	0.872*	1.004*	1.005
	F-LM	0.070***	0.481	0.000*	0.102	0.000*	0.542	0.000*	0.535	0.000*	0.000*	0.180	0.999	0.013**	0.018**	0.741	0.000*	0.000*
	LL	22975	3052	5531	5791	4666	5215	5557	6061	5396	5252	4726	4626	7259	4242	5346	4957	5275
	SIC	-24.961	-3.187	-5.897	-6.181	-4.951	-5.551	-5.926	-6.477	-5.750	-5.592	-5.018	-4.908	-7.785	-4.488	-5.695	-5.269	-5.617

1. LL: Loglikelihood ratio.
2. SIC: Schwarz Information Criterion.
3. F-LM: ARCH Test, p-value for Heteroskedasticity.
*4. *, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*

Table 2.5: GARCH Estimation Results – Japan

		ΔIR_t	$\Delta LBTC_t$	ΔLCD_t	ΔLCS_t	ΔLEN_t	$\Delta LFIN_t$	$\Delta LFTSE_t$	$\Delta LGOLD_t$	ΔLHC_t	$\Delta LIND_t$	ΔLIT_t	$\Delta LMAT_t$	$\Delta LNEER_t$	$\Delta LOIL_t$	ΔLRE_t	$\Delta LTEL_t$	$\Delta LUTI_t$
GARCH	h	5E-08*	2E-03**	1E-06*	9E-05**	6E-06*	8E-06*	4E-06*	2E-06*	4E-06*	2E-06*	1E-04**	3E-05*	4E-07*	2E-05*	6E-06*	3E-05*	8E-06*
	λ	1.084*	0.150**	0.059*	0.150*	0.038*	0.243*	0.261*	0.071*	0.071*	0.064*	0.150*	0.217*	0.051*	0.142*	0.128*	0.258*	0.060*
	α	-0.109*	0.600*	0.929*	0.600*	0.937*	0.748*	0.751*	0.904*	0.900*	0.922*	0.600*	0.623*	0.935*	0.833*	0.814*	0.604*	0.890*
	$\alpha+\lambda$	0.975	0.750	0.988	0.750	0.975	0.991	1.012	0.975	0.971	0.985	0.750	0.840	0.986	0.975	0.942	0.862	0.950
	F-LM	0.000*	0.907	0.015**	0.235	0.214	0.852	0.986	0.611	0.015**	0.032**	0.151	0.487	0.172	0.439	0.349	0.993	0.186
	LL	9842	2572	5361	4985	4562	5039	5405	5548	5185	5244	4857	5012	6557	3857	5439	4997	4987
	SIC	-11.570	-2.900	-6.226	-5.778	-5.273	-5.842	-6.278	-6.449	-6.017	-6.086	-5.625	-5.809	-7.653	-4.432	-6.319	-5.792	-5.779
EGARCH	h	-1.669*	-0.731*	-0.305*	-0.190*	-8.149	-0.246*	-0.510*	-0.313*	-0.286*	-0.256*	-0.512*	-0.131*	-0.207*	-0.403*	-0.661*	-1.101*	-0.569*
	λ	0.449*	0.242*	0.138*	0.054*	0.010	0.208*	0.034**	0.158*	0.092*	0.069*	0.185*	-0.032*	0.118*	0.219*	0.252*	0.341*	0.145*
	α	0.951*	0.908*	0.978*	0.984*	0.010	0.990*	-0.258*	0.979*	0.976*	0.978*	0.959*	0.983*	0.989*	0.968*	0.950*	-0.071*	0.948*
	β	-0.002	0.052*	-0.054*	-0.079*	0.010	0.020***	0.949*	0.012	-0.077*	-0.100*	-0.084*	-0.099*	0.015***	-0.114*	-0.050*	0.905*	-0.006
	$\alpha+\lambda$	1.400	1.202	1.062	0.959	0.020	1.217	-0.224	1.149	0.991	0.947	1.060	0.851	1.122	1.073	1.151	0.270	1.087
	F-LM	0.849	0.925	0.053***	0.063***	0.024**	0.056***	0.674	0.600	0.001*	0.007*	0.073***	0.000*	0.063***	0.409	0.259	0.864	0.177
	LL	20787	2780	5365	5446	4452	5050	5441	5551	5190	5258	5193	5031	6554	3876	5432	5008	4983
	SIC	-24.618	-3.143	-6.225	-6.322	-5.137	-5.850	-6.317	-6.447	-6.017	-6.098	-6.020	-5.828	-7.643	-4.450	-6.305	-5.800	-5.770
TARCH	h	3E-14*	2E-04*	1E-06*	2E-06*	6E-06*	9E-06*	1E-04*	2E-06*	3E-06*	4E-06*	1E-05*	2E-05*	4E-07*	3E-05*	6E-06*	3E-05*	8E-06*
	λ	0.341*	0.116*	0.000	-0.001	0.046*	0.223*	0.150	0.074*	0.022	0.002	0.090*	0.047**	0.047*	0.045*	0.070*	0.225*	0.048*
	α	0.743*	0.790*	0.948*	0.943*	0.936*	0.737*	0.050	0.904*	0.918*	0.911*	0.741*	0.710*	0.932*	0.170*	0.820*	0.063	0.894*
	β	-0.046	0.020	0.078*	0.073*	-0.013	0.063	0.600*	-0.004	0.064*	0.108*	0.160*	0.206*	0.012	0.829*	0.092*	0.615*	0.021
	$\alpha+\lambda$	1.083	0.906	1.026	1.016	0.969	1.022	0.200	0.973	1.003	1.020	0.991	0.963	0.991	0.216	0.981	0.288	0.963
	F-LM	0.730	0.639	0.005*	0.254	0.197	0.708	0.000*	0.622	0.01**	0.087***	0.863	0.735	0.126	0.744	0.632	0.855	0.163
	LL	20731	2770	5372	5437	4563	5040	4640	5549	5190	5255	5194	5024	6558	3874	5445	4998	4987
	SIC	-24.551	-3.131	-6.234	-6.312	-5.269	-5.838	-5.362	-6.445	-6.016	-6.094	-6.021	-5.818	-7.648	-4.448	-6.321	-5.788	-5.775
IGARCH	λ	0.181*	0.007*	0.044*	0.043*	0.036*	0.052*	-0.005*	0.033*	0.035*	0.054*	0.061*	0.045*	0.032*	0.104*	0.075*	0.059*	0.035*
	α	0.819*	0.993*	0.956*	0.957*	0.964*	0.948*	1.005*	0.967*	0.965*	0.946*	0.939*	0.955*	0.968*	0.896*	0.925*	0.941*	0.965*
	F-LM	0.593	0.013**	0.008*	0.010**	0.077***	0.105	0.000*	0.371	0.000*	0.016**	0.009*	0.002*	0.016**	0.599	0.000*	0.042**	0.000*
	LL	20703	2697	5353	5421	4549	5026	5008	5538	5167	5233	5172	5005	6543	3812	5416	4957	4974
	SIC	-24.531	-3.058	-6.225	-6.306	-5.266	-5.834	-5.813	-6.445	-6.003	-6.082	-6.009	-5.810	-7.644	-4.387	-6.300	-5.753	-5.773

1. LL: Loglikelihood ratio.
2. SIC: Schwarz Information Criterion.
3. F-LM: ARCH Test, p-value for Heteroskedasticity.
*4. *, ** and *** corresponds to significance level at 1%, 5% and 10% respectively.*

However, the VAR model suffers from one major drawback. It is difficult to interpret the estimation results because of sign changes for the coefficients of some lagged variables (these are illustrated in tables B4 – B6 of the appendix). To solve this problem, we generate the IRFs instead to understand the persistence, direction, and magnitude of the response of returns volatility of each sectoral stock index to one SD variation in the F4GU index. These findings are demonstrated below in figures 2.2, 2.3 and 2.4 for CAN, UK, and JAP respectively.

According to figure 2.2, returns volatility of all Canadian sectoral stock indices (aside from VAR_LHCCAN) reveal a positive response shock to a sudden increase in volatility of returns in the F4GU index. The positive spillover effect is greatly pronounced after 10 days reaching its peak at day 20. It then starts descending and becomes negligibly negative (the latter is not relevant for VAR_LITCAN) after a month's time (30 days). Eventually, the effect fades away after approximately 60 days. The shock spillover effect on VAR_LHCCAN is pretty much insignificant.

Similarly in figure 2.3 for the UK, returns volatility of all sectoral stock indices (aside from VAR_LREUK, VAR_LFINUK, VAR_LITUK and VAR_LCDUK) demonstrate a positive response shock to a sudden increase in volatility of returns in the F4GU index. The positive spillover effect is more explicit after 5 days reaching its peak at day 15. It then starts descending and becomes negligibly negative after 30 days. However, the latter impact differs slightly from the one obtained for CAN as it is not applicable for VAR_LENUK and VAR_LHCUK. Yet, the effect on all other variables disappears after approximately 60 days. This excludes VAR_LENUK as it vanishes after 30 days making it quicker when compared to all other variables for both countries. The shock spillover effect on VAR_LREUK, VAR_LFINUK, VAR_LITUK and VAR_LCDUK is insignificant.

Over to Japan in figure 2.4, returns volatility of all sectoral stock indices present a positive response shock to a sudden increase in volatility of returns in the F4GU index. The positive spillover effect is evident immediately within 5 to 10 days. This is consistent with the range of days discovered for CAN and the UK. Only two variables here experience a negative impact with that being VAR_LCSJAP and VAR_LFINJAP. The effect on most variables (excluding VAR_LCSJAP, VAR_LITJAP, VAR_LMATJAP and VAR_LTELJAP) dies out after approximately 60 days. Interestingly, none of the variables here display an insignificant response to a sudden increase in volatility of returns in the F4GU index.

Figure 2.2: Impulse Response Functions - Canada

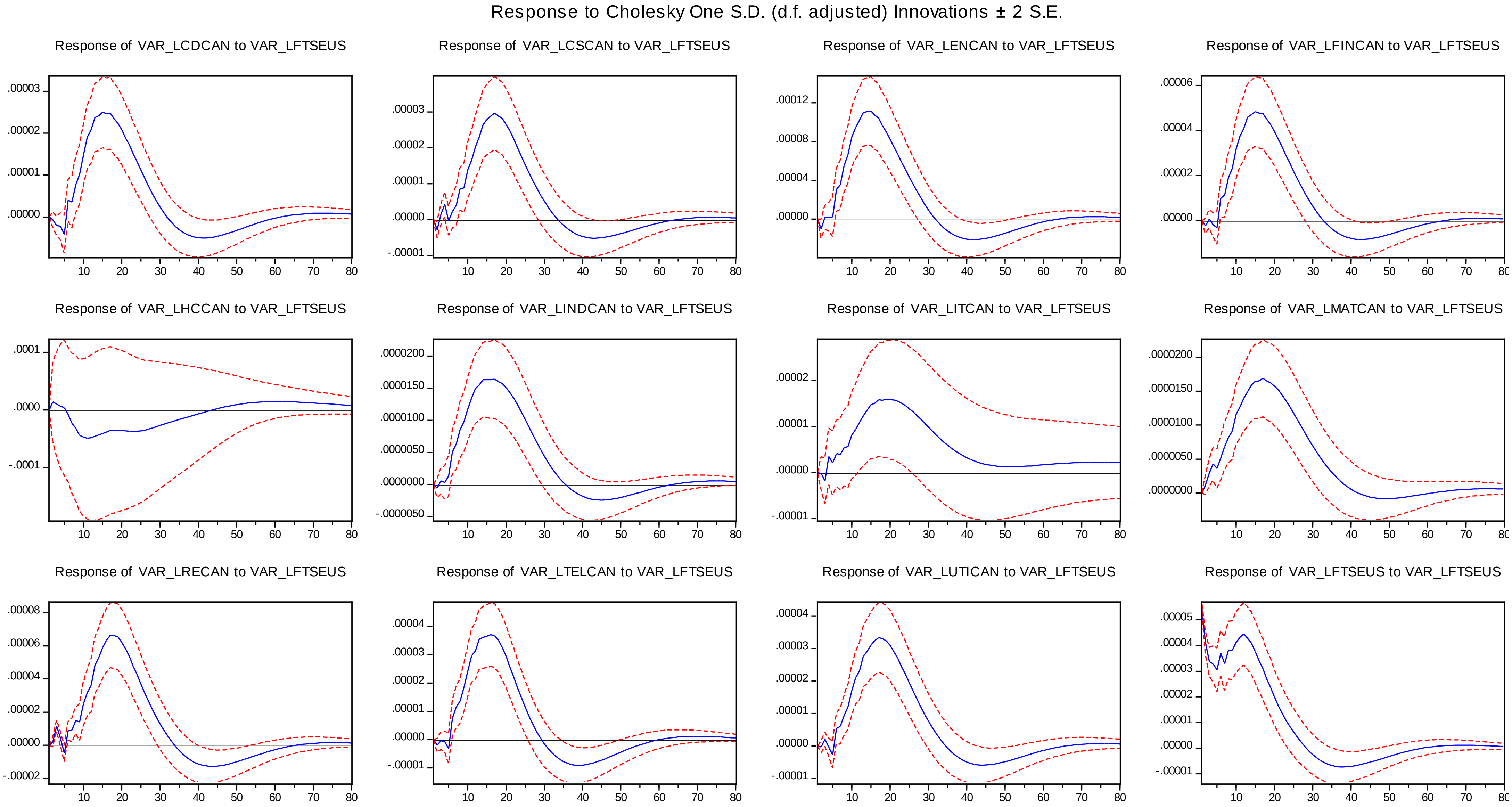


Figure 2.3: Impulse Response Functions – United Kingdom

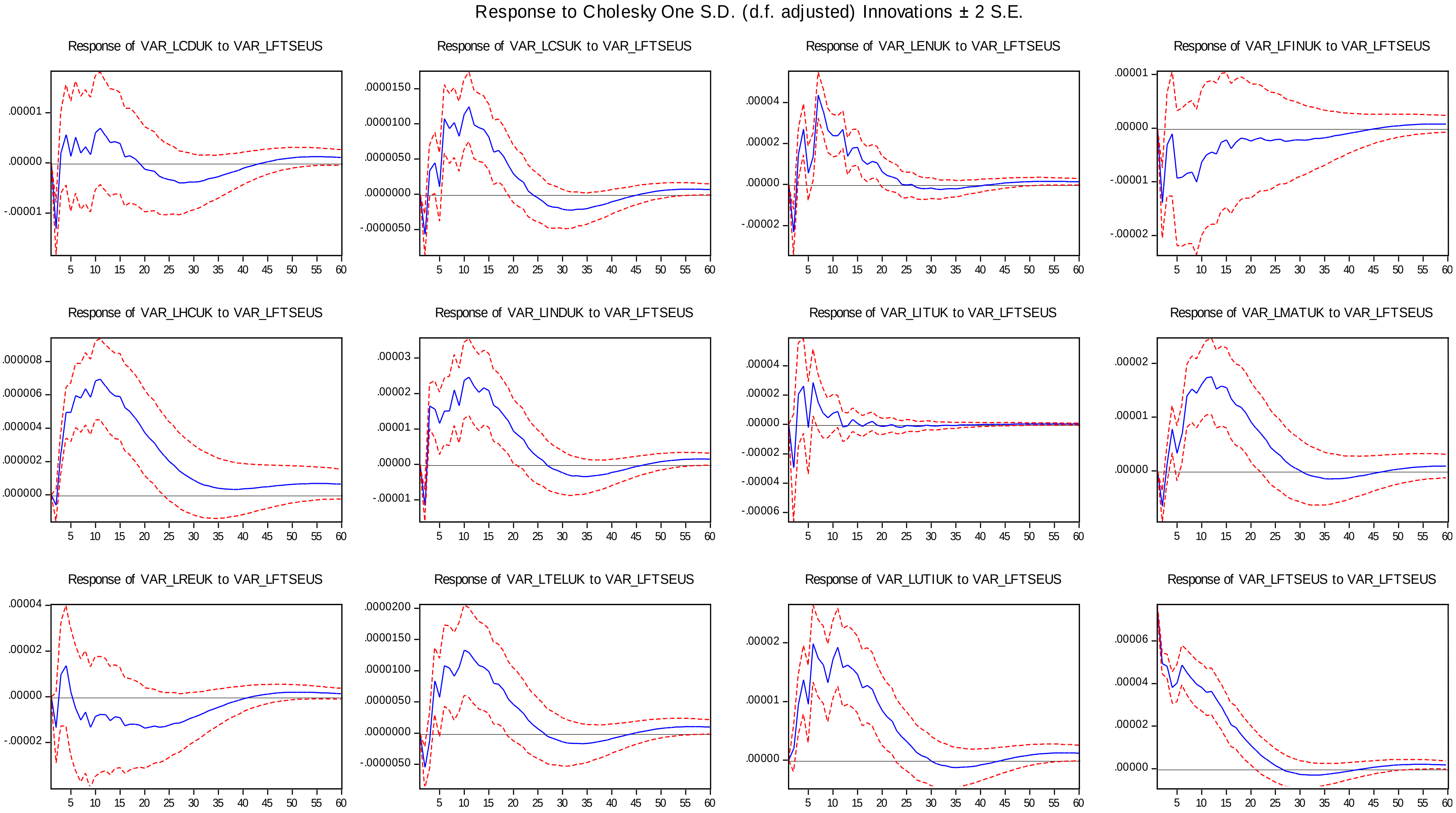
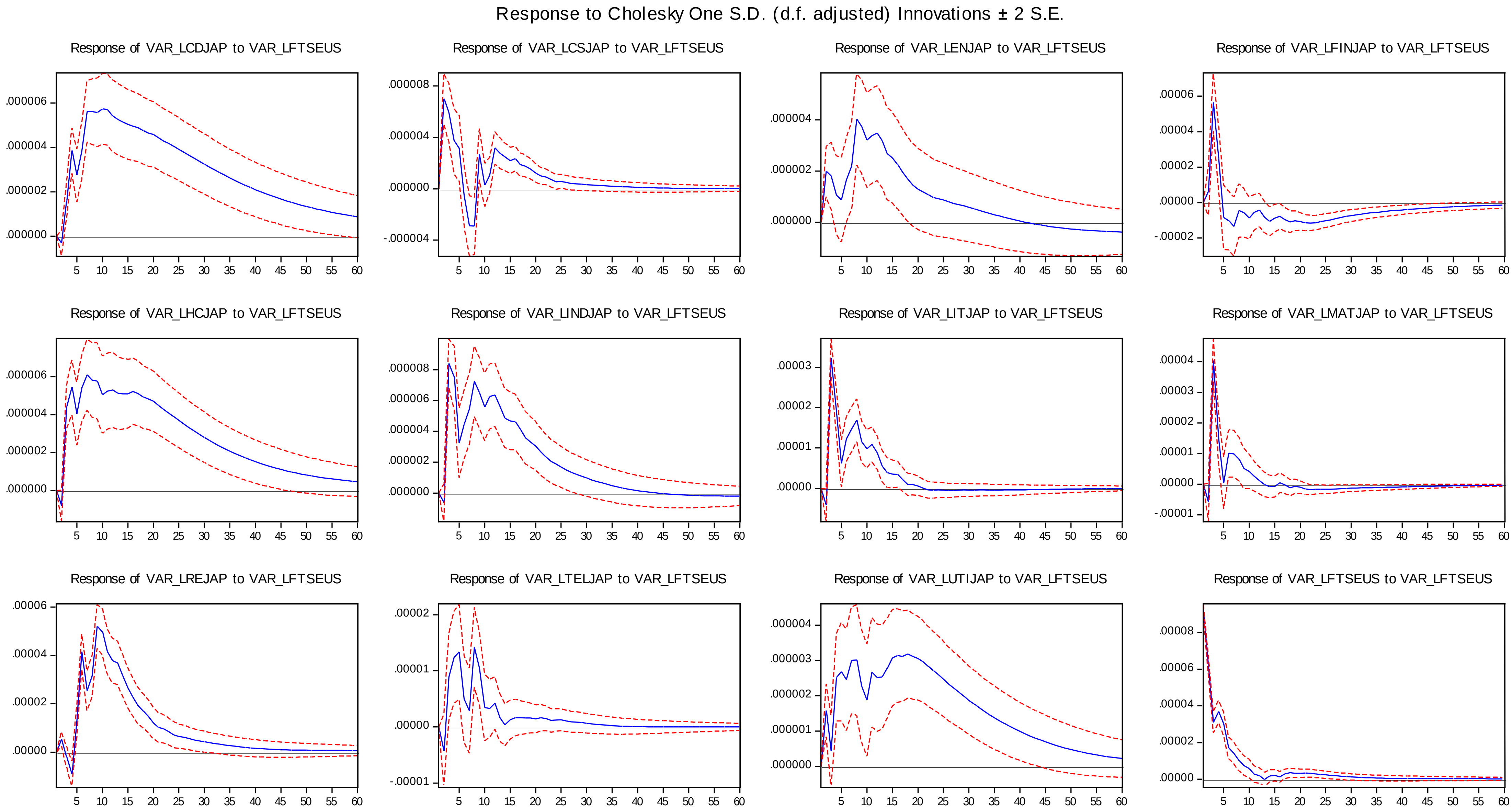


Figure 2.4: Impulse Response Functions - Japan



We then present the variance decompositions of all endogenous variables to understand the proportion of sectoral stock index returns volatility that is explained by the F4GU. These are presented for CAN, UK, and JAP in tables 2.6, 2.7 and 2.8 accordingly below for every five working days. It is important to note that the variance decomposition splits the variance of the forecasted error that belongs to the F4GU returns into elements that can be matched to each sectoral stock index included within our VAR framework.

According to table 2.6, the explanation of all Canadian sectoral stock index returns volatility (aside from VAR_LITCAN and VAR_LHCCAN) by that of the F4GU exceeds 14% on the 25th day period. It is even greater at 18.6% when considering VAR_LRECAN. However, volatility of returns in the F4GU index reveal an insignificant (less than 0.3%) and lowest (less than or equal to 3%) explanation of the volatility of returns in VAR_LHCCAN and VAR_LITCAN sectors respectively.

Over to table 2.7, the explanation of all British sectoral stock index returns volatility (aside from VAR_LREUK, VAR_LFINUK, VAR_LITUK and VAR_LCDUK) by the F4GU exceeds 3.5% on the 25th day period. The highest proportion is attributed to VAR_LHCUK at 9%. However, volatility of returns in the F4GU index display an insignificant (less than or equal to 0.6%) explanation of the volatility of returns in VAR_LREUK, VAR_LFINUK, VAR_LITUK and VAR_LCDUK. Therefore, accounting for the lowest returns volatility that is explained by F4GU index.

Last of all, in table 2.8 volatility of returns in the F4GU index demonstrate a significant explanation of returns volatility in all Japanese sectoral stock indices. They all exceed 5% (aside from VAR_LTELJAP, VAR_LENJAP and VAR_LFINJAP) on the 25th day period with the highest explanation appearing in VAR_LREJAP. This is identical to the result obtained for CAN but at 28%. On the other hand, the lowest returns volatility that is explained by F4GU index is associated with VAR_LTELJAP, VAR_LENJAP and VAR_LFINJAP (greater than or equal to 2.5%).

Table 2.6: Variance Decompositions – F4GU Index & Canadian Sectoral

Period	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
1	0	0	0	0	0	0	0	0	0	0	0	33.752
5	0.208	0.241	0.042	0.052	0.005	0.039	0.068	0.758	1.022	0.071	0.108	18.273
10	1.357	1.103	3.036	2.220	0.052	2.635	0.328	3.461	1.365	2.660	1.761	18.080
15	7.180	5.921	10.528	9.169	0.121	7.908	1.211	9.080	6.358	10.057	7.386	25.072
20	12.371	12.030	15.743	15.166	0.158	12.442	2.211	14.186	14.685	16.491	14.271	27.486
25	14.271	14.680	17.444	17.430	0.198	14.916	2.837	17.019	18.575	17.830	17.642	27.528
30	14.322	15.009	17.441	17.628	0.227	15.477	3.017	17.889	19.107	17.449	18.243	27.092
35	14.155	14.818	17.239	17.432	0.238	15.380	2.931	17.864	18.792	17.308	18.021	26.962
40	14.229	14.792	17.287	17.433	0.241	15.311	2.767	17.659	18.715	17.558	17.930	27.054
45	14.400	14.902	17.454	17.565	0.240	15.363	2.607	17.517	18.878	17.831	18.034	27.162
50	14.512	14.999	17.579	17.678	0.241	15.436	2.471	17.442	19.048	17.963	18.161	27.208
55	14.545	15.033	17.625	17.725	0.245	15.471	2.360	17.392	19.133	17.987	18.222	27.207
60	14.538	15.025	17.626	17.729	0.251	15.473	2.271	17.349	19.150	17.976	18.226	27.193

Cholesky Ordering: VAR_LCD VAR_LCS VAR_LEN VAR_LFIN VAR_LHC VAR_LIND VAR_LIT VAR_LMAT VAR_LRE VAR_LTEL VAR_LUTI VAR_LFTSE

Table 2.7: Variance Decompositions – F4GU Index & United Kingdom Sectoral

Period	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	54.944
5	0.278	0.437	1.404	0.289	2.600	1.504	0.308	0.638	0.099	0.523	1.382	27.127
10	0.285	2.819	5.039	0.462	6.101	2.942	0.485	3.222	0.155	1.888	4.913	25.662
15	0.381	4.576	6.109	0.477	8.370	4.953	0.496	5.369	0.216	3.140	7.224	27.348
20	0.376	4.887	6.326	0.487	9.039	5.601	0.497	6.020	0.344	3.515	8.171	27.092
25	0.399	4.786	6.270	0.497	8.982	5.609	0.498	5.970	0.480	3.514	8.223	26.409
30	0.457	4.759	6.224	0.510	8.706	5.531	0.499	5.776	0.568	3.474	8.071	25.925
35	0.499	4.801	6.210	0.521	8.458	5.523	0.499	5.652	0.601	3.471	7.978	25.676
40	0.512	4.822	6.198	0.525	8.278	5.530	0.499	5.582	0.606	3.468	7.931	25.539
45	0.511	4.816	6.185	0.525	8.153	5.522	0.499	5.525	0.605	3.458	7.895	25.437
50	0.513	4.809	6.180	0.525	8.071	5.511	0.499	5.477	0.608	3.451	7.870	25.364
55	0.519	4.811	6.181	0.526	8.022	5.508	0.499	5.441	0.611	3.454	7.860	25.320
60	0.524	4.816	6.183	0.527	7.993	5.511	0.499	5.418	0.612	3.460	7.858	25.295

Cholesky Ordering: VAR_LCD VAR_LCS VAR_LEN VAR_LFIN VAR_LHC VAR_LIND VAR_LIT VAR_LMAT VAR_LRE VAR_LTEL VAR_LUTI VAR_LFTSE

Table 2.8: Variance Decompositions – F4GU Index & Japan Sectoral

Period	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	92.809
5	3.279	3.607	0.685	2.674	4.568	5.778	9.423	5.951	1.177	1.340	1.637	84.123
10	12.018	4.020	2.709	2.579	9.731	9.815	12.280	6.165	18.975	2.298	3.357	79.331
15	16.749	4.815	3.938	2.710	12.857	12.735	13.069	6.142	27.072	2.382	4.992	78.475
20	19.287	5.252	4.035	2.964	15.512	13.721	13.049	6.140	28.232	2.413	7.154	78.134
25	20.854	5.329	3.940	3.288	17.183	13.912	13.015	6.171	28.250	2.438	8.722	78.007
30	21.773	5.348	3.857	3.477	18.104	13.927	13.003	6.195	28.171	2.447	9.624	77.878
35	22.270	5.355	3.783	3.573	18.581	13.904	12.998	6.211	28.082	2.449	10.113	77.783
40	22.515	5.357	3.722	3.627	18.815	13.877	12.996	6.222	28.002	2.448	10.365	77.721
45	22.623	5.358	3.680	3.656	18.923	13.858	12.996	6.228	27.943	2.448	10.489	77.679
50	22.660	5.358	3.656	3.673	18.969	13.848	12.995	6.232	27.902	2.448	10.547	77.651
55	22.664	5.358	3.648	3.682	18.986	13.843	12.995	6.234	27.875	2.448	10.573	77.632
60	22.653	5.358	3.650	3.688	18.990	13.842	12.994	6.235	27.857	2.448	10.584	77.618

Cholesky Ordering: VAR_LCD VAR_LCS VAR_LEN VAR_LFIN VAR_LHC VAR_LIND VAR_LIT VAR_LMAT VAR_LRE VAR_LTEL VAR_LUTI VAR_LFTSE

2.6 Robust Checks

To check the accuracy of the estimated VAR models and results obtained, we generate the Autoregressive Root (AR) graph of each country. These are demonstrated in figures 2.5, 2.6 and 2.7 for CAN, UK, and JAP respectively below. For twelve variables and five lags, we have a total of sixty roots. The AR graphs confirm that our estimated VAR models are stable for all three countries since all roots lie inside the unit circle. This is because, they are all less than 1 which also reinforces stationarity. The latter is also confirmed in figures 2.8, 2.9 and 2.10 for CAN, UK, and JAP respectively below after visualising the residuals of the volatility series. These are the ones included in the VAR model obtained after selecting the optimum time varying conditional variances.

Figure 2.5: AR Graph - Canada

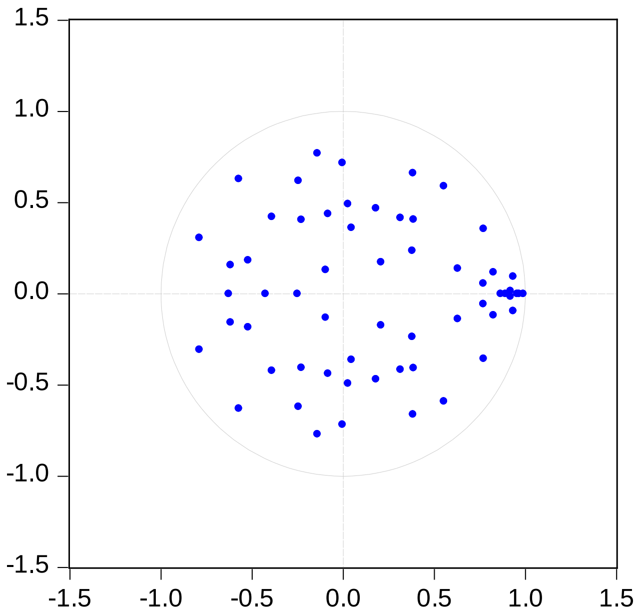


Figure 2.6: AR Graph – United Kingdom

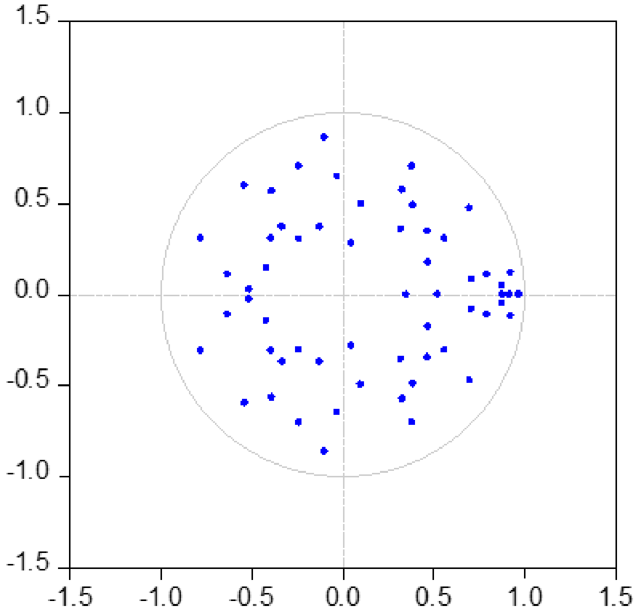


Figure 2.7: AR Graph – Japan

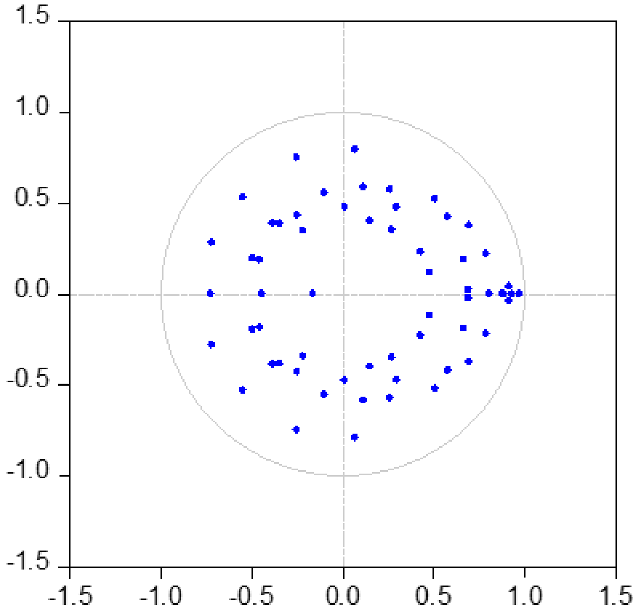


Figure 2.8: VAR Residuals - Canada

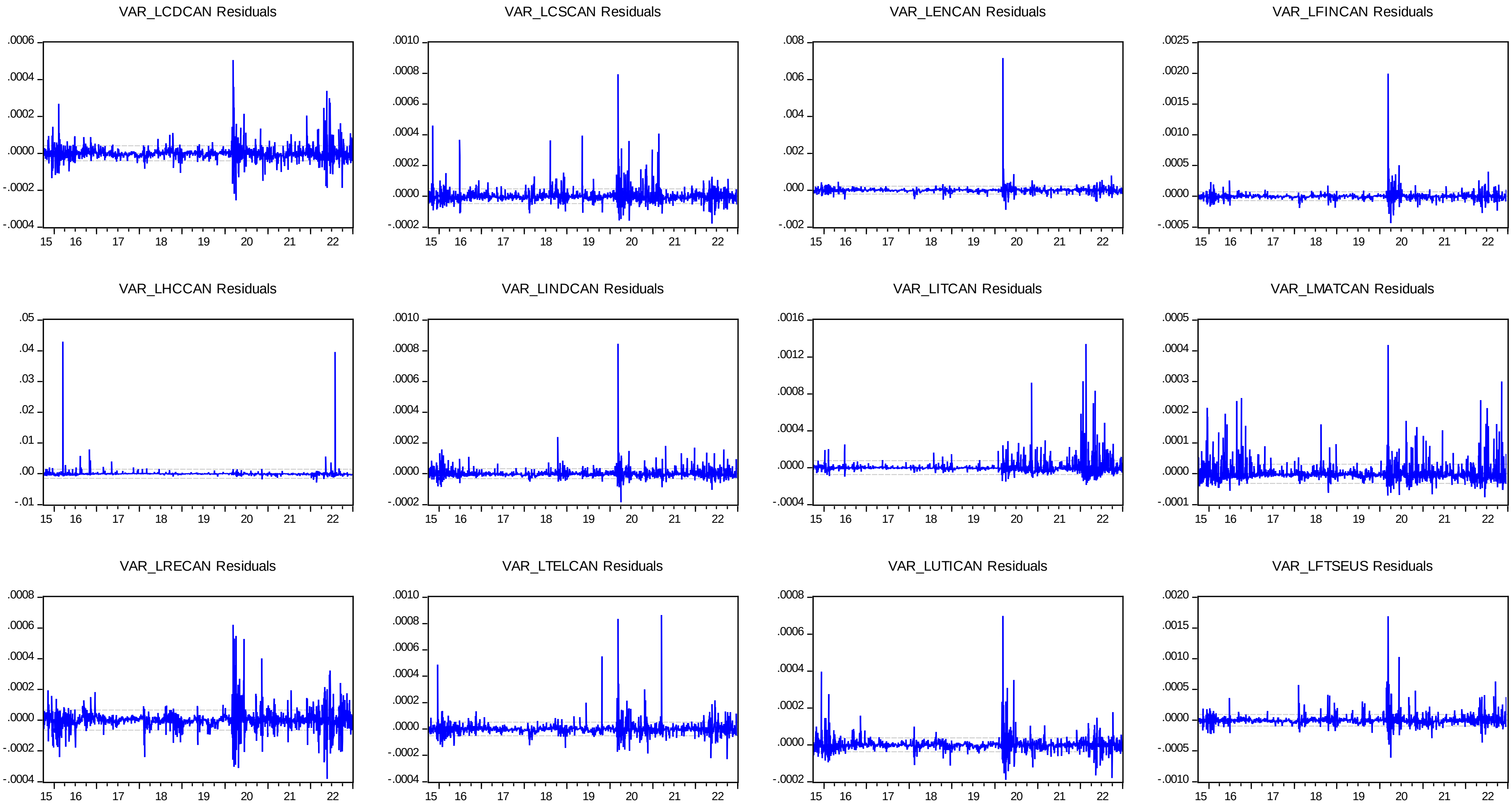


Figure 2.9: VAR Residuals – United Kingdom

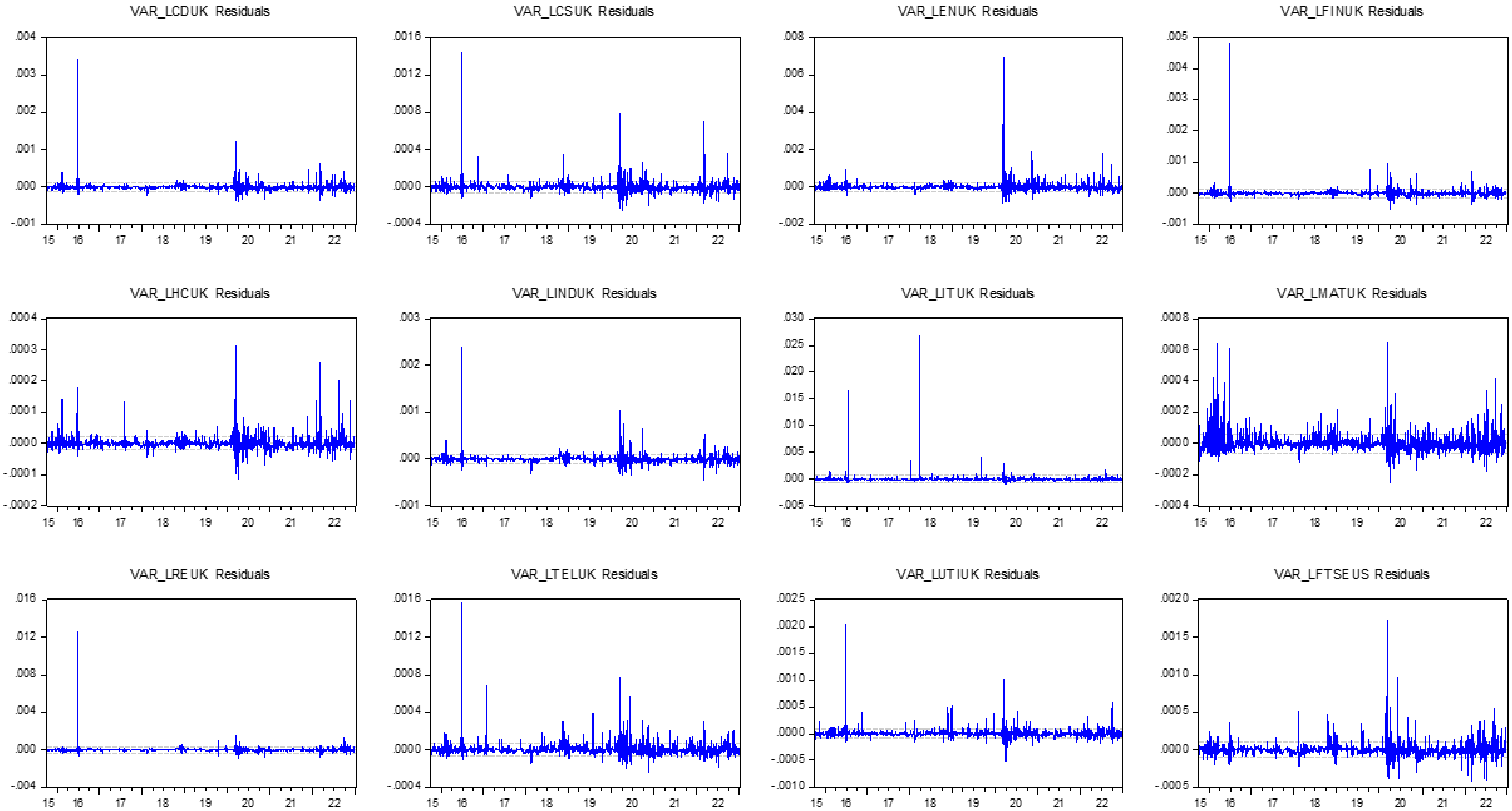
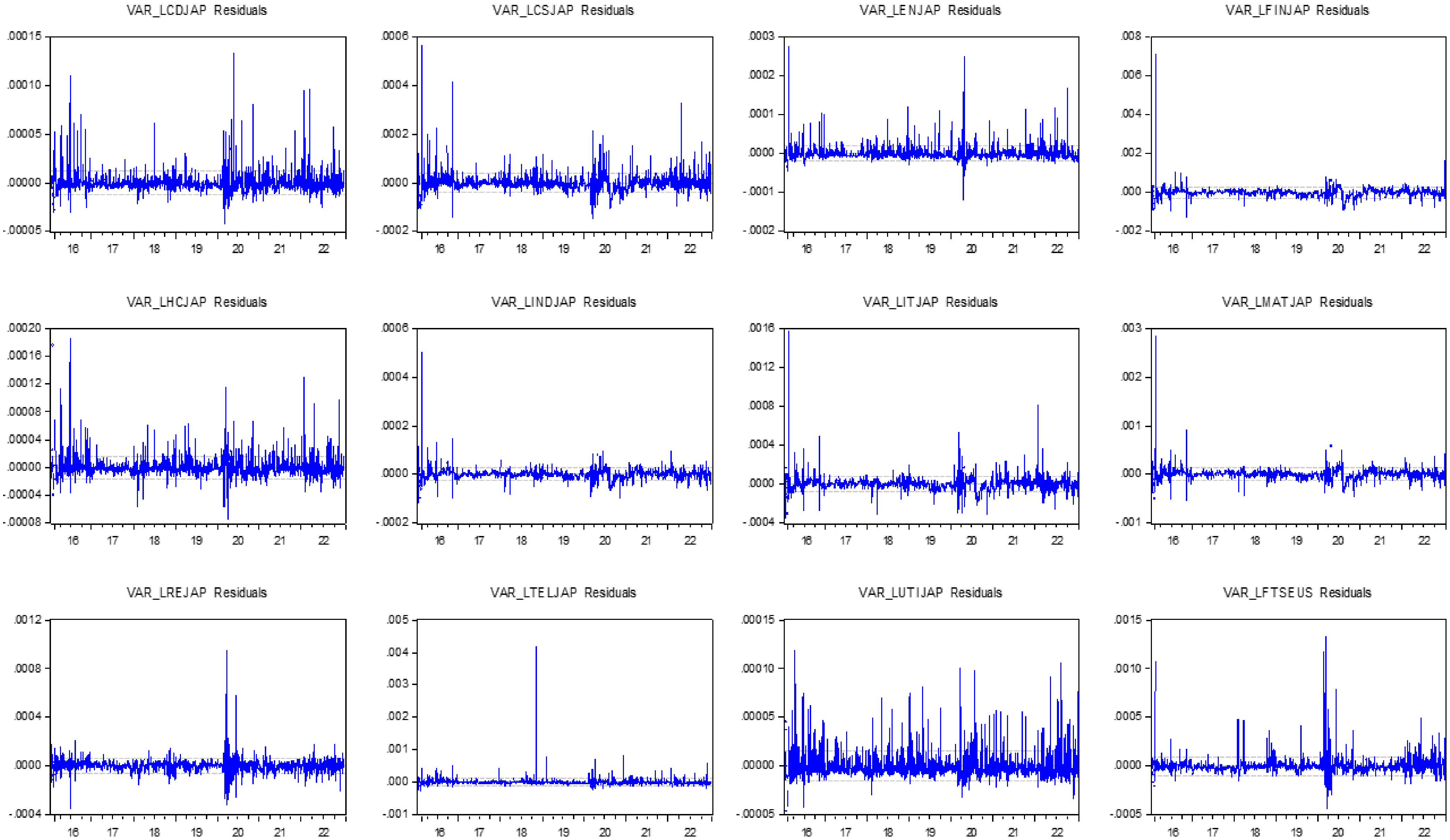


Figure 2.10: VAR Residuals - Japan



2.7 Conclusion

In the final analysis, this chapter investigates the returns volatility spillover effect of F4GU index on the returns volatility of sectoral stock indices of the US main trading partners. We begin by estimating the time varying conditional variance of both sets of variables whilst taking into account the nominal effective exchange rates, 3-month deposit rates of the countries of interest, Bitcoin, gold, and oil prices to explain the volatility of returns in the stock market. After selecting the optimum time varying conditional variances from the GARCH family, a multivariate VAR model is constructed to understand the spillover effect. All sectoral stock indices (aside from Canadian health care, British real estate, financials, information technology and consumer discretionary) reveal a positive response shock to a sudden increase in volatility of returns in the F4GU index. The spillover effect is more apparent between 5 to 15 days for all three countries. In the same light, returns volatility of the F4GU index explains more than 14%, 3.5% and 5% of returns volatility in most Canadian, British, and Japanese sectoral stock indices respectively on the 25th day period. The highest explanation corresponds to the real estate sector of CAN and JAP at 18.6% and 28% respectively while it is health care for the UK at 9% on that particular day. These findings are consistent with the ones obtained using the IRFs. In the long run, the proportion of these explanations remain valid whereby acting as a supplementary piece of information in assisting financial institutions and investors in adjusting their stock market portfolio.

Appendix B

Table B1: Descriptive Statistics - Canada

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Minimum	Maximum	Count
FTSEUS	12052.447	86.011	10953.890	10074.930	3692.456	13634233.550	-1.002	0.499	30.637	6680.700	20000.380	1843
BTC	14588.033	384.419	8208.400	236.700	16503.189	272355235.252	0.809	1.394	113.128	233.800	67527.900	1843
CDCAN	1191.708	3.927	1154.480	969.810	168.567	28414.744	-1.121	0.104	14.145	809.850	1533.200	1843
CSCAN	800.109	6.195	682.890	598.880	265.958	70733.824	-0.546	0.957	33.240	358.790	1400.730	1843
ENCAN	516.495	1.910	527.020	518.010	82.016	6726.595	0.410	-0.573	15.879	234.630	749.990	1843
FINCAN	802.649	3.317	789.260	627.390	142.405	20279.154	-0.306	0.492	17.742	467.050	1165.110	1843
GOLD	1490.979	6.293	1348.260	1107.900	270.167	72990.001	-1.454	0.305	18.120	1051.100	2063.540	1843
HCCAN	544.164	11.842	461.570	108.960	508.386	258456.273	18.769	3.965	93.425	63.360	4530.580	1843
INDCAN	884.661	6.345	823.050	487.150	272.411	74207.737	-1.287	0.277	30.793	409.810	1440.500	1843
ITCAN	77.732	0.980	62.920	40.620	42.055	1768.628	0.174	1.142	54.103	29.360	196.160	1843
IRCAN	0.000	0.000	0.000	0.000	0.000	0.000	2.140	1.296	0.000	0.000	0.000	1843
MATCAN	274.665	1.376	255.870	217.600	59.069	3489.108	-0.113	0.616	21.506	154.030	471.170	1843
NEERCAN	101.717	0.067	101.430	100.160	2.878	8.284	0.278	-0.093	2.829	90.590	108.810	1843
OIL	63.059	0.481	61.940	70.710	20.638	425.908	0.688	0.715	32.728	9.120	133.180	1843
RECAN	3077.879	8.631	3061.510	2763.800	370.532	137294.032	-0.366	-0.020	12.039	1776.090	3912.460	1843
TELCAN	1071.443	2.850	1063.240	1092.890	122.346	14968.639	0.025	0.442	11.419	741.860	1468.600	1843
UTICAN	866.073	3.955	815.670	739.470	169.808	28834.679	-0.841	0.432	19.607	503.730	1256.580	1843

Table B2: Descriptive Statistics - United Kingdom

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Minimum	Maximum	Count
FTSEUS	12066.908	86.393	10956.665	10074.930	3697.771	13673507.383	-1.012	0.492	30.644	6680.700	20000.380	1832
BTC	14645.637	386.167	8239.600	236.700	16528.651	273196311.913	0.788	1.387	112.857	233.800	67527.900	1832
CDUK	378.097	0.895	378.630	387.300	38.289	1466.036	0.079	-0.511	10.127	227.670	450.850	1832
CSUK	860.795	1.694	860.715	916.560	72.492	5255.054	-0.144	-0.111	8.422	579.710	1047.140	1832
ENUK	532.569	2.673	547.725	587.210	114.420	13091.959	-0.481	-0.400	21.485	237.450	766.930	1832
FINUK	237.916	0.819	240.145	234.920	35.038	1227.666	-0.286	-0.278	14.727	146.110	320.140	1832
GOLD	1492.135	6.316	1349.170	1107.900	270.321	73073.584	-1.460	0.297	18.116	1051.100	2063.540	1832
HCUK	548.862	1.587	530.730	608.230	67.937	4615.459	-1.038	0.326	12.378	430.820	732.450	1832
INDUK	405.539	1.556	392.410	349.020	66.590	4434.279	0.163	0.878	16.420	243.150	588.950	1832
ITUK	19.359	0.099	18.205	18.220	4.232	17.910	-0.482	0.506	21.861	11.150	30.400	1832
IRUK	0.000	0.000	0.000	0.000	0.000	0.000	8.956	2.887	0.000	0.000	0.000	1832
MATUK	316.879	2.077	308.060	277.380	88.890	7901.354	-0.595	0.165	28.052	121.050	521.940	1832
NEERUK	101.828	0.107	100.590	99.840	4.589	21.059	2.659	1.510	4.507	93.840	119.220	1832
OIL	63.112	0.483	62.020	70.710	20.675	427.471	0.674	0.710	32.759	9.120	133.180	1832
REUK	1398.427	4.526	1402.620	1410.860	193.715	37525.601	0.579	-0.161	13.852	793.430	1969.350	1832
TELUK	207.456	1.692	181.915	189.420	72.411	5243.281	-0.625	0.647	34.904	95.620	385.400	1832
UTIUK	839.076	2.490	838.950	981.430	106.585	11360.324	-0.843	0.190	12.703	579.530	1091.560	1832

Table B3: Descriptive Statistics - Japan

Variable	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	CV	Minimum	Maximum	Count
FTSEUS	12276.856	89.075	11068.160	10074.930	3649.914	13321868.904	-1.064	0.452	29.730	6799.890	20000.380	1679
BTC	15224.717	402.811	8697.500	236.700	16505.428	272429167.675	0.616	1.328	108.412	233.800	67527.900	1679
CDJAP	224.482	0.487	227.120	227.460	19.957	398.264	-0.977	0.087	8.890	179.870	267.570	1679
CSJAP	316.029	0.806	310.500	299.820	33.037	1091.454	-0.772	0.262	10.454	236.700	397.920	1679
ENJAP	95.453	0.474	91.930	86.040	19.426	377.366	0.754	1.083	20.351	60.760	161.340	1679
FINJAP	42.661	0.109	42.550	41.930	4.453	19.828	-0.239	-0.006	10.438	29.740	55.810	1679
GOLD	1508.556	6.465	1418.650	1237.970	264.927	70186.082	-1.531	0.274	17.562	1061.100	2063.540	1679
HCJAP	341.830	1.336	330.030	326.600	54.753	2997.843	-0.684	0.505	16.018	232.130	476.350	1679
INDJAP	374.109	1.610	370.280	391.220	65.968	4351.828	-0.517	0.207	17.633	218.000	538.370	1679
ITJAP	96.260	0.580	91.540	104.540	23.763	564.703	-0.486	0.619	24.686	55.030	158.650	1679
IRJAP	0.000	0.000	0.000	0.000	0.000	0.000	10.452	-2.015	0.000	0.000	0.000	1679
MATJAP	150.608	0.530	148.080	133.270	21.718	471.657	-0.867	0.067	14.420	98.200	201.520	1679
NEERJAP	93.853	0.142	94.170	94.170	5.835	34.045	0.565	-0.877	6.217	76.530	104.690	1679
OIL	64.365	0.503	62.840	70.710	20.611	424.808	0.674	0.717	32.022	9.120	133.180	1679
REJAP	2591.630	5.604	2579.830	2541.590	229.624	52727.136	0.124	-0.003	8.860	1678.560	3138.410	1679
TELJAP	366.117	1.488	351.890	332.290	60.966	3716.906	1.068	1.056	16.652	222.530	569.240	1679
UTIJAP	40.418	0.152	41.980	44.080	6.219	38.674	-0.587	-0.495	15.387	25.240	52.290	1679

Table B4: VAR Estimation Results - Canada

	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
VAR_LCD(-1)	0.606	-0.330	-0.928	-0.513	-0.652	-0.109	-0.209	-0.010	-0.479	0.000	-0.203	-0.388
	-0.040	-0.048	-0.211	-0.072	-1.477	-0.033	-0.076	-0.031	-0.065	-0.051	-0.038	-0.094
	[14.989]	[-6.854]	[-4.400]	[-7.151]	[-0.441]	[-3.317]	[-2.755]	[-0.312]	[-7.343]	[-0.010]	[-5.325]	[-4.134]
VAR_LCD(-2)	0.620	0.640	1.933	0.983	1.268	0.264	0.363	0.048	1.218	0.186	0.467	0.946
	-0.051	-0.060	-0.264	-0.090	-1.851	-0.041	-0.095	-0.039	-0.082	-0.064	-0.048	-0.118
	[12.246]	[10.621]	[7.320]	[10.931]	[0.685]	[6.441]	[3.822]	[1.226]	[14.900]	[2.900]	[9.759]	[8.043]
VAR_LCD(-3)	-0.707	-0.672	-2.078	-0.910	-0.234	-0.273	-0.258	-0.135	-1.161	-0.675	-0.612	-1.007
	-0.054	-0.064	-0.279	-0.095	-1.956	-0.043	-0.100	-0.041	-0.086	-0.068	-0.051	-0.124
	[-13.219]	[-10.549]	[-7.441]	[-9.578]	[-0.120]	[-6.290]	[-2.563]	[-3.277]	[-13.439]	[-9.961]	[-12.092]	[-8.098]
VAR_LCD(-4)	0.239	0.363	0.502	0.195	-2.230	-0.053	0.165	-0.012	0.844	0.201	0.259	-0.051
	-0.057	-0.068	-0.298	-0.101	-2.087	-0.046	-0.107	-0.044	-0.092	-0.072	-0.054	-0.133
	[4.190]	[5.345]	[1.685]	[1.920]	[-1.069]	[-1.150]	[1.538]	[-0.276]	[9.154]	[2.776]	[4.805]	[-0.386]
VAR_LCD(-5)	0.041	-0.058	0.385	0.133	2.874	0.142	-0.134	0.106	-0.421	0.213	0.037	0.381
	-0.042	-0.051	-0.221	-0.075	-1.551	-0.034	-0.080	-0.033	-0.069	-0.054	-0.040	-0.099
	[0.959]	[-1.141]	[1.739]	[1.763]	[1.852]	[4.141]	[-1.686]	[3.239]	[-6.153]	[3.958]	[0.934]	[3.862]
VAR_LCS(-1)	-0.024	0.886	0.052	-0.037	-0.204	-0.015	0.037	0.006	-0.215	-0.017	-0.057	-0.088
	-0.026	-0.031	-0.138	-0.047	-0.966	-0.021	-0.050	-0.020	-0.043	-0.033	-0.025	-0.061
	[-0.924]	[28.203]	[0.377]	[-0.778]	[-0.211]	[-0.686]	[0.751]	[0.291]	[-5.041]	[-0.521]	[-2.291]	[-1.440]
VAR_LCS(-2)	0.099	0.027	0.127	0.113	0.817	0.070	0.113	-0.017	0.030	-0.007	0.011	0.491
	-0.035	-0.041	-0.182	-0.062	-1.273	-0.028	-0.065	-0.027	-0.056	-0.044	-0.033	-0.081
	[2.835]	[0.657]	[0.700]	[1.836]	[0.642]	[2.478]	[1.729]	[-0.647]	[0.527]	[-0.161]	[0.323]	[6.069]
VAR_LCS(-3)	-0.202	-0.208	-0.724	-0.252	-1.554	-0.178	-0.152	-0.017	0.425	0.031	0.031	-0.876
	-0.033	-0.039	-0.170	-0.058	-1.192	-0.026	-0.061	-0.025	-0.053	-0.041	-0.031	-0.076
	[-6.209]	[-5.361]	[-4.256]	[-4.346]	[-1.303]	[-6.742]	[-2.480]	[-0.660]	[8.069]	[0.740]	[1.020]	[-11.570]
VAR_LCS(-4)	0.113	0.338	0.529	0.175	0.464	0.104	0.058	0.040	0.013	0.018	0.088	0.423
	-0.033	-0.039	-0.173	-0.059	-1.212	-0.027	-0.062	-0.026	-0.054	-0.042	-0.031	-0.077
	[3.422]	[8.570]	[3.061]	[2.974]	[0.383]	[3.872]	[0.932]	[1.563]	[0.236]	[0.427]	[2.792]	[5.493]
VAR_LCS(-5)	-0.021	-0.149	-0.083	-0.055	0.495	0.003	-0.063	-0.028	-0.330	-0.042	-0.097	0.014
	-0.023	-0.028	-0.121	-0.041	-0.846	-0.019	-0.043	-0.018	-0.037	-0.029	-0.022	-0.054
	[-0.920]	[-5.402]	[-0.689]	[-1.330]	[0.585]	[0.164]	[-1.454]	[-1.587]	[-8.843]	[-1.424]	[-4.447]	[0.268]
VAR_LEN(-1)	-0.038	-0.017	0.759	-0.067	-0.031	-0.026	-0.017	-0.008	-0.010	-0.021	-0.028	-0.064
	-0.013	-0.015	-0.066	-0.022	-0.460	-0.010	-0.024	-0.010	-0.020	-0.016	-0.012	-0.029
	[-3.042]	[-1.104]	[11.549]	[-3.006]	[-0.067]	[-2.544]	[-0.715]	[-0.867]	[-0.501]	[-1.305]	[-2.363]	[-2.179]

VAR_LEN(-2)	0.053	-0.043	-0.148	0.026	0.308	0.014	-0.024	0.012	-0.047	-0.020	0.019	0.077
	-0.017	-0.020	-0.090	-0.031	-0.629	-0.014	-0.032	-0.013	-0.028	-0.022	-0.016	-0.040
	[3.103]	[-2.091]	[-1.646]	[0.842]	[0.490]	[1.011]	[-0.739]	[0.936]	[-1.703]	[-0.923]	[1.168]	[1.939]
VAR_LEN(-3)	0.262	0.202	1.018	0.414	-0.002	0.048	0.132	0.048	0.319	0.395	0.256	0.260
	-0.018	-0.021	-0.092	-0.031	-0.643	-0.014	-0.033	-0.014	-0.028	-0.022	-0.017	-0.041
	[14.873]	[9.661]	[11.094]	[13.255]	[-0.002]	[3.377]	[3.996]	[3.563]	[11.224]	[17.759]	[15.378]	[6.369]
VAR_LEN(-4)	-0.279	-0.047	-0.681	-0.292	0.728	-0.062	-0.070	-0.017	-0.015	-0.184	-0.152	-0.274
	-0.019	-0.023	-0.102	-0.035	-0.712	-0.016	-0.037	-0.015	-0.031	-0.025	-0.018	-0.045
	[-14.313]	[-2.011]	[-6.700]	[-8.445]	[1.022]	[-3.937]	[-1.921]	[-1.150]	[-0.472]	[-7.443]	[-8.250]	[-6.055]
VAR_LEN(-5)	0.042	-0.072	-0.094	-0.034	-0.680	0.021	-0.004	-0.039	-0.133	-0.134	-0.060	0.027
	-0.015	-0.018	-0.079	-0.027	-0.554	-0.012	-0.028	-0.012	-0.024	-0.019	-0.014	-0.035
	[2.760]	[-4.018]	[-1.187]	[-1.256]	[-1.227]	[1.695]	[-0.141]	[-3.321]	[-5.440]	[-6.971]	[-4.156]	[0.773]
VAR_LFIN(-1)	0.134	0.133	0.808	1.247	-1.144	0.161	0.039	0.001	0.087	0.072	0.134	0.317
	-0.047	-0.056	-0.245	-0.083	-1.718	-0.038	-0.088	-0.036	-0.076	-0.059	-0.044	-0.109
	[2.844]	[2.383]	[3.296]	[14.948]	[-0.666]	[4.240]	[0.441]	[0.037]	[1.147]	[1.204]	[3.011]	[2.908]
VAR_LFIN(-2)	-0.197	-0.023	-0.188	-0.246	-0.106	-0.157	-0.128	-0.001	0.119	-0.021	-0.132	-0.375
	-0.065	-0.077	-0.337	-0.115	-2.358	-0.052	-0.121	-0.050	-0.104	-0.082	-0.061	-0.150
	[-3.051]	[-0.304]	[-0.558]	[-2.147]	[-0.045]	[-3.001]	[-1.054]	[-0.022]	[1.147]	[-0.261]	[-2.156]	[-2.500]
VAR_LFIN(-3)	-0.061	-0.110	-1.009	-0.280	0.358	0.023	-0.095	-0.084	-0.235	-0.245	-0.065	0.063
	-0.064	-0.077	-0.336	-0.114	-2.353	-0.052	-0.121	-0.050	-0.104	-0.081	-0.061	-0.150
	[-0.945]	[-1.438]	[-3.003]	[-2.454]	[0.152]	[0.447]	[-0.788]	[-1.683]	[-2.264]	[-3.010]	[-1.070]	[0.423]
VAR_LFIN(-4)	0.219	0.053	0.926	0.262	-0.004	0.066	0.107	0.107	-0.030	0.223	0.057	0.136
	-0.065	-0.077	-0.339	-0.115	-2.376	-0.053	-0.122	-0.050	-0.105	-0.082	-0.061	-0.151
	[3.375]	[0.689]	[2.732]	[2.271]	[-0.001]	[1.252]	[0.879]	[2.139]	[-0.290]	[2.712]	[0.926]	[0.903]
VAR_LFIN(-5)	-0.107	-0.042	-0.590	-0.091	1.360	-0.084	0.010	-0.066	0.160	-0.043	0.000	-0.189
	-0.046	-0.055	-0.240	-0.082	-1.684	-0.037	-0.086	-0.036	-0.074	-0.058	-0.044	-0.107
	[-2.314]	[-0.759]	[-2.457]	[-1.108]	[0.808]	[-2.261]	[0.120]	[-1.854]	[2.149]	[-0.735]	[0.006]	[-1.763]
VAR_LHC(-1)	0.000	0.000	0.001	0.000	0.918	0.000	-0.001	0.000	-0.001	0.000	0.000	0.000
	-0.001	-0.001	-0.003	-0.001	-0.024	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	[0.060]	[-0.132]	[0.389]	[0.055]	[38.749]	[0.541]	[-0.634]	[0.847]	[-0.826]	[0.185]	[-0.240]	[0.306]
VAR_LHC(-2)	-0.001	0.000	-0.004	-0.001	-0.010	0.001	0.000	0.000	0.001	0.001	0.000	-0.002
	-0.001	-0.001	-0.005	-0.002	-0.032	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002
	[-0.630]	[0.273]	[-0.879]	[-0.420]	[-0.322]	[1.262]	[-0.127]	[-0.392]	[0.891]	[0.963]	[0.100]	[-0.891]
VAR_LHC(-3)	0.000	0.000	0.006	0.001	-0.011	-0.001	0.000	0.000	0.001	-0.001	0.001	0.001

	-0.001	-0.001	-0.005	-0.002	-0.032	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002
	[0.451]	[0.004]	[1.283]	[0.814]	[-0.333]	[-1.766]	[-0.143]	[0.434]	[0.553]	[-0.624]	[1.356]	[0.374]
VAR_LHC(-4)	0.000	-0.001	-0.003	-0.001	0.042	0.000	0.000	-0.001	-0.002	-0.001	-0.001	0.000
	-0.001	-0.001	-0.005	-0.002	-0.032	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002
	[-0.561]	[-0.758]	[-0.628]	[-0.886]	[1.314]	[-0.377]	[0.267]	[-1.070]	[-1.183]	[-0.878]	[-1.721]	[-0.106]
VAR_LHC(-5)	0.001	0.001	0.001	0.001	-0.016	0.000	0.000	0.001	0.001	0.001	0.001	0.001
	-0.001	-0.001	-0.003	-0.001	-0.024	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	[1.214]	[0.714]	[0.396]	[0.861]	[-0.686]	[0.943]	[0.053]	[1.296]	[0.771]	[0.826]	[1.099]	[0.536]
VAR_LIND(-1)	-0.067	-0.050	-0.175	-0.126	3.721	0.834	0.022	-0.029	0.205	-0.160	0.011	-0.283
	-0.048	-0.057	-0.248	-0.084	-1.738	-0.039	-0.089	-0.037	-0.077	-0.060	-0.045	-0.110
	[-1.411]	[-0.884]	[-0.707]	[-1.493]	[2.141]	[21.647]	[0.243]	[-0.777]	[2.677]	[-2.657]	[0.251]	[-2.564]
VAR_LIND(-2)	0.112	0.255	0.381	0.209	-3.432	0.053	0.204	0.153	-0.018	0.189	0.148	-0.032
	-0.064	-0.077	-0.336	-0.114	-2.356	-0.052	-0.121	-0.050	-0.104	-0.082	-0.061	-0.150
	[1.738]	[3.319]	[1.134]	[1.823]	[-1.457]	[1.013]	[1.690]	[3.086]	[-0.173]	[2.316]	[2.430]	[-0.216]
VAR_LIN(-3)	0.369	-0.014	1.976	0.585	1.217	0.239	-0.042	0.069	-0.471	0.306	0.120	0.943
	-0.062	-0.073	-0.321	-0.109	-2.250	-0.050	-0.116	-0.047	-0.099	-0.078	-0.058	-0.143
	[5.996]	[-0.194]	[6.156]	[5.353]	[0.541]	[4.789]	[-0.364]	[1.450]	[-4.737]	[3.930]	[2.061]	[6.594]
VAR_LIND(-4)	-0.386	-0.426	-2.602	-0.749	-0.471	-0.244	-0.177	-0.247	0.001	-0.426	-0.363	-0.569
	-0.063	-0.075	-0.327	-0.111	-2.293	-0.051	-0.118	-0.048	-0.101	-0.079	-0.059	-0.146
	[-6.151]	[-5.704]	[-7.951]	[-6.726]	[-0.206]	[-4.806]	[-1.500]	[-5.103]	[0.009]	[-5.367]	[-6.114]	[-3.906]
VAR_LIND(-5)	0.025	0.267	0.515	0.122	-0.602	0.041	0.071	0.072	0.264	0.081	0.119	-0.014
	-0.047	-0.056	-0.244	-0.083	-1.709	-0.038	-0.088	-0.036	-0.075	-0.059	-0.044	-0.109
	[0.532]	[4.808]	[2.113]	[1.469]	[-0.352]	[1.070]	[0.814]	[2.001]	[3.493]	[1.373]	[2.695]	[-0.133]
VAR_LIT(-1)	0.034	0.031	0.169	0.062	-0.300	0.012	1.074	0.026	0.038	0.014	0.028	0.075
	-0.014	-0.016	-0.070	-0.024	-0.494	-0.011	-0.025	-0.010	-0.022	-0.017	-0.013	-0.031
	[2.533]	[1.916]	[2.393]	[2.600]	[-0.607]	[1.141]	[42.347]	[2.502]	[1.764]	[0.847]	[2.205]	[2.398]
VAR_LI(-2)	-0.032	-0.072	-0.328	-0.118	2.669	-0.020	-0.126	-0.022	-0.123	-0.016	-0.060	-0.083
	-0.020	-0.023	-0.102	-0.035	-0.715	-0.016	-0.037	-0.015	-0.032	-0.025	-0.018	-0.045
	[-1.621]	[-3.079]	[-3.213]	[-3.385]	[3.734]	[-1.281]	[-3.437]	[-1.447]	[-3.885]	[-0.641]	[-3.219]	[-1.835]
VAR_LIT(-3)	-0.013	0.055	0.225	0.079	-2.060	-0.009	-0.025	-0.012	0.146	-0.007	0.043	-0.033
	-0.020	-0.023	-0.102	-0.035	-0.715	-0.016	-0.037	-0.015	-0.032	-0.025	-0.018	-0.045
	[-0.685]	[2.357]	[2.207]	[2.263]	[-2.883]	[-0.593]	[-0.673]	[-0.816]	[4.616]	[-0.273]	[2.315]	[-0.730]
VAR_LIT(-4)	0.005	-0.030	-0.112	-0.044	0.330	0.007	0.024	0.006	-0.072	0.024	-0.012	0.037
	-0.020	-0.023	-0.103	-0.035	-0.721	-0.016	-0.037	-0.015	-0.032	-0.025	-0.019	-0.046

	[0.272]	[-1.275]	[-1.088]	[-1.266]	[0.458]	[0.461]	[0.638]	[0.419]	[-2.264]	[0.964]	[-0.651]	[0.799]
VAR_LIT(-5)	0.016	0.011	0.023	0.017	-0.684	0.011	0.046	0.001	-0.002	-0.017	-0.005	0.014
	-0.014	-0.016	-0.071	-0.024	-0.494	-0.011	-0.025	-0.010	-0.022	-0.017	-0.013	-0.031
	[1.194]	[0.692]	[0.324]	[0.689]	[-1.385]	[1.032]	[1.819]	[0.115]	[-0.086]	[-0.993]	[-0.411]	[0.460]
VAR_LMAT(-1)	0.179	0.117	0.512	0.242	1.084	0.110	-0.080	0.999	0.029	0.169	0.111	0.219
	-0.034	-0.041	-0.180	-0.061	-1.261	-0.028	-0.065	-0.027	-0.056	-0.044	-0.033	-0.080
	[5.184]	[2.844]	[2.845]	[3.955]	[0.860]	[3.932]	[-1.239]	[37.561]	[0.524]	[3.881]	[3.410]	[2.735]
VAR_LMAT(-2)	-0.238	-0.196	-0.919	-0.364	-1.754	-0.151	0.153	-0.114	-0.296	-0.215	-0.236	-0.278
	-0.047	-0.056	-0.248	-0.084	-1.735	-0.038	-0.089	-0.037	-0.077	-0.060	-0.045	-0.110
	[-5.025]	[-3.466]	[-3.712]	[-4.314]	[-1.011]	[-3.931]	[1.715]	[-3.105]	[-3.858]	[-3.580]	[-5.257]	[-2.521]
VAR_LMAT(-3)	0.024	-0.056	-0.089	0.010	0.795	-0.032	-0.126	0.042	0.484	-0.009	0.111	-0.108
	-0.047	-0.056	-0.244	-0.083	-1.708	-0.038	-0.088	-0.036	-0.075	-0.059	-0.044	-0.109
	[0.518]	[-0.998]	[-0.367]	[0.119]	[0.465]	[-0.833]	[-1.433]	[1.167]	[6.412]	[-0.155]	[2.521]	[-0.996]
VAR_LMA(-4)	0.039	0.095	0.294	0.053	-1.560	0.079	0.109	-0.022	-0.190	0.001	0.000	0.168
	-0.047	-0.056	-0.244	-0.083	-1.713	-0.038	-0.088	-0.036	-0.076	-0.059	-0.044	-0.109
	[0.836]	[1.712]	[1.201]	[0.640]	[-0.911]	[2.089]	[1.240]	[-0.605]	[-2.514]	[0.013]	[-0.002]	[1.540]
VAR_LMAT(-5)	0.000	0.036	0.149	0.055	2.207	-0.004	-0.078	0.037	-0.009	0.046	0.016	-0.007
	-0.033	-0.039	-0.173	-0.059	-1.212	-0.027	-0.062	-0.026	-0.054	-0.042	-0.031	-0.077
	[0.011]	[0.907]	[0.859]	[0.931]	[1.820]	[-0.159]	[-1.254]	[1.458]	[-0.166]	[1.107]	[0.503]	[-0.086]
VAR_LRE(-1)	-0.211	0.027	-0.610	-0.318	0.091	-0.110	-0.070	-0.024	0.781	-0.202	-0.149	-0.400
	-0.020	-0.024	-0.104	-0.035	-0.728	-0.016	-0.037	-0.015	-0.032	-0.025	-0.019	-0.046
	[-10.579]	[1.147]	[-5.871]	[-8.992]	[0.125]	[-6.821]	[-1.871]	[-1.591]	[24.288]	[-7.998]	[-7.905]	[-8.651]
VAR_LRE(-2)	-0.040	-0.162	-0.029	0.002	-1.032	-0.028	-0.024	0.049	-0.187	0.055	0.064	-0.076
	-0.024	-0.029	-0.126	-0.043	-0.885	-0.020	-0.045	-0.019	-0.039	-0.031	-0.023	-0.056
	[-1.661]	[-5.611]	[-0.231]	[0.037]	[-1.166]	[-1.422]	[-0.535]	[2.614]	[-4.780]	[1.796]	[2.812]	[-1.356]
VAR_LRE(-3)	0.348	0.110	0.634	0.364	0.113	0.108	0.085	-0.005	0.555	0.419	0.262	0.413
	-0.022	-0.026	-0.113	-0.039	-0.793	-0.018	-0.041	-0.017	-0.035	-0.027	-0.021	-0.050
	[16.030]	[4.246]	[5.601]	[9.443]	[0.143]	[6.132]	[2.084]	[-0.286]	[15.846]	[15.260]	[12.762]	[8.196]
VAR_LRE(-4)	0.000	0.035	0.255	0.016	0.624	0.128	0.020	0.038	-0.607	-0.235	-0.161	0.319
	-0.021	-0.025	-0.111	-0.038	-0.775	-0.017	-0.040	-0.016	-0.034	-0.027	-0.020	-0.049
	[-0.014]	[1.403]	[2.302]	[0.431]	[0.805]	[7.465]	[0.495]	[2.317]	[-17.742]	[-8.768]	[-8.054]	[6.474]
VAR_LRE(-5)	-0.124	-0.059	-0.348	-0.135	-0.569	-0.138	-0.001	-0.045	0.170	-0.066	-0.050	-0.311
	-0.018	-0.021	-0.093	-0.032	-0.653	-0.014	-0.034	-0.014	-0.029	-0.023	-0.017	-0.042
	[-6.916]	[-2.780]	[-3.735]	[-4.245]	[-0.870]	[-9.517]	[-0.016]	[-3.271]	[5.885]	[-2.904]	[-2.958]	[-7.483]

VAR_LTEL(-1)	0.113	0.065	0.074	0.107	0.462	0.042	-0.007	-0.043	0.031	0.894	0.022	0.346
	-0.024	-0.028	-0.125	-0.042	-0.874	-0.019	-0.045	-0.018	-0.039	-0.030	-0.023	-0.056
	[4.722]	[2.286]	[0.590]	[2.524]	[0.529]	[2.160]	[-0.155]	[-2.316]	[0.794]	[29.525]	[0.966]	[6.224]
VAR_LTEL(-2)	-0.038	-0.065	0.177	-0.018	-0.600	0.051	-0.028	0.027	0.010	-0.033	-0.005	-0.080
	-0.032	-0.038	-0.164	-0.056	-1.152	-0.026	-0.059	-0.024	-0.051	-0.040	-0.030	-0.073
	[-1.193]	[-1.737]	[1.075]	[-0.319]	[-0.521]	[1.989]	[-0.478]	[1.123]	[0.200]	[-0.827]	[-0.184]	[-1.087]
VAR_LTEL(-3)	-0.041	0.157	0.376	0.069	0.122	-0.030	0.028	0.074	-0.004	-0.101	-0.002	-0.173
	-0.030	-0.035	-0.155	-0.053	-1.084	-0.024	-0.056	-0.023	-0.048	-0.038	-0.028	-0.069
	[-1.398]	[4.448]	[2.427]	[1.308]	[0.112]	[-1.232]	[0.497]	[3.217]	[-0.086]	[-2.699]	[-0.076]	[-2.510]
VAR_LTEL(-4)	-0.019	-0.091	-0.369	-0.051	1.601	-0.074	-0.037	-0.014	0.096	0.102	0.011	-0.079
	-0.028	-0.034	-0.147	-0.050	-1.033	-0.023	-0.053	-0.022	-0.046	-0.036	-0.027	-0.066
	[-0.663]	[-2.717]	[-2.505]	[-1.013]	[1.549]	[-3.252]	[-0.689]	[-0.662]	[2.111]	[2.864]	[0.399]	[-1.200]
VAR_LTEL(-5)	0.016	-0.015	-0.016	-0.042	-1.383	0.061	0.054	-0.041	-0.048	-0.032	-0.007	0.117
	-0.021	-0.025	-0.108	-0.037	-0.754	-0.017	-0.039	-0.016	-0.033	-0.026	-0.019	-0.048
	[0.799]	[-0.602]	[-0.152]	[-1.148]	[-1.835]	[3.658]	[1.399]	[-2.597]	[-1.446]	[-1.221]	[-0.351]	[2.444]
VAR_LUTI(-1)	0.140	-0.113	-0.247	0.020	-1.050	0.040	0.123	0.035	-0.293	0.229	0.889	0.161
	-0.045	-0.054	-0.235	-0.080	-1.646	-0.036	-0.085	-0.035	-0.073	-0.057	-0.043	-0.105
	[3.112]	[-2.108]	[-1.051]	[0.247]	[-0.638]	[1.093]	[1.455]	[1.008]	[-4.026]	[4.013]	[20.892]	[1.541]
VAR_LUTI(-2)	0.166	0.054	0.469	0.130	0.870	0.063	0.115	-0.096	0.081	-0.060	0.019	0.238
	-0.060	-0.072	-0.315	-0.107	-2.208	-0.049	-0.113	-0.047	-0.097	-0.076	-0.057	-0.140
	[2.750]	[0.753]	[1.487]	[1.211]	[0.394]	[1.288]	[1.015]	[-2.057]	[0.830]	[-0.783]	[0.333]	[1.696]
VAR_LUTI(-3)	-0.574	-0.028	-1.033	-0.585	0.526	-0.077	-0.213	0.015	-0.483	-0.505	-0.370	-0.544
	-0.057	-0.068	-0.299	-0.102	-2.098	-0.047	-0.108	-0.044	-0.093	-0.073	-0.054	-0.133
	[-10.003]	[-0.408]	[-3.450]	[-5.739]	[0.251]	[-1.648]	[-1.978]	[0.340]	[-5.209]	[-6.958]	[-6.812]	[-4.078]
VAR_LUTI(-4)	0.209	0.004	0.410	0.368	-2.340	-0.070	0.158	0.024	0.692	0.299	0.329	-0.087
	-0.059	-0.070	-0.307	-0.105	-2.153	-0.048	-0.111	-0.045	-0.095	-0.075	-0.056	-0.137
	[3.556]	[0.062]	[1.335]	[3.516]	[-1.087]	[-1.460]	[1.429]	[0.528]	[7.279]	[4.011]	[5.912]	[-0.633]
VAR_LUTI(-5)	0.057	0.078	0.564	0.072	0.529	0.080	-0.163	0.065	-0.160	0.089	0.035	0.240
	-0.045	-0.054	-0.235	-0.080	-1.644	-0.036	-0.084	-0.035	-0.073	-0.057	-0.043	-0.104
	[1.259]	[1.464]	[2.405]	[0.907]	[0.322]	[2.207]	[-1.932]	[1.875]	[-2.202]	[1.564]	[0.833]	[2.299]
VAR_LFTSEUS(-1)	-0.011	-0.051	-0.179	-0.043	0.259	-0.010	-0.002	0.022	0.038	-0.036	-0.005	0.758
	-0.017	-0.021	-0.090	-0.031	-0.633	-0.014	-0.033	-0.013	-0.028	-0.022	-0.016	-0.040
	[-0.660]	[-2.465]	[-1.984]	[-1.396]	[0.410]	[-0.730]	[-0.076]	[1.621]	[1.374]	[-1.638]	[-0.332]	[18.839]
VAR_LFTSEUS(-2)	-0.016	0.107	0.348	0.089	-0.299	0.030	-0.025	0.014	0.144	0.054	0.046	0.061

	-0.022	-0.026	-0.114	-0.039	-0.798	-0.018	-0.041	-0.017	-0.035	-0.028	-0.021	-0.051
	[-0.751]	[4.131]	[3.058]	[2.292]	[-0.375]	[1.697]	[-0.620]	[0.834]	[4.076]	[1.970]	[2.244]	[1.208]
VAR_LFTSEUS(-3)	0.056	-0.005	-0.036	-0.027	0.071	0.002	0.126	0.010	-0.201	0.002	-0.044	0.190
	-0.021	-0.025	-0.111	-0.038	-0.780	-0.017	-0.040	-0.016	-0.034	-0.027	-0.020	-0.050
	[2.640]	[-0.182]	[-0.328]	[-0.719]	[0.092]	[0.136]	[3.142]	[0.586]	[-5.835]	[0.083]	[-2.168]	[3.839]
VAR_LFTSEUS(-4)	-0.022	-0.049	0.100	0.041	0.146	0.024	-0.099	-0.037	-0.006	-0.009	0.003	-0.033
	-0.022	-0.026	-0.113	-0.038	-0.789	-0.017	-0.041	-0.017	-0.035	-0.027	-0.020	-0.050
	[-0.999]	[-1.890]	[0.890]	[1.068]	[0.185]	[1.395]	[-2.435]	[-2.228]	[-0.168]	[-0.344]	[0.161]	[-0.656]
VAR_LFTSEUS(-5)	0.017	0.044	0.122	0.056	-0.549	0.001	0.019	0.026	0.157	0.074	0.053	-0.031
	-0.016	-0.020	-0.086	-0.029	-0.600	-0.013	-0.031	-0.013	-0.026	-0.021	-0.016	-0.038
	[1.041]	[2.243]	[1.428]	[1.920]	[-0.915]	[0.051]	[0.601]	[2.048]	[5.910]	[3.557]	[3.393]	[-0.821]
C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[-4.012]	[-2.146]	[-3.968]	[-4.696]	[-0.721]	[-0.818]	[-0.422]	[-0.977]	[-1.399]	[-1.979]	[-2.946]	[-3.825]
VAR_LOIL	0.001	0.000	0.006	0.003	-0.005	0.001	0.002	0.000	0.002	0.001	0.001	0.003
	0.000	0.000	-0.001	0.000	-0.010	0.000	-0.001	0.000	0.000	0.000	0.000	-0.001
	[4.106]	[1.264]	[4.360]	[6.103]	[-0.486]	[3.514]	[3.038]	[0.937]	[4.287]	[3.534]	[3.465]	[4.362]
VAR_LGOLD	0.051	0.196	0.757	0.256	-0.125	0.069	0.076	0.181	0.144	0.154	0.096	0.204
	-0.042	-0.050	-0.217	-0.074	-1.523	-0.034	-0.078	-0.032	-0.067	-0.053	-0.039	-0.097
	[1.224]	[3.960]	[3.483]	[3.456]	[-0.082]	[2.043]	[0.974]	[5.619]	[2.141]	[2.913]	[2.426]	[2.106]
VAR_LBTC	0.006	0.004	0.016	0.007	0.006	0.002	0.000	0.000	0.000	0.004	0.002	0.011
	-0.001	-0.001	-0.004	-0.001	-0.025	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	[8.279]	[4.502]	[4.519]	[5.935]	[0.239]	[3.912]	[0.256]	[0.294]	[-0.155]	[4.894]	[3.612]	[7.001]
R-squared	0.986	0.986	0.975	0.987	0.875	0.981	0.983	0.986	0.992	0.984	0.991	0.956
Adj. R-squared	0.985	0.985	0.974	0.986	0.871	0.980	0.982	0.985	0.992	0.984	0.991	0.954
Sum sq. resids	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S.E. equation	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-statistic	1942.876	1927.215	1107.668	2061.431	197.319	1452.610	1581.074	1950.138	3665.739	1760.678	3226.935	610.509
Log likelihood	16010.13	15690.65	12976.85	14955.55	9402.370	16395.760	14853.28	16486.630	15130.79	15576.910	16112.85	14462.670
Akaike AIC	-17.371	-17.022	-14.066	-16.222	-10.173	-17.791	-16.110	-17.890	-16.413	-16.899	-17.482	-15.685
Schwarz SC	-17.178	-16.830	-13.874	-16.029	-9.980	-17.598	-15.918	-17.697	-16.220	-16.706	-17.290	-15.493
Mean dependent	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S.D. dependent	0.000	0.000	0.001	0.001	0.004	0.000	0.001	0.000	0.001	0.000	0.000	0.000
Determinant resid covariance (dof adj.)		6.2E-103										

Determinant resid covariance	4.0E-103
Log likelihood	1.9E+05
Akaike information criterion	-2.0E+02
Schwarz criterion	-2.0E+02
Number of coefficients	7.7E+02

Table B5: VAR Estimation Results – United Kingdom

	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
VAR_LCD(-1)	1.244	0.253	0.696	0.279	0.101	0.285	0.996	0.245	0.208	0.230	0.363	0.464
	-0.090	-0.050	-0.193	-0.113	-0.017	-0.077	-0.634	-0.049	-0.267	-0.058	-0.067	-0.080
	[13.779]	[5.039]	[3.605]	[2.467]	[6.050]	[3.714]	[1.571]	[4.989]	[0.779]	[3.984]	[5.382]	[5.791]
VAR_LCD (-2)	-0.084	-0.060	0.504	0.044	-0.052	0.024	-0.722	-0.013	0.164	-0.073	-0.217	0.283
	-0.121	-0.067	-0.260	-0.152	-0.022	-0.103	-0.853	-0.066	-0.359	-0.078	-0.091	-0.108
	[-0.689]	[-0.889]	[1.942]	[0.286]	[-2.326]	[0.229]	[-0.846]	[-0.204]	[0.455]	[-0.939]	[-2.392]	[2.628]
VAR_LCD (-3)	-0.493	-0.472	-1.122	-0.297	-0.126	-0.528	-0.705	-0.253	-0.674	-0.281	-0.682	-0.650
	-0.117	-0.065	-0.250	-0.146	-0.022	-0.099	-0.820	-0.063	-0.346	-0.075	-0.087	-0.104
	[-4.226]	[-7.283]	[-4.495]	[-2.028]	[-5.870]	[-5.323]	[-0.859]	[-3.977]	[-1.950]	[-3.764]	[-7.822]	[-6.269]
VAR_LCD (-4)	-0.243	0.123	-0.753	-0.511	0.044	-0.041	-0.329	-0.154	-0.847	-0.132	0.299	-0.491
	-0.101	-0.056	-0.215	-0.126	-0.019	-0.085	-0.706	-0.055	-0.298	-0.064	-0.075	-0.089
	[-2.416]	[2.208]	[-3.504]	[-4.056]	[2.386]	[-0.479]	[-0.466]	[-2.812]	[-2.846]	[-2.055]	[3.987]	[-5.498]
VAR_LCD(-5)	0.517	0.231	1.062	0.615	0.044	0.353	0.875	0.307	1.376	0.282	0.291	0.556
	-0.077	-0.043	-0.164	-0.096	-0.014	-0.065	-0.538	-0.042	-0.227	-0.049	-0.057	-0.068
	[6.749]	[5.429]	[6.487]	[6.406]	[3.131]	[5.418]	[1.626]	[7.375]	[6.068]	[5.761]	[5.087]	[8.167]
VAR_LCS(-1)	-0.269	0.693	-0.018	-0.088	-0.072	-0.203	-0.165	-0.107	-0.111	0.031	-0.221	-0.189
	-0.101	-0.056	-0.216	-0.127	-0.019	-0.086	-0.710	-0.055	-0.299	-0.065	-0.075	-0.090
	[-2.662]	[12.344]	[-0.083]	[-0.698]	[-3.88]	[-2.358]	[-0.232]	[-1.94]	[-0.373]	[0.479]	[-2.934]	[-2.109]
VAR_LCS (-2)	0.146	0.030	0.018	0.030	0.060	0.158	-0.040	0.053	-0.087	-0.101	0.049	0.002
	-0.131	-0.073	-0.279	-0.164	-0.024	-0.111	-0.917	-0.071	-0.387	-0.084	-0.098	-0.116
	[1.121]	[0.41]	[0.065]	[0.181]	[2.48]	[1.423]	[-0.043]	[0.752]	[-0.226]	[-1.213]	[0.504]	[0.018]
VAR_LCS (-3)	0.091	0.038	-0.166	-0.028	-0.023	-0.089	-0.408	-0.062	0.023	0.018	0.125	-0.056
	-0.127	-0.071	-0.272	-0.160	-0.024	-0.108	-0.895	-0.069	-0.377	-0.081	-0.095	-0.113
	[0.712]	[0.541]	[-0.611]	[-0.177]	[-0.99]	[-0.823]	[-0.456]	[-0.894]	[0.062]	[0.221]	[1.31]	[-0.493]
VAR_LCS (-4)	0.153	-0.018	-0.288	0.403	-0.041	0.228	-0.183	-0.029	0.893	0.031	-0.084	0.125
	-0.125	-0.070	-0.268	-0.157	-0.023	-0.106	-0.879	-0.068	-0.370	-0.080	-0.093	-0.111
	[1.226]	[-0.252]	[-1.077]	[2.573]	[-1.795]	[2.141]	[-0.208]	[-0.427]	[2.411]	[0.387]	[-0.898]	[1.12]
VAR_LCS (-5)	-0.055	0.098	0.590	-0.241	0.067	-0.059	0.424	0.093	-0.696	0.046	0.141	-0.030
	-0.092	-0.051	-0.197	-0.115	-0.017	-0.078	-0.647	-0.050	-0.273	-0.059	-0.069	-0.082

	[-0.594]	[1.923]	[2.997]	[-2.093]	[3.925]	[-0.758]	[0.655]	[1.852]	[-2.552]	[0.788]	[2.045]	[-0.363]
VAR_LEN (-1)	0.000	0.000	0.618	0.008	0.000	0.002	0.029	0.008	-0.030	0.012	0.013	-0.034
	-0.015	-0.008	-0.033	-0.019	-0.003	-0.013	-0.107	-0.008	-0.045	-0.010	-0.011	-0.014
	[0.021]	[-0.039]	[19.003]	[0.403]	[-0.08]	[0.192]	[0.269]	[0.996]	[-0.658]	[1.186]	[1.153]	[-2.538]
VAR_LEN (-2)	0.044	0.016	-0.113	0.005	-0.003	0.011	-0.056	-0.015	0.001	0.011	-0.016	0.055
	-0.017	-0.009	-0.037	-0.021	-0.003	-0.015	-0.120	-0.009	-0.051	-0.011	-0.013	-0.015
	[2.568]	[1.655]	[-3.105]	[0.24]	[-0.95]	[0.75]	[-0.463]	[-1.644]	[0.019]	[1.017]	[-1.284]	[3.653]
VAR_LEN (-3)	0.164	0.123	0.433	0.105	0.054	0.149	0.430	0.122	0.136	0.124	0.171	0.151
	-0.018	-0.010	-0.038	-0.022	-0.003	-0.015	-0.124	-0.010	-0.052	-0.011	-0.013	-0.016
	[9.272]	[12.571]	[11.476]	[4.773]	[16.495]	[9.955]	[3.467]	[12.665]	[2.605]	[10.97]	[13.009]	[9.609]
VAR_LEN (-4)	-0.158	-0.106	-0.280	-0.124	-0.036	-0.122	-0.270	-0.060	-0.212	-0.093	-0.151	-0.081
	-0.019	-0.011	-0.041	-0.024	-0.004	-0.016	-0.133	-0.010	-0.056	-0.012	-0.014	-0.017
	[-8.289]	[-10.036]	[-6.899]	[-5.226]	[-10.376]	[-7.573]	[-2.023]	[-5.768]	[-3.767]	[-7.68]	[-10.645]	[-4.824]
VAR_LEN (-5)	0.003	-0.008	-0.066	0.032	-0.003	0.000	-0.186	-0.033	0.079	-0.001	-0.003	0.027
	-0.016	-0.009	-0.034	-0.020	-0.003	-0.014	-0.112	-0.009	-0.047	-0.010	-0.012	-0.014
	[0.188]	[-0.874]	[-1.922]	[1.598]	[-0.963]	[0.003]	[-1.66]	[-3.858]	[1.671]	[-0.061]	[-0.275]	[1.915]
VAR_LFIN (-1)	0.087	0.006	-0.006	0.886	-0.007	0.048	-0.146	-0.041	0.013	0.032	-0.042	0.035
	-0.060	-0.033	-0.128	-0.075	-0.011	-0.051	-0.421	-0.033	-0.177	-0.038	-0.045	-0.053
	[1.455]	[0.167]	[-0.046]	[11.81]	[-0.595]	[0.938]	[-0.348]	[-1.246]	[0.072]	[0.831]	[-0.946]	[0.651]
VAR_LFIN (-2)	-0.133	-0.040	-0.118	-0.044	-0.011	-0.114	0.304	0.046	-0.127	-0.043	0.030	-0.209
	-0.078	-0.044	-0.168	-0.098	-0.014	-0.067	-0.550	-0.043	-0.232	-0.050	-0.059	-0.070
	[-1.697]	[-0.912]	[-0.703]	[-0.450]	[-0.773]	[-1.706]	[0.553]	[1.076]	[-0.548]	[-0.849]	[0.516]	[-2.995]
VAR_LFIN (-3)	-0.049	-0.045	-0.170	0.003	-0.003	-0.032	-0.566	-0.088	-0.054	-0.054	-0.140	0.158
	-0.077	-0.043	-0.165	-0.097	-0.014	-0.066	-0.543	-0.042	-0.229	-0.049	-0.058	-0.069
	[-0.631]	[-1.06]	[-1.027]	[0.032]	[-0.241]	[-0.481]	[-1.043]	[-2.093]	[-0.234]	[-1.103]	[-2.429]	[2.3]
VAR_LFIN (-4)	0.466	0.238	0.452	0.490	0.049	0.319	0.818	0.098	1.295	0.264	0.373	0.162
	-0.077	-0.043	-0.165	-0.097	-0.014	-0.066	-0.542	-0.042	-0.229	-0.049	-0.058	-0.069
	[6.036]	[5.546]	[2.739]	[5.072]	[3.407]	[4.857]	[1.508]	[2.334]	[5.664]	[5.345]	[6.469]	[2.355]
VAR_LFIN (-5)	-0.317	-0.144	-0.202	-0.435	-0.022	-0.189	-0.074	-0.031	-1.094	-0.171	-0.240	-0.142
	-0.057	-0.032	-0.123	-0.072	-0.011	-0.049	-0.404	-0.031	-0.170	-0.037	-0.043	-0.051
	[-5.516]	[-4.51]	[-1.646]	[-6.047]	[-2.122]	[-3.879]	[-0.183]	[-0.98]	[-6.43]	[-4.651]	[-5.595]	[-2.779]

VAR_LHC (-1)	-0.346	-0.173	-0.847	-0.256	0.839	-0.404	-1.451	-0.076	-0.800	-0.276	-0.269	-0.252
	-0.195	-0.108	-0.417	-0.244	-0.036	-0.166	-1.370	-0.106	-0.577	-0.125	-0.146	-0.173
	[-1.773]	[-1.597]	[-2.032]	[-1.05]	[23.315]	[-2.438]	[-1.059]	[-0.713]	[-1.385]	[-2.215]	[-1.849]	[-1.454]
VAR_LHC (-2)	0.692	0.392	0.398	0.535	0.096	0.551	0.966	-0.034	1.799	0.503	0.184	1.166
	-0.258	-0.143	-0.552	-0.323	-0.048	-0.219	-1.812	-0.14	-0.764	-0.165	-0.193	-0.229
	[2.68]	[2.735]	[0.721]	[1.656]	[2.016]	[2.511]	[0.533]	[-0.241]	[2.355]	[3.048]	[0.954]	[5.088]
VAR_LHC (-3)	-0.843	-0.67	-0.848	-0.641	-0.194	-0.796	-0.895	-0.075	-1.433	-0.546	-0.311	-1.823
	-0.253	-0.14	-0.541	-0.317	-0.047	-0.215	-1.776	-0.138	-0.749	-0.162	-0.189	-0.225
	[-3.335]	[-4.767]	[-1.569]	[-2.024]	[-4.156]	[-3.703]	[-0.504]	[-0.546]	[-1.913]	[-3.379]	[-1.647]	[-8.116]
VAR_LHC (-4)	0.452	0.533	2.208	0.234	0.355	1.128	2.032	0.488	-0.001	0.221	0.486	0.828
	-0.256	-0.142	-0.547	-0.32	-0.047	-0.217	-1.796	-0.139	-0.757	-0.163	-0.191	-0.227
	[1.767]	[3.757]	[4.039]	[0.731]	[7.524]	[5.189]	[1.131]	[3.509]	[-0.002]	[1.354]	[2.546]	[3.647]
VAR_LHC (-5)	0.055	-0.118	-0.848	0.134	-0.156	-0.572	-0.83	-0.375	0.531	0.087	-0.064	0.082
	-0.189	-0.105	-0.404	-0.237	-0.035	-0.161	-1.329	-0.103	-0.56	-0.121	-0.141	-0.168
	[0.292]	[-1.125]	[-2.098]	[0.566]	[-4.465]	[-3.56]	[-0.625]	[-3.646]	[0.948]	[0.718]	[-0.452]	[0.491]
VAR_LIND (-1)	-0.283	-0.181	-0.371	-0.248	-0.055	0.531	-0.169	-0.089	-0.309	-0.185	-0.296	-0.282
	-0.069	-0.038	-0.147	-0.086	-0.013	-0.059	-0.485	-0.038	-0.204	-0.044	-0.052	-0.061
	- [4.099]	- [4.736]	- [2.513]	- [2.867]	- [4.317]	[9.054]	- [0.348]	- [2.371]	- [1.514]	- [4.184]	- [5.757]	- [4.606]
VAR_LIND (-2)	0.155	0.099	-0.337	0.072	0.031	0.124	0.27	-0.021	0.294	0.111	0.248	-0.094
	-0.079	-0.044	-0.169	-0.099	-0.015	-0.067	-0.555	-0.043	-0.234	-0.05	-0.059	-0.07
	[1.966]	[2.256]	[-1.994]	[0.726]	[2.115]	[1.85]	[0.487]	[-0.498]	[1.257]	[2.204]	[4.202]	[-1.342]
VAR_LIND (-3)	0.208	0.36	-0.079	0.17	0.074	0.388	0.671	0.042	-0.025	0.086	0.519	0.468
	-0.075	-0.042	-0.161	-0.094	-0.014	-0.064	-0.529	-0.041	-0.223	-0.048	-0.056	-0.067
	[2.764]	[8.602]	[-0.491]	[1.799]	[5.344]	[6.059]	[1.268]	[1.021]	[-0.11]	[1.777]	[9.221]	[6.994]
VAR_LIND (-4)	-0.023	-0.262	1.368	0.138	-0.058	-0.196	-0.202	0.206	0.179	-0.001	-0.457	0.086
	-0.07	-0.039	-0.149	-0.088	-0.013	-0.059	-0.491	-0.038	-0.207	-0.045	-0.052	-0.062
	[-0.332]	[-6.736]	[9.156]	[1.575]	[-4.533]	[-3.299]	[-0.411]	[5.428]	[0.867]	[-0.024]	[-8.761]	[1.385]
VAR_LIND (-5)	-0.278	-0.152	-1.202	-0.316	-0.028	-0.201	-0.685	-0.29	-0.516	-0.153	-0.14	-0.414
	-0.061	-0.034	-0.131	-0.076	-0.011	-0.052	-0.429	-0.033	-0.181	-0.039	-0.046	-0.054
	[-4.549]	[-4.477]	[-9.212]	[-4.129]	[-2.452]	[-3.875]	[-1.596]	[-8.748]	[-2.855]	[-3.931]	[-3.065]	[-7.637]
VAR_LIT (-1)	0.001	0.001	0.001	0.000	0.001	0.000	-0.014	0.001	-0.001	0.001	0.002	0.002
	-0.003	-0.002	-0.007	-0.004	-0.001	-0.003	-0.024	-0.002	-0.01	-0.002	-0.003	-0.003

	[0.229]	[0.736]	[0.115]	[0.034]	[0.805]	[0.03]	[-0.581]	[0.655]	[-0.138]	[0.454]	[0.603]	[0.642]
VAR_LIT (-2)	0.001	0.001	-0.001	-0.001	0	-0.001	-0.011	0	-0.001	-0.001	-0.001	0.002
	-0.003	-0.002	-0.007	-0.004	-0.001	-0.003	-0.024	-0.002	-0.01	-0.002	-0.003	-0.003
	[0.308]	[0.41]	[-0.104]	[-0.241]	[-0.66]	[-0.35]	[-0.469]	[-0.015]	[-0.137]	[-0.273]	[-0.479]	[0.787]
VAR_LIT (-3)	0.001	0	0	0.001	0	0.002	-0.004	0.001	0.001	0.001	0	0.007
	-0.003	-0.002	-0.007	-0.004	-0.001	-0.003	-0.024	-0.002	-0.01	-0.002	-0.003	-0.003
	[0.174]	[0.022]	[-0.067]	[0.177]	[0.634]	[0.624]	[-0.178]	[0.746]	[0.097]	[0.554]	[0.005]	[2.331]
VAR_LIT (-4)	0.004	0.001	-0.001	0.006	0	0.005	0.002	0.001	0.011	0.002	0.001	0.005
	-0.003	-0.002	-0.007	-0.004	-0.001	-0.003	-0.024	-0.002	-0.01	-0.002	-0.003	-0.003
	[1.068]	[0.71]	[-0.143]	[1.278]	[-0.27]	[1.545]	[0.071]	[0.322]	[1.055]	[0.931]	[0.25]	[1.532]
VAR_LIT (-5)	-0.001	-0.001	-0.005	-0.001	0	-0.003	-0.012	-0.002	-0.002	-0.001	-0.002	0.002
	-0.003	-0.002	-0.007	-0.004	-0.001	-0.003	-0.024	-0.002	-0.01	-0.002	-0.003	-0.003
	[-0.37]	[-0.661]	[-0.673]	[-0.295]	[-0.703]	[-0.867]	[-0.501]	[-1.211]	[-0.195]	[-0.657]	[-0.965]	[0.813]
VAR_LMAT (-1)	-0.008	0.016	-0.057	-0.026	0.008	0.001	-0.212	0.872	0.039	-0.05	-0.005	0.179
	-0.058	-0.032	-0.125	-0.073	-0.011	-0.05	-0.409	-0.032	-0.173	-0.037	-0.044	-0.052
	[-0.137]	[0.503]	[-0.454]	[-0.362]	[0.719]	[0.022]	[-0.517]	[27.521]	[0.225]	[-1.35]	[-0.121]	[3.455]
VAR_LMAT (-2)	0.059	-0.005	0.311	0.072	0.002	0.072	0.255	0.111	0.081	0.097	0.018	0.017
	-0.078	-0.043	-0.167	-0.098	-0.014	-0.066	-0.547	-0.042	-0.231	-0.05	-0.058	-0.069
	[0.759]	[-0.124]	[1.869]	[0.738]	[0.108]	[1.08]	[0.466]	[2.625]	[0.352]	[1.952]	[0.309]	[0.246]
VAR_LMAT (-3)	-0.251	-0.155	-0.523	-0.194	-0.067	-0.212	-0.725	-0.155	-0.36	-0.15	-0.221	-0.381
	-0.078	-0.043	-0.166	-0.097	-0.014	-0.066	-0.545	-0.042	-0.23	-0.05	-0.058	-0.069
	[-3.228]	[-3.591]	[-3.15]	[-1.993]	[-4.686]	[-3.22]	[-1.329]	[-3.676]	[-1.564]	[-3.03]	[-3.812]	[-5.527]
VAR_LMAT (-4)	0.224	0.179	0.164	0.159	0.071	0.261	0.54	0.074	0.425	0.074	0.283	0.058
	-0.078	-0.043	-0.166	-0.097	-0.014	-0.066	-0.544	-0.042	-0.229	-0.05	-0.058	-0.069
	[2.89]	[4.151]	[0.991]	[1.642]	[4.998]	[3.966]	[0.992]	[1.759]	[1.85]	[1.501]	[4.887]	[0.843]
VAR_LMAT (-5)	-0.019	-0.035	0.113	-0.001	-0.011	-0.103	0.122	0.061	-0.151	0.02	-0.07	0.12
	-0.058	-0.032	-0.123	-0.072	-0.011	-0.049	-0.404	-0.031	-0.17	-0.037	-0.043	-0.051
	[-0.322]	[-1.098]	[0.918]	[-0.014]	[-1.075]	[-2.114]	[0.301]	[1.96]	[-0.888]	[0.546]	[-1.632]	[2.354]
VAR_LREUK(-1)	0.115	0.003	-0.149	0.096	-0.006	0.114	-0.064	-0.033	1.168	0.012	0.005	-0.102
	-0.025	-0.014	-0.054	-0.032	-0.005	-0.021	-0.177	-0.014	-0.075	-0.016	-0.019	-0.022
	[4.562]	[0.216]	[-2.772]	[3.054]	[-1.275]	[5.348]	[-0.363]	[-2.391]	[15.675]	[0.722]	[0.258]	[-4.549]

VAR_LRE (-2)	-0.21	-0.043	0.038	-0.144	-0.002	-0.157	-0.064	-0.012	-0.439	-0.025	-0.022	-0.034
	-0.033	-0.018	-0.07	-0.041	-0.006	-0.028	-0.228	-0.018	-0.096	-0.021	-0.024	-0.029
	[-6.456]	[-2.37]	[0.549]	[-3.542]	[-0.411]	[-5.686]	[-0.279]	[-0.668]	[-4.564]	[-1.186]	[-0.891]	[-1.185]
VAR_LRE (-3)	0.156	0.078	0.23	0.038	0.022	0.11	0.189	0.079	0.199	0.043	0.114	0.022
	-0.031	-0.017	-0.067	-0.039	-0.006	-0.026	-0.219	-0.017	-0.092	-0.02	-0.023	-0.028
	[5.025]	[4.534]	[3.452]	[0.981]	[3.824]	[4.151]	[0.865]	[4.694]	[2.155]	[2.145]	[4.923]	[0.801]
VAR_LRE (-4)	-0.081	-0.047	0.052	-0.074	-0.002	-0.108	-0.041	-0.002	-0.244	-0.009	-0.083	0.147
	-0.032	-0.018	-0.067	-0.039	-0.006	-0.027	-0.221	-0.017	-0.093	-0.02	-0.024	-0.028
	[-2.556]	[-2.677]	[0.779]	[-1.878]	[-0.377]	[-4.045]	[-0.186]	[-0.138]	[-2.612]	[-0.45]	[-3.534]	[5.258]
VAR_LREL (-5)	0.018	-0.001	-0.169	0.064	-0.011	0.038	-0.095	-0.038	0.139	-0.009	-0.006	-0.047
	-0.025	-0.014	-0.053	-0.031	-0.005	-0.021	-0.173	-0.013	-0.073	-0.016	-0.018	-0.022
	[0.717]	[-0.101]	[-3.225]	[2.095]	[-2.406]	[1.8]	[-0.551]	[-2.843]	[1.91]	[-0.557]	[-0.31]	[-2.149]
VAR_LTEL (-1)	0.05	0.08	0.024	0.072	0.029	0.093	-0.047	0.061	0.033	0.881	0.028	0.108
	-0.065	-0.036	-0.138	-0.081	-0.012	-0.055	-0.454	-0.035	-0.191	-0.041	-0.048	-0.057
	[0.768]	[2.215]	[0.172]	[0.893]	[2.393]	[1.7]	[-0.103]	[1.744]	[0.17]	[21.317]	[0.582]	[1.878]
VAR_LTEL (-2)	-0.113	-0.117	-0.441	-0.218	-0.042	-0.161	-0.174	-0.201	-0.027	-0.105	-0.045	-0.1
	-0.084	-0.046	-0.179	-0.105	-0.015	-0.071	-0.588	-0.046	-0.248	-0.054	-0.063	-0.074
	[-1.35]	[-2.526]	[-2.465]	[-2.08]	[-2.709]	[-2.264]	[-0.295]	[-4.41]	[-0.11]	[-1.954]	[-0.724]	[-1.338]
VAR_LTEL (-3)	0.102	0.026	0.766	0.204	0.033	0.073	0.205	0.199	0.046	0.125	0.071	0.07
	-0.081	-0.045	-0.174	-0.102	-0.015	-0.069	-0.572	-0.044	-0.241	-0.052	-0.061	-0.072
	[1.25]	[0.57]	[4.398]	[1.999]	[2.19]	[1.05]	[0.358]	[4.489]	[0.19]	[2.407]	[1.16]	[0.965]
VAR_LTEL(-4)	0.154	0.131	-0.184	0.197	0.007	0.254	0.536	0.06	0.502	0.033	0.12	-0.151
	-0.082	-0.045	-0.174	-0.102	-0.015	-0.069	-0.573	-0.044	-0.241	-0.052	-0.061	-0.072
	[1.891]	[2.888]	[-1.058]	[1.931]	[0.436]	[3.664]	[0.936]	[1.364]	[2.079]	[0.642]	[1.967]	[-2.087]
VAR_LTEL (-5)	-0.195	-0.106	-0.077	-0.245	-0.015	-0.22	-0.527	-0.123	-0.487	-0.061	-0.14	0.054
	-0.062	-0.034	-0.133	-0.078	-0.011	-0.053	-0.435	-0.034	-0.184	-0.04	-0.046	-0.055
	[-3.137]	[-3.064]	[-0.584]	[-3.15]	[-1.338]	[-4.179]	[-1.21]	[-3.635]	[-2.652]	[-1.535]	[-3.016]	[0.972]
VAR_LUTI (-1)	-0.02	-0.039	0.15	0.054	0.007	-0.031	0.153	0.055	-0.023	-0.065	0.912	0.071
	-0.059	-0.033	-0.127	-0.074	-0.011	-0.05	-0.416	-0.032	-0.176	-0.038	-0.044	-0.053
	[-0.333]	[-1.198]	[1.183]	[0.733]	[0.664]	[-0.624]	[0.368]	[1.716]	[-0.13]	[-1.716]	[20.602]	[1.353]
VAR_LUTI (-2)	0.126	0.107	-0.154	0.003	0.011	0.05	0.01	-0.011	0.106	0.082	-0.023	0.275
	-0.079	-0.044	-0.168	-0.099	-0.015	-0.067	-0.553	-0.043	-0.233	-0.05	-0.059	-0.07

	[1.6]	[2.443]	[-0.913]	[0.034]	[0.769]	[0.743]	[0.018]	[-0.267]	[0.454]	[1.631]	[-0.391]	[3.933]
VAR_LUTI (-3)	-0.035	0.035	0.325	0.088	-0.007	0.033	0.528	0.029	0.313	0.127	-0.041	-0.041
	-0.076	-0.042	-0.162	-0.095	-0.014	-0.064	-0.532	-0.041	-0.224	-0.048	-0.057	-0.067
	[-0.465]	[0.826]	[2.008]	[0.93]	[-0.475]	[0.512]	[0.993]	[0.715]	[1.396]	[2.626]	[-0.725]	[-0.616]
VAR_LUTI (-4)	-0.089	-0.098	-0.631	-0.191	-0.024	0.033	-0.805	-0.101	-0.466	-0.155	-0.09	-0.256
	-0.075	-0.042	-0.16	-0.094	-0.014	-0.064	-0.526	-0.041	-0.222	-0.048	-0.056	-0.066
	[-1.185]	[-2.363]	[-3.945]	[-2.035]	[-1.705]	[0.527]	[-1.531]	[-2.493]	[-2.104]	[-3.234]	[-1.604]	[-3.847]
VAR_LUTI(-5)	0.08	0.026	0.244	0.119	0.012	-0.02	0.129	0.053	0.245	0.025	0.107	0.072
	-0.056	-0.031	-0.12	-0.07	-0.01	-0.048	-0.395	-0.031	-0.167	-0.036	-0.042	-0.05
	[1.414]	[0.834]	[2.029]	[1.693]	[1.166]	[-0.416]	[0.327]	[1.726]	[1.471]	[0.706]	[2.548]	[1.43]
VAR_LFTSE(-1)	-0.176	-0.076	-0.312	-0.187	-0.008	-0.156	-0.398	-0.088	-0.182	-0.074	0.027	0.663
	-0.035	-0.019	-0.075	-0.044	-0.006	-0.03	-0.246	-0.019	-0.103	-0.022	-0.026	-0.031
	[-5.041]	[-3.937]	[-4.171]	[-4.283]	[-1.298]	[-5.245]	[-1.62]	[-4.655]	[-1.756]	[-3.289]	[1.017]	[21.358]
VAR_LFTSE(-2)	0.339	0.174	0.621	0.272	0.052	0.477	0.604	0.167	0.438	0.12	0.084	0.228
	-0.045	-0.025	-0.097	-0.057	-0.008	-0.038	-0.318	-0.025	-0.134	-0.029	-0.034	-0.04
	[7.476]	[6.93]	[6.412]	[4.793]	[6.174]	[12.394]	[1.898]	[6.766]	[3.27]	[4.136]	[2.492]	[5.668]
VAR_LFTSE(-3)	-0.021	-0.005	0.113	-0.014	0.015	-0.13	0.213	0.046	-0.059	0.133	0.065	0.015
	-0.048	-0.027	-0.102	-0.06	-0.009	-0.041	-0.335	-0.026	-0.141	-0.031	-0.036	-0.042
	[-0.447]	[-0.181]	[1.111]	[-0.238]	[1.69]	[-3.197]	[0.635]	[1.756]	[-0.42]	[4.362]	[1.815]	[0.357]
VAR_LFTSE(-4)	-0.179	-0.12	-0.4	-0.188	-0.034	-0.156	-0.392	-0.143	-0.411	-0.161	-0.139	-0.003
	-0.048	-0.027	-0.103	-0.06	-0.009	-0.041	-0.338	-0.026	-0.142	-0.031	-0.036	-0.043
	[-3.731]	[-4.481]	[-3.889]	[-3.118]	[-3.865]	[-3.81]	[-1.161]	[-5.471]	[-2.887]	[-5.249]	[-3.878]	[-0.074]
VAR_LFTSE(-5)	0.078	0.087	0.391	0.11	-0.003	0.071	0.283	0.093	0.206	0.05	0.051	0.015
	-0.036	-0.02	-0.078	-0.046	-0.007	-0.031	-0.255	-0.02	-0.108	-0.023	-0.027	-0.032
	[2.138]	[4.33]	[5.03]	[2.405]	[-0.386]	[2.284]	[1.108]	[4.691]	[1.912]	[2.165]	[1.89]	[0.458]
C	-8.28E-05	-3.41E-05	0.000197	-7.80E-05	-1.03E-05	-7.09E-05	0.000361	-2.47E-05	-0.000124	-4.64E-05	-2.91E-05	-0.000114
	-1.50E-05	-8.10E-06	-3.10E-05	-1.80E-05	-2.70E-06	-1.20E-05	-0.0001	-8.00E-06	-4.30E-05	-9.40E-06	-1.10E-05	-1.30E-05
	[-5.655]	[-4.196]	[6.291]	[-4.257]	[-3.808]	[-5.698]	[3.508]	[-3.105]	[-2.851]	[-4.965]	[-2.662]	[-8.734]
VAR_LOIL	0.001	0.001	0.006	0.001	0	0.002	-0.002	0.001	-0.001	0.002	0.001	0.002
	-0.001	0.000	-0.001	-0.001	0	-0.001	-0.005	0	-0.002	0	-0.001	-0.001
	[1.963]	[3.466]	[4.065]	[0.689]	[0.855]	[3.188]	[-0.356]	[2.812]	[-0.397]	[3.57]	[1.417]	[3.785]

VAR_LGOLD	0.251	0.186	1.115	0.602	0.035	0.271	-0.096	0.296	1.093	0.246	0.199	0.185
	-0.118	-0.065	-0.251	-0.147	-0.022	-0.1	-0.826	-0.064	-0.348	-0.075	-0.088	-0.104
	[2.133]	[2.847]	[4.437]	[4.089]	[1.624]	[2.709]	[-0.116]	[4.624]	[3.142]	[3.272]	[2.267]	[1.771]
VAR_LBTC	0.012	0.007	0.013	0.01	0.002	0.01	0.021	0.005	0.024	0.007	0.008	0.01
	-0.002	-0.001	-0.004	-0.002	0	-0.002	-0.013	-0.001	-0.005	-0.001	-0.001	-0.002
	[6.347]	[6.628]	[3.477]	[4.583]	[6.547]	[6.502]	[1.66]	[4.689]	[4.469]	[5.669]	[5.609]	[6.394]
R-squared	0.939	0.922	0.722	0.932	0.977	0.963	0.060	0.976	0.862	0.948	0.925	0.949
Adj. R-squared	0.937	0.919	0.712	0.929	0.976	0.962	0.026	0.975	0.857	0.946	0.922	0.947
Sum sq. resids	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
S.E. equation	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
F-statistic	428.699	330.159	72.648	382.168	1170.628	733.568	1.784	1147.227	175.001	512.564	344.112	514.921
Log likelihood	14031.95	15105.19	12645.44	13621.40	17117.04	14328.78	10474.61	15143.78	12051.15	14848.57	14565.22	14247.98
Akaike AIC	-15.307	-16.483	-13.788	-14.857	-18.688	-15.633	-11.409	-16.526	-13.137	-16.202	-15.892	-15.544
Schwarz SC	-15.114	-16.290	-13.595	-14.664	-18.495	-15.439	-11.216	-16.333	-12.943	-16.009	-15.699	-15.351
Mean dependent	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S.D. dependent	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000

Determinant resid covariance (dof adj.)	1.90E-10
Determinant resid covariance	1.20E-10
Log likelihood	178845.4
Akaike information criterion	-195.153
Schwarz criterion	-192.834
Number of coefficients	768

Table B6: VAR Estimation Results – Japan

	VAR_LCD_t	VAR_LCS_t	VAR_LEN_t	VAR_LFIN_t	VAR_LHC_t	VAR_LIND_t	VAR_LIT_t	VAR_LMAT_t	VAR_LRE_t	VAR_LTEL_t	VAR_LUTI_t	VAR_LFTSE_t
VAR_LCD (-1)	0.901	-0.21	0.05	-0.922	0.032	-0.039	0.019	0.193	-0.166	0.2	-0.041	0.032
	-0.032	-0.108	-0.054	-0.753	-0.045	-0.066	-0.218	-0.342	-0.166	-0.354	-0.041	-0.258
	[28.327]	[-1.942]	[0.927]	[-1.225]	[0.715]	[-0.582]	[0.089]	[0.565]	[-1]	[0.566]	[-1.006]	[0.123]
VAR_LCD (-2)	0.059	0.415	-0.001	1.237	-0.102	-0.05	-0.555	-0.689	1.139	-0.789	0.051	0.591
	-0.042	-0.144	-0.073	-1.004	-0.06	-0.089	-0.291	-0.456	-0.221	-0.472	-0.055	-0.344
	[1.393]	[2.879]	[-0.009]	[1.232]	[-1.686]	[-0.564]	[-1.906]	[-1.513]	[5.151]	[-1.673]	[0.926]	[1.716]
VAR_LCD (-3)	0.009	-0.072	-0.086	-0.377	0.026	0.064	0.446	0.69	-1.877	0.082	-0.049	-0.813
	-0.043	-0.146	-0.073	-1.014	-0.061	-0.09	-0.294	-0.46	-0.223	-0.476	-0.056	-0.348
	[0.211]	[-0.495]	[-1.171]	[-0.372]	[0.433]	[0.718]	[1.517]	[1.498]	[-8.407]	[0.172]	[-0.879]	[-2.339]
VAR_LCD (-4)	-0.038	0.059	0.051	-0.43	0.029	-0.076	-0.199	-0.809	1.481	0.159	0.033	0.922
	-0.044	-0.148	-0.075	-1.033	-0.062	-0.091	-0.3	-0.469	-0.227	-0.485	-0.057	-0.354
	[-0.864]	[0.401]	[0.684]	[-0.417]	[0.467]	[-0.837]	[-0.663]	[-1.725]	[6.511]	[0.328]	[0.582]	[2.602]
VAR_LCD (-5)	0.014	-0.263	-0.086	-0.786	0.01	-0.006	0.03	0.092	-0.501	0.174	-0.002	-0.703
	-0.032	-0.108	-0.054	-0.751	-0.045	-0.066	-0.218	-0.341	-0.165	-0.353	-0.041	-0.258
	[0.434]	[-2.441]	[-1.579]	[-1.047]	[0.218]	[-0.093]	[0.137]	[0.269]	[-3.032]	[0.494]	[-0.059]	[-2.73]
VAR_LCS (-1)	-0.017	0.6	0.01	0.156	-0.001	0.026	0.076	0.034	-0.486	0.081	-0.014	0.167
	-0.011	-0.037	-0.019	-0.26	-0.016	-0.023	-0.076	-0.118	-0.057	-0.122	-0.014	-0.089
	[-1.57]	[16.039]	[0.522]	[0.6]	[-0.09]	[1.122]	[1.002]	[0.284]	[-8.483]	[0.66]	[-0.96]	[1.866]
VAR_LCS(-2)	0.041	0.182	-0.013	1.334	0.054	0.108	0.232	0.627	-0.29	-0.254	0.074	-0.313
	-0.012	-0.042	-0.021	-0.293	-0.018	-0.026	-0.085	-0.133	-0.065	-0.138	-0.016	-0.101
	[3.283]	[4.324]	[-0.628]	[4.55]	[3.088]	[4.168]	[2.724]	[4.715]	[-4.499]	[-1.847]	[4.627]	[-3.108]
VAR_LCS (-3)	-0.043	-0.198	0.067	-0.452	-0.039	-0.023	-0.016	-0.182	0.044	0.425	-0.061	0.184
	-0.012	-0.04	-0.02	-0.277	-0.017	-0.024	-0.08	-0.126	-0.061	-0.13	-0.015	-0.095
	[-3.666]	[-4.992]	[3.348]	[-1.635]	[-2.326]	[-0.924]	[-0.196]	[-1.45]	[0.718]	[3.27]	[-4.011]	[1.935]
VAR_LCS (-4)	0.016	-0.006	-0.019	-0.047	0.018	0.017	0.079	0.082	0.515	-0.02	0.017	-0.371
	-0.011	-0.039	-0.02	-0.271	-0.016	-0.024	-0.079	-0.123	-0.06	-0.127	-0.015	-0.093
	[1.406]	[-0.146]	[-0.952]	[-0.175]	[1.083]	[0.698]	[1.003]	[0.67]	[8.636]	[-0.16]	[1.133]	[-3.99]
VAR_LCS (-5)	-0.011	0.05	-0.026	-0.041	-0.052	-0.036	-0.111	-0.115	-0.273	-0.009	-0.022	0.469
	-0.01	-0.033	-0.017	-0.229	-0.014	-0.02	-0.066	-0.104	-0.05	-0.107	-0.013	-0.078
	[-1.146]	[1.531]	[-1.565]	[-0.18]	[-3.78]	[-1.781]	[-1.679]	[-1.104]	[-5.422]	[-0.08]	[-1.796]	[5.972]

VAR_LEN (-1)	-0.033	0.096	0.894	-0.234	0.007	-0.051	-0.027	-0.077	-0.159	-0.241	-0.01	0.223
	-0.016	-0.055	-0.028	-0.382	-0.023	-0.034	-0.111	-0.173	-0.084	-0.179	-0.021	-0.131
	[-2.06]	[1.752]	[32.422]	[-0.614]	[0.295]	[-1.525]	[-0.247]	[-0.444]	[-1.892]	[-1.341]	[-0.502]	[1.704]
VAR_LEN (-2)	0.059	0.142	-0.044	2.697	0.006	0.195	0.599	1.09	0.132	0.034	0.023	-0.4
	-0.022	-0.076	-0.038	-0.528	-0.032	-0.047	-0.153	-0.24	-0.116	-0.248	-0.029	-0.181
	[2.66]	[1.869]	[-1.163]	[5.108]	[0.183]	[4.188]	[3.907]	[4.549]	[1.135]	[0.135]	[0.785]	[-2.207]
VAR_LEN (-3)	-0.041	-0.119	0.02	-2.335	-0.006	-0.117	-0.42	-0.896	-0.251	0.281	-0.007	0.223
	-0.022	-0.076	-0.038	-0.532	-0.032	-0.047	-0.154	-0.241	-0.117	-0.25	-0.029	-0.182
	[-1.843]	[-1.553]	[0.523]	[-4.391]	[-0.198]	[-2.483]	[-2.719]	[-3.712]	[-2.143]	[1.123]	[-0.257]	[1.222]
VAR_LEN(-4)	0.013	-0.089	-0.02	0.125	-0.017	-0.015	-0.051	0.083	0.325	-0.294	0.039	-0.222
	-0.022	-0.076	-0.038	-0.53	-0.032	-0.047	-0.154	-0.241	-0.117	-0.249	-0.029	-0.182
	[0.581]	[-1.174]	[-0.517]	[0.236]	[-0.525]	[-0.323]	[-0.333]	[0.347]	[2.786]	[-1.183]	[1.341]	[-1.223]
VAR_LEN (-5)	0.006	0.087	0.088	0.472	0.024	0.052	0.09	0.145	-0.105	0.128	-0.023	0.186
	-0.016	-0.054	-0.027	-0.373	-0.022	-0.033	-0.108	-0.169	-0.082	-0.175	-0.02	-0.128
	[0.399]	[1.619]	[3.265]	[1.266]	[1.088]	[1.568]	[0.829]	[0.855]	[-1.279]	[0.728]	[-1.108]	[1.455]
VAR_LFIN (-1)	-0.016	-0.015	-0.003	0.72	-0.017	-0.012	-0.032	-0.08	-0.01	0.064	-0.011	-0.058
	-0.002	-0.008	-0.004	-0.058	-0.004	-0.005	-0.017	-0.027	-0.013	-0.027	-0.003	-0.02
	[-6.439]	[-1.786]	[-0.739]	[12.316]	[-4.721]	[-2.407]	[-1.904]	[-3.008]	[-0.805]	[2.326]	[-3.317]	[-2.911]
VAR_LFIN (-2)	0.002	-0.058	0.004	-0.858	0.005	-0.053	-0.169	-0.309	-0.075	-0.219	0.004	0.107
	-0.003	-0.011	-0.006	-0.078	-0.005	-0.007	-0.023	-0.035	-0.017	-0.037	-0.004	-0.027
	[0.649]	[-5.19]	[0.719]	[-11.015]	[1.068]	[-7.729]	[-7.457]	[-8.736]	[-4.353]	[-5.98]	[1.021]	[3.992]
VAR_LFIN (-3)	0.009	0.083	-0.001	0.746	0.009	0.055	0.181	0.341	-0.065	0.118	0.011	-0.006
	-0.003	-0.012	-0.006	-0.082	-0.005	-0.007	-0.024	-0.037	-0.018	-0.039	-0.004	-0.028
	[2.504]	[7.06]	[-0.153]	[9.103]	[1.901]	[7.622]	[7.586]	[9.17]	[-3.582]	[3.076]	[2.412]	[-0.21]
VAR_LFIN (-4)	0	-0.025	-0.007	-0.096	0.003	-0.003	-0.014	-0.037	0.155	-0.015	0	-0.064
	-0.003	-0.012	-0.006	-0.081	-0.005	-0.007	-0.024	-0.037	-0.018	-0.038	-0.004	-0.028
	[0.115]	[-2.152]	[-1.222]	[-1.187]	[0.696]	[-0.387]	[-0.593]	[-1.011]	[8.679]	[-0.396]	[0.019]	[-2.31]
VAR_LFIN (-5)	0.001	-0.003	0.001	-0.004	-0.001	-0.005	-0.016	-0.007	-0.05	-0.015	-0.002	0.019
	-0.002	-0.008	-0.004	-0.058	-0.003	-0.005	-0.017	-0.026	-0.013	-0.027	-0.003	-0.02
	[0.252]	[-0.314]	[0.2]	[-0.075]	[-0.392]	[-1.045]	[-0.96]	[-0.276]	[-3.938]	[-0.538]	[-0.681]	[0.978]
VAR_LHC (-1)	0.062	0.129	-0.014	0.5	0.91	0.012	0.116	0.147	0.384	-0.429	0.074	0.343

	-0.024	-0.081	-0.041	-0.563	-0.034	-0.05	-0.163	-0.256	-0.124	-0.265	-0.031	-0.193
	[2.62]	[1.599]	[-0.34]	[0.887]	[26.938]	[0.232]	[0.711]	[0.577]	[3.096]	[-1.621]	[2.396]	[1.773]
VAR_LHC (-2)	-0.075	-0.336	0.021	-1.533	-0.085	-0.057	-0.182	-0.307	0.092	0.712	-0.091	-0.209
	-0.032	-0.108	-0.054	-0.751	-0.045	-0.066	-0.218	-0.341	-0.165	-0.353	-0.041	-0.258
	[-2.368]	[-3.115]	[0.385]	[-2.042]	[-1.892]	[-0.863]	[-0.837]	[-0.9]	[0.556]	[2.019]	[-2.225]	[-0.811]
VAR_LHC (-3)	0.058	0.299	0.014	2.651	0.145	0.201	0.572	0.938	0.485	-0.162	0.071	0.059
	-0.031	-0.106	-0.054	-0.741	-0.044	-0.065	-0.215	-0.337	-0.163	-0.348	-0.041	-0.254
	[1.849]	[2.81]	[0.269]	[3.575]	[3.269]	[3.07]	[2.659]	[2.786]	[2.973]	[-0.464]	[1.745]	[0.231]
VAR_LHC (-4)	-0.026	-0.143	0.058	-1.04	0.000	-0.033	-0.362	-0.405	-1.558	-0.007	0.011	-0.319
	-0.031	-0.104	-0.052	-0.726	-0.044	-0.064	-0.211	-0.33	-0.16	-0.341	-0.04	-0.249
	[-0.861]	[-1.373]	[1.113]	[-1.432]	[0.002]	[-0.513]	[-1.716]	[-1.23]	[-9.746]	[-0.021]	[0.266]	[-1.282]
VAR_LHC (-5)	-0.006	0.154	-0.003	0.893	-0.054	0.007	0.158	0.248	0.654	-0.119	-0.042	0.171
	-0.023	-0.079	-0.04	-0.551	-0.033	-0.049	-0.16	-0.25	-0.121	-0.259	-0.03	-0.189
	[-0.269]	[1.949]	[-0.067]	[1.619]	[-1.623]	[0.135]	[0.987]	[0.991]	[5.39]	[-0.458]	[-1.38]	[0.903]
VAR_LIND (-1)	0.088	-0.23	-0.187	-2.032	0.09	0.824	-0.327	-0.509	-0.141	1.283	-0.003	-0.742
	-0.037	-0.125	-0.063	-0.871	-0.052	-0.077	-0.253	-0.395	-0.192	-0.409	-0.048	-0.299
	[2.396]	[-1.842]	[-2.975]	[-2.334]	[1.733]	[10.718]	[-1.293]	[-1.287]	[-0.735]	[3.137]	[-0.053]	[-2.484]
VAR_LIND(-2)	-0.154	0.263	0.209	4.872	0.040	0.317	1.084	1.613	1.010	0.848	-0.104	1.201
	-0.05	-0.171	-0.086	-1.191	-0.071	-0.105	-0.346	-0.54	-0.262	-0.559	-0.065	-0.408
	[-3.064]	[1.541]	[2.427]	[4.092]	[0.559]	[3.02]	[3.136]	[2.985]	[3.852]	[1.516]	[-1.601]	[2.941]
VAR_LIND (-3)	0.065	0.148	-0.081	-2.854	-0.193	-0.398	-1.283	-1.805	0.681	-2.985	0.152	-0.633
	-0.05	-0.171	-0.086	-1.194	-0.072	-0.105	-0.347	-0.542	-0.263	-0.561	-0.065	-0.41
	[1.296]	[0.864]	[-0.936]	[-2.39]	[-2.691]	[-3.772]	[-3.703]	[-3.329]	[2.59]	[-5.319]	[2.321]	[-1.546]
VAR_LIND (-4)	-0.038	-0.264	0.072	-0.086	0.096	0.19	0.568	0.961	-2.272	1.109	-0.089	0.564
	-0.048	-0.163	-0.082	-1.137	-0.068	-0.1	-0.33	-0.516	-0.25	-0.534	-0.062	-0.39
	[-0.792]	[-1.615]	[0.88]	[-0.076]	[1.413]	[1.889]	[1.719]	[1.862]	[-9.072]	[2.075]	[-1.424]	[1.446]
VAR_LIND (-5)	0.024	-0.062	-0.034	-1.32	-0.042	-0.118	-0.381	-0.872	0.864	-0.081	0.027	-0.456
	-0.033	-0.112	-0.056	-0.782	-0.047	-0.069	-0.227	-0.355	-0.172	-0.367	-0.043	-0.268
	[0.722]	[-0.549]	[-0.599]	[-1.689]	[-0.899]	[-1.714]	[-1.681]	[-2.459]	[5.02]	[-0.222]	[0.624]	[-1.702]
VAR_LITJAP(-1)	0.01	0.069	0.053	0.151	0.031	0.019	0.759	0.008	-0.111	-0.051	0.013	0.399
	-0.009	-0.031	-0.016	-0.219	-0.013	-0.019	-0.064	-0.1	-0.048	-0.103	-0.012	-0.075
	[1.132]	[2.192]	[3.369]	[0.69]	[2.389]	[0.99]	[11.924]	[0.081]	[-2.302]	[-0.494]	[1.118]	[5.311]

VAR_LIT (-2)	-0.022	-0.106	-0.034	-1.325	-0.024	-0.104	-0.224	-0.474	0.06	-0.047	0.039	-0.352
	-0.012	-0.039	-0.02	-0.274	-0.016	-0.024	-0.08	-0.124	-0.06	-0.129	-0.015	-0.094
	[-1.881]	[-2.703]	[-1.711]	[-4.832]	[-1.446]	[-4.3]	[-2.818]	[-3.807]	[0.999]	[-0.362]	[2.589]	[-3.738]
VAR_LIT (-3)	-0.002	-0.042	0.005	0.231	0.013	0.057	0.119	0.264	-0.117	0.336	-0.03	0.116
	-0.012	-0.039	-0.02	-0.275	-0.016	-0.024	-0.08	-0.125	-0.06	-0.129	-0.015	-0.094
	[-0.147]	[-1.064]	[0.25]	[0.843]	[0.817]	[2.338]	[1.499]	[2.12]	[-1.941]	[2.6]	[-2.012]	[1.235]
VAR_LIT (-4)	0.025	0.054	-0.028	0.426	-0.02	-0.021	-0.036	-0.102	0.14	-0.068	0.001	-0.156
	-0.012	-0.039	-0.02	-0.275	-0.016	-0.024	-0.08	-0.125	-0.061	-0.129	-0.015	-0.094
	[2.14]	[1.362]	[-1.428]	[1.549]	[-1.203]	[-0.871]	[-0.449]	[-0.814]	[2.306]	[-0.523]	[0.053]	[-1.658]
VAR_LIT (-5)	-0.002	0.055	0.024	0.595	0.02	0.071	0.231	0.376	0.027	-0.035	-0.011	0.199
	-0.009	-0.03	-0.015	-0.208	-0.012	-0.018	-0.06	-0.094	-0.046	-0.098	-0.011	-0.071
	[-0.187]	[1.846]	[1.618]	[2.86]	[1.591]	[3.867]	[3.825]	[3.982]	[0.584]	[-0.356]	[-0.955]	[2.784]
VAR_LMAT (-1)	0.013	-0.002	0.003	0.078	-0.009	0.009	-0.037	0.679	0.204	-0.155	0.018	-0.044
	-0.008	-0.026	-0.013	-0.181	-0.011	-0.016	-0.053	-0.082	-0.04	-0.085	-0.01	-0.062
	[1.679]	[-0.087]	[0.263]	[0.428]	[-0.795]	[0.545]	[-0.708]	[8.243]	[5.112]	[-1.818]	[1.767]	[-0.71]
VAR_LMAT (-2)	0.027	0.12	-0.008	1.376	0	0.099	0.305	0.638	-0.013	0.118	-0.026	-0.165
	-0.009	-0.032	-0.016	-0.219	-0.013	-0.019	-0.064	-0.1	-0.048	-0.103	-0.012	-0.075
	[2.923]	[3.824]	[-0.524]	[6.27]	[0.013]	[5.106]	[4.795]	[6.405]	[-0.279]	[1.145]	[-2.205]	[-2.195]
VAR_LMAT (-3)	-0.018	-0.167	-0.01	-1.224	-0.008	-0.093	-0.276	-0.577	0.096	-0.036	-0.021	-0.06
	-0.009	-0.031	-0.016	-0.218	-0.013	-0.019	-0.063	-0.099	-0.048	-0.102	-0.012	-0.075
	[-1.976]	[-5.343]	[-0.607]	[-5.611]	[-0.6]	[-4.823]	[-4.367]	[-5.829]	[1.992]	[-0.354]	[-1.761]	[-0.803]
VAR_LMAT (-4)	-0.016	0.017	0.016	-0.353	-0.017	-0.037	-0.114	-0.166	-0.199	-0.069	0.002	0.195
	-0.009	-0.029	-0.015	-0.202	-0.012	-0.018	-0.059	-0.092	-0.044	-0.095	-0.011	-0.069
	[-1.891]	[0.599]	[1.086]	[-1.748]	[-1.444]	[-2.084]	[-1.945]	[-1.81]	[-4.471]	[-0.731]	[0.157]	[2.817]
VAR_LMAT (-5)	-0.006	-0.025	-0.006	-0.186	0.003	-0.014	-0.049	-0.098	0.027	0.057	0.011	-0.167
	-0.006	-0.022	-0.011	-0.15	-0.009	-0.013	-0.044	-0.068	-0.033	-0.071	-0.008	-0.052
	[-0.88]	[-1.149]	[-0.526]	[-1.24]	[0.342]	[-1.043]	[-1.117]	[-1.44]	[0.823]	[0.805]	[1.349]	[-3.236]
VAR_LRE (-1)	0.001	0.034	-0.015	-0.006	0.022	0.006	0.105	0.117	1.001	-0.062	-0.003	-0.048
	-0.005	-0.016	-0.008	-0.109	-0.007	-0.01	-0.032	-0.049	-0.024	-0.051	-0.006	-0.037
	[0.182]	[2.153]	[-1.864]	[-0.055]	[3.314]	[0.674]	[3.318]	[2.368]	[41.786]	[-1.211]	[-0.502]	[-1.28]
VAR_LRE (-2)	0.006	-0.115	0.028	0.274	-0.027	0.054	0.103	0.015	-0.2	0.147	0.012	-0.155

	-0.006	-0.02	-0.01	-0.138	-0.008	-0.012	-0.04	-0.062	-0.03	-0.065	-0.008	-0.047
	[0.967]	[-5.829]	[2.802]	[1.991]	[-3.256]	[4.467]	[2.573]	[0.246]	[-6.593]	[2.279]	[1.635]	[-3.287]
VAR_LRE (-3)	-0.019	0.206	-0.012	-0.109	0.016	-0.036	-0.155	-0.107	0.181	-0.07	-0.009	0.171
	-0.006	-0.02	-0.01	-0.137	-0.008	-0.012	-0.04	-0.062	-0.03	-0.064	-0.007	-0.047
	[-3.307]	[10.508]	[-1.204]	[-0.802]	[1.898]	[-3.025]	[-3.918]	[-1.726]	[6.025]	[-1.088]	[-1.184]	[3.655]
VAR_LRE (-4)	0.016	-0.095	-0.012	0.092	-0.026	-0.016	-0.037	0.076	-0.008	-0.16	-0.004	-0.049
	-0.006	-0.021	-0.01	-0.145	-0.009	-0.013	-0.042	-0.066	-0.032	-0.068	-0.008	-0.05
	[2.594]	[-4.548]	[-1.129]	[0.636]	[-2.993]	[-1.242]	[-0.872]	[1.16]	[-0.236]	[-2.358]	[-0.494]	[-0.978]
VAR_LRE (-5)	-0.002	0.001	0.000	-0.215	0.023	-0.004	0.01	-0.074	-0.11	0.121	0.011	0.054
	-0.004	-0.014	-0.007	-0.099	-0.006	-0.009	-0.029	-0.045	-0.022	-0.046	-0.005	-0.034
	[-0.555]	[0.093]	[0.004]	[-2.184]	[3.913]	[-0.409]	[0.363]	[-1.647]	[-5.054]	[2.61]	[2.096]	[1.604]
VAR_LTEL (-1)	0.000	0.003	-0.001	0.013	0.001	0.003	0.002	-0.001	0.03	0.645	0.002	0.006
	-0.002	-0.008	-0.004	-0.055	-0.003	-0.005	-0.016	-0.025	-0.012	-0.026	-0.003	-0.019
	[-0.204]	[0.329]	[-0.271]	[0.241]	[0.177]	[0.627]	[0.114]	[-0.059]	[2.475]	[24.953]	[0.533]	[0.318]
VAR_LTEL (-2)	0.000	0.011	-0.002	-0.025	-0.004	-0.007	-0.022	-0.022	-0.061	-0.040	0.000	-0.019
	-0.003	-0.009	-0.005	-0.065	-0.004	-0.006	-0.019	-0.030	-0.014	-0.031	-0.004	-0.022
	[-0.114]	[1.123]	[-0.434]	[-0.375]	[-1.018]	[-1.274]	[-1.169]	[-0.735]	[-4.206]	[-1.315]	[0.096]	[-0.865]
VAR_LTEL (-3)	0.000	-0.003	0.002	0.007	0.006	0.003	0.012	0.009	0.053	0.013	-0.001	0.006
	-0.003	-0.009	-0.005	-0.065	-0.004	-0.006	-0.019	-0.03	-0.014	-0.031	-0.004	-0.022
	[0.174]	[-0.305]	[0.357]	[0.112]	[1.53]	[0.441]	[0.649]	[0.291]	[3.646]	[0.408]	[-0.405]	[0.252]
VAR_LTEL (-4)	0.003	0.007	0.007	0.034	-0.002	0.007	0.01	0.022	-0.048	-0.013	0.001	-0.009
	-0.003	-0.009	-0.005	-0.064	-0.004	-0.006	-0.019	-0.029	-0.014	-0.03	-0.003	-0.022
	[1.051]	[0.755]	[1.62]	[0.532]	[-0.554]	[1.302]	[0.534]	[0.751]	[-3.408]	[-0.447]	[0.227]	[-0.407]
VAR_LTEL (-5)	-0.002	-0.008	0.008	-0.028	0.000	-0.004	-0.005	-0.012	0.031	0.014	0.003	-0.004
	-0.002	-0.008	-0.004	-0.052	-0.003	-0.005	-0.015	-0.024	-0.012	-0.025	-0.003	-0.018
	[-0.895]	[-1.103]	[2.112]	[-0.528]	[-0.077]	[-0.767]	[-0.334]	[-0.524]	[2.713]	[0.567]	[1.083]	[-0.222]
VAR_LUTI (-1)	0.030	-0.047	0.026	-0.655	0.11	0.022	-0.065	0.079	0.200	0.031	0.905	-0.362
	-0.021	-0.072	-0.036	-0.505	-0.03	-0.045	-0.147	-0.229	-0.111	-0.237	-0.028	-0.173
	[1.397]	[-0.646]	[0.715]	[-1.298]	[3.637]	[0.487]	[-0.445]	[0.343]	[1.799]	[0.131]	[32.74]	[-2.09]
VAR_LUTI (-2)	0.022	-0.013	-0.034	-0.434	-0.069	-0.054	-0.057	-0.365	-0.087	-0.069	0.048	0.043
	-0.029	-0.097	-0.049	-0.676	-0.041	-0.06	-0.196	-0.307	-0.149	-0.318	-0.037	-0.232
	[0.777]	[-0.13]	[-0.689]	[-0.642]	[-1.702]	[-0.898]	[-0.292]	[-1.189]	[-0.585]	[-0.218]	[1.292]	[0.184]

VAR_LUTI (-3)	-0.029	-0.095	0.027	-0.285	-0.009	-0.089	-0.248	-0.301	-0.215	0.123	-0.029	0.288
	-0.028	-0.096	-0.048	-0.668	-0.04	-0.059	-0.194	-0.303	-0.147	-0.314	-0.037	-0.229
	[-1.017]	[-0.991]	[0.553]	[-0.426]	[-0.22]	[-1.507]	[-1.281]	[-0.993]	[-1.463]	[0.391]	[-0.783]	[1.258]
VAR_LUTI(-4)	-0.019	0.049	-0.046	0.410	-0.010	0.014	0.140	0.172	0.891	0.040	-0.042	0.057
	-0.028	-0.095	-0.048	-0.660	-0.040	-0.058	-0.191	-0.299	-0.145	-0.310	-0.036	-0.226
	[-0.697]	[0.514]	[-0.974]	[0.622]	[-0.249]	[0.236]	[0.732]	[0.575]	[6.132]	[0.129]	[-1.162]	[0.252]
VAR_LUTI (-5)	-0.005	0.019	0.008	-0.126	-0.001	0.015	-0.048	-0.002	-0.776	-0.053	0.024	-0.117
	-0.021	-0.071	-0.036	-0.498	-0.03	-0.044	-0.144	-0.226	-0.11	-0.234	-0.027	-0.171
	-0.25	0.269	0.211	-0.253	-0.049	0.344	-0.33	-0.01	-7.082	-0.225	0.872	-0.686
VAR_LFTSEUS(-1)	-0.003	0.076	0.022	0.069	-0.009	-0.007	-0.045	-0.063	0.059	-0.046	0.017	0.674
	-0.003	-0.011	-0.005	-0.074	-0.004	-0.007	-0.021	-0.033	-0.016	-0.035	-0.004	-0.025
	[-1.037]	[7.193]	[4.048]	[0.939]	[-1.946]	[-1.006]	[-2.11]	[-1.892]	[3.646]	[-1.332]	[4.269]	[26.68]
VAR_LFTSEUS(-2)	0.028	-0.033	-0.013	0.522	0.061	0.102	0.403	0.52	-0.073	0.148	-0.018	-0.108
	-0.004	-0.013	-0.007	-0.091	-0.005	-0.008	-0.026	-0.041	-0.02	-0.043	-0.005	-0.031
	[7.153]	[-2.491]	[-1.946]	[5.73]	[11.204]	[12.637]	[15.254]	[12.567]	[-3.615]	[3.465]	[-3.598]	[-3.452]
VAR_LFTSEUS(-3)	-0.006	-0.001	-0.007	-0.519	-0.033	-0.072	-0.269	-0.404	-0.015	-0.028	0.012	0.211
	-0.005	-0.015	-0.008	-0.107	-0.006	-0.009	-0.031	-0.049	-0.024	-0.05	-0.006	-0.037
	[-1.378]	[-0.073]	[-0.924]	[-4.838]	[-5.136]	[-7.571]	[-8.643]	[-8.292]	[-0.616]	[-0.551]	[2.119]	[5.744]
VAR_LFTSEUS(-4)	-0.01	-0.017	-0.01	-0.15	-0.009	-0.025	-0.041	-0.035	0.186	-0.06	-0.003	-0.065
	-0.005	-0.016	-0.008	-0.111	-0.007	-0.01	-0.032	-0.05	-0.024	-0.052	-0.006	-0.038
	[-2.102]	[-1.036]	[-1.234]	[-1.348]	[-1.354]	[-2.58]	[-1.261]	[-0.695]	[7.621]	[-1.145]	[-0.484]	[-1.702]
VAR_LFTSEUS(-5)	0.013	-0.009	0.024	0.158	0.012	0.032	0.071	0.089	-0.033	0.039	0.000	0.021
	-0.004	-0.013	-0.007	-0.092	-0.005	-0.008	-0.027	-0.042	-0.02	-0.043	-0.005	-0.031
	[3.265]	[-0.713]	[3.68]	[1.729]	[2.176]	[3.935]	[2.687]	[2.129]	[-1.624]	[0.913]	[-0.086]	[0.665]
C	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[-1.79]	[5.252]	[-0.066]	[-5.714]	[-1.506]	[-7.367]	[-6.427]	[-6.48]	[2.665]	[-0.623]	[0.479]	[2.226]
VAR_LOIL	0.000	0.000	0.001	0.002	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.003
	0.000	0.000	0.000	-0.002	0.000	0.000	-0.001	-0.001	0.000	-0.001	0.000	-0.001
	[-0.647]	[-1.3]	[11.204]	[1.123]	[-1.354]	[1.441]	[0.533]	[1.132]	[2.466]	[0.448]	[-2.824]	[5.195]
VAR_LGOLD	0.041	0.419	0.039	4.321	0.062	0.323	1.007	1.795	-0.011	0.312	0.026	0.242

	-0.007	-0.023	-0.011	-0.157	-0.009	-0.014	-0.046	-0.071	-0.035	-0.074	-0.009	-0.054
	[6.149]	[18.535]	[3.461]	[27.443]	[6.582]	[23.242]	[22.039]	[25.108]	[-0.306]	[4.217]	[3.045]	[4.487]
VAR_LBTC	0.001	0.001	0.000	-0.004	0.001	0.001	0.004	0.005	0.008	0.000	0.001	0.012
	0.000	-0.001	0.000	-0.005	0.000	0.000	-0.001	-0.002	-0.001	-0.002	0.000	-0.002
	[2.833]	[1.377]	[0.713]	[-0.932]	[5.126]	[2.642]	[2.79]	[2.286]	[7.843]	[0.019]	[4.474]	[7.507]
R-squared	0.979	0.763	0.967	0.866	0.970	0.979	0.883	0.840	0.973	0.605	0.936	0.691
Adj. R-squared	0.978	0.754	0.965	0.860	0.969	0.978	0.878	0.834	0.972	0.589	0.934	0.679
Sum sq. resids	2.23E-07	2.58E-06	6.53E-07	0.000125	4.50E-07	9.75E-07	1.05E-05	2.58E-05	6.06E-06	2.76E-05	3.75E-07	1.47E-05
S.E. equation	1.18E-05	4.00E-05	2.02E-05	0.000279	1.67E-05	2.46E-05	8.10E-05	0.000127	6.14E-05	0.000131	1.53E-05	9.57E-05
F-statistic	1207.202	82.278	742.290	164.590	838.739	1168.691	191.731	133.982	922.561	39.085	376.407	57.169
Log likelihood	16634.950	14590.16	15738.21	11344.830	16049.86	15403.160	13413.09	12665.560	13874.99	12607.780	16201.980	13133.660
Akaike AIC	-19.822	-17.376	-18.749	-13.494	-19.122	-18.348	-15.968	-15.074	-16.520	-15.005	-19.304	-15.634
Schwarz SC	-19.614	-17.168	-18.542	-13.286	-18.914	-18.141	-15.760	-14.866	-16.313	-14.797	-19.096	-15.426
Mean dependent	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
S.D. dependent	8.04E-05	8.07E-05	0.000	0.001	9.55E-05	0.000165	0.000	0.000	0.000	0.000	0.000	0.000
Determinant resid covariance (dof adj.)		1.10E-107										
Determinant resid covariance		6.70E-108										
Log likelihood		177841.5										
Akaike information criterion		-211.81										
Schwarz criterion		-209.32										
Number of coefficients		768										

Chapter 3

Unintended Effects of the Regional Greenhouse Gas Initiative: Evidence from the United States

Note: This essay was co-authored with Khaled Albastaki, who is a PhD Economics student at the University of Essex; kb20190@essex.ac.uk. Khaled acknowledges that I had a significant contribution to this paper and can therefore appear within this thesis.

3.1 Introduction

Climate change has become a major issue worldwide resulting from its various consequences such as, rising sea levels, droughts, extreme weather conditions etc. To tackle this vital problem, several countries have enacted climate change mitigating policies including subsides, carbon taxes, cap-and-trade programmes. The latter have been classified as the most effective policy in minimising greenhouse gas emissions, slowing the rate of climate change and reducing the impact on economic growth (Kearns and Cassady, 2015). Examples of cap-and-trade programmes involve the European Union Emissions Trading System (EUETS), the Regional Greenhouse Gas Initiative (RGGI) in the United States (US), New Zealand's cap-and-trade system etc. Our chapter evaluates the impacts of RGGI on average income, weeks worked and unemployment in the US. An event study is undertaken to capture the impact of RGGI on these variables. This will enable us to understand the heterogenous and unintended effects of RGGI through a comparison between treated (i.e., states which participated in the framework) and control states (i.e., those which did not participate).

The vast majority of existing literature on the impact of RGGI is concerned with energy generation, consumption, switching, emissions, and leakages[28]. When looking at energy generation and emissions, Lee and Melstrom (2018) uncovered an increase in the

[28] See, Bernard et al., 2007; Hasegawa and Salant, 2014; Hibbard et al., 2018; Murray and Maniloff, 2015; Fell and Maniloff, 2018; Huang and Zhou, 2019; Chan and Morrow, 2019; Yan, 2021; Zhou and Huang, 2021.

flow of electricity in the US northeast post the introduction of RGGI. Further, they stated that electricity markets permit the minimisation of emissions achieved at a particular region to be offset by rising emissions from other electricity-generating regions, since local production is replaced with electricity imports. To put differently, carbon emissions and electricity generation has increased in regions that did not implement RGGI.

Equally as interesting, Paul et al. (2010) assessed the association between energy consumption and RGGI. It was revealed that an increase in a state's expenditure on energy efficiency programmes was associated with a reduction in electricity consumption at the state in question. This brought about a decrease in electricity spending. They also claimed that implementation of programmes such as RGGI drives the creation of jobs, rise in wages and results in state-wide economic benefits. Furthermore, Kim and Kim (2016) performed a comparative study to investigate the impacts of RGGI on energy switching. They found that RGGI implementation has expedited energy switching from coal to gas. Specifically, RGGI states experienced an increase in gas share and electricity generation by approximately 10 to 15% when compared to the synthetic RGGI.

None of the above studies examined the link between RGGI and labour market outcomes. The allegations made by Paul et al. (2010) in relation to the creation of jobs and rise in wages were based on a projection. Such analysis is subjective and is not always accurate. We contribute to these investigations by evaluating the impacts of RGGI on US labour market outcomes. Our findings reveal a noticeable decline in annual income of workers in energy intensive sectors at RGGI states when compared to non-RGGI ones. On average, the decline in annual income from wages accounts for about 7% 4 years after the reform. However, when looking at the impact of RGGI on weeks worked and probability of unemployment, the effect is insignificant throughout the post treatment period. Finally, the impact of RGGI on annual income from wages of workers at non-energy intensive sectors, workers possessing a college or high school degree at energy intensive sectors is also insignificant.

The rest of this chapter is divided in the following way: Section 3.2 provides some background information and presents the conceptual framework. Section 3.3 analysis the econometric methodology employed. Section 3.4 explains the data set used. Section 3.5 illustrates the necessary robust checks after which it discusses the generated results. Section 3.6 concludes the chapter by summarising the main findings.

3.2 Background and Conceptual Framework

The electricity transmission system in the US is an extensive and sophisticated network specified to transfer electricity from power plants to end users across the nation. According to the U.S. Department of Energy (2002), the system operates at multiple voltage levels to efficiently transfer electricity over long distances. Initially, electricity is generated at power plants using different energy sources such as renewables, fossil fuels and nuclear energy. Electricity generated at these plants is between 13,000 to 25,000 volts which are then transferred to step up transformers (substations) located close to power plants. Step up transformers raise the voltage to extremely high levels (between 115,000 to 765,000 volts) as this minimises energy losses when transferring electricity over long distances. High voltage transmission lines are used for the latter action because they are backed up by pylons and run across the US. Before electricity reaches to the end users, it goes through step down transformers (distribution stations). These transformers decrease the high transmission voltages to lower ones (between 4,000 to 35,000 volts) making them compatible for domestic distribution. The minimised electricity voltage then passes through a distribution system which comprises of low voltage power lines that supplies electricity directly to the end users. Finally, step down transformers depress the voltage even further so that it reaches the standard levels (between 120 to 240 volts).

Under a cap-and-trade programme, permits are either distributed for free or sold at an auction to the highest bidder. Revenue collected from these auctions is used to enhance renewable and energy efficient programmes. Firms can also trade permits amongst each other. In the event where firms were successful in minimising emissions to less than their permissible level, they could sell their remining permits. Whereas, if polluting firms are surpassing the number of permits that they acquired, purchase of additional ones would be essential. Otherwise, they will end up exceeding government limits on emissions and thus be fined for violations. Since the price of permits is determined by the forces of demand and supply, these actions would undoubtably increase the price of remaining permits. Hence, contributing towards diminishing countrywide emissions.

On the 1st of January 2009, the first regional cap-and-trade programme called RGGI (which is still in effect today) was introduced in the US. It is a collaborative agreement between eleven states to cap and minimise carbon dioxide emissions from the electricity generation sector. To be more specific, initially ten states joined the initiative (New York, New Hampshire, New Jersey, Massachusetts, Connecticut, Rhode Island, Maryland, Vermont, Maine, and Delaware) after which it increased to eleven (Virginia) on the 1st of January 2021. A cap on total carbon dioxide emissions is set by each member state. This is then decreased overtime to minimise overall carbon emissions generated by power plants. Purchase of allowances is necessary as they permit a regulated power plant to emit an extra ton of carbon dioxide. As a result, regulated firms are encouraged to invest in environmentally friendly production techniques to ensure that they adhere with pre-determined levels of emissions.

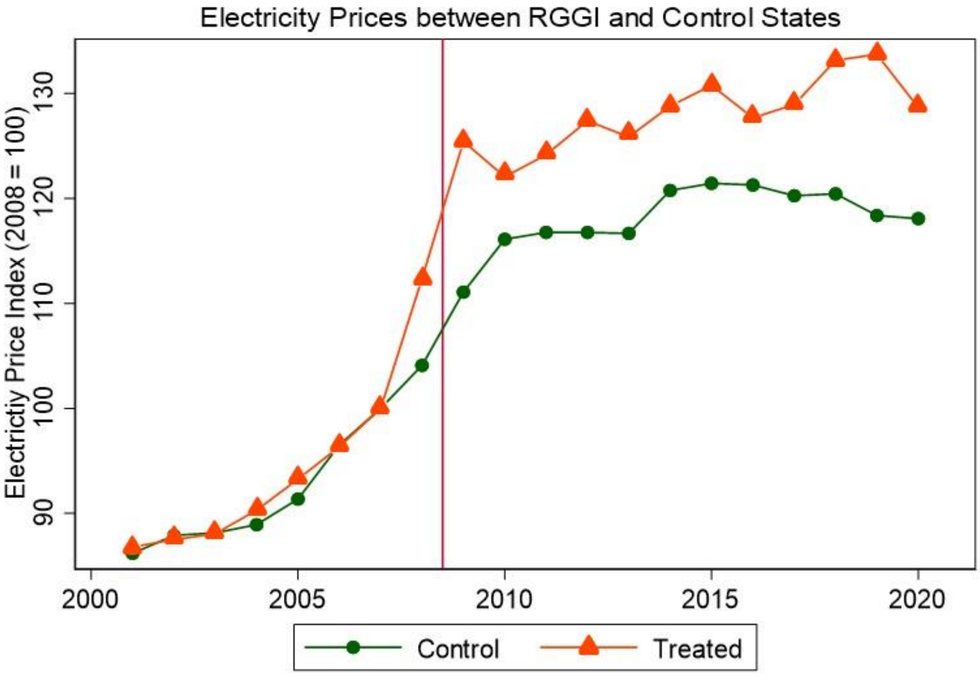
RGGI states allocated allowances by conducting auctions on quarterly basis. These are purchased by electricity generating sectors, environmental and national governmental organisations. Revenue generated from these auctions is invested in renewable and energy efficient programmes such as energy star, weatherisation assistance programme, leadership in energy and environmental design (U.S. Department of Energy). Since the RGGI programme began during the economic crisis, the price of permits from auctions were low. Yet, a price floor in auctions existed to maintain the price of permits at approximately $2 per ton. According to the RGGI 101 fact sheet, some states choose to hold a confined number of allowances in set-aside accounts to sell them at a certain price outside the auction process. This creates a secondary market for allowances. It is worth noting that imported power into RGGI states is neither controlled by the emission cap nor any other border restriction framework. Therefore, electricity generation within RGGI states could experience a decline but these can be covered by importing more power from generating sources beyond RGGI states.

Figure 3.1 highlights the impact on states joining the RGGI through a visualisation of trends in electricity prices. In the pre-treatment period, electricity prices at RGGI and non-RGGI states were on average similar. After joining the RGGI (post 2008), we can see a rapid increase in electricity prices at both RGGI and non-RGGI states. However, the surge is greatly pronounced in the former when compared to the latter, given the restrictions imposed on emissions within RGGI states. These findings are consistent with existing literature suggesting that the pass-through from a rise in carbon dioxide costs to electricity prices is statistically significant[29]. For instance, Bai and Okullo (2023) studied drivers and pass-through of EUETS to the power sector. They found that there is greater than full pass-through of allowance costs to wholesale electricity markets in seven European countries. However, Gullì and Chernyavs'ka (2013) added that the carbon price pass-through to energy prices tends to vary substantially over time, across countries and even markets. This is because electricity supply curves reflect the marginal costs of various producers that have different intensity emissions. It would then be important to understand how this may have had an impact on wages and employment, especially within sectors that are highly energy intensive.

It is important to note that the notable electricity price differences between RGGI and non-RGGI states are affected by various convoluted factors. According to the Federal Energy Regulatory Commission (2024), regulatory, logistical and economic issues hinder the complete mitigation of price differences despite the potential for increased supply of electricity from non-RGGI states. The capacity of transmission facilities to transfer large amounts of electricity from non-RGGI to RGGI states is quite limited. Additionally, the existing electricity grid structure is divided into three interconnections (Texas, Eastern and Western states) and it is restricted to transfer electricity across these states. Even if non-RGGI states where able to increase supply, the cost advantage would be offset by the carbon pricing regulation implemented at RGGI states. For the same reason, the end user at RGGI states cannot benefit from lower wholesale electricity market prices when power is imported from non-RGGI states. RGGI states are also moving towards renewable sources of energy such as solar, wind and hydroelectric power. This yields higher costs which is reflected in the electricity price differential since non-RGGI states rely on cheaper non-renewable energy sources such as fossil fuels. Lastly, transferring electricity to RGGI states is expensive when compared to non-RGGI ones. This is because, the latter is located closer to energy generating units (such as those in the Midwest).

[29] See, Kim et al., 2010; Sijm et al., 2012; Jouvet and Solier, 2013; Huisman and Kiliç, 2015; Nazifi et al., 2021; Wang et al., 2023.

Figure 3.1



Note: Figure shows the electricity price index for US states between 2000 and 2020, with 2008 being the base year. Control refers to non-RGGI states while treated corresponds to RGGI ones. Data on energy prices retrieved from US Energy Information Administration (EIA).

3.2.1 The Impact of EUETS on Labour Market Outcomes

Before we embark onto the discussion of RGGI's impact on wages and employment, it is worth shedding light on the impact of a similar and one of the most prominent cap-and-trade programmes in Europe called EUETS.

All of the empirical evidence which investigated the impact of EUETS on employment and wages suggests that the effect is insignificant on both variables[30]. Dechezlepretre et al. (2023) showed that the implementation of EUETS had an insignificant impact on the number of employees working at regulated firms. They also emphasised that EUETS has encouraged regulated firms to boost investment that may have resulted in an increase in productivity. In addition, Chan et al. (2013) compared the impact of EUETS on regulated and non-regulated firms. They concluded that differences between both groups in terms of employment, material costs and turnover is statistically insignificant. Likewise, an insignificant relationship was detected when examining employment levels at energy intensive sectors such as power, cement, iron, and steel. When looking at the impact on

[30] See, Anger and Oberndorfer, 2008; Fæhn et al., 2009; Abrell et al., 2011; Commins et al., 2011; Petrick and Wagner, 2014; Colmer et al., 2024.

wages, Marin et al. (2018) argued that EUETS had no influence on neither wages or total factor productivity. This reflects wage rigidity in EU countries and lack of EUETS impact on labour force structure.

3.2.2 The Impact of Energy Prices on Employment

Several studies examined the relationship between energy prices and employment in the last decade. Results have proven to be contradictory as on one hand, some studies revealed that there exists a negative relationship between energy prices and employment[31]. For example, Bijnens et al. (2022) showed that there is a negative responsiveness between increasing electricity prices and employment for European firms operating in electricity intensive sectors. The elasticity between the two variables was -0.05 on average and rises to -0.13 for most industrialised countries. In other words, when electricity prices increase by 1%, employment levels fall by 0.05% to 0.13% for sectors that are highly energy intensive. In the same light, Kahn and Mansur (2013) supported the negative relationship between electricity prices and employment across all manufacturing industries with a normalised electricity index that is greater than 0.094. The highest impact was captured by the most electricity intensive sector (i.e., primary metals) where price elasticity of employment was -1.65.

While on the other, positive, or weak relationship was detected between energy prices and employment[32]. Namely, Deschenes, (2010) examined all sectors within the US economy and stated that a rise in electricity prices results in a negligible decline in employment rates. The cross-price elasticity of full-time workers with respect to electricity ranges between -0.16% and -0.1%. Although in the short run, he stated that climate polices that lead to 3% or 4% rise in electricity prices would cause aggregate full-time employment to fall by 0.6%. However, Cox et al. (2014) found small positive conditional cross price elasticity of labour demand with respect to electricity prices in Germany. This signifies that electricity as an input factor can be replaced by labour to a certain degree when output level is held constant. However, when production varies, they

[31] See, Doğrul and Soytas, 2010; Arshad et al., 2016; Cuestas and Ordóñez, 2018; Kocaaslan, 2019; Kocaarslan et al., 2020; Marin and Vona, 2021; Li et al., 2022b.

[32] See, Bjørnland, 2000; Aldy and Pizer, 2013; Shetty et al., 2013; Herrera et al., 2017; Jung and Das, 2018; Hille and Möbius, 2019; Nusair, 2020; Raifu et al., 2020; Vatsa and Hu, 2021; Wang et al., 2022.

obtain negative unconditional cross-price elasticities where higher electricity prices generate a reduction in labour demand and output.

3.2.3 The Impact of Energy Prices on Wages

The analysis conducted to understand the link between energy prices and wage rates revealed a negative relationship between the two variables[33]. In particular, Marin and Vona (2021) found that higher energy costs in French energy intensive sectors are translated into lower average wages. They added that small firms operating at one location respond to energy price shocks by minimising wages as opposed to employment while the reverse is true for large firms operating at multiple locations. Wildauer et al. (2023) went a step further by showing that non-energy intensive firms in the US have raised prices when responding to energy price shocks. Because of this, workers experienced a decline in real wages. They explained, when workers suffer a decline in living standards, they start demanding higher nominal wages. Firm's costs increases if they choose to abide by their workers' demands. Consequently, prices are increased leading to a fall in real wages.

3.3 Empirical Strategy

Following Huang and Zhou (2019), we compare labour market outcomes between treated and control states across time using an events study approach. The model, which includes lags and leads of the treatment, is implemented as follows:

$$Y_{ist} = \sum_{t=-q}^{-2} \alpha_t T_{is} + \sum_{t=0}^{m} \beta_t T_{is} + \gamma_s + \gamma_t + \epsilon_{ist} \qquad (3.1)$$

Where, *i* indicates an individual working in state *s* at year *t*. The outcomes of interest are log annual income from wages, annual weeks worked and a binary variable taking value one if a person is unemployed. The vector of coefficients α_t and β_t are estimates of the lags and leads of the treatment variable T. Moreover, γ_s and γ_t represent state and year fixed effects respectively. It is important to note that here we only consider the impact on energy-intensive industries[34]. The probability of unemployment is estimated

[33] See, Pindyck, 1980; Mork and Hall, 1980; Mountain, 1986; Keane and Prasad, 1996; Rotemberg and Woodford, 1996; Kehrig and Ziebarth, 2017; Battistini et al., 2022.

[34] Although they represent a greater portion of the economy, it is not expected that non-energy intensive industries will exhibit any significant difference in outcomes across RGGI states. This is because the underlying hypothesis of the impact of RGGI is mainly due to energy prices rising substantially within RGGI

through a linear probability model. Standard errors in all specifications are clustered at the state level (50 states / cluster groups).

We examine states within the US and compare those that entered the RGGI agreement versus those that did not. RGGI states, primarily include north-eastern states of the country (mentioned in section 3.1). The control group encompasses of all other states except for those that border treated states to minimise potential spillovers which would imply a violation of the Stable Unit Treatment Value Assumption (SUTVA)[35]. To be more specific, if there is a sizable impact of RGGI, then it would be difficult to isolate the effect between treated and non-treated states that are intertwined economically (workers and firms operating between borders) due to proximity.

Along with that there is the absence of pre-treatment differences in the trends of outcomes. Although this cannot be directly tested, Figure 3.2 does motivate this consideration through visual inspection for the main outcome variable. For example, the average annual income from wages is largely parallel during the pre-treatment period.

3.4 Data

The data used in this chapter has been obtained from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). ASEC comprises of responses from individuals relating to their socio-economic status which includes unemployment durations, number of jobs held, reasons for unemployment, information on income, movements into and out of the labour force along with several other economic factors[36].

Following Hasanbeigi et al. (2012) study on California, table C1 of the appendix sheds light on energy and non-energy intensive sectors. Energy intensive sectors are defined as sectors that consume high amounts of energy per unit of output produced such as industrial, manufacturing etc. Whereas non-energy intensive sectors have low energy consumption relative to output. They have greater reliance on services and technology. In table 3.1 below, we present the descriptive statistics for our variables of interest (labour market factors) at treated and control states.

states when compared to non-RGGI ones, greatly impacting energy intensive sector. Nevertheless, we examine the impact on non-energy intensive sectors as a robustness.

[35] The excluded neighbouring states are West Virginia, Pennsylvania, Virginia, North Carolina, and Ohio.

[36] Those include health expenditure, household finance, childcare and poverty status etc.

Table 3.1: Descriptive Statistics

	Annual Income		Annual Weeks Worked		Years of Education		Energy Intensive Industry	Sample
Treated	Mean	SD	Mean	SD	Mean	SD	Share	N
Connecticut	43325.93	54737.1	46	13	13	2	0.22	12553
Delaware	38232.29	46930.82	47	13	12	2	0.21	9621
Maine	31482.93	36681.02	46	13	12	1	0.23	11508
Maryland	39624.04	48406.35	46	13	12	2	0.18	11119
Massachusetts	37272.64	46327.31	46	14	12	2	0.21	16511
New Hampshire	42222.95	49151.44	47	12	13	1	0.26	14590
New Jersey	37475	47145.76	46	14	12	2	0.22	20710
New York	34795.78	44287.97	46	14	12	2	0.18	34062
Rhode Island	35810.98	40390.96	46	14	12	2	0.22	10680
Vermont	33681.6	40342.19	47	12	12	1	0.23	10428
Average	37304.53		46		12		0.21	
Control	35495.27	44618.85	46	13	12	2	0.23	645153

Notes: The table contains summary statistics about the labour market outcomes of the treated and control states between 1990 and 2020. It also includes a description of the share of energy intensive industries. The variables are based on averages from the Current Population Survey of individuals working at those states.

Overall, we can see that treated and control states do not differ significantly. The share of energy intensive industries is relatively similar supporting the choice of our control group. Among treated states, New Hampshire has the highest share (26%), versus New York which has the lowest (18%). Similarities in overall averages are also seen for years of education between treated and control states. Annual income is average real wages deflated against the price index in 2015 (the base year). There exists variation in annual income between treated states where the highest wages are found in Connecticut and lowest in Maine. Yet, the overall average is identical to the control group across the years. Annual income and weeks worked are outcomes that we are investigating, and we are primarily interested in their trend after states began complying with the RGGI framework.

3.5 Results and Discussion

In this section, we present our key findings derived from comparing labour market outcomes between RGGI and non-RGGI states followed by a heterogeneity analysis considering education and industry characteristics.

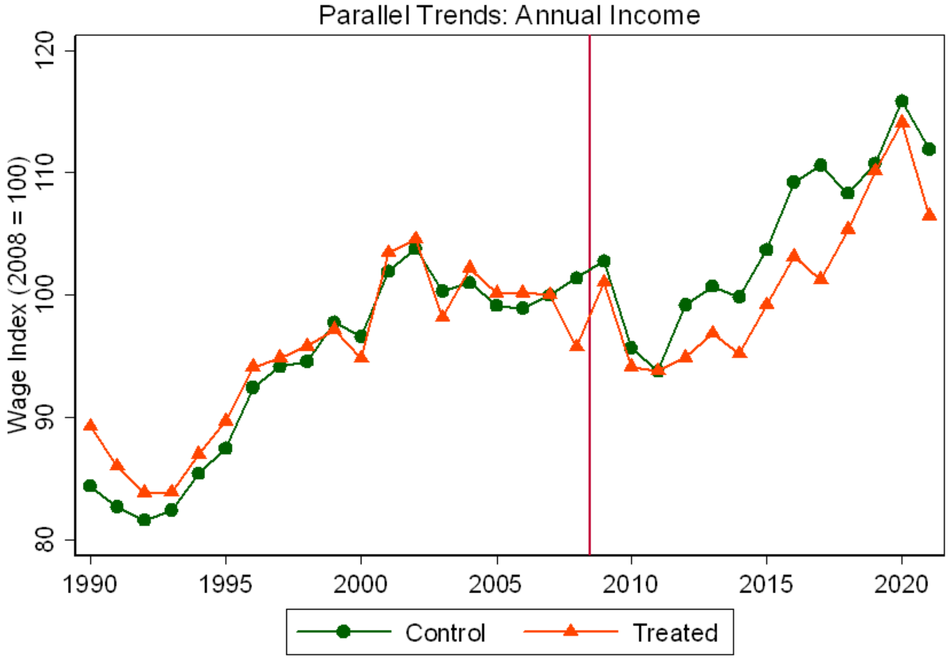
3.5.1 Main Results

We initially plot the trends of annual income from wages between the two groups. Figure 3.2 illustrates that annual income from wages follow parallel trajectories up to 2011, after which we witness a notable gap in earnings. We provide a formal test for the absence of pre-trends by employing the event study equation (3.1) to generate a better understanding.

Figure 3.3 presents estimates obtained from equation (3.1) considering annual income as the outcome variable. Focusing on the years prior to joining the RGGI, coefficients are close to zero and are not significantly significant. This confirms the absence of pre-trends between RGGI and non-RGGI states. Whereas after joining the RGGI, we observe a noticeable decline in annual income from wages at RGGI states when compared to non-RGGI ones starting from 4 years after the reform. On average, this is equivalent to 7% which supports the hypothesis that joining the RGGI had a negative impact on annual income for energy-intensive industries. In general, these findings are consistent with those obtained by Marin and Vona (2021) which showed that higher energy costs at French energy intensive sectors are translated into lower average wages. However, our findings contradict those studies which examined the impact of EUETS on wages. This reinforces the conclusions made by Marin et al. (2018) where they stated that wages are more rigid in EU countries.

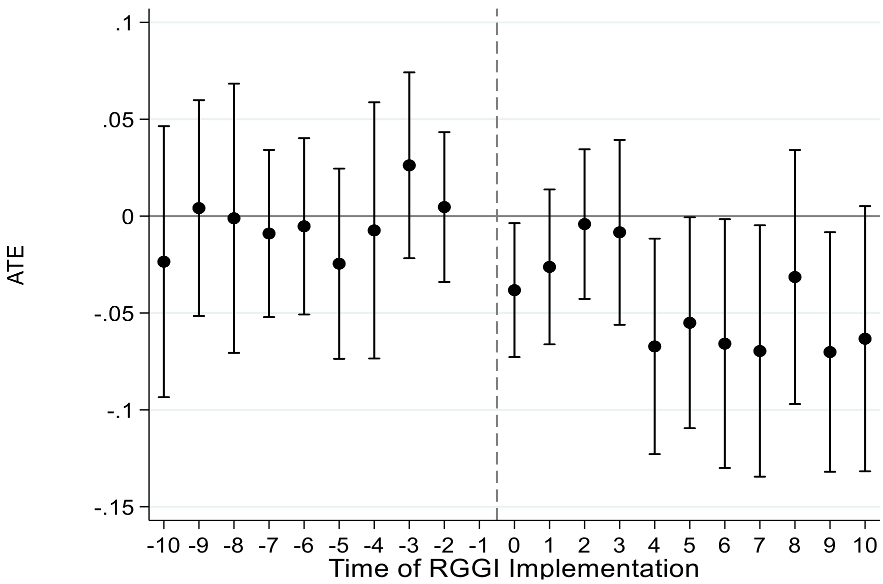
We also assess the impact of joining the RGGI by considering average weeks worked in a year and probability of unemployment. According to figures 3.4 and 3.5, one can see a weak negative impact occurring 4 years after joining the RGGI for treated states. There is a decline in average weeks worked (indicating reduced income) and a rise in probability of unemployment. These would be classified as an attempt by firms to cut costs on overtime hours and total wage bill. However, the outcomes are not statistically significant throughout the post-treatment period. This goes in hand with Deschenes (2010) who revealed that a rise in electricity prices had a negligible impact on employment rates in the US. We capture higher electricity prices post the imposition of RGGI in figure 3.1 of section 3.2. Our results are also consistent with Dechezlepretre et al. (2023) who found that the implementation of EUETS had an insignificant impact on the number of employees working in regulated states. As a result, the impact of RGGI on employment is identical to that of EUETS but differs when considering wages.

Figure 3.2



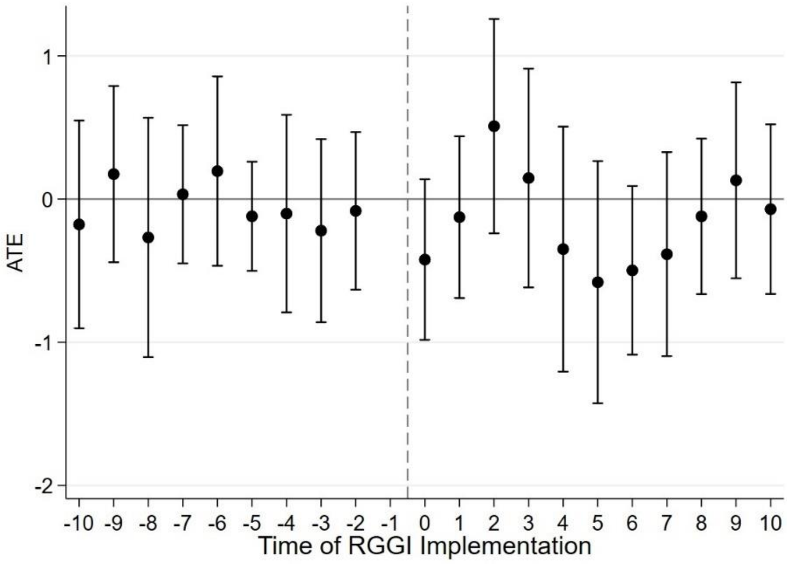
Notes: Figure 3.2 shows average annual income from wages for workers across US states between 1990 and 2020, with 2008 being the base year. Data is based on annual estimates from the Current Population Survey.

Figure 3.3: ATE on Treated of Log Annual Income from Wages



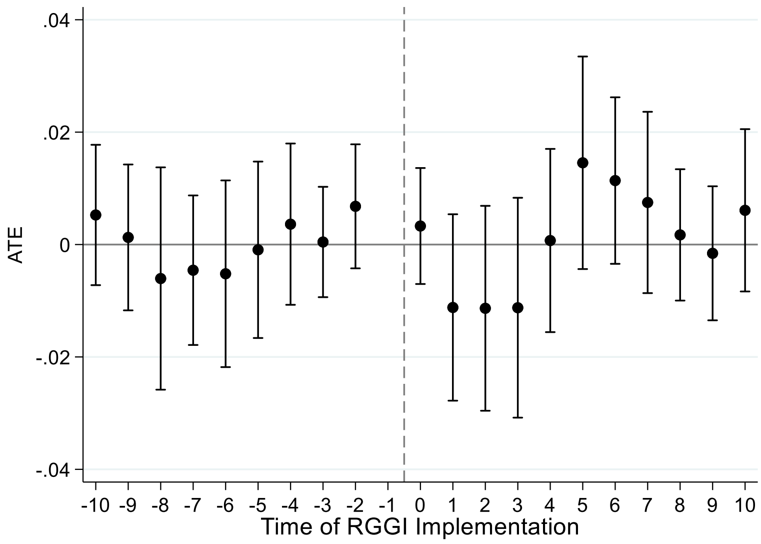
Notes: The figure shows an event study on the effect of states joining the RGGI framework on average income from wages of individuals working in energy intensive industries between 2000 and 2020. Coefficients are shown with 95% confidence interval (represented by vertical bars). These results are produced based on the event study model shown in equation (3.1) excluding neighbouring states.

Figure 3.4: ATE on Treated of Average Weeks Worked



Notes: The figure shows an event study on the effect of states joining the RGGI framework on average annual weeks worked of individuals working in energy intensive industries between 2000 and 2020. Coefficients are shown with 95% confidence interval (represented by vertical bars). These results are produced based on the event study model shown in equation (3.1) excluding neighbouring states.

Figure 3.5: ATE on Treated of Probability of Unemployment



3.5.2 Robustness

It is important to note that some non-RGGI states already have other carbon emission policies in place. These are listed in table C2 of the appendix. On that basis, our results are measuring the net effect of RGGI on variables of interest. Furthermore, we test the robustness of our results first, by assessing whether carbon emission policies at these states drive the impact on log annual income from wages, weeks worked and probability of unemployment. Figures 3.6 – 3.8 below demonstrate the outcome of this after dropping the list of states mentioned in table C2 of the appendix. We can see that our results remain unchanged meaning that carbon emission policies at these states have an insignificant impact on our variables of interest.

Figure 3.6: ATE on Treated of Log Income

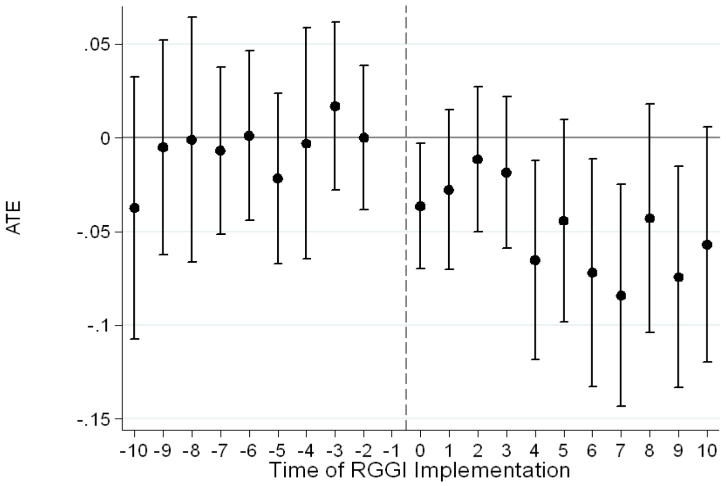


Figure 3.7: ATE on Treated of Average Weeks Worked

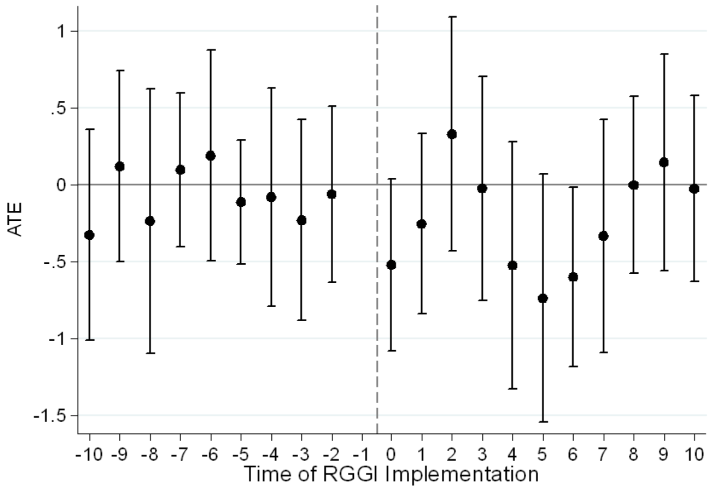
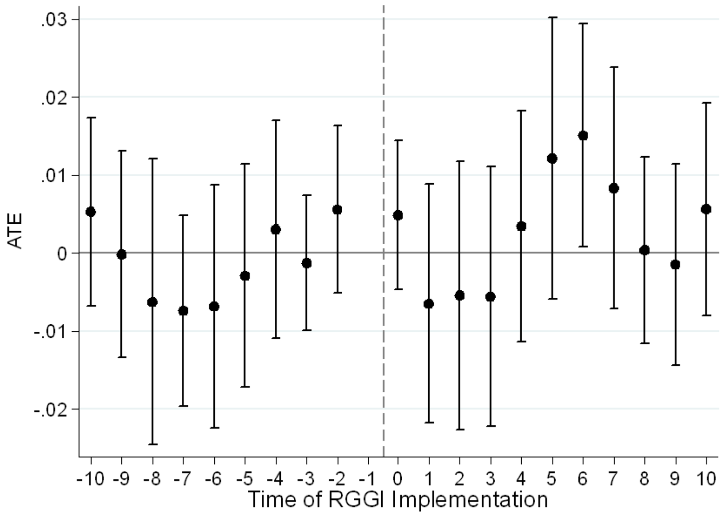


Figure 3.8: ATE on Treated of Probability of Unemployment



Notes: The figure shows an event study on the effect of states joining the RGGI framework on average annual weeks worked of individuals working in energy intensive industries between 2000 and 2020. Coefficients are shown with 95% confidence interval (represented by vertical bars). These results are produced based on the event study model shown in equation (3.1) excluding states mentioned in table C2.

Second, we examine how all treated states would be impacted and whether certain states might drive the impact of joining the RGGI. We do this by estimating equation (3.1) and excluding each treated states at a time. These findings are depicted in tables 3.2 - 3.4 for log annual income from wages, average weeks worked and probability of unemployment respectively below.

Table 3.2: Effects of RGGI on Log Annual Income from Wages

	Excludes										
	All States	Connecticut	Delaware	Maine	Maryland	Massachusetts	New Hampshire	New Jersey	New York	Rhode Island	Vermont
RGGI*Post	-0.055*	-0.053*	-0.048*	-0.059*	-0.053*	-0.057*	-0.058*	-0.049*	-0.056*	-0.057*	-0.056*
	(-0.016)	(-0.017)	(-0.015)	(-0.016)	(-0.017)	(-0.017)	(-0.017)	(-0.016)	(-0.018)	(-0.017)	(-0.017)
Observations	632,411	621,213	623,618	622,447	622,461	617,699	619,307	613,606	602,048	622,722	623,339

Table 3.3: Effects of RGGI on Average Weeks Worked

	Excludes										
	All States	Connecticut	Delaware	Maine	Maryland	Massachusetts	New Hampshire	New Jersey	New York	Rhode Island	Vermont
RGGI*Post	-0.052	-0.024	-0.010	-0.067	-0.011	-0.056	-0.095	-0.049	-0.113	-0.006	-0.093
	(0.143)	(0.145)	(0.140)	(0.149)	(0.140)	(0.152)	(0.147)	(0.154)	(0.151)	(0.138)	(0.145)
Observations	810,577	798,024	800,956	799,069	799,458	794,066	795,987	789,867	776,515	799,897	800,149

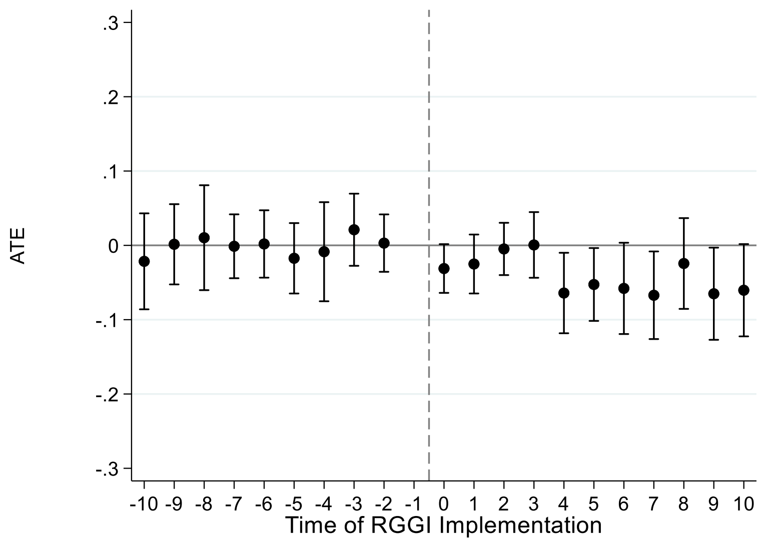
Table 3.4: Effects of RGGI on Probability of Unemployment

	Excludes										
	All States	Connecticut	Delaware	Maine	Maryland	Massachusetts	New Hampshire	New Jersey	New York	Rhode Island	Vermont
RGGI*Post	-0.004	-0.004	-0.004	-0.003	-0.005	-0.003	-0.002	-0.004	-0.001	-0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	810,577	798,024	800,956	799,069	799,458	794,066	795,987	789,867	776,515	799,897	800,149

*Note: The tables present Difference-in-Difference estimates of joining RGGI on the dependant variables Log Wages, Average Weeks Worked and Probability of Unemployment in 3.2, 3.3 and 3.4 respectively. Standard errors within the parenthesis are clustered at the state level. *Indicates that values are significant at 1%.*

Table 3.2 reports that the overall Difference-in-Difference (DiD) effect shows a 6% reduction in wages at RGGI states. The overall effect is similar across specifications meaning that no state drives the impact of joining RGGI. This is in line with what we obtained in the event study although with a negligible difference of 1% which is attributed to year 5 and 8 driving the average to 6%. When looking at tables 3.3 and 3.4, the overall DiD effect shows an insignificant decline in average weeks worked and probability of unemployment at RGGI states. The overall effect is also similar across specifications meaning that no state drives the impact of joining RGGI. This confirms our findings from the event study. Lastly, we introduce controls for race, sex and migration status of individuals and cluster standard errors by state. Figure 3.9 below shows that the impact remains valid for 4 years after the reform where it is statistically significant reinforcing our initial findings on log annual income from wages.

Figure 3.9: Event Study with Controls

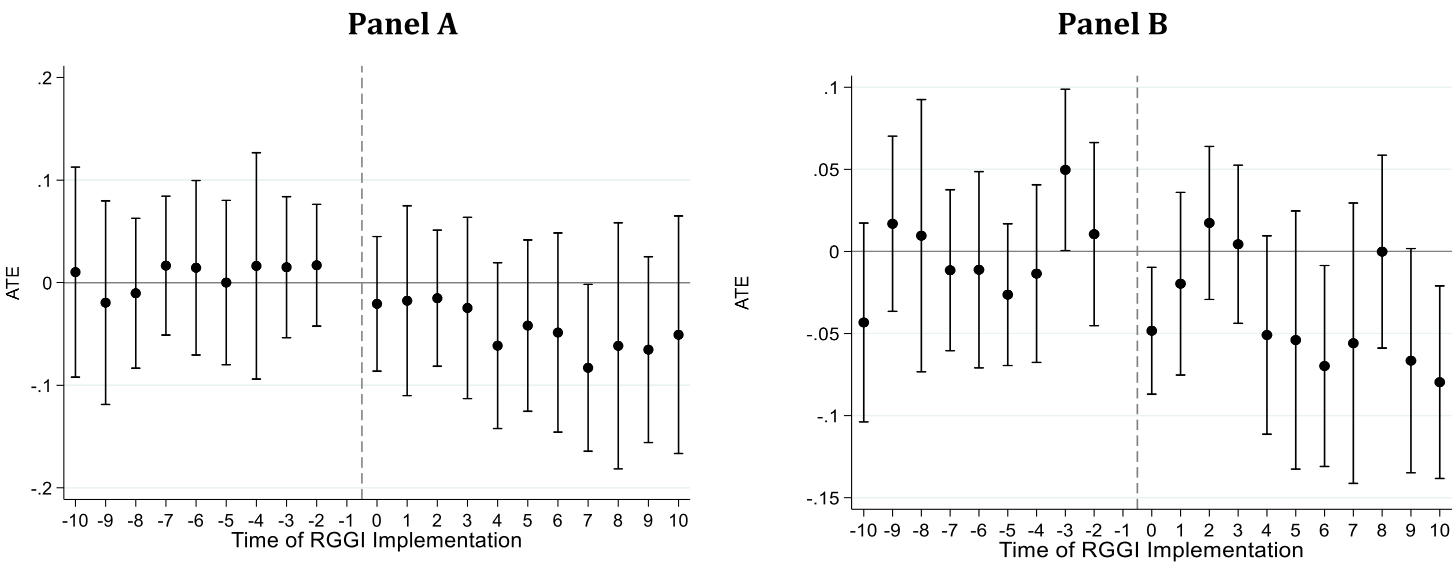


3.5.3 Heterogeneity Results

Workers' Education

Firm's response to labour market conditions could impact workers differently based on their characteristics. For that reason, we investigate the effect on workers in energy intensive sectors based on their education background proxied by having or not having a college education. Figure 3.10 presents estimation results from the event study model revealing a weak decline in log income for both groups but with no statistical significance in the post-treatment period. It is worth noting that, the effects are particularly more volatile for those with high school backgrounds (Panel B) when compared to those with college education (Panel A).

Figure 3.10: ATE on Treated of Log Income for Workers with and without College Education

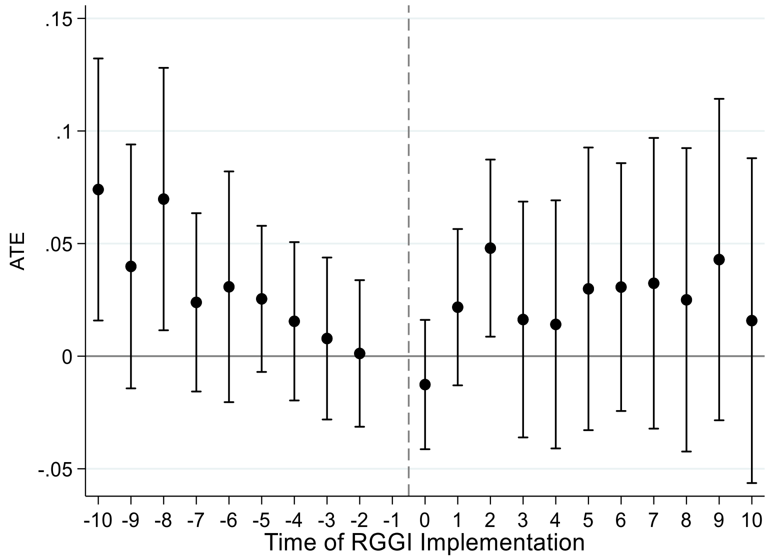


Notes: The figure shows an event study on the effect of states joining the RGGI framework on annual income from wages of individuals working in energy intensive industries between 2000 and 2020. Panel A shows the effect for college educated individuals while Panel B refers to those with high school education. Coefficients are shown with 95% confidence interval (represented by vertical bars). These results are produced based on the event study model shown in equation (3.1) excluding neighbouring states.

Non-Energy Intensive Industries

For completeness, we also examine the impact on individuals working at non-energy intensive sectors. Unlike our previous findings, figure 3.11 demonstrates that the impact of joining the RGGI seems to have a weak positive effect on annual income from wages for workers in non-energy intensive sectors. Yet, this effect is not significant for any of the post-treatment years.

Figure 3.11: ATE on Treated of Log Income for Non-Energy Intensive Industries



Notes: The figure shows an event study on the effect of states joining the RGGI framework on annual income from wages of individuals working in non-energy intensive industries between 2000 and 2020. Coefficients are shown with 95% confidence interval (represented by vertical bars). These results are produced based on the event study model shown in equation (3.1) excluding neighbouring states.

3.5.4 Discussion

Firms have multiple techniques to minimise the impact of higher energy costs. They could increase prices, enhance productivity, cut other costs etc. Indeed, Wildauer et al. (2023) found that non-energy intensive firms respond to energy price shocks by raising prices which undermines real wages. While Dechezlepretre et al. (2023) showed that the implementation of EUETS has encouraged firms to boost investment to increase productivity. The RGGI framework has had a noticeable increase in energy prices for states that adopted the cap-and-trade programme when compared to those that did not. The mechanism being that regulated firms were more likely to experience a rise in costs due to compliance with the scheme. As regulated firms grapple with higher costs stemming from compliance with the scheme, they are compelled to transfer these expenses downstream to firms who are more energy dependent. On average, the decline in annual income from wages accounts for about 7% 4 years after the reform. These results contradict the ones predicted by Paul et al. (2010) where they alleged that RGGI drives the creation of jobs and rise in wages. Instead, energy intensive firms operating in RGGI states renegotiated contracts to cut costs which justifies the decline in wages. Likewise, our findings are inconsistent with those which examined the impact of EUETS on wages. This reinforces the conclusions made by Marin et al. (2018) where they stated that wages are more rigid in EU countries. Instead, our results are aligned with existing literature undertaken to evaluate the impact of energy prices on wage rates (look at Marin and Vona, 2021; Battistini et al., 2022 for example).

When looking at the impact of RGGI on average weeks worked and probability of unemployment at energy intensive sectors, the effect is insignificant throughout the post treatment period. These findings confirm those in existing literature which concludes that the effect is negative but weak (see for example, Bijnens et al., 2022; Deschenes, 2010). They are also consistent with studies undertaken to assess the impact of EUETS on employment in Europe (see for example, Dechezlepretre et al., 2023; Chan et al., 2013). Lastly, the same insignificant result is also valid for our heterogeneity study which we used to examine the impact of RGGI on annual income from wages of workers at non-energy intensive sectors, workers holding a college or high school degree at energy intensive sectors. The former goes in hand with Wildauer et al. (2023) where non-energy intensive firms respond to energy price shocks by raising prices which undermines real wages. This re-emphasis the weak effect as it is not a direct impact on nominal wages. Never mind that prices and wages are sticky and are less likely to change by a large proportion within a short period of time.

3.6 Conclusion

To sum up, this chapter investigates the impacts of RGGI on annual income from wages, average weeks worked, and probability of unemployment in the US. Using data from ASEC of the CPS, we conduct an event study to capture the impact of RGGI post its implementation on the latter variables. A comparative study is also undertaken to account for the difference between the effect on states which enforced the policy versus those that did not. Our findings reveal a noticeable decline in annual income from wages of energy intensive workers at treated states when compared to control ones. On average, the decline in annual income from wages accounts for about 7% 4 years after the reform supported by (Pindyck, 1980; Mork and Hall, 1980; Mountain, 1986; Keane and Prasad, 1996; Rotemberg and Woodford, 1996; Kehrig and Ziebarth, 2017; Marin and Vona, 2021; Battistini et al., 2022). When looking at the impact of RGGI on average weeks worked and probability of unemployment at energy intensive sectors, the effect is not significant throughout the post treatment period in line with (Doğrul and Soytas, 2010; Arshad et al., 2016; Cuestas and Ordóñez, 2018; Kocaaslan, 2019; Kocaarslan et al., 2020;

Marin and Vona, 2021; Bijnens et al., 2022; Li et al., 2022b). Finally, the same insignificant result is also valid for our heterogeneity study which we used to examine the impact of RGGI on annual income from wages of workers at non-energy intensive sectors (consistent with Wildauer et al. (2023)), workers possessing a college or high school degree at energy intensive sector.

Appendix C

Table C1: Hasanbeigi et al. (2012) Energy and Non-Energy Intensive Sector Classification

Label	Energy	Non-Energy
AGRICULTURE, FORESTRY, AND FISHERIES		
Agricultural production, crops		✓
Agricultural production, livestock		✓
Veterinary services		✓
Landscape and horticultural services		✓
Agricultural services, n.e.c.		✓
Forestry		✓
Fishing, hunting, and trapping		✓
MINING		
Metal mining	✓	
Coal mining	✓	
Oil and gas extraction	✓	
Non-metallic mining and quarrying, except fuels	✓	
CONSTRUCTION		
All construction	✓	
MANUFACTURING		
Nondurable Goods		
Food and kindred products:		
Meat products		✓
Dairy products		✓
Canned, frozen, and preserved fruits and vegetables		✓
Grain mill products		✓
Bakery products		✓
Sugar and confectionery products		✓
Beverage industries		✓
Misc. food preparations and kindred products		✓
Food industries, n.s.		✓
Tobacco manufactures		✓
Textile mill products:		
Knitting mills	✓	
Dyeing and finishing textiles, except wool and knit goods	✓	
Carpets and rugs	✓	
Yarn, thread, and fabric mills	✓	
Miscellaneous textile mill products	✓	
Apparel and other finished textile products:		
Apparel and accessories, except knit	✓	
Miscellaneous fabricated textile products	✓	
Paper and allied products:		
Pulp, paper, and paperboard mills	✓	

Miscellaneous paper and pulp products	✓	
Paperboard containers and boxes	✓	
Printing, publishing, and allied industries:		
Newspaper publishing and printing	✓	
Printing, publishing, and allied industries, except newspapers	✓	
Chemicals and allied products:		
Plastics, synthetics, and resins		✓
Drugs		✓
Soaps and cosmetics		✓
Paints, varnishes, and related products		✓
Agricultural chemicals	✓	
Industrial and miscellaneous chemicals	✓	
Petroleum and coal products:	✓	
Petroleum refining	✓	
Miscellaneous petroleum and coal products	✓	
Rubber and miscellaneous plastics products:		
Tires and inner tubes	✓	
Other rubber products, and plastics footwear and belting	✓	
Miscellaneous plastics products	✓	
Leather and leather products:		
Leather tanning and finishing	✓	
Footwear, except rubber and plastic	✓	
Leather products, except footwear	✓	
Manufacturing, non-durable - allocated		
Durable Goods		
Lumber and woods products, except furniture:		
Logging	✓	
Sawmills, planning mills, and millwork	✓	
Wood buildings and mobile homes	✓	
Miscellaneous wood products	✓	
Furniture and fixtures	✓	
Stone, clay, glass, and concrete products:	✓	
Glass and glass products	✓	
Cement, concrete, gypsum, and plaster products	✓	
Structural clay products	✓	
Pottery and related products	✓	
Misc. non-metallic mineral and stone products	✓	
Metal industries:		
Blast furnaces, steelworks, rolling and finishing mills	✓	
Iron and steel foundries	✓	
Primary aluminium industries	✓	
Other primary metal industries	✓	
Cutlery, hand tools, and general hardware	✓	
Fabricated structural metal products	✓	

Screw machine products	✓	
Metal forgings and stampings	✓	
Ordnance:		
Miscellaneous fabricated metal products	✓	
Metal industries, n.s.	✓	
Machinery and computing equipment:	✓	
Engines and turbines	✓	
Farm machinery and equipment	✓	
Construction and material handling machines	✓	
Metalworking machinery	✓	
Office and accounting machines	✓	
Computers and related equipment	✓	
Machinery, except electrical, n.e.c.	✓	
Machinery, n.s.	✓	
Electrical machinery, equipment, and supplies:	✓	
Household appliances	✓	
Radio, TV, and communication equipment		✓
Electrical machinery, equipment, and supplies, n.e.c.	✓	
Electrical machinery, equipment, and supplies, n.s.	✓	
Transportation equipment:		
Motor vehicles and motor vehicle equipment	✓	
Aircraft and parts	✓	
Ship and boat building and repairing	✓	
Railroad locomotives and equipment	✓	
Guided missiles, space vehicles, and parts	✓	
Cycles and miscellaneous transportation equipment	✓	
Professional and photographic equipment, and watches:		
Scientific and controlling instruments		
Medical, dental, and optical instruments and supplies		✓
Photographic equipment and supplies	✓	
Watches, clocks, and clockwork operated devices	✓	
Toys, amusement, and sporting goods	✓	
Miscellaneous manufacturing industries	✓	
Manufacturing industries, n.s.		
TRANSPORTATION, COMMUNICATIONS, AND OTHER PUBLIC UTILITIES		
Transportation:		
Railroads	✓	
Bus service and urban transit	✓	
Taxicab service	✓	
Trucking service	✓	
Warehousing and storage	✓	
U.S. Postal Service		✓
Water transportation	✓	
Air transportation	✓	

Pipelines, except natural gas	✓	
Services incidental to transportation		
Communications:		
Radio and television broadcasting and cable		✓
Wired communications		✓
Telegraph and miscellaneous communications services		✓
Utilities and sanitary services:		
Electric light and power	✓	
Gas and steam supply systems	✓	
Electric and gas, and other combinations	✓	
Water supply and irrigation	✓	
Sanitary services	✓	
Utilities, n.s.	✓	
WHOLESALE TRADE		
Durable Goods:		
Motor vehicles and equipment	✓	
Furniture and home furnishings	✓	
Lumber and construction materials	✓	
Professional and commercial equipment and supplies	✓	
Metals and minerals, except petroleum	✓	
Electrical goods	✓	
Hardware, plumbing and heating supplies	✓	
Machinery, equipment, and supplies	✓	
Scrap and waste materials	✓	
Miscellaneous wholesale, durable goods	✓	
Nondurable Goods:		
Paper and paper products		✓
Drugs, chemicals, and allied products		✓
Apparel, fabrics, and notions		✓
Groceries and related products		✓
Farm-product raw materials		✓
Petroleum products	✓	
Alcoholic beverages		✓
Farm supplies		
Miscellaneous wholesale, nondurable goods		
Wholesale trade, n.s.		
RETAIL TRADE		
Lumber and building material retailing	✓	
Hardware stores	✓	
Retail nurseries and garden stores		✓
Mobile home dealers		✓
Department stores		✓
Variety stores		✓
Miscellaneous general merchandise stores		✓

Grocery stores		✓
Dairy products stores		✓
Retail bakeries		
Food stores, n.e.c.		✓
Motor vehicle dealers	✓	
Auto and home supply stores	✓	
Gasoline service stations	✓	
Miscellaneous vehicle dealers	✓	
Apparel and accessory stores, except shoe	✓	
Shoe stores	✓	
Furniture and home furnishings stores	✓	
Household appliance stores		
Radio, TV, and computer stores		✓
Music stores		✓
Eating and drinking places		✓
Drug stores		✓
Liquor stores	✓	
Sporting goods, bicycles, and hobby stores	✓	
Book and stationery stores	✓	
Jewellery stores	✓	
Gift, novelty, and souvenir shops	✓	
Sewing, needlework, and piece goods stores	✓	
Catalogue and mail order houses	✓	
Vending machine operators	✓	
Direct selling establishments	✓	
Fuel dealers	✓	
Retail florists	✓	
Miscellaneous retail stores	✓	
Retail trade, n.s.		
FINANCE, INSURANCE, AND REAL ESTATE		
Banking		✓
Savings institutions, including credit unions		✓
Credit agencies, n.e.c.		✓
Security, commodity brokerage, and investment companies		✓
Insurance		✓
Real estate, including real estate-insurance offices		✓
BUSINESS AND REPAIR SERVICES		
Advertising		
Services to dwellings and other buildings		✓
Personnel supply services		✓
Computer and data processing services		✓
Detective and protective services		✓
Business services, n.e.c.		✓
Automotive rental and leasing, without drivers	✓	

Automobile parking and carwashes	✓	
Automotive repair and related services	✓	
Electrical repair shops	✓	
Miscellaneous repair services		✓
PERSONAL SERVICES		
Private households		✓
Hotels and motels		✓
Lodging places, except hotels and motels		✓
Laundry, cleaning, and garment services		✓
Beauty shops		✓
Barber shops		✓
Funeral service and crematories		✓
Shoe repair shops		✓
Dressmaking shops		✓
Miscellaneous personal services		✓
ENTERTAINMENT AND RECREATION SERVICES		
Theatres and motion pictures		✓
Video tape rental		✓
Bowling centres		✓
Miscellaneous entertainment and recreation services		✓
PROFESSIONAL AND RELATED SERVICES		
Offices and clinics of physicians		✓
Offices and clinics of dentists		✓
Offices and clinics of chiropractors		✓
Offices and clinics of optometrists		✓
Offices and clinics of health practitioners, n.e.c.		✓
Hospitals		✓
Nursing and personal care facilities		✓
Health services, n.e.c.		✓
Legal services		✓
Elementary and secondary schools		✓
Colleges and universities		✓
Vocational schools		✓
Libraries		✓
Educational services, n.e.c.		✓
Job training and vocational rehabilitation services		✓
Child day care services		✓
Family childcare homes		✓
Residential care facilities, without nursing		✓
Social services, n.e.c.		✓
Museums, art galleries, and zoos		✓
Labor unions		✓
Religious organisations		✓

Membership organisations, n.e.c.	✓
Engineering, architectural, and surveying services	✓
Accounting, auditing, and bookkeeping services	✓
Research, development, and testing services	✓
Management and public relations services	✓
Miscellaneous professional and related services	✓
PUBLIC ADMINISTRATION	
Executive and legislative offices	✓
General government, n.e.c.	✓
Justice, public order, and safety	✓
Public finance, taxation, and monetary policy	✓
Administration of human resources programmes	✓
Administration of environmental quality and housing programmes	✓
Administration of economic programmes	✓
National security and international affairs	✓
ACTIVE DUTY MILITARY	
Armed Forces:	✓
Army	✓
Air Force	✓
Navy	✓
Marines	✓
Coast Guard	✓
Armed Forces, branch not specified	✓
Military Reserves or National Guard	✓
Unknown	✓

Table C2: Non-RGGI States with Other Carbon Emission Policies

State	Carbon Emission Policy (Date of Implementation)
California	California Global Warming Solutions Act (2006)
Colorado	Greenhouse Gas Pollution Reduction Roadmap (2019)
Hawaii	Hawaii Climate Change Mitigation and Adaptation Initiative (2007)
Minnesota	Next Generation Energy Act (2007)
Nevada	Nevada Climate Initiative (2019)
Oregon	Oregon Climate Action Program (2007)
Washington	Climate Commitment Act (2008)

Source: Energy Information Administration (2022)

Conclusion

This thesis offered an empirical investigation of the impacts of oil prices and stock market volatility in the United States (US), Canada (CAN), France (FRA), the United Kingdom (UK), and Japan (JAP) accompanied by the effects of Regional Greenhouse Gas Initiative (RGGI) on US labour market outcomes. Its aim was to address the following research questions:

1. Can volatility of oil prices explain the volatility of returns in sectoral stock indices, exchange rates, interest rates, precious metals, and cryptocurrencies?

2. Does this explanation differ; (a) between oil exporting and oil-importing countries (b) before and during the COVID-19 pandemic?

3. Do returns volatility of each sectoral stock index respond to shocks from the FTSE4Good USA (F4GU) index?

4. What is the proportion of sectoral stock index returns volatility explained by that of the F4GU index?

5. Does RGGI has an impact on average income, weeks worked and unemployment?

6. Is there a difference between the impact on employees working at energy and non-energy intensive sectors?

Each chapter addresses two research questions separately. When dealing with questions (1) and (2), the first chapter sheds light on the impacts oil price volatility on two sets of countries; oil-exporting (US, and CAN) and oil-importing (UK, FRA, and JAP). We begin by estimating the univariate GARCH model prescribed by Gibson et al. (2017) for all sixteen variables (i.e., crude oil price, eleven sectoral stock indices, 3-month deposit rate, nominal effective exchange rate, gold price and Bitcoin) individually and for the summation of crude oil prices with each of the remaining fifteen variables. This technique enables us to overcome the dimensionality issues posed by traditional MGARCH models along with other restrictions discussed in previous literature. The time varying conditional correlations are then generated which are used to answer our research questions. Pre COVID-19, our findings reveal that oil-exporting countries share the same significant positive correlation between oil price and all sectoral stock index returns (aside from Canadian energy and United States telecommunication sectors).

However, results are rather ambiguous for oil-importing countries. During the pandemic, we found that sectoral stock index returns of all countries share the same significant positive correlation (aside from Canadian energy sector) with oil price. Finally, gold and oil price are found to be significantly positively correlated before and during the pandemic.

Speaking of questions (3) and (4), the second chapter makes use of the F4GU index to investigate its returns volatility spillover effect on the sectoral stock indices of the US main trading partners (CAN, JAP, and the UK). Initially, we conduct an estimation of the GARCH family to obtain the optimum time varying conditional variances. The corresponding volatility series are then generated and assessed in a multivariate VAR model. To answer question (3), we obtain the Impulse Response Functions (IRF) to comprehend the persistence, direction, and magnitude of the response of each sectoral stock index returns volatility to one standard deviation variation in the F4GU index. The variance decompositions are then calculated to understand the proportion of sectoral stock index returns volatility explained by that of the F4GU index (answering question 4). All sectoral stock indices (aside from Canadian health care, British real estate, financials, information technology and consumer discretionary) reveal a positive response shock to a sudden increase in volatility of returns in the F4GU index. The spillover effect is greatly pronounced between 5 to 15 days for all three countries. In addition, returns volatility of the F4GU index explains more than 14%, 3.5% and 5% of the returns volatility in most Canadian, British, and Japanese sectoral stock indices respectively on the 25th day period. The highest explanation corresponds to the real estate sector of CAN and JAP at 18.6% and 28% while it’s health care for the UK at 9% on that particular day.

Addressing questions (5) and (6), the third chapter evaluates the impacts of RGGI on US labour market outcomes. To answer question (5), an event study is undertaken to capture the impact of RGGI post its imposition on average income, weeks worked and unemployment. This also assists us in conducting a comparison between employees working at energy and non-energy intensive sectors thereby addressing question (6). Our findings reveal a noticeable decline in annual income from wages of unskilled workers (without a college or high school degree) in energy intensive sectors. On average, the decline in annual wages accounts for about 7% 4 years after the reform. However, no effect was detected for skilled workers in these sectors. Similarly, we do not find any significant impact of RGGI on average weeks worked and probability of unemployment. Let alone any impact on wages and employment status of workers in non-energy intensive sectors.

When looking at all of the possibilities, this thesis was limited to the key questions addressed in each chapter. Areas of future potential research in relation to chapter 1 could examine whether volatility of Bitcoin prices is able to explain the volatility of returns in sectoral stock indices. Supplementing this would be an investigation of the spillover effect from the former to latter set of variables in line with chapter 2. Daily data with a large sample size converted into sub-samples covering the Great Financial Crisis, Brexit, COVID-19 pandemic, Russian and Ukrainian war would provide an insight of the impact of Bitcoin across multiple economic and political episodes. Financial institution, investors and portfolio managers would be interested in findings from such studies when deciding on their investment decisions. Speaking of our third chapter, analysis of the impacts of RGGI on the level of output at energy and non-energy intensive sectors has not been addressed. Let alone the impacts of other climate change mitigation policies on labour market outcomes. A comparative study could be undertaken to assess which policy would yield the greatest minimisation in carbon emissions whilst having the least impact on the labour market and overall economy. This would equip policy makers with a comprehensive analysis of the impacts of climate change mitigation policies.

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