Three essays on the effects of oil prices on imports and exports to China

by

Jiazhen Liu

B.S., Guangxi University, 2017
M.S., Rutgers University, New Brunswick, 2019
M.A., Kansas State University, 2021

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

This dissertation consists of three essays: In the first study, I investigate the macroeconomic response of Asian crude oil importers to oil supply news shocks based on OPEC public announcements using a Structural VAR framework. I look into the macro aspects of the seven largest crude oil importers in Asia through exchange rate channels. My empirical results on the economic aspects indicate that Asian oil importers' economies receive insignificant effect from oil supply news shocks, especially aggregated exports and aggregated imports. My analysis suggests that the effective exchange rate can be an additional channel through which oil news shocks affect the Asian economies indirectly.

In terms of the second study, I investigate the export prices for primary agricultural commodities in responses to oil supply news shocks based on the OPEC public announcements. The research is carried out using a Structural VAR instrumented variable framework. I look into the primary agricultural commodities sold from ASEAN members to China, including rubber, palm oil and rice. My empirical results indicate that export prices for primary agricultural commodities in ASEAN receive in but short-run effects from oil supply news shocks. My findings also suggest that the shipping costs between ASEAN and China may be a key channel for the information transmitted from the oil supply news shocks to the ASEAN agricultural commodities prices.

The third essay looks into the Chinese non-ferrous metal imports in response to the oil supply news shocks based on the OPEC public announcements as well as the Chinese trade policy uncertainty. The research on oil supply news is carried out using a Structural VAR instrumented variable framework while the trade policy uncertainty is investigated with TVP-

VAR model. In this paper, I look into the primary non-ferrous metals imported by China, including copper, nickel, aluminum, lead, zinc and tin. My empirical results indicate that the values and spot prices of Chinese non-ferrous metal imports receive little effects from the oil supply news shocks due to contract settlement method. My findings also suggest that an increasing of the Chinese trade policy uncertainty leads to diverse responses of the non-ferrous metal import values but negative responses for the non-ferrous metal import prices.

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Major Professor
Steve.P.Cassou

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Acknowledgements

This dissertation is a product of the help, support, and guidance of people I look up to. First and foremost, I am very grateful to have had Dr. Steven P. Cassou as my major professor. It is an often cliché, but in this case, it is no overstatement to say that this dissertation only exists because of his consistent guidance, tutelage, support, unparalleled knowledge, and encouragement. He has always been there for me, either in the office or an email away. His willingness to help me has significantly contributed to instilling a love of econometrics. The extensive discussions held with him on both Macroeconomic Modelling class and research have inspired me a lot, and I look forward to working with him in the future.

In addition to serving on my dissertation committee, I want to thank Dr. Peri da Silva first for taking the time to serve as the member of my dissertation committee. Without his help and support, I couldn’t have the progress today. I owe my deep gratitude to Dr. Yoonjin Lee, for her teaching of Econometrics I and Dr. Jisang Yu, for his teaching of Quantitative Topics of Agricultural Economics, was a driving force in my decision to choose econometrics as the field of specialization.

Undoubtedly, I have been blessed with the constant support of my family members, especially my parents and cousins. I am truly thankful for and extremely appreciative of their love, support, and unwavering belief in me. Without them, I would not be the person I am today.

Finally, to everyone who has offer me with their helps in my life (and, consequently, in this work) without mentioning their names therein, I would like to present my appreciations for everything you have done for me.

Chapter 1 - The impact of oil supply news shocks on Asian crude oil importers: An empirical approach via the exchange rate channel

1.1 Introduction

A long-standing question in the economics is how the expectation for oil prices affects ASEAN agricultural commodity price has been attracting the attention of economists due to the turbulence in the world economies over the past decade. One of the challenges in answering this question is the endogeneity of future oil prices and its response to global trade flows. To provide a potential explanation, the researcher needs to exploit the foundations that drives future oil prices.

In this paper, I examine the effects of oil news shocks driving the economies of major oil importers in Asia, under different condition of currency regimes. I use the structural Vector Auto Regression (SVAR) model with oil news shocks to investigate this issue. The oil news shocks are identified by following the design in Känzig (2021) which exploits the official announcements of the meeting of the Organization of the Petroleum Exporting Countries (OPEC) and information implied by oil future price..

It is revealed that oil supply news shocks have statistically and economically effects on the main Asian oil importers' economies. Negative OPEC news about future oil supplies lead to a short run increase in Chinese industrial production and Japanese industrial production and persistent increases for five other major Asian oil importers. However, we obtain diverse responses to positive oil news shocks for CPI and real GDP. Oil status variations across Asian oil importers contribute to different responses of effective exchange rates to oil news shocks. For instance, Chinese effective exchange rates perform similarly to U.S. effective exchange rates found by Känzig (2021) when a positive oil shock happen because China is the second largest oil importer and consumer in the world with little oil product export. However, for India, as the third largest oil importer in Asia, I found that the Indian effective exchange rate depreciates in response to positive oil supply news shocks because India is the second largest refined oil exporter in Asia. In terms of aggregated trade, the impulse response function results reveal that aggregated export and aggregated import react positively and in response to oil news shocks while the terms of trade decreases in response to the shocks.

A comprehensive set of sensitivity checks indicate that my results are robust along several dimensions such as the term structure and sample period. I also show that my elasticity result is not lag sensitive as I choose a different lag.

The rest of the paper is organized as follows: Section 1.2 reviews the literatures. Section 1.3 presents the data sources. Section 1.4 describes the methodology. Section 1.5 reports and discusses the results. Section 1.6 concludes the paper.

1.2 Literature Review

1.2.1 Institutional Background

The identification of the expectations-driven component of oil shocks has been a contentious topic for researchers and policymakers and has been investigated by Kilian (2009). The drivers for oil fluctuations consist of oil demand, oil supply and oil precautionary demand. An approach to address this identification problem is to utilize oil inventory data on the standard oil market model. Kilian and Murphy (2014) applied US crude oil inventories data and OECD petroleum stocks data on the structural VAR model. They found out that demand expectation shifts can be identified with oil inventories and these shifts drive the oil price shock in the short run. Juvenal and Pettrella (2015) included similar data in their dataset for analyzing the role of speculation under a dynamic factor framework. Their finding revealed that speculation shocks, or oil precaution demand shocks, were the second strongest driver in the oil market. Although these existing inventory-based strategies identify oil precaution demand, they are not able to disentangle how different types of news affect the oil market.

In identifying the news shocks, traditionally, the literature focuses on technological changes, shocks in monetary policy and fiscal policy shocks. In terms of the response to technological changes, Beaudry and Portier (2006) found out the economy reacted strongly to technological news and Barskey and Sims (2011) concluded that the technological news shock is a subtle driver of the business cycle. Turning to monetary policy shocks, Christiano, L. J., Ilut, C. L., Motto, R., & Rostagno, M. (2008) provided evidence that a Taylor-rule-based monetary policy helped in generating a welfare-reducing “boom-bust” cycle in response to a news shock. and Cúrdia, V., & Woodford, M. (2016) extended the New Keynesian model with an interest spread and investigated the consequences of a variable credit spread for the effects of a variety of shocks. A typical example of fiscal policy shocks was investigated by Leeper, E. M., Walker, T. B., and Yang, S.-C. S. (2013). In the paper, the authors studied the tax policy changes and found that fiscal news reduced quantitative inference errors generated by macro policy analysis models.

Recently, interest in oil news shocks effect on economic variables has been increasing as there is growing literature on this topic. Su, Z., Lu, M., & Yin, L. (2018) exploited the relationship between news implied volatility (NVIX) and classic oil shocks. They wanted to investigate whether the world price of oil and oil shocks promoted by Kilian (2009) affected news-based uncertainty or Vice versa. Their results illustrate that oil prices exhibit a statistically and economically leading role on NVIX, especially in the long run. In terms of specific oil shocks, the authors found out that NVIX had the opposite direction with classic oil shocks except for the oil supply shocks. Känzig (2021) studied the OPEC announcement news shocks on the global market as well as the U.S. macroeconomy under a structural VAR framework with external instruments. The instrument is the OPEC announcement news shocks series which is constructed by utilizing WTI future prices in a tight window of announcements. The outcome of this paper provided evidence that the OPEC announcement news can be a strong channel through which researchers can study the wide effects on an oil importer's oil supply expectations. Liu, D., Wang, Q., & Yan, K. X. (2022) focused on similar oil supply news shocks for the Chinese economy. Their work provided evidence that the oil supply news shock only affected the Chinese economy through the exchange rate and trade balance.

All the previous works focus on analyzing the impact of news shocks on individual markets. However, there is little literature focusing on how news shocks, especially oil news shocks, affect cross-country markets or economies simultaneously, conditioning on the different status of oil trade and currency regimes. My study tries to fill the gap in the literature and shed light on the effect of oil news shocks on the economies of the 7 largest oil importers in Asia, which accounts for about 45% of total oil imports in the world.

This paper is not the first to investigate the impact of oil prices on exchange rate. Historically, there are numerous articles analyzing the co-movement of oil prices and exchange rates (Sari, R., Hammoudeh, S., & Soytas, U. (2010); Ghosh, S. (2011); Volkov, N. I., & Yuhn, K. H. (2016); Reboredo, J. C., & Rivera-Castro, M. A. (2013), Hussain, M., Zebende, G. F., Bashir, U., & Donghong, D. (2017), among others). Also, researchers have tried to find the linkage between oil shocks and a single economy through the macro aspects in which the exchange rate is one of the endogenous elements. For instance, Aliyu, S. U. R. (2009) assessed the impact of oil price shocks and real exchange rate volatility on real economic growth in Nigeria via Granger causality test and Johansen VAR-based co-integration techniques. His results showed that there were unidirectional causality from oil prices to real GDP and bidirectional causality from real exchange rate to real GDP and vice versa. These findings further showed that oil price shock and appreciation in the level of the exchange rate exert positive impacts on real economic growth in Nigeria. Then, in 2015, Basnet, H. C., & Upadhyaya, K. P. (2015) exploit the SVAR model to study the impact of oil price shocks on real output, inflation and the real exchange rate in Thailand, Malaysia, Singapore, the Philippines and Indonesia (ASEAN-5). According to their findings, ASEAN-5 countries share common trends of macroeconomic variables in the long run. The oil price fluctuations do not impact the ASEAN-5 economies in the long run and much of its effect is absorbed within five to six quarters. Later, Yildirim, Z., & Arifli, A. (2021) attempt to ascertain how the macroeconomic effects of adverse oil price shocks on a small oil-exporting economy — the Azerbaijan economy. With the help of a recursive (near) VAR model, they manage to provide evidence that the Azerbaijan economy is adversely influenced by an oil price decline. Furthermore, their findings imply that the oil price-led devaluation shapes the inflationary and recessionary consequences of the oil shock. All these previous works focus on a single market or single oil exporting country. In this paper, the research expands the objective by studying oil importers with different macro characters. In addition, in contrast to the previous existing studies that only include a few macro variables such as GDP, trade balance and CPI when they study the effect of oil shocks on exchange rate. This paper extends the study by adding up industrial production and world market analysis.

1.2.2 Oil Importers Status

The majority of the demand for the global oil market is made up of only a few economics. Aside from the U.S., from 1995 to 2020, the largest buyer of crude oil was China in total value. The following part presents background used in this study for the sample oil importers in the global oil market. This background information is based on the database from the Observatory of Economic Complexity (OEC). Graphic presentations can also be found in Appendix A.3, see through Figure A.3.1 to Figure A.3.13.

1.2.2.1 China

During the period from 1995 to 2020, China imported the 2nd largest value of crude oil with total value of $2.29 trillion. Crude oil is mostly imported by China from Saudi Arabia ($384 billion, 16.8%), Angola ($317 billion, 13.8%), Russia ($257 billion, 11.2%), Oman ($196 billion, 8.56%), Iran ($162 billion, 6.93%), and Iraq ($158 billion, 6.92%). In 2019, according to the U.S. Energy Information Administration's 2020 report, China consumed an estimated 14.5 million barrels per day (b/d) of petroleum, along with an approximate production level of 3.92 million b/d.

Turning to refined petroleum, in the 25 years from 1995 to 2020, China had imported $398 billion of refined oil, which was close to its $323 billion refined oil export.

1.2.2.2 Japan

From 1995 to 2020, Japan imported the 3rd largest value of crude oil with a total value of $1.71 trillion. Crude oil is mostly imported by Japan from Saudi Arabia ($518 billion, 30.4%), United Arab Emirates ($431 billion, 25.3%), Qatar ($165 billion, 9.67%), Iran ($146 billion, 8.56%), Kuwait ($124 billion, 7.3%), and Russia ($69.3 billion, 4.06%). The 2020 EIA analysis summary report regarding Japan revealed that Japan's oil consumption was an estimated 3.7 million b/d in 2019, making it the fifth-largest petroleum consumer in the world behind the United States, China, India, and Russia.

Then, in terms of refined petroleum, over this 25-year sample period, Japan purchased about $356 billion of refined oil from abroad while only selling $171 billion of refined oil in abroad total.

1.2.2.3 India

The OEC visual data indicated that India had imported the 4th largest value of crude oil with a total value of $1.29 trillion throughout 1995 to 2020. The main seller of crude oil to India included Saudi Arabia ($250 billion, 30.4%), Iraq ($181 billion, 14.1%), Russia ($147 billion, 11.5%), the United Arab Emirates ($107 billion, 8.29%), Kuwait ($106 billion, 8.27%), and Iran ($104 billion, 8.06%). EIA's 2020 summary report for India indicated that India was the third-largest consumer of crude oil and petroleum products after the United States and China in 2019. Meanwhile, the gap between India's oil demand and supply is widening. Demands for crude oil in 2019 reached 4.9 million b/d, compared to less than 1 million b/d of total domestic liquids production.

In consideration of refined petroleum, from 1995 to 2020, India exported $594 billion value of refined oil and only imported $103 billion of refined oil. This makes India the largest net refined oil exporter in my sample economies.

1.2.2.4 South Korea

As the 5th largest crude petroleum importer in the world from 1995 to 2020, South Korea had total imports of crude oil valued at $1.18 trillion. For South Korea, the main source of crude oil import came from Saudi Arabia ($367 billion, 31.1%), Kuwait ($146 billion, 12.4%), the United Arab Emirates ($145 billion, 12.3%), Iran ($81.8 billion, 6.94%), Iraq ($81.4 billion, 6.91%), and Russia ($65.7 billion, 5.58%). The EIA 2020 summary report for Korea mentioned that South Korea consumed 2.5 million barrels per day (b/d) of petroleum and other liquids in 2019, making it the eighth-largest consumer of oil in the world.

South Korea is a net exporter of oil products. The country exported an estimated 1.4 million b/d of refined oil products in 2019, mostly in the form of middle distillates such as gasoil, gasoline, and jet fuel. Oil product imports, accounting for almost 1.0 million b/d in 2019 and were primarily naphtha and LPG.

1.2.2.5 Chinese Taiwan

Chinese Taiwan had the 8th highest crude oil import in the world from 1995 to 2020, after importing $806 billion in crude oil. Crude oil was mainly purchased from countries like Saudi Arabia ($272 billion, 33.8%), Iran ($181 billion, 22.5%), Venezuela ($72.9 billion, 9.82%), Kuwait ($74.3 billion, 9.21%), and the United Arab Emirates ($46.5 billion, 5.77%). According to the EIA's report in 2016, oil made up 48% of Chinese Taiwan's total primary energy consumption in 2015, which was almost 1.1 million b/d of petroleum.

Due to a 98% total energy import dependence, as claimed by the administrative agency of Chinese Taiwan, Chinese Taiwan was also a net importer of refined petroleum from 1995 to 2020 when it imported $295 billion of refined oil and exported $188 billion.

1.2.2.6 Singapore

Crude petroleum was Singapore's fourth-most-imported product in 2020. Over the period from 1995 to 2020, Saudi Arabia ($115 billion, 25.5%), the United Arab Emirates ($87.2 billion, 19.3%), Qatar ($70.7 billion, 15.6%), Kuwait ($43.9 billion, 9.69%), and Australia ($21.1 billion, 4.65%) were the main suppliers for a total $453 billion value of crude oil to Singapore. According to EIA's 2021 report, Singapore is the fifth-largest refinery and export hub in the world and among the top 10 exporters of petrochemicals. From 1995 to 2020, Singapore exported $911 billion of refined oil in total. Most of Singapore's refined petroleum products and petrochemical exports were destined for neighboring Asian countries. China, Indonesia, India, Malaysia, Thailand, and Vietnam were the top destinations for Singapore's petrochemical exports.

1.2.2.7 Thailand

During the 25-year period from 1995 to 2020, the United Arab Emirates ($129 billion, 33.3%), Saudi Arabia ($71.3 billion, 18.4%), Oman ($32.9 billion, 8.49%), Malaysia ($29 billion, 4.47%), and Qatar ($22.3 billion, 5.74%) were the main countries from which Thailand received crude oil with a value of $388 billion. Regarding Thai oil production and consumption in EIA's 2017 summary report, from 2016, Thailand's petroleum and other liquids production was an estimated to be 525,000 barrels per day while its total oil consumption was estimated to be nearly 1.3 million b/d.

As a net refined oil exporter, Thailand had the second largest capacity (1.2 million b/d) in Southeast Asia, behind Singapore in 2016, according to FACTS Global Energy. Thailand exported $118 billion of refined oil to the regional markets nearby, lasting from 1995 to 2020, with an import of $58.8 billion over the same period.

1.2.3 About OPEC

Founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela, OPEC is an intergovernmental organization of petroleum production countries. By the end of 2019, OPEC consisted of 13 member countries in total. In the year 2019, its output of crude petroleum took up 48.03% of crude oil exports (based on the Observatory of Economic Complexity 2019 data for crude petroleum exporters), making it the largest supplier in the world oil trade.

By its declamation in its statute, OPEC focuses on the coordination and unification of petroleum policies across member countries. Their mission also tries to ensure the stabilization of oil markets for the security of providing an efficient, economic and regular supply of petroleum to consumers, a steady income to producers and a fair return on capital for those investing in the petroleum industry.

Before 2021, the decision for oil production policies mainly came from the announcement released after the OPEC conferences concluded. These conferences, being held twice a year regularly with extraordinary meetings supplemented if necessary, aimed to coordinate members in agreement for oil production policies such as production ceilings and individual quotas. For instance, when there was an adjustment for the oil production quota that was going to become effective (normally 30 days) in January 2017 the announcement published on November 16 2016 after the 171st conference included such a statement:

The Conference recorded its deep appreciation to the commitment and valued contribution of the High-level Committee on the implementation of the 'Algiers Accord'. The

Committee's efforts helped form a consensus among Member Countries on the basis of a proposal put forward by Algeria to implement a new range of targeted production levels.

Accordingly, and in line with the 'Algiers Accord', the Conference decided to implement a new OPEC-14 production target of 32.5mb/d, in order to accelerate the ongoing drawdown of the stock overhang and bring the oil market rebalancing forward. The Agreement will be effective from January 1, 2017.

In response to OPEC conference announcements, the market usually pays significant attention to them with strong price reactions. For example, Lin and Tamvakis (2010) applied an event study to examine the effects of OPEC announcements on world oil prices. They found differentiation in the magnitude and significance of market responses to OPEC quota decisions under different price bands. Later, Schmidbauer and Rösch fitted a GARCH-based model to crude oil returns to investigate the impact of OPEC announcements on the expectation and volatility of daily oil price changes (returns). In their results, they provided evidence for a post-announcement effect on expectations, which was negative in the case of a cut decision and positive in the case of an increase or unchanged decision. Meanwhile, there was a positive pre-announcement effect on volatility, which was strongest in the case of a cut decision.

1.3 Model Specification and Data

1.3.1 Methodology

The empirical analysis considers the following reduced-form structural vector auto regression model,

$$y_t = b + B_1 y_{t-1} + ... + B_p y_{t-p} + u_t, \tag{1.1}$$

where p is the lag order determined by the AIC of the data series, $\mathbf{x}_t$ is a n×1 vector of endogenous macro variables I am interested in, $\mathbf{u}_t$ is the reduce-form innovations vector with covariance matrix Var($\mathbf{u}_t$) = Σ, **b** is a constant vector with size n×1, and $\mathbf{A}_1$, …, $\mathbf{A}_p$ are the n-order coefficient matrices.

The reduced-form innovations can be linearly represented by the structural shocks with the following mapping,

$$\mathbf{u}_t = \Theta\varepsilon_t \tag{1.2}$$

where Θ is a non-singular n×n matrix indicating the structural impact, εt is a n×1 vector of structural shocks. The structural shocks are assumed to be serially and mutually uncorrelated, i.e. E(εt) = 0 and Var(εt) = Λ = diag(σ21,…,σ2n). The mapping of the shocks implies that

$$\Sigma = \Theta\Lambda\Theta' \tag{1.3}$$

Following the design of Känzig (2021) and Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021), I focus on identifying impulse response function to the first order shock in the VAR, ε1,t, which is denoted as the oil supply news shocks, without loss of generality. The impulse response with respect to oil news shocks will be determined by identifying the structural impact vector θ1, which corresponds to the first column of Θ.

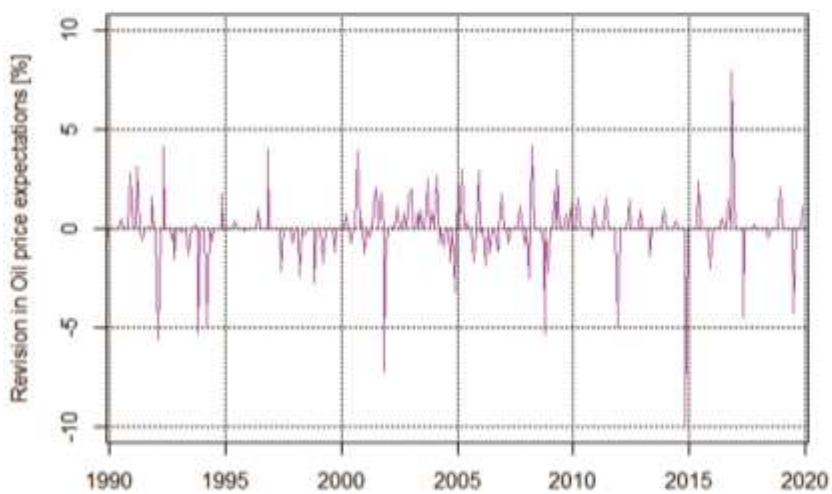
Next I try to identify the structural impact vector using the external instruments approach. Let us denote zt as an external instrument variable. In my empirical work, zt is the oil surprise series corresponding to the OPEC announcements.

In particular, the oil supply surprise series, is constructed as the log difference of the average oil futures price on the day of the OPEC announcement and the average price on the last trading day before the announcement, that is:

$$z_t = surprise_{t,d}^h = \begin{cases} F_{t,d}^h - F_{t,d-1}^h, & \text{if there is an ann} \\ 0, & \text{otherwise} \end{cases} \tag{1.4}$$

Where $F_{t,d}^{h}$ is the log settlement price of the *h*-months ahead oil futures contract in month *t* on announcement date *d*. For the selection of h, the h = 0 (spot), 1(front), …,4 and $h_{composite}$ (average contract price). The baseline h used for estimation is $h_{composite}$. Figure 1.1 displays the series over 1991 to 2019. According to the figure, most of the oil prices variation results from oil supply surprises are within 5% percent with a few exceptions. In these 7 exceptions, the largest one is up to 9.3%. The further details of oil surprise series are provided in appendix A.

Figure 1.1. The Oil supply surprise series



So, for z_t to be valid, z_t needs to satisfy,

$$E[z_t \varepsilon_{1,t}] = \delta \neq 0 \tag{1.5}$$

$$E[z_t \varepsilon_{j,t}] = 0 \text{ for any } j \neq 1 \tag{1.6}$$

Where $\varepsilon_{1,t}$ denotes the oil supply news shock and $\varepsilon_{j,t}$ is an (n-1) ×1 vector corresponding for other structural shocks.

Using assumptions (1.5)-(1.6), θ_1 is identified up to sign and scale by the covariance of innovations $\mathbf{u}_t$, Σ and instrument z_t:

$$E[\mathbf{z}_t\mathbf{u}_t] = \Theta E[\mathbf{z}_t\,\varepsilon_t] = \begin{pmatrix} E[\mathbf{z}_t\mathbf{u}_{1,t}] \\ E[\mathbf{z}_t\mathbf{u}_{2:n,t}] \end{pmatrix} = \begin{pmatrix} \theta_{1,1}\delta \\ \theta_{2:n,1}\delta \end{pmatrix} = \theta_1\delta$$

$$\tilde{\theta}_{2:n,1} = \theta_{2:n,1} / \theta_{1,1} = E[\mathbf{z}_t\mathbf{u}_{2:n,t}] / E[\mathbf{z}_t\mathbf{u}_{1,t}] \tag{1.7}$$

Applying the scale normalization suggested by Känzig(2021) that $\theta_{1,1} = \theta$, which can be inferred that one unit of positive shock $\varepsilon_{1,t}$ would lead to a positive effect on macro variable $x_{1,t}$ with magnitude θ, so that

$$\tilde{\varphi}_1 = \begin{pmatrix} \varphi_{1,1} \\ \tilde{\varphi}_{2:n,1}\varphi_{1,1} \end{pmatrix}$$

where $\tilde{\theta}_{2:n,1}$ can be interpreted as the IV innovation estimates scaling on the oil announcement innovations. After obtaining the impact vector, one can apply it onto the computations of interested objects such as IRFs and $\varepsilon_{1,t}$. i.e. $\varepsilon_{1,t} = \tilde{\theta}_1' \Sigma^{-1} u_t$

1.3.2 Data

My base dataset consists of the following parts. The first part is general oil indicators. The general oil indicators include four standard variables of classic oil market VAR models: The real price of oil, world industrial production, world oil inventories, and world oil production. In the construction of the real price of oil, I followed Känzig (2021) to use the WTI spot price, deflated by U.S CPI. The data for WTI spot price and U.S. CPI are obtained from the St. Louis Federal Reserve database. For world industrial production, I use Baumeister and Hamilton’s (2019) index for OECD countries and six other major economies. For world oil inventories, I use a measure based on OECD petroleum stocks, as proposed by Känzig (2021) and Kilian and Murphy (2014). In terms of world oil production, I use the world oil production data suggested by Känzig (2021). In the second part, I obtain national industrial production and national CPI data from the World Bank's Global Economic Monitor (GEM) database, covering 7 major oil import economies in Asia. Ranked by the value of oil import, these economies are China, Japan, India, South Korea, Chinese Taiwan, Singapore and Thailand. For each economy, I follow Känzig (2021) to set up individual baseline specifications by augmenting general oil indicators with individual national industrial production and individual national consumer price index (CPI). The data in the baseline is monthly with a span from 1991M1 to 2019M12. I use this baseline specification to analyze the effect of oil supply news shocks on the individual economy. A detailed overview of the baseline data and its source can be found in Appendix A.

To estimate the wider effects of oil supply news shock on the macroeconomy, I use the macroeconomic variables suggested by Beaudry and Portier (2014), Gertler and Karadi (2015) and Känzig (2021). These variables include the nominal effective exchange rate, the real effective exchange rate, import values, export values and terms of trade. The data corresponding to these macroeconomic variables, covering the same seven economies in the base set, is collected from the GEM database under the same period. Appendix A offers a more detailed description of these data. Finally, in order to better capture the effect of exchange rates in response to oil shocks, I also include currency regimes of Asian economics as a dummy variable for the analysis. For currency regimes, I follow the design of Accominoti, Cen, Chambers and Marsh (2019) using cross-rate volatility as regimes' classification. In this paper, the cross-rate is set to be nominal effective exchange rate. According to the definition of IMF, the nominal effective exchange rate is a measure of the value of a local currency against a weighted average of a varying basket of foreign currencies in which the local currency is in the numerator. The range of foreign currencies comes from the country's major trade partners, competitors and euro area. While the real effective exchange rate (REER) is the nominal effective exchange rate divided by a price inflator. And an increase in REER implies that exports become more expensive and imports become cheaper; therefore, an increase in REER indicates a loss in trade competitiveness. The volatility λ is measured as an exponentially moving average of spot returns for the nominal effective exchange rate i at month t,

$$\lambda_t^i = \sqrt{12} * (1-\rho) \sum_{u=0}^{t-1} \rho^u \left| \Delta s_{t-u}^i \right| \tag{1.8}$$

where ρ = 0.9 is chosen such that the half-life of the past exchange rate is approximately one month, and sit is the spot exchange rate return for the nominal effective exchange rate i at month t.

Based on the volatility measure, at month t, the classification of each currency can be assigned into two regimes l which is defined as

$$l = \begin{cases} \text{Fixed,} & \text{if } \lambda_t^i < V, \\ \text{Floating} & \text{if } \lambda_t^i \geq V, \end{cases} \tag{1.9}$$

where V is the volatility threshold. The volatility threshold of V = 0.33% per month, was chosen following the 4% per annum setting given by Accominoti, Cen, Chambers and Marsh (2019) on behave of the G10 exchange rates against the U.S. dollar in the post-euro period. The 4% per annum setting is also in line with classification of exchange rate arrangement by IMF regarding the difference between the pegged exchange rate (values fluctuate within 4% per annum) and the floating exchange rate (fluctuation is larger than 4% per annum). The volatility measurement results can be found in Appendix A.4.

1.4 Empirical Results

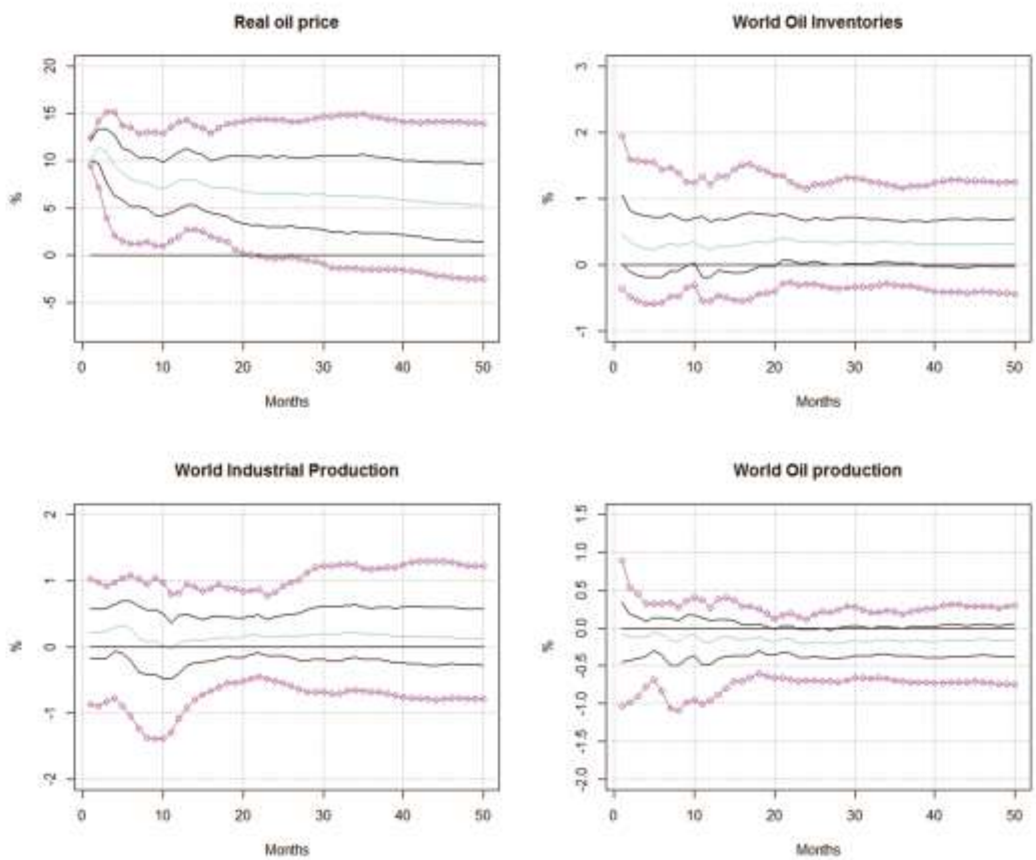
1.4.1 Effects on aggregated economy

1.4.1.1 Effects on the world oil market and global macroeconomic

In this section, I present the basic impulse response results from the baseline model, identified using the external approach, as proposed by Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021). Because all the variables are transformed into log terms, the impulse responses can be interpreted as elasticities. Figure 1.2 illustrates both the 95 percent confidence band and the 68 percent confidence band. The key for interpreting the graphs is that the cyan solid lines are the median estimates, the black lines are the bounds of estimates with a 68 percent confidence band and the magenta lines are the bounds of the estimates for the 95 percent confidence band. This graphic notation will be applied to all the figures in the following figures.

Figure 1.2 illustrates the effect of a 10% oil price increment due to positive oil supply news shocks on world market values. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change, ignore the fact that the changes are in. The same setting also applies to impulse responses of the rest figures in the Section 1.4 and Section 1.5. Figure 1.2 shows that a positive oil supply news shock leads to an in increase in the price of oil. World oil production experiences an in and persistent decline over time in response to the positive oil supply news shock. World oil inventories increase in and persistently. Past studies have also documented these relationships (see Känzig, 2021; Liu, D., Wang, Q., & Yan, K. X, 2022). World industrial production experienced an in but persistent increase over time. This is in line with the notion that oil importers might not benefit in the short run from higher oil prices and lower expectations of oil supply in the market. As a response to these, the oil importers may need to maintain their inventories at a higher level to meet the domestic demands in industrial production or turn to other consumable energy such as natural gas as an energy source for industrial production.

Figure 1.2. Worldwide impulse responses to an oil news shock



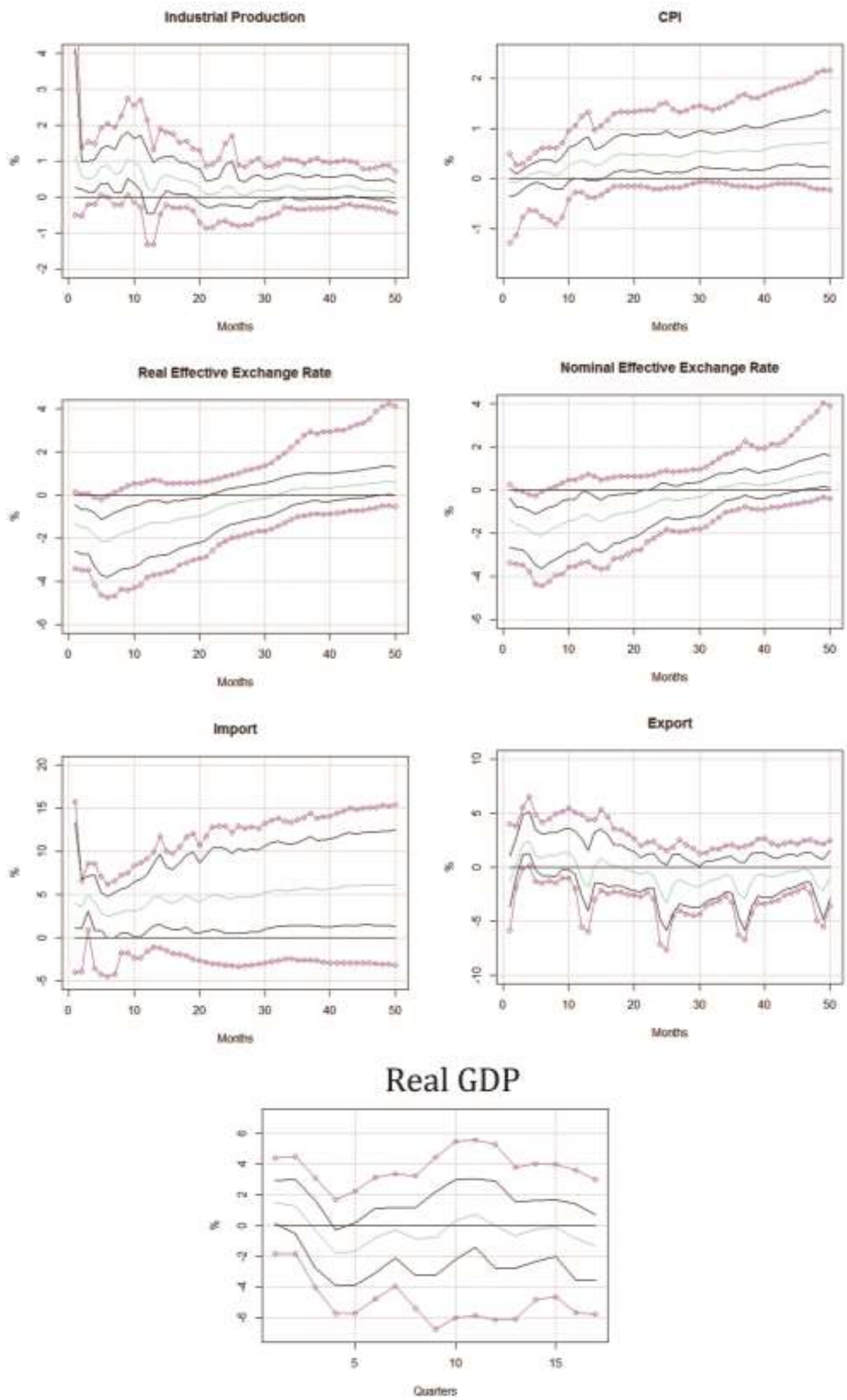
1.4.1.2 Effects on the Chinese economy

Turning to the Chinese economy, the first panel in the Figure 1.3 illustrates the response of Chinese industrial production. The shock leads to a positive short run increment in it but the effect fades 10 months after the shock happens. Then, in the second panel Figure 1.3, Chinese CPI reacts with a sustain increase in response to a positive oil news shock. The result corresponds to the fact that China had been the second largest oil importer in total value from 1995 to 2020, the fixed currency regime as Figure A.4.1 indicate that China was vulnerable to higher oil price in the spot market of oil due to paying extra cost in the short run. The response is highly statistically and features a considerable degree of persistence.

By the end of 2019, the crude oil trade between China and oil exporters had been cleared using U.S. dollars. Thus, I should also investigate the relationship between oil supply news shocks and the effective exchange rate, and the link between oil supply news shocks and trade. According to the definition of IMF, the nominal effective exchange rate is a measure of the value of a currency against a weighted average of several foreign currencies. The range of foreign currencies comes from major trade partners, competitors and euro area. While the real effective exchange rate (REER) is the nominal effective exchange rate divided by a price inflator. And an increase in REER implies that exports become more expensive and imports become cheaper; therefore, an increase indicates a loss in trade competitiveness.

According to Figure 1.3, in terms of the real effective exchange rate, positive oil supply shocks lead to a short run depreciation of Renminbi but persistent tendency of reverse after 30 months. Similar results hold for the nominal effective exchange rate of Renminbi. Under a fixed currency regime, the variation of Chinese effective exchange rate is relatively small in response to oil supply shocks. The reverse tendency in effective exchange rate complies with the finding in Känzig (2021) for the U.S. effective exchange rate. Further, the output for effective exchange rate reveals that oil supply news rises the future cost to China in oil imports in short run, but in the long run, the impact may be mitigated by the appreciation of domestic currency. This is also in line with the finding in M. Hussain et al. (2017) that there is a weak negative correlation between oil prices and Chinese exchange rate in the short run.

Figure 1.3. IRFs of Chinese economic variables



When investigating Chinese trade status in response to oil news shocks, a positive oil new shock leads to an increase of up to 5% upon the impact, and this increment lasts persistently over fifty months after the shock happen. Meanwhile, the same oil supply news shock does not change exports much in the first year but then decreases export and persistently over time. Overall, my findings suggest that an oil supply news shock increases China's imports but decreases China's exports. And as a result, there is a trade deficit on China's trade balance. This can be explained by the depreciation of Chinese effective exchange rate, in response to the same oil supply news shock simultaneously, turns the cost of Chinese import and cost of production of export good to be more expensive. Also, the increasing CPI of the trade partner due to higher oil price reduces the consumption and orders of Chinese goods. These results are aligned with those of Cunado et al. (2015) for China, Allegret, J. P., Mignon, V., & Sallenave, A. (2015) for net oil-importing countries in general, and Yalta and Yalta (2017) for Turkey, another oil-importing country.

Lastly, I look at the real GDP of China, even though it is a bit less precise in a quarterly measure. In response to a positive oil news shock, Chinese real GDP illustrates a drop shortly after the oil news shock occurs. This result supports the notion that a possible channel of oil news shocks is via its impact on the exchange rates. For instance, by creating a trade deficit under exchange rate appreciations, the oil supply news shock deteriorates foreign consumption demands (see Känzig, 2021). This may be confirmed by looking into the responses of trade sectors and the exchange rate channel: by the end of 2019, about 25% of Chinese GDP is contributed by trade. The rising oil price shrinks foreign expenditures on goods which undermines exports while the depreciation of effective exchange rate rises costs for import goods such as crude oil and raw materials.

1.4.1.3 Effects on Japanese economy

In terms of the Japanese economy, for Japanese industrial production, the shock leads to a similar pattern as Chinese industrial production. Japan's CPI responded to the shock with cyclical drops in the first 20 months after the shock occurred, followed by a mere increase in the long run. The CPI result was in line with the notion that Japan suffered from deflation from late 1990s until 2013 (see Bernanke, B. S, 2002; Ito, T., & Mishkin, F. S, 2006; Vithessonthi, C. 2016), during which the oil shocks impact pass to Japanese inflation was small and in. This means that Japan may improve its net-energy position over time because it becomes less vulnerable to oil supply news shocks (Baumeister, C., Peersman, G., & Van Robays, I, 2010). This is again conformed by the increment of world oil inventories in response to oil supply news shocks.

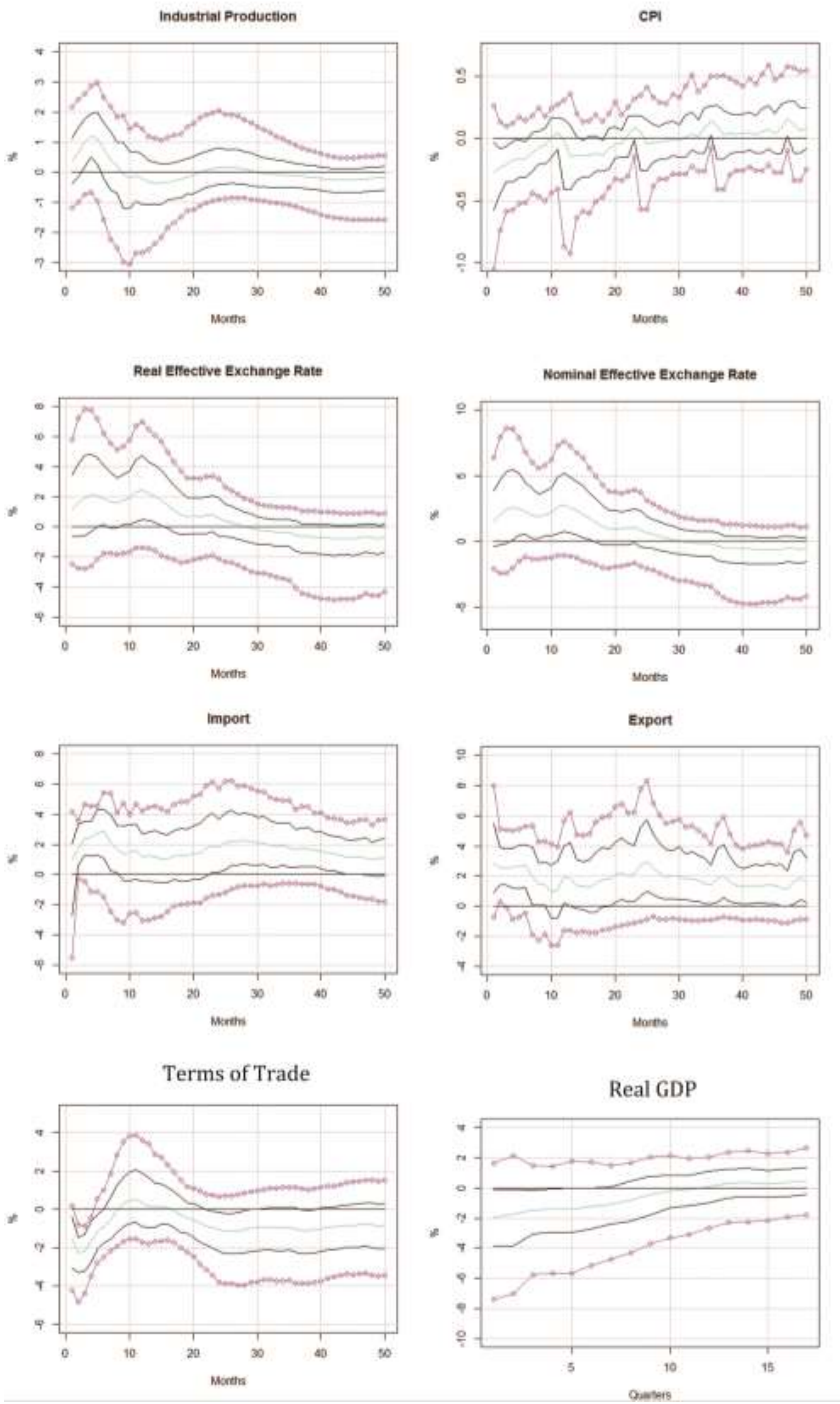
Although the Japanese Yen is one of the world's reserve currencies, Japan still needs to exchange Yen with U.S. dollars before purchasing crude oil. Under a floating currency regime displayed in Figure A.4.2, Japanese effective exchange may be more volatile in response to an oil supply news shock. Thus, I should also investigate the relationship between oil supply news shocks and exchange rate. The effective exchange rate panels in Figure 1.4 display the responses for the nominal effective exchange rate and the responses for the real effective exchange rate. According the both graphs, oil supply shocks lead to a short run appreciation of Yen but a long run insignificance. Comparing with Chinese exchange rates, Japanese exchange rate experiences larger variation in the short run after the oil supply news shock occurs as JPY floats with weak dollar. Overall, these results provide evidence with the finding that there is negative correlation between oil price and U.S. dollar (Klitgaard, Pensenti, and Wang, 2019; Känzig, 2021).

Japan has a long history of being one of the major crude oil importers. Thus, I expect that the oil supply news shock would also lead to a trade deficit for Japan with a strong JPY in response to the shock. My results support my expectation. As trade panels in Figure 1.4 illustrate, a positive oil supply news shock rises both import and export over time. Comparing to export, the import has larger increments in response to oil supply news shocks. The strong JPY to U.S. dollar reduces Japanese importers cost of purchasing abroad but weaken Japanese export competiveness in prices. This result again supports Känzig (2021) finding with U.S. data that oil supply news shock can lead to a deficit in trade balance.

The appreciation, along with a trade deficit, potentially have a negative effect on terms of trade. The panels in Figure 1.4 show the IRF results of Japanese terms of trade. In the panels, the Japanese terms of trade deteriorates and persistently. These results supports the notion in Baumeister, Kilian, and Zhou (2018) that oil price shocks transmit as shocks to the terms of trade during which oil shocks lead to larger changes in import prices than export prices and drop down terms of trade. During the effect transmission, the floating JPY plays a role of distorting price ratio of Japanese foreign trade.

Japan is a trade-oriented country of which trade makes up 26% of its GDP on average from 1991 to 2019, the deterioration of trade caused by high oil price and JPY appreciation would result in a decline of its domestic GDP. From the last panel of Figure 1.4, it can be learned that a positive oil news shock leads to a persistent decrease of Japanese real GDP, through either the channel of exchange rate, or risk taking for the lack of oil trade diversification (e.g. An, H., Zhong, W., Chen, Y., Li, H., & Gao, X. 2014). The latter is conformed from the oil import structure of Japan from 1995 to 2019 (see Appendix A.3) in which half of Japanese oil is imported from Saudi Arabia and the UAE.

Figure 1.4. Impulse response of Japanese Economic to oil supply news shocks



1.4.1.4 Effects on Indian macroeconomic

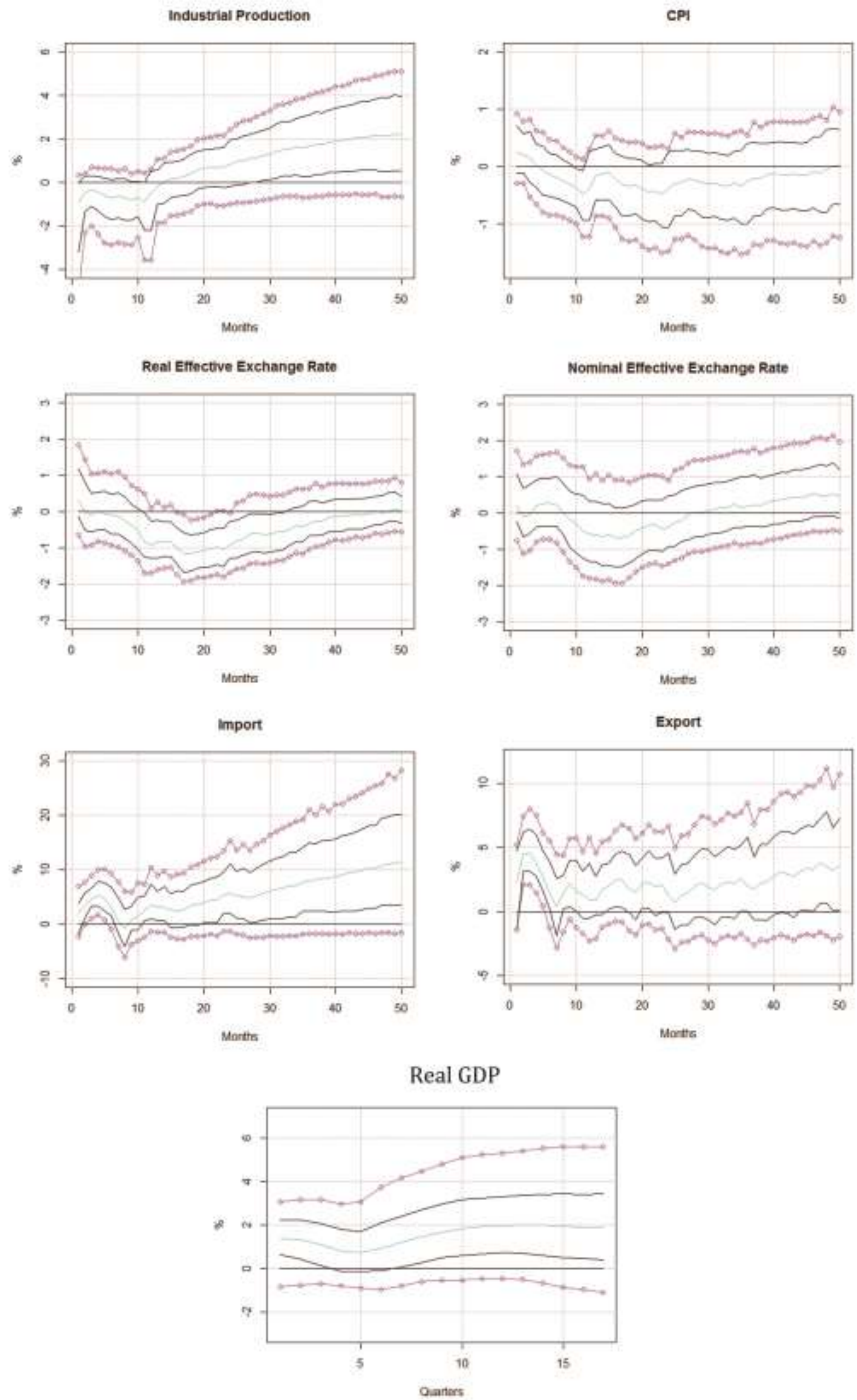
I now offer presentation for the basic Indian results fusing macro data from India. In my impulse response function results shown in Figure 1.5, a positive oil supply news shock leads to little increment of Indian industrial production in the short run but an increase one year after the shock happens. The Indian CPI experiences a mere fall in the first place, it does not take a reverse until 40 months after the short happens. This result supports the Sakashita, Y., & Yoshizaki, Y. (2016) finding that positive oil supply shocks brings down CPI in India during aggregated demand expansion of industry production. During the expansion of industry production, India, as the sixth largest exporter of refined oil from 1995 to 2020, increased its production of refined oil for export revenue when the oil price grew.

The Indian Rupee is a floating currency during the sample period. However, INR is not a currency used for international trade clearance. This means Indian importers need to exchange Rupee with U.S. dollar before purchasing crude oil. Thus, it is natural to detect a relationship between oil supply news shocks and the exchange rate, and the link between oil supply news shocks and trade values through an exchange rate channel. The effective exchange rate panels in Figure 1.5 displays the responses of the nominal effective exchange rate and the responses of the real effective exchange rate separately. In the both graphs, oil supply shocks lead to a depreciation of Indian Rupee against major currencies such as the U.S. dollars and euros. Comparing the depreciation of the Indian Rupee for both effective exchange rates, it can be seen that the real effective exchange rate experiences larger and persistent depreciation relative to the nominal effective exchange rate. Overall, these results are line with the finding that there is strong positive correlation between oil price and oil exporter's currency (Lizardo and Mollick, 2010) as India is the 5th largest country for exporting refined petroleum in the world (OEC data, 2020).

Historically, Indian has been one of the major crude oil importers but also a major exporter of refined oil. One interpretation for the response of trade to oil shock is that it leads to a trade deficit for India as the depreciation of Indian Rupee boosts refine oil export but also increases the cost of other manufactured goods import. The expectation is confirmed. The trade panels in Figure 1.5 illustrate that both the export values and import values rise persistently. In the first 30 months, the increment of export fluctuates around 2% while the import has a positive vibration around 4%. In the long run, the response of both tend to be larger and import has a larger increment. This result supports Känzig (2021) finding with U.S. data that oil supply news shock can lead to a deficit in the trade balance.

For Indian real GDP, along with increment of industrial production, favorable exchange rates and controllable trade deficit, the positive oil news shock causes a rise of real GDP over time.

Figure 1.5. IRFs of Indian economy



1.4.1.5 Effects on small Asian oil importers economies

In this section I investigate the response of small Asian oil importers to oil news shocks. Starting from industrial production, for Korean industrial production, the shock leads to a persistent increment over time. Comparing to the world benchmark, this shock is larger and more persistent. This is in line with the notion that Korea is the sixth largest oil importer but also the 6th refined petroleum exporter in 2020. This means Korea can be benefit from high oil price from refine oil export. Similar pattern holds for other small Asian oil importers such as Chinese Taiwan, Singapore and Thailand in which their industrial productions experience an increase over time. In these economics, the buildup of refined oil inventory contributes to the increment of industrial production in response to oil news shocks.

By looking at impulse response function results for the CPIs in Korea, Chinese Taiwan, Singapore and Thailand, it can only be seen in but positive responses, although Singaporean result shows an upward trend. These results support the Känzig (2021) finding that oil news shocks increase oil importer CPI. Also, the in responses may be associated with the notion that the appreciation in the real exchange rate posts downward pressure on the CPI (see Cunado, J., Jo, S., & de Gracia, F. P, 2015, for further discussion).

Turning to the relationship between oil supply news shocks and effective exchange rates, it is revealed that for these four economics, Singapore and Chinese Taiwan apply fixed currency regimes while Korea and Thailand (started from 1998) have floating regimes. The effective exchange rates in each economy displays the responses of the nominal effective exchange rate and the responses of the real effective exchange rate. According to these graphs, oil supply shocks lead to an in but persistent appreciation in effective exchange rates for all four small Asian oil importers in the sample. The insignificance of response may represent some modest government intervention for stabilizing exchange rate which is one of target for the central banks of these economics.

With regard to the link between oil supply news shocks and aggregated trade, the export and import panels from Figure 1.6 to 1.9 illustrate the IRF results for the four small Asian economics who are major oil importers in international oil market from 1995 to 2020. Since these economies have high reliance on crude oil imports, one expectation for the IRF results is that a positive oil supply news shock would be expected to lead to a trade deficit for these economics as higher oil price lead to appreciation of local currencies. The IRF response results of export and import panels confirm my expectations. As the panels display, for all the small Asian oil importers, both the export values and import values rise persistently over time. Comparing to exports, the import has larger increment (the gaps range from 0.5% to 1%) in response to oil supply news shocks in both short run and long run as import gets cheaper while export cost become more expensive. The appreciation, along with trade deficits, potentially have an effect on terms of trade. The panels for the terms of trade show the IRF results for small Asian oil importers. In the panels, all the terms of trade deteriorates persistently over time. The impaired terms of trade supports the results in Känzig (2021) that oil supply news shocks lead to a decline in the terms of trade.

Finally, in terms of real GDPs for small Asian oil importers, it can be seen that the response results of real GDP to oil news shocks perform differently. Korean real GDP increases persistently over time. While the real GDP of Chinese Taiwan only shows an increase in the first five quarters after the news shock occurs. The impulse response results of Singaporean real GDP illustrates that the Singaporean real GDP does not have variation at first for the oil news shock. However, an upward tendency comes up 6 quarters after the shock happens. Last for the Thai real GDP, it has a decrease initially, then it reverses with an upward trend. The variation of IRFs for real GDPs of small Asian importers to oil news shocks may be due to their differences in oil market status and trade departments.

Overall, I find out that oil supply news has in effects on the macro aspects of Asian oil importers. The main reason may lie in the higher moments suffered from weak identification suggested by Montiel Olea, J. L., Plagborg-Møller, M., & Qian, E. (2022, May) in which higher moments are insufficient for providing extra information. During the sample period I investigate, under higher oil prices and weaker dollars, the aggregated trade aspect of Asian oil importers receive the largest impact, either from the news directly or transmitted from the channel of effective exchange rate. Regarding the channel of effective exchange rate, the size of transmission effect is determined by currency regimes and the central bank's willingness of intervene the exchange rate. Therefore, the exchange rate can be an additional channel through which the oil shock affects the economy of an oil importer.

Figure 1.6. Impulse Response Functions of Korean economy

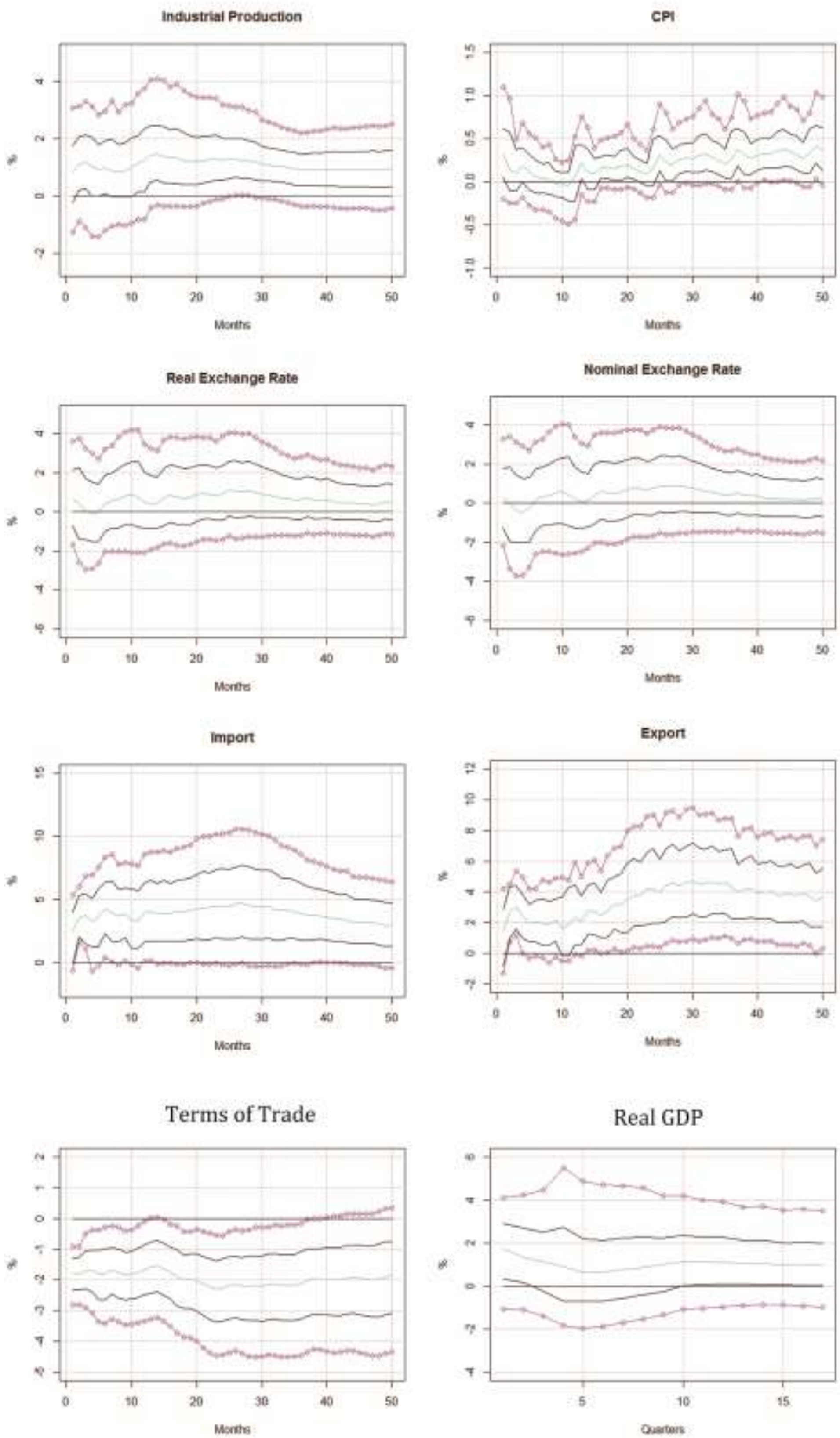


Figure 1.7. Impulse Response Functions of Chinese Taiwan economy

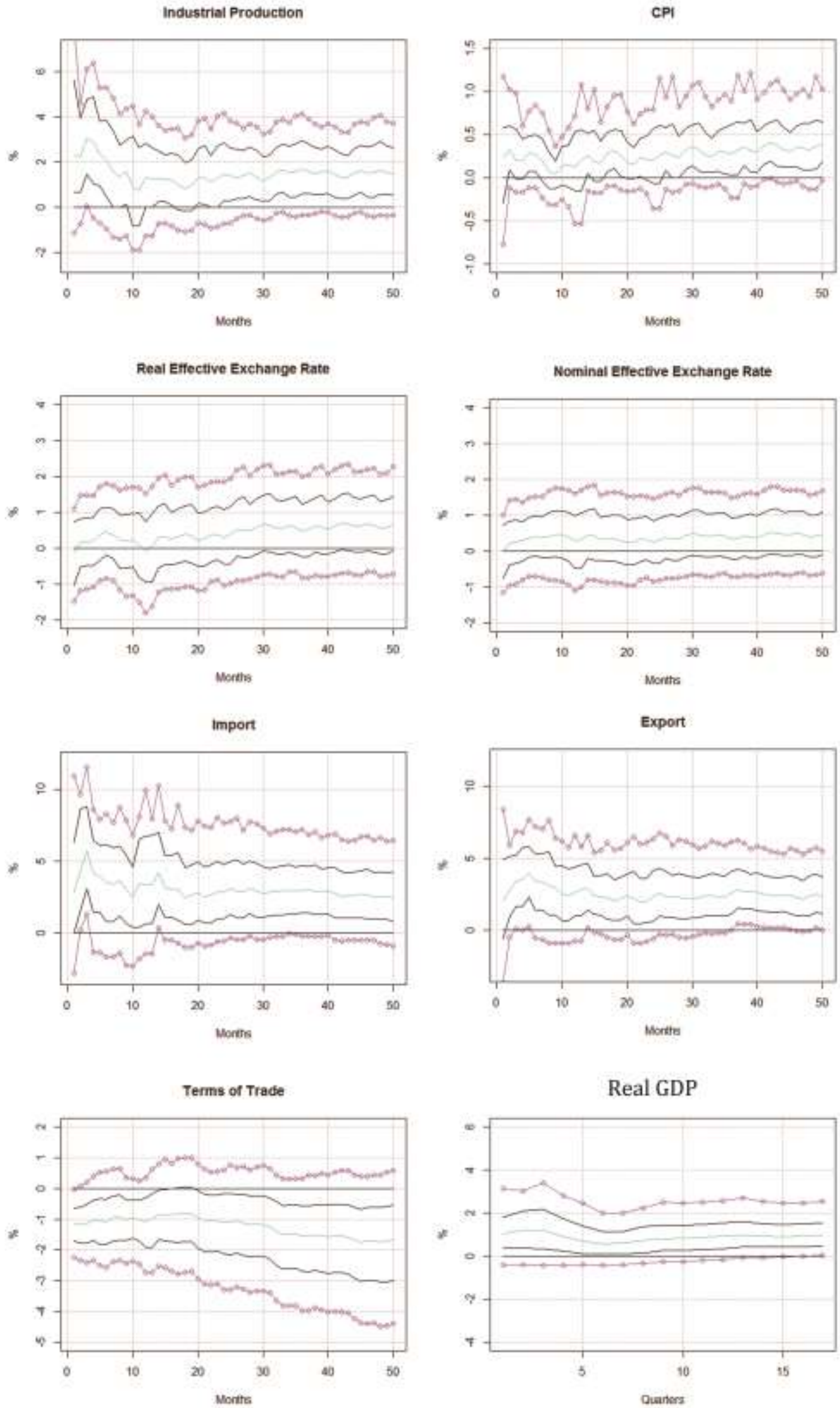


Figure 1.8. Impulse Response Functions of Singaporean economy

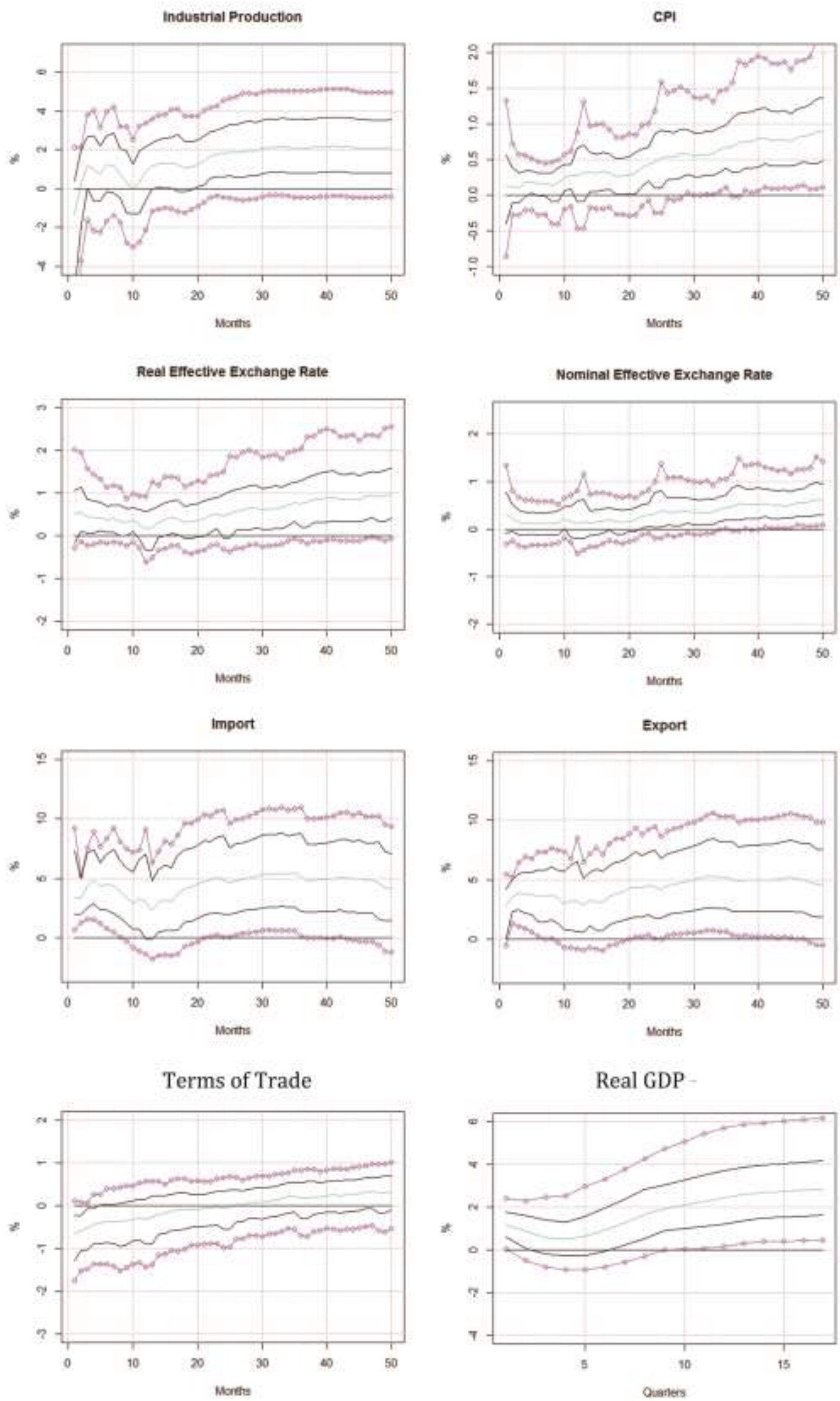
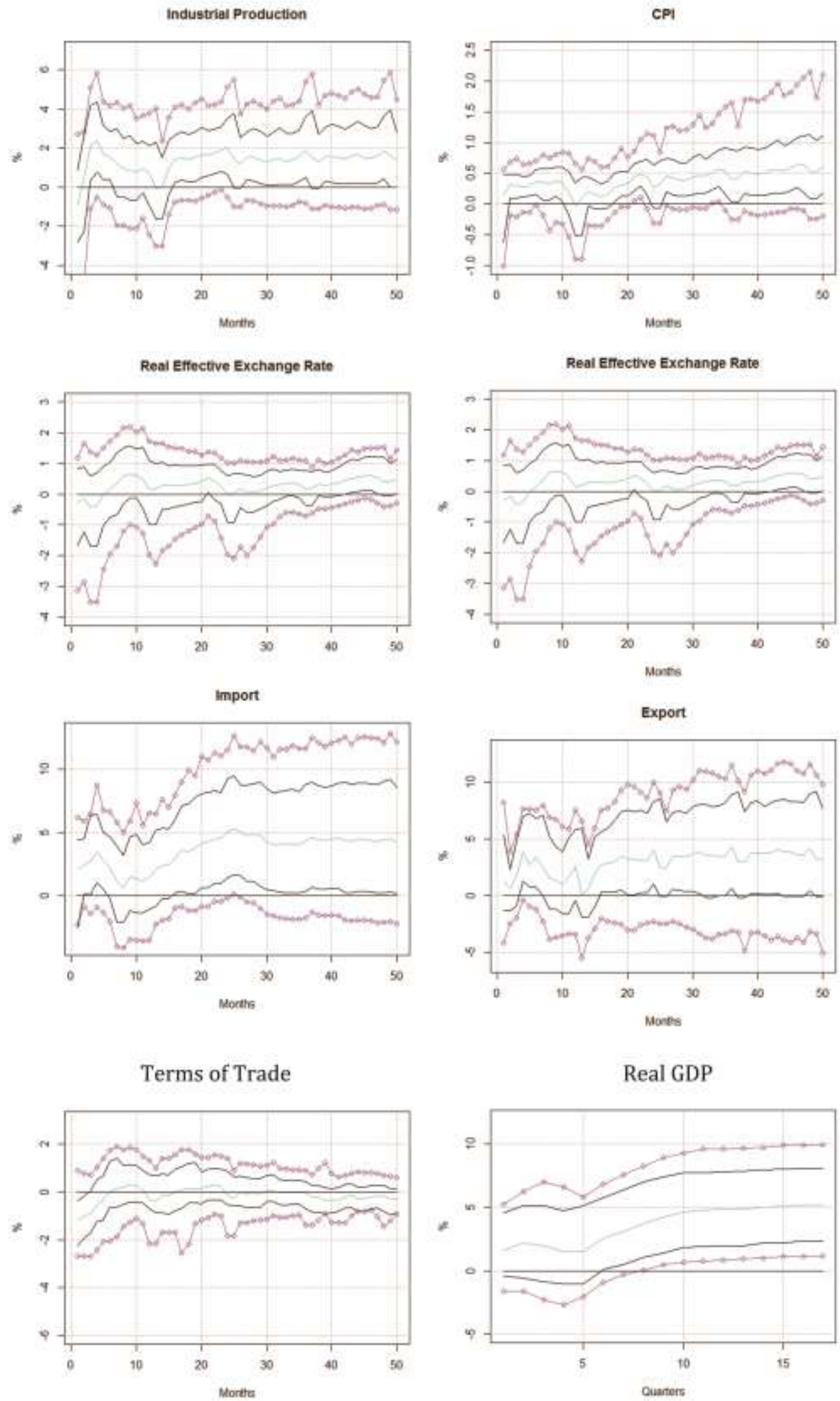


Figure1.9. Impulse Response Functions of Thai economy



1.5 Sensitivity Analysis

In this section, I conduct the following robustness checks on Japan and Singapore to test the sensitivity of my results. The robustness checks for the IRF results of aggregated trade have two parts. I first check if the maturities of WTI oil futures would be a sufficient factor to my IRF results. To do this, I alternate the oil surprise series from WTI composite future price with the WTI front future price. The impulse response results are illustrated in Figure 1.10 and Figure 1.11. Figure 1.10 and Figure 1.11 show that my results are robust in maturities. In the Figure 1.10, the IRF results from WTI front future price is similar to IRFs based on WTI composite future price. Meanwhile, Figure 1.11 reveals that Singaporean IRFs for alternate maturity holds the same pattern as Singaporean IRFs based on WTI composite future measure. Thus my results are robust to different maturities.

As another robustness investigation, I investigate whether the IRF results are affected by different oil regimes in the U.S. because the shell oil boom changes the oil market in which the U.S. starts to compete with OPEC members in oil production. To achieve this, I narrow the sample period from 1991M01 to 2013M12 and use Japan and Singapore for the check. The alternative IRF results are displayed in Figure 1.12 and Figure 1.13. According to Figure 1.12, the IRFs for Japanese economy based on a narrowed sample have little difference from the full sample IRFs Figure 1.13 shows there are similar results with the full Singaporean sample. My results indicate that the response of Japanese economy and Singaporean economy to oil supply news shocks are relatively robust when excluding the period of the U.S. shell oil revolution started from 2010.

Figure 1.10. IRFs for Japanese economic variables using an alternative maturity

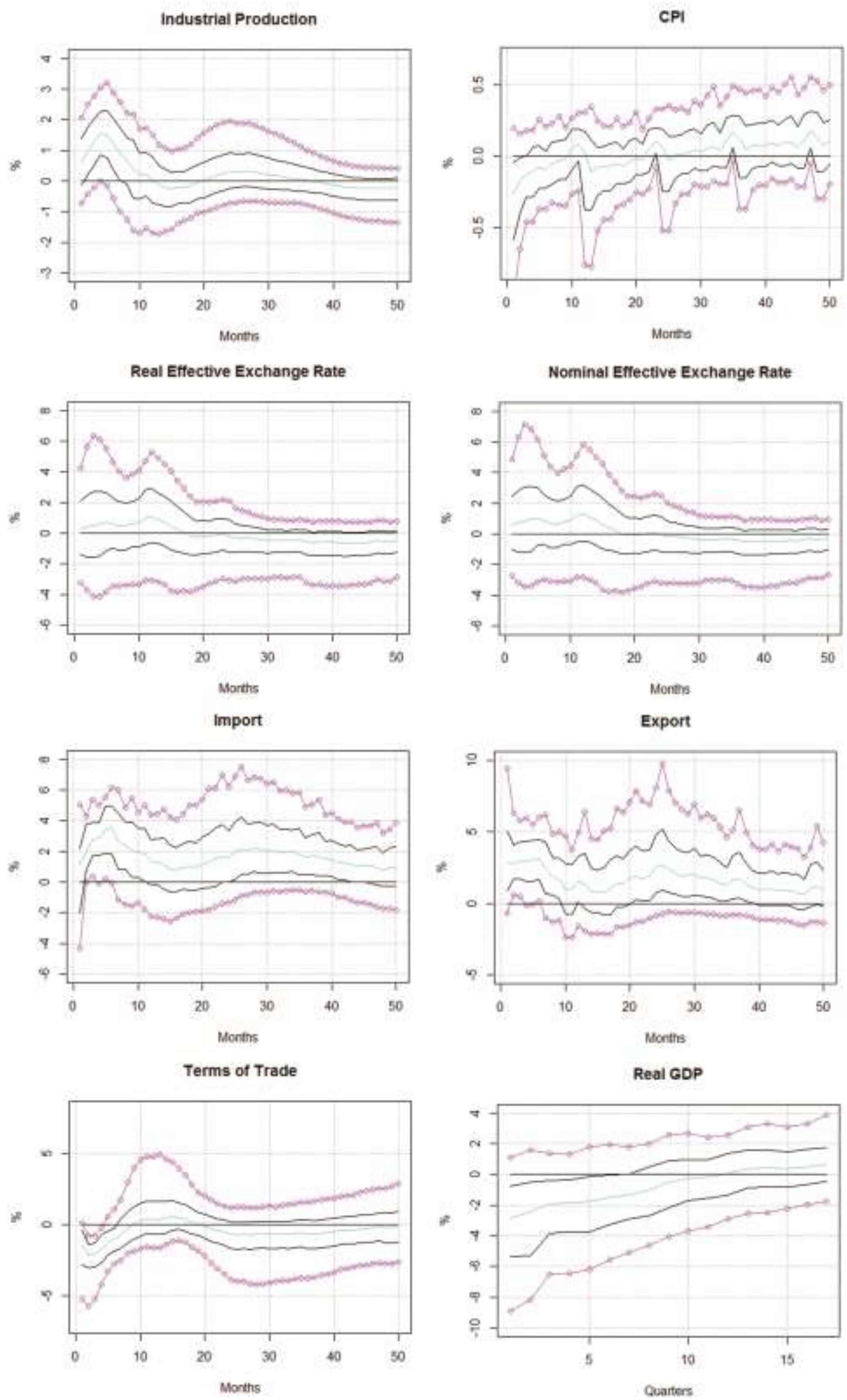


Figure 1.11. IRFs for Singaporean economic variables using an alternative maturity

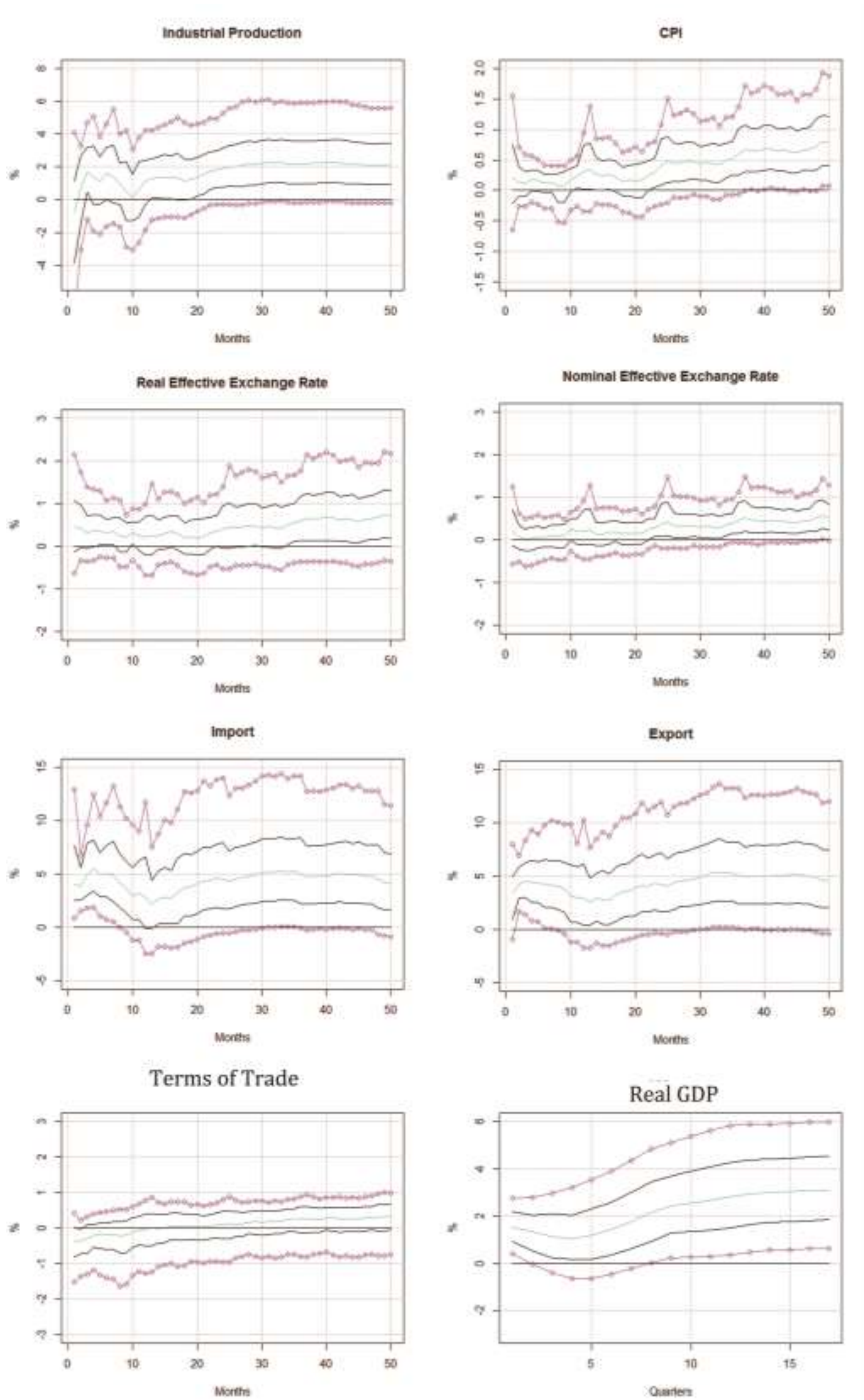


Figure 1.12. IRFs for Japanese economic variables using an alternative sample

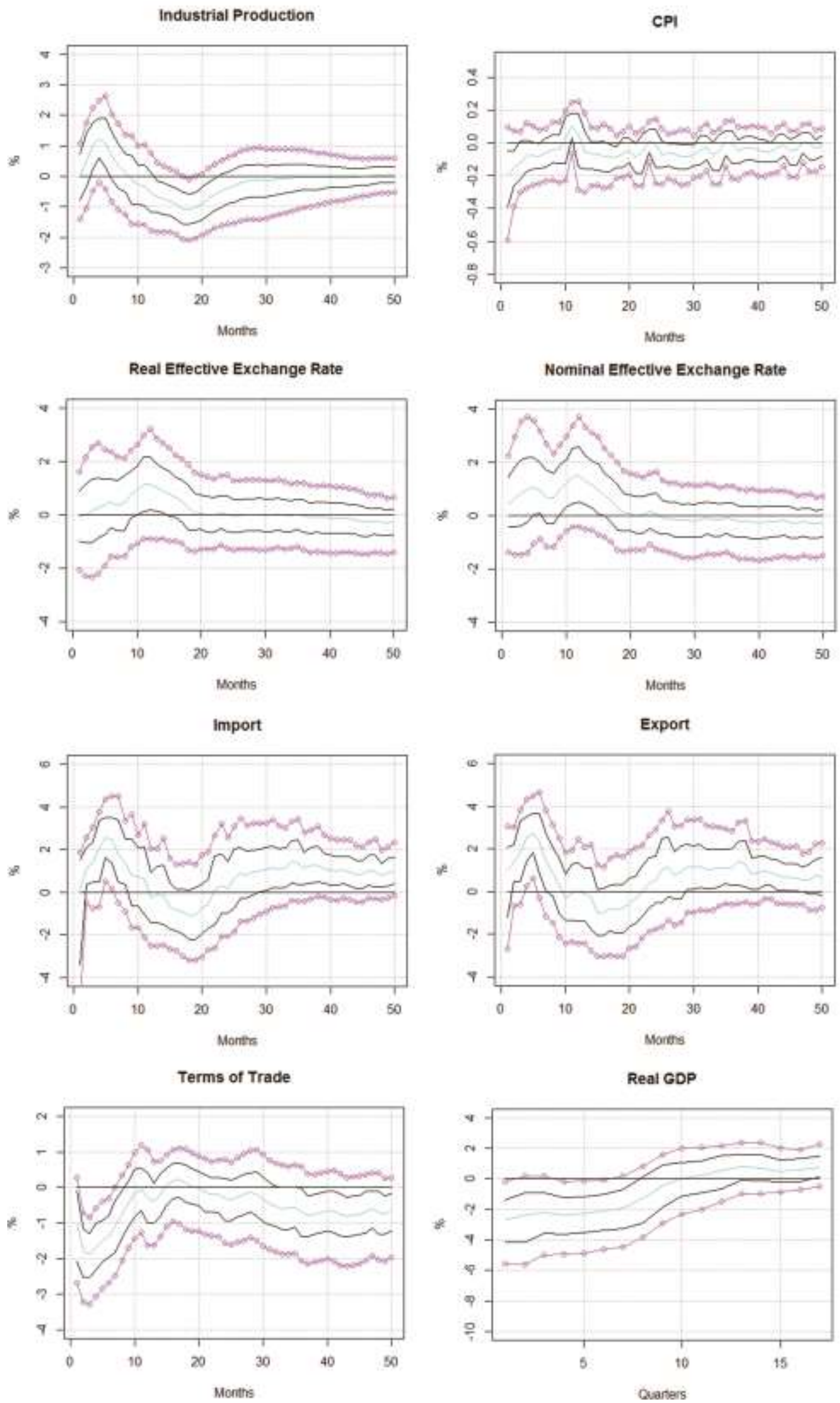
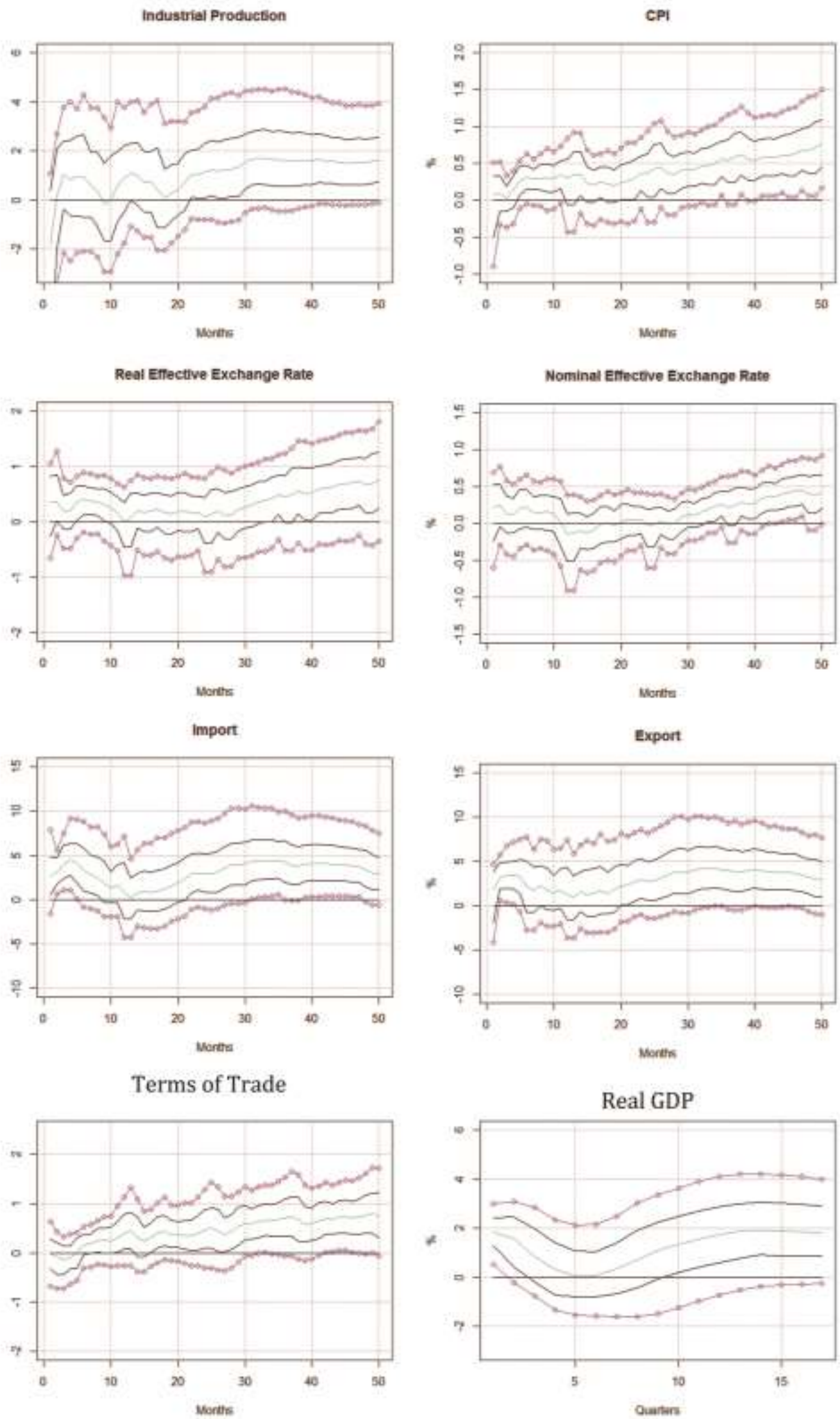


Figure 1.13. IRFs of Singaporean economy from alternative sample



1.6 Conclusion

In this paper, I study the effects of an oil supply news shock on the major Asian oil importers using an external instrument structural VAR model. Following Känzig (2021), I use the changes of WTI composite oil futures prices around OPEC meeting announcements as an instrument. My results find that positive oil supply news shocks lead to increments in Asian oil importers in industrial productions, aggregated export and aggregated import and decreases in the terms of trades. However, I only find in and diversify changes in CPI and effective exchange rate in response to oil news shocks. My finding in aggregated trade suggested that effective exchange rate can be an additional channel for studying the impact of oil news shocks. My results are robust to excluding the period after the agreement of ACFTA from my sample, and an alternative term structure and model specification. Future research may focus on the effect of oil news shocks on trade with high frequency data. For example, the asymmetric effects of oil supply news shocks on agriculture product trades or how this shock affects the trade structure of an oil importer over time.

Chapter 2 - The impact of oil supply news shocks on ASEAN agricultural products exports to China

2.1 Introduction

A long-standing question in the economics is how the expectation for oil prices affects ASEAN agricultural commodity price has been attracting the attention of economists due to the turbulence in the world economies over the past decade. One of the challenges in answering this question is the endogeneity of future oil prices and its response to agricultural commodity export price in a single market, such as China. To provide a potential explanation, the researcher needs to exploit the foundations that drives future oil prices. Therefore, there is a need for examining the changes of ASEAN agricultural product prices when there is an exogenous oil news shock.

In this paper, I examine the effects of oil news shocks driving primary agricultural product export prices of ASEAN when trading with China. I use the structural Vector Auto Regression (SVAR) model with a single oil news shock to investigate this issue. The oil news shocks are identified by following the design in Känzig (2021) which exploits the official announcements of the meeting of the Organization of the Petroleum Exporting Countries (OPEC) and information implied by oil future price.

It is found that the oil supply news shocks lead to change in a short period of time in terms of sample ASEAN economies export prices to China, usually within three quarters after the shock occurs. These results provide further evidence for the findings by Wang, Wu and Yang (2014) in which the response of agricultural product prices are insignificant to oil supply shocks in a short period of time. In terms of the primary agricultural product export prices, I find out in-persistent increases in the export prices of rubber for Thailand and Malaysia, in response to the oil news shocks. Similar results are observed in the export prices of palm oil for Indonesia and Malaysia. My finding in the export prices of rice for Thailand and Vietnam suggested that the trade structure difference of rice causes the variation of IRFs when the oil supply news shocks happen.

A comprehensive set of sensitivity checks indicate that my results are robust along several dimensions such as the sample period, lag sensitivity and oil status variations.

The rest of the paper is organized as follows: Section 2.2 reviews the literatures. Section 2.3 presents the data sources. Section 2.4 describes the methodology. Section 2.5 reports and discusses the results. Section 2.6 concludes the paper.

2.2 Literature Review

2.2.1 Literature Background

Recently, interest in oil news shocks effect on economic variables has been increasing as there is growing literature on this topic. Su, Z., Lu, M., & Yin, L. (2018) exploited the relationship between news implied volatility (NVIX) and classic oil shocks They wanted to investigate whether the world price of oil and oil shocks promoted by Kilian (2009) affected news-based uncertainty or Vice versa. Their results illustrate that oil prices exhibit a statistically and economically significant leading role on NVIX, especially in the long run. In terms of specific oil shocks, the authors found out that NVIX had the opposite effect to classic oil shocks except for the oil supply shocks. Känzig (2021) studied the OPEC announcement news shocks on the global market as well as the U.S. economy under a structural VAR framework with external instruments. The instrument is the OPEC announcement news shocks series which is constructed by utilizing WTI future prices in a tight window of announcements. The outcome of this paper provided evidence that the OPEC announcement news can be a strong channel through which the researchers can study the wide effects on an oil importer's economy from oil supply expectations. Liu, D., Wang, Q., & Yan, K. X. (2022) focused on similar oil supply news shocks for the Chinese economy. Their work provided evidence that the oil supply news shock only affected the Chinese economy through the exchange rate and trade balance.

All the previous work focuses on analyzing the impact of news shocks on individual markets. However, there is little literature focusing on how news shocks, especially oil news shocks, affect commodity trading in a region with a single export destination. This paper tries to fill the gap in the literature by investigating the effect of oil news shocks on the Chinese agricultural products imports from ASEAN countries.

The relationship between oil shocks and agricultural commodities has been studied by many economists. Al-Maadid et al. (2017) exploited the bivariate VAR-GARCH (1, 1) model to examine the linkage between oil and food. They found a significant linkage between food and both ethanol and oil prices. The 2006 food crisis and the GFC drove the most significant shifts in the spillovers between the prices series considered. Later, Shahzad et al. (2018) studied the tail dependence and spillover effect between the WTI crude oil price and crops (rice, wheat, corn and soybeans) with conditional VaR and delta CoVaR approaches. Their findings provided evidence that there was asymmetric tail dependences between oil and all agricultural commodities. Also, their paper demonstrated evidence of bilateral and asymmetric upside and downside spillovers from oil to agricultural commodities. In 2020, Mokni and Youssef (2020) investigated the effect of crude oil prices on agricultural prices via an ARMA-FIGARCH model and copula models. They concluded that over their sample period (2003 – 2017), there was a delayed effect of crude oil prices on the agricultural commodities prices which was lower than the immediate effect.

Furthermore, the dependence effect was strongly persistent and more affected by the food crisis than the oil crisis.

Although these papers contributed forward explaining the general relationship between oil shock and agricultural commodities prices, they provided little information about the potential variations of these effects on the agricultural commodities trade for individual countries or regions.

This paper fills the gap for the oil shocks on trade by analyzing the effect of oil shocks on ASEAN agricultural commodities exports to China. Previous related research focused on oil shocks on aggregated trade balances rather than agricultural commodities trades (i.e., Baek & Choi (2020), Baek (2022) and Ran, S., & Baek, J. (2022)), in which the oil shocks are decomposed under the design of Kilian (2009). Meanwhile, other research on the effects on agricultural product trade emphasized the effect of economic variables but ignored the effect of the exogenous oil shocks. For instance, Darmanto, E. B., Handoyo, R. D., & Wibowo, W. (2021) analyze the impact of the ASEAN-China Free Trade Area (ACFTA) on the 4 major exports of plantation commodities (including the commodities of coffee, cocoa, rubber, and palm oil) in Indonesia under a GMM framework containing economic variables such as the GDP and the exchange rates. Their finding showed that trade creation exists within the commodities of coffee, rubber, and palm oil while the trade diversion exists in the commodity of cocoa. Recently, Ya, Z., & Pei, K. (2022) studied macroeconomic factors influencing agricultural product trade between China and Africa using gravity model proposed by Tinbergen (1962). Therefore, there is a need to measure the effect of exogenous oil shocks on agricultural commodity exports of a region to an individual market.

This paper may have important contributions to the literature. The first, and most important, is that of testing the effect of the exogenous oil supply news shocks on ASEAN-China agricultural commodities trade. If the effect can be identified and be significant in both contemporary and lagged terms, as has been claimed in some of the literature discussed above for the general effect of oil shock on agricultural commodities, it is plausible that the oil supply news shocks can be applied as an indicator for monitoring the ASEAN-China agricultural commodities trades. Second, since ASEAN members include both oil exporters and oil importers who are the price takers of oil, I want to investigate if the oil status leads to different effects regarding the same commodities exported from ASEAN members to China over time. Third, in contrast to the few related existing studies that rely on gravity models to study the effect of oil news shock on trade involving multiple exporters and one market, I use a structural Vector Auto Regression (SVAR) model that provides results consistent with the methods used in the energy literature.

2.2.2 Status of ASEAN sample economies

The role of ASEAN economies on global oil market is complicated. From 2004 to 2021, the value of crude oil production of ASEAN for export decreased from $21.65 billion to $14.54 billion. At the same time, the refined oil production increased from $30 billion to $83.9 billion. In terms of trade of these two oil products, in 2021, about $7 billion of crude oil and $45 billion of refined oil were exchanged within ASEAN members.

During the 17-year period from 2004 to 2021, the ASEAN countries' aggregated export to China increased from $46.1 billion to $283 billion. Since 2010, China has become the largest export destination of ASEAN countries. The following presents background information used in this study for the sample of oil importers in the global oil market that also have the trade status with China from 2004 to 2021. These countries include Thailand, Malaysia, Indonesia and Vietnam. This background information is based on the data from Observatory of Economic Complexity (OEC) and the analysis reports from the Energy Information Administration (EIA). Meanwhile the resource of trade data with China comes from the OEC and the Chinese Custom.

2.2.2.1 Thailand

During the 25-year period from 1995 to 2020, the United Arab Emirates ($129 billion, 33.3%), Saudi Arabia ($71.3 billion, 18.4%), Oman ($32.9 billion, 8.49%), Malaysia ($29 billion, 4.47%), and Qatar ($22.3 billion, 5.74%) were the main countries from which Thailand received crude oil with a value of $388 billion totally. Regarding Thai oil production and consumption in EIA's 2017 summary report, from 2016, Thailand's petroleum and other liquids production was an estimated to be 525,000 barrels per day while its total oil consumption was estimated to be nearly 1.3 million b/d.

As a net refined oil exporter, Thailand had the second largest capacity (1.2 million b/d) in Southeast Asia, behind Singapore in 2016, according to FACTS Global Energy. Thailand exported $118 billion of refined oil to the regional markets nearby, lasting from 1995 to 2020, with an import of $58.8 billion over the same period.

Starting from 2004, the aggregated Thai exports to China had increased from $7.48 billion in 2004 to $37.7 billion in 2021, making China the second largest destination of Thai exports in 2021. In terms of Thai agricultural commodities export to China, in 2004, the top three agricultural products were rubber, rice and cassava with a total value of around $1 billion. When it came to 2021, the top three agricultural products were other fruits, rubber and cassava with a total value of around $10 billion. In particular, for rubber sold to China, the trade value climbed from $465 million in 2004 to $1.94 billion in 2021 with a market proportion changes from 32% to 52%. As for rice exports to China, the trade value rose from $225 million in 2004 to $327 million in 2021. However, the proportion dropped from 92% of Chinese import of rice in 2004 to 15% in 2021.

2.2.2.2 Malaysia

According to the EIA 2021 analysis report, Malaysia was the second largest oil producer in the Southeast Asia with a crude oil production about 600,000 b/d in 2019. The country is one of the major members in non-OPEC oil producers. From 2004 to 2021, OEC revealed that its main crude oil export destinations were other ASEAN members (31% on average) and Australia (26% on average).

Although Malaysia had about 880,000 barrels per day (b/d) of refining capacity at seven facilities by 2020, it was relatively smaller comparing with Singaporean crude oil refining capacity of 1.3 million barrels per day (b/d). Thus Malaysia oil product trades mainly occurred with neighboring Singapore with oil refining and storage hub.

From 2004 to 2021, the export of Malaysia to China increased by $38.25 billion and its trade portion in Chinese imports increased from 6.53% to 14.3%. The rise of Malaysian exports to China turned China to be the largest trade partner of Malaysia apart from the ASEAN companions in 2021. In consideration of the agricultural product exports to China, Malaysian palm oil and rubber have been the major agricultural commodities. For Malaysian palm oil export, the export to China had a small growth from $959 million in 2004 to $1.1 billion in 2021. Over the same time, Chinese imports on Malaysian rubber went up from $358 million to $518 million.

2.2.2.3 Indonesia

It was revealed by both the EIA 2004 report and 2021 report that the aging oil fields and competition of cheaper energy such as coal and natural gas drove down Indonesian crude oil production from 1.08 million barrels per day in 2004 to about 0.89 Mb/d in 2021, accounting for approximately 1% of world production. After the quit from OPEC in 2016, Indonesia becomes a net importer of crude petroleum of which Saudi Arabia and Nigeria are the main providers.

By 2020, Indonesia had an estimated oil refinery capacity to be 1.1 Mb/d, ranking the third in Southeast Asia. However, the refining capacity was insufficient to meet the domestic demand for refined oil consumption, and Indonesia used imports to meet about half of its domestic petroleum product consumption. In 2021, Indonesia imported $7.35 billion refined oil of which 51.8% came from Singapore.

Over the period from 2004 to 2021, the values of Indonesian exports to China increased from $5.34 billion in 2004 to $54.5 billion in 2021. In the Indonesian exports to China, agricultural oil products took up the largest portion of Indonesian agriculture export to China with a share of around 90% in 2021. For instance, by the end of 2021, the palm oil export to China was $4.22 billion which was nine folds comparing to 2004 value. Meanwhile, the portion of palm oil exports in total agricultural exports to China grew from about 50% in 2004 to around 72% in 2021.

2.2.2.4 Vietnam

The OEC visual data indicated that Vietnam had imported crude oil with a total value of $17.5 billion throughout 2004 to 2021. The main sellers of crude oil included Kuwait ($12.2

billion, 69.8%), Brunei ($1.76 billion, 10.1%), Azerbaijan ($875 million, 5.01%), and Malaysia ($769 million, 4.41%). EIA 2017 summary report for Vietnam indicated that Vietnamese oil consumption increased from 250,000 b/d to estimated 445,000 b/d in the decade between 2006 and 2016. However, by the end of 2018, Vietnam only had a small refinery capacity of around 330,000 b/d. Thus, it had to import refined petroleum from neighbor economies. For example, from 2004 to 2021, Vietnam had purchased $42.2 billion refined oil from Singapore which was 34% of its total import for refined oil.

Over the 17-year period from 2004 to 2021, Vietnamese exports to China grown from $2.87 billion to $57.8 billion with a portion increase from 0.69% to 2.93% in Chinese import market. In terms of its rice export to China, the trade values had an increment from $19 million to $522 million from 2004 to 2021.

2.2.3 About OPEC Announcement

Founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela, OPEC is an intergovernmental organization of petroleum production countries. By the end of 2019, OPEC consisted of 13 member countries total. In the year 2019, its output of crude petroleum took up 48.03% of crude oil exports (based on the Observatory of Economic Complexity 2019 data for crude petroleum exporters), making it the largest supplier in the world oil trade.

Before 2021, the decision for oil production policies mainly came from the announcement released after the OPEC conferences concluded. These conferences, being held twice a year regularly with extraordinary meetings supplemented if necessary, aimed to coordinate members in agreement for oil production policies such as production ceilings and individual quotas. For instance, when there was an adjustment for the oil production quota that was going to become effective (normally 30 days) in January 2016, the announcement published on November 8, 2015 after the 168th conference included the following statement:

"….Having reviewed the oil market outlook for 2015, and the projections for 2016, the Conference observed that global economic growth is currently at 3.1% in 2015 and is forecast to expand by 3.4% next year. In terms of supply and demand, it was noted that non-OPEC supply is expected to contract in 2016, while global demand is anticipated to expand again by 1.3 mb/d."

Since 2021, the policy adjustments of oil production for OPEC, in order to enhance the coordination with non-OPEC oil producers, have been published through the announcements of OPEC and non-OPEC ministerial meetings. In these meetings, the decisions are declared using the following typical statement below after the OPEC and non-OPEC participants reach an agreement.

"The 30th OPEC and non-OPEC Ministerial Meeting was held via videoconference on 30 June 2022. In view of current oil market fundamentals and the consensus on its outlook, the OPEC and participating non-OPEC oil producing countries agreed to: …….

2. Reconfirm the production adjustment plan and the monthly production adjustment mechanism approved at the 19th and 29th OPEC and non-OPEC Ministerial Meetings and the decision to adjust upward the monthly overall production for the month of August 2022 by 0.648 mb/d.….."

In response to OPEC conference announcements, the market usually pays significant attention to them with strong price reactions. For example, Lin and Tamvakis (2010) applied an event study to examine the effects of OPEC announcements on world oil prices. They found differentiation in the magnitude and significance of market responses to OPEC quota decisions under different price bands. Later, Schmidbauer and Rösch (2012) fitted a GARCH-based model to crude oil returns to investigate the impact of OPEC announcements on the expectation and volatility of daily oil price changes (returns). In their results, they provided evidence for a post-announcement effect on expectation, which was negative in the case of a cut decision and positive in the case of an increase or unchanged decision. Meanwhile, there was a positive pre-announcement effect on volatility, which was strongest in the case of a cut decision.

2.3 Model Specification and Data

2.3.1 Methodology

The empirical analysis considers the following reduced-form structural vector auto regression model,

$$x_t = b + A_1 x_{t-1} + ... + A_p x_{t-p} + u_t,\ p = 1, 2, ..., 4 \tag{2.1}$$

where p is the lag order determined by the AIC of the data series, $\mathbf{x}_t$ is a n×1 vector of endogenous macro variables I am interested in, $\mathbf{u}_t$ is the reduce-form innovations vector with covariance matrix Var($\mathbf{u}_t$) = Σ, **b** is a constant vector with size n×1, $\mathbf{A}_1$, …, $\mathbf{A}_p$ are the n-order coefficient matrices.

The reduced-form innovations can be linearly represented by the structural shocks with the following mapping,

$$\mathbf{u}_t = \Phi \varepsilon_t \tag{2.2}$$

where **Φ** is a non-singular n×n matrix indicating the structural impact, ε_t is a n×1 vector of structural shocks. The structural shocks are assumed to be serially and mutually uncorrelated, i.e. E(ε_t) = 0 and Var(ε_t) = Λ = diag(σ^2_1,…,σ^2_n). The mapping of the shocks implies that

$$\Sigma = \Phi \Lambda \Phi' \tag{2.3}$$

Following the design of Känzig (2021) and Montiel Olea, J. L., Stock, J. H., & Watson,

M. W. (2021), I focus on identifying impulse response function to the first order shock in the VAR, $\varepsilon_{1,t}$, which is denoted as the oil supply news shocks, without loss of generality. The impulse response with respect to oil news shocks will be determined by identifying the structural impact vector φ_1, which corresponds to the first column of Φ.

Next I try to identify the structural impact vector using the external instruments approach. Let us denote z_t as an external instrument variable. In my empirical work, z_t is the oil surprise series corresponding to the OPEC announcements. Since the announcements are published monthly for the most time of our sample, the structural impact vector is derived with one instrument and one shock.

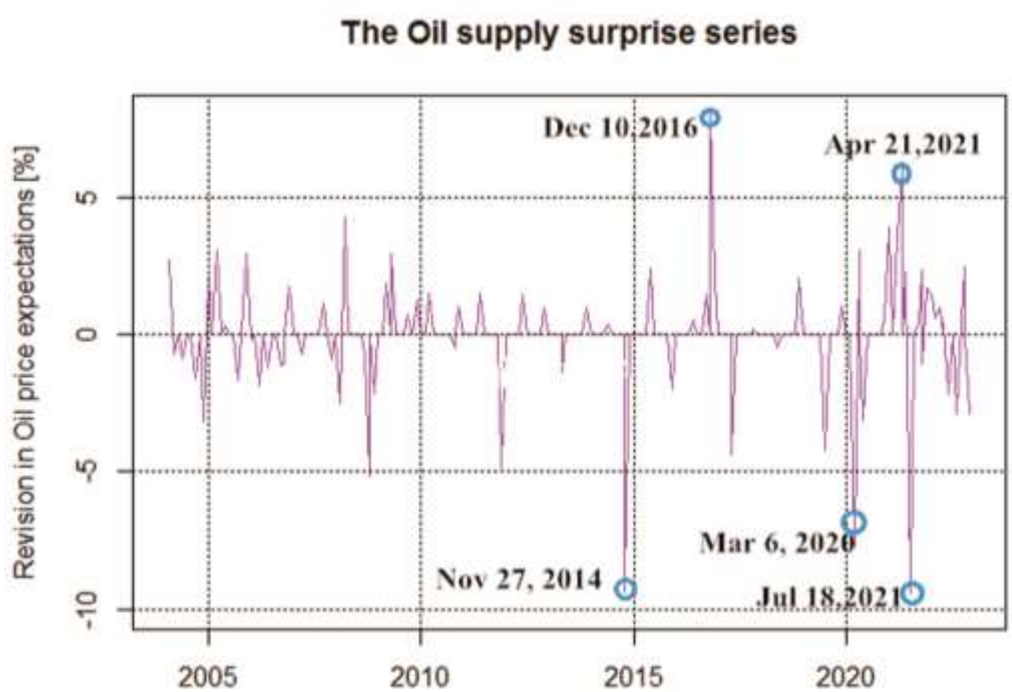
In particular, the oil supply surprise series, is constructed as the percentage change of the average oil futures price on the day of the OPEC announcement and the average price on the last trading day before the announcement, that is:

$$z_t = surprise_{t,d}^{h} = \begin{cases} \dfrac{f_{t,d}^{h} - f_{t,d-1}^{h}}{f_{t,d-1}^{h}}, \text{ if there is an announcement} \\ 0, \text{ otherwise} \end{cases} \tag{2.4}$$

Where $F_{t,d}^{h}$ is the settlement price of the *h*-months ahead oil futures contract in month *t* on announcement date *d*. For the selection of h, the h = 0 (spot), 1(front), …,4 and $h_{composite}$ (average contract price). The baseline h used for estimation is $h_{composite}$.

Figure 2.1 displays the series over 2004 to 2022. The further details of oil surprise series are provided in appendix B.

Figure 2.1. The oil supply series based on OPEC announcements



So, for z_t to be valid, z_t needs to satisfy,

$$E[z_t\varepsilon_{1,t}] = \delta \neq 0 \tag{2.5}$$

$$E[z_t\varepsilon_{j,t}] = 0 \text{ for any } j \neq 1 \tag{2.6}$$

where $\varepsilon_{1,t}$ denotes the oil supply news shock and $\varepsilon_{j,t}$ is an (n-1) ×1 vector corresponding for other structural shocks.

Using assumptions (5)-(6), φ_1 is identified up to sign and scale by the covariance of innovations $\mathbf{u}_t$, Σ and instrument z_t:

$$E[z_t u_t] = \Phi E[z_t\, \varepsilon_t] = \begin{pmatrix} E[z_t u_{1,t}] \\ E[z_t u_{2:n,t}] \end{pmatrix} = \begin{pmatrix} \varphi_{1,1}\delta \\ \varphi_{2:n,1}\delta \end{pmatrix} = \varphi_1\delta$$
$$\tilde{\varphi}_{2:n,1} = \varphi_{2:n,1} / \varphi_{1,1} = E[z_t u_{2:n,t}] / E[z_t u_{1,t}] \tag{2.7}$$

$$\tilde{\varphi}_1 = \begin{pmatrix} \varphi_{1,1} \\ \tilde{\varphi}_{2:n,1}\varphi_{1,1} \end{pmatrix} \tag{2.8}$$

where $\tilde{\varphi}_{2:n,1}$ can be interpreted as the IV innovation estimates scaling on the oil announcement innovations. After obtaining the impact vector, one can apply it onto the computations of interested objects such as IRFs and $\varepsilon_{1,t}$. i.e. $\varepsilon_{1,t} = \tilde{\varphi}_1 \Sigma^{-1} u_t$

2.3.2 Data

My dataset consists of the following parts. The first part is general indicators. Using the framework from Wang, Wu and Yang (2014), the general indicators include three variables of classic oil market VAR models: The real price of oil, ASEAN economic activities and oil production. In the construction of the real price of oil, I followed Känzig (2021) to apply the WTI spot price from EIA, deflated by U.S CPI for oil and its products. The data of U.S. CPI for oil and its products is obtained from the St. Louis Federal Reserve database. In this paper, the monthly change of ASEAN economic activities is captured using seasonal adjusted Baltic Panamax Index as a proxy because of data availability and the vessels used for Southeast Asian exports to China. According to Baltic Exchange benchmark statement (2022), the index measured the prevailing market shipment rate for freight for all of its component routes in which the Panamax class ships were used for freight. The freight under consideration consisted of commodities shipped aboard dry bulk carriers, such as building materials, coal, metallic ores, and grains. Therefore, this index can be used to proxy the shift of commodity demanded in response to oil supply news shocks. In terms of oil production, I obtain the crude oil production data of ASEAN members from Energy Information Administration (EIA) in the US Department of Energy (EIA) as the proxy of ASEAN oil supply. In addition, in order to measure the shipment costs between China and ASEAN, I collect the China Forwarder’s Freight Index of Southeast Asia routes from the Wind database.

In the second part, I first obtain data for ASEAN national aggregated exports to China, including agricultural commodity trades data from the Chinese Custom database. This data covers 4 major economies in ASEAN due to data availability and completeness. The economies in my sample are Malaysia, Indonesia, Vietnam and Thailand. For each economy, I also collected the data of spot exchange rates between U.S. dollar and local currencies as U.S. dollar is the main clearance currency for trade between China and ASEAN. The selection of spot exchange rates is supported by FED report on Oct.6, 2021 regarding U.S. dollar’s international role. In the report, from 1999 to 2019, about 74% export of Asia-Pacific area was cleared by the U.S. dollar. The exchange rate data comes from St. Louis FRED database and Wind database from China. All the data above is monthly based, with a span from 2004M1 to 2019M12. I use these data to analyze the effects of oil supply news shocks on the individual economy aggregate export to China. A detailed overview of the general data and its sources can be found in Appendix A.

To estimate the wider effects of oil supply news shock on the ASEAN members’ main agricultural products export to China, I use the nominal monthly export prices of three key agricultural commodities (rubber from Malaysia and Thailand, palm oil from Malaysia and Indonesia, and rice from Vietnam and Thailand). The nominal agricultural commodity prices are deflated by the CPI of the local economies to obtain the real prices. The agricultural prices data is collected from Wind database. Appendix A offers a more detailed description of these data.

2.3.3 Data Test

2.3.3.1 Unit Root Test

Table 2.1 provides the results of unit root tests based on augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP) and Kwiatkowski et al. (1992) (KPSS) methods. The null hypothesis of the ADF and PP tests is that the time series contains a unit root. For the KPSS test, it is the data stationary test. The test model I consider contains drift and trend under the lag of 4. For the percentage series, according to the ADF and PP statistics, all the series do not follow the unit root processes, while for the KPSS statistics, they consistently reveal that 16 of 17 series are stationary at the 5% significance level and 1 series is stationary at the 10% significance level. Overall, I can generally conclude that, at 5% significance level, according to the results of unit root tests and results of stationary tests, all the percentage series are stationary and do not have unit root problem.

Table 2.1. Results of unit root tests[1]

	ADF	PP	KPSS
	Percentage series	Percentage series	Percentage series
ASEAN oil production	-17.35***	-214.40***	0.0352
Baltic Panamax Index	-12.66***	-174.63***	0.0193
CFFISA	-12.61***	-187.84***	0.0804
WTI	-13.46***	-172.24***	0.0230
Malay Rubber	-11.38***	-167.36***	0.0397

[1] Note: *, ** and *** denote rejection of the null hypothesis at 10%, 5% and 1% significance levels, respectively.

Thai Rubber	-11.57***	-170.96***	0.0337
Malay Palm Oil	-11.31***	-169.13***	0.0587
Indo Palm Oil	-11.09***	-154.32***	0.0527
Thai Rice	-9.71***	-120.51***	0.0430
Viet Rice	-11.01***	-146.14***	0.0250
MAEXPCN	-22.18***	-259.82***	0.0223
THEXPCN	-21.52***	-260.51***	0.0163
IDNEXPCN	-21.44***	-266.37***	0.0538
VNEXPCN	-22.60***	-269.64***	0.0157
USD/MYR	-15.10***	-212.99***	0.0623
USD/THB	-13.54***	-187.19***	0.0388
USD/IDR	-14.88***	-207.92***	0.0409
USD/VND	-17.51***	-298.42***	0.128*

2.4 Empirical Results

2.4.1 Effects on individual markets

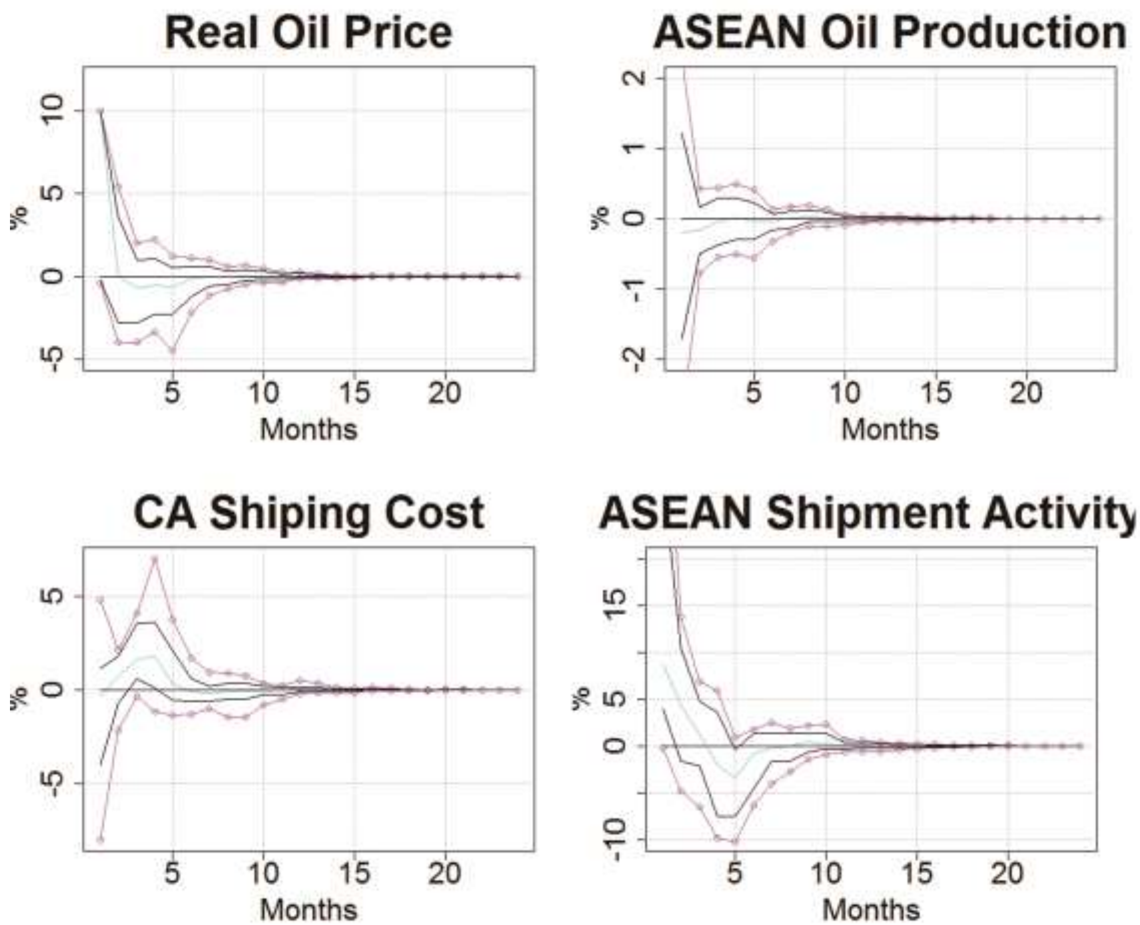
In order to get a better comprehension of how oil supply news shocks affect the ASEAN primary agricultural products exported to China, I study the effects on a variety of economic variables related to ASEAN-China trade. To compute the impulse responses, I start by calculating the SVAR-IV of the general ASEAN market, the variables include real oil prices, ASEAN oil production, ASEAN shipping activity and ASEAN shipping costs to China. Next, for individual market exports to China, I first build up a baseline VAR using oil price, ASEAN oil production, ASEAN shipping costs to China, the local spot exchange rates with USD and the local aggregated exports to China. Then I augment the baseline VAR by one agricultural product at a time for computing the impulse responses. The lag order is set to 4 based on the AIC test results. As all the variables are transformed into percentage changes, the impulse response results can be interpreted as elasticities between the variables and oil prices when an oil supply news shock happens.

2.4.1.1 Effects on the general ASEAN market

In this section, I present the impulse response results from the baseline model focusing on the ASEAN market. The model is identified using the external approach, as proposed by Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021). Because all the variables are transformed into percentage terms, the impulse responses can be interpreted as elasticities. Figure 2.2 illustrates both the 95 percent confidence band and the 68 percent confidence band. The key for interpreting the graphs is that the cyan solid lines are the median estimates, the black lines are the bounds of estimates with a 68 percent confidence band and the magenta lines are the bounds of the estimates for the 95 percent confidence band. This graphic notation will be applied to all the figures in the following figures.

Figure 2.2 illustrates the effect of a 10% oil price increment due to positive oil supply news shocks on general ASEAN market. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change, ignore the fact that the changes are in. The same setting also applies to impulse responses of the rest figures in the Section 2.4 and Section 2.5. It is showed in Figure 2.2 that a positive oil supply news shock leads to an increase in the real price of oil right after the shock happens. However, the increment is short-lived as the impact of a real oil price increase is offset soon by a decline due to markets rebalance. After six months, the influence of this single oil supply news shock is reduced to zero as the international market has digested this news. ASEAN oil production only exhibits an in decline in the first quarter after the oil supply news shock happens in response to an OPEC proposal for future oil production. The inelasticity of ASEAN oil production in response to an external oil supply news shock from OPEC is contributed to the oil status of ASEAN members. In ASEAN, the oil produced within ASEAN economics are mainly consumed by themselves, which forms a relative closed oil market for ASEAN members. The China –ASEAN shipping cost shows an increment which lasts for about six months after the shock happens. The increment occurs immediately after the rise in the real oil price. This result of shows that shipping costs, especially fuel costs, is elastic to oil price in the short run. ASEAN shipping activity initially experiences an increase in response to oil news shock. However, the IRF turns negative in the third month after the shock happens. This decrease lasts for around one more quarter before the IRF goes to zero. This is in line with the notion that external importers for ASEAN commodities might want to build up commodities stocks in advance with the expectation of higher shipment costs due to higher oil prices. When oil prices remain high, the commodities importers will reduce the import volumes of ASEAN commodities until the oil prices fall back to the level before the shock happens. So, the shipping cost can be a potential channel through which oil prices affect commodity prices.

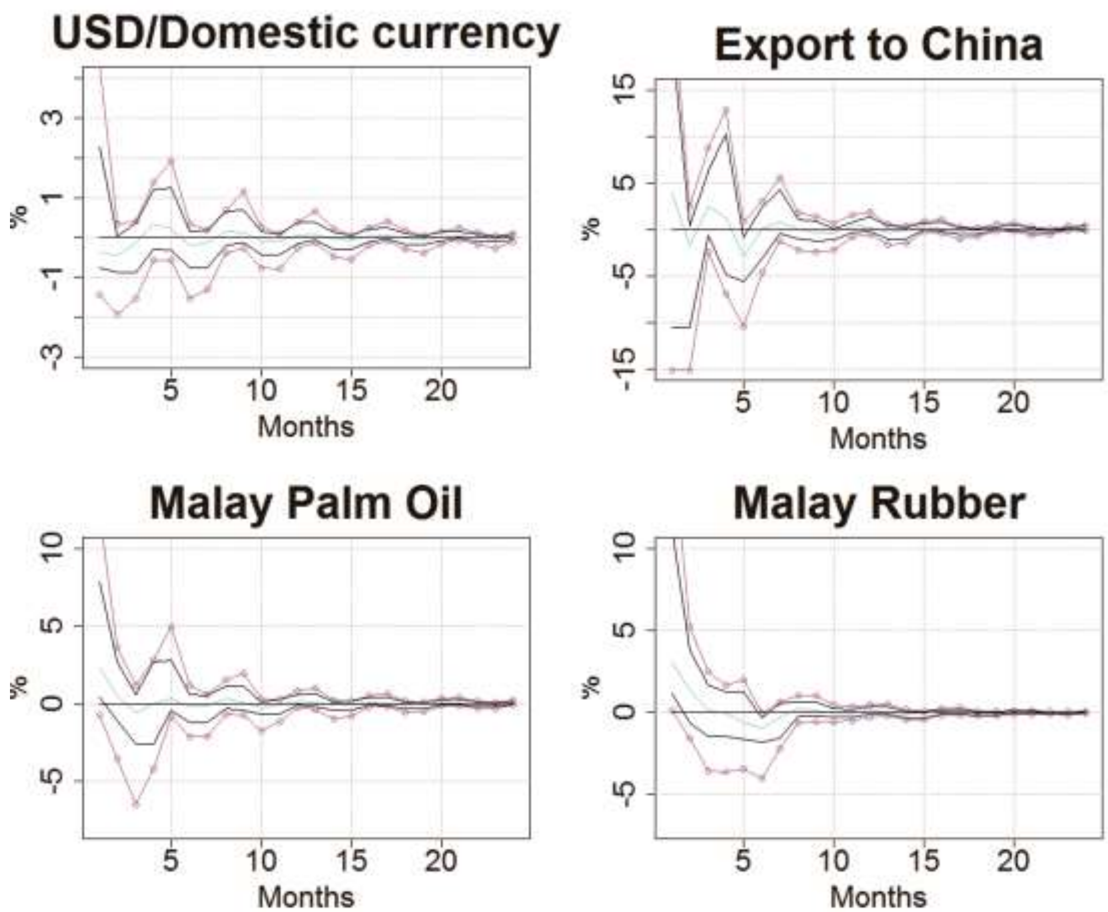
Figure 2.2. ASEAN general market IRF to an oil news shock



2.4.1.2 Effects on the Malaysian export

Turning to individual economies, Figure 2.3 illustrates the response of Malaysian exports to China when a positive oil supply news shock happens. In the first panel of Figure 2.3, the shock only leads to an in short run appreciation in the Malaysia Ringgit. And the impact of the shock fades six months after the shock happens. The result supports the finding by Känzig (2021) that oil supply news shock would lead to an appreciation of oil exporter's bilateral exchange rate with U.S. dollar. The reason of in IRF may lie in that although Malaysia is a net oil exporter, oil trade only makes up 10% to 20% of its total trade value and mainly takes place within ASEAN members. However, according to BNM Annual Report 2022, the Malaysian exchange rate was mainly influenced by trade outside ASEAN in which oil trade is less involved.

Figure 2.3. Impulse Response of Malaysia



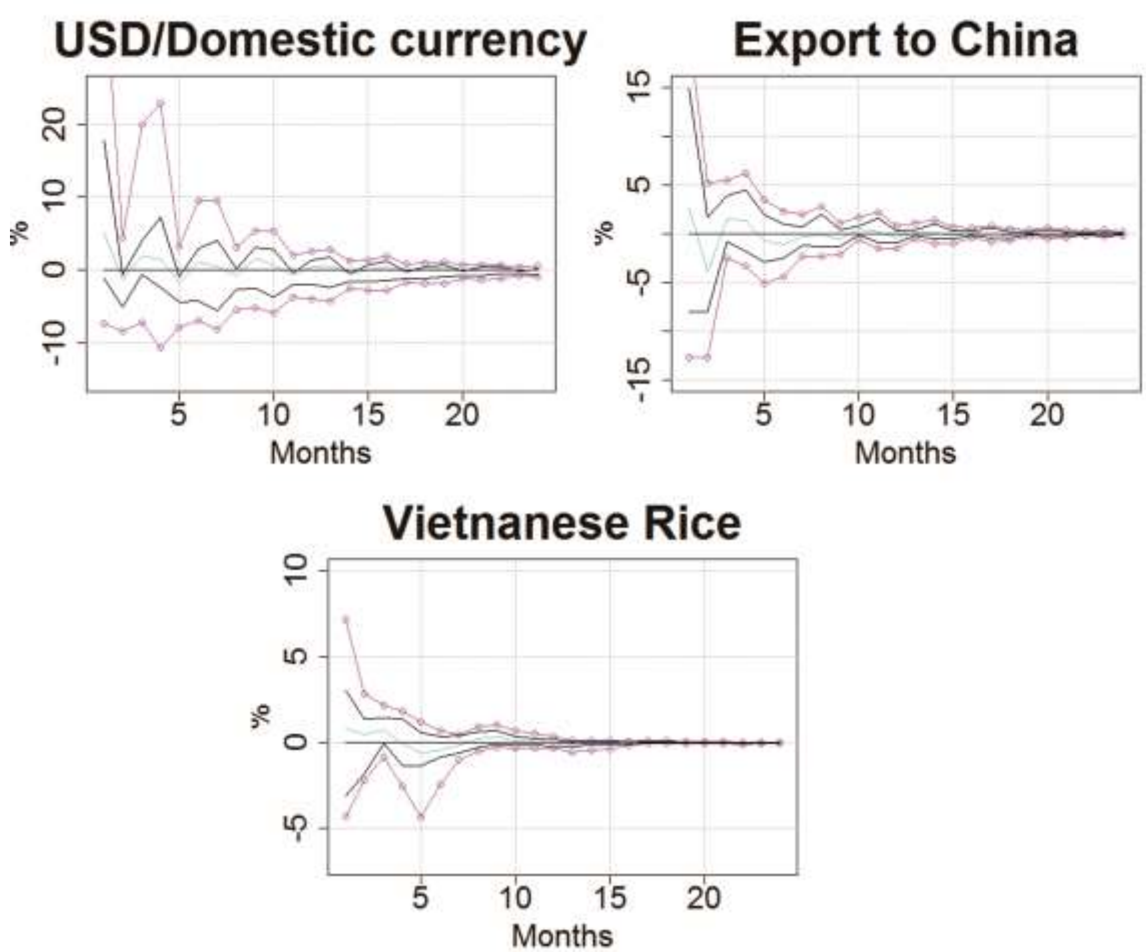
Since 2006, China has become the largest trade partner outside of ASEAN with Malaysia. Thus, I also investigate the relationship between oil supply news shocks and aggregated trade export to China before looking to primary agricultural products export to China. According to the second panel of Figure 2.3, in terms of the aggregated export to China, positive oil supply shocks lead to a short run increase in the first three months but this effect immediate reverses for the following two months. Within two quarters, the influence of oil supply news shocks decline to zero. The trend for the IRF may be caused by the anticipation of future increments to shipping costs. Under this expectation, Chinese importers want to complete the delivery for its import contracts from Malaysia immediately in order to avoid extra costs associated with higher oil prices. In other words, an oil supply news shock increases China's aggregated imports from Malaysia in the short run. These results are aligned with those of Cunado et al. (2015) for China which is a major oil importer in the world, Allegret, J. P., Mignon, V., & Sallenave, A. (2015) for net oil-importing countries in general, and Yalta and Yalta (2017) for Turkey, another oil-importing country.

The final two panels illustrate that the impulse response functions for the real export prices of two primary agricultural commodities that Malaysia exports to China. The panel of real palm oil export prices shows that a positive oil new shock leads to an increase up to 2% of Malaysian palm oil immediately, but this increment does not last more than two months after the shock happens. After an in fluctuation over three months, the effect of an oil supply news shock turns to zero. The short-run elasticity that Malay palm oil performs in response to higher oil prices are in line with the result in Nazlioglu and Soytas (2012) that the oil prices can transmit information to agricultural products prices. The relative independence and closure of ASEAN oil market means that the external shipping cost of ASEAN exports may play a role as the information transmission channel through which the oil price leads to the movement of palm oil price in the same direction.

Lastly, we look at the real export price of Malaysian rubber. As the panel shows, in response to a positive oil news shocks, the real export prices of Malaysian rubber have a short period of increment. The size of the effect is a 4.2% increment of the rubber price. After that, the IRF reverse to an in change as the rubber market between China and Malaysia rebalances the export price along with digesting the impact of oil supply news shocks. This result supports the idea that another possible channel of oil news shocks is via its impact on exchange rate which is different from the shipping cost channel discussed in Malay palm oil. In the exchange rate channel, a domestic currency appreciation caused by the oil supply news shock will enhance the short run deterioration of Chinese demand on Malaysian rubber by pulling down the Malaysian rubber prices due to a weak dollar (see Nazlioglu and Soytas, 2012). This may be confirmed by looking into the responses of trade sectors: rising oil price shrinks foreign expenditures on commodities import when the higher oil price is realized.

2.4.1.3 Effects on Vietnamese macroeconomic

Figure 2.4. Impulse Response of Vietnam



In terms of the Vietnamese IRF results, in the left panel of Figure 2.4, the oil supply news shock leads to an in-persistent short run depreciation of Vietnam Dong whose value is one of the lowest currencies in the world. The impact diminishes to around zero 15 months after the shock happens. The result is in line with the finding that there is negative correlation between oil price and oil importer's currency (Klitgaard, Pensenti, and Wang, 2019; Känzig, 2021) as Vietnam is a net oil importer in ASEAN.

In the next panel, the link between oil supply news shocks and Vietnamese exports to China are short. Note, Vietnam is the largest trade partner in ASEAN with China. It is showed that a positive oil supply news shock lead to a short run increase immediately. Then it reverses and the effect of the shock reduced to zero over time. The elasticity of Vietnamese export to China might be explained by the adjustment of Chinese demand for foreign consumption goods during which an oil supply news shock changes Chinese importers' expectation of short-run shipping cost of Vietnamese commodities. The results also supports Känzig's (2021) finding with U.S. data that an oil supply news shock lead to a decrease in consumption of the oil importer.

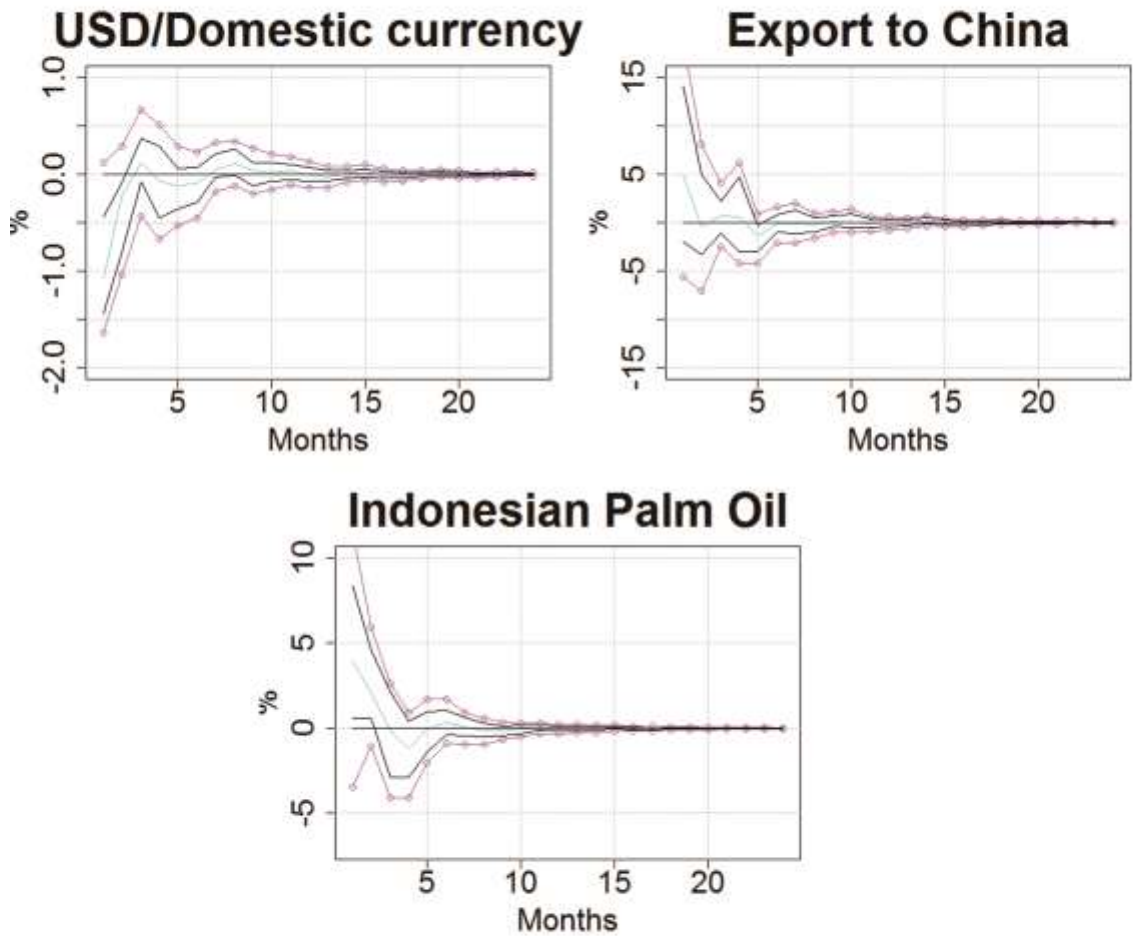
The last panel displays the impulse response result of the Vietnamese rice export prices. It can be seen that a positive oil supply news shock leads to a short-lived increment on the rice prices due to the potential increase of shipping costs driven by higher oil prices. The high rice prices prevent Chinese investors from importing Vietnamese rice. According to OEC database, in 2021, about 64% the Vietnamese rice sold to China is broken rice which is used for animal feeds. This result provides support for Känzig (2021) that positive oil news shocks shrink investment of oil importers. Then the response turns negative and reduces to zero over time. The reverse is contributed to the elasticity of Chinese demand for Vietnamese broken rice whose share is about 22%. When Vietnamese broken rice prices go up in response to oil news shocks, Chinese investors may turn to India (38%) or Pakistan (17%) for cheaper broken rice. Thus, Vietnamese rice exporters have to bring down the prices until the shipping cost goes back to normal. Overall, the IRF result of Vietnam rice price is in line with finding in Wang, Wu and Yang (2014) that oil supply shock causes short run changes in rice commodity.

2.4.1.4 Effects on Indonesian market

This section presents the IRF results for the Indonesian exports to China. In the first panel of Figure 2.5, a positive oil supply news shock leads to an appreciation of Indonesia Rupiah immediately. Then the effect declines to zero over time. The result support the Känzig (2021) finding again that positive oil supply news shocks rise up the bilateral exchange rate between US Dollar and Indonesia Rupiah. When the shock happens, Indonesia, as a main oil exporter in ASEAN, its currency appreciates in response to the oil supply news shock.

With the result of export to China above, one expectation for the Indonesian palm oil is that the oil supply news shock would lead to a price increase for Indonesian palm oil. The expectation is confirmed in the right panel of Figure 2.5. It can be seen in the graph that the palm oil export prices of Indonesia experience a short run increment. Then, the effect of the shock decreases zero over time. Indonesian geographic characters determines that its high reliance on shipping transportation makes its palm oil price be more elastic when comparing with Malaysian palm oil price. Thus, when the impact higher oil prices is transmitted through the channel of shipping costs, Indonesian palm oil price responses due to its sensitivity to shipping costs. This result provides supplements to Wang, Wu and Yang (2014) that oil supply shock causes short run changes in agricultural commodity.

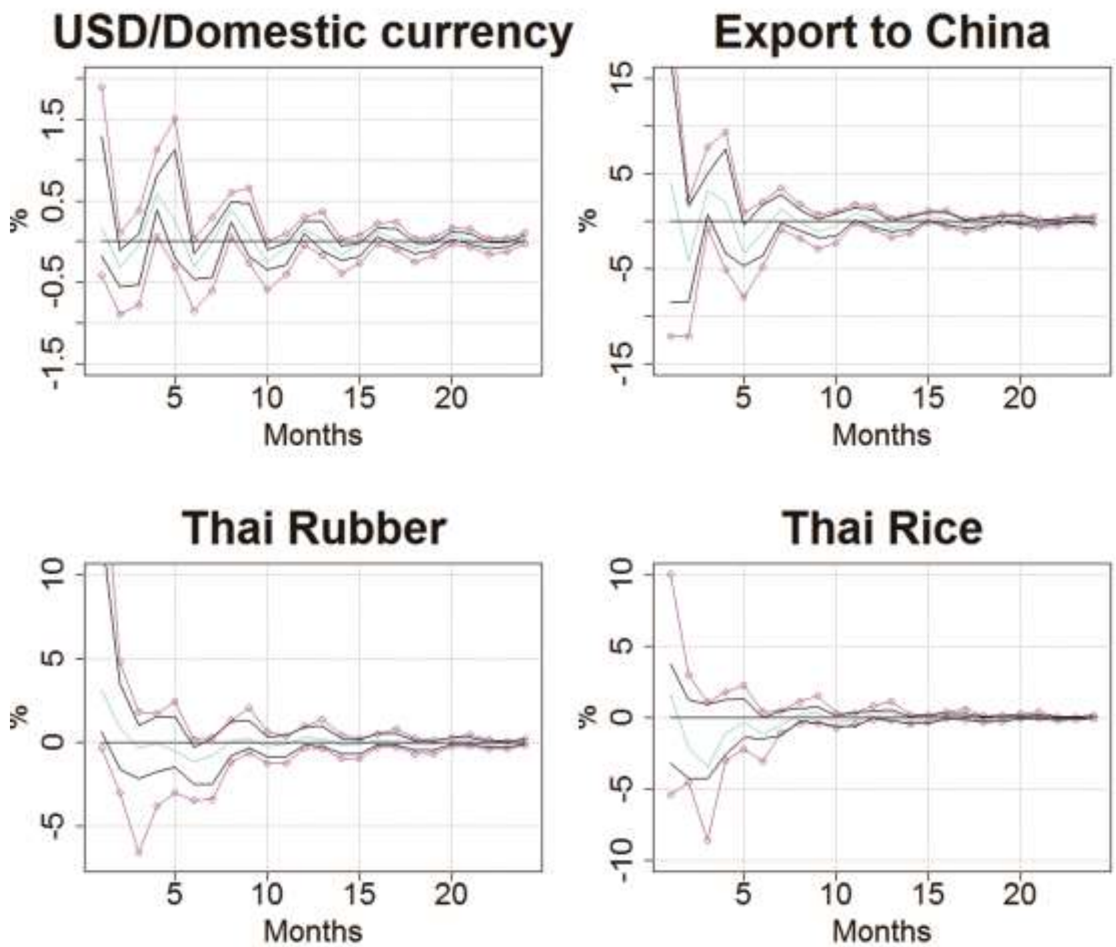
Figure 2.5. Impulse Response of Indonesia



2.4.1.5 Effects on Thai market

Turning to IRFs for Thai market from an oil supply news shock. Starting with the first panel in Figure 2.6, for Thai exchange rate, a positive oil supply news shock leads to in-persistent depreciations of Thai Baht over time. The depreciation of Thai Baht under the supply news shocks may be contributed to the need of boosting the short run exports of Thailand, as implied by Cunado, J., Jo, S., & de Gracia, F. P. (2015).

Figure 2.6. Impulse Response Functions of Thai market



Then, by looking at impulse response function result of Thai export to China when a negative oil supply news shock happens, it shows very short run positive responses due to expectation of rising shipping cost and the Chinese demand for finish the import delivery, as well as weak Thai Baht promotes the exports. When the shipping cost increases and dominates short-run exports, the Thai exports to China turns negative and lasts for a month before the effect of the shock reduces to zero.

Now I turn to look at the relationship between oil supply news shocks and the export price of Thai rubber. As the panel in Figure 2.6 displays, the oil supply news shocks lead to a short-lived rise of Thai rubber price in the first place. Then the IRF turns negative as the local market rebalance the price. At last the IRF diminishes to around zero in 8 months after the shock happens. The result again reveals that the higher oil prices disrupted the short run shipping costs of Thai rubber, leading the Thai rubber export prices to rise. As a result, this disruption leads to a reduction of expenditure of rubber from Chinese investment demand (Känzig, 2021). My result is also in line with the finding in Naeem, M. A., Karim, S., Hasan, M., Lucey, B. M., & Kang, S. H. (2022) that there is a short term correlation between oil supply shocks and rubber prices.

With regard to the link between the oil supply news shocks and the rice prices, the last panel of Figure 2.6 illustrate the IRF result of Thailand rice export price to China. As the panel displays, for the rice export price, there is an in-persistent decline which lasts about 8 months in response to a negative supply news shock. The impaired rice export prices may be caused by the impact of channels of Chinese consumption and investment, through which oil supply news shocks deteriorate Chinese demands for Thai rice in regular consumption and animal feeds. In Chinese demand for Thai rice, the ratio of regular consumption and animal feeds were 3:1 according to OEC database regarding Thai 2021 exports. This finding supports Känzig (2021) that oil supply news shocks lead to a decline in an oil importer's demands.

Overall, I find out that the oil supply news shocks only have short run impact on ASEAN main agricultural products exported to China during the sample period I investigate. The reason may lie in two parts. First, the impact that the oil supply news shock transits through shipping cost only changes the Chinese importers' expectations and demands for ASEAN agricultural products in the short term. Second, the relative independence of ASEAN oil market to world oil market such that the impacts of oil supply news shock is in-persistent on ASEAN commodities price changes in the long run.

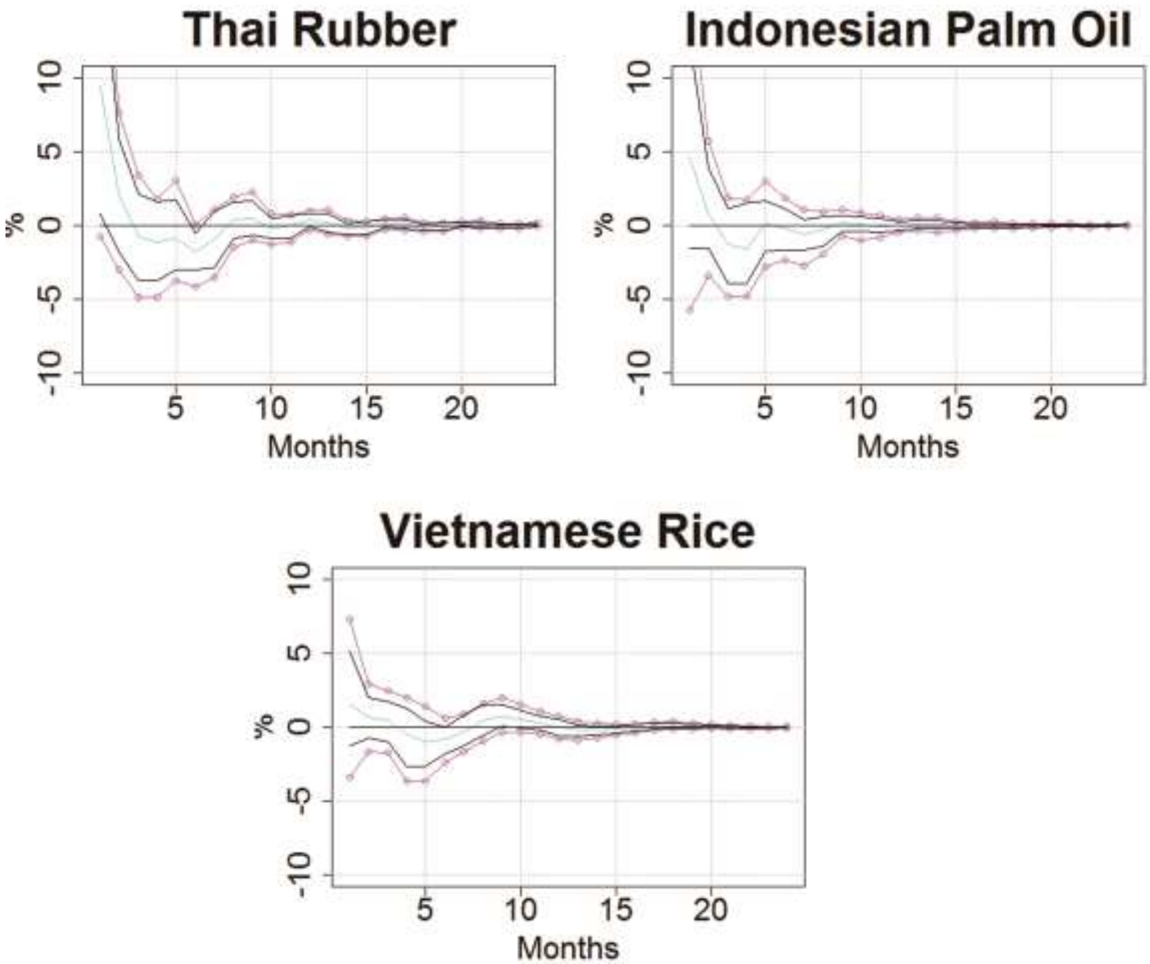
2.5 Sensitivity Analysis

In this section, I conduct the following robustness checks on agricultural products to test the sensitivity of my results. The robustness checks for IRF results of aggregated trade have two parts. I first check if the IRF results would be sensitive to the impact of COVID-pandemic which brought down global economy in both supply and demand. To do this, I narrow the sample period from 2004M01 to 2019M12 and focus on the largest export countries for each product, namely Thailand for rubber, Indonesia for palm oil and Vietnam for rice. The impulse response results are illustrated in Figure 2.7. Figure 2.7 shows that my results are robust to the influence of COVID. In the Figure 2.7, the IRF results before the pandemic are similar to IRFs containing the pandemic period. Thus my results are robust when considering the potential impact of COVID.

After that, I alter the lags of SVARIV model for agricultural products from 4 to 12 to check if the IRF results are sensitive to different lags. As the results in the Figure 2.8 show, under the lag(12) model, the IRFs of agricultural products are similar to IRFs of lag(4) model except for two difference. The first difference lies in that the IRFs of lag(12) model are slower to converge to zero than the lag(4) model. The second difference comes from that Thai rice in which the IRF is in. The Thai rice result under the lag(12) model shows that Thai rice price is inelastic to oil supply news shock in the long run as Chinese consumption demands for Thai rice are inelastic in the long run. So, my result are also robust when considering different lags for my model.

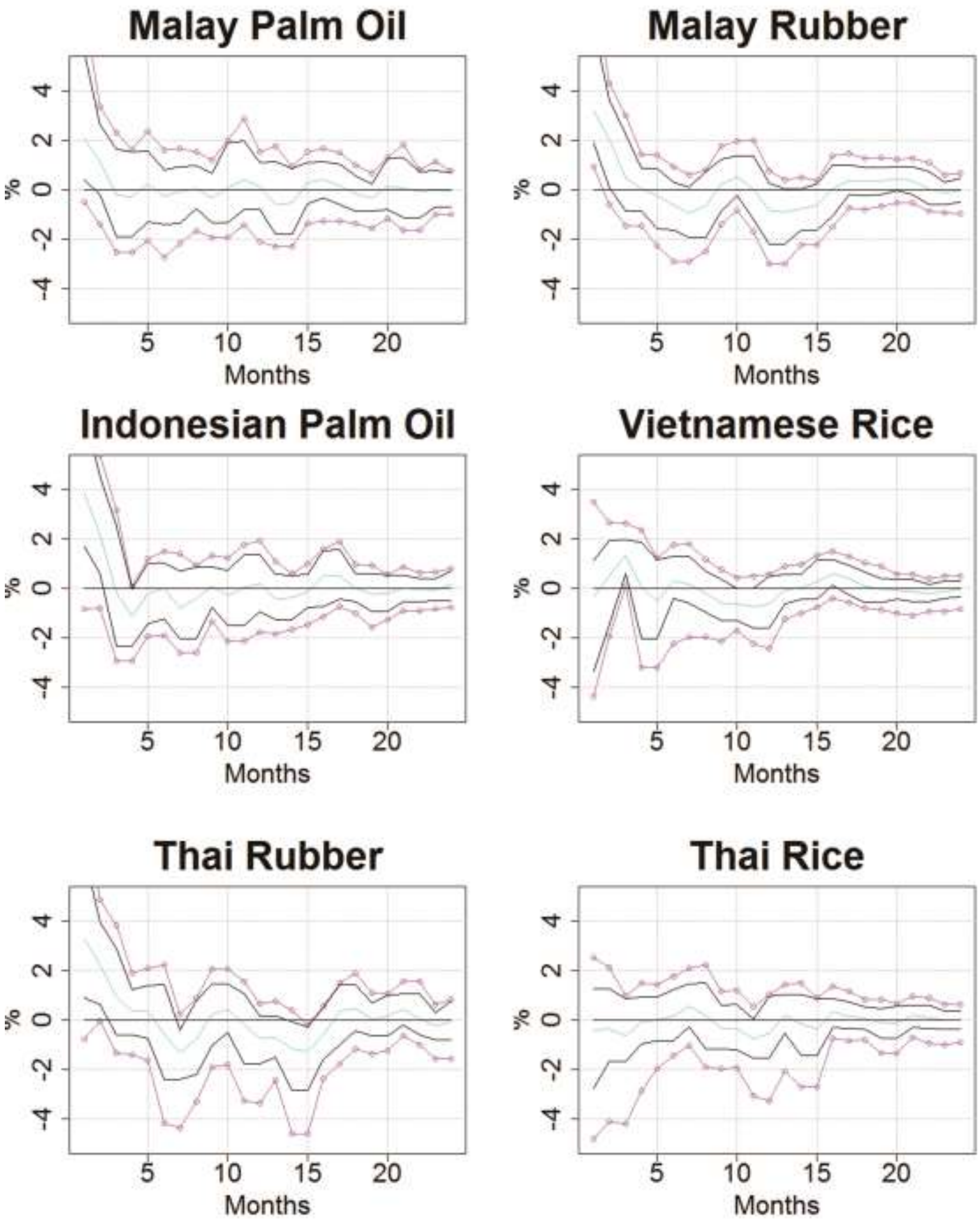
Then I investigate whether the IRF results of the same agricultural product are affected by the positions of oil production of sample ASEAN countries in which Malaysia and Indonesia are oil producers while Thailand and Vietnam are oil importers. To achieve this, I first select rubber as the primary agricultural product for analysis because all the four countries get involved with rubber trade with China and their rubber trade values take up a portion of around 91% of Chinese rubber import in total.

Figure 2.7. IRFs of primary agricultural export prices from alternative sample



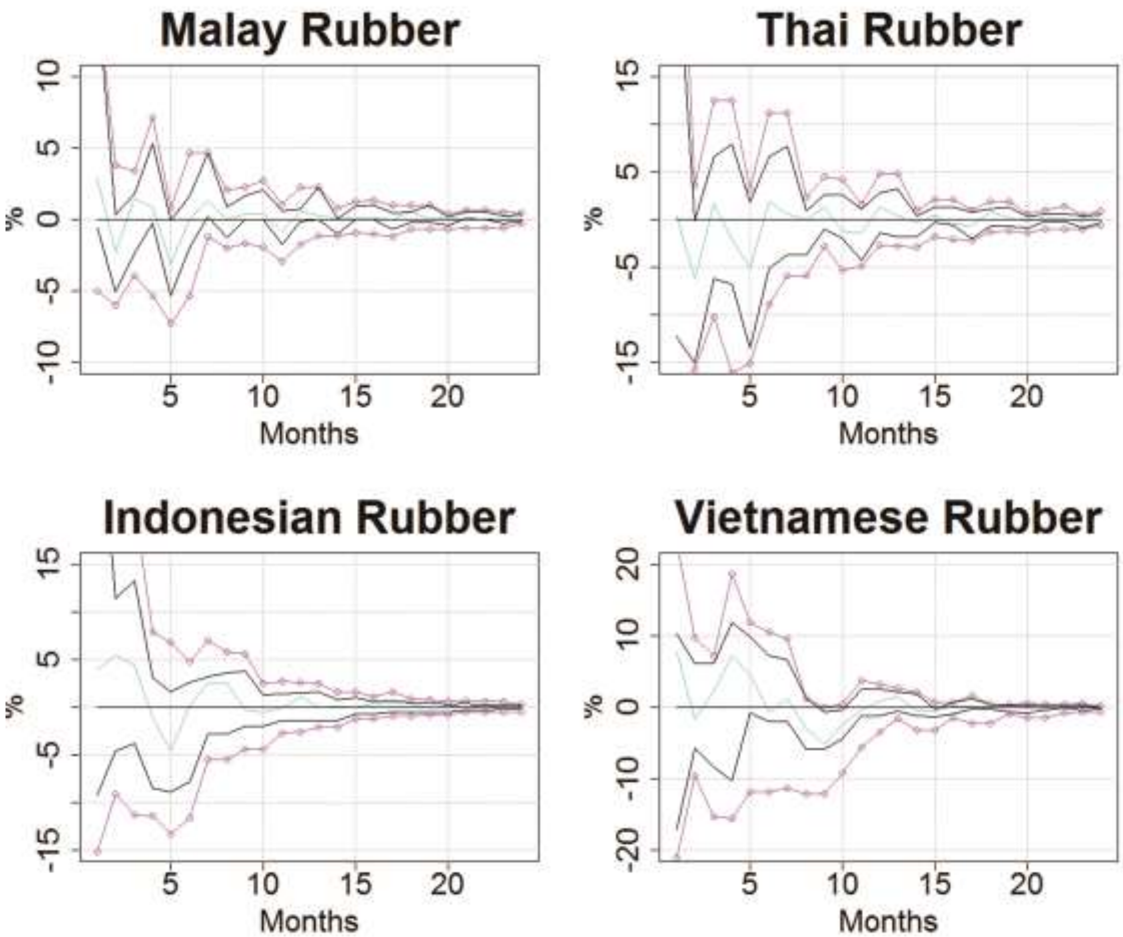
Second, I narrow the sample period from 2009M01 to 2022M12, due to data availability of rubber trade value with China for Indonesia and Vietnam. The alternative IRF results are displayed in Figure 2.9. According to Figure 2.9, the IRF of rubber exports to China from the four economies illustrate that when the rubber prices increase in both Malaysia and Thailand in response to high oil prices, Chinese demands to rubber become diverse by purchasing more rubber from Indonesia and Vietnam.

Figure 2.8. IRFs of agricultural export prices from lag(12) model



This can be explained by the oil consumptions and productions of ASEAN members mainly occur within the organization itself and their effects do not transmit to country outside. Therefore, my results indicate that the oil positions do not affect the robust of my IRF results.

Figure 2.9. IRFs of rubber exports to China by values[2]



2.6 Conclusion

In this paper, I study the effects of the oil supply news shock on the ASEAN primary agricultural products export to China. The effect is approached using an external instrument structural VAR model which is suggested by Känzig (2021). Following the design of Känzig (2021), I use the percentage changes of WTI composite oil futures prices around OPEC meeting

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[2] Top left: IRF of Malaysian rubber; Top right: IRF of Thai rubber; Bottom left: IRF of Indonesian rubber; Bottom right: IRF of Vietnamese Rubber.

announcements as an instrument. My results find that the oil supply news shocks lead to changes in a short period of time in terms of sample ASEAN economies export to China, usually within three quarters after the shocks occur. These results provide further support evidence for the findings by Wang, Wu and Yang (2014). In terms of primary agricultural product export prices, I find out in-persistent increases in export prices of rubber for Thailand and Malaysia, in response to the oil news shocks. Similar results are observed in the export prices of palm oil for Indonesia and Malaysia. My findings in export prices of rice for Thailand and Vietnam suggested that the trade structure difference of rice causes the variation of IRFs when the oil supply news shocks happen. In the agricultural export prices results, the shipping cost plays as an important channel through which the oil price transmits its impact to agricultural product price by adjusting the shipping costs. My results are robust to cases such as COVID pandemic, lag sensitivity and different oil status when considering the same product like rubber.

For future research, it may be important to investigate the effect of the oil news shocks on other ASEAN-China FTA sectors, such as freight prediction as an extension of trade, service trade, and the structure of commodities. Also, researcher may find it interest to study how OPEC+ members (Brunei and Malaysia) and OPEC exit (Indonesia, left OPEC in 2016) respond to oil news shocks when dealing with trade to China. This type of research will help policymakers in formulating sound fiscal and monetary policies in maintaining the stability of ASEAN-China trade in response for exogenous oil shocks.

Chapter 3 - Do oil supply news shocks and trade policy uncertainty matter for Chinese imports? Evidence from non-ferrous metals import in 21st century

3.1 Introduction

The long-standing question of identifying the factors affect a country's commodities imports has been attracting the attention of economists due to the turbulence in the past decade. One of the challenges in answering this question is the endogeneity of future oil prices and domestic economic policy uncertainty along with their effects on commodity import of a single market, for example, China. To provide a potential explanation, the researcher needs to exploit how the foundations that drives future oil prices affect commodities trades in a single market. Also, there is a demand in examining the changes of commodities imports when there is a domestic economic policy uncertainty event.

In this paper, I first examine the effects of the oil news shocks driving the import values and spot prices of non-ferrous metals imported by China. I use the structural Vector Auto Regression (SVAR) model with a single oil news shock to investigate this issue. The oil news shocks are identified by following Känzig (2021) design which exploits the official announcements of the meeting of Organization of the Petroleum Exporting Countries (OPEC) and information implied by oil future prices. Then I apply a Time-Varying Vector Auto Regression (TVP-VAR) framework suggested by Huang, Dong, Chen and Zhong (2022) to investigate the dynamic effect of the Chinese trade policy uncertainty on the import values and spot prices of non-ferrous metals imported by China.

In my empirical results, for Chinese non-ferrous metal import, in term of the effect of oil supply news shock, I find out that oil supply news shocks has little effect on both the value and price of Chinese non-ferrous metals import during the sample period I investigate. The long run contract and annual clearance for settlement may contribute to the negligible variation of Chinese non-ferrous metals when the oil supply shock happens. Regarding the Chinese trade policy uncertainty, it has diverse effects on its non-ferrous metal import which may be caused by different economic conditions. For example, the Australian non-ferrous metals exports to China indicate that the level of non-ferrous metal reliance on imports can be a reason lead to divergent responses. Meanwhile, a major Chinese trade policy uncertainty event may have negative effect on the spot prices of non-ferrous metals. The reason may lie in that the Chinese trade policy uncertainty lowers market demand expectations of non-ferrous metals as China is the biggest buyer for them. Consequentially, the potential demand declines bring down the market prices of non-ferrous metals. Finally, a comprehensive sensitivity checks indicate that my results are robust to lag sensitivity.

The rest of the paper is organized as follows: Section 3.2 reviews the literatures. Section 3.3 presents the data source. Section 3.4 describes the methodology. Section 3.5 reports and discusses the results. Section 3.6 concludes the paper.

3.2 Literature Review

3.2.1 Literature Background

Recently, interest in oil news shocks effects on economic variables has been increasing as there is growing literature on this topic. Su, Z., Lu, M., & Yin, L. (2018) exploited the relationship between news implied volatility (NVIX) and classic oil shocks. They investigated whether the world price of oil and oil shocks promoted by Kilian (2009) affected news-based uncertainty or Vice versa. Their results illustrate that oil prices exhibit a statistically and economically significant leading role on NVIX, especially in the long run. In terms of specific oil shocks, the authors found out that NVIX had the opposite direction with classic oil shocks except for the oil supply shocks. Känzig (2021) studied the OPEC announcement news shocks on the global market as well as the U.S. macroeconomic under a structural VAR framework with external instruments. The instrument is the OPEC announcement news shocks series which is constructed by utilizing WTI future prices in a tight window of announcements. The outcome of this paper provided evidence that OPEC announcement news can be a strong channel through which the researchers can study the wide effects on oil importer's macroeconomic concerning oil supply expectations. Liu, D., Wang, Q., & Yan, K. X. (2022) focused on similar oil supply news shocks for the Chinese economy. Their work provided evidence that the oil supply news shock only affected the Chinese economy through the exchange rate and trade balance.

All the previous works focus on analyzing the impact of news shocks on the macro aspects of an individual market. However, there is few literature focusing on how news shocks, especially oil news shocks, affect non-ferrous metals trades with a single export destination.

The studies for the relationship between crude oil and precious metal market have received much attention, especially the relationship between the oil market and precious metals returns or volatility. In a general way, oil prices affect precious metal prices through the inflation channel (Behmiri & Manera, 2015), exchange rate channel (Zhang and Wei, 2010), and export revenue channel (Tiwari & Sahadudheen, 2015). In addition, Huang, J., Dong, X., Chen, J., & Zhong, M. (2022) applied the time-varying parameter vector autoregression (TVP-VAR) framework to study the dynamic effects of the oil price shocks and the U.S. economic policy uncertainty on precious metal returns. Using monthly data from April 1990 to April 2018, they found opposite effects of oil shocks on precious metal returns before 2008 financial crisis and after. Also, the effects of economic policy uncertainty on precious metal returns changed over time and were positive in most cases. In the channels of uncertainty transmission, they provided evidence that news uncertainty and inflation uncertainty were the most significant.

However, these works emphasized on the financial interactions of the precious metal markets with oil prices only without considering the actual supply and demand. Also, there are less attention on the non-ferrous metals. Therefore, this paper tries to fill the gap by studying the effect of oil prices on Chinese non-ferrous metals imports.

In the a few literatures analyzing the effect of crude oil on non-ferrous metals, Zhang & Chen (2014) studied the reaction of Chinese aggregated markets (including metals, petrochemicals, grains and oil fats) to oil price shocks by utilizing autoregressive conditional jump intensity (ARJI) model, incorporating with the EGARCH method. In their findings, the aggregate commodity market was affected by both expected and unexpected oil price volatilities in China. However, the metals indices did not significantly respond to the expected volatility in oil prices. Later, Zhang & Tu (2016) investigated the impacts of global oil price shocks on the whole metal market and two typical metal markets: copper and aluminum, with the help of the autoregressive conditional jump intensity (ARJI) model, and the generalized conditional heteroscedasticity (GRACH) method. Their results indicated that crude oil price shocks had significant impacts on China's metal markets and the impacts are symmetric. When compared with aluminum, copper was more easily affected by oil price shocks. Recently, Gong & Xu (2022) used the improved Diebold-Yilmaz method to measure connectedness between commodities. They found out that the energy, industrial metal, and precious metal commodity markets are the information transmitters in commodity markets, and the agriculture and livestock commodity markets play the roles of information receivers. Furthermore, they employ the GARCH-MIDAS model to study the influence of geopolitical risk on the dynamic connectedness between the five commodity markets. According to their results, geopolitical risk has negative effects on industrial commodity markets.

Despite these papers contribute to analyzing the general relationship between oil shock and aggregated industrial metal sectors, especially on financial market, there is still a room left for discussing how individual industrial metal markets (i.e, nickel, lead, etc.) response to oil news shock and economic policy uncertainty. For instance, Zhang & Tu (2016) indicated that there were spillover effect of oil shocks on individual industrial metal markets.

Since proper evaluation of the effect of oil shocks over time depended on its sources as Kilian (2009) suggested, as well as the level of policy uncertainty, the effect of such shocks may vary sharply over time as they work on individual non-ferrous metal markets. In this project, the main objective is to contribute to the literature on oil supple news shocks-industrial metals relationship by examining the possible impact of oil news shocks on Chinese non-ferrous metal import in a VAR approach framework, along with Chinese trade policy uncertainty.

3.2.2 Status of Major Industrial Metals Import of China

Ever since 2000, the role of China on global non-ferrous market has been growing. From 2000 to 2021, the value of non-ferrous metal imported by China had increased from about \$6.55 billion to about \$156 billion. Since 2008, China has become the largest importer of non-ferrous metals in the world. The following part presents the background of Chinese import of main non-ferrous metals from 2000 to 2022. These non-ferrous metals, according to the classification of the Chinese Custom, include copper, nickel, aluminum, zinc, lead and tin. The metal import background information is based on the database from the Observatory of Economic Complexity (OEC) and the Chinese Custom.

3.2.2.1 Copper

During the 22-year period from 2000 and 2021, Chile ($106 billion, 32.1%), Peru ($70.7 billion, 21.4%), Mongolia ($24.3 billion, 7.33%), Australia ($21.2 billion, 6.41%), and Mexico ($19.4 billion, 5.86%) were the main countries from which China receives copper ores worth 241.6 billion totally. Over the same time, the shares of Chinese copper ore imports grew from 11.2% in 2000 to 57.5% in 2021. Starting from 2011, China has become the largest importer of copper ores in the world.

As to copper articles, according to Chinese Custom, in the year of 2022, China imported copper articles worth $55.7 billion from abroad with a market share of 24.7%. In the main sources of copper articles, Chile ($8.15 billion, 14.6%) and Democratic Republic of the Congo ($5.6 billion, 10.1%) were the main exporters to China in 2022.

3.2.2.2 Nickel

The OEC visual data indicated that China had imported the largest value of nickel ore from a 2008 worth of $3.98 billion to a 2021 worth of $4.24 billion. In 2021, the main seller of nickel to China included Philippines ($1.39 billion, 58.9%), New Caledonia ($280 million, 11.9%), Finland ($225 million, 9.55%), Australia ($72.8 million, 3.09%) and Zimbabwe ($70.6 million, 3%). From 2000 to 2021, the Chinese import value of nickel ore increased by $2.36 billion with an increment of market portion from 0.12% to 55.6%.

Meanwhile, in terms of Chinese import of nickel articles, Australia ($18.4 billion, 21.8%), Russia ($14.8 billion, 17.5%) and Canada ($8.65 billion, 10.2%) were the leading exporter over the period from 2000 to 2021.

3.2.2.3 Aluminum

From 2000 to 2021, the world market share of Chinese import for aluminum ore rose from 0.75% to 68.4% with an average value growth of $1 billion per year. Before 2012, most aluminum ore imported by China came from Indonesia ($2.16 billion, 67.5%) and Australia ($0.712 billion, 22.3%). After 2012, Guinea became the largest exporter of aluminum ore to China with an average share of 39.9% and a total value of $10.3 billion. Following Guinea, Australia ($7.9 billion, 30.9%) ranked the second place and Indonesia ($4.26 billion, 16.5%) was in the third place.

3.2.2.4 Lead

China had diverse import sources of lead ores in the world market from 2000 to 2021 with an aggregated value of $34 billion. Lead ore was mainly purchased from countries like Peru ($6.72 billion, 19.8%), Russia ($4.32 billion, 12.7%), United States ($4.15 billion, 12.2%), Mexico ($3.61 billion, 10.6%), and Australia ($3.57 billion, 10.5%). Meanwhile, according to the OEC database, China had a small import of lead articles worth $3.64 billion over 22 years. These products were purchased from Asian countries and Australia mainly.

3.2.2.5 Zinc

Comparing with lead ores, China had a smaller but less diverse import of zinc ores with an aggregated import of $29.4 billion over the period from 2000 to 2021. During the 22-year period, Australia ($9.73 billion, 33.1%), Peru ($5.51 billion, 18.7%), Mongolia ($1.93 billion, 6.57%), Bolivia ($1.31 billion, 4.46%), and Russia ($1.02 billion, 3.47%) were the main suppliers of zinc ores to China. According to OEC 2021 report, China was the largest importer of zinc ores with a market portion of 26.8%. From 2000 to 2021, China had imported zinc articles worth $27.1 billion, which was equivalent to zinc ores import. Like lead, these products were also purchased from Asian countries and Australia mainly.

3.2.2.6 Tin

According to OEC data, China only had a very small tin ores import from 2000 to 2021, with a total worth of $1.67 billion over the period. China imports tin ores mostly from the following countries: Australia ($342 million, 20.5%), Bolivia ($341 million, 20.5%), Democratic Republic of the Congo ($278 million, 16.7%), Sierra Leone ($237 million, 14.2%), and Burma ($150 million, 8.99%). In the OEC summary report for Chinese tin articles import over the same period, it was displayed that China had imported $5.72 billion zinc articles aggregately of which were also purchased from Asian countries and Bolivia mainly.

3.2.3 OPEC Announcement

OPEC, an intergovernmental organization of petroleum production countries, was founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela to co-ordinate and unify the petroleum policies among membership oil producers. By the end of 2021, OPEC consists of 13 member countries in total. In the year 2021, its output of crude petroleum took up about 45% of crude oil exports (based on the Observatory of Economic Complexity 2021 data for crude petroleum exporters), making it the largest supplier in the world crude oil trade.

Before 2021, the decision for oil production policies mainly came from the announcement released after the OPEC conferences concluded. These conferences, being held twice a year regularly with extraordinary meetings supplemented if necessary, aimed to coordinate members in agreement for oil production policies such as production ceilings and individual quotas. For instance, when there was an adjustment for the oil production quota that was going to become effective (normally 30 days) in January 2020, the announcement published on December 5, 2019 after the 177th conference included such a statement:

"…. Accordingly, the Conference decided to support an additional adjustment of 500 tb/d to the adjustment levels as agreed at the 175th Meeting of the OPEC Conference and 5th OPEC and non-OPEC Ministerial Meeting, subject to approval by the 7th OPEC and non-OPEC Ministerial Meeting to be held on 6 December 2019. This additional adjustment would be effective as of 1 January 2020 and is subject to full conformity by every country participating in the DoC (Declaration of Cooperation)."

Since 2021, the policy adjustments of oil production for OPEC, in order to enhance the coordination with non-OPEC oil producers, are published through the announcements of OPEC and non-OPEC ministerial meetings. In these meetings, the decisions are declared using the following typical statement below after the OPEC and non-OPEC participants reach an agreement.

"In light of the uncertainty that surrounds the global economic and oil market outlooks, and the need to enhance the long-term guidance for the oil market, and in line with the successful approach of being proactive, and pre-emptive, which has been consistently adopted by OPEC and non-OPEC Participating Countries in the Declaration of Cooperation, the Participating Countries decided to: …….

3. Adjust downward the overall production by 2 mb/d from the August 2022 required production levels, starting November 2022 for OPEC and non-OPEC Participating Countries as per the attached table. …..”

In response to OPEC conference announcements, the market usually pays significant attention to them with strong price reactions. For example, Demirer and Kutan (2010) applied an event study methodology to examine the abnormal returns in crude oil spot and futures markets around OPEC conference dates between 1983 and 2008. The examination was carried out using market models and ARCH models. Their main finding regarding OPEC announcement indicated that there was an asymmetry in that only OPEC production cut announcements yield a statistically impact on oil price with the impact diminishing for longer maturities. Later, Schmidbauer and Rösch (2012) fitted a GARCH-based model to crude oil returns to investigate the impact of OPEC announcements on the expectation and volatility of daily oil price changes (returns). In their results, they provided evidence for a post-announcement effect on expectation, which negative in the case of a cut decision and positive in the case of an increase or unchanged decision. Meanwhile, there was a positive pre-announcement effect on volatility, which was strongest in the case of a cut decision.

3.2.4 Economic Policy Uncertainty

3.2.4.1 Chinese Policy Uncertainty

The index of Chinese trade policy uncertainty was developed by Steven J. Davis, Dingqian Liu and Xuguang S. Sheng, based on their 2019 working paper, "Economic Policy Uncertainty in China Since 1949: The View from Mainland Newspapers." They quantified uncertainty-related concepts from 2000 onwards using two mainland Chinese newspapers: the

Renmin Daily and the Guangming Daily. Table C.1 in the Appendix C reports the terms in their Trade Policy, Economics and Uncertainty term sets using Chinese characters and the corresponding English translations.

3.2.4.2 Australian Policy Uncertainty

The Economic Policy Uncertainty (EPU) Index for Australia, according to www.economicpolicyuncertainty.com, is constructed using standardized methodology suggested by Baker, Bloom and Davis (2016). The sources of Australian EPU were the text achieves for eight Australian newspapers from January 1998 onwards: Daily Telegraph, Courier Mail, The Australian, The Age, The Advertiser, Mercury, Sydney Morning Herald, and The Herald Sun (from November 1999). For each paper, they counted the number of articles containing the terms "uncertain" or "uncertainty", "economic" or "economy", and one or more policy-relevant terms: regulation, "Reserve Bank of Australia", RBA, deficit, tax, taxation, taxes, parliament, senate, "cash rate", legislation, tariff, war.

3.3 Model Specification and Data

3.3.1 Methodology

3.3.1.1 SVAR-IV framework

The empirical analysis considers the following reduced-form structural vector auto regression model,

$$x_t = b + A_1 x_{t-1} + ... + A_p x_{t-p} + u_t,\ p = 1, 2, ..., 13 \tag{3.1}$$

where p is the lag order determined by the AIC of the data series, $\mathbf{x}_t$ is a n×1 vector of endogenous macro variables I am interested in, $\mathbf{u}_t$ is the reduce-form innovations vector with covariance matrix $\mathrm{Var}(\mathbf{u}_t) = \Sigma$, $\mathbf{b}$ is a constant vector with size $n\times1$, $\mathbf{A}_1, \ldots, \mathbf{A}_p$ are the n-order coefficient matrices.

The reduced-form innovations can be linear represented by the structural shocks with the following mapping,

$$\mathbf{u}_t = \mathbf{\Phi}\varepsilon_t \tag{3.2}$$

where Φ is a non-singular $n\times n$ matrix indicating the structural impact, ε_t is a $n\times1$ vector of structural shocks. The structural shocks are assumed to be serially and mutually uncorrelated, i.e. $E(\varepsilon_t) = 0$ and $\mathrm{Var}(\varepsilon_t) = \Lambda = \mathrm{diag}(\sigma^2_1,\ldots,\sigma^2_n)$. The mapping of the shocks implies that

$$\Sigma = \mathbf{\Phi}\Lambda\mathbf{\Phi}' \tag{3.3}$$

Following the design of Känzig (2021) and Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021), I focus on identifying impulse response function to the first order shock in the VAR, $\varepsilon_{1,t}$, which is denoted as the oil supply news shocks, without loss of generality. The impulse response with respect to oil news shocks will be determined by identifying the structural impact vector φ_1, which corresponds to the first column of Φ.

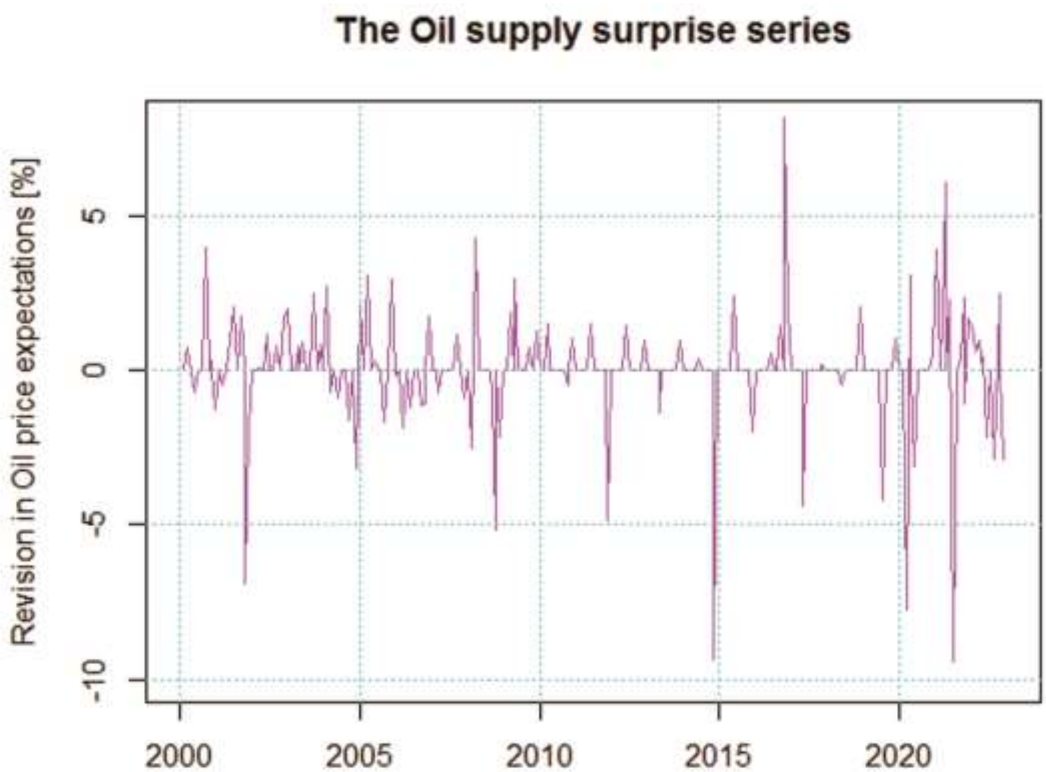
Next I try to identify the structural impact vector using the external instruments approach. I denote z_t as an external instrument variable. In my empirical work, z_t is the oil surprise series corresponding to the OPEC announcements. Since the announcements are published monthly for the most time of our sample, the structural impact vector is derived with one instrument and one shock.

In particular, the oil supply surprise series, is constructed as the percentage change of the average oil futures price on the day of the OPEC announcement and the average price on the last trading day before the announcement, that is:

$$z_t = surprise_{t,d}^h = \begin{cases} \dfrac{f_{t,d}^h - f_{t,d-1}^h}{f_{t,d-1}^h}, \text{ if there is an announcement} \\ 0, \text{ otherwise} \end{cases} \tag{3.4}$$

Where $F_{t,d}^h$ is the settlement price of the *h*-months ahead oil futures contract in month *t* on announcement date *d*. For the selection of h, the h = 0 (spot), 1(front), …,4 and $h_{composite}$ (average contract price). The baseline h used for estimation is $h_{composite}$. The details of oil surprise series are provided in appendix C.

Figure 3.1. The Oil supply surprise series



So, for z_t to be valid, z_t needs to satisfy,

$$E[z_t \varepsilon_{1,t}] = \delta \neq 0 \tag{3.5}$$

$$E[z_t \varepsilon_{j,t}] = 0 \text{ for any } j \neq 1 \tag{3.6}$$

where $\varepsilon_{1,t}$ denotes the oil supply news shock and $\varepsilon_{j,t}$ is an (n-1) ×1 vector corresponding for other structural shocks.

Using assumptions (5)-(6), φ_1 is identified up to sign and scale by the covariance of innovations $\mathbf{u}_t$, Σ and instrument z_t:

$$\begin{gathered} E[z_t u_t] = \Phi E[z_t \varepsilon_t] = \begin{pmatrix} E[z_t u_{1,t}] \\ E[z_t u_{2:n,t}] \end{pmatrix} = \begin{pmatrix} \varphi_{1,1}\delta \\ \varphi_{2:n,1}\delta \end{pmatrix} = \varphi_1 \delta \\ \tilde{\varphi}_{2:n,1} = \varphi_{2:n,1}/\varphi_{1,1} = E[z_t u_{2:n,t}]/E[z_t u_{1,t}] \end{gathered} \tag{3.7}$$

Applying the scale normalization suggested by Känzig(2021) that $\varphi_{1,1} = \theta$, which can be inferred that one unit of positive shock $\varepsilon_{1,t}$ would lead to a positive effect on macro variable $x_{1,t}$ with magnitude θ, so that

$$\tilde{\varphi}_1 = \begin{pmatrix} \varphi_{1,1} \\ \tilde{\varphi}_{2:n,1}\varphi_{1,1} \end{pmatrix}$$

where $\tilde{\varphi}_{2:n,1}$ can be interpreted as the IV innovation estimates scaling on the oil announcement innovations. After obtaining the impact vector, one can apply it onto the computations of interested objects such as IRFs and $\varepsilon_{1,t}$. i.e. $\varepsilon_{1,t} = \tilde{\varphi}_1 \Sigma^{-1} u_t$

3.3.1.2 TVP-VAR framework

In order to capture the dynamic endogenous effect of Chinese trade policy uncertainty on Chinese non-ferrous metal imports, this paper uses the TVP-VAR model promoted by Huang, Dong, Chen and Zhong (2022) for analysis.

To begin with, I rewrite (1) as

$$x_t = B^{-1}c + B^{-1}Q_1 x_{t-1} + ... + B^{-1}Q_p x_{t-p} + B^{-1}\Psi\zeta_t,\ p = 1, 2, ..., 13 \tag{3.8}$$

Where B and Q_p are n×n coefficient matrices, c is the constant drift, the innovation $\mathbf{u}_t$ is supposed to have a distribution $\mathbf{u}_t \sim N(0, \Psi\Psi')$, $\Psi = \text{diag}(\delta_k)$, k = 1, 2,…, n, $\xi_t \sim N(0, I_n)$. For simplicity, I assume that B is the lower triangular matrix which is shown as

$$\begin{pmatrix} 1 & 0 & .... & 0 \\ b_{21} & 1 & ... & 0 \\ ... & ... & ... & ... \\ b_{n1} & b_{n2} & ... & 1 \end{pmatrix} \tag{3.9}$$

Then I convert the elements of each row of $\mathbf{B^{-1}Q_p}$ into a column vector $\beta_{n^2\times 13}$. Also, the endogenous lag variables are rewritten as $Y_t = I_n \times (c, x'_{t-1}, ..., x'_{t-p})$, which is the Kronecker product. Thus, model (8) can be denoted as the time varying format below,

$$x_t = Y_t\beta_t + B_t^{-1}\Psi_t\zeta_t,\ p = 1, 2, ..., 13 \tag{3.10}$$

In the model (10), the paper tries to estimate parameters including $\boldsymbol{\beta}_t$, $\boldsymbol{B}_t$ and $\boldsymbol{\Psi}_t$. According to the research of Primiceri (2005), the elements of the lower triangle in matrix $\boldsymbol{B}_t$ can be transformed into $b_t = (b_{21}, b_{31}, b_{32}, b_{41}, \ldots, b_{n,n-1})_t'$ and $h_t = (h_{1t}, h_{2t}, \ldots, h_{nt})'$, $h_{jt} = \ln(\delta^2_{jt})$. To reduce the estimated parameters, I assume that the parameters obey the random walk process, i.e: $\beta_{t+1} = \beta_t + u_{\beta t}$, $b_{t+1} = b_t + u_{bt}$, $h_{t+1} = h_t + u_{ht}$ and

$$\begin{pmatrix} \zeta_t \\ u_{\beta_t} \\ u_{b_t} \\ u_{h_t} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum\beta & 0 & 0 \\ 0 & 0 & \sum b & ... \\ 0 & 0 & 0 & \sum h \end{pmatrix} \right)$$

In order to estimate (10), the paper needs to estimate β_t, b_t, $\ln\delta_t$, $\Sigma\beta$, Σb and Σh.

To do this, I use the linear constant nonparametric method suggested by Casas, I., Ferreira, E., and Orbe, S. (2017) for estimation. According to this method, distribution of x_t is firstly captured by the “Triweight” kernel function which is chosen based on Jacque-Bella tests. Then the minimized one-leave-out cross-validation function is calculated to select the bandwidth for estimation over time. Last, estimate the errors variance-covariance matrix and plug into tv-SURE regression for coefficient estimation.

3.3.2 Data

3.3.2.1 Data Contents

My dataset consists of the two parts. The first part is general industrial metal imports of China, this subset contains Chinese general non-ferrous metals imports, Chinese real oil prices, the Chinese real effective exchange rates, Chinese aggregated imports, Chinese non-ferrous metal trade activities and Chinese trade policy uncertainty. Using the framework from Huang, Dong, Chen and Zhong (2022), the Chinese general industrial metals import include the monthly import values and spot prices of the following non-ferrous metals: copper, nickel, aluminum, lead, zinc and tin. In this subset, the import values are used for trade analysis while the prices are used for studying the importer’s market expectation of starting new contracts and risk hedging in the secondary market. I exclude ferrous metals from my sample because of their market status. The markets of ferrous metals are sellers’ markets in which the oligarch firms have the pricing powers in the market. For instance, according to its website information and OEC database, the Vale. S.A in Brazil controlled about 80% of iron ore production in Brazil which was 40% of world’s production. All the series of original non-ferrous metals imports are transformed into percentage change in order to capture the impacts of oil supply news and economic policy uncertainty shocks. In the construction of the real prices of oil, I followed the design of both Huang, Dong, Chen and Zhong (2022) and Känzig (2021). I first collect the Chinese monthly refiner oil acquisition cost from Wind database as the Chinese nominal oil prices. Then I deflate it by U.S monthly CPI of oil and its products due to U.S. dollar is the clearance currency of oil trade. The data of U.S. CPI for oil and its products is obtained from the St. Louis Federal Reserve database. For the Chinese real effective exchange rates and Chinese aggregated imports, I collected the relevant monthly data from the World Bank's Global Economic Monitor database. In this paper, the monthly change of Chinese non-ferrous metal trade activities is captured using seasonal adjusted Baltic Capesize Index (BCI) as a proxy because of data availability and the transport of ores and metals to China. According to Baltic Exchange benchmark statement (2022), the index seeks to measure the prevailing market shipment rate for freight for all of its component routes in which the Capesize class ships are used for freight. The freight under consideration consists of commodities shipped aboard dry bulk carriers, such as coal and metallic ores and metal articles. Also, in the routes from which BCI is measured, 7/10 has Chinese ports as starts/destinations. Therefore, this index can be used to proxy the shift of non-ferrous metal trades of China.

To reflect the change of Chinese trade policy, I refer to Huang, Dong, Chen and Zhong (2022), Kang et al. (2017b, 2017c) and Chen et al. (2019) to select the Chinese trade policy uncertainty index developed by Davis, Liu and Sheng (2019), derived from the website www.economicpolicyuncertainty.com. Details of the index are displayed in the Appendix C.3. The periods of all the variables in the general non-ferrous metal imports of China dataset range from 2000M1 to 2022M12.

In the second part, I focus on how the Chinese trade policy uncertainty and oil supply news shock affect Chinese non-ferrous metal imports from a specific exporter. For the specific exporter, I first obtain non-ferrous metal exports from Australia to China from the Wind database due to data availability and completeness. The non-ferrous metal exports set contains the percentage change of monthly export value of copper, nickel, aluminum, and zinc from Australia to China. A detailed overview of the Australian export data and its source can be found in Appendix C.

3.3.2.2 Data Tests

Table 3.1 provides the results of unit root tests based on augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP) and Kwiatkowski et al. (1992) (KPSS) methods. The null hypothesis of ADF and PP tests is that the time series contains a unit root, while that of KPSS test is the stationarity. The test model I consider contains drift and no trend under the lag of 13. For percentage series, according to the ADF and PP statistics all the series do not follow the unit root processes. KPSS statistics consistently reveal that all the series are stationary at 1% significance level except Chinese TPU using the original series. Overall, at 1% significance level, according to the results of unit root tests and results of stationary tests, all the series are integrated with the order of one process rather than unit root process.

Table 3.1. Results of unit root tests for commodity and uncertainty index[3]

	ADF	PP	KPSS
	Original series	Original series	Original series
Chinese TPU	-4.27***	-78.6***	2.2348***

[3] Note: *, ** and *** denote rejection of the null hypothesis at 10%, 5% and 1% significance levels, respectively.

	Percentage series	Percentage series	Percentage series
Real oil price	-11.58***	-179.19***	0.0405
Value			
Copper value	-17.47***	-282.60***	0.1434
Nickel value	-16.65***	-329.98***	0.2156
Aluminum value	-14.31***	-296.12***	0.0654
Lead value	-11.81***	-284.09***	0.0849
Zinc value	-14.20***	-294.11***	0.0602
Tin value	-11.09***	-296.84***	0.5085
Price			
Copper price	-9.31***	-170.30***	0.1099
Nickel price	-9.96***	-195.80***	0.0781
Aluminum price	-9.71***	-202.48***	0.0371
Lead price	-9.83***	-203.31***	0.1541
Zinc price	-9.51***	-215.15***	0.0494
Tin price	-8.50***	-190.48***	0.0641

3.4 Empirical Results

3.4.1 Effects on general non-ferrous metal imports

In order to get a better comprehension of how oil supply news shocks affects the Chinese non-ferrous metal imports, I study the effects on a variety of economic variables related to Chinese non-ferrous metal trade. To compute the impulse responses, I start by augmenting the macro variables of SVAR-IV for the general non-ferrous metal imports, the variables include Chinese real oil acquisition cost, Chinese trade policy uncertainty index, Chinese industrial production Chinese aggregated import as well as Chinese non-ferrous metals import activity. Next, for individual non-ferrous metal exports to China, I combine the economic variables with one non-ferrous metal import at a time for computing the impulse response of SVAR-IV. The lag order selected is 13 based on the AIC results of lag selection. Also, the lag 13 selection helps the SVAR-IV model to capture the effects over a year. As all the variables are transformed into percentage changes and seasonal adjusted. Thus the impulse response results can be interpreted as elasticities of variables to oil prices when oil supply news shocks happen.

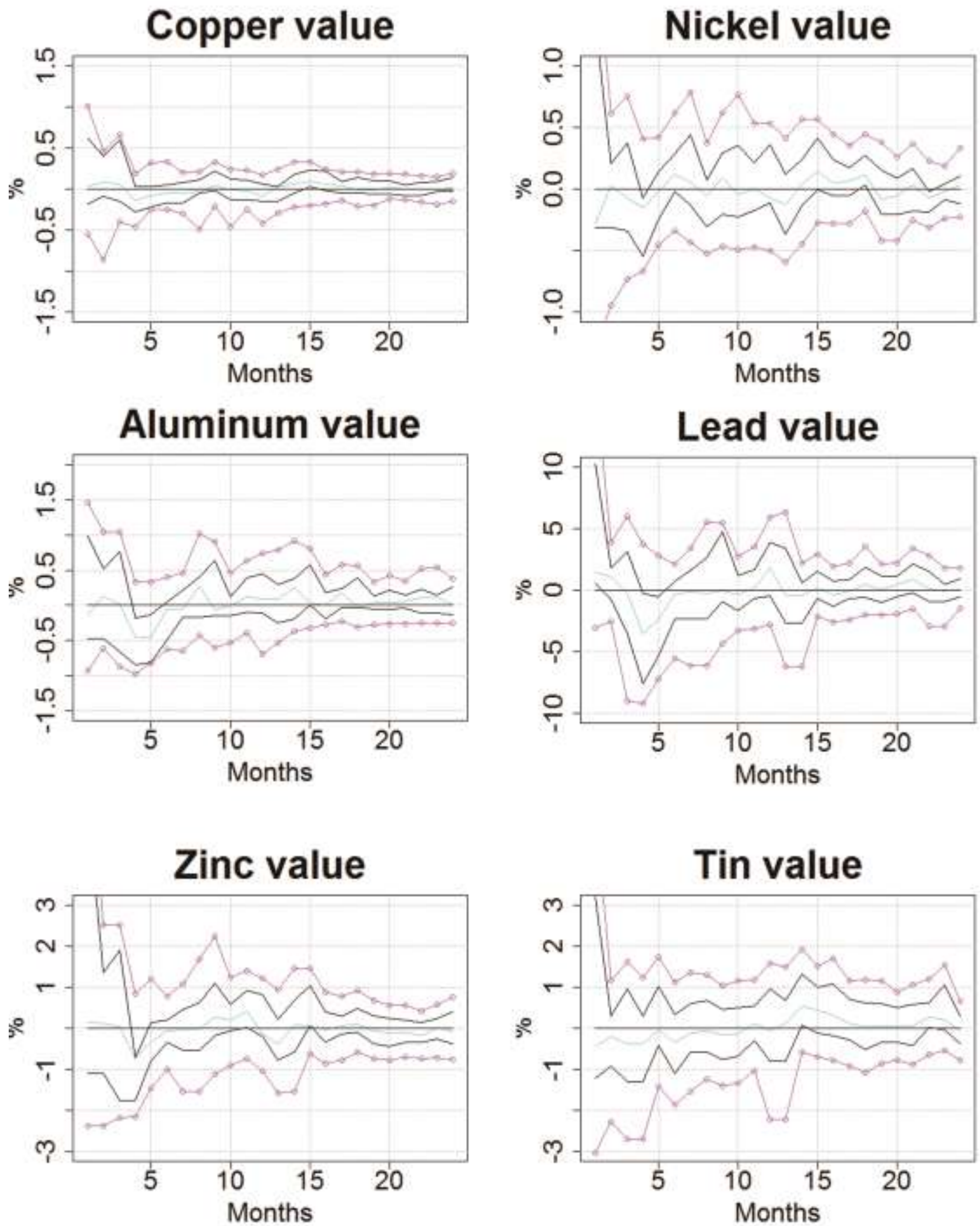
3.4.1.1 Oil supply news effects on the general non-ferrous metal imports

In this subsection, I present the impulse response results from general non-ferrous metal imports considering both import prices and aggregated import values. The model is identified using the external approach, as proposed by Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021). Since all the variables are transformed into percentage terms, the impulse responses can be interpreted as elasticities. In the graphs, both the 95 percent confidence band and the 68 percent confidence band are displayed. The key for interpreting the graphs is that the cyan solid lines are the median estimates, the black lines are the bounds of estimates with a 68 percent confidence band and the magenta lines are the bounds of the estimates for the 95 percent confidence band. This graphic notation will be applied to all the figures in the following figures.

3.4.1.1.1 Effects on non-ferrous metals trade values

Figure 3.2 illustrates the effect of a 10% oil price increment due to oil supply news shocks on various non-ferrous metal values. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change, ignore the fact that the changes are in. The same setting also applies to impulse responses of Figure 3.3 in Subsection 3.4.1.1.2. Figure 3.2 shows that a positive oil supply news shock leads to little variations in the import values of all the non-ferrous metals, except lead, after the shock happens. The inelastic responses of the three non-ferrous metal imports to oil supply news shock may be contributed to their trade modes between China and exporting countries. According to the 2023 trade handbook of concentrate ores by the ministry of commerce of China, the imports of non-ferrous metals had two types. The first type is investment in which Chinese importers will either purchase mines aboard or set up portfolio investments with local producers. Meanwhile the second type is purchasing concentrate ores from local producers by signing long run contracts whose prices are stable. And the contracts could be renewed annually. Both paths provide stable non-ferrous metals supplies to China which are inelastic to the variations of oil prices caused by the OPEC announcements. In terms of the lead import values, the response has an in-persistent short run decline. The short run elasticity may contributed to the transaction method of lead ores. Different from other non-ferrous metals imports, Chinese lead imports, as the 2023 trade handbook of concentrate ores by the ministry of commerce of China mentioned, was spot trading as lead ores may be mixed with other precious metals such as gold or silver. Under the spot trading mode, Chinese importers have to cover the shipping costs by spot prices for each single contract. So, high oil prices increase the expectations of higher shipment costs in Chinese importers. This will reduce the import values of lead until the oil price falls back to the normal level.

Figure 3.2. Chinese non-ferrous metal import values IRF to an oil news shock



3.4.1.1.2 Effects on non-ferrous metals trade prices

Next I study the responses of non-ferrous metals trade prices to the oil news shocks to investigate whether there are potential demands for Chinese importers to hedge the price risks of non-ferrous metals in the secondary market due to the oil supply shocks. As Figure 3.2 illustrates, all the non-ferrous metal spot prices are inelastic to oil news shocks, this is in line with the evidence by Gong and Xu (2022) that non-ferrous metals market, as a part of industrial metals market, is an information transmitter for the oil demand shocks and the oil specific demand shocks but not the oil supply shocks when oil prices change. Also, the inelasticity may be contributed to treatment and refining charges for processing concentrates (TC/RC), a stable determinant of non-ferrous metal prices settled in terms of long run contract. Thus, the oil supply news shocks may not provide sufficient motivations for Chinese importers to hedge potential price risks in non-ferrous metal imports.

3.4.1.2 Chinese trade policy uncertainty on the general non-ferrous metal imports

In this subsection, the paper looks into the impact of individual economics Chinese trade policy uncertainty on the general non-ferrous metal imports. It is assumed that a Chinese trade policy uncertainty event increases the index by 1 unit. According to the design by Huang, Chen, Dong and Zhong (2022), the IRF results are obtained from local linear point estimation in order to capture the dynamic average effects of the trade policy uncertainty shock. Under this point estimation, only the mean values of responses after smoothing will be provided.

Figure 3.4 illustrates the effect of a 1 unit Chinese trade policy uncertainty index increment due to the occurrence of a Chinese trade policy uncertainty event. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change, ignore the fact that the changes are in. The same setting also applies to impulse responses of Figure 3.5. As Figure 3.4 reveals, when Chinese trade policy uncertainty increases by 1 unit, within a one-year period, the impulse responses of Chinese non-ferrous metals imports fluctuate around zero with negative trends. In the fluctuations, the impulse responses tend to be negative. These results indicate that during a major trade uncertainty event or a trade policy update, non-ferrous metal importers tend to be conservative to open new contracts before uncertainty get settled. For each type of non-ferrous metals import, copper import value has the smallest variations when a trade policy uncertainty event occurs. According to Wind database, by the end of 2020, Chinese reliance on copper imports had a level of 90% and copper import was the largest non-ferrous metal import of China. The high reliance on import may contributed to an stable demand for maintaining long run copper import contracts and keeping less impact of policy appliance on copper imports. Meanwhile, the lead import suffers the most severe decline due to small import size and spot price settlements.

In terms of spot prices of non-ferrous metals, Figure 3.5 shows the impulse responses of various non-ferrous metal price changes to Chinese trade policy uncertainty. It can be seen that a negative major trade policy uncertainty event brings down the non-ferrous spot price for Chinese import persistently. The results show that China has the largest demand for non-ferrous metals in the world, its trade policy uncertainty would lower the expectation of future demand of non-ferrous metals. Consequentially, the potential demand shock on non-ferrous metals market decrease the prices of non-ferrous metals.

Figure 3.3. Chinese non-ferrous metal import prices IRF to an oil news shock

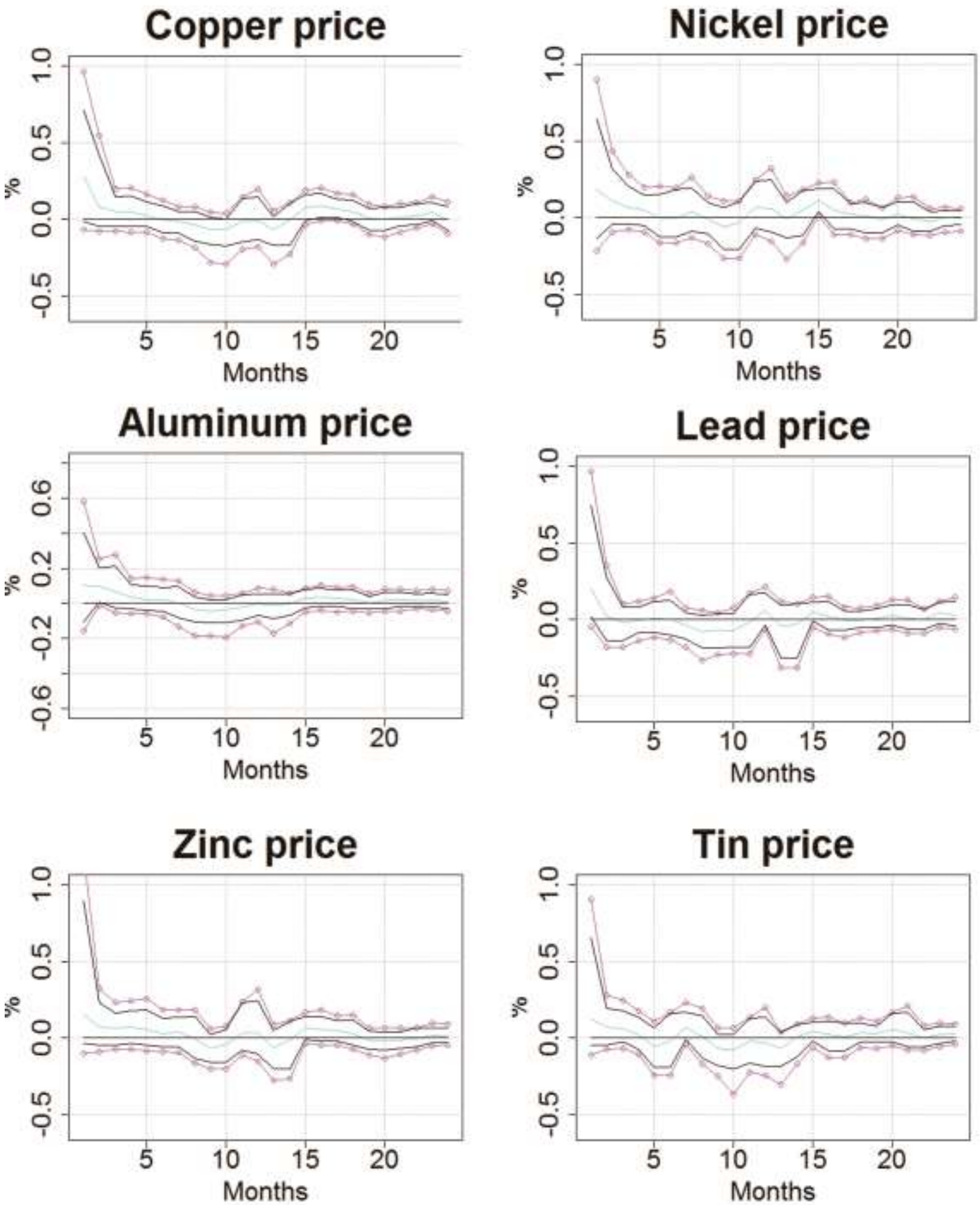


Figure 3.4. Chinese non-ferrous metal import values IRF to Chinese trade policy uncertainty

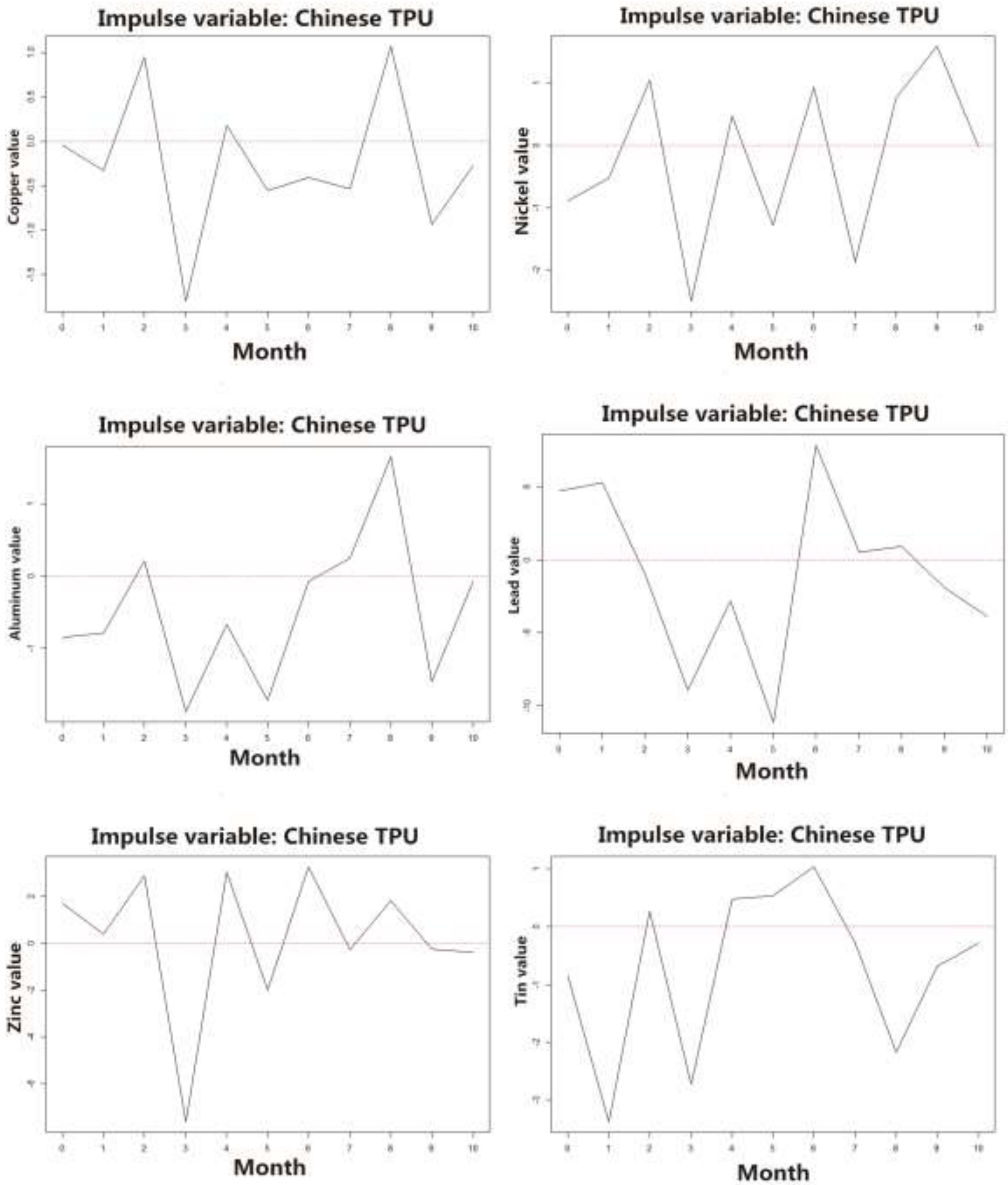
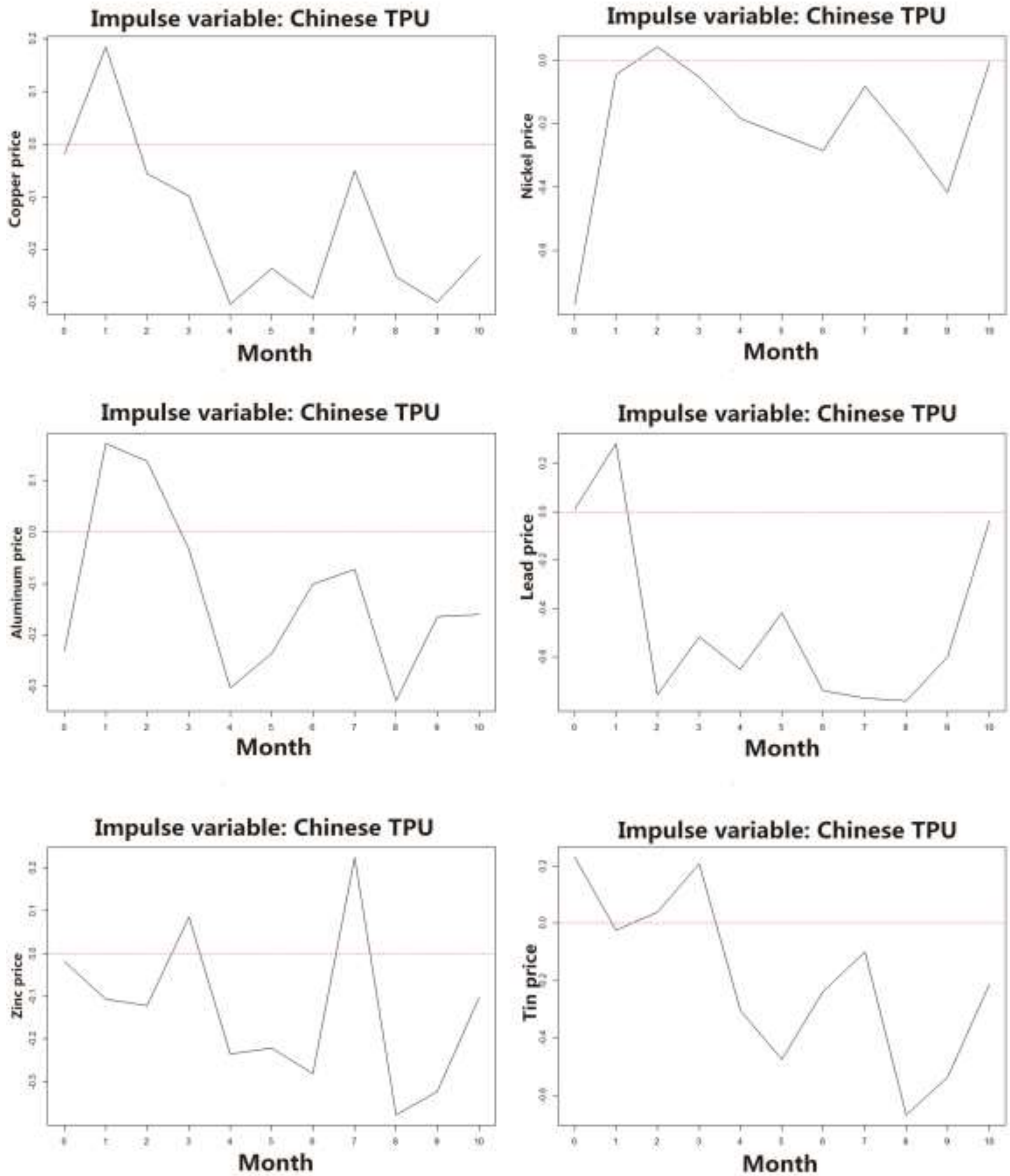


Figure 3.5. Chinese non-ferrous metal import prices IRF to Chinese trade policy uncertainty



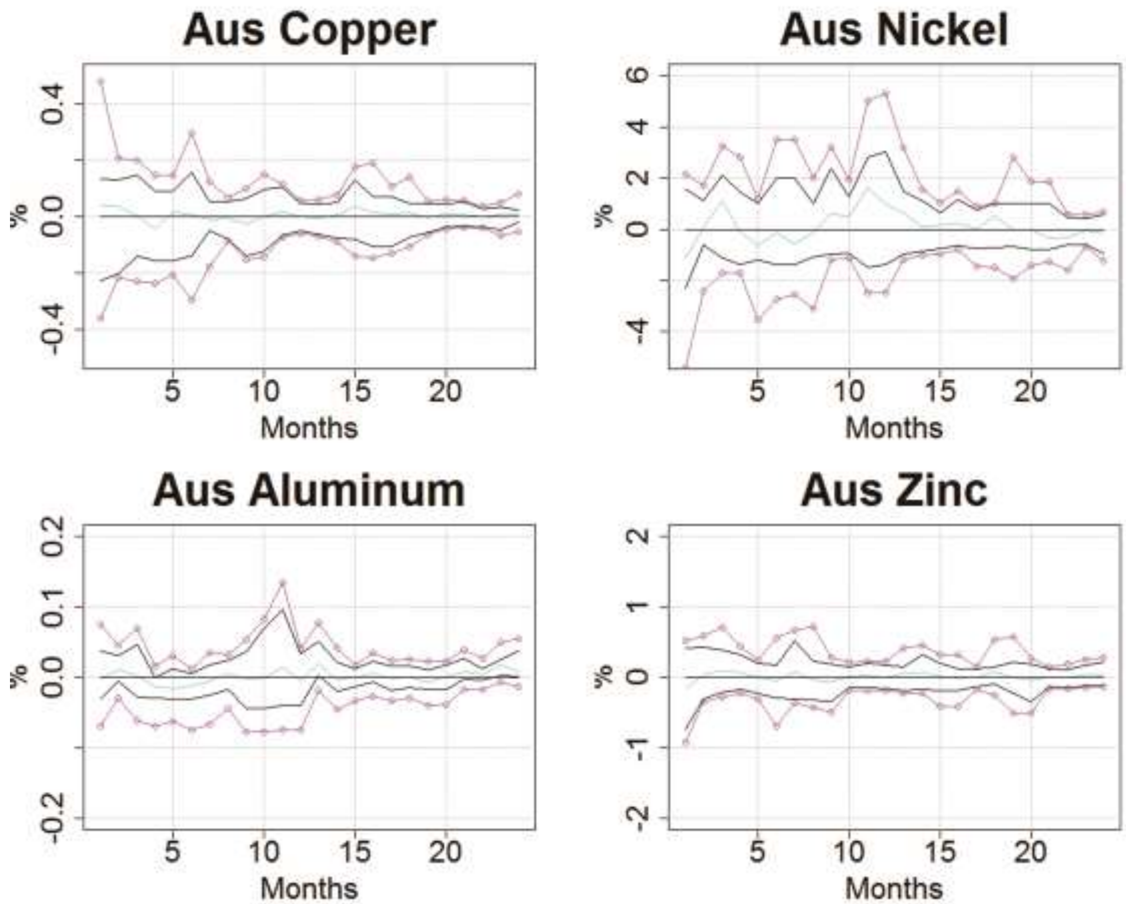
3.4.2 Effects on China-Australia non-ferrous metal trade

3.4.2.1 Effects of oil supply news on Chinese non-ferrous metal imports from Australia

To get a better understanding of how oil supply news and economic policy uncertainty transmit their impact into Chinese non-ferrous metal imports with individual country, I analyze a special exporter, Australia, who is one of the biggest non-ferrous metal suppliers to China with various metal exports. For the VAR analysis, I replace Chinese import data with Chinese import data from Australia. Figure 3.6 illustrates the effect of a 10% oil price increment due to oil supply news shocks on various non-ferrous metal imports from Australia. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change for Australian non-ferrous metal exports to China, ignore the fact that the changes are in.

The new data, ranging from 2000M1 to 2022M12, includes aggregated import from Australia and main non-ferrous metals import values. In terms of non-ferrous metals, I choose copper, nickel, aluminum and zinc due to data availability. Figure 3.6 depicts the IRF results of Chinese import of four main non-ferrous metals from Australia. Overall, the four Australian non-ferrous metals exports to China performs similarly to Chinese general non-ferrous metals imports who display little variations in response to the oil supply news shock. These results indicate that the oil supply news may not be an efficient channel through which the oil prices affect Chinese non-ferrous metal imports from Australia.

Figure 3.6. Impulse Response for oil supply news

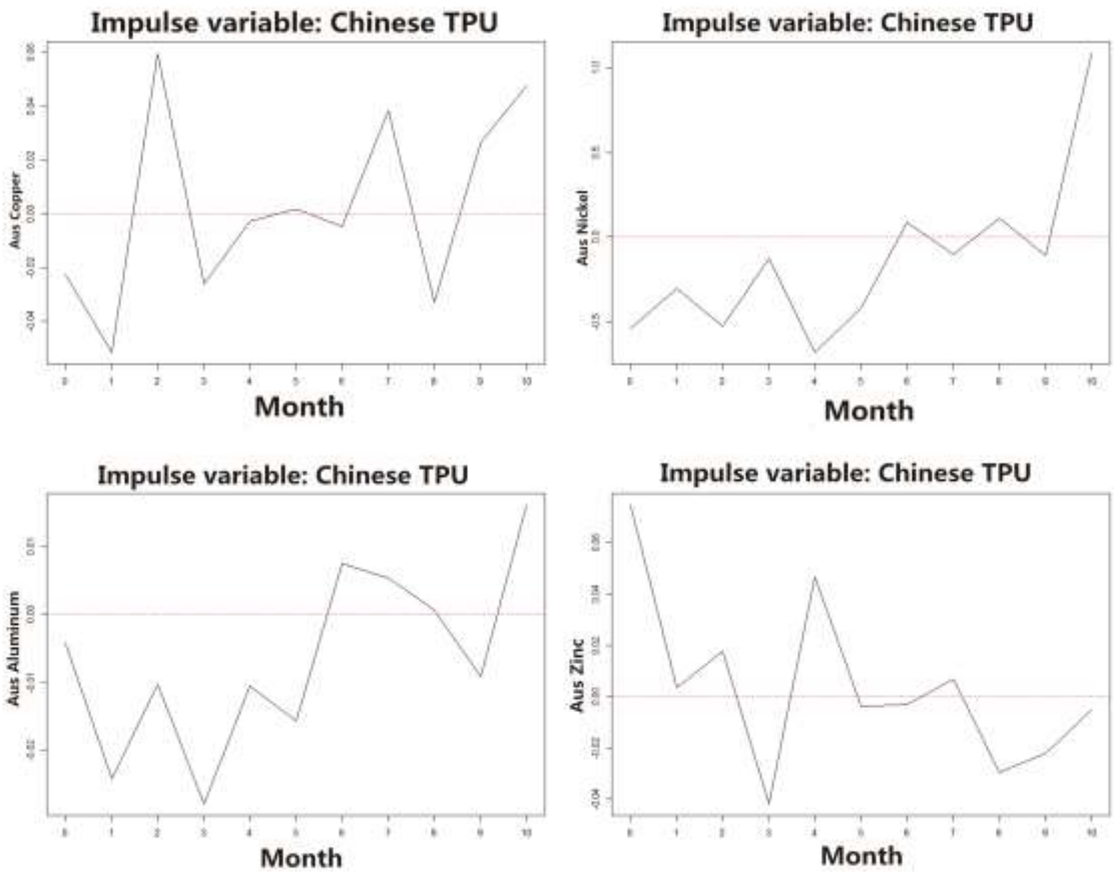


3.4.2.2 Effects of policy uncertainty on Chinese non-ferrous metal import from Australia

I now offer presentation of the Australian results in response to Chinese policy uncertainty. Figure 3.7 illustrates the effect of a 1 unit Chinese trade policy uncertainty index increment on Chinese non-ferrous metal imports from Australia, due to the occurrence of a Chinese trade policy uncertainty event. It is important to note that all the impulse responses are in. Here the paper discusses the properties of the change, ignore the fact that the changes are in. Figure 3.7 illustrates that a main trade policy uncertainty in China leads to various responses of Australian non-ferrous metals export to China. In terms of each metal exports, Australian copper fluctuates in around zero. The inelasticity shows that with the high reliance on foreign copper, Chinese government tries to mimic impact of trade policy changes on copper import and maintain the diversification and stability of copper trade. Then for nickel and aluminum for which Australia is not the primary exporter, a Chinese trade policy uncertainty event decreases both the import values of Australian nickel and aluminum in the short run. Then, the IRFs fluctuate around zero and become positive at the end. The short run declines in nickel and aluminum reveal that Chinese importers may have elastic demand to non-primary source of non-ferrous metals on which China has relatively low reliance. When a trade policy uncertainty event happens, Chinese importers tend to reduce the diversification of non-ferrous metals import while waiting the uncertainty to be settled. Also, during the same time, they may turn to primary exporter for stable supply in the short run. For instance, as the panel of Australian zinc export display, Australia is the primary zinc exporter to China, when Chinese trade policy uncertainty occurs, the event leads to a short run increment on Australian zinc export to China before the effect reduces to zero. The results provide extra support for the finding from Huang, Dong, Chen and Zhong (2022) that policy uncertainty shocks lead to diverse responses of metal market which depend on economic conditions.

Overall, for Chinese non-ferrous metal imports, in term of the effect of an oil supply news shock, I find that oil supply news shocks has little impact on both the values and prices of Chinese non-ferrous metals imports during the sample period I investigate. The long run contracts and annual clearance for settlements may contribute to the negligible variation of Chinese non-ferrous metals when the oil supply shock happens. Regarding the Chinese trade policy uncertainty shock, Chinese trade policy uncertainty has diverse effects on its non-ferrous metal imports which may be caused by different economic conditions such as the levels of non-ferrous metals reliance on imports. Meanwhile, a major Chinese trade policy uncertainty event may have negative effects on the spot prices of non-ferrous metals. The reason may lie in that Chinese trade policy uncertainty lowers the market expectation of non-ferrous metals demands from China. The potential demand decline brings down the market prices of non-ferrous metals because China is the biggest non-ferrous metals importer in the world.

Figure 3.7. Impulse Response of Chinese policy uncertainty



3.5 Sensitivity Analysis

In this section, I conduct the sensitivity checks on Chinese non-ferrous metal imports to test the robustness of my results. In order to reduce the biases caused by reliance level, settlement method and small trade values, I select aluminum and zinc for sensitivity check. In the test, I alter the lags of both SVAR-IV model and TVP-VAR model for non-ferrous metal import from 13 to 2, 4 and 15 to check if the IRF results are sensitive to different lags and terms. Figure 3.8 illustrates the lag(2) results, while Figure 3.9 shows the lag(4) outcomes and Figure 3.10 displays lag(15) results. As the results show, in term of the responses to oil supply news shocks, both the import value and spot price of non-ferrous metals perform inelastic under all the three lagged models, similar to the IRF results using lag(13) model. Therefore, my results are robust using SVAR-IV model in different lags. Next, in the investigation of whether the responses to Chinese trade policy uncertainty are sensitive to lag variations, in either the short run or long-term, the IRF results are consistent with results from lag(13) model. However, under lag(2) and lag(4) model, there are positive responses right after the uncertainty shock happen. The difference comes from that with the expectation of future demand shrinks due to potential limit from new trade policy, the Chinese importers try to finish the delivery and settle the preferable contract as soon before new policy become effective. When new policy is settled down, Chinese importers need time for adjustment during which they will cut down the import and be less involved with secondary market for risk hedging. So, the reduced demand of non-ferrous metals lead the IRF results of TVP-VAR model under lag 2, 4 and 15 consistent to lag 13 results in both short-run and long run. Thus, my result are also robust when considering different lags for TVP-VAR model.

Figure 3.8. IRFs of Chinese non-ferrous metal imports from lag(2) model

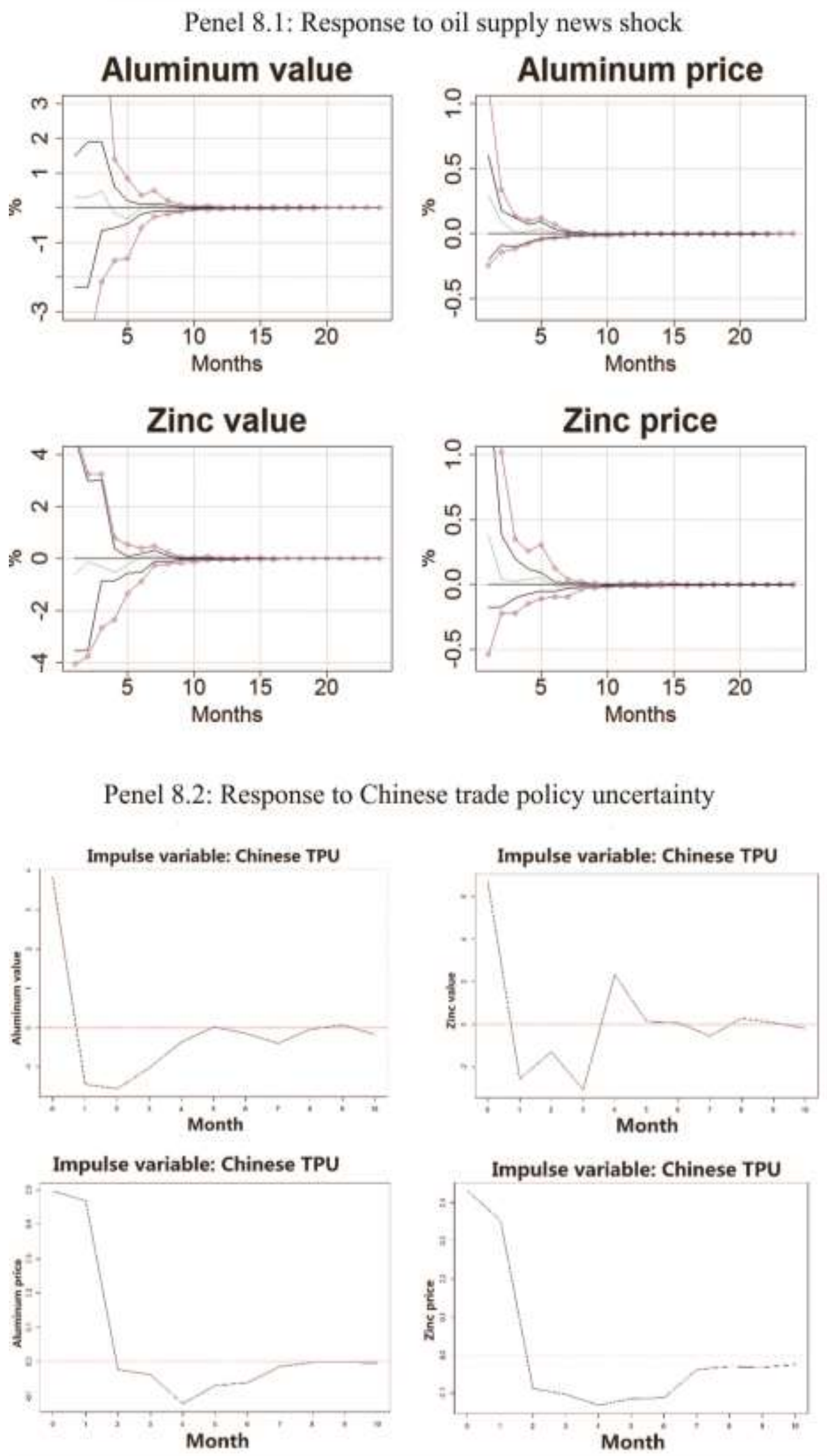
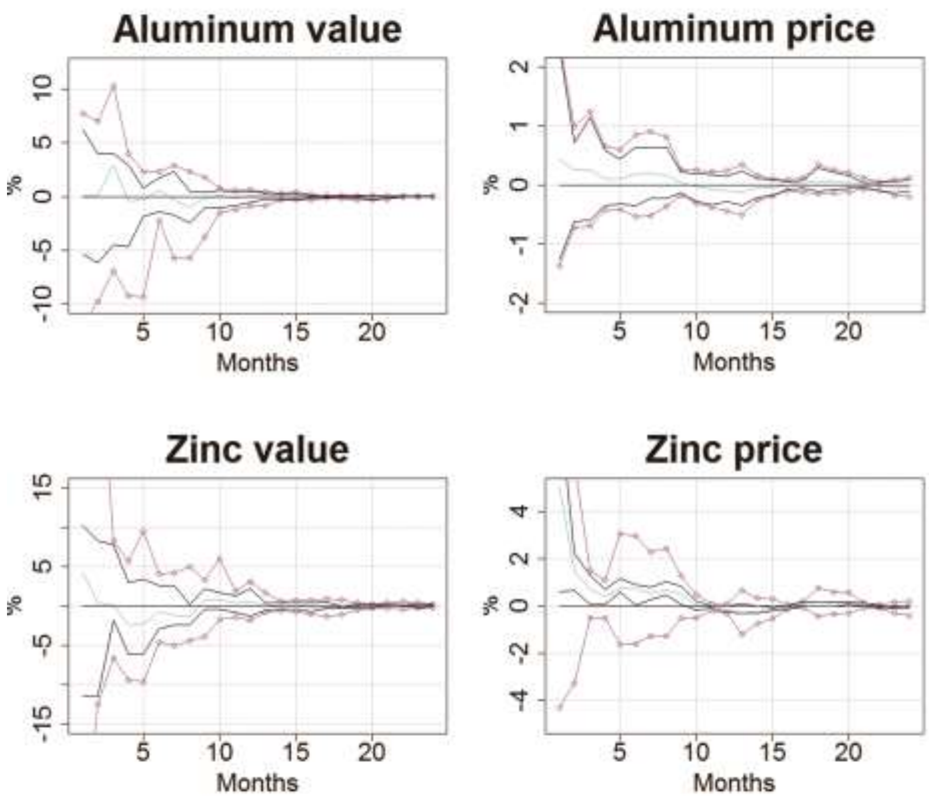


Figure 3.9. IRFs of Chinese non-ferrous metal imports from lag(4) model

Pannel 9.1:Response for an oil supply news shock



Penel 9.2: Response for a Chinese trade policy uncertainty shock

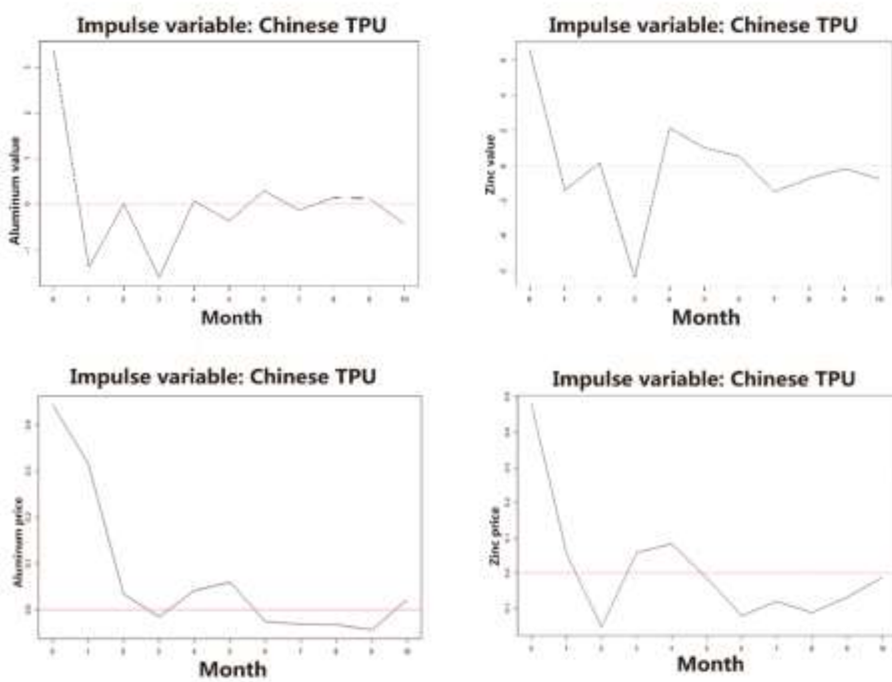
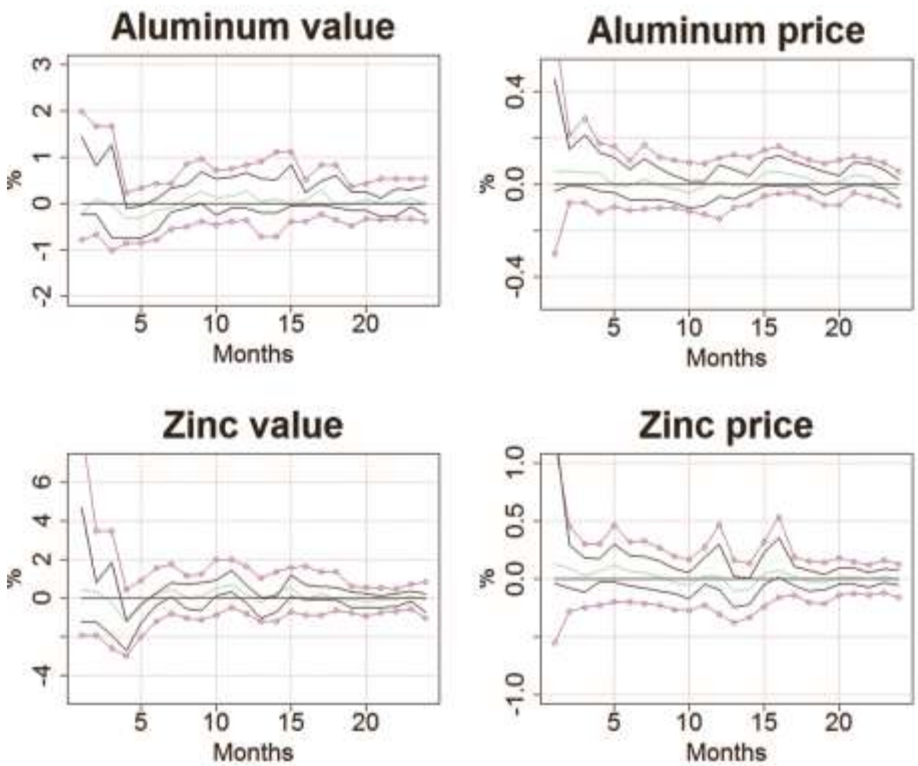
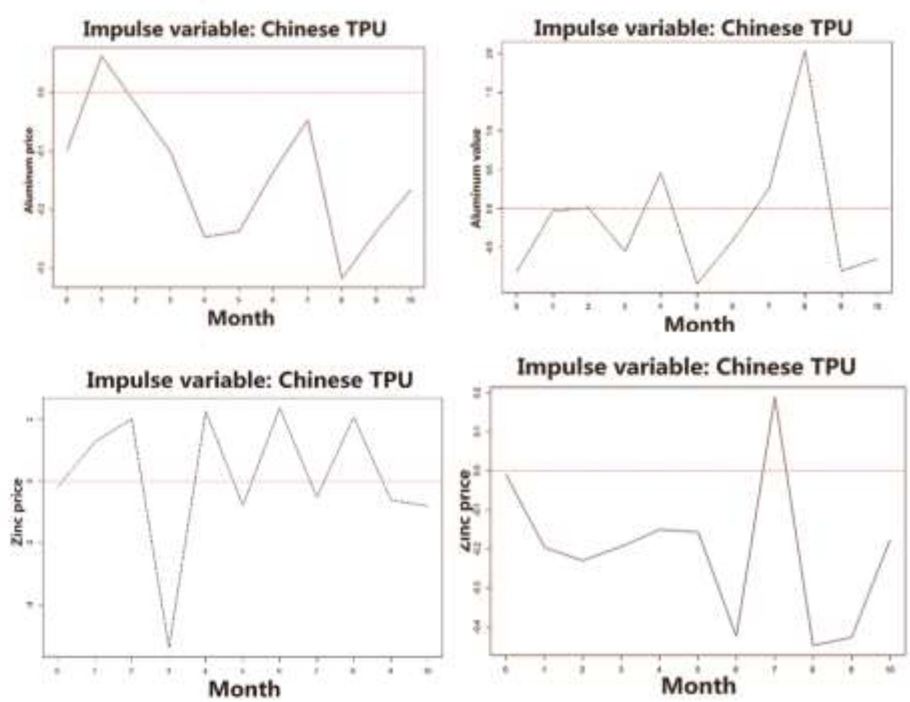


Figure 3.10. IRFs of Chinese non-ferrous metal imports from lag(15) model

Panel 10.1: Response for an oil supply news shock



Panel 10.2 :Response for a Chinese trade policy uncertainty shock



3.6 Conclusion

In this paper, I study the effects of the oil supply news shock and Chinese trade policy uncertainty on the Chinese non-ferrous metal imports. The effect the oil supply news shocks is approached using an external instrument structural VAR model which is suggested by Känzig (2021). Following the design of Känzig (2021), I use the percentage changes of WTI composite oil futures prices around OPEC meeting announcements as an instrument. Over the same time, I investigate the dynamic effect of Chinese trade policy uncertainty with a TVP-VAR framework proposed by Huang, Dong, Chen and Zhong (2022). According to my empirical results, for Chinese non-ferrous metal imports, in term of the effect of oil supply news shocks, I find that oil supply news shocks have little impact on both the values and prices of Chinese non-ferrous metals imports during the sample period I investigate. The long run contracts and annual clearance for settlements may contribute to the negligible variation of Chinese non-ferrous metals imports when the oil supply shock happens. Regarding the Chinese trade policy uncertainty, Chinese trade policy uncertainty has diverse effects on its non-ferrous metal import which may be caused by different economic conditions. For example, the Australian non-ferrous metal export to China indicate that the level of non-ferrous metal reliance on import can be a reason contribute to divergent responses. Meanwhile, a major Chinese trade policy uncertainty event may have negative effect on the spot prices of non-ferrous metals. The reason may lie in that Chinese trade policy uncertainty lowers market demand expectation of non-ferrous metals as China is the biggest buyer for them. Consequentially, the potential demand decline brings down the market prices of non-ferrous metals. My sensitivity check shows that my results are robust to lag variations.

For future research, it may be important to investigate the short run effect of the oil news shocks on the diversification level of commodities for either the commodity importers or exporters. Also, researcher may find it interest to study how policy uncertainties and other oil shocks affect commodity importers with risk hedging decisions in the secondary market. This type of research will help commodities traders to avoid price risks and maintain the stability of commodities trades in response to surprises in both politics and the oil market.

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Appendix A: Appendix for Chapter 1

Appendix A. Data

Table A.1 provides details on the data used in chapter 1, including information on the coverage, data sources and countries/regions

Table A.1 Data description, sources, coverage and county/region

Variable	Description	Source	Sample	Trans	Country/Region
Instrument					
Proxy	Surprise series based on WTI crude oil futures composite contract and OPEC announcements	Känzig's webpage	1991M1-2019M12	100* Δ log	N.A
Baseline variables					
POIL	WTI spot crude oil price deflated by U.S. CPI	Känzig's webpage/Own calculation	1991M1-2019M12	100*log	N.A
OILPROD	World oil production	Känzig's webpage	1991M1-2019M12	100*log	N.A
WIP	Industrial production of OECD + 6 (	Känzig's webpage/Baumeister's webpage	1991M1-2019M12	100*log	N.A
OILSTOCKS	9	Känzig's	1991M1-	100*log	N.A

		webpage/Own calculation	2019M12		
IP	Industrial production index	World Bank's G.E.M Database	1991M1-2019M12	100*log	Samples[1][2][3]
CPI	CPI Index, 2010 = 100	G.E.M	1991M1-2019M12	100*log	Samples
USCPI	CPI Index for average U.S urban fuel oil consumption	FRED	1991M1-2019M12	100*log	U.S.
Additional variables					
Neer	Nominal Effective Exchange Rate	G.E.M/FRED	1991M1-2019M12	100*log	Samples
Reer	Real Effective Exchange Rate	G.E.M/FRED	1991M1-2019M12	100*log	Samples
Imp	Import Merchandise, constant US$	G.E.M	1991M1-2019M12	100*log	Samples
Exp	Export Merchandise, constant US$	G.E.M	1991M1-2019M12	100*log	Samples
ToT	Terms of Trade	G.E.M	1991M1-	100*log	Samples[4][5]

			2019M12		
GDP	GDP	FRED	1991Q1- 2019Q12	100*log	Samples[4][5][4]

[4] Note 1: Sample countries/regions include: China, Chinese Taiwan, India, Japan, South Korea, Singapore, and Thailand.

Note 2: India starts from 1994M1.

Note 3: Thailand starts from 1998M1

Note 4: China starts from 1999M1

Note 5: China's and India's terms of trade are not available due to data availability.

Appendix A.1: Transformed baseline macroeconomic variables of individual economy

Figure A.1.1 shows the general series included in the baseline VAR over the sample period 1991-2019. All variables are depicted in logs.

Figure A.1. 1 Transformed standard data series in the baseline VAR

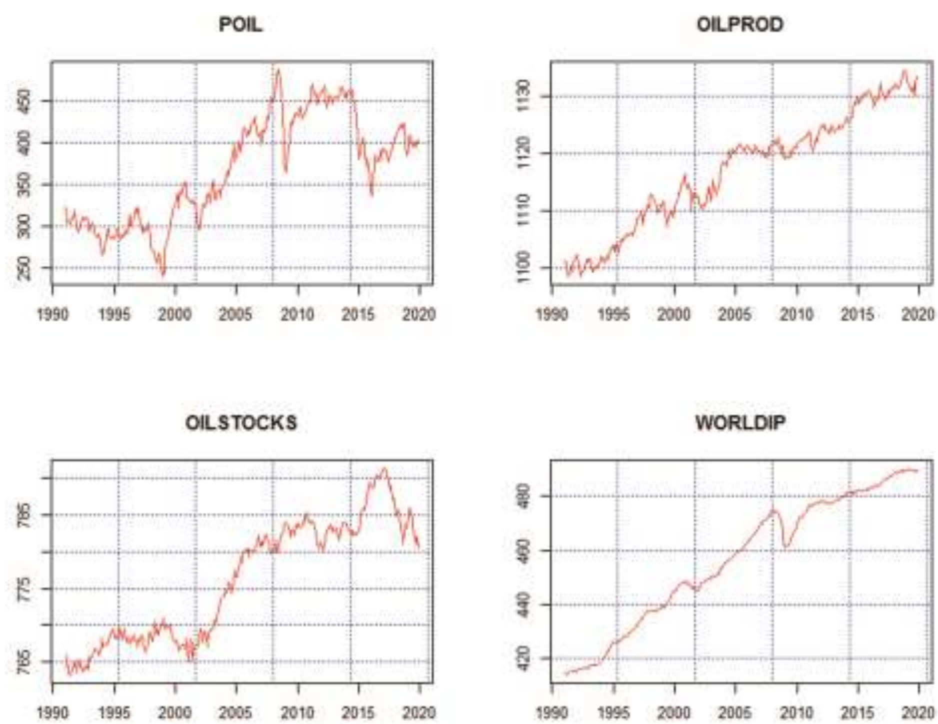


Figure A.1.2 – Figure A.1.8 show the macroeconomic series of individual economy included in the baseline VAR over the sample period 1991-2019 (China starts on 1999, India starts on 1994 and Thailand starts on 1998). All variables are depicted in logs.

Figure A.1. 2 Transformed macro data series of China in the baseline VAR

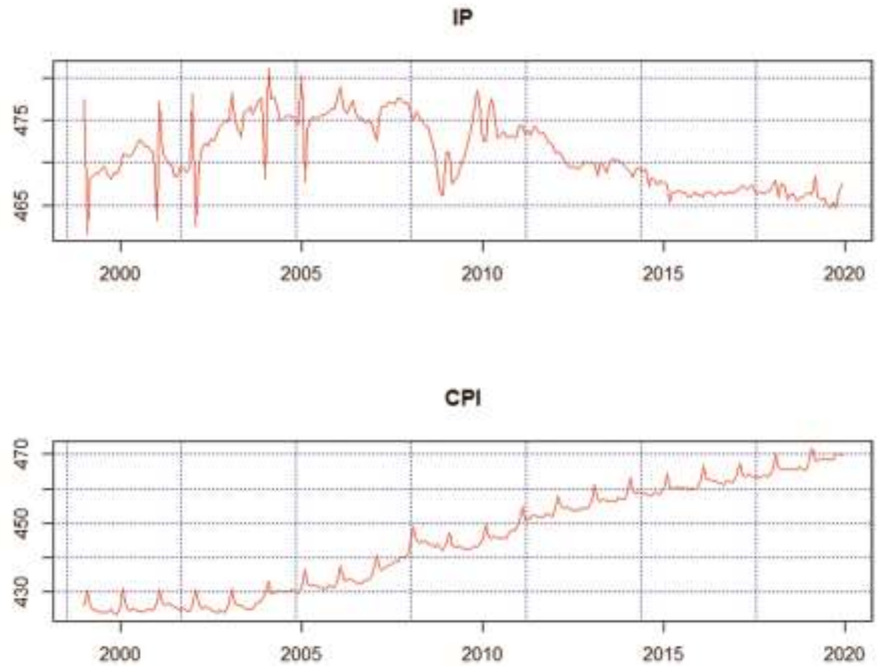


Figure A.1. 3 Transformed macro data series of Japan in the baseline VAR

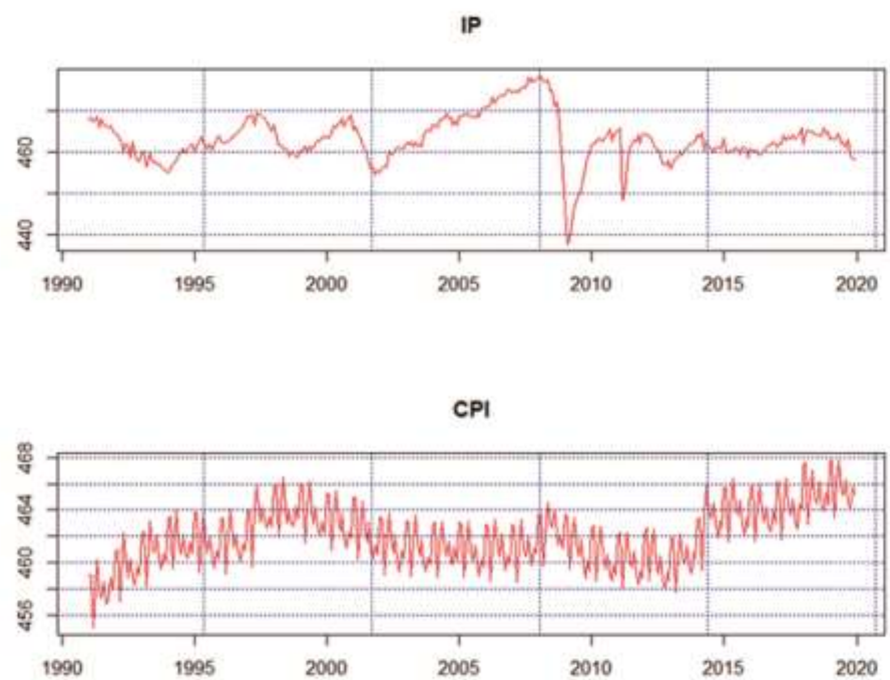


Figure A.1. 4 Transformed macro data series of India in the baseline VAR

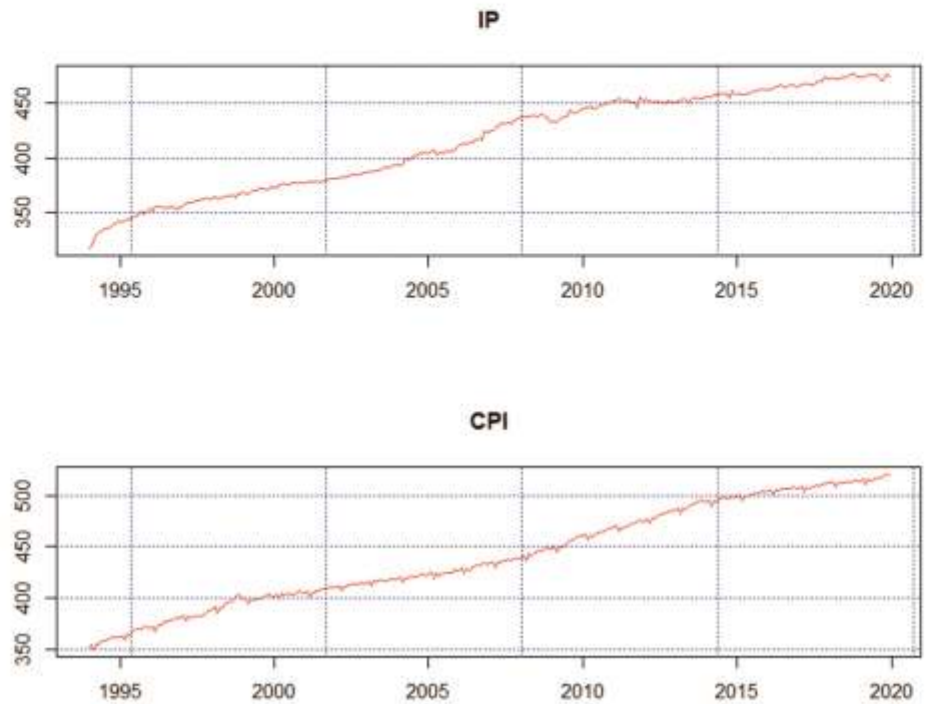


Figure A.1. 5 Transformed macro data series of South Korea in the baseline VAR

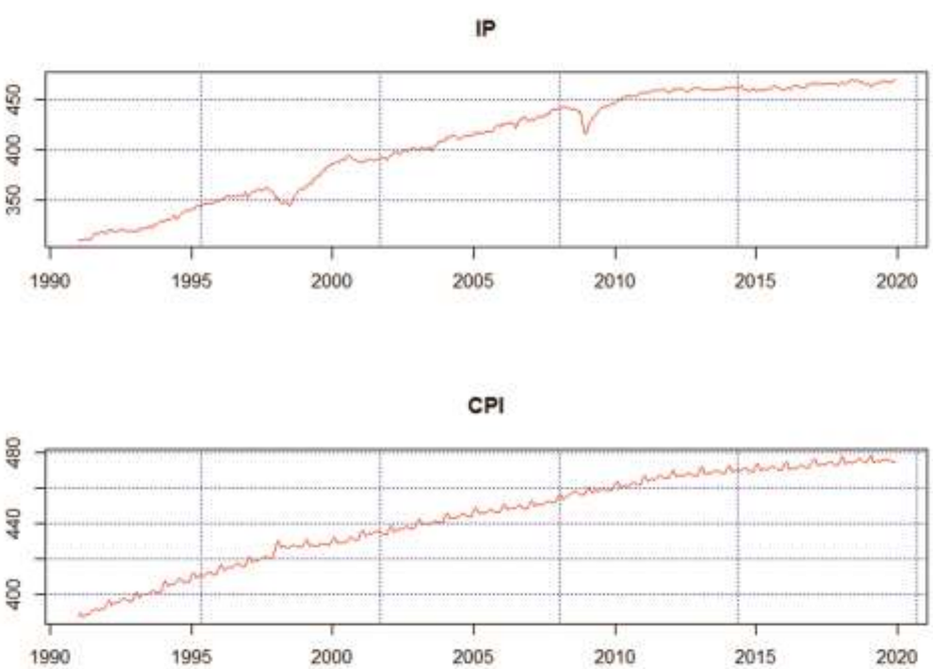
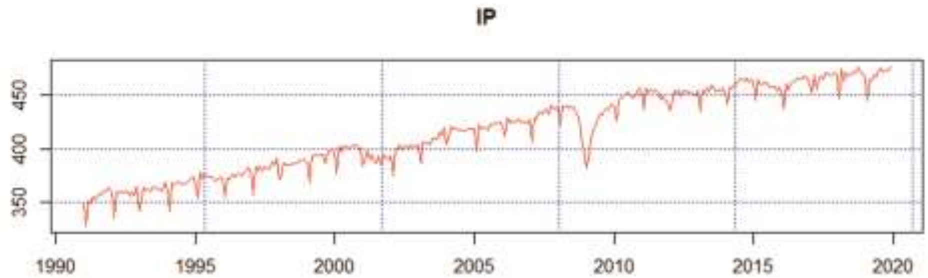


Figure A.1. 6 Transformed macro data series of Chinese Taiwan in the baseline VAR



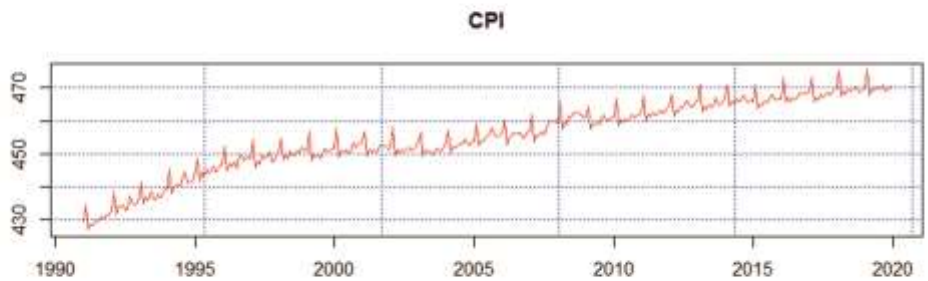
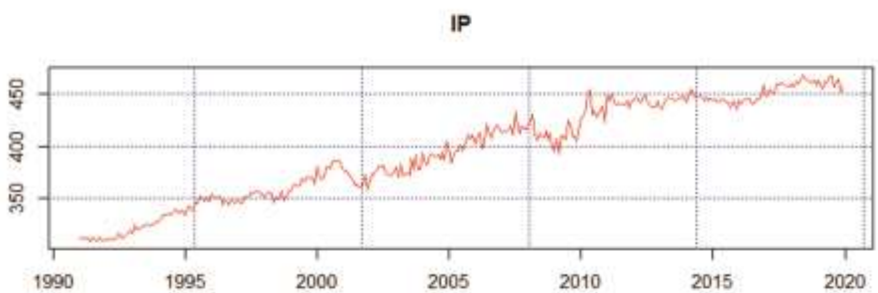


Figure A.1. 7 Transformed macro data series of Singapore in the baseline VAR



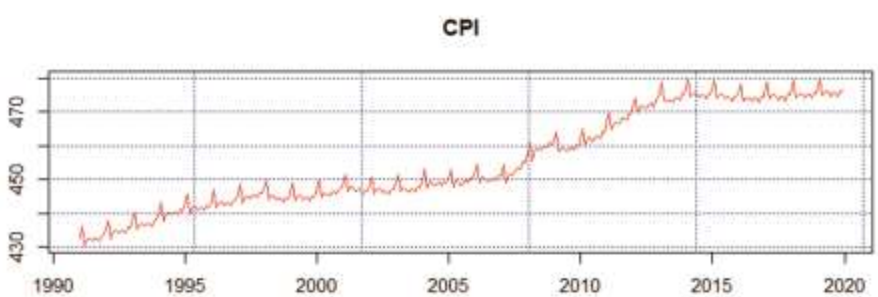
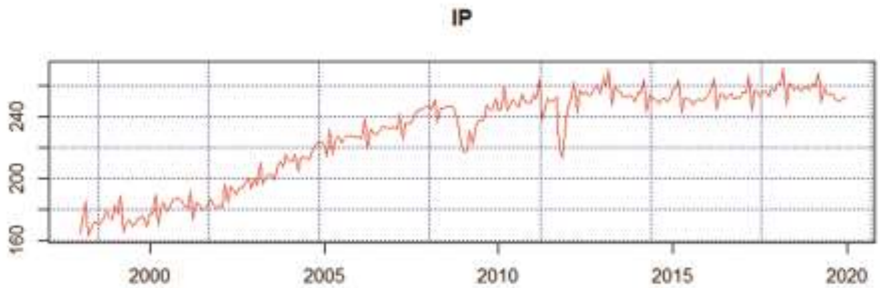
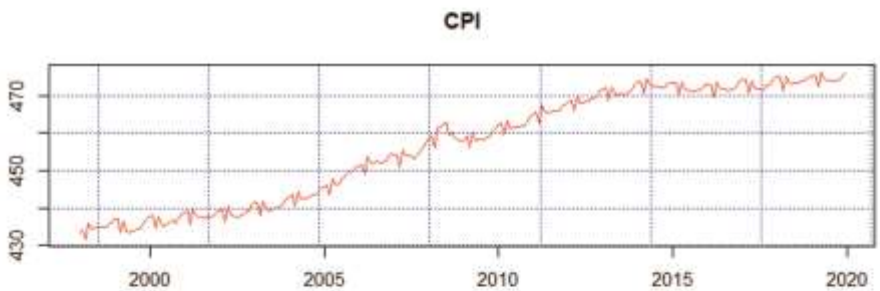


Figure A.1. 8 Transformed macro data series of Thailand in the baseline VAR





Appendix A.2: Transformed extensive macroeconomic variables of individual economy

Figure A.2.1 – Figure A.2.7 show the macroeconomic series of individual economy included in the extension VAR over the sample period 1991-2019 (China starts on 1999, India starts on 1994 and Thailand starts on 1998). All variables are depicted in logs.

Figure A.2. 1 Transformed macro data series of China in the extension VAR

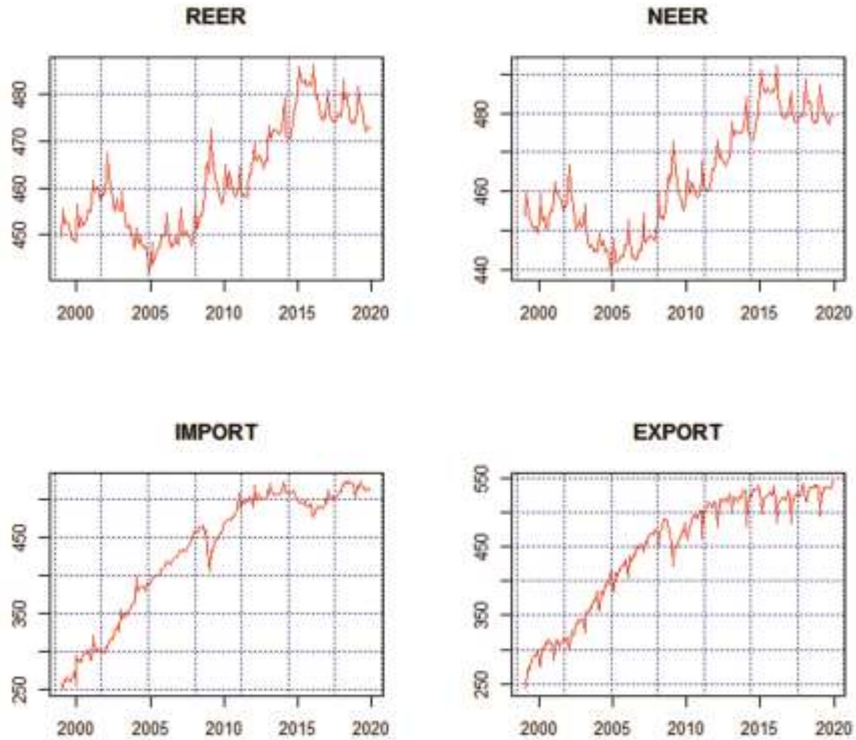


Figure A.2. 2 Transformed macro data series of Japan in the extension VAR

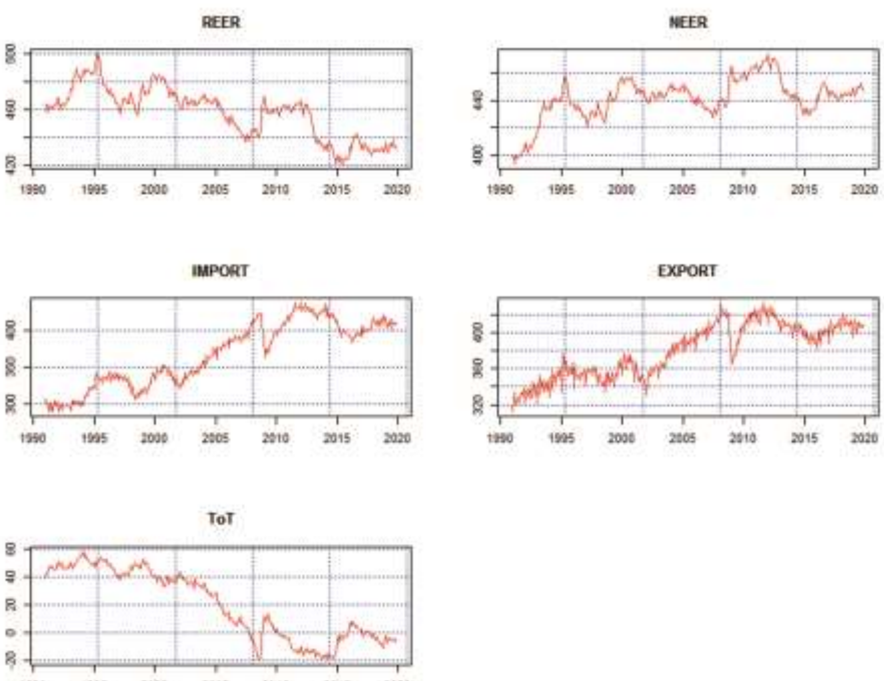


Figure A.2. 3 Transformed macro data series of India in the extension VAR

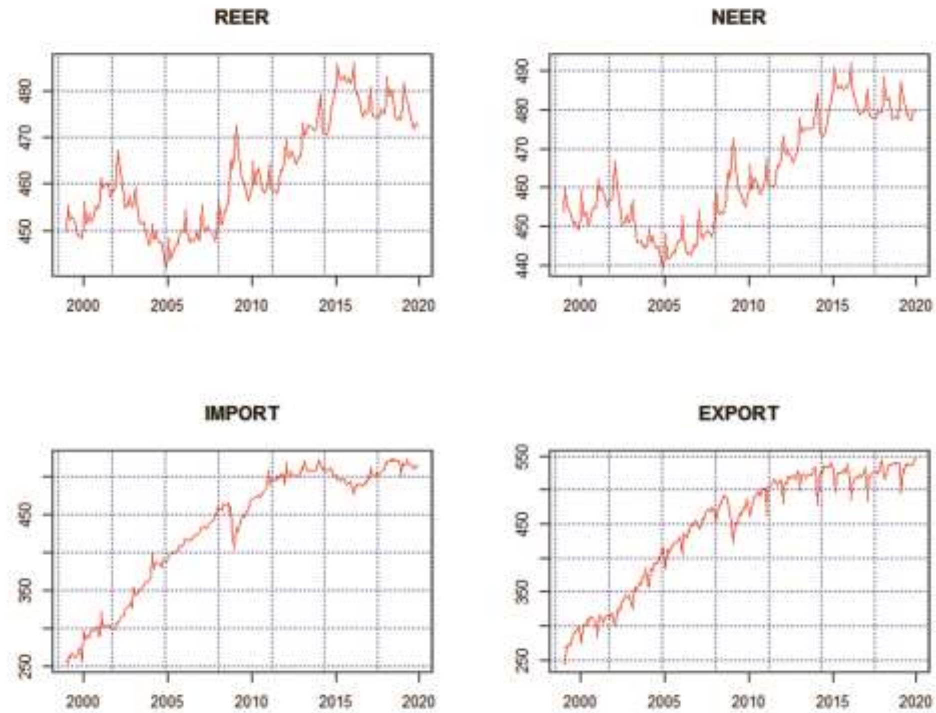


Figure A.2. 4 Transformed macro data series of South Korea in the extension VAR

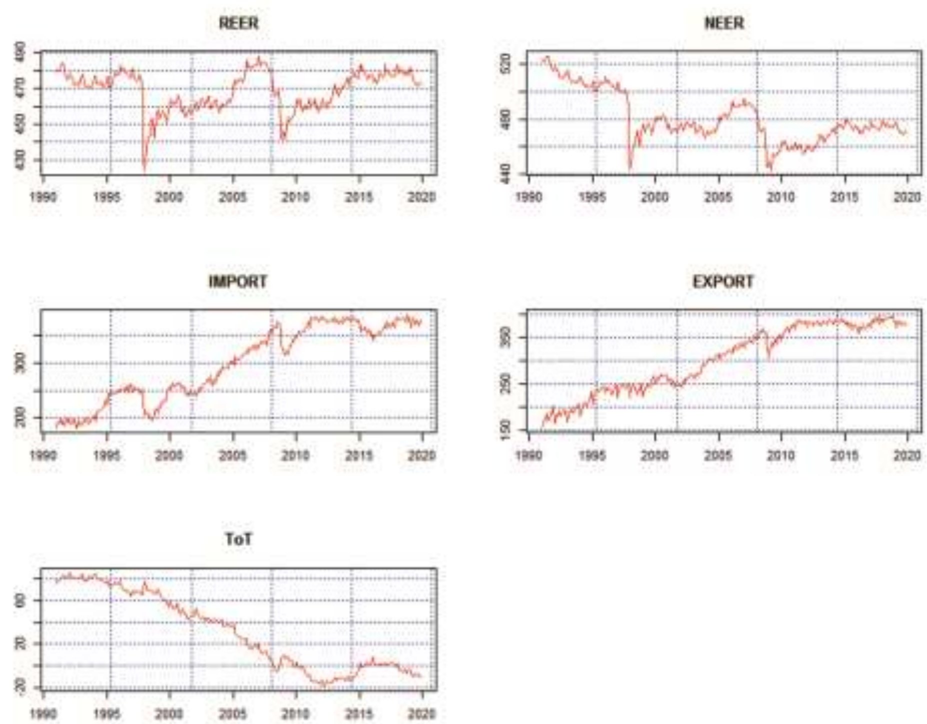


Figure A.2. 5 Transformed macro data series of Chinese Taiwan in the extension VAR

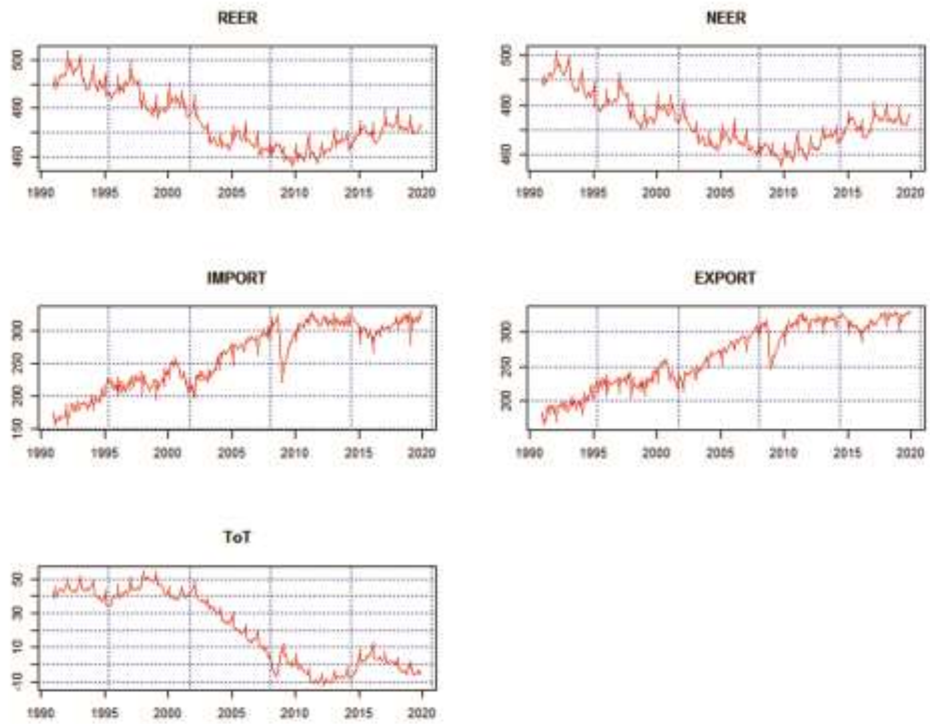


Figure A.2. 6 Transformed macro data series of the Singapore in the extension VAR

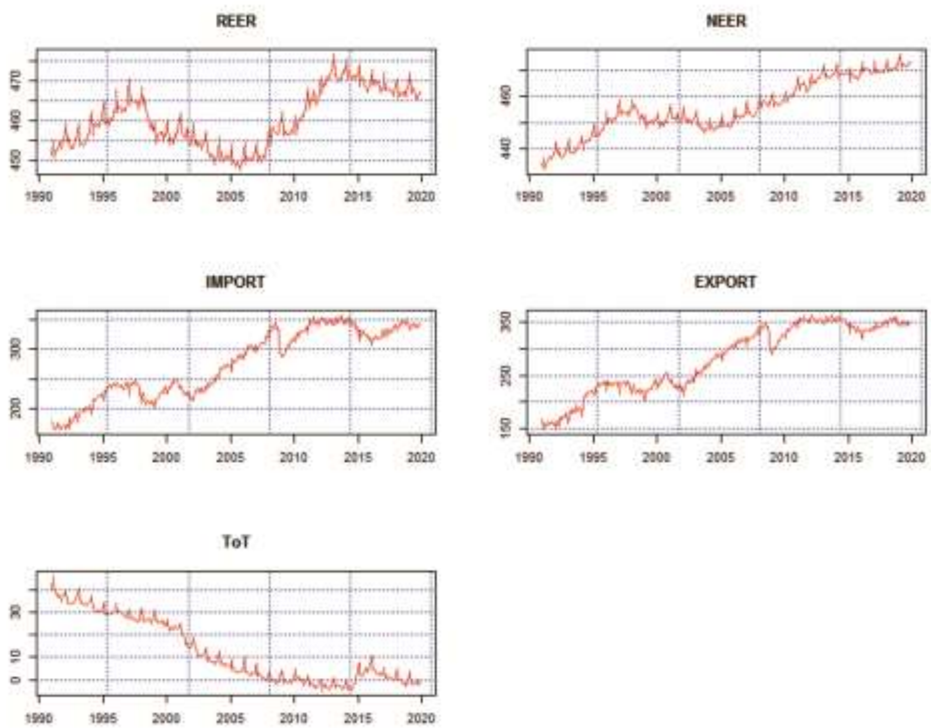
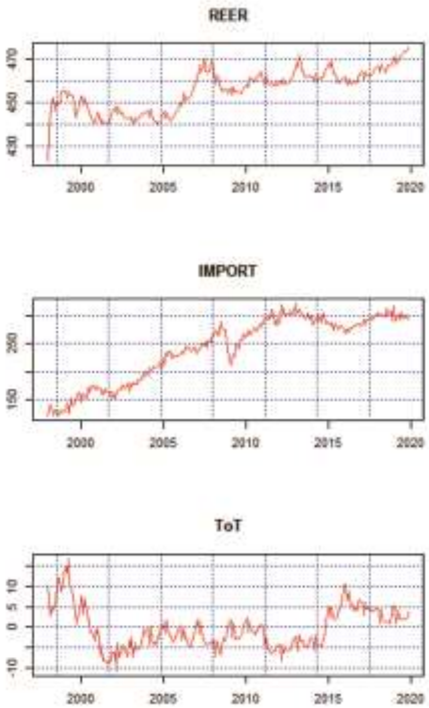


Figure A.2. 7 Transformed macro data series of Thailand in the extension VAR



Appendix A.3: Oil import status complements

Figure A.3.1 to Figure A.3.14 illustrate the oil import status for sample oil importers. The individual oil import status is measured by the accumulative nominal value of crude oil imported from 1995 to 2020 by each economic. These figures are generated by the database of the Observatory of Economic Complexity (OEC).

Figure A.3. 1 Aggregated crude oil import of China, 1995 to 2020

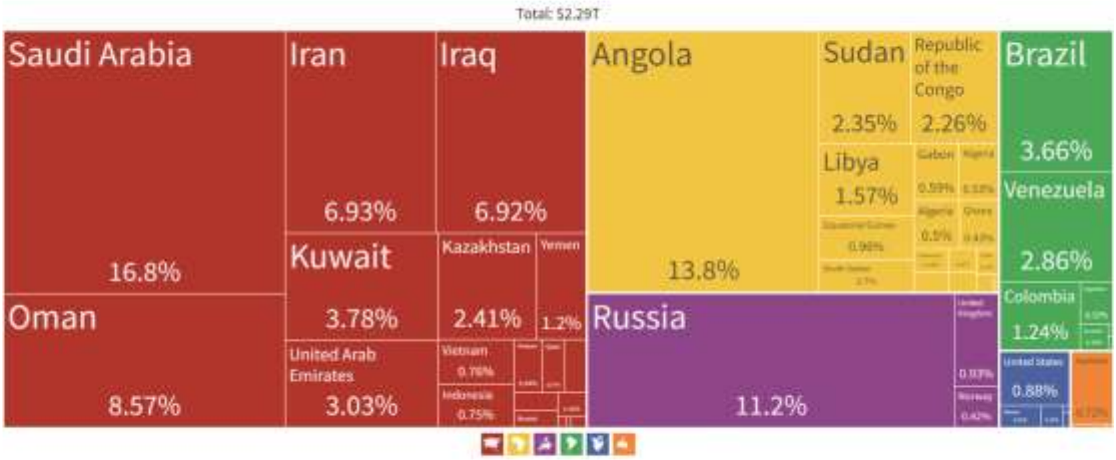


Figure A.3. 2 Aggregated crude oil import of Japan, 1995 to 2020

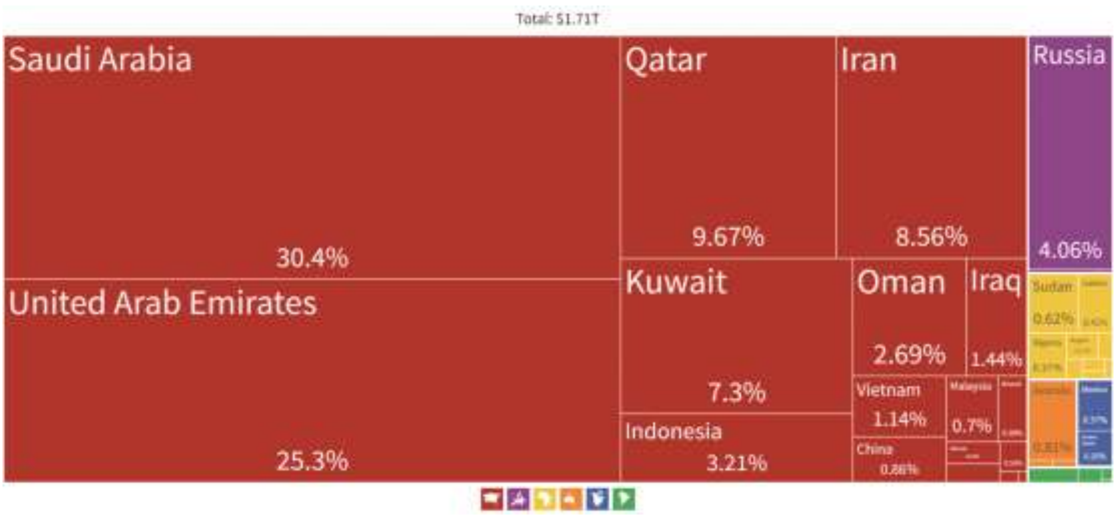


Figure A.3. 3 Aggregated crude oil import of India, 1995 to 2020

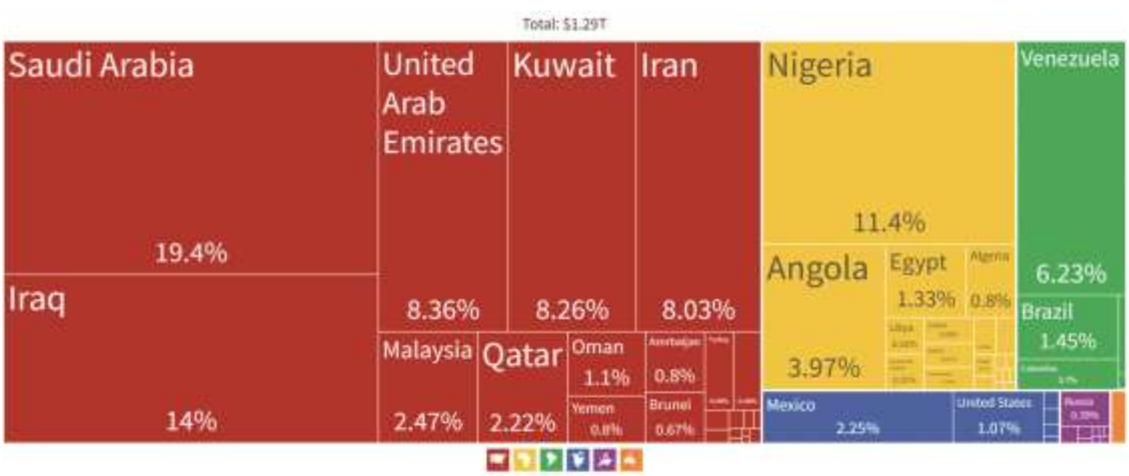


Figure A.3. 4 Aggregated crude oil import of South Korea, 1995 to 2020

Figure A.3. 5 Aggregated crude oil import of Chinese Taiwan, 1995 to 2020

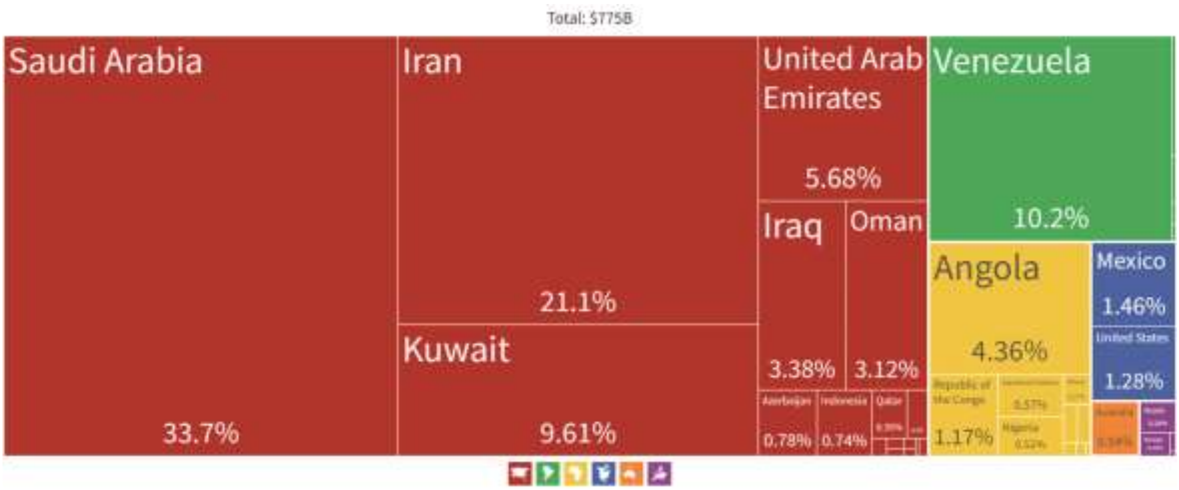


Figure A.3. 6 Aggregated crude oil import of Singapore, 1995 to 2020

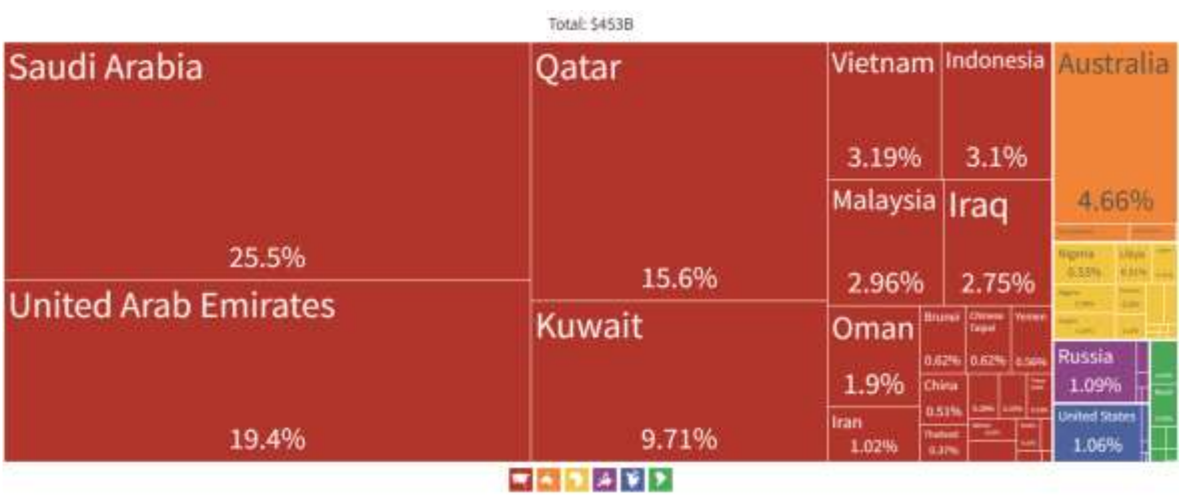
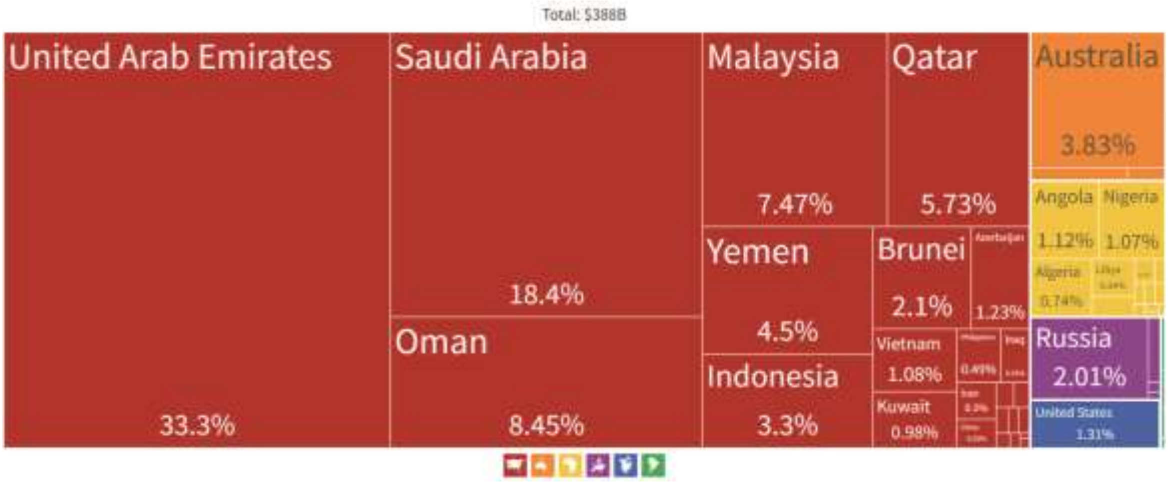


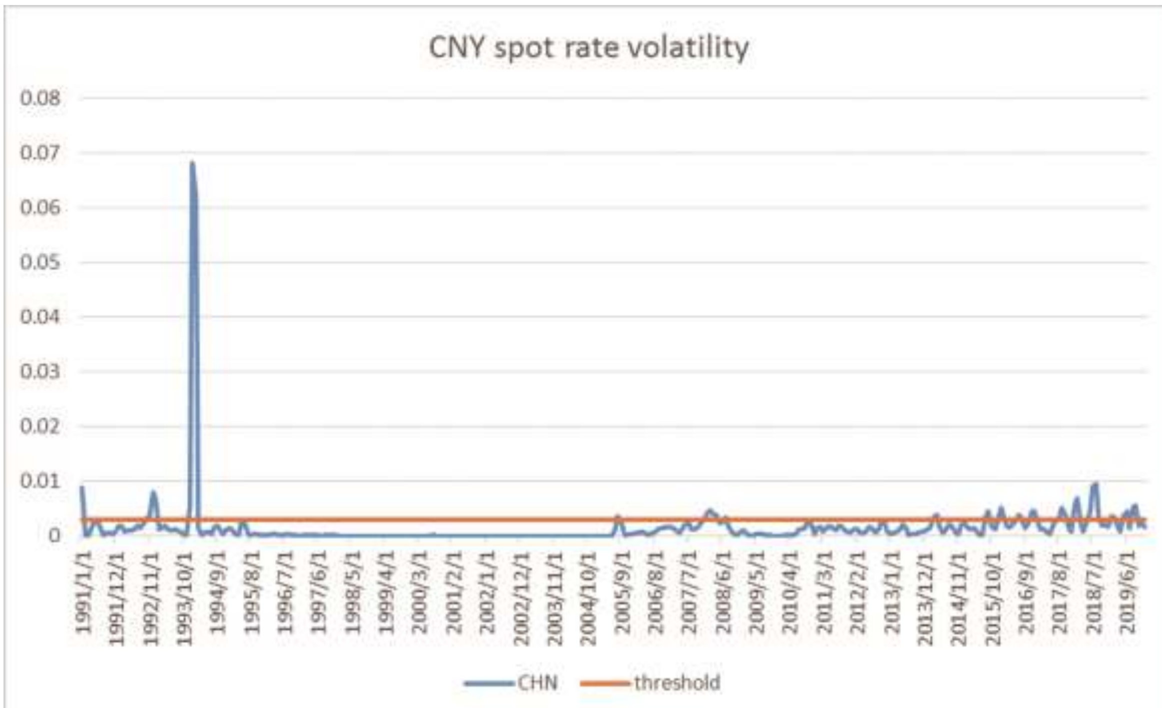
Figure A.3. 7 Aggregated crude oil import of Thailand, 1995 to 2020



Appendix A.4: Spot rate volatility

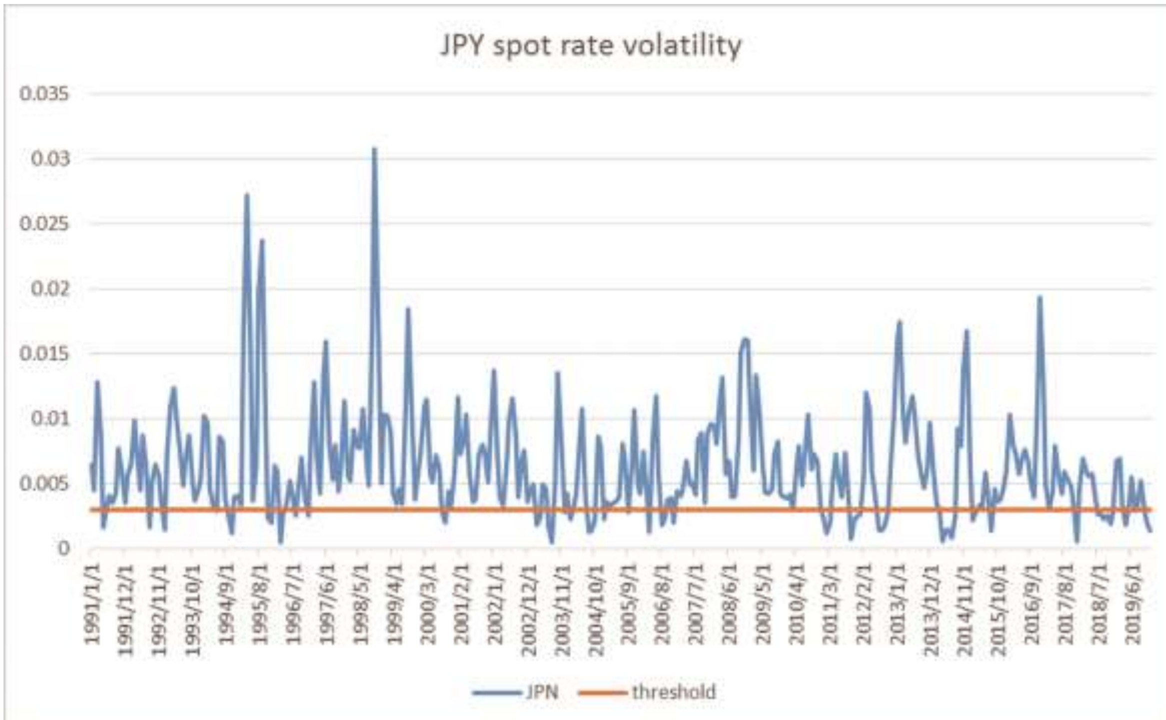
Figure A.4.1 to Figure A.4.7 illustrate the monthly spot rates volatilities of Asian oil importers with a threshold 0.0033 which is suggested by Accominoti, Cen, Chambers and Marsh (2019). The spot rates I look into are the nominal exchange rates between local currency and U.S. dollar.

Figure A.4. 1 CNY spot rate volatility



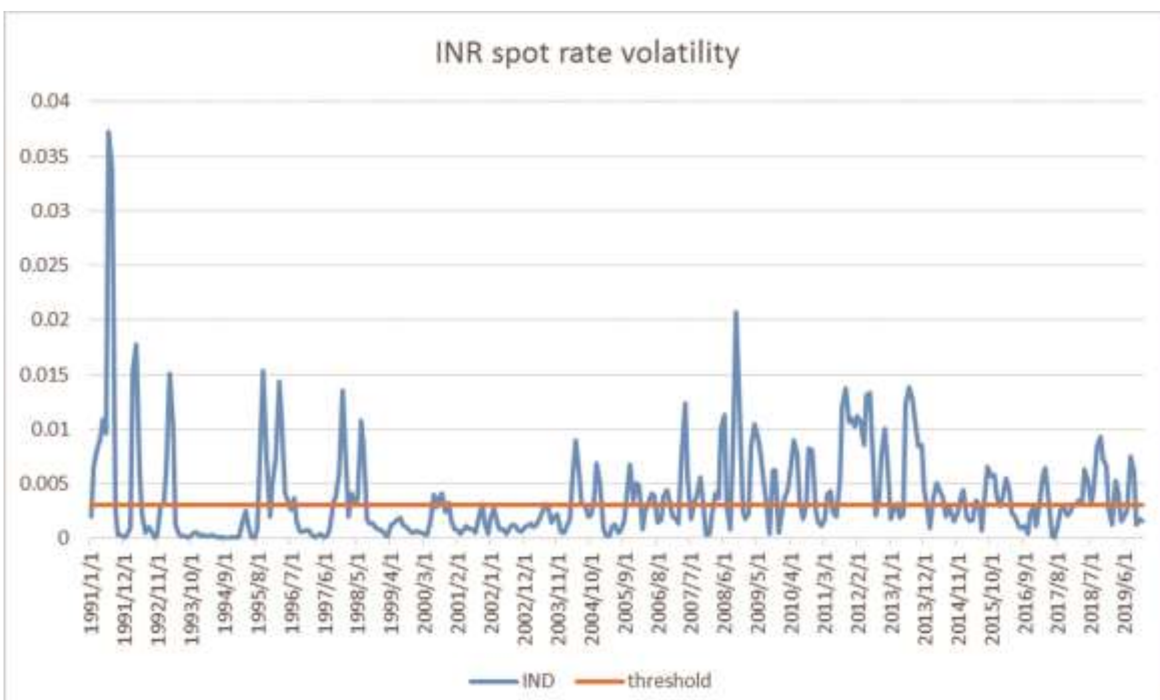
According to Figure A.4.1, from 1991 to 2019, Chinese spot rate volatility was mostly below the threshold. Thus, CNY was under a fixed currency regime.

Figure A.4. 2 JPY spot rate volatility



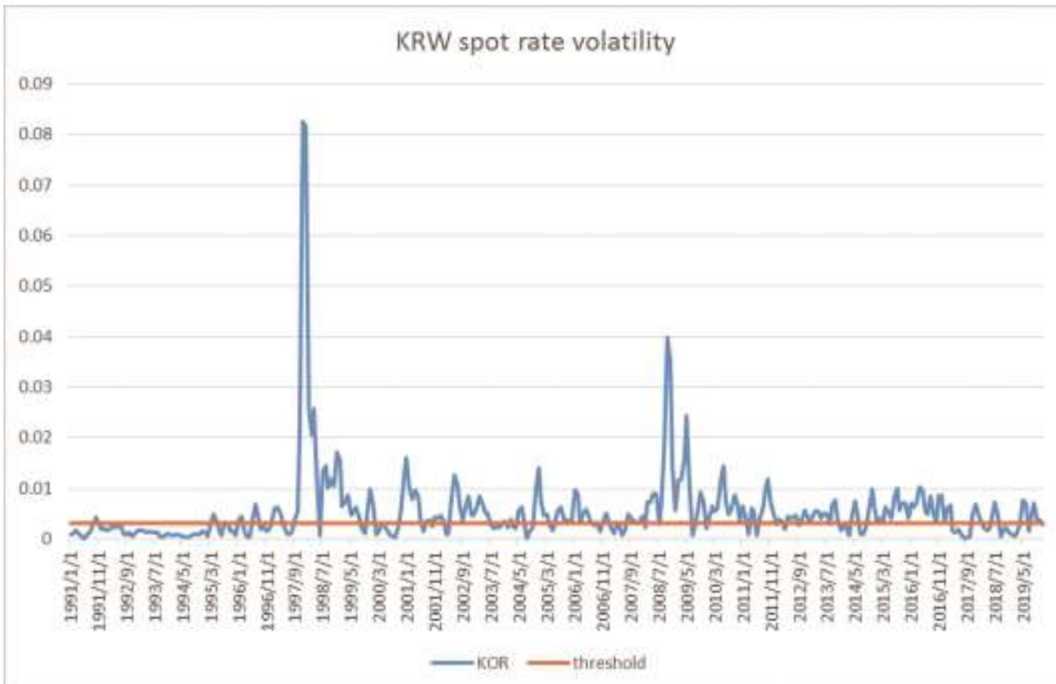
According to Figure A.4.2, from 1991 to 2019, Japanese spot rate volatility was mostly above the threshold. Thus, JPY was under a floating currency regime.

Figure A.4. 3 INR spot rate volatility



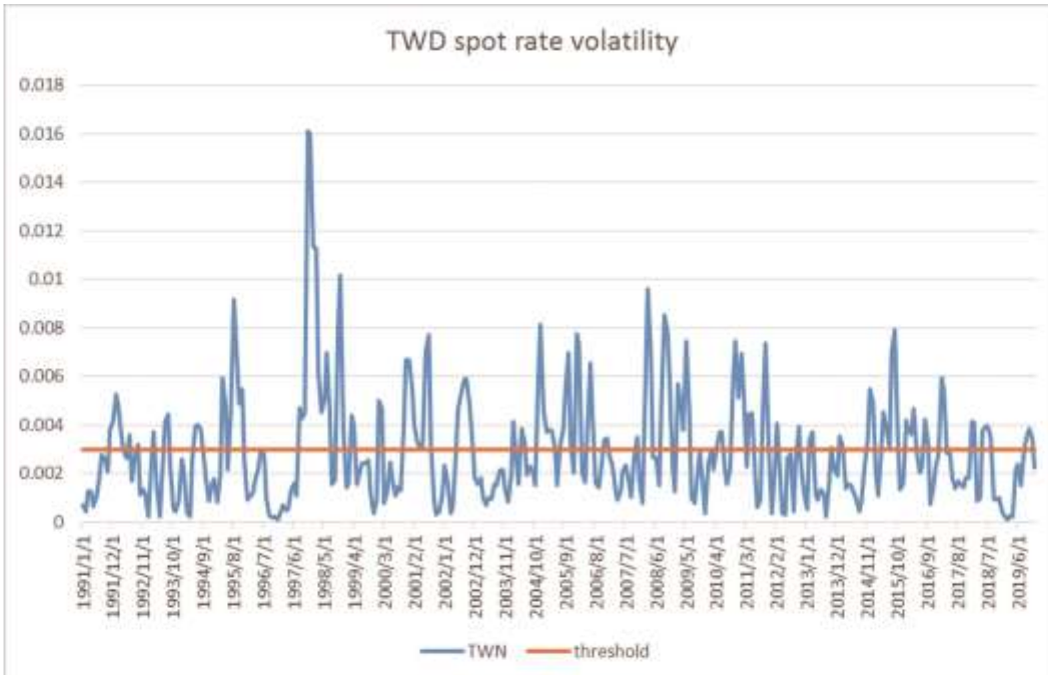
According to Figure A.4.3, from 1991 to 2003, Indian spot rate volatility was mostly below the threshold. However, over the period of 2004 to 2019, Indian spot rate volatility was mainly above the threshold. Thus, INR experienced a currency regime switch in which it was under a fixed currency regime from 1991 to 2003 then turned to floating regime from 2004 to 2019.

Figure A.4. 4 KRW spot rate volatility



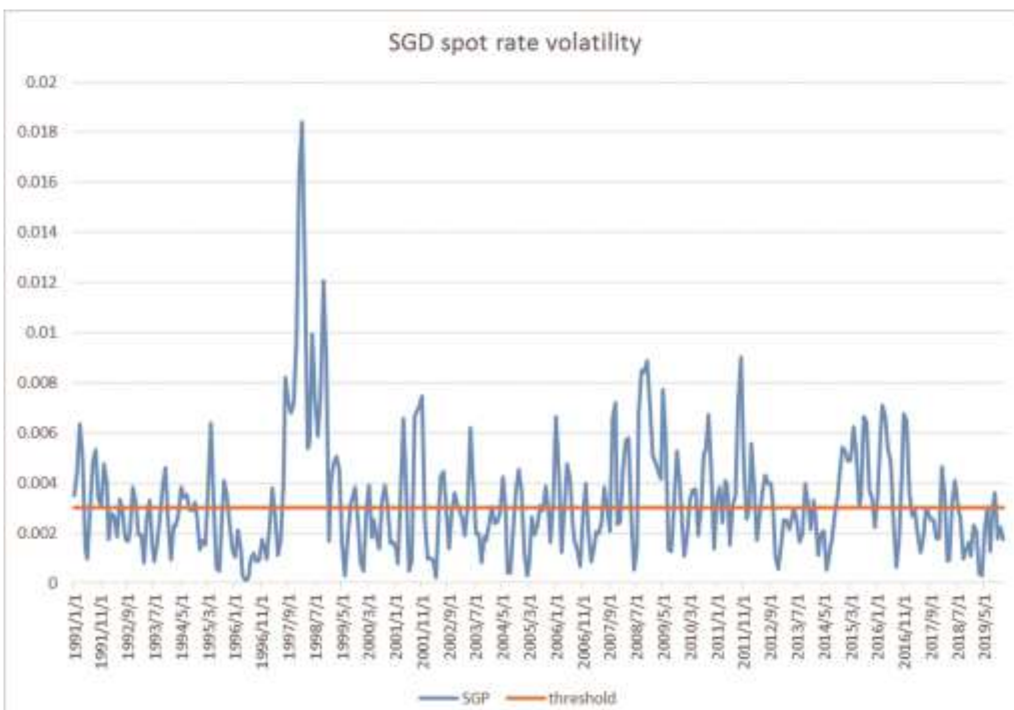
According to Figure A.4.4, from 1991 to 2019, Korean spot rate volatility was mostly above the threshold. Thus, KRW was under a floating currency regime.

Figure A.4. 5 TWD spot rate volatility



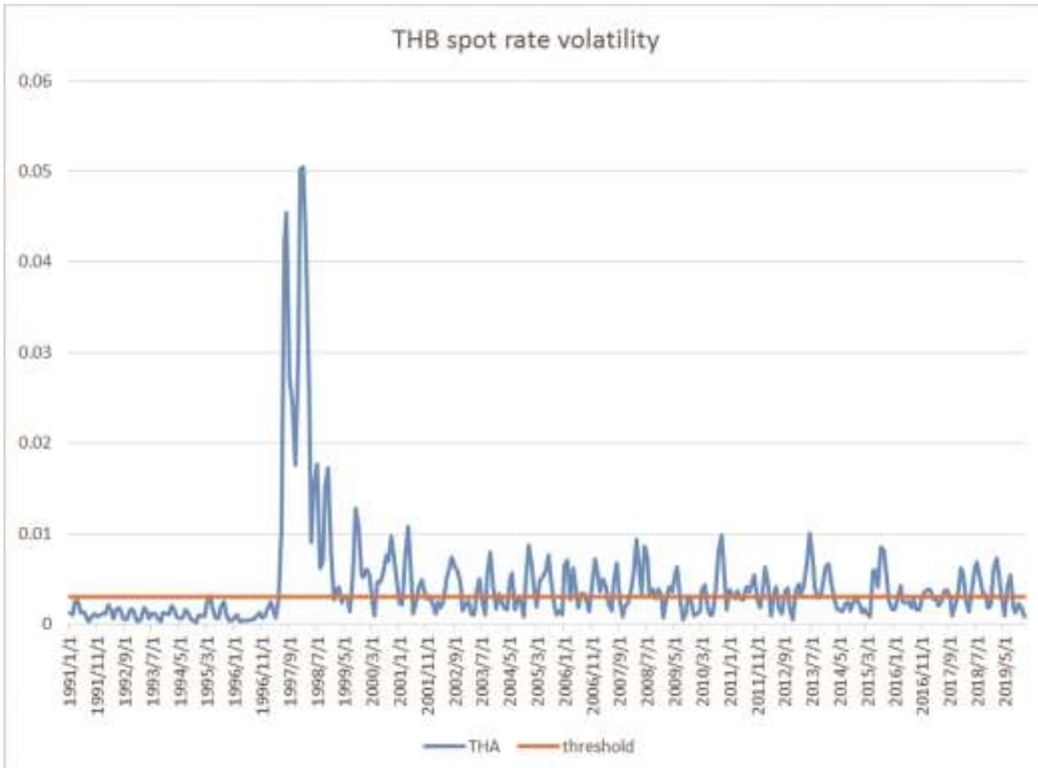
According to Figure A.4.5, from 1991 to 2019, Chinese Taiwan spot rate volatility was mostly below the threshold. Thus, KRW was under a fixed currency regime.

Figure A.4. 6 SGD spot rate volatility



According to Figure A.4.6, from 1991 to 2019, Singaporean spot rate volatility was mostly below the threshold. Thus, SGD was under a fixed currency regime.

Figure A.4. 7 THB spot rate volatility



According to Figure A.4.7, from 1991 to 1998, Thai spot rate volatility was mostly below the threshold. However, over the period of 1998 to 2019, Thai spot rate volatility was mainly above the threshold. Thus, THB experienced a currency regime switch in which it was under a fixed currency regime from 1991 to 1998 then turned to floating regime from 1998 to 2019.

Appendix A.5: Surprise Series of OPEC announcements

The table below demonstrates part of the extreme events that led to fluctuation of surprise series being more than 5%.

Table A.5 Extraordinary Dates

Date	Announcement Event
Nov.14, 2001	After 9-11, OPEC pledged to cut oil production conditionally lowered oil price expectation
Nov.27, 2014	Ending of high oil price era. Saudi and poor OPEC members kept increasing oil production
Dec.10, 2016	Cut down oil production level with non-OPEC members

In the following figure, it illustrates the oil supply news shock solely related to the oil supply surprise series generated by OPEC announcements.

Figure A.5 Oil supply shock series correlated to oil supply surprises solely

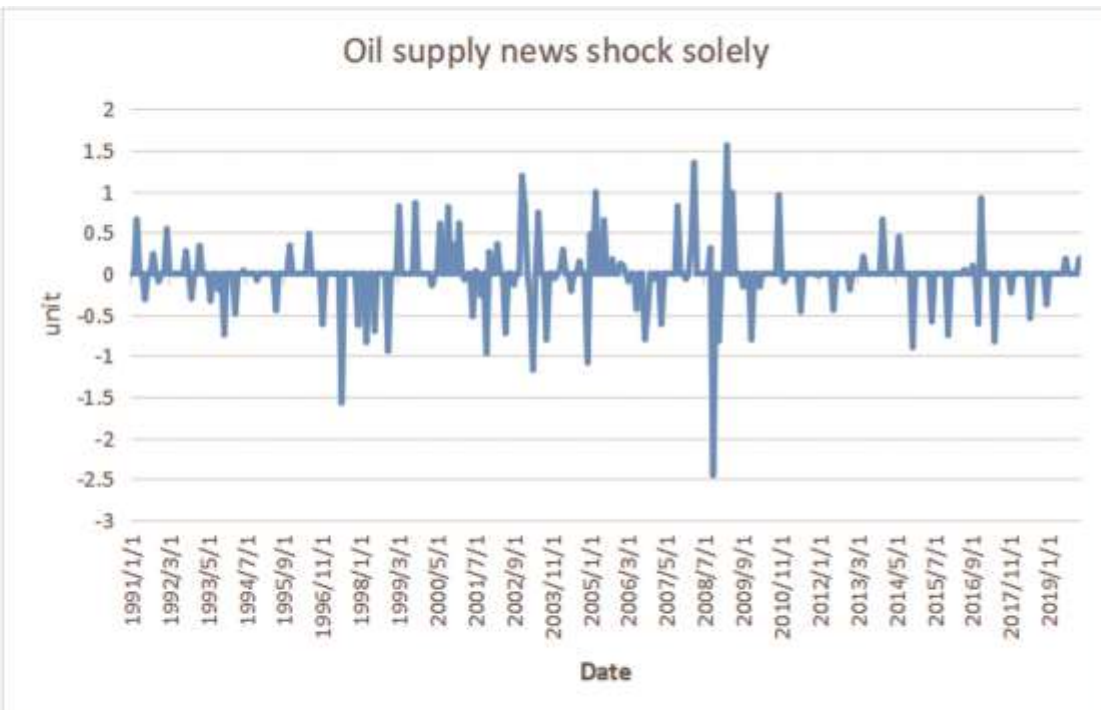


Figure A.5 shows that before 2010, the frequency that the magnitude of the shock is larger than 0.5 unit is 17 times every 10 years on average. After 2010, the frequency drops to 9 times from 2010 to 2019 as the impact from OPEC diminishes due to oil competition from Russia and the U.S.

Appendix B Appendix for Chapter 2

Appendix B. Data

Table B. 1 Data description, sources, coverage and country/region

Variable	Description	Source	Sample	Trans	Country/Region
Instrument					
Proxy	Surprise series based on WTI crude oil futures composite contract and OPEC announcements	Känzig's webpage	2004M1-2022M12	Percentage Change	N.A
Baseline variables					
POIL	WTI spot crude oil price deflated by U.S. CPI	EIA/FRED/Own calculation	2004M1-2022M12	Percentage Change	N.A
OILPROD	ASEAN oil production	EIA	2004M1-2022M12	Percentage Change	ASEAN
BPI	Baltic Panamax Index	Wind Database	2004M1-2022M12	Percentage Change	N.A
CFFISA	China Forwarder's Freight Index of Southeast	Wind Database	2004M1-2022M12	Percentage Change	China,ASEAN

	Asian				
Additional variables					
CPI	CPI Index, seasonal adjusted, 2010 = 100	G.E.M	2004M1-2022M12	Percentage Change	Samples
CPIUS	CPI Index for average U.S urban fuel oil consumption	FRED	2004M1-2022M12	Percentage Change	U.S.
NFX	Nominal Spot Exchange Rate between USD and LCD	FRED/Wind Database	2004M1-2022M12	Percentage Change	Samples
PALMUSD	Export price of palm oil, USD	Wind Database	2004M1-2022M12	Percentage Change	Malaysia, Indonesia
RUBBERUSD	Export price of rubber, USD	Wind Database	2004M1-2022M12	Percentage Change	Thailand, Malaysia
EXPCH	Export Value of Merchandise to China, constant US$	Chinese Custom	2004M1-2022M12	Percentage Change	Samples
RICEUSD	Export price of rice, USD	Wind Database	2004M1-2022M12	Percentage Change	Vietnam, Thailand
RUBBERV	Import Value	Chinese Custom	2008M1-	Percentage	Samples

	of Rubber		2022M12	Change	
					5

Table B.1 provides details on the data used in chapter 2, including information on the coverage, data sources and countries/regions

Table B.1: Descriptive statistics of commodity export prices (percentage).

Commodity	Rubber(MA)	Rubber(TH)	PalmOil(MA)	PalmOil(IDN)	Rice(TH)	Rice(VN)	WTI
Mean	0.0032	0.0045	0.0038	0.0027	0.0032	0.0008	0.0053
Std.Dev	0.0717	0.0771	0.0726	0.0828	0.0632	0.0759	0.0971
Max	0.1782	0.2201	0.1902	0.2727	0.4824	0.3849	0.7841
Min	-0.2987	-0.2964	-0.2672	-0.2928	-0.1792	-0.2543	-0.3977
Skewness	0.430	0.1437	0.3528	0.1820	3.0309	0.8635	1.8719
Kurtosis	4.494	3.9188	4.0498	4.052	22.502	8.893	22.39
Jarque-Bera	28.119***	8.7656**	15.133***	11.725***	3944.8***	356.69***	3688.8***

Appendix B.2: Surprise Series of OPEC announcements

The table below demonstrate part of the extreme events that led to fluctuation of surprise series being more than 5%.

[5] Note:Sample countries include: Malaysia, Vietnam, Indonesia, and Thailand

Table B. 2 Extraordinary Dates

Date	Announcement Event
Nov.27, 2014	Ending of high oil price era. Saudi and poor OPEC members kept increasing oil production
Dec.10, 2016	Cut down oil production level with non-OPEC members
Mar.6, 2020	Global oil demand shrinks due to COVID pandemic. Production level drops accordingly
April, 2021	OPEC and non-OPEC decrease oil production twice for rebalancing oil market
July.18, 2021	OPEC decided to increase oil production until phasing out the 5.8 mb/d production adjustment

Appendix B.3: Other Supplements

Figure B.3 illustrates the Sample ASEAN members' exports to China from 2004 to 2022 during which Malaysia was the largest exporter in the sample economies.

Table B. 3.1 Sample ASEAN members' exports to China (original series)

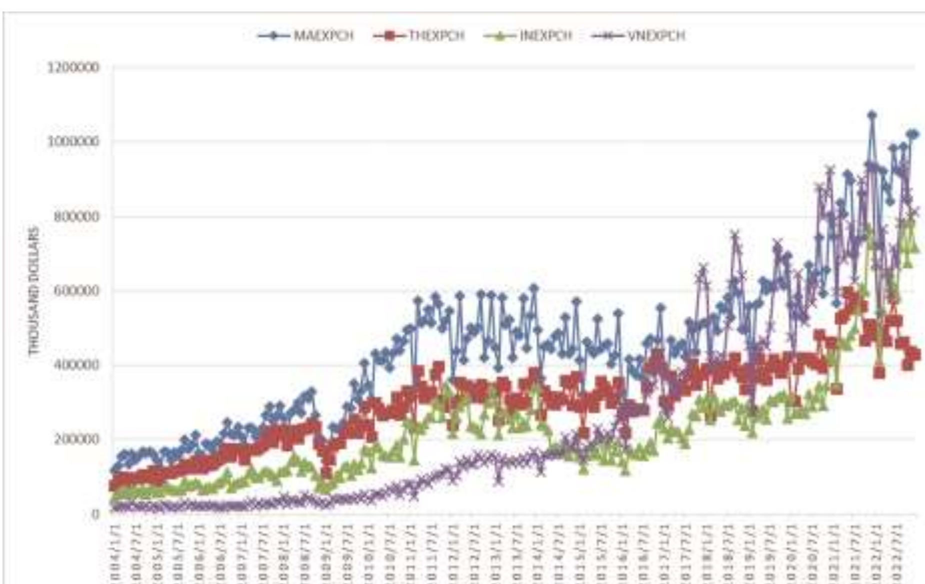
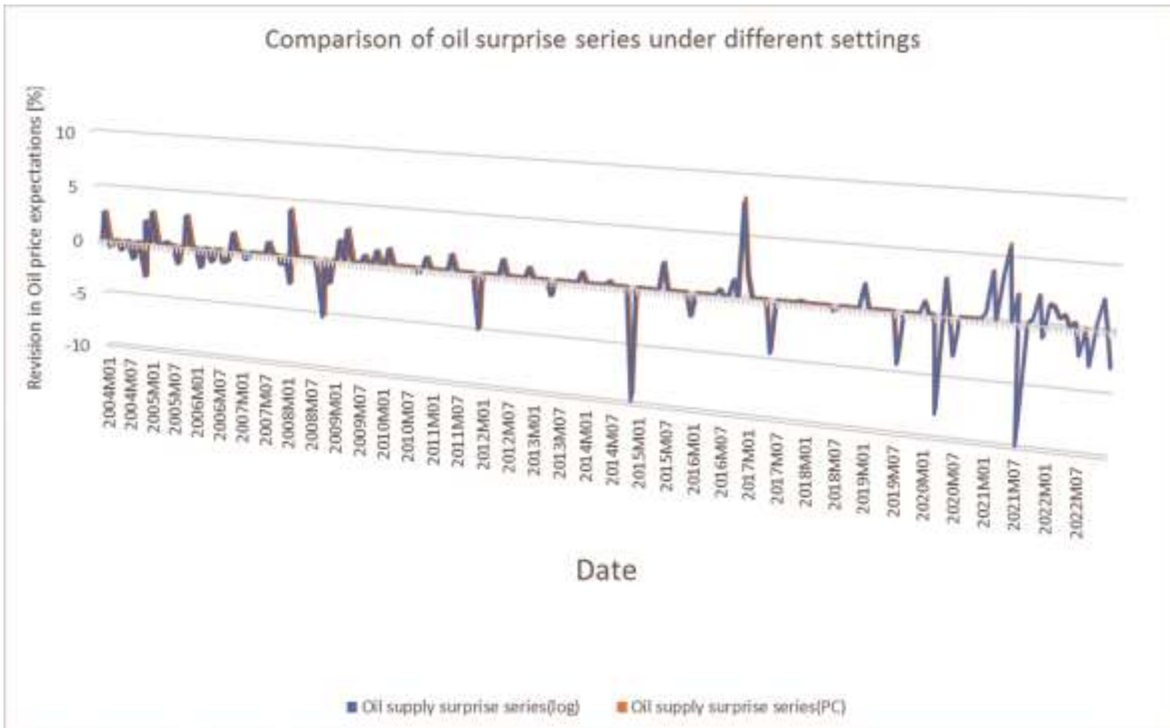


Figure B.3.2 compares the oil supply surprises series under logarithm difference and percentage change. According to the figure, two series are equivalent over time.

Figure B.3.2 oil supply surprises series setting comparison



Appendix C: Appendix for Chapter 3

Appendix C. Data

Table C.1 provides details on the data used in this paper, including information on the coverage, data sources and countries/regions

Table C. 1 Data description, sources, coverage

Variable	Description	Source	Sample	Trans
Instrument				
Proxy	Surprise series based on WTI crude oil futures composite contract and OPEC announcements	Känzig's webpage	2000M1-2022M12	Percentage Change
Macro variables				
POIL	Chinese oil refiner acquisition cost deflated by U.S. CPI	Wind database/FRED/Own calculation	2000M1-2022M12	Percentage Change
TPU	Chinese trade policy uncertainty	website	2000M1-2022M12	None
CHNIMP	Chinese import	Global Economic Monitor (G.E.M) database	2000M1-2022M12	Percentage Change
BCI	Baltic Capesize Index	Wind Database	2000M1-2022M12	Percentage Change
CHNIP	Chinese industrial production	G.E.M.	2000M1-2022M12	Percentage Change
CHNREFX	Chinese real	G.E.M.	2000M1-	Percentage

	effective exchange rate		2022M12	Change
CHNAUSIMP	Chinese import from Australia	Chinese Custom	2000M1-2022M12	Percentage Change
Commodity variables				
Copper	Spot price of copper, Chinese copper import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change
Nickel	Spot price of nickel, Chinese nickel import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change
Aluminum	Spot price of aluminum, Chinese aluminum import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change
Lead	Spot price of lead, Chinese lead import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change
Zinc	Spot price of zinc, Chinese zinc import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change
Tin	Spot price of tin, Chinese tin import	Price: FRED Import value: Chinese Custom	2000M1-2022M12	Percentage Change

Table C.2 Descriptive statistics of commodity import values (percentage)

Commodity	Copper	Nickel	Aluminum	Lead	Zinc	Tin
Mean	0.02581	0.04727	0.03755	0.25106	0.08367	0.08029
Std.Dev	0.1930	0.2644	0.3470	2.0447	0.5237	0.5031
Max	0.57503	0.94791	4.44114	31.83463	5.21903	5.20273
Min	-0.46491	-0.56947	-0.86508	-1.00416	-0.90863	-0.2543
Skewness	0.1195	0.3005	7.4981	13.641	4.2793	4.6879
Kurtosis	2.977	2.8535	95.802	208.97	37.471	43.413
Jarque-Bera	0.6609	4.387	101259***	494648***	14455***	19721***

Table C.3 Descriptive statistics of commodity import prices (percentage)

Commodity	Copper	Nickel	Aluminum	Lead	Zinc	Tin	Real Oil Cost
Mean	0.0075	0.0083	0.0025	0.0080	0.0057	0.0072	0.0053
Std.Dev	0.0637	0.0872	0.0512	0.0717	0.0677	0.0646	0.0685
Max	0.2439	0.4197	0.1637	0.2633	0.2551	0.1753	0.1948
Min	-0.2790	-0.2977	-0.1918	-0.2493	-0.2338	-0.2012	-0.2675
Skewness	0.1834	0.3896	0.2715	0.1914	0.0887	0.0856	0.8081
Kurtosis	6.0493	4.653	3.8511	4.567	3.7689	3.4826	5.4918
Jarque-Bera	108.09***	38.267***	11.68**	29.816***	7.1359**	3.0053	101.08***

Appendix C.2: Surprise Series of OPEC announcements

The table below demonstrates part of the extreme events that led to fluctuation of surprise series being more than 5%.

Table C.4 Extraordinary Dates

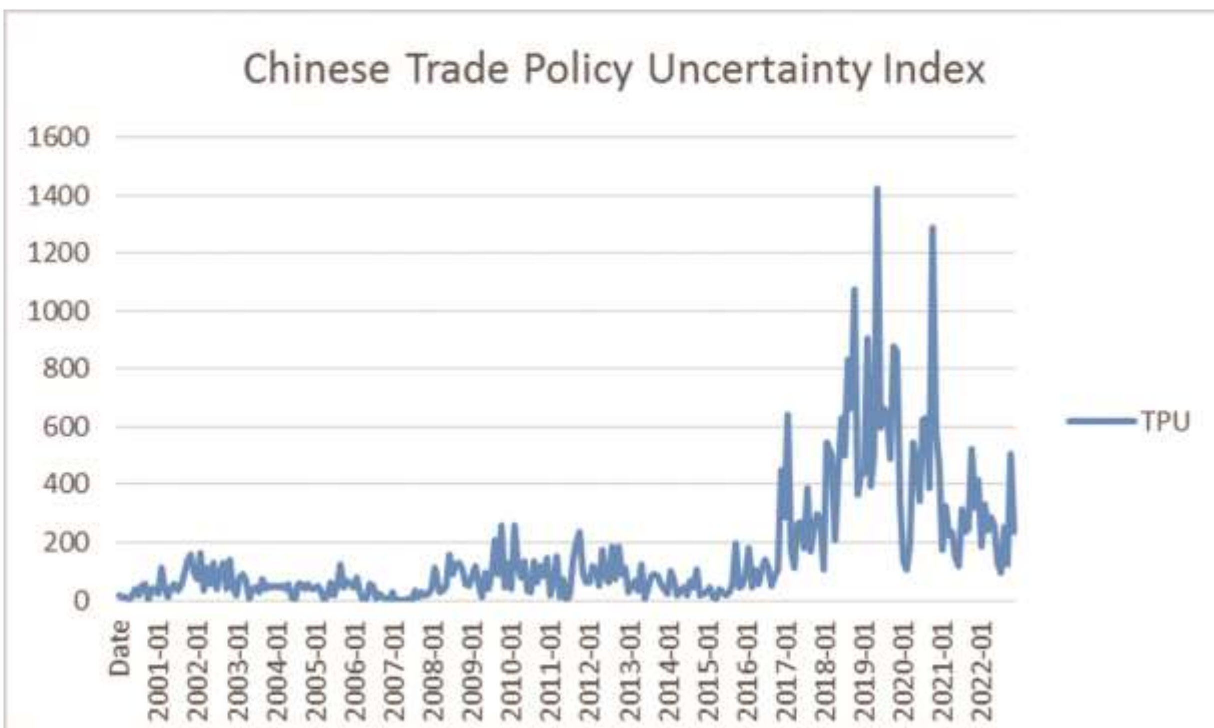
Date	Announcement Event
Nov.14, 2001	After 9-11, OPEC pledged to cut oil production conditionally lowered oil price expectation
Nov.27, 2014	Ending of high oil price era. Saudi and poor OPEC members kept increasing oil production
Dec.10, 2016	Cut down oil production level with non-OPEC members
Mar.6, 2020	Global oil demand shrinks due to COVID pandemic. Production level drops accordingly
April, 2021	OPEC and non-OPEC decrease oil production twice for rebalancing oil market
July.18, 2021	OPEC decided to increase oil production until phasing out the 5.8 mb/d production adjustment

Appendix C.3: Surprise Series of Policy Uncertainty

Figure C. 1 Chinese Trade Policy Uncertainty Index Setting

Category	English Terms	In Chinese Characters
Uncertainty	uncertain/uncertainty/ not certain/unsure/ not sure/hard to tell/ unpredictable/unknown	不确定/不明确/不明朗/未明/难料/难以预计/难以估计/难以预测/难以预料/未知
Economic	economy/business	经济/商业
Trade Policy	import tariffs/ import duty/ import barrier/ WTO/ world trade organization (2)/ trade treaty/ trade agreement/ trade policy/ trade act/ Doha round/ Uruguay round/ GATT/ General Agreement on Tariffs and Trade/ dumping/ protectionism/trade barrier/ export subsidies	进口关税/进口税/进口壁垒/WTO/世界贸易组织/世贸组织/贸易条约/贸易协定/贸易政策/贸易法/多哈回合/乌拉圭回合/GATT/关贸总协定/倾销/保护主义/贸易壁垒/出口补贴

Figure C. 2 Chinese Trade Policy Uncertainty Index



According to Steven J. Davis, Dingqian Liu and Xuguang S. Sheng (2019), the Chinese trade policy uncertainty index is constructed using the four steps below.

They first obtained monthly counts of articles that contain at least one term in each of three term sets: Economics, Policy, and Uncertainty. The sets are listed in Figure C.1.

In a second step, they scaled the raw monthly EPU counts by the number of total articles for the same newspaper and month.

In a fourth step, they computed the simple average of the standardized series over newspapers by month.

In a final step, they normalized each period's index value to an average of 100.