Essays on crude oil price differentials, oil price shocks, and the economy of Saudi Arabia

By

Modhi Hadyan Albaqami

B.S., Princess Nora Bint Abdul Rahman University, Riyadh, Saudi Arabia, 2006
M.A., King Saud University, Riyadh, Saudi Arabia, 2013
M.A., Kansas State University, Manhattan, USA, 2021

AN ABSTRACT OF A DISSERTATION

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Abstract

This dissertation incorporates three essays to examine the price differential between different-quality crude oils and the effect of oil price shocks on the Saudi economy. The first essay examined how price differences depending on crude oil quality have different regimes using a Markov switching model. The main difference between the two regimes is in the mean; the mean in the first regime shows no difference from zero, whereas the mean in the second regime is significantly positive, indicating consistency with a capacity constraint.

The second essay compared two situations: one involving three shocks applying Kilian's (2009) methodology versus one with only one shock to investigate whether considering a single shock is sufficient. Using three shocks showed a difference in how Saudi Arabia's industrial production and consumer price index respond to oil supply and demand shocks, suggesting that it is not sufficient to consider only one shock.

Finally, the third essay explored the reactions of Saudi Arabia's stock market to oil market shocks using Kilian's (2009) methodology and found that Saudi Arabia's stock sectors react differently to oil price shocks. Saudi Arabia's stock sectors reacted positively to oil-specific demand shocks but negatively to oil supply shocks; they showed no response to aggregate demand shocks.

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Approved by:
Major Professor
Dr. Lance J. Bachmeier

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Dedication

I dedicate this work to my charming mother for her unconditional love, support, and inspiration.

Chapter 1- Price Differential between Different Quality Crude Oils: Saudi Heavy Sour Crude Oil and U.S. WTI Light Sweet Crude Oil

1.1 Introduction

Crude oils have different physical and chemical characteristics. Saudi Arabia's crude oil varies from Arab heavy through Arab super light. However, the market price depends on two characteristics of a crude oil: sulfur content, which is the percentage level of sulfur in the crude oil, and API[1] gravity, which is the index used to measure the density of crude oil and is calculated as a degree. The API gravity of Arab heavy is less than 29° while the sulfur content is greater than 2.9% which is reported as a percentage (Aramco, 2021). Thus, Saudi Arabia's heavy sour oils are sold at a discount based on quality. Saudi Arabia's economy is heavily dependent on oil exports, and it is one of the largest oil exporters. As a member of OPEC, Saudi Arabia has the second largest oil reserves in the world (EIA, 2014). Despite all of the advantages that Saudi Arabia enjoys, it is still concerned about its oil quality. Its revenues are affected by the price of its crude oil, which is less expensive than high quality crude oil due to difficulties refining heavy sour crude oil, which requires specific equipment. Oil exporting countries, oil importing countries, and the owners of oil refineries all care about the price differentials due to quality.

In a certain sense, oil market participants and refiners are affected by the quality differentials in two ways: their profits and their investment decisions to improve their refineries in order to process the lower quality of crude oil. Different factors affect the price of oil, including the quality of crude oil, environmental regulations, and refineries' abilities to process crude oil. In terms of the quality of crude oil, heavy sour crude oil and light sweet crude oil sell at different prices. Heavy

[1] American Petroleum Institute.

sour crude oil sells at a discount because importing countries would like to protect their refineries from corrosion resulting from the corrosive nature of the sulfur and its unpleasant odor, which also pollutes the atmosphere. In addition, heavy sour crude oil has a very high resistance to flow and is difficult to desalinate (Figueroa & Boue, 2002).

Meanwhile, regarding environmental regulations, sulfur emissions are considered a pollutant, so in 2004 the Environmental Protection Agency (EPA) established regulations to reduce such emissions and then continued to further restrict sulfur levels (EPA, 2022). Finally, it is not possible to use simple types of refineries, which have only a distillation unit, to refine both types of oil. If simple refineries are used to process them, the percentage of residual fuel oil that cannot be converted into valuable products in heavy sour crude oil is higher than the percentage of light sweet crude oil. Meanwhile, complex refineries can lower the residual fuel oil from refining heavy sour crude oil even beyond the levels from refining light sweet crude oil. Thus, the differences in the cost of refining sour and sweet crude oils stem from complex refineries' using expensive equipment and their ability to greatly reduce the percentage of residual fuel oil and convert almost the entire barrel to high value products (HART Energy & MathPro Inc, 2011).

The refining capacity issue limits the price of heavy sour crude oil (Bacon & Tordo, 2005). Refineries use both crudes until a kind of disconnect occurs between them. This disconnect means the price differential is no longer restricted, as sweet crude prices can go up, but there are only minor increases in sour crude demand, because it is not physically possible for refineries to process high sulfur crude. This will lead to a sharp increase in demand for low sulfur crude. Thus, Saudi Arabia's crude oil is not substituted due to the capacity constraint as processing its crude oil is too expensive.

Saudi Arabia is keen to build more complex refineries to refine its heavy sour crude oil as this type of refinery reduces pollution by decreasing the level of sulfur in the final products. However, the country's projects focused on refining capacity are small compared to its production capacity. In addition, periods of low oil prices have made it difficult to provide sufficient funding to achieve its plans. Saudi Arabia has only 10 refineries locally (EIA, 2014).

Most previous studies have examined the price differential of the same type of oil-namely, light and sweet, to investigate whether the oil market has become closer to a great pool (e.g., Bachmeier & Griffin, 2006; Gulen, 1997-1999; Sauer, 1994), yet nobody has looked at the price differential of different types of oil using a Markov switching model. Therefore, we decided to investigate the different qualities of crude oil, focusing in particular on the price of crude oil in Saudi Arabia, which is considered the biggest exporter and a very important source of heavy sour crude oil, and the price of WTI, which is the most important source of light sweet crude oil. In addition, in this chapter we investigate changes that occur over time in the different regimes using a Markov switching model. For the reasons described above, a regime switching model may be a better way to characterize the properties of the price differential, where the regime depends on whether or not the capacity constraints (no more capacity to refine heavy sour crude oil) are binding. Since there is no way to identify in the data that the capacity constraint is binding, we estimate a Markov switching model as in Hamilton (1989). There are assumed to be two regimes, one with a higher average price differential, and/or more persistence, as the markets are disconnected in one of the regimes. Switching between the regimes happens randomly. We estimate the dynamics within both regimes as well as the probability of switching regimes. Our results demonstrate that the main difference between the regimes is the mean, as the mean in the first regime is no different from zero, suggesting no capacity constraint. Meanwhile, the mean in

the second regime is positive and significant, meaning it is consistent with the capacity constraint. Thus, the price of WTI in the second regime, which is light sweet crude oil, is permanently higher and the gap between heavy sour and light sweet crude oil prices does not disappear.

Section 1.2 provides a background on the price differential between crude oils and refineries. Section 1.3 reviews some of the previous studies. Section 1.4 presents the data. In Section 1.5, we describe the methodology of the Markov switching model. Section 1.6 discusses our results. Section 1.7 presents the conclusion.

1.2 Background on Price Differentials Between Crude Oils and Refineries

Crude oils are a liquid composed of several compounds, with carbon and hydrogen making up about 98% of the crude oil content while the rest is made up of sulfur, nitrogen, oxygen, and small amounts of other minerals (Bacon & Tordo, 2005). Heavier crude oil has a higher percentage of carbon and hydrogen (Scheitrum et al., 2018). The differences in the proportions of components in crude oil result in differences in its physical and chemical characteristics. In addition, variations in the composition of the crude oil affects refineries' investment requirements for new equipment and the use of their capacity. The exact composition of crude oil also determines the light or final products that can be obtained by refining it (Bacon & Tordo, 2005).

Crude oil has different qualities in terms of API gravity and sulfur content. Depending on its API gravity, crude oil is classified as light, medium, or heavy. An API degree equal to or higher than 35 refers to lighter crudes while an API degree equal to or less than 26 refers to heavier crudes (Scheitrum et al., 2018). Table 1-1 shows that, with higher API gravity, crude oil becomes lighter. Meanwhile, sweet versus sour crude oil depends on whether it has a low or high sulfur content. If the sulfur level is less than 0.5%, it is sweet; if the sulfur level is higher, it is sour. Figure 1-1 shows that most crude oils have a sulfur level higher than 0.5 according to the U.S. Energy

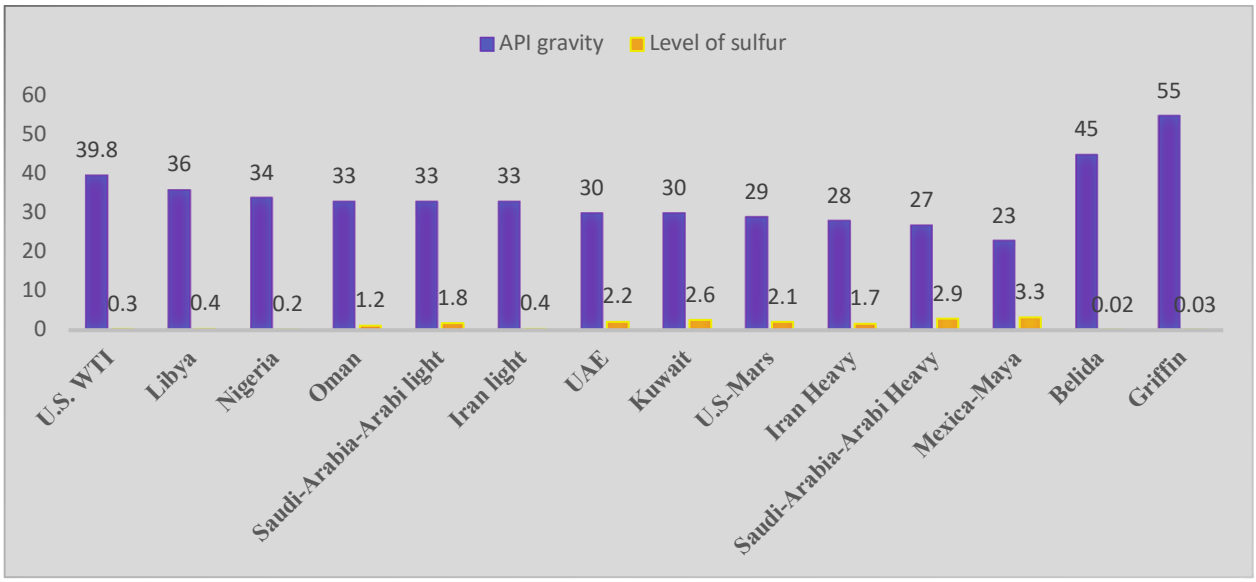
Information Administration (EIA). The lightest crude oil is Griffin, with an API gravity equal to 55; the sweetest crude oil is Belida, with a sulfur level equal to 0.02. Heavy and sour crude oil is a low-quality crude oil, whereas light sweet crude oil is a high-quality crude oil. However, the oil itself has a limited value for use, so refineries are needed to process the crude oil and turn it into light and high-value products such as gasoline, diesel, kerosene, jet fuel, asphalt, and heating oil.

Table 1-1 Crude Oil Classes

Type of crude oil	API gravity	Sulfur content (wt%)
Light-sweet crude oil	$35^0 - 60^0$	Less than 0.5
Light-sour crude oil	$35^0 - 60^0$	Greater than 0.5
Medium-sweet crude oil	$26^0 - 35^0$	Less than 0.5
Medium-sour crude oil	$26^0 - 35^0$	Greater than 0.5
Heavy-sweet crude oil	$10^0 - 26^0$	Less than 0.5
Heavy-sour crude oil	$10^0 - 26^0$	Greater than 0.5

Source: HART Energy and MathPro Inc (2011).

Figure 1-1 Gravity and Sulfur Levels of Crude Oils



Source: Independent statistics and analysis by the U.S. Energy Information Administration (2013).

To satisfy the light products market, more crude oil must be produced, and the processing capacity must be increased. According to Pieterse and Correlje (2008), refineries can follow several strategies to meet the product market demand:

- Not make any significant change and simply sell their final products according to their capable capacity;
- Adopt a short-term strategy by changing their operating systems using different catalysts, such as changing the pressure in the conversion processes or changing the boiling point;
- Adopt a medium-term strategy by renewing refinery operations so the refinery can change their final product; or
- Adopt a long-term strategy by investing in new equipment, which enables them to change the quality of crude oil as well as the final product, although this strategy is very expensive.

Refineries differ according to their processing units, so they can be categorized into the following groups (HART Energy & MathPro Inc., 2011; Pieterse & Correlje, 2008):

- Simple refineries contain a distillation unit only, offering a primary treatment for crude oil. This type of refinery does not have the ability to change the level of sulfur in the final products because it does not contain any unit to control the level of sulfur.
- Semi-complex refineries contain not only distillation units but also heat treatment units such as catalytic reforming and hydrotreating units. Catalytic reform is one of the most common processes used in U.S. refineries and increases the production of octane, which leads to the production of high-efficiency gasoline. This unit also produces the hydrogen necessary for the cracking process. Meanwhile, the hydrotreating unit is used to remove sulfur from diesel. It is not suitable for gasoline, despite removing sulfur from gasoline, because it lowers the level of octane.
- Complex refineries (cracking refineries) have all the units of semi-complex refineries as well as a fluid catalytic cracker (FCC), hydro catalytic cracker (HCC), or both. An FCC is a basic conversion process characterized by the production of high-quality gasoline, so it is only used to produce gasoline; diesel produced using an FCC is considered low quality. This process produces olefins, which are used as a raw material to upgrade the refinery to produce high-octane and low-sulfur gasoline. Refineries use sulfur-removal units before the FCC units because sulfur reduces the effectiveness of catalysts in the FCC. In addition, hydrocracking is a catalytic process that uses hydrogen as a catalyst. Catalyzed hydrogen works to break down the large particles or molecules as well as lead to the removal of sulfur. Therefore, light products produced from this process are lower in sulfur than when using FCC, but this process is considered expensive due to the high hydrogen consumption.

It is used to produce high-quality diesel but low-quality gasoline. It also produces more light products than the FCC unit does. Most refineries (329) have a FCC unit whereas only 141 have an HCC unit, indicating that refineries around the world tend to produce gasoline. However, the shift in demand from gasoline to diesel has led to refineries with FCC units to add HCC units.

- Very complex refineries, such as deep conversion or coking refineries, have all the refinery units in addition to a coking unit, which basically destroys or completely transforms almost all the residual fuel oil into light products, meaning it produces the maximum amount of light products. It is expensive to build and operate such refineries, but they are the preferred process for refineries, especially those in the U.S., that want to have a complete conversion of heavy crude oil into light products.

The U.S. imports heavy sour crude, which is responsible for domestic gasoline production in the U.S. The U.S. consumes approximately 60% of all low-quality crude oil according to Boue and Figueroa (2002) because it is home to a large number (68) of different complex refineries and 62 very complex refineries. Moreover, the capacity of the U.S. refineries fluctuated for both types of crude oil was fluctuated over the years. On the other hand, the Middle East has 23 complex refineries and 2 very complex refineries, as shown in Table 1-2. Moreover, the capacity of all types of U.S. refineries fluctuated over the years. Their capacity was more than 17 million barrels in the 1880s, which decreased by more than 2 million in the 1990s before returning to its their highest capacity in 2022, as shown in the Appendix (see Table A.1).

Table 1-2 Different Types of Refineries

	Simple	Semi-complex	Complex FCC	Complex HCC	Complex FCC & HCC	Very complex	Very complex FCC	Very complex HCC	Very complex FCC &HCC
Middle East	13	3	5	14	4	1	0	1	0
North America	8	11	48	8	12	4	24	2	32
World	120	103	172	42	44	23	66	8	47

Source: Pieterse and Correlje (2008)

According to Bacon and Tordo (2005), several factors lead to differences in the prices of oil of different quality:

- Refining capacity used
- Costs and availability of complex refineries
- Supply of different types of crude oils (e.g., heavy sour and light sweet crude oils)
- Increasing demand for high-value and light petroleum products such as gasoline, diesel, and kerosene

The limited refinery capacity means refineries want to process high-quality crude oil, not low-quality crude oil, which results in a further expansion of the differences in oil prices. Tighter environmental regulations also put pressure on current refineries' capacity to reach a permissible level of sulfur. In 2004, the Environmental Protection Agency (EPA) set emissions standards that require the use of gasoline, which has a specific level of sulfur. In 2017, the regulations were tightened to lower the sulfur levels even further (EPA, 2022). Regarding the costs and availability of refineries, heavy sour crude oil needs to be processed in complex refineries, which are much more expensive than those used to refine light sweet crude oil; such refineries are also limited in number, with most being located in the U.S.

We write the following model to describe the cause of price differentials. If sweet crude sells for price p^{sweet} and sour crude sells for price p^{sour}, the difference in crude types is evident in the different cost of refining them. Letting c^{sweet} be the cost of refining a barrel of sweet crude, c^{sour} be the cost of refining a barrel of sour crude, q^{sweet} be the quantity of sweet crude refined, and q^{sour} be the quantity of sour crude refined, we have:

$$c^{sweet} = \mathcal{F}(q^{sweet}) \tag{1.1}$$

$$c^{sour} = g(q^{sour}) \tag{1.2}$$

The properties of $\mathcal{F}$ and g, which are the properties of the two different qualities of crude oil, ensure that $c^{sour}(\bar{q}) > c^{sweet}(\bar{q})$ for any positive quantity $\bar{q}$. The goal of this formula is to capture the reason for price differentials. In a world in which adjustments can be made continuously, the price differential will always be a constant amount, but price differentials could persist temporarily due to the time it takes to transport crude oil. Refineries would always produce where the cost of using the two crudes is exactly the same (otherwise they would not use the higher priced crude). Assuming a competitive market for the purchases of wholesale crude oil, price differentials are driven by differences in the cost of refining the two crude oils.

In addition, changes in the quality of supply affect the price differences. Thus, in the event of a shortage of crude oil supplies, such as during wars and global events, OPEC members, especially Saudi Arabia, increase their production. Such an increase is only possible by increasing the production of heavy sour crude oil because most crude oil reserves in the world are of low gravity (heavy) and high sulfur content (sour). Saudi Arabia does not use heavy sour crude oil for trade in the market of oil, but rather stores it, using it only when demand exceeds supply. In this case,

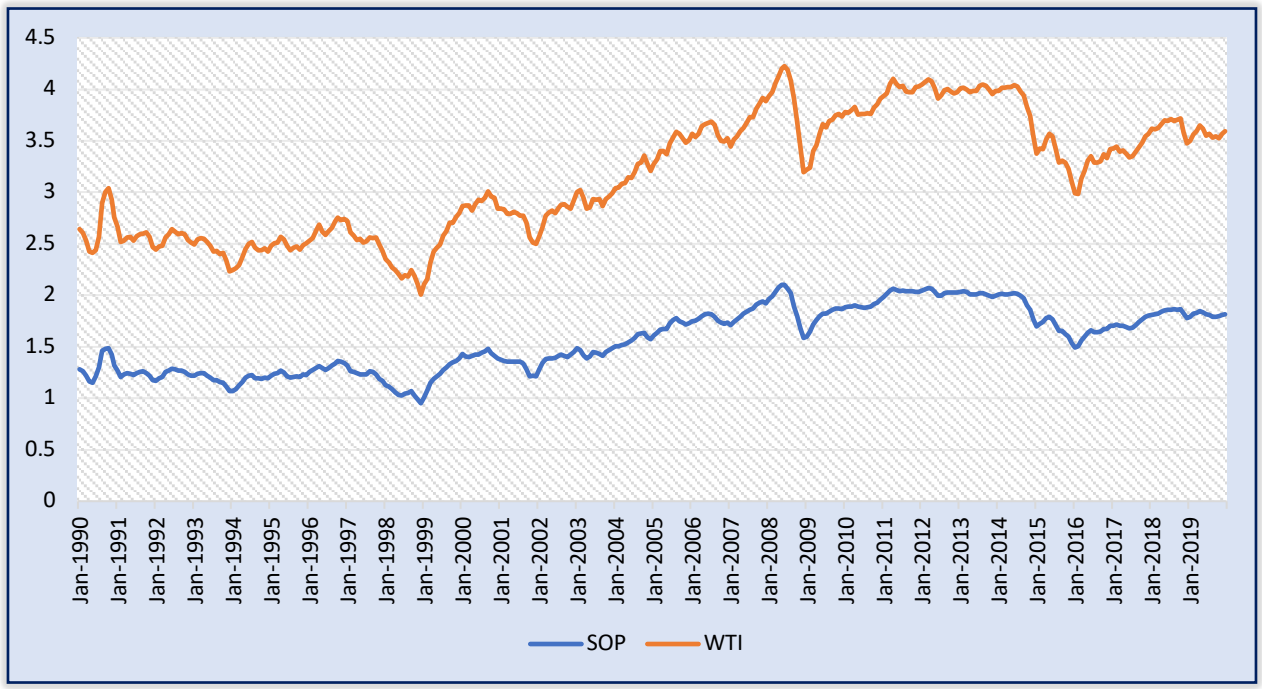
refineries will try to use their maximum capacity to process heavy sour crude oil in order to meet the demand, although at some point, they will face capacity constraints.

Finally, an increase in the demand for valuable or light products leads to an increase in their prices and, as a result, the prices of crude oil increase. In such a situation, refineries prefer to use light sweet crude oil, which is capable of producing a high percentage of light products and to avoid capacity constraints resulting from refining heavy sour crude oil. According to Pieterse and Correlje (2008), the demand for light products changes for various reasons, including economic growth, which affects the size of energy consumption in some countries, such as India and China, where both the transportation sector and electricity consumption are growing rapidly. In addition, the demand for some light products may increase while the demand for others decreases. Since the 1990s, Europe has been shifting from gasoline consumption to diesel consumption in the transportation sector as the latter is more efficient. Diesel cars account for 30% of all cars in Europe; this ratio is gradually increasing to 45%, resulting in a surplus of gasoline. Meanwhile, in America and Canada, gasoline is the most important, accounting for 41% of total consumption. As a result, most of the refining capacity in Europe focuses on diesel production, while refineries in America focus on producing gasoline.

Heavy sour oil sells at a discount compared to light sweet crude oil, which sells at a higher price, as shown in Figure 12 plots the two crude oil prices from 1990 through 2019, for various reasons according to Figueroa and Boue (2002). For example, heavy crudes make pumping more difficult, which means heavy crudes have a very high resistance to flow. Another reason is desalination, which is done by passing electricity to remove the salts. Heavy crudes are difficult to desalinate because of the low flow. Heavy crudes also contain unwanted impurities such as sulfur, which causes pollution and poses health and safety risks. As a result, policies limit sulfur content

in gasoline and diesel. Sulfur also corrodes the refining equipment and can poison or deactivate the catalysts, thereby affecting the chemical processes. Refineries must be able to control the level of sulfur, but treating it involves an increased cost. Furthermore, refineries convert the sulfur into hydrocarbons and hydrogen sulfide gas during the removal process, which is then removed for sale or safe disposal (U.S. Department of Energy, 2010). To reduce corrosion, refineries combine crude oils containing sulfur with other crude oils that do not contain sulfur before the refining process, but this process is expensive and not worth the outcome (Bacon & Tordo, 2005). Instead, refineries need to invest in corrosion-resistant machines or remove sulfur through special units.

Figure 1-2 Price of heavy sour crude oil (SOP) and light sweet crude oil (WTI)

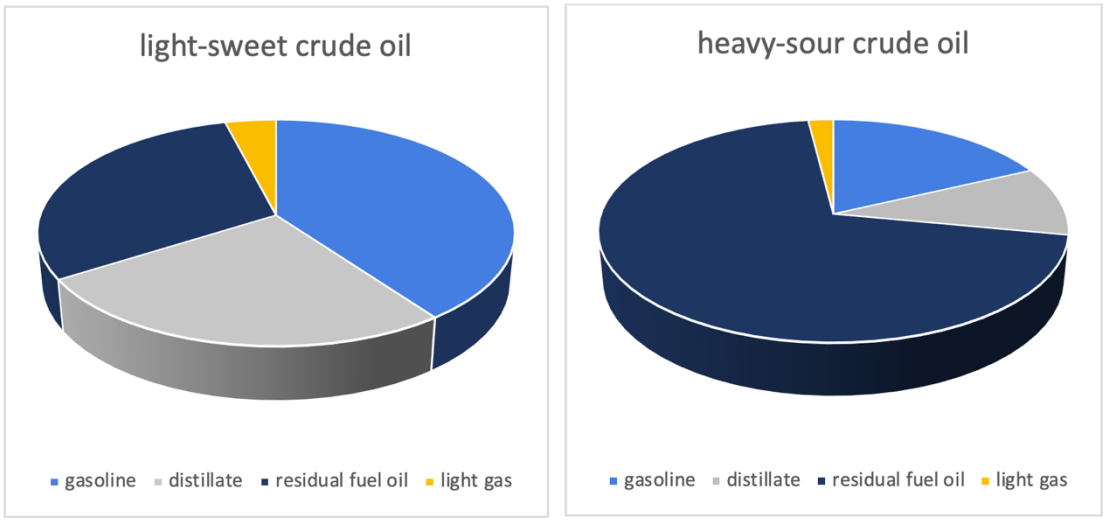


Source: The U.S. Energy Information Administration (EIA) (2020), and the Federal Reserve Economic Data (FRED) (2021)

Regardless of the type of refinery, the first step in refining crude oil is distillation. Each type of crude oil is distilled into different parts: gasoline, distillate, light gas, and the residual fuel oil at the bottom of the barrel. Increased API gravity decreases the percentage of residual fuel oil. Thus, light sweet crude oil provides a greater percentage of gasoline and a smaller percentage of

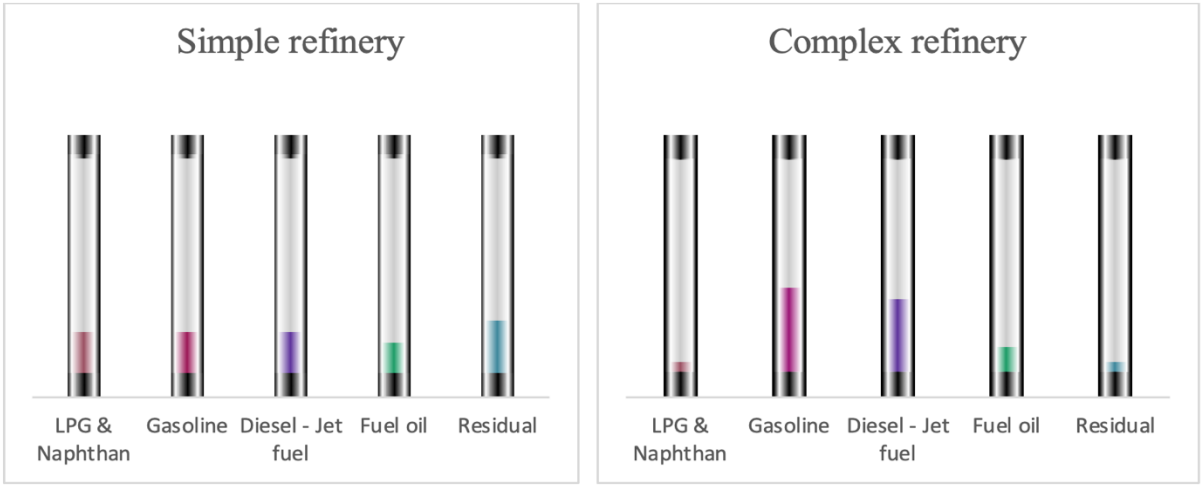
residual fuel oil than heavy sour crude oil, as shown in Figure 1-3. Residual fuel oil is sold at a discount compared to gasoline and distillate, which is why heavy sour crude oil is less valuable than light sweet crude. However, to mitigate the growth in the demand for light sweet crude oil and avoid surplus residual fuel from processing heavy sour crude oil, it is necessary to use complex refineries with the ability to turn the residual into light or high-value products. Using complex or deep conversion operations to process heavy sour crude oil will decrease the percentage of the residual fuel oil to be even less than the percentage of the residual fuel oil from processing light sweet crude oil by simple refineries, as shown in Figure 1-4. Thus, complex refineries increase their demand for residual fuel depending on the price of light products, capacity of the refinery, and increased conversion capacity.

Figure 1-3 Natural Yields of Different Crude Oils



Source: HART Energy and MathPro Inc (2011)

Figure 1-4 Light Products Yielded from Processing Heavy-Sour and Light-Sweet Crude Oils



Source: Oil Sands Magazine (2015)

The price differential between different types of crude oil in terms of quality, changes with the increase in the price of crude oil. When oil prices rise, refineries will process crude oil that is less expensive and contains a high percentage of sulfur until reaching a point when there is no more capacity. In 2003, when there was a sharp increase in crude oil prices, the difference between heavy sour crude oil and light sweet crude oil increased (Bacon & Tordo, 2005). Although there is a difference in the quality of crude oils, their prices move together. Over time, the price difference between different crude oils has become smaller due to the increase in the number of complex refineries. In addition, the shale oil boom in the U.S. led to an increase in light sweet crude oil, which can be processed by simple refineries (Plante & Strickler, 2019).

Most oil-exporting countries such as Saudi Arabia depend heavily on oil revenues, so they seek to obtain accurate forecasts for crude oil prices. However, the large number of crude oils makes forecasting difficult. Increasing the global demand for oil leads to an increase in countries' desire to locate new oil fields, ultimately resulting in the number of crude oils exceeding 150 types with differing qualities. To understand this challenge, Robert and Tordo (2005) compared two types of crude oil that differ in their API gravity but have identical sulfur content: super light sweet

crude oil and light sweet crude oil. If the difference in API gravity between them is 10 degrees and if we assume that each degree of API is equal to 20 cents, then the price difference between them is 2 dollars per barrel. However, if two types of oil are similar in API gravity but differ in sulfur content, such as light sweet and light sour crude oils, each percentage point of sulfur content lowers the price by, for example, 1 dollar. According to Robert and Tordo (2005), as the gravity of API crude oil increases by one degree, the price of crude oil increases by \$0.007; as sulfur content increases by 1%, the price decreases by \$0.056. Robert and Tordo (2005) wrote the multiple regression analysis in its simplest form as follows to estimate the effect of each quality difference on the price differential:

$$diff_j = \alpha + \Sigma_i \, b_i\left(\Delta \, quality_{ij}\right) \tag{1.3}$$

where $diff_j$ indicates the difference between two prices (price of crude j and marker price, which is the WTI), $\Delta \, quality_{ij}$ indicates the difference of the quality i between a given crude oil and WTI, and b_i measures the impact on the price differential in each quality different between crude j and WTI.

The Saudi Arabian oil company Aramco, which is owned by the Saudi government, has the power to decide policy, such as target production levels, so it determines its production according to refineries' demand. Aramco is the largest oil company in the world in terms of its production capacity due to its ability to produce more than 10 million barrels per day, and its proven oil reserves are estimated at more than 260 billion barrels according to the EIA (2014). Thus, Aramco affects the oil market by changing the level of its production as well as changing the quality of the oil produced. It owns more than 100 oil and natural gas fields, but most of its reserves are concentrated in its eight largest fields, as Table 1-3 indicates. Ghawar field, the largest

oil field in the world, produces more than 5.8 million barrels per day and holds reserves worth more than an estimated 74 billion dollars (EIA, 2014).

Saudi Arabia produces five different types of crude oil (i.e., Arab super light, Arab extra light, Arab light, Arab medium, and Arab heavy), with API gravity degrees ranging from heavy to light; the light crudes are produced from land fields while the heavy crudes are produced from marine fields. Most of the five types are classified as sour as the sulfur content is higher than 0.5% (EIA, 2014). The sour nature of the oil produced in Saudi Arabia is concerning because it affects the price of oil and, in turn, revenue flows. Thus, Aramco is looking to diversify its revenue sources to protect its revenues. The rise in oil prices provides Aramco with sufficient funds for investment, which encourages the exploration of new fields, the construction of new refineries, and updates to existing refineries to overcome its weakness regarding oil quality for medium sour and heavy sour crude (Lahn & Stevens, 2011).

Table 1-3 Main Saudi Fields

Name of field	Found	API gravity	Sulfur content	Type	Capacity
Ghawar	1948	35^0	1.91% – 2.15%	Light-sour	5.8 m b/d
Manifa	1957	28^0	2.97% – 3.66%	Heavy-sour	0.9 m b/d
Safaniya	1951	27^0	2.93% – 2.96%	Heavy-sour	1.2 m b/d
Qatif		35^0	2.45% – 2.92%	Light-sour	0.5 b/d
Zuluf	1968	32^0	2.41%	Medium-sour	0.5 b/d
Khursaniyah	1956	36^0	1.89%	Light-sour	0.5 b/d
Shaybah	1967	42^0	0.07%	Extra Light-sweet	0.75 m b/d
Abqaiq	1940	37^0	---	Extra Light-sweet	0.4 b/d
Khurais	1957	33^0 - 36^0	1% – 1.5%	Light-sour	1.2 m b/d

Source: Independent statistics and analysis by the U.S. Energy Information Administration (2014) and Shammas (2000)

Saudi Arabia exports most of its production to Asia (68%), followed by America (19%), Europe (10%), and the rest of the world (3%). The largest importers of Saudi Arabia production are, in order, Japan, China, South Korea, and India (EIA, 2014). Of Saudi Arabia's 10 refineries (see Table 1-4), Ras Tanura has the highest capacity. Saudi Arabia invested in several projects to provides light products, as shown in Table 1-5, with Yanbu/Jubail having the highest budget of 30 billion dollars. With regard to Saudi Arabia's refining projects abroad, Aramco is focusing on the Asian market due to it is dependence on Saudi oil. According to Lahn and Stevens (2011), Aramco owns shares in the S-oil company and plans to build a new refinery in South Korea. Aramco is also keen to deal with Total and ConocoPhillips to export light products resulting from refining heavy sour crude oil due to its experience over the years. Aramco recently announced intentions to invest 100 billion dollars in refineries domestically and overseas for refining its own production (EIA, 2014).

Table 1-4 Saudi Arabia's 10 Refineries

Name	Ownership	Capacity (thousand b/d)
Ras Tanura	Saudi Aramco	550
Yanbu	Saudi Aramco	250
Riyadh	Saudi Aramco	122
Jeddah	Saudi Aramco	85
SATORP Jubail	Saudi Aramco, Total S.A.	400
Petro Rabigh	Saudi Aramco, Sumitomo Chemical	400
SAMREF Yanbu	Saudi Aramco, Mobil Yanbu Refining Company Inc. (ExxonMobil)	400
SASREF Jubail	Saudi Aramco, Sell Saudi Arabia Refining Ltd.	305

Source: Independent statistics and analysis by the U.S. Energy Information Administration (2014)

Table 1-5 New Refinery Projects in Saudi Arabia

Project Name	Location	Budget (U.S. $)	Starting Data
Saudi Aramco & Sabic Crude oil – chemical project (COTC)	Yanbu/Jubail	$ 30 billion	2014
Saudi Aramco – Yanbu Refinery and Petrochemical complex	Yanbu/ Red Sea	$ 20 billion	2014
Yansab – Ethylene Glycol DBN	Yanbu	$ 100 million	2015
Pan Asia – Jizan Economic City – purified Terephthalic Acid (PTA) Plant	Jizan	$ 3 billion	2015
Farabi Petrochemicals Company – Yanbu Linear AlkylBenzene (LAB) Plant	Yanbu	$ 450 million	2013
Basic Chemical Industries Compant (BCI) – CP Kelco – Xanthan Gum	Jubail	$ 105 million	2013
RCC – Hydrocarbon Resin Complex	Jubail	$ 500 million	2015
Sabic – Debottlenecking and Expansion of Petrokemya Butadiene Extraction Plant	Jubail	$ 450 million	2019
IMC – Methanol Plant Enhancment	Jubail	$ 150 million	2016
Saudi Aramco – Ras Tanura Refinery – Clean Fuels Project	Ras Tanura	$ 2 billion	2011
Petro Rabigh Refinery & Petrochemical Complex Expansion – Phase 2 Clean Fuel Package	Rabigh	$ 948 million	2010

Source: Special Advisor of Energy & Infrastructure, Al Abdulrahman (2017)

1.3 Literature Review

Several papers have tested Adelman's hypothesis of the world oil market: "the world oil market, like the world ocean, is one great pool" (Gulen, 1997). Sauer (1994) investigated whether crude oil from different regions belongs to a single economic market using both a cointegration test and the vector error correction models to evaluate the impulse response functions and variance decompositions. Their results demonstrated long-run relationships among importing regions, but the test was not sufficient. By examining IRF and variance decompositions for each price series, the author concluded that the relative levels of markets for imports of crude oil are globally unified.

Gulen (1997) tested whether the oil market is unified using 15 different crude oils, dividing them into different groups with the same quality. He applied a cointegration analysis to investigate if the series move together over time and found that most groups are cointegrated, especially if they are of similar quality. Gulen (1999) investigated the same hypothesis using 11 different crude oils with two groups of similar quality and found cointegration in shorter periods of time (i.e. weekly), thereby demonstrating that the oil market is unified.

Rodriguez and Williams (1993) tested if four crude oils (i.e., WTI, Brent, ANS, and Dubai) have a long-term relationship. Their results showed long-term relationships among them, which supports Adelman's claim. Kleit (2001) adopted the arbitrage cost approach to investigate if the market is unified by using seven light crude oils and found that the market became more unified by gradually reducing transaction costs. Meanwhile, Milonas and Henker (2001) examined the price differential and the volatility behavior of two crude oils: WTI and Brent. Their paper found that WTI's cash price is higher than Brent's cash price, while Brent's volatility shows similar behavior as the prices.

Bachmeier and Griffin (2006) used daily observations of coal, oil, and natural gas for different geographical and quality classifications. They focused on the error-correction model, which revealed the degree of market integration. Their results indicated a very weak integration, and coal, oil, and natural gas are not substitutes in the short run.

Borenstein and Kellogg (2014) studied how a decrease in oil prices affects the price of light crude oil products. According to their analysis, in 2011, the price of WTI was below the price of Brent and Light Louisiana Sweet. They determined that a decrease in the price of oil did not cause a decrease in gasoline and diesel prices, which means that refineries benefit.

Fattouh (2008) investigated the price of different quality, such as Sahara-Maya, and similar quality, such as Sahara-Bonny. He found that the oil price differential follows a stationary process for both different qualities and the same qualities of crude oils using the threshold autoregressive (TAR) method. He also mentioned the different dynamics in the price differential due to transaction costs.

Several studies also examined the effect of structural breaks in the differentials of light sweet crude, such as WTI and Brent. Buyvksahin et al. (2012) investigated the difference between two oils, WTI and Brent crude oil, as WTI is higher quality than Brent. They used Chow tests for structural breaks using daily observations, and their results showed a structural break. On the other hand, the authors used the ARDL model to estimate a long-term relationship and found a long-term relationship between both crude oils.

Chen et.al (2015) tested persistence changes in the price differential of the same type of light-sweet crude oils specifically, WTI and Brent. Using the sum of the squares-based test, their results indicated that a structural break occurred in 2010. Meanwhile, Ye and Karali (2016) tested the possible structural breaks in the price differential of the same type of crude oil (i.e., Brent-

WTI) to study the effect of the U.S. ban on crude oil exports and identified three breaks in 2005, 2010, and 2013, where the price of Brent was higher than that of WTI. They applied different methods, such as the Bai-Perron structural break test, to revel structural breaks.

Agerton and Upton (2017) explored the reason behind crude price differential between WTI and Brent to understand if they are due to a constraint on an export ban or pipeline congestion. Their test for structural breaks in price differentials indicated that large breaks were caused by pipeline congestion. Furthermore, export bans were not a reason for the differentials, meaning internal shipping constraints were the main cause. However, their Engle-Granger test for different series of sweet crude oils confirmed that the price of crude oil in one market moves together, thereby indicating a long-term relationship.

Scheitrum et al (2018) studied the difference between WTI and Brent to explain the difference in the shape of the WTI and Brent futures curves in 2011 due to discounts in WTI. Their results showed a structural break in January 2011 by using a Wald test structural break at an unknown break data; they also produced robust results by performing the Gregory-Hansen test to test for a break in the cointegration between WTI and Brent. However, we explore the price differential of two different crude oils, Saudi Arabia's sour crude oil and U.S. sweet crude oil, using the Markov switching model to detect the effect of capacity constraint.

Table 1.6 Summary of the Literature Review

Citation	Purpose	Method	Conclusions
Sauer (1994)	investigated whether crude oil from different regions belongs to a single economic market	a cointegration test and the vector error correction models	Their results demonstrated long-term relationships among importing regions, but the test was not sufficient. By examining IRF and variance decompositions for each price series, the author concluded that the relative levels of markets for imports of crude oil are globally unified.
Gulen (1997)	tested whether the oil market is unified using 15 different crude oils, grouped according to the same quality.	a cointegration analysis	The author found that most groups are cointegrated, especially if they are of similar quality.
Gulen (1999)	investigated whether the oil market is unified using 11 different crude oils with two groups of similar quality	a cointegration analysis	The author found cointegration in shorter periods of time (i.e. weekly), thereby demonstrating that the oil market is unified.
Rodriguez and Williams (1993)	tested if four crude oils (i.e., WTI, Brent, ANS, and Dubai) have a long-term relationship	a cointegration analysis	Their results showed long-term relationships among the four crude oils, thereby supporting Adelman's claim.
Kleit (2001)	investigated if the market is unified based on seven light crude oils.	adopted cost approach.	The author found that the market became more unified by gradually reducing transaction costs.
Milonas and Henker (2001)	examined the price differential and the volatility behavior of two crude oils: WTI and Brent	daily estimates of convenience yields following Brennan (1986)	The authors found that WTI's cash price is higher than Brent's cash price, while Brent's volatility shows similar behavior as the prices.
Bachmeier and Griffin (2006)	used daily observations of coal, oil, and natural gas for different geographical and quality classifications to reveal the degree of market integration.	error-correction model.	Their results indicated a very weak integration, and coal, oil, and natural gas are not substitutes in the short term.
Borenstein and Kellogg (2014)	studied how a decrease in oil prices affects the price of light crude oil products.	analysis of pass-through.	The authors determined that a decrease in the price of oil did not cause a decrease in gasoline and diesel prices, which means that refineries benefit.
Fattouh (2008)	investigated the price of different qualities, such as Sahara-Maya, and similar	threshold autoregressive (TAR) method	The author found that the oil price differential follows a stationary process for both different qualities and the same

	qualities, such as Sahara-Bonny.		qualities of crude oils. He also mentioned the different dynamics in the price differential due to transaction costs.
Buyvksahin et al. (2012)	investigated the difference between two oils, WTI and Brent crude oil, as WTI is higher quality than Brent and estimated a long-term relationship	Chow tests for structural breaks and the ARDL model	The results showed a structural break and highlighted a long-term relationship between both crude oils.
Chen et.al (2015)	tested persistent changes in the price differential of the same type of light sweet crude oils specifically, WTI and Brent	sum of the squares-based test	The results indicated that a structural break occurred in 2010.
Ye and Karali (2016)	tested the possible structural breaks in the price differential of the same type of crude oil (i.e., Brent-WTI) to study the effect of the U.S. ban on crude oil exports	the Bai-Perron structural break test	The authors revealed three different structural breaks in 2005, 2010, and 2013.
Agerton and Upton (2017)	explored the reason behind crude price differential between WTI and Brent to understand if they are due to a constraint on an export ban or pipeline congestion	structural breaks test and Engle-Granger test	Their results indicated that large breaks were caused by pipeline congestion. Furthermore, export bans were not a reason for the differentials, meaning internal shipping constraints were the main cause. Also, the price of crude oil in one market moves together, thereby indicating a long-term relationship.
Scheitrum et al (2018)	studied the difference between WTI and Brent to explain the difference in the shape of the WTI and Brent futures curves	a Wald test to examine a structural break and the Gregory-Hansen test	Their results showed a structural break in January 2011.

1.4 Data

The data used for estimation were monthly observations of Saudi crude oil price (SOP), which is sour crude, and WTI crude oil prices (WTIOP), which is sweet crude. The data were collected from January 1990 to December 2019, resulting in 360 observations. The SOP data were obtained from the U.S. Energy Information Administration (EIA), whereas the WTIOP data were obtained from the Federal Reserve Economic Data (FRED). We consider the differences between these two series using the following equation:

$$\mathrm{WTIOP_t} - \mathrm{SOP_t} = \mathrm{diff_t} \tag{1.4}$$

where $\mathrm{diff_t}$ is the crude oil price differential.

1.5 Markov Switching Model

The Markov switching model, also known as a regime switching model, is used to capture the dynamics of time series within different regimes. This model allows the coefficients to switch between different regimes. That model can be used to represent how our price difference series depend on their qualities have two different regimes by giving different coefficient for each regime. One of the regimes is assumed to capture when the capacity constraint (no more capacity for refining heavy sour crude oil) holds and the other when it does not hold. For example, the first below equation (1.5) is in the regime where the capacity constraint holds. Meanwhile, equation (1.6) captures the regime when the capacity constraint does not hold.

$$diff_t = \alpha + diff_{t-1} + \varepsilon_{1t} \tag{1.5}$$

where $\beta_1 = 1$.

$$diff_t = \delta + \beta_1 diff_{t-1} + \varepsilon_{2t} \tag{1.6}$$

where $\beta_1 < 1$.

Hamilton (1989) designed the Markov switching model (MSM) to show a change in a time series by revealing the time-variation in the selected variable in the form of regimes. The Markov switching autoregressive model can be written as follows, assuming we have two states:

$$\begin{aligned} \text{diff}_t &= c_1 + \alpha_{11}\,\text{diff}_{t-1} + \textstyle\sum_{p=1}^{n} \alpha_{p1}\,\text{diff}_{t-p} + \varepsilon_{1t} \qquad s_t = 1 \quad N(\mu_1, \sigma_1^2) \\ \text{diff}_t &= c_2 + \alpha_{12}\,\text{diff}_{t-1} + \textstyle\sum_{p=1}^{n} \alpha_{p2}\,\text{diff}_{t-p} + \varepsilon_{2t} \qquad s_t = 2 \quad N(\mu_2, \sigma_2^2) \end{aligned} \tag{1.7}$$

where diff_t indicates the difference between heavy-sour and light-sweet crude oil prices, s_t indicates the state or the regime, p indicates the number of the lags, c_i indicates the intercept, and α_{ij} indicates the parameters of autoregressive parts, which are considered to be time varying.

In our model, one of the regimes describes the period of capacity constraint (no more capacity for refining heavy sour crude oil) of Saudi Arabia crude oil whereas the other regime describes the period of no constraint. The parameter estimates are used to infer the regime at any point in time. To determine which of these regimes has a constraint in capacity, we can look to the persistence of the deviation and the intercept.

In our two-state model, the probability of s_t being j depends on s_{t-1}.

$$p\,(\,s_t = j \mid s_{t-1} = i, s_{t-2} = k) \tag{1.8}$$

$$= p\,(\,s_t = j \mid s_{t-1} = i\,) = \; p_{ij} \tag{1.9}$$

$$where \quad \sum_{i,j=1}^{2} p_{ij} \; = 1 \tag{1.10}$$

The transition probability matrix of the two-states, shown below, can also be summarized as the probability of switching, which are p_{12} and p_{21}.

$$p = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{1.11}$$

where p_{12} and p_{21} are:

$$p_{12} = 1 - \; p_{11}\,, \text{ and } \qquad p_{21} = \; 1 - p_{22} \tag{1.12}$$

If we suppose $p_{11} = 0$, then there is no possibility of remaining in Regime 1. In this case, the probability of switching is $1 - p_{11} = 1$, which indicates that the system immediately jumps to Regime 2. On other hand, if we suppose $p_{22} = 0.87$, then the probability of transitioning from Regime 2 to Regime 2 is very high, indicating that the system tends to stay in Regime 2. The probability of switching to Regime 1 is $1 - p_{22} = 0.13$, which is very low. As the preceding matrix shows, we can get the expected duration of the regime (i) to persist, which is written as follows:

$$\text{Expected duration} = \frac{1}{1-p_{ii}} \tag{1.13}$$

The autoregressive model where the parameter can change from one regime to other results from an unobserved Markov chain. As shown in Equation (1.7), diff_t in Regime 1 is drawn from $N(\mu_1, \sigma_1^2)$, while diff_t in Regime 2 is drawn from $N(\mu_2, \sigma_2^2)$. As a result, diff_t is conditional on s_t, which is equal to the value of j.

$$f(\text{diff}_t | s_t = j;\ \theta) = \frac{1}{\sqrt{2\pi\sigma_1}} \exp\left\{\frac{-(\text{diff}_t - \mu_j)^2}{2\sigma_j^2}\right\} \tag{1.14}$$

where j=1,2. Θ indicates a vector of parameters that include μ_j and σ_j^2. Regime s_t is generated by probability distribution, and the unconditional probability of $s_t = j$ is

$$p(s_t = j;\ \theta) = \pi_j \tag{1.15}$$

If the probability of s_t and diff_t fall in the same period, then:

$$p(\text{diff}_t, s_t = j;\ \theta) = f(\text{diff}_t | s_t = j;\ \theta)\ .\ p(s_t = j;\ \theta) \tag{1.16}$$

Equation (1.16) can be rewritten from both Equations (1.14) and (1.15):

$$p(\text{diff}_t, s_t = j;\ \theta) = \frac{\pi_j}{\sqrt{2\pi\sigma_1}} \exp\left\{\frac{-(\text{diff}_t - \mu_j)^2}{2\sigma_j^2}\right\} \tag{1.17}$$

One method used to estimate the parameters of the MSM is the maximum likelihood estimate, as shown in Equation (1.18), subject to the constraints $\pi_1 + \pi_2 = 1$ and $\pi_j \geq 0$.

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \log \sum_{s=1}^{2} p(\text{diff}_t\ , s_t = j;\ \theta) \tag{1.18}$$

The maximum likelihood estimates of the parameters (θ) give us the solution for the following nonlinear equation by starting from a random initial guess for the value of θ in order to

calculate the subsequent equations. Another initial value is then used to recalculate these equations until the algorithm finds the maximum likelihood estimate.

$$\widehat{\mu_j} = \frac{\sum_{t=1}^{T} diff_t \,.\, p(s_t=j \mid diff_T ; \hat{\theta})}{\sum_{t=1}^{T} p(s_t=j \mid diff_T ; \hat{\theta})} \qquad \text{for } j = 1,2 \qquad (1.19)$$

$$\widehat{\sigma_j^2} = \frac{\sum_{t=1}^{T} (diff_t - \widehat{\mu_j})^2 .\, p(s_t=j \mid diff_T ; \hat{\theta})}{\sum_{t=1}^{T} p(s_t=j \mid diff_T ; \hat{\theta})} \qquad \text{for } j = 1,2 \qquad (1.20)$$

$$\widehat{p_{jj}} = \frac{\sum_{t=1}^{T} p(s_t=j, s_{t-1}=j \mid diff_T ; \hat{\theta})}{\sum_{t=1}^{T} p(s_{t-1}=j \mid diff_T ; \hat{\theta}) + \hat{\rho} - p(s_t=1 \mid diff_T ; \hat{\theta})} \qquad \text{for } j = 1,2 \qquad (1.21)$$

Equation (1.19) indicates $\widehat{\mu_1}$ is the average value of $diff_t$ for observations from Regime 1while $\widehat{\mu_2}$ is for Regime 2. Equation (1.20) shows the variance $\widehat{\sigma_j^2}$, which is a weighted sum of squared deviations for both regimes around the mean. Finally, Equation (1.21) indicates the Markov transition probability estimation ($\widehat{p_{11}}, \widehat{p_{22}}$). Once we have the probability estimation, the system calculates the transition probability using the following equations: $p_{12} = 1 - p_{11}$ and $p_{21} = 1 - p_{22}$. However, the probability gives the same unity for any observation within Regime j and zero for the other regimes.

To estimate the coefficients of the two-state MSM,[2] we conducted different regressions with different lags, as shown below, to determine the number of lags using the log likelihood and AIC:

The first regression has one lag:

$$diff_t = \alpha + \beta diff_{t-1} + \varepsilon_t \qquad (1.22)$$

The second regression has two lags:

[2] The estimate of the MSM was done in R (version 1.4) using the msmFit function.

$$diff_t = \alpha + \beta_1 diff_{t-1} + \beta_2 diff_{t-2} + \varepsilon_t \quad (1.23)$$

We then continued until we determined the number of the lags:

$$diff_t = \alpha + \beta_1 diff_{t-1} + \beta_2 diff_{t-2} + \beta_3 diff_{t-p} + \varepsilon_t \quad (1.24)$$

where p indicates the number of the lags.

As demonstrated, the parameters of the autoregression switch between the two regimes, meaning that the estimated parameters of the autoregression can be used to conclude which regime is captured when the capacity constraint holds and when it does not. Moreover, from the transition probabilities matrix, we can determine the probability of staying in Regime 1, the probability of staying in Regime 2 and the probability of switching between these two regimes.

1.6 Results of Markov Switching Model Estimates

We first chose the appropriate model of lagged values of the price differential. Table 1-7 summarizes the estimates of these different measures-namely, the lag likelihood and AIC of a two-state MSM. As shown in the table, the third model among these estimates of the two-state MSM had the lowest AIC (1563.338) and the highest value of likelihood (-773.6692); thus, it was selected.

Table 1-7 Different Lags of Two-State Markov Switching Model

Lags	Number of states	AIC	Log likelihood
1	2	1571.15	-781.58
2	2	1571.92	-779.96
3	2	1563.34	-773.67
4	2	1756.12	-872.06

Table 1-8 summarizes the estimation results of the two-state MSM and confirms that, in Regime 2, all the autoregressive estimated coefficients are significant, whereas in Regime 1, the autoregressive estimated coefficient of the first lag is significant.

The first regime is:

$$Diff_t = \underset{(0.22)}{-0.0959} + \underset{(0.07)}{0.8561}\, Diff_{t-1}^{***} + \underset{(0.06)}{0.0308}\, Diff_{t-2} + \underset{(0.04)}{0.0007}\, Diff_{t-3} \qquad (1.25)$$

Meanwhile, the second regime is:

$$Diff_t = \underset{(0.17)}{0.6410^{***}} + \underset{(0.09)}{0.8255}\, Diff_{t-1}^{***} - \underset{(0.11)}{0.3653}\, Diff_{t-2}^{***} + \underset{(0.08)}{0.2915}\, Diff_{t-3}^{***} \quad (1.26)$$

These parameter estimates are used to infer the regime at any point in time. To determine which of these regimes has a constraint in capacity, we can look to the persistence and the intercept, which is the change in the mean. Therefore, for persistence of the deviation, we plotted the IRF using the half-life of the IRFs for deviations in each regime, which we calculated using Equations (1.25) and (1.26), by conducting a forecast to see how much these deviations tend to be, as shown in Figure 1-5. The persistence is similar across the two regimes, with the exception of months 3 and 4, where Regime 2 is somewhat less persistent. On the other hand, Equation (1.25) implies that the mean in the first regime is not significantly different from zero, indicating that the change in the price differential is zero on average in this regime. The mean in Equation (1.26) is positive and significant, suggesting that the change in the price differential is positive in the second regime, where the price of light sweet crude oil is permanently higher; no force will pull the prices of light sweet crude oil and heavy sour crude oil back together. Table 1-8 also shows the transition probabilities matrix; the estimated transition probabilities indicate a higher probability in both regimes as P_{11} and P_{22} equal 98% and 97% respectively. In this case, the probability of each regime is very high, indicating that each regime tends to stay. The probabilities of switching (1-P_{11}) and (1-P_{22}) are 0.02 and 0.03, respectively. Figure 1.6 depicts Regime 1 (with no capacity constraint) and Regime 2 (capacity constraint). Regime 1 (top panel) shows a high probability of persisting in the regime with no constraint; it is also expected that the change in the price differential would be zero because of the increasing number of complex refineries refining heavy

sour crude oil. Regime 2 (bottom panel) shows how historical events affect probabilities in this regime. The capacity constraint is permanent at the beginning of our sample, with the high probability in this regime occurring in the 1990s and in 2001-2004. The first constraint emerged in the 1990s. In 1980, the United States was refining an estimated 85% of the world's refined oils; by the 1990s, oil fields were discovered in several states in the United States, which led to an increase in production from about 26 million barrels annually to about 64 million barrels annually. The almost tripled production led to a decrease in imports by an average of 17% according to the Council on Foreign Relations (2022). As a result, the percentage of U.S. imports from Saudi Arabia declined the equivalent of 9% (Metz, 1992). Moreover, the capacity of U.S. refineries decreased by more than 2 million barrels in the mid-1990s, as shown in Table A.1 in the Appendix. During this same time period, most countries signed the Kyoto protocol to reduce the level of greenhouse gases to mitigate climate change; this affected refineries' ability to produce low sulfur products using heavy crude oil (Council on Foreign Relations, 2022). The other period of constraint, 2001-2004, was also affected by refineries' inability to carry out any additional processing of heavy sour crude oil because of tightening environmental regulations aimed at reducing pollution. Such efforts put pressure on refineries to produce light products containing less sulfur than before (EPA, 2022), which made it very expensive for refineries to meet the requirements. As result, the refineries replaced the heavy sour crude oil with light sweet crude oil to increase the percentage of light products while simultaneously avoiding the difficulty of decreasing sulfur beyond the predetermined level (Hamilton, 2004). On the right side, we can see the price differential does not change except in two periods, 2013 and 2016, where the probability is higher than 0.5. In 2013, the price of light products such as gasoline and diesel increased, which led refineries to increase their use of light sweet crude oil to produce a higher percentage of light products and avoid the

capacity issues. In 2016, it was affected by the U.S. decision to increase its use of light sweet crude oil and decrease its imports of heavy sour crude oil (American Fuel and Petrochemical Manufacturers, 2015).

Table 1.8 Estimation Results of MS-AR (3) Model

	Regime 1		Regime 2	
	Coefficient	P-value	Coefficient	P-value
Regime intercept				
C	-0.09	0.67	0.64	0.00***
Autoregressive coefficients				
$Diff_{t-1}$	0.86	0.00***	0.83	0.00***
$Diff_{t-2}$	0.03	0.62	-0.37	0.00***
$Diff_{t-3}$	0.00	0.99	0.29	0.00***
Residual standard error				
RSE	3.36		0.78	
R-squared				
R^2	0.77		0.68	
	Transition probability			
	Regime 1		Regime 2	
Regime 1	0.98		0.03	
Regime 2	0.02		0.97	

Figure 1.5 Half-life IRF of Regime 1 and Regime 2

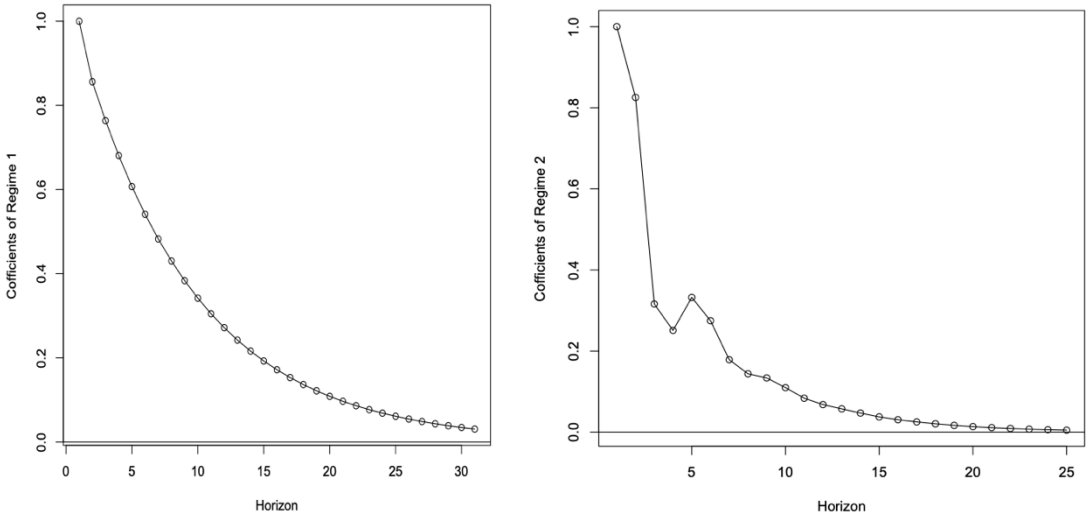
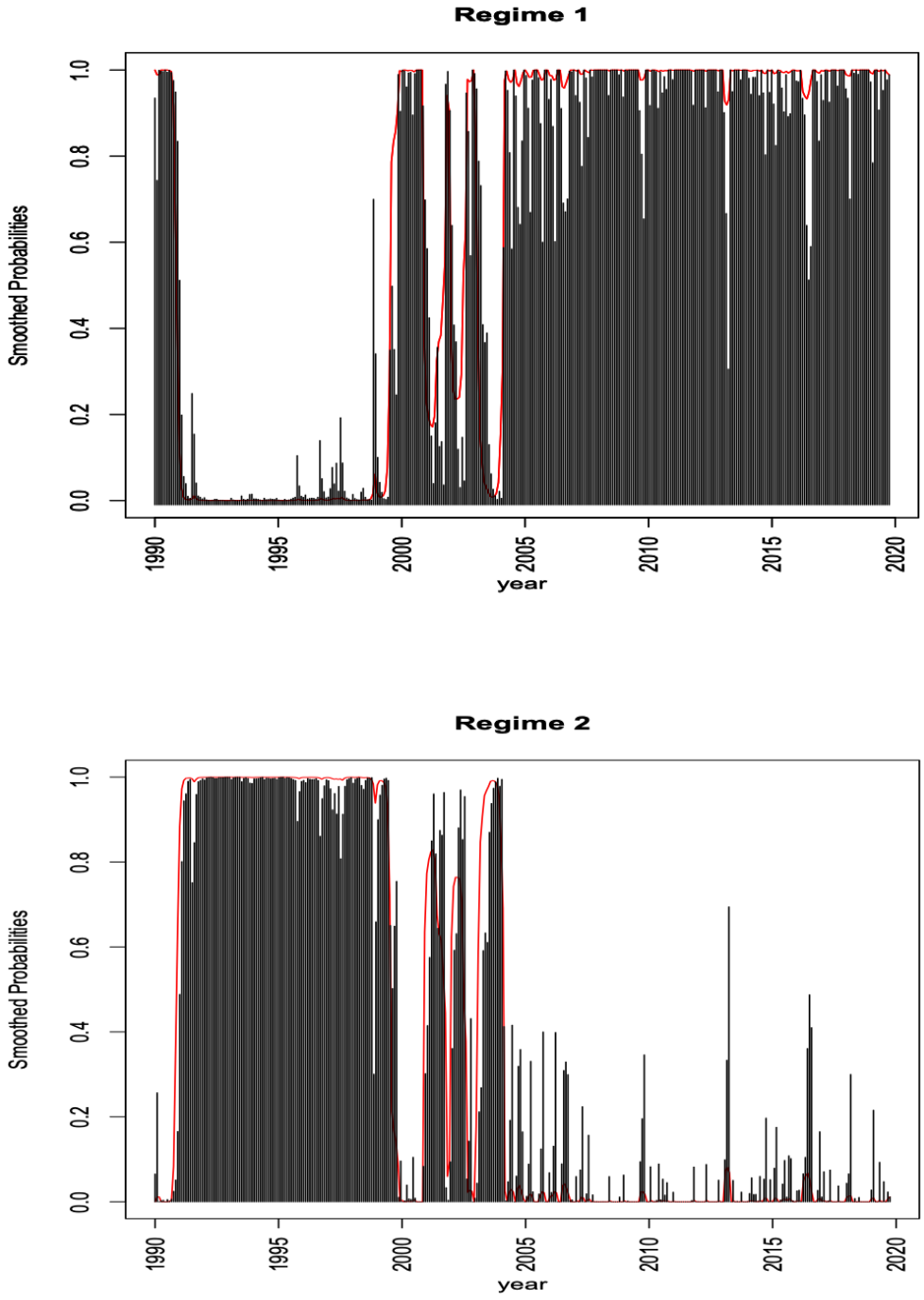


Figure 1.6 Smoothed and Filtered Probabilities of Regime 1, with No Constraint, and Regime 2, with Constraint



1.7 Conclusion

Crude oil is not a homogeneous commodity, as it varies according to its quality, from light-sweet crude to heavy-sour crude. Heavy-sour crude is sold at a lower price than light-sweet crude. Saudi Arabia has five different types of oil, all of them containing a high percentage of sulfur, making its crude oil sour. As a result, Saudi Arabia is concerned about its profits, especially as oil accounts for a greater proportion of its revenues. The quality differences affect not only profits, but also the country's investment decisions to improve its refineries to enable it to process its low-quality crude oil. Indeed, processing heavy-sour crude oil in simple refineries causes corrosion problems in the refineries as well as difficulty in flow due to its low gravity. In addition, the yield percentage of residual fuel oil is very high, which cannot be converted into a benefit from this type of refinery. Thus, differences between light-sweet and heavy-sour crude oil emerge in terms of both supply and demand. Countries are keen to reduce such differences by building complex refineries that can handle low-quality crude oils. Over time, the difference between the two-quality level has moved closer to zero due to the increase in complex refineries; the supply of light-sweet crude oil has also increased. Based on our results, the persistence of the deviation is similar. The main difference between the regimes is the mean. The mean in the first regime is not significantly different from zero, but in the second regime it is positive and significant, indicating that the change in the price differential is positive in the second regime. In this essay, we aimed to help Saudi Aramco leadership understand the impact of insufficient capacity on their heavy sour crude price. They can decrease their production during a specific period to prevent crude oil prices from falling or look at the heavy sour crude oil demand in other complex refineries in different countries. Future studies should look at the effect of lower refinery capacity on OPEC countries to see how the capacity constraint affects their prices.

Chapter 2: Is One Shock Enough to Study the Saudi Economy's Response to an Oil Shock?

2.1 Introduction

Oil is a necessary source for many human needs, so oil-producing countries compete to sell their product, while maximizing their profits and maintaining their market shares. Meanwhile, importing countries want to get oil at lower prices. At the same time, oil prices are exposed to different shocks, both positive and negative, due to political and economic events, thereby causing fluctuations in the price of oil. For example, oil prices quadrupled in 1973 as a result of the Arab oil embargo and continued to increase overall until reaching 148 dollars per barrel in 2008 during the global financial crisis. Meanwhile, in 1998, during the Asian Crisis, the price of oil fell to less than 12 dollars per barrel (Hamilton, 2011). In the U.S., the economy was subjected to nine recessions in response to oil price increases (Hamilton, 2008).

As these events continued to happen, their impact on countries' economies continued, sparking the curiosity of many economists. Hamilton (1983) was a pioneer in this area who examined the impact of oil price shocks on the U.S. economy. In his paper, he demonstrated that most recessions were a response to positive oil price shocks. Economists subsequently studied how the prices of oil shocks affect economies as exogenous shocks. They found that, over time, the relationship between oil shocks and economic activity collapsed (Kilian, 2009).

According to Hamilton (2008), economists explained the instability of the relationship between oil price shocks and macroeconomic aggregates as the result of a third factor or several factors that contribute to the unpredictability of the impact of oil prices on macroeconomic variables. Kilian (2009) showed that much of the variation in oil prices was due to changes in the demand for oil, driven by changes in global economic activity. He allowed for three types of oil shocks: shocks to

oil demand, shocks to oil supply, and precautionary oil demand shocks. Kilian treated the price of oil as endogenous, where oil demand and oil supply shocks affected the price of oil. Disruptions in oil production, such as the Iran-Iraq War in 1980-1988, lead to decreases in oil production and, thus, are considered oil supply shocks (Hamilton, 2011). In addition, oil demand shocks happen as a result of global economic growth (e.g., in 2003) stemming from major industrialized countries' increase in consumption (Kilian, 2009). Finally, precautionary demand shocks result from a growing fear about the shortage of oil supplies in the future such as the Iraq and Kuwait War in 1990-1991 (Hamilton, 2011).

For the United States, an increase in the price of oil does not always have the same effect on the economy, including recessions. Kilian (2009) concluded that the reason for the different effects on the U.S. economy is the specific cause of the oil price increase. In 2003, the price of oil increased because of the positive aggregate demand shocks. In a big economy such as the U.S., aggregate demand shocks cause an increase in both oil prices and international trade because the U.S. influences the world economy. When an economic activity shock, which is treated by Kilian as an aggregate demand shock, causes an increase in oil prices, it leads to a recession in the U.S. economy; however, increasing the demand of commodities for which the U.S produces a lot of goods causes an increase in the U.S.'s GDP, which prevents an economic recession. Thus, the different effects are a result of the shock which caused the increase (Kilian, 2009).

The situation in Saudi Arabia is different because Saudi Arabia's economy is different from other economies due to its reliance on oil revenues. This situation raises the question of whether there is any need to distinguish between the sources of oil price fluctuations for the Saudi economy. Another question is whether all of the oil shocks Kilian (2009) studied have a positive effect on the Saudi economy given that all the Saudi leadership cares about is the price of oil because its

economy depends on oil revenues. In this chapter, we question whether differences exist in the responses of the country's industrial production and consumer price index to oil supply and oil demand shocks. In other words, should oil prices be treated as an endogenous rather than an exogenous variable in Saudi Arabia? We compare two cases using three shocks identified by Kilian (2009) versus only one shock in the Saudi economy to investigate if significant differences exist. Given the scarcity of studies on Saudi Arabia's economy, we aim to fill the gap by studying the responses of Saudi Arabia's economy to oil market shocks to see if the responses differ or not. Ultimately, we find differences in how Saudi Arabia's industrial production and consumer price index respond to oil supply and oil demand shocks; thus, we believe it is not sufficient to consider only one type of shock.

In Section 2.2, we review some of the most important literature relevant to the focus of this chapter. Section 2.3 presents the data. In Section 2.4, we describe Kilian's (2009) methodology using three shocks and another methodology using only one shock. Section 2.5 discusses our results. Section 2.6 concludes the chapter.

2.2 Literature Review

Most relevant studies focused on oil-importing countries, particularly the United States. Hamilton (1983) developed the first paper to establish the basic footprint in studying the impact of oil prices on the U.S. economy. He used a VAR model to examine the impact of oil price shocks on the U.S. macroeconomic aggregates. His results indicated a negative effect of an oil price shock on U.S. GDP growth, which explains many of the U.S. recessions. Hamilton (2003) subsequently investigated the nonlinear relationship between an oil price change and GDP. Although the results of this study showed a nonlinear relationship between oil prices and GDP, they demonstrated the effects of oil price increases are important to consider when predicting U.S. GDP.

Hamilton also used the five Middle Eastern wars as an instrument for determining the effect of oil production disturbances and regressions. He concluded that oil production disturbances have a statistically significant effect on U.S. GDP. Kilian (2008c) used the oil supply shocks as an exogenous variable to study their effect on U.S. economy considering a new measure. However, his analysis was based on an OLS regression of GDP growth and CPI on lagged oil supply shocks. The results indicated that oil supply shocks have a small effect on the U.S. economy. GDP growth responds negatively, but not immediately, while CPI responds positively.

Kilian (2009) then explored how oil price shocks affect the U.S. economy using a new model in which oil price shocks where endogenous rather than exogenous. His study used structural demand and supply shocks that drive oil prices to change. The results indicated that oil price changes driven by global demand shocks have a different effect on the U.S. economy than changes driven by an oil supply shocks and oil-specific demand shocks. Kilian and Park (2009) also examined the effect of oil prices driven by three different shocks on U.S. stock returns. Their result showed that U.S. stock return responses to these shocks differ.

Kilian and Zhou (2019) investigated the variance analysis in both the U.S. real exchange rate and the interest rate, taking into account oil market shocks by adding one additional shock: oil inventories with sign restrictions in identification. They found that oil market shocks explained more than 50% of the variation in the real exchange rate and that real exchange rates shocks played an important role in determining real global commodity prices. In addition, the U.S. real interest rate affects the U.S. real exchange rate, but not vice versa. Baumeister et al (2010) studied the effect of oil shocks on different industrialized economies. They demonstrated that the consequences of oil price shocks depend on the cause of the oil price shifts in all countries, which make their economies' responses different depending on the shock.

Eifayoumi (2018) estimated the impact of oil market shocks (adding an additional shock: oil inventories) on U.S. firms using the industry level of manufacturing. His results indicated that oil supply shocks have a negative effect on firm profits while global oil demand shocks have a positive effect. Meanwhile, speculative demand shocks have different effects on firm profits. Habib et al. (2016) studied the relationship among three oil structural shocks and their effects on the exchange rate of various developed and developing countries. They found no relationship between oil and commodity trade balance and the real exchange rate following oil market shocks. In addition, they found that, in countries adopting a floating exchange rate policy, oil demand shocks affect their exchange rate.

Apergis and Miller (2008) studied the impact of oil supply and demand shocks on stock market returns in eight countries: Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. They found that oil market shocks have a very small effect on the return of the select stock markets. Ekong and Effiong (2018) investigated the effects of oil

demand and supply shocks on Nigeria's macroeconomy and found that Nigeria's economy responded differently to oil market shocks, and the effect on macroeconomic variables was small.

The rest of the studies focus on oil prices in oil-producing countries, Basher et al. (2018) analyzed the impact of oil market shocks on stock prices in oil-exporting countries using Kilian's (2009) approach with sign restrictions and the elasticity of oil supply, oil demand, a speculative oil demand, and oil specific demand shocks. During the second stage, they estimated the effect of these shocks on the stock prices using a Markov switching model. They found the shocks affected the stock returns in all selected countries except Mexico. In addition, they rejected the nonlinearity relationship with structural shocks on stock returns in most countries. Dąbrowski et al. (2022) examined the effect of oil market shocks (oil price uncertainty shocks, global demand shocks, oil price shock) on economic activity and exchange rates in different oil-exporting countries using the interacted panel VAR model. They found that oil price and oil price uncertainty shocks affected the selected economics; the impact was greater in developing countries than in developed countries.

Fang and You (2014) investigated whether oil price shocks driven by supply or demand affect stock prices in the Chinese, Indian, and Russian economies using the structural vector autoregressive model (SVAR) approach developed by Kilian and Park (2009). The authors found that the response of Chinese, Indian, and Russian stock returns to oil price shocks is different where the supply shock impact is not significant in all the selected countries. Mahboub and Ahmad (2016) studied Saudi Arabia's manufacturing sector response to oil price shocks using the Johansen cointegration test. Their results suggested no long-term effect of oil price shock on the manufacturing sector. They also used the IRF to assess the effect of oil price shocks on the

manufacturing sector and other control variables, but the effect of oil prices was found not to be significant on the manufacturing sector.

Ftiti et al. (2016) determined the degree of interdependence between oil prices and GDP. They used monthly data of variables such as oil prices and GDP, focusing on the United Arab Emirates, Kuwait, Saudi Arabia and Venezuela. The authors applied the frequency approach, which is the evolutionary co-spectral analysis to analyze the time-varying dynamic correlation for the short and medium term as well as the Engle and Granger method for analyzing the time-varying dynamic correlation for the long-term testing of the cointegration. Their results indicated that oil price fluctuations have a slight effect on the economic environment and showed the cointegration relationship between real activity and oil price in all counties included in their study. However, there are limited studies on Saudi Arabia's economy.

To fill this gap, we study the response of Saudi Arabia's economy to oil price shocks using all three shocks from Kilian's (2009) methodology while treating oil price as endogenous and using only one shock while treating oil price as exogenous. Using this approach, we aim to conclude if it is sufficient to consider only one shock or if we need to include all three shocks to study how Saudi Arabia's economy responds.

Table 2.1 Summary of the Literature Review

Citation	Purpose	Method	Conclusions
Hamilton (1983)	Studied the impact of oil prices on the U.S. economy	VAR model	The results indicated a negative effect of an oil price shock on U.S. GDP growth, which explains many of the U.S. recessions.
Hamilton (2003)	Investigated the nonlinear relationship between an oil price change and GDP	Ordinary least-squares (OLS) and a flexible approach to nonlinear inference	The results of this study showed a nonlinear relationship between oil prices and GDP, demonstrating that the effects of oil price increases are important to consider when predicting U.S. GDP. Hamilton also used the five Middle Eastern wars as an instrument for determining the effect of oil production disturbances and regressions, concluding that oil production disturbances have a statistically significant effect on U.S. GDP.
Kilian (2008c)	Used the oil supply shocks as an exogenous variable to study their effect on the U.S. economy	OLS regression of GDP growth and CPI on lagged oil supply shocks	Oil supply shocks have a small effect on the U.S. economy. GDP growth responds negatively, but not immediately, while CPI responds positively.
Kilian (2009)	How oil price shocks affect the U.S. economy	SVAR model in which oil price shocks were endogenous rather than exogenous	Oil price changes driven by global demand shocks have a different effect on the U.S. economy than changes driven by oil supply shocks and oil-specific demand shocks.
Kilian and Park (2009)	Examined the effect of oil prices driven by three different shocks on U.S. stock returns	SVAR model	U.S. stock return responses to these shocks differ.
Kilian and Zhou (2019)	Investigated the variance analysis in both the U.S. real exchange rate and interest rate, taking into account oil market shocks by adding one additional shock: oil inventories with sign restrictions in identification	SVAR model	Oil market shocks explained more than 50% of the variation in the real exchange rate and that real exchange rate shocks played an important role in determining real global commodity prices. In addition, the U.S. real interest rate affects the U.S. real exchange rate, but not vice versa.
Baumeister et al (2010)	Studied the effect of oil shocks on different industrialized economies	SVAR model	The consequences of oil price shocks depend on the cause of the oil price shifts in all countries, which make their economies' responses different depending on the shock.

Eifayoumi (2018)	Estimated the impact of oil market shocks (adding an additional shock: oil inventories) on U.S. firms using the industry level of manufacturing	using a SVAR model	Oil supply shocks have a negative effect on firm profits while global oil demand shocks have a positive effect. Meanwhile, speculative demand shocks have different effects on firm profits.
Habib et al. (2016)	Studied the relationship among three oil structural shocks and their effects on the exchange rate of various developed and developing countries	Using a SVAR model	The study found no relationship between oil and commodity trade balance and the real exchange rate following oil market shocks. In addition, in countries adopting a floating exchange rate policy, oil demand shocks affect their exchange rate.
Apergis and Miller (2008)	Studied the impact of oil supply and demand shocks on stock market returns in eight countries: Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.	Vector error-correction (VEC)	Oil market shocks have a very small effect on the return of the select stock markets.
Ekong and Effiong (2018)	Investigated the effects of oil demand and supply shocks on Nigeria's macroeconomy	Using a SVAR model	Nigeria's economy responded differently to oil market shocks, and the effect on macroeconomic variables was small.
Basher et al. (2018)	Analyzed the impact of oil market shocks on stock prices in oil-exporting countries	using Kilian's (2009) approach with sign restrictions and the elasticity of oil supply, oil demand, a speculative oil demand, and oil-specific demand shocks as well as a Markov switching model	The shocks affected the stock returns in all selected countries except Mexico. In addition, the results rejected the nonlinearity relationship with structural shocks on stock returns in most countries.
Dąbrowski et al. (2022)	Examined the effect of oil market shocks (oil price uncertainty shocks, global demand shocks, oil price shock) on economic activity and exchange rates in different oil-exporting countries	Interacted panel VAR model.	Oil price and oil price uncertainty shocks affected the selected economies; the impact was greater in developing countries than in developed countries.
Fang and You (2014)	Investigated whether oil price shocks driven by	SVAR model employing the	Chinese, Indian, and Russian stock returns responded differently to oil price shocks

	supply or demand affect stock prices in the Chinese, Indian, and Russian economies	generalized impulse response functions	where the supply shock impact is not significant in all the selected countries.
Mahboub and Ahmad (2016)	Studied Saudi Arabia's manufacturing sector response to oil price shocks	Johansen cointegration test	Their results suggested no long-term effect of oil price shock on the manufacturing sector. The authors also used the IRF to assess the effect of oil price shocks on the manufacturing sector and other control variables, but the effect of oil prices was not found to be significant on the manufacturing sector.
Ftiti et al. (2016)	Determined the degree of interdependence between oil prices and GDP using monthly data of variables such as oil prices and GDP, focusing on the United Arab Emirates, Kuwait, Saudi Arabia and Venezuela	Frequency approach, which is the evolutionary co-spectral analysis, to analyze the time-varying dynamic correlation for the short and medium term as well as the Engle and Granger method.	Oil price fluctuations have a slight effect on the economic environment, and a cointegration relationship exists between real activity and oil price in all counties included in the study.

2.3 Data

We use monthly data from January 1988 to February 2014, which is the data available in Saudi Arabia, resulting in 314 total observations related to Saudi Arabia's industrial production (IP), Saudi Arabia's consumer price index (CPI), world crude oil production (WOP), global real economic activity (GIP), and Brent crude oil price (OP). However, data were obtained from different sources. World crude oil production data were obtained from the U.S. Energy Information Administration (EIA), whereas global real economic activity data were obtained from the Federal Reserve Bank of Dallas. Brent crude oil price data and Saudi Arabia's consumer price index were obtained from the Federal Reserve Economic Data (FRED). Saudi Arabia's industrial production data were obtained from the International Monetary Fund (IMF).

2.4 Methodology

Kilian (2009) argued that three factors affect oil prices, each having different effects on the economy: oil supply shock, aggregate demand shock, and oil-specific demand shock. Kilian's (2009) methodology found a significant difference in how the U.S., a large country, responds to oil price shocks. However, in Saudi Arabia, the economy is driven by oil revenues, suggesting the possibility of different adjustments. Thus, we investigate whether it is sufficient to consider one shock (i.e., an oil price shock) as economic activity shocks do not cause significant changes in the Saudi economy, because it mainly produces oil, while a large economy such as the U.S., which produces a lot of goods, experiences a positive effect. To this end, we compare two situations using three shocks versus one shock to determine their effect on the Saudi economy. We apply Kilian's (2009) methodology to explore whether these shocks have direct and indirect effects on the Saudi economy.

We consider the following VAR model:

$$A_0 Y_t = \alpha_i + \sum_{i=1}^{q} A_i Y_{t-q} + \varepsilon_t \quad (2.1)$$

where $\mathrm{Y_t} = (\mathrm{dWOP_t}, \mathrm{dWIP_t}, \mathrm{dOP_t})$, $\mathrm{dWOP_t}$ is the percentage change of world crude oil production, $\mathrm{dWIP_t}$ denotes the percentage change of the world's real economic activity created by Kilian, and $\mathrm{dOP_t}$ refers to the percentage change of oil prices. All variables are expressed in logs. The lag length of one lag is chosen according to the Akaike information criteria (AIC). Finally, ε_t is the VAR residuals.

Meanwhile, the structural VAR representation is

$$Y_t = \acute{\alpha}_i + \sum_{i=1}^{q} \acute{A}_i Y_{t-q} + e_t \quad (2.2)$$

where $e_t = A_0^{-1} \varepsilon_t$

$$e_t = \begin{pmatrix} e_{1t}\,^{\mathrm{dWOP_t}} \\ e_{2t}\,^{\mathrm{dGIP_t}} \\ e_{3t}\,^{\mathrm{dOP_t}} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}\,^{\text{oil supply shock}} \\ \varepsilon_{2t}\,^{\text{aggregate demand shock}} \\ \varepsilon_{3t}\,^{\text{oil-specific demand shock}} \end{pmatrix} \quad (2.3)$$

The recursive identification of these shocks depends on their effect on each in the short run: where the world's oil production does not respond contemporaneously to both oil demand shocks, meaning $\alpha_{12} = \alpha_{13} = 0$. In addition, real economic activity does not contemporaneously respond to oil price shock; thus, $\alpha_{23} = 0$. In the second step, we need to see how these shocks (oil supply shock, aggregate demand shock, and oil-specific demand shock) may relate to Saudi Arabia's industrial production ($\mathrm{IP_t}$), and inflation ($\mathrm{CPI_t}$). To examine the effect of these shocks on $\mathrm{IP_t}$, and $\mathrm{CPI_t}$, we treat both as the most endogenous variables, where all three shocks contemporaneously affected them, as shown below.

$$e_t = \begin{pmatrix} e_{1t}\,^{\mathrm{dWOP_t}} \\ e_{2t}\,^{\mathrm{dGIP_t}} \\ e_{3t}\,^{\mathrm{dOP_t}} \\ e_{4t}\,^{\mathrm{IP_t,CPI_t}} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}\,^{\text{oil supply shock}} \\ \varepsilon_{2t}\,^{\text{aggregate demand shock}} \\ \varepsilon_{3t}\,^{\text{oil-specific demand shock}} \\ \varepsilon_{4t}\,^{\text{industrial production,or inflation shock}} \end{pmatrix} \quad (2.4)$$

However, we cannot treat all economies in the same way, so we may not need to include all three shocks to study the effect of oil price increases on the Saudi economy to determine if it is sufficient. If there is no difference in how oil supply and demand shocks affect the Saudi economy, then we may only need to consider precautionary demand shocks (oil price shocks). According to Kilian (2009), an oil supply shock causes a small increase in the price of oil, but the aggregate demand shock does not necessarily lead to an increase in Saudi Arabia's industrial production because it mainly produces oil and is a net import country.

Our model of only one oil shock, an oil price shock, can be written as the following equation, which indicates the OLS regression, we use to estimate the relationship between the price of oil and the lag of oil prices to get oil price shocks:

$$dOP_t = \alpha + dOP_{t-p} + \varepsilon_t \quad (2.5)$$

where ε_t is the estimated residual of the oil price shock, including lags up to 3 by determining the lowest value of the AIC.

In the second step, once we get oil price shocks from equation (2.5), we study their effect on Saudi Arabia's industrial production and Saudi Arabia's consumer price index by running the OLS regression as shown in equations (2.6) and (2.7), respectively.

$$IP_t = \sigma_i + \sum_{i=0}^{12} \gamma_i \ \varepsilon_{t-i} + \eta_t \quad (2.6)$$

$$CPI_t = \tau_i + \sum_{i=0}^{12} \varphi_i \ \varepsilon_{t-i} + \omega_t \quad (2.7)$$

where γ_i and φ_i are the impulse response coefficients, in which the number of lags (i) determines the horizon number of IRF which is from zero to 12.

2.5 Results

2.5.1 Unit Root Test

The first step in the macroeconomic paper is to check whether the variables selected are stationary in the level or in the first difference. Researchers usually use the augmented Dickey-fuller (1979) test (ADF) and Philips-Perron (1988) test (PP) to check their data. Most macroeconomic data have a unit root, indicating non-stationarity, which we cannot use before taking considering the first difference. We used these tests to determine whether a unit root exists or not. Tables 2.2 and 2.3 summarize the results of these tests at each level as well as in the first difference. The null hypothesis of ADF and PP is that there is a unit root. Thus, it can be concluded that the logarithm of the selected variables in the ADF and PP tests are not stationary at the level but stationary in the first difference at the 5% level of significance. Therefore, the variables need to be transformed into a stationary series, which is the first different logarithm form.

Table 2.2 Augmented Dickey-Fuller (1979) Unit Root Test

Variables	Level			First Difference		
	None	Drift	Trend	None	Drift	Trend
lWOP	2.03	0.18	-2.06	-12.96	-13.18	-13.23
WIP	-1.32	-2.39	-3.41	-12.04	-12.02	-12.01
lOP	0.71	-1.12	-3.13	-11.08	-11.13	-11.12
lCPI	4.71	2.49	0.46	-9.46	-10.51	-10.86
lIP	0.88	-4.05	-3.16	-14.16	-14.19	-14.24

Note: The 5% critical values are as follows: none = -1.95, drift = -2.87, and trend= -3.42.

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Table 2.3 Phillip-Perron (1981) Unit Root Test

Variables	Level		First Difference	
	Constant	Trend	Constant	Trend
lWOP	0.30	-2.09	-18.96	-19.01
WIP	-2.79	-2.79	-12.13	-12.11
lOP	-0.89	-2.88	-13.28	-13.26
lCPI	2.28	0.32	-15.76	-16.04
lIP	-2.03	-3.41	-25.29	-25.44

Note: The 5% critical values are as follows: constant = -2.87 and trend= -3.43.

2.5.2 Impulse Response Functions

Impulse response functions provided evidence of dynamic responses, to one standard deviation, in order to investigate the effect of oil supply and demand shocks on Saudi Arabia's economy.

Figure 2.1 displays the responses of Saudi Arabia's industrial production and consumer price to only one shock: oil price shock as an exogenous factor. Industrial production is shown in the first graph while the consumer price index is shown in the second graph. The response of Saudi Arabia's industrial production to oil price shock is positive and becomes significant after 2 months. In addition, the CPI response to oil price shock is positive and becomes significant after 5 months.

Figure 2.2 represents the responses of Saudi Arabia's industrial production to each structural shock. The effect of oil supply and oil-specific demand shocks on Saudi Arabia's industrial production is positive at all horizons; the positive response to oil supply shock is statistically significant for 4 months, while oil-specific demand shock response is statistically significant for almost 6 months. For the aggregate demand shock, Saudi Arabia's industrial production response fluctuates but is statistically insignificant. Meanwhile, Figure 2.3 represents the responses of Saudi Arabia's consumer price index to each structural shock. The CPI response to the oil supply shock is positive for 10 periods but statistically insignificant. Its responses to the oil aggregate demand and oil-specific demand shocks are positive in all periods, being, being statistically significant for 6 months to oil aggregate demand shock and after 8 months for oil-specific demand shock.

Tables 2.4 and 2.5 compare the three different shocks (i.e., oil supply, aggregate demand, and oil-specific demand shocks) as different sources of oil price increases to using the sum of the three shocks into one shock, which is equivalent to constraining the coefficients on all shocks to

be the same, by testing the equality of the shock coefficients using the F-statistic. Table 2.4 presents the test of the hypothesis regarding the equality of each lag of the shock coefficients on Saudi Arabia's industrial production to determine if these shocks had similar or different effects on industrial production. We reject the null hypothesis of equality of the three market shocks in different lags as most of the time there is no difference, but at some of the horizons, we can reject equality of the coefficients, which means we need to use multiple shocks to study the Saudi industrial production response at those horizons. Table 2.5 summarizes the results of testing the hypothesis of the equality of each lag of the shock coefficients on Saudi Arabia's consumer price index. The null hypothesis of equality of the three shocks is not rejected in any of the lags, as there are no differences in the coefficients of the three shocks in all time periods, which confirms that it is sufficient to use only one shock to study the response of the Saudi consumer price index.

We then compared the fitted values from a model with all three shocks against the fitted values from a model with only the sum of the three shocks. Figure 2.4 illustrates two different fitted values of Saudi Arabia's industrial production, showing no difference in the average. However, in certain time periods, there is a difference between the fitted values of three shocks versus one shock, such as during Iraq's invasion of Kuwait in 1990–1991, as shown at point A in the figure. According to Kilian (2008c), at the end of 1990, global oil production increased when OPEC production increased and continued at the same level until the war started, at which point global oil production decreased due to the loss of production in Iraq and Kuwait, whose production accounted for 9% of global oil production. In response, OPEC increased production again to cover the shortage. A second period of oil supply shock that caused differences between the fitted values is 1999–2000, as shown at point B in the figure, which was the result of the growth of the global economy (Hamilton, 2004). Such growth caused global oil production to increase at the same time

that Iraq's oil production was recovering to its previous levels. Global oil production then collapsed in 2001, as shown at point C in the figure, as a result of the global economic downturn. Another period showing differences between the fitted values occurred in 2009, as shown at point D in the figure, during the global recovery that, according to the IMF (2001), led to an increase in oil production.

Figure 2.5 shows the different fitted values of Saudi Arabia's consumer price index. Differences between the fitted values of the three shocks versus one shock occurred during almost the exact same time periods, as shown in Figure 2.4 (i.e., 1990 –1991, 2000, 2009). In addition, global economic growth in 2005, as shown at point E in the figure, led to an increase in global oil production (Hamilton, 2011). Finally, in 2003, as shown at point F in the figure, Venezuelan unrest and the second Gulf War caused the loss of more than two mb/d of oil production from Venezuela (Hamilton, 2011). Thus, differences emerge between the fitted values of both Saudi Arabia's industrial production and consumer price index only in certain time periods, which means that if we want to study the effect in certain time periods, we need to include all three shocks, while if we want to study the effect of these shocks on average, it is enough to have only one shock.

In summary, oil supply shock and oil-specific demand shock lead to increases in oil prices, thereby positively affecting Saudi Arabia's industrial production in the short run, while the global real economic activity shock has both direct and indirect effect in any big country, but Saudi Arabia experiences no effect on Saudi industrial production. On the other hand, disruptions to oil supply have no effect on the Saudi consumer price index, since oil supply shocks are somewhat different for the Saudi economy, where the government decides to change production, which in turn affects their revenues. While disruptions to aggregate demand have a short run effect in Saudi consumer price index, disruptions to oil-specific demand have a long run effect on the Saudi consumer price

index. In other words, oil market shocks have a different effect on the Saudi economy. In addition, we can conclude that a difference exists in how Saudi Arabia's economy responds to three shocks versus a single shock in certain time periods. Although on average there is no difference, Figures 2.4 and 2.5 show the fitted values of Saudi Arabia's industrial production and consumer price index. Thus, in some scenarios it is not sufficient to consider oil price shocks as exogenous when studying the response of Saudi Arabia's economy, yet it is often a good approximation to do so.

Figure 2.1 Responses of Saudi Arabia's Industrial Production and Consumer Price Index to only One Shock: Exogenous Oil Price Shocks.

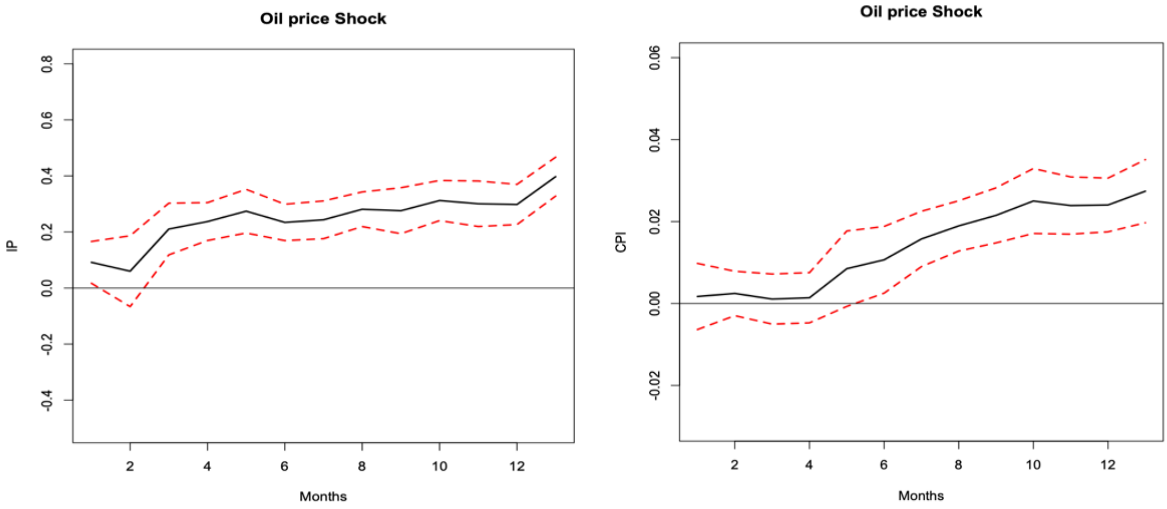


Figure 2.2. Responses of Saudi Arabia's Industrial Production to Three Structural Shocks

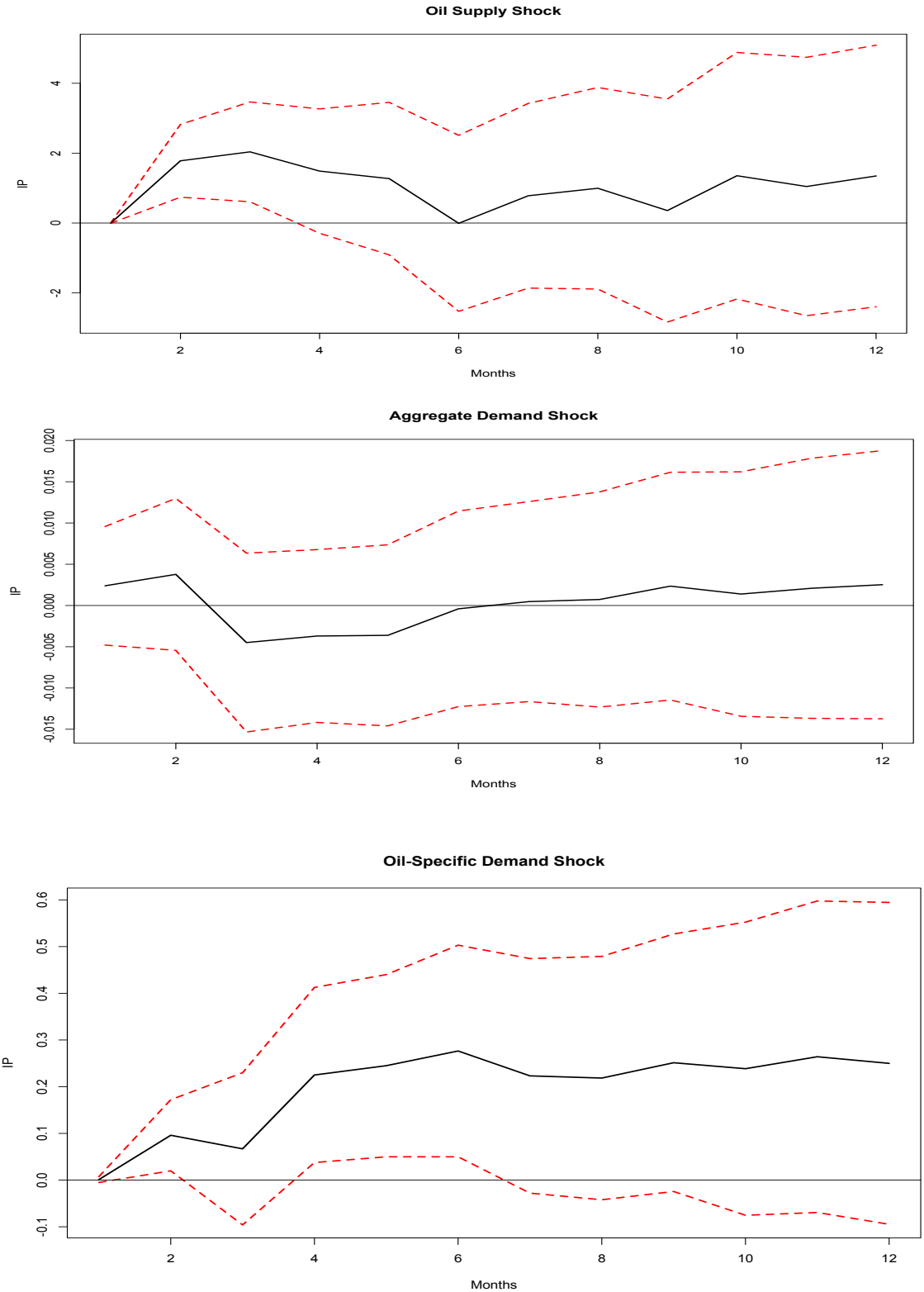


Figure 2.3. Responses of Saudi Arabia's Consumer Price Index to Three Structural Shocks

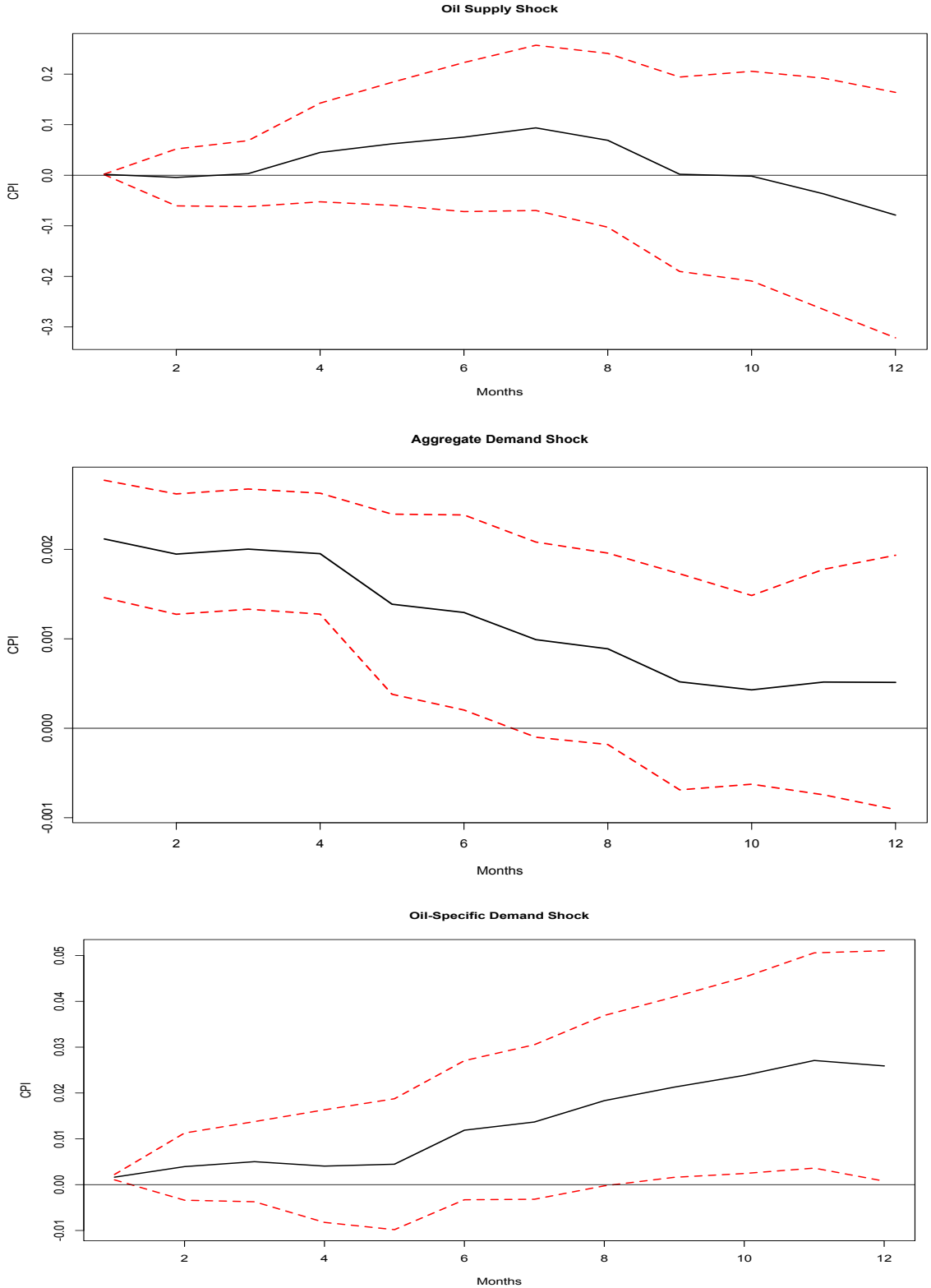


Table 2.4 Testing Equality of Three Shock Coefficients on Saudi Arabia's Industrial Production

Lag	Oil Supply Shocks	Aggregate Demand-Shocks	Oil-Specific-Shocks	F-test	Decision
1	0.379	-0.009	-0.009	0.652	Fail to reject
2	-0.424	-0.001	0.152	7.792	Reject
3	-0.399	0.001	0.005	0.696	Fail to reject
4	-1.194	0.005	0.011	6.413	Reject
5	0.579	0.002	-0.049	2.349	Fail to reject
6	0.098	0.001	-0.027	0.265	Fail to reject
7	-0.815	0.003	0.007	3.134	Reject
8	1.152	-0.001	-0.019	6.559	Reject
9	-0. 297	0.000	0.019	0.548	Fail to reject
10	0.329	-0.001	-0.004	0.508	Fail to reject
11	-0.636	-0.004	-0.002	1.892	Fail to reject
12	0.390	0.004	0.107	3.319	Reject

Note: Testing the null hypothesis $H_0 = \beta_1^i = \beta_2^i = \beta_3^i$ for the model of all oil market shocks $IP_t = \beta_1^i \varepsilon_{1,t-i} + \beta_2^i \varepsilon_{2,t-i} + \beta_3^i \varepsilon_{3,t-i}$, the 5% critical value is equal to 3:00.

Table 2.5 Testing Equality of Three Shock Coefficients on Saudi Arabia's Consumer Price Index

Lag	Oil Supply Shocks	Aggregate Demand Shocks	Oil-Specific Shocks	F-test	Decision
1	0.001	0.000	0.000	0.048	Fail to reject
2	0.044	-0.0001	-0.001	1.116	Fail to reject
3	0.023	-0.0005	0.001	0.300	Fail to reject
4	0.033	-0.0003	0.008	2.259	Fail to reject
5	0.035	-0.0004	0.002	0.826	Fail to reject
6	-0.012	-0.0002	0.005	0.915	Fail to reject
7	-0.059	-0.0002	0.003	2.346	Fail to reject
8	0.009	-0.0001	0.002	0.160	Fail to reject
9	-0.029	0.0002	0.002	0.644	Fail to reject
10	-0.041	0.0001	-0.003	1.182	Fail to reject
11	-0.036	-0.0001	-0.001	0.723	Fail to reject
12	0.047	0.0003	0.002	1.255	Fail to reject

Note: Testing the null hypothesis $H_0 = \beta_1^i = \beta_2^i = \beta_3^i$ for the model of all oil market shocks $\text{CPI}_t = \beta_1^i \varepsilon_{1,\text{t-i}} + \beta_2^i \varepsilon_{2,\text{t-i}} + \beta_3^i \varepsilon_{3,\text{t-i}}$, the 5% critical value is equal to 3:00.

Figure 2.4. Different Fitted Values of Saudi Arabia's Industrial Production

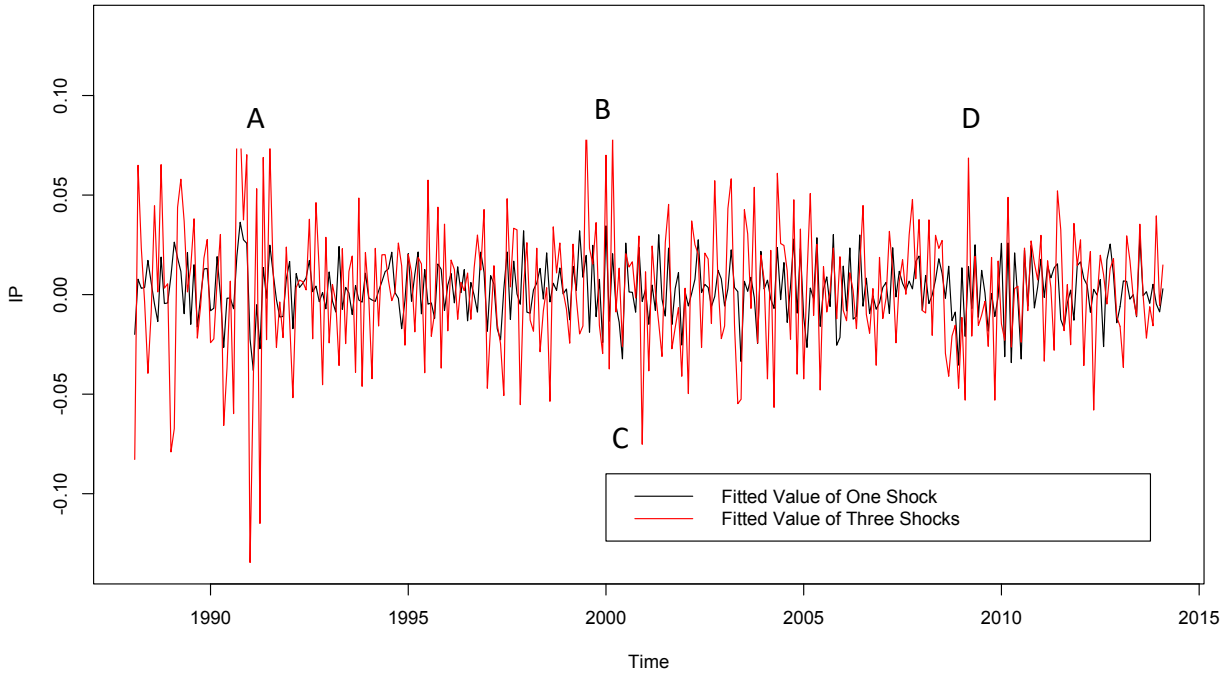
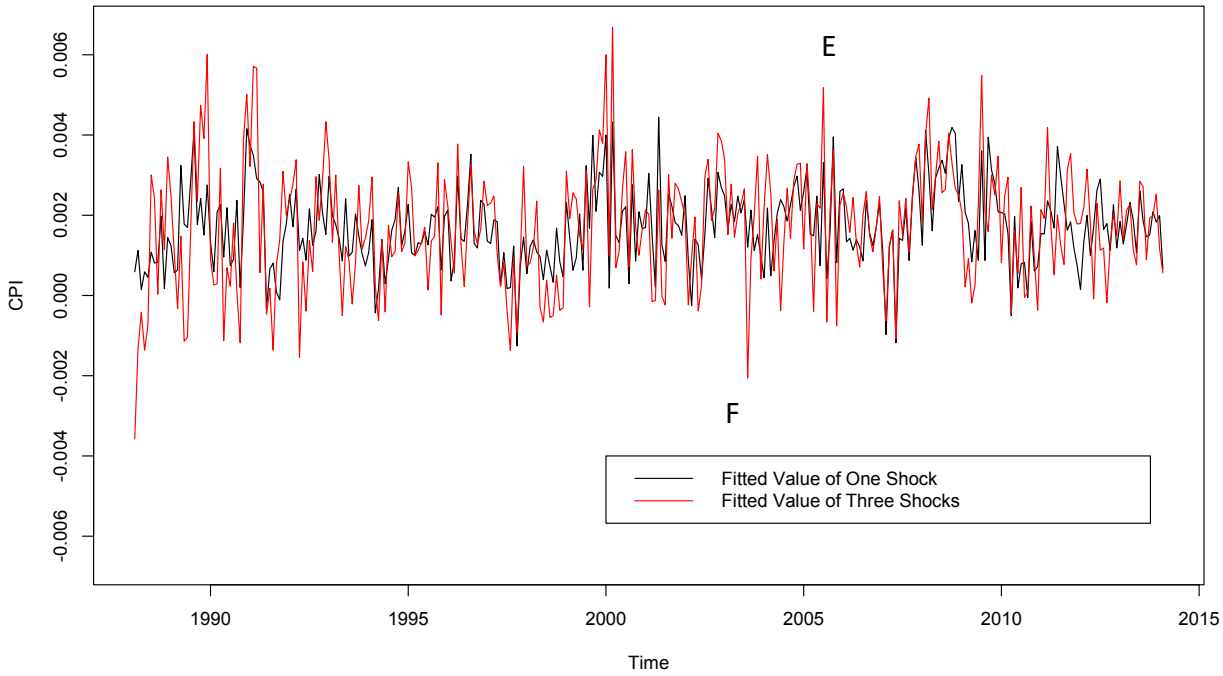


Figure 2.5. Different Fitted Values of Saudi Arabia's Consumer Price Index



2.6 Conclusion

In recent years, many studies have found differences in how oil price shocks affect economies. For the U.S., one of the biggest economies, studies have found increases in the price of oil in some periods cause a recession while in other periods they do not. Kilian (2009) included oil market shocks, which cause oil price increases, in his study and found that the response of the U.S. economy to oil price shocks differs depending on the type of shock causing oil prices to increase.

In this chapter, we have asked whether three shocks that cause increases in oil prices have different effects on Saudi Arabia's economy. Saudi Arabia is one of the biggest exporter economies, meaning its government cares about oil prices because its economy depends on oil for revenues. As Saudi Arabia is focused on increasing the price of oil, oil market shocks do not necessarily have different effects on its industrial production, especially aggregate demand shock given the small economy. We applied Kilian's (2009) methodology to study the response of Saudi Arabia's economy to oil market shocks compared to its response to only one shock: oil price shock.

Our results indicated differences in how Saudi Arabia's economy responds to oil market shocks, meaning we need to include all of these shocks when studying the responses of Saudi Arabia's economy. This essay aims to help Saudi leadership understand how the different sources of oil price shocks affect their economy so they can predict how their revenues well be affected by these shocks. In future studies, the BSVAR model should be used to identify the three shocks and study their impact on the Saudi economy. Using BSVAR allows for the inclusion of more prior information, which leads to increased credibility.

Chapter 3: The Response of the Saudi Stock Market to Oil Price Shocks

3.1 Introduction

This essay estimates the responses of Saudi Arabia's stock prices in different sectors to an oil price shock. Saudi Arabia is an oil-exporting country that is very heavily dependent upon revenues from exporting oil, so any fluctuation in oil prices creates instability in the country by affecting Saudi Arabia's financial markets. Indeed, when most stock markets experienced a downturn in 2002, Saudi Arabia continued to achieve gains as a result of the rise in oil prices (Hammoudeh & Choi, 2005). Meanwhile, when oil prices fell almost $73 between 2014 and 2016, Saudi's Arabia's stock markets dropped by 15%. Due to the decline in oil prices throughout history because of different events and damage to its stock market as a result of the impact of its revenues, in 2013 Saudi Arabia developed several solutions to reform its economy and reduce its dependence on oil. Specifically, Saudi Aramco listed at least 5% of its shares on the stock market (Tong et al., 2018). Saudi Arabia's stock market includes 180 listed companies, yet only four are oil companies, despite it being the most important sector in Saudi Arabia (Tong et al., 2018).

Oil price shocks affect companies' profits, whether directly or indirectly, because crude oil is used in the production of many products (Belanes et al., 2022). Such shocks affect stock prices through their impact on production costs and income, which affects corporate profits and, consequently, stock profits. Oil-exporting countries experience different effects. One such effect was that increased oil prices cause increased production costs. Yet increases in oil prices have a positive impact on income as a result of the increase in oil revenues, which leads to an increase in aggregate demand and thus raises production. As a result, the positive effect of higher income outweigh the negative impact on production costs (Degiannakis et al., 2018).

Researchers have determined that oil price fluctuations impact economies in various ways according to whether the country is an exporter or importer of oil and according to the period studied. Some researchers have studied the long-term impact while others examined the short-term impact (Belanes et al., 2022). Kilian (2009) demonstrated that there are multiple shocks that affect the price of oil, resulting in different impacts on the economy. Kilian concluded that studying the impact of oil price shocks without knowing their source is not helpful because the impact of a supply shock has a different effect than the impact of a demand shock for oil. In the wake of recent oil price increases, economists expected to see a decrease in the U.S. stock market, but they discovered a relationship of a different nature between oil prices and stock prices. Kilian and Park (2009) found that only oil-specific demand shocks produced a negative relationship, whereas shocks to the oil supply and to aggregate demand showed a positive relationship.

This subject has attracted the attention of researchers, policymakers, and investors seeking to hedge against sudden changes. This essay quantifies the reaction of the Saudi Arabian stock market to different types of oil price shocks. The Saudi Arabian stock market was an unclassified market until 2018; in addition, it is a small market and under the control of the government. Foreign investment is limited in the market, which means that there is no diversification of capital sources while being heavily dependent on oil revenues. Furthermore, individual investors account for more than 70% of the trading activity on the stock market, so their behavior affects the market itself. Investors usually protect their capital by diversifying their investment portfolios. Thus, in the Saudi Arabian stock market, which is a weak market, investors diversify their portfolios to remove/largely reduce the risk associated with oil price shocks. Considering the three different oil shocks-namely, oil supply, aggregate demand, and oil specific-demand shocks, the diversification opportunities might differ according to the type of shock.

To date, nobody has examined the response of the Saudi Arabian stock sectors to crude oil market shocks. This chapter fills this gap. We use an updated global real economic activity index relative to Kilian's (2019) data from the Federal Reserve Bank of Dallas. Our results show that Saudi Arabia's sectoral stock prices react differently to oil price shocks. Responses to oil supply shocks are negative, which means that the shock to oil supply also hurts Saudi business prospects (e.g., uncertainty due to war in neighboring countries). Meanwhile, responses to oil-specific demand shocks are positive, which is consistent with previous findings. Finally, the aggregate demand shock has no effect on Saudi Arabia's stock sectors, possibly because it is a small economy that does not benefit from an expanding world economy, beyond the effect on the price of oil.

Section 3.2 presents background information on the Saudi Arabia stock market. Section 3.3 reviews previous studies. Section 3.4 presents the data, while Section 3.5 describe Kilian's (2009) methodology. Section 3.6 discusses our results. Section 3.7 concludes the chapter.

3.2 Background on Saudi Arabia's Stock Market

As one of the largest oil-exporting countries, Saudi Arabia receives surpluses of oil revenues, but oil price fluctuations mean the kingdom's leadership is constantly concerned about periods of low prices as the Saudi economy is highly dependent on oil. According to the IMF (2014), oil revenues accounted for approximately 90% of Saudi Arabia's revenues. Thus, the increase in oil prices from 2003 to 2013 supported the Saudi economy as it led to its growth by 5% while its GDP more than tripled (Al-Tamimi, 2016). In 2014 and 2015, oil prices decreased by 70% (Degiannakis et al., 2018), resulting in the deterioration of the Saudi economy. Where the fiscal deficit amounted to 100 billion dollars, or 15% of GDP, which caused the growth of the Saudi economy to slow down (Al-Tamimi. 2016). The decline in economic growth lowered expectations for firms' profits and in turn negatively affected stock returns (Belanes et al. 2022).

The relationship between oil prices and stock market returns can be clarified by the stock valuation using the following equations according to Degiannakis et al. (2018). The first equation uses to define stocks returns:

$$R_{i,t} = \log(p_{i,t}/p_{i,t-1}) \quad (3.1)$$

where $R_{i,t}$ denotes stock returns and $p_{i,t}$ denotes the stock price of listed firm i at time t. The second equation follows the economic theory where future cash flows are used to determine current stock prices:

$$p_{i,t} = \sum_{n=t+1}^{n}(E(cf_t)/1 + E(r)^t) \quad (3.2)$$

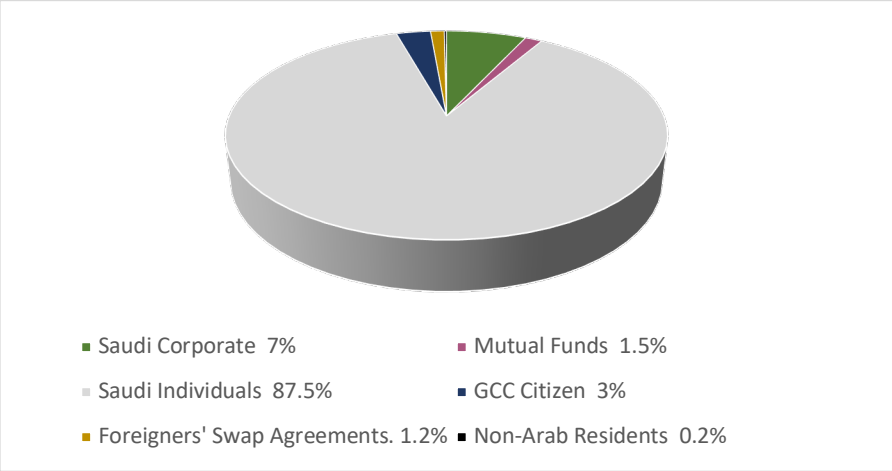
where $\mathrm{E}(cf_t)$ is the expected cash flow at time t and $E(r)^t$ is the expected discount rate.

However, oil price fluctuations affect the expected cash flows or discount rate, which is the expectation of both inflation and the interest rate. In general, decreasing cash flows or increasing the discount rate will lead to decreased stock prices. Although an increase in oil prices has a negative impact on the cost of production, this effect is almost negligible compared to the positive effect of the increase in oil revenues in oil-exporting countries, which in turn leads to a rise in aggregate demand. Stock returns then respond positively as a result of the increase in the expectations of companies' cash flows (Degiannakis et al. 2018).

In addition to the Saudi economy being highly dependent on oil revenues, its stock market was unclassified until recently, because it took time to meet the required standards. In 2017, the FTSE Russel Index refused to transform Saudi Arabia's stock market from unclassified market status to developing market status to attract global investors, while MSCI had added Saudi Arabia's stock market to its watch list (Tong et al. 2018). With regard to investments, the opportunity for trading was not available to all investors. In the beginning, only Saudi citizens, Saudi companies, and citizens of Gulf countries were allowed to participate directly in the market,

while foreigners could only participate through banks' mutual funds (Ramady, 2010). As a result, there was no diversification of capital sources, but rather a heavy dependence on oil revenues due to restrictions affecting foreign investors. Individual investors make up the majority of investors in Saudi Arabia's market, with the value of their monthly trading representing an estimated 87.5% of all trading, as shown in Figure 3.1. Their behaviors significantly affect the stock market. Indeed, Saudi Arabia's stock market may be susceptible to herd mentality, which has been documented by Chang et al. (2000) and drives investors to engage in the same behavior regardless of the market situation.

Figure 3.1 Ratios of Trading Values for Different Investors in the Saudi Market



Source: Tadawul (2009)

Saudi Arabia's stock market was established in the early eighties, and it faced difficulty in development. As it was under the government's control, it was not considered independent; the market was also small, and the investors were ignorant of the issuance and trading of shares (Adnan & Shook, 1984; Ramady, 2010). In addition, according to Abdeen and Shook (1984), the number of listed companies was very limited at the time, numbering only 35; in comparison, Kuwait, which has a smaller economy, had 48 listed companies. Furthermore, some members of boards of

directors or founders owned large percentages of shares, allowing them to determine market prices. For example, in 1982 the Arab National Bank had a number of shareholders, including six founders, who owned approximately 130,000 shares with a nominal price of 100 riyals; the price for these investors was changed to 1120 riyals. Furthermore, the lack of sufficient information for Saudi investors regarding stock operations and transactions resulted in the trading of shares of companies that are not yet operational.

Saudi Arabia has been keen to develop its stock market. Some modifications have been made in the trading process through the Monetary Agency. In 1990, trading began through an electronic system called the Electronic Securities Information System to facilitate the process of buying or selling, which led to an increase in trading volume as well as tracking price movement through the Bakheet and CCFI indicators. In 2001, the Tadawul system was launched, which developed and facilitated the trading process as well as reflected the performance of all companies listed on the stock market. In addition, it has continued to advance technologically, which contributed to the emergence of a new index in 2004: the TASI, the official indicator that has continued until today (Ramady, 2010).

In 2002, the Saudi Shura Council issued a law, with 67 articles, that was implemented in 2003 to address the defects in the stock market. In 2006, Arabs residing in the kingdom were allowed to invest in the market to boost the stock exchange. In 2008, new rules were enacted allowing foreigners to trade through licensed local brokers (Ramady, 2010). Although, Saudi Arabia's desire to open its market to foreign investment increased, foreign investors are still only allowed to invest indirectly through institutions and by meeting several conditions, including that the institution be present on the market for no less than 5 years and own assets of no less than 5 billion riyals (Tong et al., 2018). Despite the desire and keenness of Saudi Arabia to develop, one

of its basic principles is that its markets must be in compliance with Islamic religion, which creates some restrictions. In 2009, Saudi Arabia's stock market launched indicators to enable it to monitor companies in order to be compatible with the Islamic religion (Ramady, 2010).

Saudi Arabia's stock market contains 15 sectors, with the insurance sector having the most listed companies (i.e., 26) and the energy sector having the fewest (i.e., 3). Sectors are evaluated by determining the level of the floating shares, which is the total number of shares available for trading. The multi-investment sector has the lowest level of flotation at 8.4%, while the retail and transportation services sectors have the highest, reaching 71% according to the Capital Market Authority (CMA). In addition, in terms of trading volume, in 2009 the highest trading volume was in the petrochemical sector, followed by insurance, banking and financial services, and industrial investment; the lowest trading volume was energy (Tadawul, 2009).

However, according to Ramady (2005), the number of currently listed companies is still much lower than the capabilities of Saudi Arabia as it has the potential to expand its stock market, making it necessary to list more companies by easing strict laws to enable new companies to become joint stock companies. Saudi Arabia has sought to increase the number of listed companies from 68 companies in 2002, with a capital of 38 billion Saudi riyals. By 2009, the number of companies had reached 134, with a capital of 596 billion Saudi riyals (see Table 3.1). Recently, the listing of Aramco in the market became important for the development of its economy by providing a source of cash flows for investment. Aramco currently represents 70% of the market capitalization. Aramco was put up for subscription in 2018 due to a 15% drop in shares as a result of the drop in oil prices in 2014 (Belanes et al., 2022). The inclusion of Aramco increases the weight of the Saudi stock market, doubling it from 2.5% to 5% on the FTSE index. According to recent developments in the stock market (Tong et al., 2018), Saudi Arabia was included in the

MSCI and FTSE Russel indexes at the end of 2018, thereby opening up more opportunities for foreign investment.

Table 3.1 Saudi Listed Companies and Total Shares Issued (in Millions)

Years	Number of Listed Companies	Number of Shares Issued
2002	68	9,807
2006	86	19,328
2007	111	30,728
2008	127	39,728
2009	134	41,223

Source: Ramady (2005)

3.3 Literature Review

Most previous studies have examined the impact of oil prices on economies, considering oil prices as an exogenous variable. However, Kilian (2009) introduced shocks affecting oil prices, demonstrating that oil prices were an endogenous variable. For example, Kilian and Park (2009) examined the response of U.S. stock returns to oil demand and oil supply shocks and found a negative response only with oil-specific demand shocks; this finding explains why U.S. stock returns have not decreased in response to oil price increases in recent years. Subsequent papers used Kilian's (2009) methodology in different countries. Apergis and Miller (2009) investigated the response of stock market returns in eight developed countries to oil price shocks. They found that all oil market shocks have a small effect on stock markets in each of the countries and demonstrated how these shocks explain the small variations of each stock market. Meanwhile, Abhyankar et al (2013) investigated the effect of three oil market shocks on the Japanese stock market and found the response is not always negative; indeed, the aggregate demand shock has a positive effect. In addition, the effect of oil supply plays a small role compared to oil-specific demand shocks on Japanese stock returns.

Several papers used Kilian's (2009) methodology with some changes. Jung and Park (2011) investigated the effect of oil price shocks on stock returns and volatility in Norwegian and Korean markets, adding exchange rate as one of the endogenous variables. The responses differed depending on the cause of the oil price increase and whether the countries were a net oil exporter or importer. Kang and Ratti (2013) also studied the response of stock market returns to oil price shocks by adding economic policy uncertainty as one of the endogenous variables. They identified a negative effect and determined that all three oil market shocks explained more than 10% of the variations in U.S. stock returns while economic policy uncertainty explained more than 15%. In

addition, the response of U.S. stock returns to all three oil market shocks differed. Gupta and Modise (2013) explored the effect of oil market shocks on the South African stock market using Kilian's (2009) methodology and imposing sign restrictions. Their results indicated in South African, an oil importer, the stock market returns responded positively only to aggregate demand shocks, indicating all three oil market shocks should be used to study how stock return responses in this country. Kang et al. (2015) studied the effect of different oil price shocks on U.S. stock market returns using a time-varying mixture innovation. They found that oil market shocks contribute to more than 25% of the long-term variations in U.S. stock market returns. In addition, the aggregate demand shock had a larger effect on stock market returns than other shocks. Cunado and de Gracia (2014) examined stock returns' responses to oil price shocks in 12 oil-importing countries using only two shocks: oil supply shocks and oil-specific demand shocks. They demonstrated a negative relationship between oil price and stock market returns using VECM. However, they concluded that the effect of oil price shocks on the selected stock returns differed; although the effect of these two shocks was negative, the effect of oil supply shock was greater.

Few studies have studied the Saudi Arabia stock market, and no study has dealt with oil prices as an endogenous variable to determine the reason for the different results of the impact of oil prices on stock markets returns. Dahel and Laabas (1999) studied the behavior of stock markets with regard to their efficiency in four Gulf countries, including Saudi Arabia, using three tests of the market efficiency hypothesis-namely, unit root test, variance ration test, and autocorrelation structure of returns. They found that the first two tests showed that Saudi Arabia's stock market is considered weak, although the third test does not support this result. Hammouden and Choi (2005) considered the impact of oil prices on GCC countries using vector error correction and causal relationships. Their results showed that oil prices positively affect Saudi Arabia. In addition, the

results of the variance decomposition analysis showed that local shocks and the shocks of other GCC countries contribute significantly to the changes in the returns of Saudi Arabia's index. Alhayki (2014) investigated the effect of oil prices on stock market returns in GCC countries using a wavelet analysis and found that the response of GCC stock returns to oil price shocks differ; some are positive while others are negative. Specifically, for Saudi Arabia, the results indicated that the effect of oil prices on stock returns is negative. In addition, the correlation between oil prices and stock returns become strong in the long run. Cheikh et al (2018) examined the asymmetric relationship between GCC stock markets and oil price shocks using LSTR models to separate the price of oil into positive and negative shocks. They found asymmetrical relationships in Kuwait, Oman, and Qatar, but not in Bahrain, Saudi Arabia, or the UAE. Belanes et al. (2022) investigated the relationship of oil price changes to the movements in the Saudi Arabia's stock market and found a co-integration relationship between oil prices and the stock market index. In addition, using ARDL, they found that Saudi Arabia's stock market is strongly affected by oil price fluctuations. In this chapter, we used Kilian's (2009) methodology to investigate if the responses of Saudi Arabia's stock market return as sectors to oil price shocks differ depend on which shock causes oil prices to increase.

Table 3.2 Summary of the Literature Review

Citation	Purpose	Method	Conclusions
Kilian and Park (2009)	examined the response of U.S. stock returns to oil demand and oil supply shocks	SVAR model	The authors a negative response only with oil-specific demand shocks; this finding explains why U.S. stock returns have not decreased in response to oil price increases in recent years.
Apergis and Miller (2009)	investigated the response of stock market returns in eight developed countries to oil price shocks	SVAR model	The authors found that all oil market shocks have a small effect on stock markets in each of the countries and demonstrated how these shocks explain the small variations of each stock market.
Abhyankar et al (2013)	investigated the effect of three oil market shocks on the Japanese stock market	SVAR model	The authors concluded that the response is not always negative; indeed, the aggregate demand shock has a positive effect. In addition, the effect of oil supply plays a small role compared to oil-specific demand shocks on Japanese stock returns.
Jung and Park (2011)	investigated the effect of oil price shocks on stock returns and volatility in Norwegian and Korean markets, adding exchange rate as one of the endogenous variables	SVAR model	The results showed that the responses differed depending on the cause of the oil price increase and whether the countries were a net oil exporter or importer.
Kang and Ratti (2013)	studied the response of stock market returns to oil price shocks by adding economic policy uncertainty as one of the endogenous variables	SVAR model	The authors identified a negative effect and determined that all three oil market shocks explained more than 10% of the variations in U.S. stock returns while economic policy uncertainty explained more than 15%.
Gupta and Modise (2013)	explored the effect of oil market shocks on the South African stock market while imposing sign restrictions	SVAR model	The results indicated that in South African, an oil importer, the stock market returns responded positively only to aggregate demand shocks, indicating all three oil market shocks should be used to study stock return responses in this country.
Kang et al. (2015)	studied the effect of different oil price shocks on U.S. stock market returns	a time-varying mixture innovation	The authors found that oil market shocks contribute to more than 25% of the long-term variations in U.S. stock market returns.

Cunado and de Gracia (2014)	examined stock returns' responses to oil price shocks in 12 oil-importing countries using only two shocks: oil supply shocks and oil-specific demand shocks	using VECM.	The authors concluded that the effect of oil price shocks on the selected stock returns differed; although the effect of both shocks was negative, the effect of oil supply shock was greater.
Dahel and Laabas (1999)	studied the behavior of stock markets with regard to their efficiency in four Gulf countries, including Saudi Arabia	Using unit root test, variance ration test, and autocorrelation structure of returns	The authors found that the first two tests showed that Saudi Arabia's stock market is considered weak, although the third test did not support this result.
Hammouden and Choi (2005)	investigated the impact of oil prices on GCC countries	vector error correction and causal relationships	Their results showed that oil prices positively affect Saudi Arabia. In addition, the results of the variance decomposition analysis showed that local shocks and the shocks of other GCC countries contribute significantly to the changes in the returns of Saudi Arabia's index.
Alhayki (2014)	investigated the effect of oil prices on stock market returns in GCC countries	wavelet analysis	The results indicated that the responses of GCC stock returns to oil price shocks differ; some are positive while others are negative. For Saudi Arabia, the results indicated that the effect of oil prices on stock returns is negative.
Cheikh et al (2018)	examined the asymmetric relationship between GCC stock markets and oil price shocks	LSTR models	The authors found asymmetrical relationships in Kuwait, Oman, and Qatar, but not in Bahrain, Saudi Arabia, or the UAE.
Belanes et al. (2022)	investigated the relationship of oil price changes to the movements in Saudi Arabia's stock market	cointegration test and ARDL.	The authors found a co-integration relationship between oil prices and the stock market index. In addition, they found that Saudi Arabia's stock market is strongly affected by oil price fluctuations.

3.4 Data

We gathered data to investigate the effect of oil price shocks on Saudi Arabia's stock sectors-specifically, world crude oil production (WOP_t), global real economic activity (GIP_t), and Brent crude oil price (OP_t). We considered monthly data from January 1980 to December 2016, resulting in 444 total observations, to ensure enough periods with shocks. In addition, we included Tadawul all-share indexes (TASI), which include all the sectors, which are 15 sectors, from January 2008 to December 2016, resulting in 108 observations for estimations. These data from Saudi Arabia's exchange are available until 2016, when new sectors were introduced. The data were obtained from different sources. World crude oil production data were obtained from the U.S. Energy Information Administration (EIA), whereas global real economic activity data were obtained from the Federal Reserve Bank of Dallas. Brent crude oil price data were obtained from the Federal Reserve Economic Data (FRED). The petrochemical industry, energy, retail, insurance, cement, telecom, mult-investment, building, industrial investment, hotel, bank, transport, real estate development, agriculture, and media sectors were obtained from Saudi Arabia's exchange.

3.5 Methodology

We investigated the response of Saudi stock sectors to oil market shocks-specifically, oil supply shock, aggregate demand shock, and oil-specific demand shock. We adopted these three shocks using Kilian's (2009) method as these three shocks were found to affect oil prices and, thus, the U.S. economy. Kilian (2009) also found that the impact of these shocks on the U.S. economy differed. Therefore, we investigate whether their impact on Saudi Arabia's stock market is similar or different. First, we identified these shocks as Killian (2009) did, using the developed real economic activity index; after ensuring the stability of the variables, we also determined the appropriate lag length using the Akaike information criteria (AIC). However, we included a different number of total observations of shocks and all-share indexes because we wanted sufficient data for the oil market shocks. In addition, the way Kilian (2009) built his method allowed us to include a different number of observations.

We considered the following VAR model:

$$A_0 Y_t = \alpha_i + \sum_{i=1}^{q} A_i Y_{t-q} + \varepsilon_t \quad (3.3)$$

where $Y_t = (dWOP_t, dWIP_t, dOP_t)$, $dWOP_t$ is the percentage change of world crude oil production, $dWIP_t$ denotes the percentage change of the world's real economic activity created by Kilian (2009), and dOP_t refers to the percentage change of oil prices. The lag length (q) is determined by using AIC.

The reduced form of Equation (3.3) can be written as the structural VAR by divide Equation (3.3) by A_0

$$Y_t = \acute{\alpha}_i + \sum_{i=1}^{q} \acute{A}_i Y_{t-q} + e_t \quad (3.4)$$

where $e_t = A_0^{-1}\varepsilon_t$ is the vector of reduced form residuals.

$$e_t = \begin{pmatrix} e_{1t}^{\,dWOP_t} \\ e_{2t}^{\,dWIP_t} \\ e_{3t}^{\,dOP_t} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{\,\text{oil supply shock}} \\ \varepsilon_{2t}^{\,\text{aggregate demand shock}} \\ \varepsilon_{3t}^{\,\text{oil-specific demand shock}} \end{pmatrix} \quad (3.5)$$

Our recursive identification of the three shocks indicated that world oil production does not respond contemporaneously to both oil demand shocks. In addition, world real economic activity does not contemporaneously respond to oil price shocks. Once we compute the shocks, we examine how they (oil supply shock, aggregate demand shock, and oil-specific demand shock) affect Saudi Arabia's sectoral stock returns. To this end, we allow all three shocks to affect all sectors contemporaneously, as shown below.

$$e_t = \begin{pmatrix} e_{1t}^{\,dWOP_t} \\ e_{2t}^{\,dGIP_t} \\ e_{3t}^{\,dOP_t} \\ e_{4t}^{\,Ass_t} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{\,\text{oil supply shock}} \\ \varepsilon_{2t}^{\,\text{aggregate demand shock}} \\ \varepsilon_{3t}^{\,\text{oil-specific demand shock}} \\ \varepsilon_{4t}^{\,\text{all-stock sectors}} \end{pmatrix} \quad (3.6)$$

3.6 Results

3.6.1 Unit Root Test

We first checked whether the variables selected were stationary in the level or in the first difference. We used the augmented Dickey-Fuller (1979) test (ADF) and Philips-Perron (1988) test (PP) to check whether a unit root exists or not. The null hypothesis of ADF and PP is that there is a unit root. However, most macroeconomic variables have a unit root, which means we must take the first difference. Table 3.3 summarizes the results of these tests in the level while Table 3.4 summarizes the results in the first difference. We concluded that the selected variables are not stationary at the level but are stationary in the first difference at the 5% level of significance for most variables. Therefore, we transformed them into a stationary series by considering the difference.

Table 3.3 Unit Root and Stationary Tests for Variables in Level

	Augmented Dickey-Fuller test (1979) Test		Phillip-Perron (1981) Test	
	Constant	Trend	Constant	Trend
WOP	-0.36	-6.38	-0.13	-5.74
WIP	-1.56	-1.62	-5.74	-1.64
OP	-1.85	-2.91	-5.67	-2.49
Tadawul All-share Indexes				
Cem	-1.65	-1.85	-5.23	-1.78
Pet	-3.23	-3.20	-13.21	-2.66
Ret	-0.89	-1.62	-1.37	-1.44
Ban	-3.32	-3.23	-13.86	-2.94
Ins	-3.60	-4.64	-14.57	-3.55
Tra	-1.19	-2.85	-2.62	-2.40
Med	-3.23	-3.56	-12.68	-2.92
Rea	-1.31	-2.99	-3.13	-2.61
Agr	-1.03	-2.05	-2.29	-1.93
Tel	-2.45	-2.41	-8.85	-2.29
Minv	-2.61	-3.05	-8.79	-2.66
Bui	-2.39	-2.81	-6.28	-2.35
Ene	-0.71	-3.85	-2.65	-3.24
Ind	-2.37	-3.34	-8.54	-2.84
Hot	-1.10	-1.39	-2.74	-1.19

Note: The 5% critical values for ADF test: Drift=-2.88 and Trend=-3.43; for PP test: Constant=-2.88 and Trend=-3.44

Table 3.4 Unit Root and Stationary Tests for Variables in Different

	Augmented Dickey-Fuller test (1979) Test		Phillip-Perron (1981) Test	
	Constant	Trend	Constant	Trend
WOP	-15.66	-15.71	-366.16	-20.45
WIP	-14.01	-14.05	-430.52	-20.59
OP	-12.83	-12.83	-291.75	-15.23
Tadawul All-share Indexes				
Cem	-5.38	-5.35	-90.81	-8.28
Pet	-5.92	-5.91	-75.77	-7.71
Ret	-5.32	-5.31	-73.90	-7.45
Ban	-7.14	-7.14	-120.87	-11.62
Ins	-6.88	-6.94	-92.00	-9.43
Tra	-7.43	-7.43	-68.81	-7.80
Med	-8.35	-8.34	-74.23	-8.72
Rea	-6.68	-6.84	-90.16	-9.16
Agr	-6.69	-6.67	-100.63	-9.34
Tel	-7.35	-7.29	-75.83	-7.99
Minv	-6.72	-6.70	-86.44	-8.49
Bui	-6.93	-6.92	-65.86	-7.24
Ene	-6.52	-6.73	-124.83	-11.89
Ind	-7.26	-7.24	-79.57	-8.80
Hot	-6.54	-6.55	-109.61	-9.96

Note: The 5% critical values for ADF test: Drift=-2.88 and Trend=-3.43; for PP test: Constant=-2.88 and Trend=-3.44

3.6.2 Impulse Response Functions

Figures 3.2-3.9 display the impulse response functions with one standard deviation error bands for all sectors. These figures demonstrate that higher oil prices as a result of oil supply shocks are bad for Saudi Arabia's stock market. Oil supply shocks might reasonably be expected to have a negative effect on the Saudi economy. On the other hand, the precautionary demand shocks are quite positive for the Saudi Arabia's stock market, which would be expected because Saudi Arabia is an oil-exporting country; according to the theory, oil price shocks have a positive effect on an oil exporter's stock market. Meanwhile, the aggregate demand shocks have no effect, which would also be expected because aggregate demand shocks have a good effect on a country that produces a lot of goods. However, Saudi Arabia is a net import country.

Figures 3.2 and 3.3 show the responses of the petrochemical industry sector, energy sector, retail sector, and insurance sector. Oil supply shock is bad for the Saudi industries which are petrochemical, energy and retail in addition for the demand of property insurance as the response of these sectors are negative to oil supply shocks. Meanwhile, oil-specific demand shocks, the other type of shocks causing oil price to increase, are good for the Saudi industries: petrochemical, energy, retail, and property insurance as the response of these sectors are positive. Finally, aggregate demand shocks, which also cause oil prices to increase, have no effect on these sectors.

Figures 3.4-3.6 show the responses of the cement sector, telecom sector, multi-investment sector, building sector, industrial investment sector, and hotel sector. Increasing the price of oil as a result of oil supply shocks reduces telecom companies' demand as this sector has a negative response to oil supply shocks. In addition, oil supply shocks cause uncertainty about both building and construction activities, thereby affecting the demand for cement as building and cement sectors

are fluctuates to oil supply shocks. Increasing the price of oil as a result of precautionary demand shocks increases the demand on telecom companies, building and construction activities, and the demand for cement as their responses are positive to such shocks. In addition, disruptions to the oil supply reduce Saudi Arabia's multi-investments as its response is negative and uncertainty about industrial investments as its response is fluctuates. Meanwhile, disruptions to the oil-specific demand increase both multiple investments and industrial investments as their responses are positive. Finally, oil supply shocks decrease the demand for travel in Saudi Arabia as the hotel sector's response is negative, whereas precautionary demand shocks increase the demand for travel in Saudi Arabia as the hotel sector's response is positive. This finding makes sense because oil supply shocks are times of turmoil in that part of the world. Such events likely hurt travel, and with reduced oil production, there is less travel related to oil production. Precautionary demand shocks help the economy and lead to more travel related to oil production.

Finally, Figures 3.7-3.9 include the bank sector, transport sector, real estate development sector, agriculture sector, and media sector. Oil supply shocks that cause oil prices to increase lead to increasing foreign and local savings and developments in both the transportation and real estate sectors, after three months of decreases, as these sectors' responses are immediately negative for three months and then continue to be positive responses. Oil-specific demand shocks, which also cause oil prices to increase, have a positive effect on foreign and local savings, transportation, and real estate development, which respond positively. On the other hand, oil supply disruptions cause uncertainty for the agriculture and media sectors, whose responses fluctuate, while oil-specific demand disruptions have a positive effect on them.

In conclusion, our results show the differences in stock sector prices' responses to oil market shocks. Stock sector prices respond negatively to oil supply shocks, which means the shock

harms Saudi Arabia's business prospects. This result may be due to oil supply shocks, which explain small variations in oil prices, as Kilian's (2009) methodology demonstrated. Oil-specific demand shocks showed positive effects, which is consistent with economic theory as shown in Section 3.2. Aggregate demand shocks showed no effect on Saudi Arabia's stock sectors, which is expected because the price of oil is driven by the world aggregate demand, as Kilian modeled it. A higher aggregate demand would be good for economies like the US and China, which produce lots of goods. Saudi Arabia produces mainly oil, so that logic would not apply to the Saudi economy. Based on our results, investors can minimize the impact of oil supply shocks by diversifying their investment portfolios. They can balance the risk-return ration before making their investment decision. Some sectors show a negatively and statistically significant response, including the petrochemical industry sector, energy sector, retail sector, multi-investment sector, building sector, industrial investment sector, and hotel sector. In other sectors, the decrease is not significant, which means oil supply shocks have no effect. Thus, investors can protect themselves by diversifying their portfolios. Finally, our results indicate that Saudi Arabia's stock sectors have a similar response to each of the oil market shocks. This outcome is expected as oil prices drive all of them, causing the correlation among sectors to be high, as shown in Table 3.5.

Figure 3.2 Responses of petrochemical industry sector and energy sector to the three structural shocks

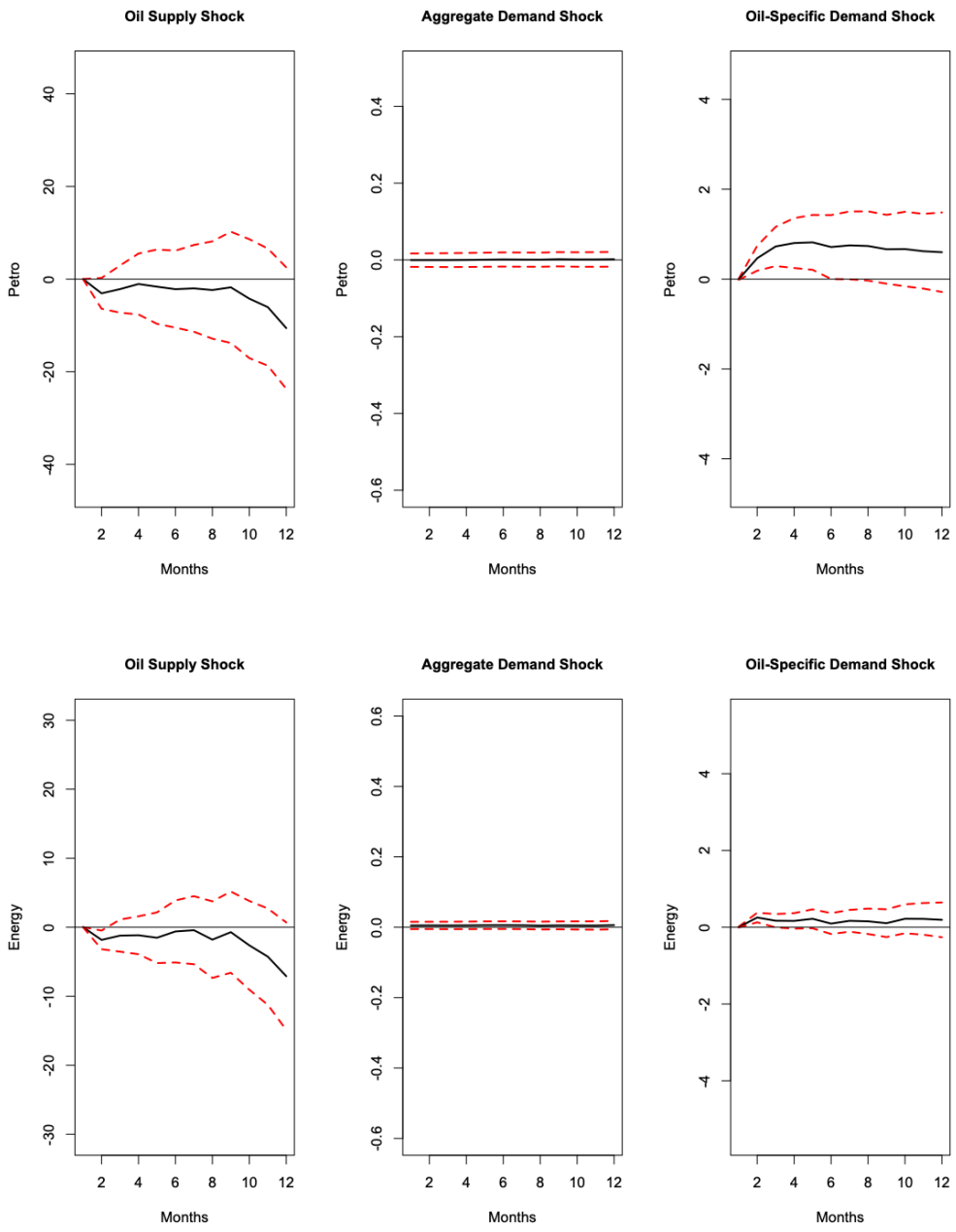


Figure 3.3 Responses of retail sector and insurance sector to the three structural shocks

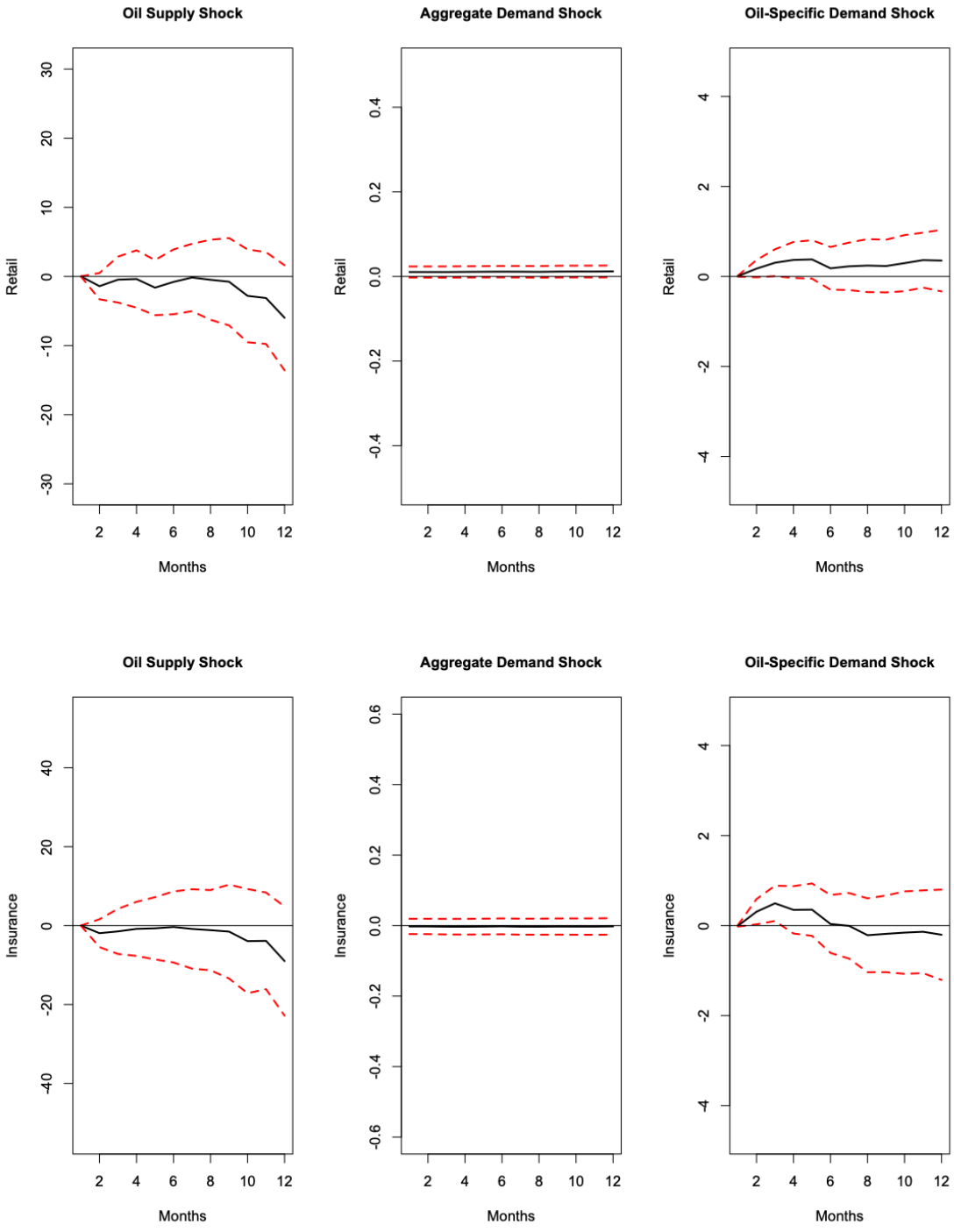


Figure 3.4 Responses of cement sector and telecom sector to the three structural shocks

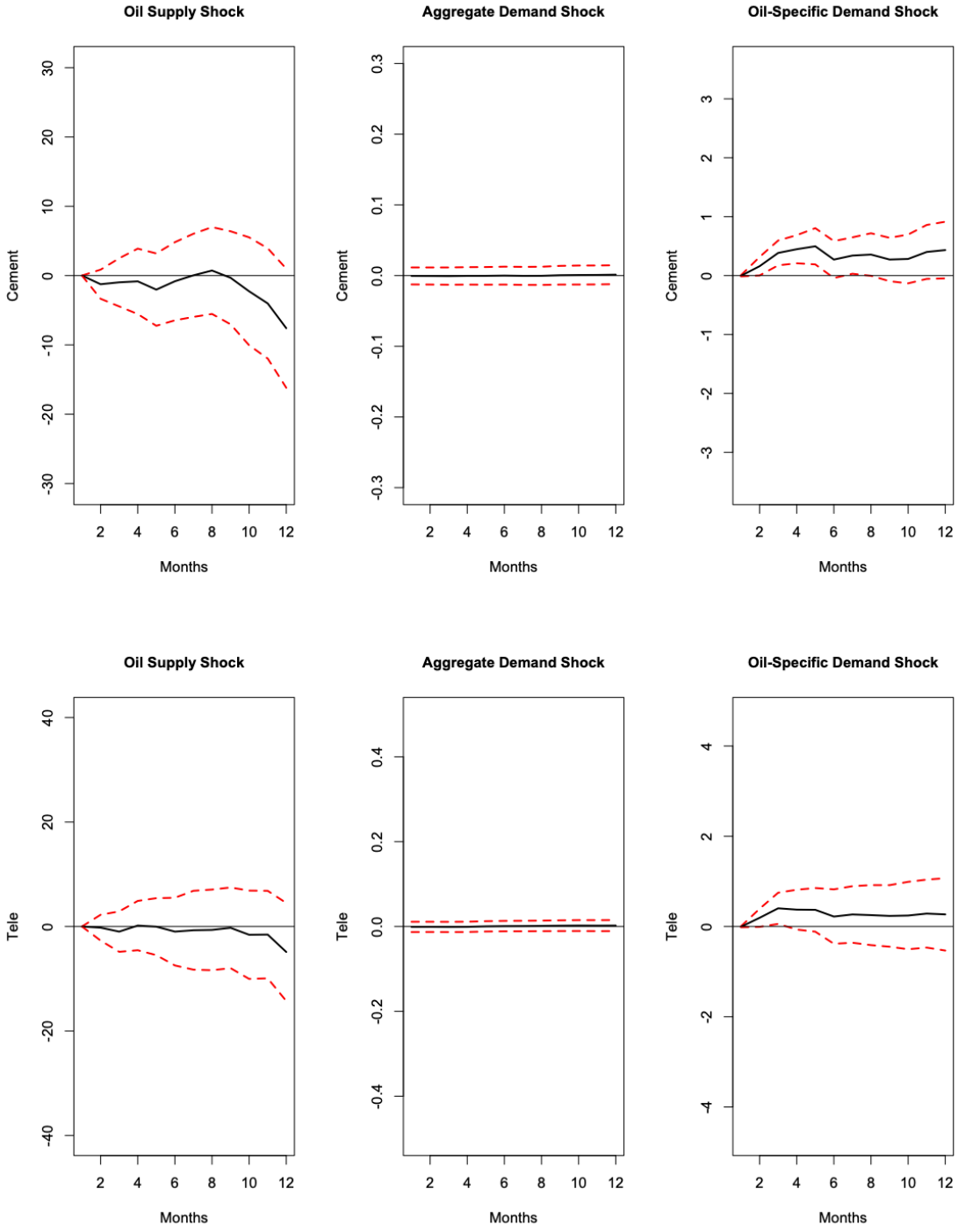


Figure 3.5 Responses of multiple investment sector and building sector to the three structural shocks

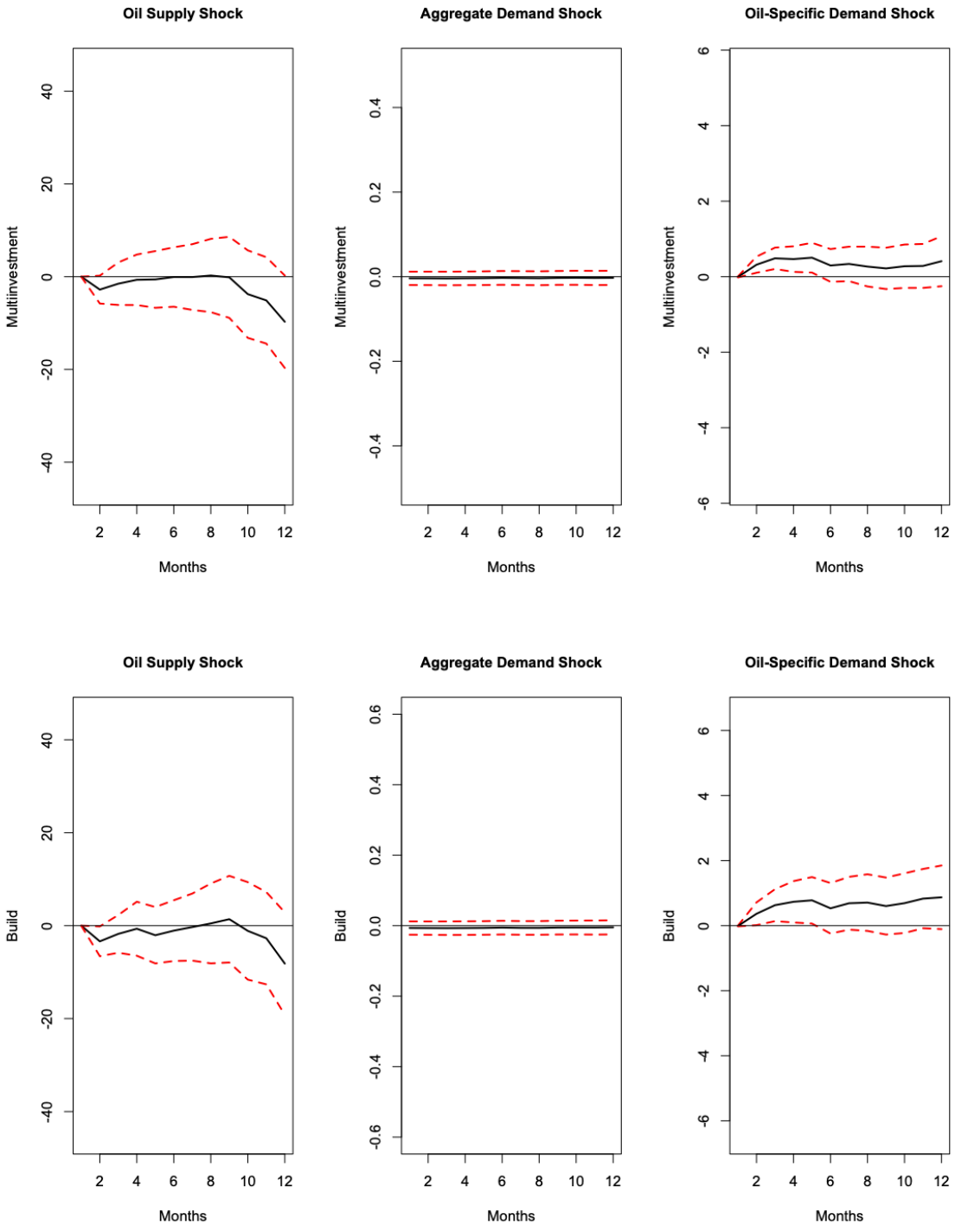


Figure 3.6 Responses of industrial investment sector and hotel sector to the three structural shocks

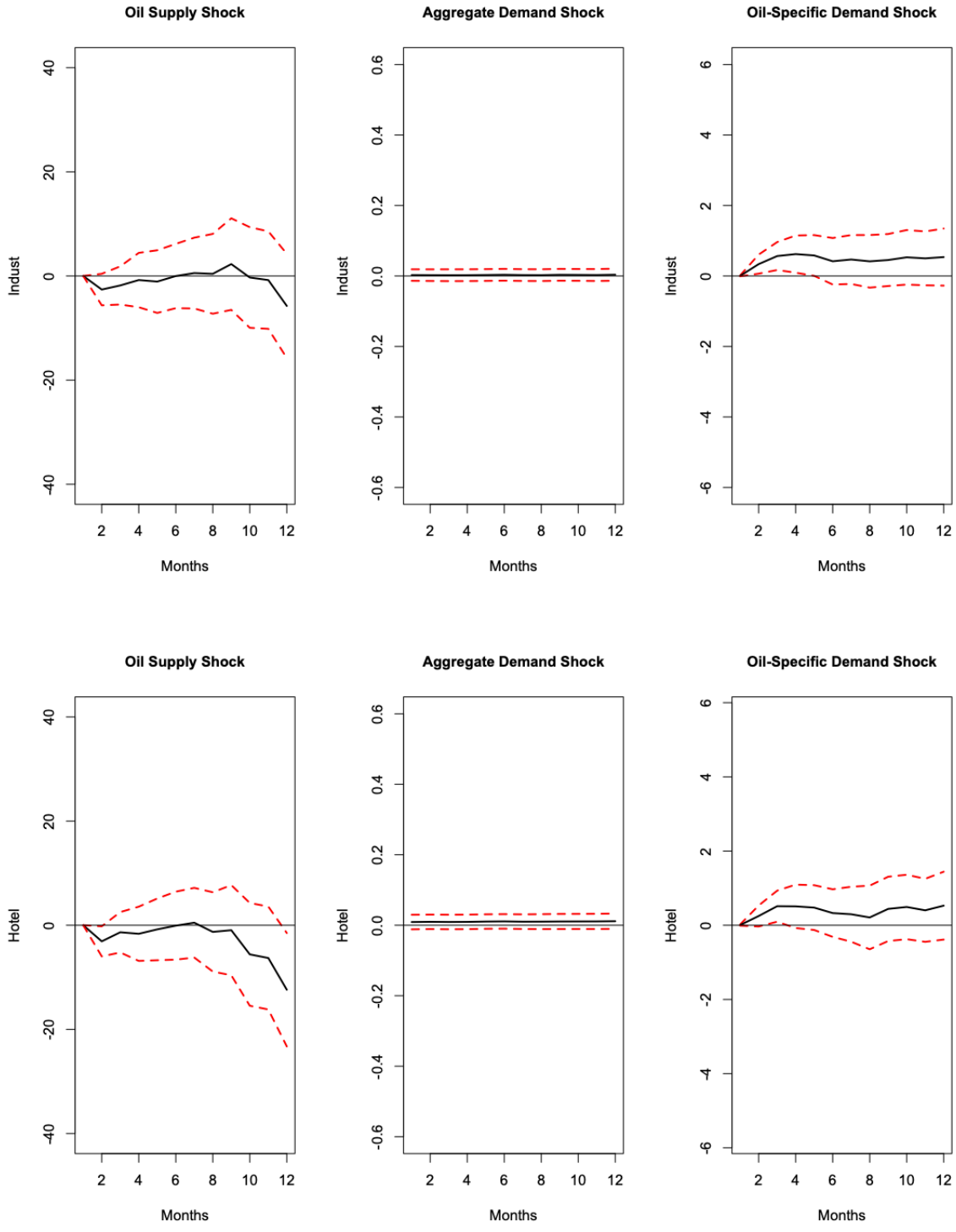


Figure 3.7 Responses of bank sector and transport sector to the three structural shocks

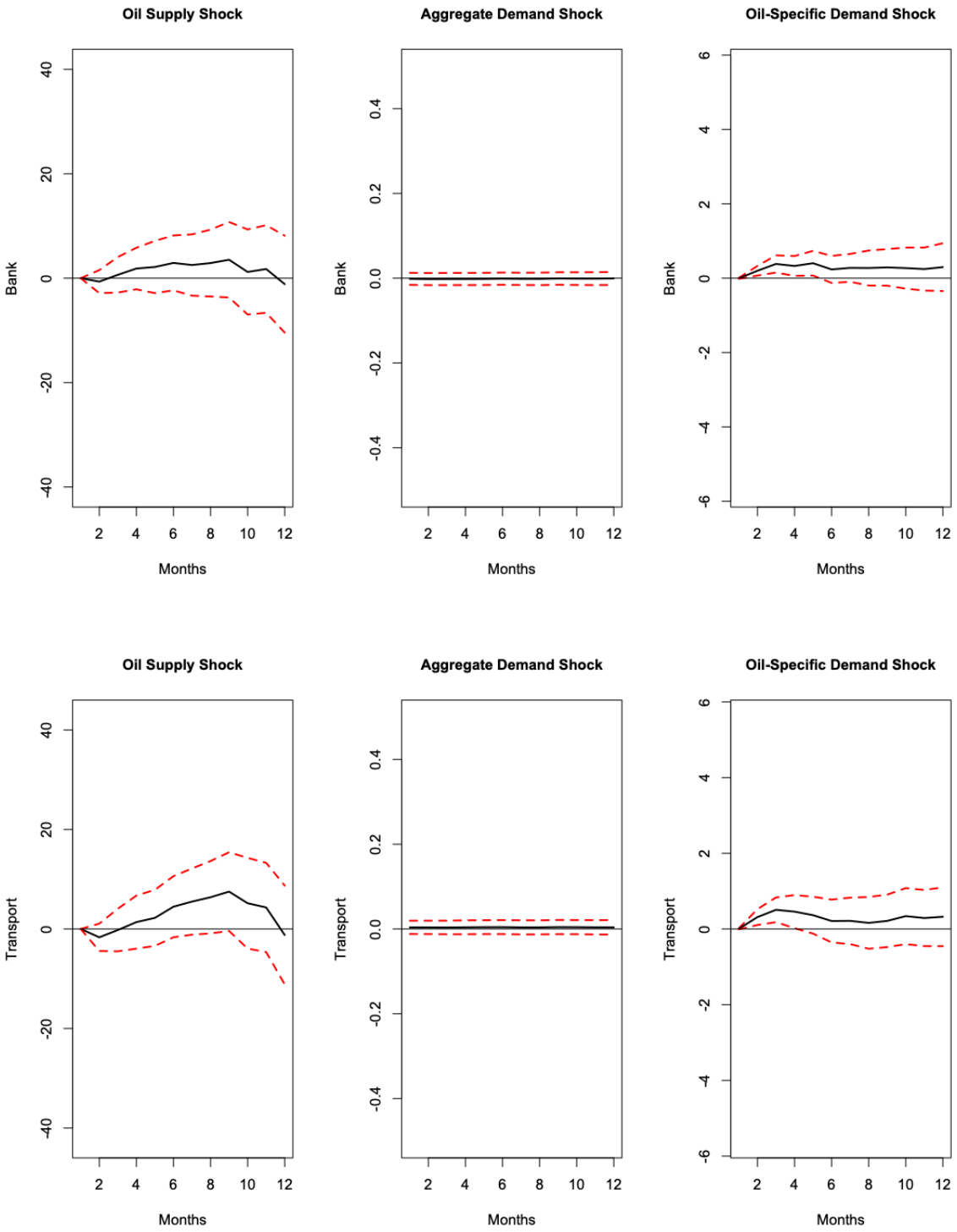


Figure 3.8 Responses of real estate development sector and agriculture sector to the three structural shocks

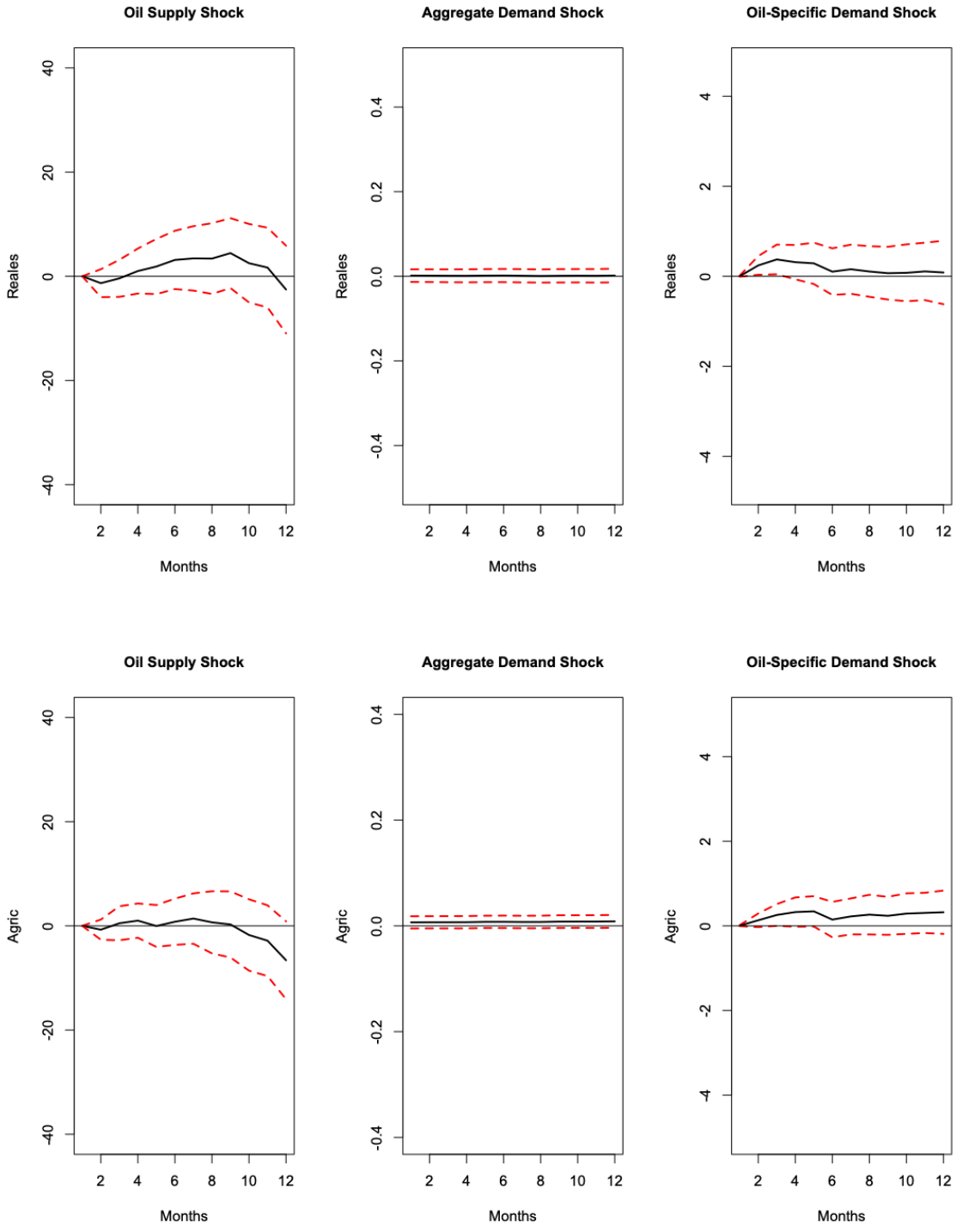


Figure 3.9 Responses of media sector to the three structural shocks

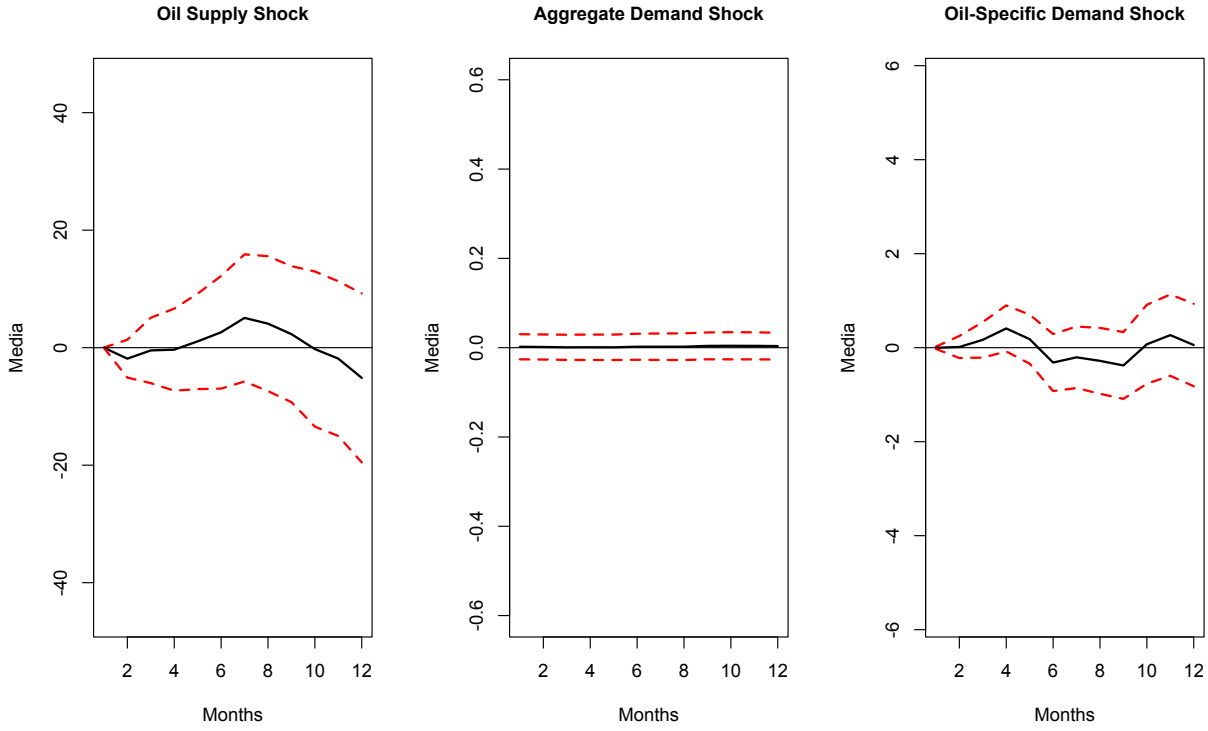


Table 3.5 Correlation Among Saudi Sectoral Stock Returns

	dCem	dPet	dRet	dBan	dIns	dTra	dMed	dRea	dAgr	dTel	dMinv	dBui	dEne	dInd	dHot
dCem	1.00	0.66	0.68	0.66	0.62	0.62	0.51	0.61	0.71	0.66	0.70	0.77	0.40	0.66	0.56
dPet	0.66	1.00	0.68	0.76	0.74	0.71	0.44	0.73	0.75	0.75	0.74	0.80	0.54	0.87	0.64
dRet	0.68	0.68	1.00	0.66	0.66	0.70	0.57	0.76	0.84	0.71	0.73	0.81	0.50	0.74	0.72
dBan	0.66	0.76	0.66	1.00	0.69	0.64	0.41	0.74	0.73	0.73	0.70	0.71	0.58	0.77	0.63
dIns	0.62	0.74	0.66	0.69	1.00	0.65	0.53	0.70	0.73	0.67	0.81	0.75	0.48	0.77	0.72
dTra	0.62	0.71	0.70	0.64	0.65	1.00	0.55	0.76	0.74	0.72	0.82	0.79	0.52	0.78	0.72
dMed	0.51	0.44	0.57	0.41	0.53	0.55	1.00	0.55	0.54	0.60	0.57	0.57	0.31	0.55	0.52
dRea	0.61	0.73	0.76	0.74	0.70	0.76	0.55	1.00	0.78	0.75	0.77	0.82	0.59	0.79	0.71
dAgr	0.71	0.75	0.84	0.73	0.73	0.74	0.54	0.78	1.00	0.75	0.78	0.82	0.53	0.76	0.73
dTel	0.66	0.75	0.71	0.73	0.67	0.72	0.60	0.75	0.75	1.00	0.71	0.72	0.49	0.73	0.61
dMinv	0.70	0.74	0.73	0.70	0.81	0.82	0.57	0.77	0.78	0.71	1.00	0.83	0.54	0.77	0.72
dBui	0.77	0.80	0.81	0.71	0.75	0.79	0.57	0.82	0.82	0.72	0.83	1.00	0.53	0.87	0.76
dEne	0.40	0.54	0.50	0.58	0.48	0.52	0.31	0.59	0.53	0.49	0.54	0.53	1.00	0.57	0.47
dInd	0.66	0.87	0.74	0.77	0.77	0.78	0.55	0.79	0.76	0.73	0.77	0.87	0.57	1.00	0.76
dHot	0.56	0.64	0.72	0.63	0.72	0.72	0.52	0.71	0.73	0.61	0.72	0.76	0.47	0.76	1.00

3.7 Conclusion

Saudi Arabia's dependence on its oil revenues means that its leaders are constantly worried about the kingdom’s economic growth. As an oil-exporting country, any drop in oil prices negatively affects cash flows and, consequently, stock prices. However, a number of researchers have noted that different types of oil price shocks have different effects on the stock market. Therefore, we considered the impact of the various oil shocks on Saudi Arabia’s stock market, which was not classified until 2018 and in which Saudi individual investors constitute more than 70% of investors, meaning their behavior may affect the nature of the market. We used Kilian’s (2009) method to study the impact of these shocks on 15 stock sectors and found that the responses differed according to the type of shock. However, the aggregate demand shocks have no effect because Saudi Arabia’s economy is small. The information presented in this essay can help the Capital Market Authority understand the impact of each structural shock on Saudi Arabia’s stock market, where there are different impacts of each oil market shock.

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Appendix

The following three tables relate to Chapter 1. Table A.1 summarizes the U.S. refineries' capacity for all types of refineries while Tables A.2 and A.3 summarizes the estimation results of the MS-AR(1) and MS-AR(2) Models.

Table A.2 U.S. Refinery Annual Crude Oil Distillation Capacity as of January 1 (Barrels per Calendar Day)

Date	Capacity
1982	17889734
1983	16859337
1984	16137141
1985	15658769
1986	15458948
1987	15565513
1988	15915418
1989	15654874
1990	15571966
1991	15675627
1992	15696155
1993	15120630
1994	15034160
1995	15434280
1996	NA
1997	15451785
1998	NA
1999	16261290
2000	16511871
2001	16595371
2002	16785391
2003	16757370
2004	16894314
2005	17124870
2006	17338814
2007	17443492
2008	17593847
2009	17671550
2010	17583790
2011	17736370

2012	17322178
2013	17823659
2014	17924630
2015	17967088
2016	18317036
2017	18617027
2018	18598497
2019	18802435
2020	18976085
2021	18127700
2022	17943810

Source: U.S. Energy Information Administration (2022)

Table A.2 Estimation Results of MS-AR (1) Model

	Regime 1		Regime 2	
	Coefficient	P-value	Coefficient	P-value
Regime intercept				
C	-0.09	0.69	0.78	0.00***
Autoregressive coefficients				
$Diff_{t-1}$	0.88	0.00***	0.70	0.00***
Residual standard error				
RSE	3.32		0.79	
R-squared				
R^2	0.78		0.55	
	Transition probability			
	Regime 1		Regime 2	
Regime 1	0.98		0.02	
Regime 2	0.02		0.98	

Table A.3 Estimation Results of MS-AR (2) Model

	Regime 1		Regime 2	
	Coefficient	P-value	Coefficient	P-value
Regime intercept				
C	-0.09	0.68	0.86	8.145e-05***
Autoregressive coefficients				
$Diff_{t-1}$	0.86	2e-16***	0.79	2.038e-11***
$Diff_{t-2}$	0.03	0.65	-0.12	0.25
Residual standard error				
RSE	3.32		0.79	
R-squared				
R^2	0.78		0.56	

Transition probability		
	Regime 1	Regime 2
Regime 1	0.98	0.02
Regime 2	0.02	0.98

The following three tables relate to Chapter 2. Tables A.4 and A.5 summarizes the parameter estimates from the reduced form VAR model with industrial production and consumer price index. The variables dWOP, dGIP, dOP, dIP, and dCIP denote that the percent change in world oil production, the global economic activity index, oil price, industrial production, and consumer price index, respectively.

Table A.4 Parameters Estimates of Reduced Form VAR Model with IP

	WOP	GIP	OP	IP
$dWOP_{t-1}$	-0.143	2.881	-0.363	0.022
	(-2.167)*	(0.806)	(-0.650)	(0.079)
$dGIP_{t-1}$	0.002	0.208	0.018	0.01
	(1.619)	(3.239)**	(1.754).	(1.981)*
dOP_{t-1}	-0.002	1.344	0.199	0.057
	(-0.245)	(3.233)**	(3.061)**	(1.778).
dIP_{t-1}	0.005	-0.183	0.055	-0.187
	(0.364)	(-0.258)	(0.495)	(-3.428)***
$dWOP_{t-2}$	-0.15	-7.258	-0.933	-0.412
	(-2.247)*	(-2.009)*	(-1.654).	(-1.484)
$dGIP_{t-2}$	0	0.253	0.014	-0.005
	(-0.035)	(3.885)***	(1.405)	(-0.908)
dOP_{t-2}	0.017	0.039	-0.03	0.087
	(2.153)*	(0.092)	(-0.455)	(2.677)**
dIP_{t-2}	-0.004	-0.045	-0.139	-0.079
	(-0.283)	(-0.062)	(-1.239)	(-1.420)
$dWOP_{t-3}$	-0.087	6.079	-0.306	-0.406
	(-1.288)	(1.666).	(-0.536)	(-1.446)
$dGIP_{t-3}$	0	0.169	0.013	0.006
	(-0.347)	(2.550)*	(1.307)	(1.252)
dOP_{t-3}	0.003	0.109	-0.065	0.028
	(0.331)	(0.253)	(-0.972)	(0.851)
dIP_{t-3}	-0.009	-0.848	-0.109	-0.05
	(-0.677)	(-1.184)	(-0.973)	(-0.903)
$dWOP_{t-4}$	-0.041	6.727	1.176	-0.949
	(-0.604)	(1.841).	(2.060)*	(-3.379)***
$dGIP_{t-4}$	0.001	0.005	-0.004	-0.008
	(0.962)	(0.074)	(-0.339)	(-1.549)
dOP_{t-4}	0.007	-0.003	-0.088	-0.023
	(0.836)	(-0.007)	(-1.303)	(-0.689)
dIP_{t-4}	0.015	-0.327	-0.115	0.035
	(1.140)	(-0.467)	(-1.050)	(0.641)
$dWOP_{t-5}$	-0.102	-8.139	-0.038	0.22
	(-1.473)	(-2.158)*	(-0.064)	(0.759)
$dGIP_{t-5}$	-0.001	-0.002	0.001	-0.002
	(-0.866)	(-0.023)	(0.078)	(-0.429)
dOP_{t-5}	0.005	-0.686	-0.023	0.003
	(0.652)	(-1.604)	(-0.338)	(0.093)
dIP_{t-5}	-0.024	-0.131	-0.127	0.007
	(-1.884).	(-0.192)	(-1.195)	(0.139)

	WOP	GIP	OP	IP
$dWOP_{t-6}$	-0.12	-2.222	-0.106	-0.335
	(-1.710).	(-0.586)	(-0.178)	(-1.150)
$dGIP_{t-6}$	0.002	0.06	0.007	0.004
	(1.836).	(0.899)	(0.631)	(0.824)
dOP_{t-6}	0.007	-0.597	-0.101	0.048
	(0.874)	(-1.397)	(-1.511)	(1.456)
dIP_{t-6}	0.012	0.065	-0.202	-0.075
	(0.989)	(0.096)	(-1.903).	(-1.434)
$dWOP_{t-7}$	-0.169	-1.162	0.325	-0.302
	(-2.441)*	(-0.309)	(0.553)	(-1.044)
$dGIP_{t-7}$	0	0.041	0.01	0.006
	(-0.184)	(0.613)	(0.983)	(1.253)
dOP_{t-7}	-0.007	-0.369	-0.007	0.017
	(-0.898)	(-0.862)	(-0.100)	(0.511)
dIP_{t-7}	0.017	-0.402	-0.217	-0.062
	(1.324)	(-0.593)	(-2.044)*	(-1.190)
$dWOP_{t-8}$	-0.005	-4.979	-0.046	0.641
	(-0.078)	(-1.336)	(-0.078)	(2.237)*
$dGIP_{t-8}$	-0.001	0.02	-0.019	-0.004
	(-0.963)	(0.293)	(-1.833).	(-0.694)
dOP_{t-8}	0.007	-0.286	0.025	0.049
	(0.939)	(-0.669)	(0.382)	(1.495)
dIP_{t-8}	-0.02	0.605	-0.086	-0.095
	(-1.579)	(0.886)	(-0.810)	(-1.800).
$dWOP_{t-9}$	-0.051	-1.05	-0.876	0.18
	(-0.739)	(-0.281)	(-1.499)	(0.625)
$dGIP_{t-9}$	0	0.036	0	-0.004
	(0.040)	(0.533)	(-0.033)	(-0.810)
dOP_{t-9}	0	-0.322	-0.044	0.047
	(0.006)	(-0.763)	(-0.659)	(1.445)
dIP_{t-9}	-0.01	0.224	0.146	-0.029
	(-0.818)	(0.333)	(1.393)	(-0.559)
$dWOP_{t-10}$	-0.014	0.282	-0.311	-0.236
	(-0.198)	(0.075)	(-0.532)	(-0.822)
$dGIP_{t-10}$	-0.001	-0.174	-0.018	-0.003
	(-0.893)	(-2.689)**	(-1.742).	(-0.535)
dOP_{t-10}	0.013	0.048	0.095	0.043
	(1.711).	(0.113)	(1.440)	(1.326)
dIP_{t-10}	0	-0.683	0.113	0.029
	(0.000)	(-1.024)	(1.086)	(0.557)

	WOP	GIP	OP	IP
$dWOP_{t-11}$	0.015	-4.047	-0.306	-0.258
	(0.218)	(-1.093)	(-0.529)	(-0.907)
$dGIP_{t-11}$	0.001	0.012	0.004	0.004
	(0.952)	(0.190)	(0.373)	(0.727)
dOP_{t-11}	0	-0.003	0.102	-0.024
	(0.038)	(-0.008)	(1.562)	(-0.745)
dIP_{t-11}	0	-0.937	-0.189	-0.173
	(-0.003)	(-1.417)	(-1.831).	(-3.393)***
$dWOP_{t-12}$	0.03	1.87	0.87	-0.75
	(0.454)	(0.517)	(1.539)	(-2.697)**
$dGIP_{t-12}$	0	0.036	0.003	0.003
	(-0.326)	(0.585)	(0.351)	(0.700)
dOP_{t-12}	0.013	-0.236	-0.006	0.04
	(1.644)	(-0.570)	(-0.096)	(1.255)
dIP_{t-12}	0.01	0.142	0.007	0.478
	(0.823)	(0.212)	(0.064)	(9.278)2e-16 ***
constant	0.001	0.061	0.005	0.001
	(1.737).	(1.915).	(0.913)	(0.451)
R2	0.2309	0.432	0.2835	0.6226
F statistic	1.576	3.992	2.078	8.663

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A.5 Parameters Estimates of Reduced Form VAR Model with CPI

	dWOP	dGIP	dOP	dCPI
$dWOP_{t-1}$	-0.18	2.667	-0.128	0.01
	(-2.944)**	(0.837)	(-0.245)	(0.264)
$dGIP_{t-1}$	0.002	0.204	0.018	0
	(1.610)	(3.211)**	(1.711).	(0.223)
dOP_{t-1}	0	1.155	0.231	0.002
	(-0.029)	(2.942)**	(3.600)***	(0.371)
$dCPI_{t-1}$	0.095	-4.22	0.433	0.073
	(0.912)	(-0.776)	(0.487)	(1.164)
$dWOP_{t-2}$	-0.163	-5.285	-1.234	0.024
	(-2.647)**	(-1.645)	(-2.350)*	(0.640)
$dGIP_{t-2}$	0.001	0.241	0.014	0
	(0.560)	(3.748)***	(1.283)	(0.227)
dOP_{t-2}	0.019	0.222	-0.079	0
	(2.512)*	(0.553)	(-1.209)	(0.045)
$dCPI_{t-2}$	-0.185	-6.933	-0.949	0.045
	(-1.797).	(-1.292)	(-1.083)	(0.736)
$dWOP_{t-3}$	-0.097	3.925	-0.119	0.027
	(-1.539)	(1.196)	(-0.222)	(0.708)
$dGIP_{t-3}$	-0.001	0.153	0.014	0
	(-0.568)	(2.364)*	(1.326)	(-0.141)
dOP_{t-3}	0.003	-0.069	-0.057	0.002
	(0.353)	(-0.170)	(-0.859)	(0.474)
$dCPI_{t-3}$	0.037	-0.705	1.18	0.08
	(0.358)	(-0.130)	(1.337)	(1.292)
$dWOP_{t-4}$	-0.03	6.487	0.807	0.009
	(-0.477)	(2.000)*	(1.523)	(0.251)
$dGIP_{t-4}$	0.001	-0.007	0	0
	(0.558)	(-0.115)	(-0.026)	(-0.134)
dOP_{t-4}	0.007	0.169	-0.098	0.006
	(0.941)	(0.420)	(-1.482)	(1.351)
$dCPI_{t-4}$	-0.051	3.995	-1.546	0.085
	(-0.487)	(0.739)	(-1.752).	(1.369)
$dWOP_{t-5}$	-0.135	-8.089	-0.428	0.025
	(-2.167)*	(-2.496)*	(-0.808)	(0.666)
$dGIP_{t-5}$	-0.001	-0.002	0.001	0
	(-0.545)	(-0.033)	(0.114)	(-0.036)
dOP_{t-5}	0	-0.756	-0.063	0
	(-0.024)	(-1.870).	(-0.948)	(0.050)
$dCPI_{t-5}$	-0.111	-9.855	0.61	0.049
	(-1.056)	(-1.805).	(0.683)	(0.786)

	dWOP	dGIP	dOP	dCPI
$dWOP_{t-6}$	-0.099	-1.15	0.085	-0.021
	(-1.567)	(-0.349)	(0.158)	(-0.557)
$dGIP_{t-6}$	0.002	0.067	0.006	0
	(1.671).	(1.028)	(0.524)	(0.077)
dOP_{t-6}	0.014	-0.595	-0.131	0.004
	(1.785).	(-1.465)	(-1.973)*	(0.934)
$dCPI_{t-6}$	0.02	5.824	0.617	0.098
	(0.192)	(1.066)	(0.691)	(1.551)
$dWOP_{t-7}$	-0.111	-1.583	-0.317	-0.073
	(-1.787).	(-0.488)	(-0.597)	(-1.959).
$dGIP_{t-7}$	0	0.03	0.01	-0.001
	(0.027)	(0.463)	(0.906)	(-0.778)
dOP_{t-7}	-0.007	-0.325	-0.048	0
	(-0.836)	(-0.790)	(-0.721)	(-0.030)
$dCPI_{t-7}$	-0.06	2.364	0.145	0.018
	(-0.572)	(0.433)	(0.162)	(0.287)
$dWOP_{t-8}$	-0.04	-5.486	-0.088	-0.02
	(-0.638)	(-1.670).	(-0.165)	(-0.521)
$dGIP_{t-8}$	-0.001	0.009	-0.015	0
	(-1.071)	(0.138)	(-1.445)	(0.179)
dOP_{t-8}	0.006	-0.226	0.031	-0.001
	(0.763)	(-0.551)	(0.461)	(-0.123)
$dCPI_{t-8}$	-0.029	0.559	0.917	0.039
	(-0.279)	(0.103)	(1.030)	(0.629)
$dWOP_{t-9}$	-0.023	-1.52	-0.45	-0.059
	(-0.364)	(-0.463)	(-0.838)	(-1.550)
$dGIP_{t-9}$	0	0.029	-0.004	0
	(-0.197)	(0.452)	(-0.372)	(0.212)
dOP_{t-9}	0.002	-0.133	-0.046	0.004
	(0.320)	(-0.329)	(-0.695)	(0.819)
$dCPI_{t-9}$	-0.024	-11.279	-1.094	-0.001
	(-0.226)	(-2.082)*	(-1.235)	(-0.016)
$dWOP_{t-10}$	-0.012	-1.458	0.186	-0.052
	(-0.187)	(-0.449)	(0.350)	(-1.402)
$dGIP_{t-10}$	-0.001	-0.168	-0.021	0.001
	(-0.559)	(-2.698)**	(-2.045)*	(0.796)
dOP_{t-10}	0.012	-0.153	0.107	-0.003
	(1.543)	(-0.381)	(1.628)	(-0.540)
$dCPI_{t-10}$	0.023	-10.583	-0.657	0.008
	(0.215)	(-1.939).	(-0.737)	(0.133)

	dWOP	dGIP	dOP	dCPI
$dWOP_{t-11}$	-0.004	-6.663	-0.604	-0.014
	(-0.062)	(-2.101)*	(-1.165)	(-0.389)
$dGIP_{t-11}$	0.001	0.027	0.007	-0.001
	(0.822)	(0.432)	(0.674)	(-0.720)
dOP_{t-11}	0	0.016	0.086	0.001
	(0.051)	(0.039)	(1.329)	(0.222)
$dCPI_{t-11}$	0.225	8.196	-0.814	0.036
	(2.138)*	(1.499)	(-0.911)	(0.572)
$dWOP_{t-12}$	0.119	-0.419	0.69	0.045
	(1.959).	(-0.133)	(1.339)	(1.248)
$dGIP_{t-12}$	0	0.035	0.001	0
	(-0.206)	(0.589)	(0.069)	(0.247)
dOP_{t-12}	0.012	-0.392	-0.008	0.004
	(1.620)	(-0.992)	(-0.124)	(0.830)
$dCPI_{t-12}$	0.083	-6.577	0.507	0.025
	(0.786)	(-1.192)	(0.563)	(0.401)
constant	0.001	0.119	0.005	0.001
	(1.087)	(3.004)**	(0.834)	(1.610)
R2	0.2077	0.4627	0.2581	0.1427
F statistic	1.376	4.521	1.827	0.874

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The following tables relate to Chapter 3. They summarize the parameter estimates of the reduced form VAR model with all shock sectors. The variables dWOP, dGIP, dOP, dCem, dPet, dRet, dBan, dIns, dTra, dMed, dRea, dAgr, dTel, dMinv, dBui, dEne, d Ind, and dHot denote the percent change in world oil production, the global economic activity index, oil price, cement sector, petrochemical industry sector, retail sector, bank sector, insurance sector, transport sector, media sector, real estate development sector, agriculture sector, telecom sector, multi-investment sector, building sector, energy sector, industrial investment sector, and hotel sector, respectively.

Table A. 6 Parameters Estimates of Reduced Form VAR Model with Cement Sector

	dWOP	dGIP	dOP	dCem
$dWOP_{t-1}$	0.08	48.5	-0.986	0.066
	(0.557)	(0.094)	(-0.553)	(0.050)
$dGIP_{t-1}$	0	-0.04	0.001	0
	(-1.367)	(-0.267)	(1.356)	(-0.874)
dOP_{t-1}	0.016	69.69	0.059	0.119
	(1.338)	(1.623)	(0.396)	(1.074)
$dCem_{t-1}$	-0.033	91.24	0.88	-0.046
	(-2.030)*	(1.589)	(4.431)***	(-0.308)
$dWOP_{t-2}$	-0.239	-735.2	-0.066	-2.378
	(-1.627)	(-1.399)	(-0.037)	(-1.757).
$dGIP_{t-2}$	0	0.065	0.001	0
	(-2.072)*	(0.428)	(1.174)	(0.682)
dOP_{t-2}	-0.01	-36.78	-0.028	0.01
	(-0.855)	(-0.852)	(-0.190)	(0.088)
$dCem_{t-2}$	-0.008	19.51	-0.081	0.082
	(-0.387)	(0.281)	(-0.337)	(0.457)
$dWOP_{t-3}$	-0.288	77.31	4.837	-0.67
	(-1.854).	(0.139)	(2.519)*	(-0.469)
$dGIP_{t-3}$	0	-0.243	0	0
	(0.363)	(-1.568)	(-0.165)	(0.231)
dOP_{t-3}	0.017	56.16	-0.096	0.019
	(1.391)	(1.315)	(-0.652)	(0.177)
$dCem_{t-3}$	0.015	14.15	-0.345	-0.087
	(0.842)	(0.216)	(-1.521)	(-0.516)
$dWOP_{t-4}$	-0.054	139.9	-0.727	0.067
	(-0.335)	(0.244)	(-0.366)	(0.046)

$dGIP_{t-4}$	0	-0.089	0.001	0
	(-1.514)	(-0.563)	(1.441)	(0.136)
dOP_{t-4}	0.002	3.5	-0.047	-0.239
	(0.181)	(0.084)	(-0.330)	(-2.238)*
$dCem_{t-4}$	-0.004	-36.77	0.063	-0.063
	(-0.236)	(-0.609)	(0.301)	(-0.408)
$dWOP_{t-5}$	-0.232	765.8	0.734	0.37
	(-1.492)	(1.377)	(0.381)	(0.258)
$dGIP_{t-5}$	0	-0.01	0.001	0
	(0.565)	(-0.062)	(1.796).	(-0.958)
dOP_{t-5}	-0.013	57.49	0.315	0.174
	(-1.054)	(1.322)	(2.092)*	(1.553)
$dCem_{t-5}$	0.006	47.66	-0.322	0.242
	(0.337)	(0.803)	(-1.567)	(1.581)
$dWOP_{t-6}$	-0.137	-1056	0.131	1.559
	(-0.964)	(-2.076)*	(0.074)	(1.191)
$dGIP_{t-6}$	0	-0.051	0	0
	(-0.051)	(-0.314)	(-0.102)	(0.431)
dOP_{t-6}	0.006	-15.47	-0.347	0.068
	(0.473)	(-0.334)	(-2.164)*	(0.567)
$dCem_{t-6}$	0.023	-72.28	-0.139	-0.139
	(1.350)	(-1.199)	(-0.666)	(-0.895)
$dWOP_{t-7}$	-0.015	-179	-2.093	-2.528
	(-0.110)	(-0.357)	(-1.205)	(-1.955).
$dGIP_{t-7}$	0	-0.154	0.001	0.001
	(-1.789).	(-0.946)	(1.894).	(2.181)*
dOP_{t-7}	0.008	61.23	-0.135	-0.186
	(0.590)	(1.339)	(-0.852)	(-1.577)
$dCem_{t-7}$	0.008	-40.89	0.244	-0.071
	(0.458)	(-0.676)	(1.165)	(-0.459)
$dWOP_{t-8}$	-0.226	-182.4	1.753	-1.282
	(-1.561)	(-0.351)	(0.976)	(-0.959)
$dGIP_{t-8}$	0	-0.232	-0.001	0
	(0.700)	(-1.327)	(-1.869).	(0.271)
dOP_{t-8}	-0.006	-62.97	0.167	0.024
	(-0.439)	(-1.399)	(1.072)	(0.205)
$dWOP_{t-9}$	-0.247	-37.58	1.889	-1.053
	(-1.751).	(-0.074)	(1.081)	(-0.810)

$dGIP_{t-9}$	0	0.073	0	0
	(-1.216)	(0.403)	(-0.351)	(-0.409)
dOP_{t-9}	0.009	43.4	-0.093	0.139
	(0.726)	(0.988)	(-0.610)	(1.230)
$dCem_{t-9}$	-0.008	32.75	-0.116	0.177
	(-0.527)	(0.577)	(-0.588)	(1.213)
$dWOP_{t-10}$	-0.195	213	-0.318	-2.924
	(-1.379)	(0.421)	(-0.182)	(-2.243)*
$dGIP_{t-10}$	0	-0.218	0.001	0
	(-1.977).	(-1.240)	(1.220)	(1.025)
dOP_{t-10}	0.003	21.36	-0.109	-0.118
	(0.235)	(0.475)	(-0.700)	(-1.020)
$dCem_{t-10}$	0.013	-49.04	-0.169	0.113
	(0.807)	(-0.852)	(-0.851)	(0.763)
$dWOP_{t-11}$	-0.181	679.8	0.501	-1.773
	(-1.339)	(1.409)	(0.300)	(-1.428)
$dGIP_{t-11}$	0	-0.211	0.001	0
	(-0.748)	(-1.137)	(0.964)	(-0.390)
dOP_{t-11}	-0.016	29.89	0.166	0.011
	(-1.234)	(0.656)	(1.050)	(0.091)
$dCem_{t-11}$	0.009	-38.4	-0.109	-0.116
	(0.555)	(-0.670)	(-0.549)	(-0.788)
$dWOP_{t-12}$	0.022	429	-0.027	-0.43
	(0.177)	(0.958)	(-0.017)	(-0.373)
$dGIP_{t-12}$	0	-0.089	0.001	0
	(-0.801)	(-0.469)	(2.101)*	(-0.030)
dOP_{t-12}	0.021	-2.616	0.057	0.158
	(1.915).	(-0.066)	(0.411)	(1.542)
$dCem_{t-12}$	0.004	6.364	-0.119	0.043
	(0.240)	(0.109)	(-0.588)	(0.284)
constant	0.002	-3.443	0.003	0.017
	(2.544)*	(-1.091)	(0.253)	(2.101)*
Observations	95	95	95	95
R2	0.5546	0.4102	0.6341	0.616
F statistic	1.193	0.6666	1.661	1.537

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 7 Parameters Estimates of Reduced Form VAR Model with Petrochemical Industry Sector

	dWOP	dGIP	dOP	dPet
$dWOP_{t-1}$	0.008	222.513	1.24	-0.102
	(0.057)	(0.432)	(0.706)	(-0.069)
$dGIP_{t-1}$	0	-0.231	0.001	0
	(-0.737)	(-1.602)	(1.283)	(-0.801)
dOP_{t-1}	0.003	140.529	0.074	0.249
	(0.249)	(3.076)**	(0.476)	(1.908).
$dPet_{t-1}$	0.012	-35.338	0.633	0.242
	(0.750)	(-0.655)	(3.444)**	(1.569)
$dWOP_{t-2}$	-0.204	-344.973	-2.977	-2.425
	(-1.394)	(-0.680)	(-1.723).	(-1.672)
$dGIP_{t-2}$	0	-0.089	0.001	0
	(-0.990)	(-0.618)	(1.334)	(1.004)
dOP_{t-2}	-0.02	-14.614	-0.299	-0.03
	(-1.509)	(-0.314)	(-1.888).	(-0.227)
$dPet_{t-2}$	0.02	8.011	-0.196	-0.317
	(1.393)	(0.159)	(-1.145)	(-2.203)*
$dWOP_{t-3}$	-0.173	229.866	5.956	2.841
	(-1.102)	(0.423)	(3.219)**	(1.829).
$dGIP_{t-3}$	0	-0.211	0	0
	(0.450)	(-1.548)	(0.342)	(0.798)
dOP_{t-3}	0.001	48.696	-0.115	-0.085
	(0.100)	(1.039)	(-0.721)	(-0.632)
$dPet_{t-3}$	0.01	25.165	0.262	0.116
	(0.729)	(0.549)	(1.677)	(0.883)
$dWOP_{t-4}$	0.045	-30.271	-3.473	-2.832
	(0.302)	(-0.059)	(-1.973).	(-1.916).
$dGIP_{t-4}$	0	-0.04	0.001	0.001
	(-1.926).	(-0.278)	(1.195)	(1.276)
dOP_{t-4}	0.005	41.617	-0.227	-0.177
	(0.379)	(0.902)	(-1.444)	(-1.342)
$dPet_{t-4}$	0.013	-24.37	-0.072	-0.048
	(0.939)	(-0.519)	(-0.449)	(-0.359)
$dWOP_{t-5}$	-0.29	1079.519	2.924	1.55
	(-1.967).	(2.116)*	(1.681).	(1.062)

$dGIP_{t-5}$	0	-0.111	0.001	0
	(0.355)	(-0.748)	(2.641)*	(-0.858)
dOP_{t-5}	0	76.922	0.095	0.182
	(0.034)	(1.616)	(0.587)	(1.337)
$dPet_{t-5}$	-0.006	-18.611	0.156	0.218
	(-0.462)	(-0.422)	(1.040)	(1.729).
$dWOP_{t-6}$	-0.179	-355.122	-0.001	0.845
	(-1.253)	(-0.718)	(-0.001)	(0.597)
$dGIP_{t-6}$	0	-0.29	0	0
	(0.483)	(-1.774).	(-0.431)	(-0.558)
dOP_{t-6}	-0.001	54.016	-0.379	-0.027
	(-0.083)	(1.160)	(-2.389)*	(-0.201)
$dPet_{t-6}$	-0.005	-57.754	0.026	-0.254
	(-0.405)	(-1.330)	(0.178)	(-2.042)*
$dWOP_{t-7}$	-0.105	287.225	-1.763	-1.905
	(-0.746)	(0.588)	(-1.058)	(-1.363)
$dGIP_{t-7}$	0	-0.163	0.001	0.001
	(-1.686).	(-1.014)	(2.647)*	(2.986)**
dOP_{t-7}	-0.008	161.409	0.115	0.012
	(-0.558)	(3.360)**	(0.702)	(0.086)
$dPet_{t-7}$	0.025	-112.849	-0.059	0.013
	(1.918).	(-2.491)*	(-0.382)	(0.099)
$dWOP_{t-8}$	-0.175	-147.721	1.044	0.054
	(-1.216)	(-0.296)	(0.614)	(0.038)
$dGIP_{t-8}$	0	-0.292	-0.001	-0.001
	(0.214)	(-1.710).	(-1.474)	(-2.982)**
dOP_{t-8}	-0.007	16.71	-0.109	0.077
	(-0.481)	(0.350)	(-0.673)	(0.567)
$dPet_{t-8}$	0.011	-76.638	-0.061	-0.142
	(0.787)	(-1.644)	(-0.382)	(-1.067)
$dWOP_{t-9}$	-0.219	184.956	1.714	0.137
	(-1.609)	(0.393)	(1.068)	(0.102)
$dGIP_{t-9}$	0	-0.084	0	0.001
	(-0.781)	(-0.456)	(0.596)	(1.198)
dOP_{t-9}	-0.006	113.942	0.113	-0.052
	(-0.467)	(2.465)*	(0.719)	(-0.393)
$dPet_{t-9}$	0.022	-86.866	0.105	0.249
	(1.648)	(-1.864).	(0.659)	(1.865)

$dWOP_{t-10}$	-0.206	104.788	-1.608	-5.209
	(-1.565)	(0.229)	(-1.033)	(-3.985)***
$dGIP_{t-10}$	0	-0.257	0.001	0.001
	(-1.468)	(-1.544)	(0.955)	(1.146)
dOP_{t-10}	-0.007	106.94	0.031	0.004
	(-0.539)	(2.390)*	(0.206)	(0.034)
$dPet_{t-10}$	0.008	-108.823	-0.496	-0.315
	(0.526)	(-2.160)*	(-2.886)**	(-2.185)*
$dWOP_{t-11}$	-0.067	556.05	2.139	-0.644
	(-0.451)	(1.081)	(1.221)	(-0.438)
$dGIP_{t-11}$	0	-0.292	0	-0.001
	(-1.483)	(-1.623)	(0.666)	(-2.148)*
dOP_{t-11}	-0.015	87.837	0.135	0.21
	(-1.133)	(1.981).	(0.895)	(1.655)
$dPet_{t-11}$	0.008	-53.562	0.26	0.068
	(0.665)	(-1.255)	(1.788).	(0.558)
$dWOP_{t-12}$	0.19	553.81	-1.099	-1.484
	(1.488)	(1.249)	(-0.727)	(-1.169)
$dGIP_{t-12}$	0	-0.296	0.001	0
	(-0.223)	(-1.508)	(1.755).	(0.722)
dOP_{t-12}	0.009	39.995	0.156	0.111
	(0.826)	(1.034)	(1.179)	(1.006)
$dPet_{t-12}$	0.011	-65.151	-0.424	-0.158
	(0.890)	(-1.554)	(-2.970)**	(-1.321)
constant	0.002	-5.337	0.004	0.016
	(1.895).	(-1.714).	(0.366)	(1.843).
Observations	95	95	95	95
R2	0.5732	0.4701	0.6809	0.7046
F statistic	1.287	0.8502	2.045	2.286

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 8 Parameters Estimates of Reduced Form VAR Model with Retail Sector

	dWOP	dGIP	dOP	dRet
$dWOP_{t-1}$	0	411.9	1.369	0.094
	(0.002)	(0.792)	(0.686)	(0.073)
$dGIP_{t-1}$	0	-0.191	0	0
	(-1.219)	(-1.321)	(0.372)	(-0.336)
dOP_{t-1}	0.016	125.5	0.195	0.182
	(1.225)	(2.724)**	(1.102)	(1.601)
$dRet_{t-1}$	0	-16.54	0.191	0.086
	(0.021)	(-0.279)	(0.843)	(0.591)
$dWOP_{t-2}$	-0.223	-355	-2.002	-1.983
	(-1.557)	(-0.700)	(-1.029)	(-1.583)
$dGIP_{t-2}$	0	-0.006	0	0
	(-1.804).	(-0.045)	(0.521)	(0.794)
dOP_{t-2}	-0.017	-0.645	-0.06	0.006
	(-1.145)	(-0.013)	(-0.306)	(0.051)
$dRet_{t-2}$	-0.008	23.06	-0.316	0.12
	(-0.503)	(0.401)	(-1.431)	(0.841)
$dWOP_{t-3}$	-0.162	186.3	4.431	1.462
	(-0.963)	(0.312)	(1.933).	(0.991)
$dGIP_{t-3}$	0	-0.154	0	0
	(0.049)	(-1.100)	(0.654)	(0.176)
dOP_{t-3}	0.017	8.739	-0.097	-0.049
	(1.431)	(0.206)	(-0.597)	(-0.467)
$dRet_{t-3}$	0.007	92.51	0.251	-0.091
	(0.487)	(1.711).	(1.210)	(-0.684)
$dWOP_{t-4}$	-0.127	433.5	-0.87	-0.672
	(-0.795)	(0.765)	(-0.400)	(-0.480)
$dGIP_{t-4}$	0	-0.061	0.001	0
	(-1.968).	(-0.426)	(0.995)	(0.122)
dOP_{t-4}	0.002	28.76	-0.143	-0.153
	(0.223)	(0.736)	(-0.953)	(-1.586)
$dRet_{t-4}$	0.004	-14.1	-0.129	0.035
	(0.258)	(-0.247)	(-0.590)	(0.251)
$dWOP_{t-5}$	-0.174	954.1	2.313	-0.087
	(-1.138)	(1.760).	(1.112)	(-0.065)
$dGIP_{t-5}$	0	-0.046	0.001	0
	(0.133)	(-0.309)	(2.479)*	(-0.352)

dOP_{t-5}	-0.001	36.02	0.1	0.077
	(-0.062)	(0.906)	(0.654)	(0.788)
$dRet_{t-5}$	0.008	-32.15	0.008	0.27
	(0.497)	(-0.574)	(0.037)	(1.955).
$dWOP_{t-6}$	-0.175	-479.2	1.403	0.058
	(-1.249)	(-0.966)	(0.737)	(0.048)
$dGIP_{t-6}$	0	-0.186	0	0
	(0.106)	(-1.189)	(-0.810)	(-1.114)
dOP_{t-6}	0.001	-14.84	-0.316	-0.023
	(0.096)	(-0.385)	(-2.137)*	(-0.247)
$dRet_{t-6}$	0.001	-10.2	0.195	0.072
	(0.095)	(-0.188)	(0.937)	(0.541)
$dWOP_{t-7}$	-0.008	77.09	-0.273	-1.933
	(-0.055)	(0.153)	(-0.141)	(-1.555)
$dGIP_{t-7}$	0	-0.103	0.001	0.001
	(-1.599)	(-0.616)	(1.759).	(1.536)
dOP_{t-7}	0.009	98.12	0.135	-0.002
	(0.766)	(2.443)*	(0.874)	(-0.019)
$dRet_{t-7}$	0.036	-97.27	-0.37	-0.141
	(2.237)*	(-1.715).	(-1.703).	(-1.007)
$dWOP_{t-8}$	-0.155	-350.5	-0.594	-0.211
	(-1.052)	(-0.671)	(-0.297)	(-0.163)
$dGIP_{t-8}$	0	-0.104	0	0
	(-0.561)	(-0.613)	(-0.472)	(-0.586)
dOP_{t-8}	-0.001	-41.69	-0.113	0.139
	(-0.089)	(-1.030)	(-0.725)	(1.387)
$dRet_{t-8}$	0.012	-72.02	-0.166	0.023
	(0.661)	(-1.153)	(-0.693)	(0.152)
$dWOP_{t-9}$	-0.15	248.9	2.15	0.21
	(-1.093)	(0.512)	(1.152)	(0.175)
$dGIP_{t-9}$	0	0.096	0	0
	(-0.918)	(0.563)	(-0.313)	(-0.470)
dOP_{t-9}	0.015	8.099	0.063	0.034
	(1.302)	(0.201)	(0.408)	(0.342)
$dRet_{t-9}$	-0.002	23.71	-0.025	0.258
	(-0.125)	(0.415)	(-0.112)	(1.832).
$dWOP_{t-10}$	-0.173	120.8	-1.862	-3.236
	(-1.356)	(0.267)	(-1.073)	(-2.896)**

$dGIP_{t-10}$	0	-0.104	0.001	0.001
	(-2.123)*	(-0.627)	(1.529)	(1.497)
dOP_{t-10}	0.001	42.49	-0.063	-0.069
	(0.095)	(1.110)	(-0.429)	(-0.728)
$dRet_{t-10}$	-0.012	-24.97	-0.251	-0.171
	(-0.673)	(-0.387)	(-1.015)	(-1.071)
$dWOP_{t-11}$	-0.056	521.8	-0.502	-1.773
	(-0.422)	(1.119)	(-0.281)	(-1.539)
$dGIP_{t-11}$	0	-0.138	0.001	0
	(-1.695).	(-0.718)	(1.371)	(-0.372)
dOP_{t-11}	-0.002	27.97	0.036	-0.018
	(-0.160)	(0.726)	(0.243)	(-0.193)
$dRet_{t-11}$	0.002	-62.05	0.141	0.012
	(0.159)	(-1.163)	(0.689)	(0.087)
$dWOP_{t-12}$	0.063	544.8	-1.01	0.342
	(0.501)	(1.224)	(-0.591)	(0.311)
$dGIP_{t-12}$	0	-0.196	0.001	0
	(-0.768)	(-1.064)	(1.019)	(0.150)
dOP_{t-12}	0.019	-18.8	0.096	0.182
	(1.909).	(-0.538)	(0.719)	(2.106)*
$dRet_{t-12}$	-0.02	0.125	-0.357	0.012
	(-1.111)	(0.002)	(-1.486)	(0.079)
constant	0.002	-3.088	0.015	0.016
	(1.777).	(-1.025)	(1.295)	(2.161)*
Observations	95	95	95	95
R2	0.564	0.4333	0.5679	0.6149
F statistic	1.24	0.7326	1.26	1.531

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 9 Parameters Estimates of Reduced Form VAR Model with Bank Sector

	dWOP	dGIP	dOP	dBan
$dWOP_{t-1}$	0.061	208.4	-0.581	0.262
	(0.411)	(0.393)	(-0.284)	(0.177)
$dGIP_{t-1}$	0	-0.162	0.001	0
	(-1.138)	(-1.059)	(1.389)	(0.131)
dOP_{t-1}	0.016	94.4	-0.022	0.236
	(1.381)	(2.252)*	(-0.134)	(2.014)*
$dBan_{t-1}$	0.003	21.56	0.537	0.019
	(0.217)	(0.400)	(2.584)*	(0.124)
$dWOP_{t-2}$	-0.151	-404	-2.24	-0.196
	(-1.013)	(-0.763)	(-1.098)	(-0.132)
$dGIP_{t-2}$	0	-0.007	0	0
	(-2.027)*	(-0.049)	(0.637)	(-0.381)
dOP_{t-2}	-0.016	-35.89	-0.094	-0.122
	(-1.261)	(-0.808)	(-0.549)	(-0.982)
$dBan_{t-2}$	-0.021	31.31	0.099	-0.281
	(-1.387)	(0.586)	(0.479)	(-1.882).
$dWOP_{t-3}$	-0.182	-45.77	2.97	1.756
	(-1.223)	(-0.087)	(1.458)	(1.190)
$dGIP_{t-3}$	0	-0.17	0	0
	(0.512)	(-1.138)	(0.439)	(0.180)
dOP_{t-3}	0.016	21.86	-0.007	0.07
	(1.311)	(0.494)	(-0.040)	(0.570)
$dBan_{t-3}$	0.02	41.04	-0.05	-0.134
	(1.268)	(0.741)	(-0.234)	(-0.867)
$dWOP_{t-4}$	-0.047	-53.78	-1.581	-2.024
	(-0.311)	(-0.100)	(-0.761)	(-1.345)
$dGIP_{t-4}$	0	-0.034	0	0.001
	(-1.608)	(-0.221)	(0.817)	(1.621)
dOP_{t-4}	0.002	10.35	-0.19	-0.217
	(0.174)	(0.245)	(-1.168)	(-1.842).
$dBan_{t-4}$	0.009	15.18	-0.153	0.098
	(0.531)	(0.267)	(-0.698)	(0.617)
$dWOP_{t-5}$	-0.16	862	1.3	-0.256
	(-1.055)	(1.605)	(0.628)	(-0.171)
$dGIP_{t-5}$	0	-0.085	0.001	-0.001
	(0.794)	(-0.527)	(1.262)	(-1.180)

dOP_{t-5}	-0.006	54.08	0.273	0.012
	(-0.507)	(1.252)	(1.642)	(0.100)
$dBan_{t-5}$	0.008	-5.372	-0.093	0.141
	(0.526)	(-0.095)	(-0.427)	(0.891)
$dWOP_{t-6}$	-0.204	-569.9	0.994	1.833
	(-1.499)	(-1.180)	(0.534)	(1.359)
$dGIP_{t-6}$	0	-0.175	0	0
	(0.935)	(-1.029)	(-0.333)	(-0.209)
dOP_{t-6}	-0.01	7.114	-0.143	0.011
	(-0.850)	(0.163)	(-0.850)	(0.089)
$dBan_{t-6}$	0.019	-68.1	-0.148	0.077
	(1.291)	(-1.278)	(-0.720)	(0.520)
$dWOP_{t-7}$	-0.062	190.2	-1.565	-1.834
	(-0.444)	(0.384)	(-0.821)	(-1.328)
$dGIP_{t-7}$	0	-0.144	0.001	0.001
	(-1.854).	(-0.874)	(1.543)	(2.987)**
dOP_{t-7}	0.01	106	-0.022	-0.114
	(0.828)	(2.415)*	(-0.132)	(-0.934)
$dBan_{t-7}$	0.027	-90.97	-0.234	0.053
	(1.752).	(-1.693).	(-1.132)	(0.354)
$dWOP_{t-8}$	-0.16	-287.7	-0.386	-0.154
	(-1.150)	(-0.582)	(-0.203)	(-0.112)
$dGIP_{t-8}$	0	-0.237	-0.001	-0.001
	(-0.415)	(-1.286)	(-0.814)	(-1.680).
dOP_{t-8}	0.004	-30.31	-0.085	0.096
	(0.335)	(-0.681)	(-0.497)	(0.776)
$dBan_{t-8}$	0.004	-86.17	-0.018	0.166
	(0.252)	(-1.530)	(-0.082)	(1.054)
$dWOP_{t-9}$	-0.212	161.3	1.365	-0.496
	(-1.571)	(0.337)	(0.739)	(-0.371)
$dGIP_{t-9}$	0	0.048	0	0
	(-0.506)	(0.251)	(-0.298)	(0.524)
dOP_{t-9}	0.01	47.8	0.006	-0.044
	(0.779)	(1.095)	(0.034)	(-0.363)
$dBan_{t-9}$	-0.007	-57.35	0.011	0.009
	(-0.477)	(-1.051)	(0.053)	(0.057)
$dWOP_{t-10}$	-0.212	203.6	-1.322	-3.732
	(-1.613)	(0.437)	(-0.737)	(-2.871)**

$dGIP_{t-10}$	0	-0.266	0	0.001
	(-2.139)*	(-1.495)	(0.719)	(1.535)
dOP_{t-10}	0	58.57	-0.09	-0.047
	(-0.015)	(1.352)	(-0.539)	(-0.392)
$dBan_{t-10}$	0.001	-86.84	-0.084	-0.007
	(0.059)	(-1.603)	(-0.404)	(-0.048)
$dWOP_{t-11}$	-0.022	705.9	-0.642	-2.027
	(-0.164)	(1.473)	(-0.348)	(-1.516)
$dGIP_{t-11}$	0	-0.247	0.001	-0.001
	(-1.101)	(-1.253)	(0.950)	(-1.789).
dOP_{t-11}	-0.006	47.85	0.064	-0.005
	(-0.458)	(1.096)	(0.383)	(-0.040)
$dBan_{t-11}$	0.002	-53.87	0.099	0.072
	(0.164)	(-1.095)	(0.524)	(0.527)
$dWOP_{t-12}$	0.034	652.8	0.343	-1.607
	(0.272)	(1.489)	(0.203)	(-1.313)
$dGIP_{t-12}$	0	-0.192	0.001	0
	(-0.234)	(-0.916)	(1.076)	(0.250)
dOP_{t-12}	0.018	-10.86	0.115	0.21
	(1.828).	(-0.313)	(0.861)	(2.172)*
$dBan_{t-12}$	-0.005	-36.39	-0.232	-0.122
	(-0.344)	(-0.776)	(-1.285)	(-0.935)
constant	0.002	-5.715	0.008	0.012
	(2.125)*	(-1.696).	(0.607)	(1.296)
Observations	95	95	95	95
R2	0.5526	0.4182	0.5518	0.567
F statistic	1.184	0.6888	1.18	1.255

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 10 Parameters Estimates of Reduced Form VAR Model with Insurance Sector

	dWOP	dGIP	dOP	dIns
$dWOP_{t-1}$	-0.003	266.3	0.362	-2.626
	(-0.022)	(0.525)	(0.174)	(-1.347)
$dGIP_{t-1}$	0	0.006	0.001	-0.001
	(-1.809).	(0.040)	(0.985)	(-0.956)
dOP_{t-1}	0.014	69.69	0.02	0.273
	(1.192)	(1.679)	(0.117)	(1.715).
$dIns_{t-1}$	0.007	18.78	0.077	0.026
	(0.602)	(0.473)	(0.470)	(0.172)
$dWOP_{t-2}$	-0.126	-523.8	-2.699	-0.408
	(-0.827)	(-0.991)	(-1.246)	(-0.201)
$dGIP_{t-2}$	0	-0.074	0	0
	(-1.497)	(-0.506)	(0.539)	(0.072)
dOP_{t-2}	-0.018	15.95	0.098	-0.045
	(-1.627)	(0.410)	(0.617)	(-0.301)
$dIns_{t-2}$	0.012	-33.6	-0.012	-0.121
	(1.126)	(-0.916)	(-0.080)	(-0.863)
$dWOP_{t-3}$	-0.125	-365.7	2.272	3.079
	(-0.796)	(-0.670)	(1.016)	(1.469)
$dGIP_{t-3}$	0	-0.199	0	0
	(0.421)	(-1.373)	(0.622)	(0.661)
dOP_{t-3}	0.013	37.3	-0.1	-0.064
	(1.173)	(0.970)	(-0.635)	(-0.435)
$dIns_{t-3}$	0.012	25.54	-0.093	-0.129
	(1.261)	(0.746)	(-0.662)	(-0.984)
$dWOP_{t-4}$	0.007	269.2	-0.488	-2.035
	(0.045)	(0.508)	(-0.225)	(-1.000)
$dGIP_{t-4}$	0	-0.085	0	0.001
	(-1.347)	(-0.572)	(0.567)	(1.240)
dOP_{t-4}	0.013	24.7	-0.205	-0.437
	(1.180)	(0.655)	(-1.326)	(-3.013)**
$dIns_{t-4}$	0.007	-68.98	-0.056	0.138
	(0.692)	(-2.090)*	(-0.413)	(1.092)
$dWOP_{t-5}$	-0.16	538.6	0.832	-0.074
	(-1.092)	(1.057)	(0.399)	(-0.038)
$dGIP_{t-5}$	0	-0.076	0.001	-0.001
	(0.334)	(-0.495)	(2.318)*	(-1.430)

dOP_{t-5}	0.004	47.75	0.109	0.002
	(0.338)	(1.137)	(0.632)	(0.011)
$dIns_{t-5}$	-0.012	16.04	0.013	0.324
	(-1.232)	(0.457)	(0.092)	(2.401)*
$dWOP_{t-6}$	-0.146	-835.3	0.242	0.945
	(-1.079)	(-1.767).	(0.125)	(0.520)
$dGIP_{t-6}$	0	-0.068	0	0
	(0.118)	(-0.396)	(-0.311)	(0.569)
dOP_{t-6}	0.009	-22.06	-0.153	-0.166
	(0.751)	(-0.540)	(-0.912)	(-1.060)
$dIns_{t-6}$	-0.005	-41.2	0.019	-0.009
	(-0.432)	(-1.126)	(0.127)	(-0.067)
$dWOP_{t-7}$	-0.085	-15.65	-1.922	-2.989
	(-0.633)	(-0.033)	(-1.001)	(-1.660)
$dGIP_{t-7}$	0	-0.238	0.001	0.001
	(-1.779).	(-1.423)	(1.421)	(1.605)
dOP_{t-7}	0.01	76.89	-0.068	0.04
	(0.924)	(1.944).	(-0.423)	(0.265)
$dIns_{t-7}$	0.001	2.23	-0.129	0.019
	(0.142)	(0.065)	(-0.909)	(0.144)
$dWOP_{t-8}$	-0.139	-639.3	-1.551	1.105
	(-1.009)	(-1.330)	(-0.788)	(0.599)
$dGIP_{t-8}$	0	0.016	0	-0.001
	(-0.658)	(0.089)	(0.032)	(-1.862).
dOP_{t-8}	0.007	-95.59	-0.144	0.154
	(0.648)	(-2.374)*	(-0.875)	(0.997)
$dIns_{t-8}$	0.007	-45.47	-0.093	0.05
	(0.714)	(-1.356)	(-0.677)	(0.386)
$dWOP_{t-9}$	-0.2	-16.41	0.529	2.578
	(-1.460)	(-0.034)	(0.271)	(1.406)
$dGIP_{t-9}$	0	-0.048	-0.001	0.001
	(-0.661)	(-0.261)	(-0.884)	(0.829)
dOP_{t-9}	0.001	32.94	-0.068	0.103
	(0.126)	(0.804)	(-0.405)	(0.653)
$dIns_{t-9}$	-0.001	44.37	0.187	-0.029
	(-0.117)	(1.420)	(1.462)	(-0.244)
$dWOP_{t-10}$	-0.178	21.59	-1.557	-4.603
	(-1.394)	(0.048)	(-0.854)	(-2.691)**

$dGIP_{t-10}$	0	-0.193	0.001	0.001
	(-1.673)	(-1.081)	(1.088)	(2.039)*
dOP_{t-10}	-0.005	2.336	-0.147	-0.017
	(-0.382)	(0.055)	(-0.837)	(-0.106)
$dIns_{t-10}$	0.009	1.988	0.03	-0.083
	(0.946)	(0.063)	(0.231)	(-0.680)
$dWOP_{t-11}$	-0.062	510.4	-1.724	-1.377
	(-0.460)	(1.085)	(-0.894)	(-0.762)
$dGIP_{t-11}$	0	-0.025	0.001	-0.001
	(-1.655)	(-0.132)	(1.710).	(-1.650)
dOP_{t-11}	-0.011	40.89	0.014	0.168
	(-0.859)	(0.952)	(0.080)	(1.017)
$dIns_{t-11}$	0.007	-18.04	0.078	-0.188
	(0.843)	(-0.657)	(0.689)	(-1.782).
$dWOP_{t-12}$	0.174	176.8	-0.548	0.945
	(1.370)	(0.401)	(-0.303)	(0.558)
$dGIP_{t-12}$	0	-0.066	0.001	0
	(-0.560)	(-0.340)	(1.376)	(0.319)
dOP_{t-12}	0.026	-40.03	0.052	-0.078
	(2.503)*	(-1.103)	(0.349)	(-0.563)
$dIns_{t-12}$	-0.002	39.92	0.068	-0.153
	(-0.232)	(1.357)	(0.568)	(-1.354)
constant	0.001	-2.358	0.015	0.013
	(1.683).	(-0.800)	(1.283)	(1.108)
Observations	95	95	95	95
R2	0.5544	0.4403	0.5131	0.6427
F statistic	1.192	0.7538	1.01	1.724

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 11 Parameters Estimates of Reduced Form VAR Model with Transport Sector

	dWOP	dGIP	dOP	dTra
$dWOP_{t-1}$	0.093	473	1.981	2.386
	(0.632)	(0.961)	(1.014)	(1.429)
$dGIP_{t-1}$	0	-0.054	0.001	0
	(-1.327)	(-0.364)	(1.223)	(-0.909)
dOP_{t-1}	0.013	86.28	0.109	0.319
	(1.146)	(2.192)*	(0.697)	(2.386)*
$dTra_{t-1}$	0.016	40.77	0.228	0.038
	(1.228)	(0.936)	(1.321)	(0.259)
$dWOP_{t-2}$	-0.263	-707.3	-3.26	-0.955
	(-1.731).	(-1.392)	(-1.616)	(-0.554)
$dGIP_{t-2}$	0	-0.006	0	0
	(-1.275)	(-0.044)	(0.859)	(0.543)
dOP_{t-2}	-0.021	-56.5	-0.072	0.022
	(-1.675)	(-1.373)	(-0.442)	(0.154)
$dTra_{t-2}$	-0.005	-17.53	-0.22	-0.149
	(-0.460)	(-0.438)	(-1.385)	(-1.100)
$dWOP_{t-3}$	-0.083	46.02	3.733	2.86
	(-0.517)	(0.086)	(1.759).	(1.577)
$dGIP_{t-3}$	0	-0.221	0	0
	(0.371)	(-1.609)	(-0.123)	(0.922)
dOP_{t-3}	0.011	39.11	-0.083	-0.267
	(0.963)	(0.993)	(-0.533)	(-1.993).
$dTra_{t-3}$	0.019	88.27	0.06	0.11
	(1.819).	(2.556)*	(0.441)	(0.934)
$dWOP_{t-4}$	-0.119	-399.5	-1.123	0.376
	(-0.764)	(-0.767)	(-0.543)	(0.213)
$dGIP_{t-4}$	0	-0.016	0.001	0
	(-2.484)*	(-0.110)	(1.563)	(0.480)
dOP_{t-4}	0.012	17.77	-0.069	-0.158
	(0.993)	(0.452)	(-0.439)	(-1.183)
$dTra_{t-4}$	-0.004	-46.23	-0.179	0.157
	(-0.344)	(-1.213)	(-1.186)	(1.215)
$dWOP_{t-5}$	-0.181	793.3	0.069	0.77
	(-1.201)	(1.570)	(0.034)	(0.449)
$dGIP_{t-5}$	0	-0.047	0.002	0
	(0.476)	(-0.318)	(2.659)*	(-0.373)

dOP_{t-5}	0.002	36.57	-0.021	0.042
	(0.199)	(0.950)	(-0.137)	(0.318)
$dTra_{t-5}$	-0.005	8.198	0.048	0.223
	(-0.425)	(0.214)	(0.317)	(1.718).
$dWOP_{t-6}$	-0.206	-798.2	1.814	2.099
	(-1.483)	(-1.719).	(0.984)	(1.332)
$dGIP_{t-6}$	0	-0.167	-0.001	-0.001
	(0.004)	(-1.058)	(-0.887)	(-1.061)
dOP_{t-6}	0.001	-10.89	-0.195	-0.039
	(0.118)	(-0.297)	(-1.339)	(-0.313)
$dTra_{t-6}$	-0.005	-11.77	0.179	-0.021
	(-0.428)	(-0.324)	(1.243)	(-0.170)
$dWOP_{t-7}$	-0.086	85.17	-1.33	-1.223
	(-0.587)	(0.173)	(-0.683)	(-0.734)
$dGIP_{t-7}$	0	-0.035	0.001	0.001
	(-1.467)	(-0.220)	(2.084)*	(1.625)
dOP_{t-7}	0.009	94.87	0.041	0.08
	(0.850)	(2.650)*	(0.291)	(0.655)
$dTra_{t-7}$	0.021	-38.2	-0.338	-0.068
	(2.000).	(-1.061)	(-2.366)*	(-0.557)
$dWOP_{t-8}$	-0.175	-387.4	0.116	-2.059
	(-1.216)	(-0.805)	(0.061)	(-1.261)
$dGIP_{t-8}$	0	-0.137	0	-0.001
	(-0.557)	(-0.834)	(-0.520)	(-0.944)
dOP_{t-8}	0	-62.04	-0.08	0.087
	(-0.030)	(-1.674)	(-0.547)	(0.688)
$dTra_{t-8}$	0.002	-47.12	-0.082	0.039
	(0.155)	(-1.256)	(-0.548)	(0.306)
$dWOP_{t-9}$	-0.171	81.22	2.013	0.581
	(-1.208)	(0.172)	(1.072)	(0.362)
$dGIP_{t-9}$	0	0.101	0	0
	(-1.129)	(0.616)	(-0.709)	(-0.655)
dOP_{t-9}	0.012	35.97	0.038	-0.08
	(1.033)	(0.958)	(0.256)	(-0.631)
$dTra_{t-9}$	0.002	-32.62	-0.017	0.241
	(0.193)	(-0.883)	(-0.118)	(1.925).
$dWOP_{t-10}$	-0.264	282	-1.5	-7.553
	(-1.904).	(0.607)	(-0.813)	(-4.791)***

$dGIP_{t-10}$	0	-0.201	0.001	0
	(-1.789).	(-1.271)	(1.976).	(0.786)
dOP_{t-10}	0.002	37.92	-0.084	-0.025
	(0.170)	(1.005)	(-0.561)	(-0.199)
$dTra_{t-10}$	-0.008	-27.47	-0.17	-0.261
	(-0.668)	(-0.722)	(-1.127)	(-2.024)*
$dWOP_{t-11}$	0.069	1054	0.666	-1.571
	(0.412)	(1.866).	(0.297)	(-0.820)
$dGIP_{t-11}$	0	-0.114	0.001	-0.001
	(-1.725).	(-0.652)	(1.518)	(-1.065)
dOP_{t-11}	-0.002	10.58	-0.101	0.186
	(-0.150)	(0.285)	(-0.684)	(1.477)
$dTra_{t-11}$	0.007	-13.92	0.17	0.134
	(0.642)	(-0.380)	(1.171)	(1.080)
$dWOP_{t-12}$	0.061	270.1	-1.377	0.423
	(0.414)	(0.543)	(-0.698)	(0.251)
$dGIP_{t-12}$	0	-0.045	0.001	0
	(-0.337)	(-0.257)	(1.283)	(0.395)
dOP_{t-12}	0.016	-24.04	0.095	0.059
	(1.609)	(-0.727)	(0.723)	(0.527)
$dTra_{t-12}$	-0.011	-4.33	-0.05	-0.087
	(-0.993)	(-0.114)	(-0.330)	(-0.680)
constant	0.002	-3.042	0.011	0.01
	(1.939).	(-1.107)	(1.005)	(1.101)
Observations	95	95	95	95
R2	0.5537	0.4817	0.5768	0.6504
F statistic	1.189	0.8907	1.306	1.783

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 12 Parameters Estimates of Reduced Form VAR Model with Media Sector

	dWOP	dGIP	dOP	dMed
$dWOP_{t-1}$	0.073	-191.3	0.44	-0.827
	(0.516)	(-0.438)	(0.229)	(-0.321)
$dGIP_{t-1}$	0	0.007	0	0
	(-0.820)	(0.055)	(0.632)	(-0.118)
dOP_{t-1}	0.011	83.78	0.026	0.105
	(0.902)	(2.225)*	(0.155)	(0.472)
$dMed_{t-1}$	-0.002	-52.28	-0.003	0.307
	(-0.195)	(-1.999).	(-0.025)	(1.986).
$dWOP_{t-2}$	-0.181	-414.9	-1.802	0.076
	(-1.369)	(-1.011)	(-1.000)	(0.032)
$dGIP_{t-2}$	0	0.073	0.001	0.001
	(-2.087)*	(0.559)	(0.995)	(0.835)
dOP_{t-2}	-0.015	3.843	-0.03	-0.212
	(-1.263)	(0.107)	(-0.190)	(-1.001)
$dMed_{t-2}$	0.001	104	-0.057	-0.354
	(0.158)	(3.745)***	(-0.471)	(-2.159)*
$dWOP_{t-3}$	-0.153	-265.8	2.385	4.795
	(-1.114)	(-0.625)	(1.277)	(1.910).
$dGIP_{t-3}$	0	-0.262	0	-0.001
	(0.298)	(-1.967).	(0.299)	(-1.877).
dOP_{t-3}	0.015	21.25	-0.09	0.076
	(1.345)	(0.615)	(-0.596)	(0.373)
$dMed_{t-3}$	-0.007	-17.93	0.092	0.139
	(-0.698)	(-0.607)	(0.712)	(0.797)
$dWOP_{t-4}$	0.001	109.9	-1.747	-4.309
	(0.009)	(0.243)	(-0.881)	(-1.617)
$dGIP_{t-4}$	0	-0.175	0	0.003
	(-0.872)	(-1.253)	(0.067)	(3.613)***
dOP_{t-4}	0.007	49.39	-0.069	-0.568
	(0.644)	(1.455)	(-0.460)	(-2.834)**
$dMed_{t-4}$	-0.001	10.2	0.068	-0.303
	(-0.061)	(0.350)	(0.532)	(-1.762).
$dWOP_{t-5}$	-0.211	33.3	0.815	4.921
	(-1.403)	(0.071)	(0.398)	(1.789).
$dGIP_{t-5}$	0	0.274	0.002	-0.001
	(-0.081)	(1.728).	(2.791)**	(-0.847)

dOP_{t-5}	-0.007	-11.73	0.013	0.356
	(-0.590)	(-0.305)	(0.075)	(1.567)
$dMed_{t-5}$	0.003	-22.58	0.022	0.586
	(0.295)	(-0.763)	(0.168)	(3.353)**
$dWOP_{t-6}$	-0.059	-492.4	-0.735	-2.745
	(-0.397)	(-1.075)	(-0.365)	(-1.014)
$dGIP_{t-6}$	0	-0.361	0	0.001
	(-0.047)	(-2.314)*	(-0.477)	(0.839)
dOP_{t-6}	0.009	48.39	-0.17	-0.452
	(0.750)	(1.269)	(-1.014)	(-2.007).
$dMed_{t-6}$	-0.007	82.34	0.24	-0.527
	(-0.643)	(2.487)*	(1.648)	(-2.696)**
$dWOP_{t-7}$	-0.035	-529.4	-2.067	0.667
	(-0.234)	(-1.152)	(-1.024)	(0.246)
$dGIP_{t-7}$	0	-0.111	0.001	0.002
	(-1.124)	(-0.710)	(1.339)	(2.239)*
dOP_{t-7}	0.006	9.755	-0.001	0.136
	(0.501)	(0.248)	(-0.004)	(0.584)
$dMed_{t-7}$	0.012	-119.9	-0.24	0.284
	(1.080)	(-3.522)***	(-1.604)	(1.410)
$dWOP_{t-8}$	-0.12	-93.63	-0.523	-0.547
	(-0.829)	(-0.208)	(-0.265)	(-0.206)
$dGIP_{t-8}$	0	-0.092	-0.001	0
	(0.350)	(-0.571)	(-0.739)	(-0.481)
dOP_{t-8}	-0.003	-19.46	-0.026	0.191
	(-0.260)	(-0.522)	(-0.159)	(0.869)
$dMed_{t-8}$	0.006	47.54	-0.043	-0.22
	(0.656)	(1.563)	(-0.322)	(-1.225)
$dWOP_{t-9}$	-0.187	-244.2	-0.838	1.081
	(-1.355)	(-0.569)	(-0.445)	(0.427)
$dGIP_{t-9}$	0	0	0	0
	(-2.095)*	(-0.002)	(-0.686)	(0.433)
dOP_{t-9}	0.015	13.73	0.056	0.14
	(1.287)	(0.376)	(0.351)	(0.648)
$dMed_{t-9}$	0.001	-17.4	-0.153	0.119
	(0.153)	(-0.617)	(-1.234)	(0.715)
$dWOP_{t-10}$	-0.233	597.8	-0.418	-3.1
	(-1.782).	(1.473)	(-0.235)	(-1.293)

$dGIP_{t-10}$	0	-0.346	0	-0.001
	(-0.731)	(-2.088)*	(0.066)	(-0.794)
dOP_{t-10}	-0.003	47.29	0.052	-0.336
	(-0.297)	(1.313)	(0.327)	(-1.581)
$dMed_{t-10}$	-0.009	22.09	0.014	-0.359
	(-1.073)	(0.827)	(0.118)	(-2.275)*
$dWOP_{t-11}$	-0.075	-116.1	-1.928	-0.498
	(-0.557)	(-0.278)	(-1.052)	(-0.202)
$dGIP_{t-11}$	0	-0.158	0.001	0
	(-1.553)	(-0.953)	(1.049)	(0.148)
dOP_{t-11}	-0.005	-60.83	-0.126	-0.044
	(-0.451)	(-1.642)	(-0.774)	(-0.203)
$dMed_{t-11}$	0.021	-46.1	-0.101	0.256
	(2.490)*	(-1.803).	(-0.898)	(1.693).
$dWOP_{t-12}$	0.067	725.7	-0.518	1.371
	(0.560)	(1.955).	(-0.318)	(0.625)
$dGIP_{t-12}$	0	0.105	0.001	0.001
	(-0.874)	(0.630)	(1.870).	(1.254)
dOP_{t-12}	0.022	26.26	0.07	-0.092
	(2.181)*	(0.842)	(0.511)	(-0.500)
$dMed_{t-12}$	-0.008	84.93	0.03	0.026
	(-0.964)	(3.254)**	(0.260)	(0.170)
constant	0.002	-2.15	0.015	0.005
	(2.107)*	(-0.870)	(1.366)	(0.347)
Observations	95	95	95	95
R2	0.572	0.5736	0.5736	0.688
F statistic	1.281	1.289	1.289	2.113

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 13 Parameters Estimates of Reduced Form VAR Model with Real Estate Development Sector

	dWOP	dGIP	dOP	dRea
$dWOP_{t-1}$	-0.017	56.37	1.192	0.276
	(-0.120)	(0.107)	(0.594)	(0.154)
$dGIP_{t-1}$	0	-0.152	0	0
	(-1.436)	(-1.058)	(0.325)	(0.004)
dOP_{t-1}	0.013	105.626	0.174	0.19
	(1.185)	(2.475)*	(1.072)	(1.308)
$dRea_{t-1}$	0.011	-14.913	0.026	0.009
	(0.929)	(-0.340)	(0.158)	(0.058)
$dWOP_{t-2}$	-0.096	-477.639	-3.208	-1.347
	(-0.712)	(-0.935)	(-1.647)	(-0.774)
$dGIP_{t-2}$	0	0.038	0	0
	(-2.117)*	(0.277)	(0.507)	(-0.381)
dOP_{t-2}	-0.019	-1.66	0.023	0
	(-1.757).	(-0.040)	(0.149)	(-0.003)
$dRea_{t-2}$	-0.008	52.743	-0.118	-0.103
	(-0.790)	(1.297)	(-0.759)	(-0.744)
$dWOP_{t-3}$	-0.174	-38.307	4.132	4.271
	(-1.308)	(-0.076)	(2.146)*	(2.483)*
$dGIP_{t-3}$	0	-0.192	0	0.001
	(0.391)	(-1.407)	(0.609)	(1.368)
dOP_{t-3}	0.017	2.173	-0.152	-0.081
	(1.663)	(0.057)	(-1.038)	(-0.622)
$dRea_{t-3}$	0.001	27.536	0	0.003
	(0.062)	(0.705)	(-0.003)	(0.019)
$dWOP_{t-4}$	-0.09	13.318	-0.949	-0.692
	(-0.625)	(0.024)	(-0.454)	(-0.370)
$dGIP_{t-4}$	0	-0.051	0	0.001
	(-1.962).	(-0.351)	(0.474)	(1.070)
dOP_{t-4}	0.009	25.467	-0.176	-0.267
	(0.972)	(0.693)	(-1.259)	(-2.129)*
$dRea_{t-4}$	0.007	-3.65	0	0.186
	(0.714)	(-0.101)	(-0.002)	(1.514)
$dWOP_{t-5}$	-0.062	270.914	0.103	0.322
	(-0.457)	(0.521)	(0.052)	(0.182)
$dGIP_{t-5}$	0	-0.091	0.002	0
	(0.036)	(-0.596)	(3.129)**	(-0.235)

dOP_{t-5}	-0.001	47.218	0.079	0.104
	(-0.086)	(1.216)	(0.531)	(0.789)
$dRea_{t-5}$	-0.009	-16.316	0.031	0.226
	(-0.970)	(-0.443)	(0.218)	(1.800).
$dWOP_{t-6}$	-0.161	-734.936	1.309	0.546
	(-1.327)	(-1.587)	(0.741)	(0.346)
$dGIP_{t-6}$	0	-0.213	-0.001	-0.001
	(0.729)	(-1.256)	(-1.109)	(-1.104)
dOP_{t-6}	-0.003	7.754	-0.204	-0.063
	(-0.323)	(0.208)	(-1.433)	(-0.495)
$dRea_{t-6}$	-0.003	-21.38	0.243	-0.131
	(-0.321)	(-0.564)	(1.680).	(-1.011)
$dWOP_{t-7}$	-0.026	-129.914	-2.077	-1.626
	(-0.212)	(-0.274)	(-1.147)	(-1.005)
$dGIP_{t-7}$	0	-0.133	0.001	0.001
	(-1.397)	(-0.801)	(1.205)	(1.194)
dOP_{t-7}	0.003	68.697	0.057	-0.064
	(0.314)	(1.849).	(0.405)	(-0.503)
$dRea_{t-7}$	0.036	-50.721	-0.413	-0.059
	(3.482)**	(-1.290)	(-2.753)**	(-0.440)
$dWOP_{t-8}$	-0.106	-419.746	-0.685	-1.308
	(-0.858)	(-0.894)	(-0.383)	(-0.817)
$dGIP_{t-8}$	0	-0.077	0	-0.001
	(-1.024)	(-0.461)	(0.194)	(-0.940)
dOP_{t-8}	0.004	-52.125	-0.019	0.09
	(0.380)	(-1.427)	(-0.133)	(0.720)
$dRea_{t-8}$	0.012	1.784	-0.102	-0.001
	(1.028)	(0.040)	(-0.603)	(-0.006)
$dWOP_{t-9}$	-0.278	71.836	1.593	0.088
	(-2.285)*	(0.155)	(0.902)	(0.056)
$dGIP_{t-9}$	0	0.043	-0.001	0
	(-0.322)	(0.249)	(-1.772).	(-0.323)
dOP_{t-9}	0.008	17.057	0.002	0.039
	(0.850)	(0.467)	(0.012)	(0.311)
$dRea_{t-9}$	-0.009	26.55	0.12	0.179
	(-0.800)	(0.630)	(0.744)	(1.247)
$dWOP_{t-10}$	-0.261	136.116	-1.605	-5.081
	(-2.153)*	(0.295)	(-0.912)	(-3.234)**

$dGIP_{t-10}$	0	-0.201	0.001	0.001
	(-2.055)*	(-1.196)	(1.556)	(2.082)*
dOP_{t-10}	0.001	62.792	-0.025	-0.211
	(0.092)	(1.684).	(-0.176)	(-1.662)
$dRea_{t-10}$	0	-44.618	-0.337	0.001
	(0.039)	(-1.108)	(-2.193)*	(0.009)
$dWOP_{t-11}$	-0.041	372.826	-1.062	-1.963
	(-0.316)	(0.760)	(-0.567)	(-1.174)
$dGIP_{t-11}$	0	-0.189	0.001	0
	(-2.517)*	(-0.976)	(1.569)	(-0.173)
dOP_{t-11}	0.004	17.057	-0.012	0.088
	(0.355)	(0.442)	(-0.084)	(0.670)
$dRea_{t-11}$	0.002	-53.442	0.12	0.184
	(0.223)	(-1.414)	(0.835)	(1.431)
$dWOP_{t-12}$	0.063	762.877	-0.271	-1.87
	(0.541)	(1.724).	(-0.161)	(-1.240)
$dGIP_{t-12}$	0	-0.237	0	0
	(-0.256)	(-1.216)	(0.616)	(0.461)
dOP_{t-12}	0.02	-20.932	0.108	0.054
	(2.258)*	(-0.615)	(0.833)	(0.468)
$dRea_{t-12}$	-0.022	42.822	-0.064	0.003
	(-2.132)*	(1.069)	(-0.420)	(0.020)
constant	0.002	-3.332	0.01	0.017
	(2.262)*	(-1.169)	(0.963)	(1.724).
Observations	95	95	95	95
R2	0.6314	0.4482	0.5841	0.5512
F statistic	1.642	0.7783	1.346	1.177

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 14 Parameters Estimates of Reduced Form VAR Model with Agriculture Sector

	dWOP	dGIP	dOP	dAgr
$dWOP_{t-1}$	-0.109	363.9	1.792	-0.6
	(-0.739)	(0.651)	(0.843)	(-0.611)
$dGIP_{t-1}$	0	-0.151	0	0
	(-1.654)	(-1.043)	(0.790)	(-0.493)
dOP_{t-1}	0.008	135.1	0.128	0.176
	(0.719)	(3.027)**	(0.757)	(2.239)*
$dAgr_{t-1}$	0.041	-76.09	0.49	0.112
	(1.860).	(-0.916)	(1.553)	(0.766)
$dWOP_{t-2}$	-0.147	-553.3	-2.113	-2.655
	(-1.061)	(-1.048)	(-1.053)	(-2.864)**
$dGIP_{t-2}$	0	-0.009	0.001	0
	(-1.832).	(-0.060)	(0.927)	(-0.511)
dOP_{t-2}	-0.025	-2.488	-0.024	-0.004
	(-2.171)*	(-0.057)	(-0.142)	(-0.046)
$dAgr_{t-2}$	0.027	7.858	-0.525	0.017
	(1.483)	(0.112)	(-1.969).	(0.141)
$dWOP_{t-3}$	-0.086	-114.4	3.734	1.402
	(-0.590)	(-0.206)	(1.771).	(1.439)
$dGIP_{t-3}$	0	-0.244	0	0.001
	(0.530)	(-1.787).	(0.644)	(2.165)*
dOP_{t-3}	0.011	33.3	-0.108	-0.052
	(0.973)	(0.784)	(-0.670)	(-0.693)
$dAgr_{t-3}$	0.02	77.43	0.087	0.128
	(1.306)	(1.322)	(0.389)	(1.241)
$dWOP_{t-4}$	-0.116	300.1	-0.841	-1.421
	(-0.813)	(0.553)	(-0.408)	(-1.491)
$dGIP_{t-4}$	0	-0.03	0	0
	(-2.157)*	(-0.203)	(0.107)	(-0.230)
dOP_{t-4}	0.008	41.93	-0.062	-0.261
	(0.785)	(1.059)	(-0.413)	(-3.753)***
$dAgr_{t-4}$	0.002	-35.23	-0.254	0.076
	(0.132)	(-0.596)	(-1.129)	(0.733)
$dWOP_{t-5}$	-0.149	837.9	1.694	-0.296
	(-1.083)	(1.603)	(0.853)	(-0.322)
$dGIP_{t-5}$	0	-0.053	0.002	0
	(-0.283)	(-0.332)	(3.270)**	(-1.252)

dOP_{t-5}	0.012	18.05	0.162	0.129
	(1.009)	(0.403)	(0.954)	(1.637)
$dAgr_{t-5}$	-0.01	-55.99	-0.147	0.441
	(-0.637)	(-0.977)	(-0.674)	(4.388)***
$dWOP_{t-6}$	-0.15	-558.7	0.408	-0.068
	(-1.146)	(-1.124)	(0.216)	(-0.078)
$dGIP_{t-6}$	0	-0.294	0	0
	(0.614)	(-1.715).	(-0.766)	(-0.830)
dOP_{t-6}	0.007	-0.781	-0.382	0.041
	(0.559)	(-0.018)	(-2.270)*	(0.529)
$dAgr_{t-6}$	-0.031	15.15	0.088	-0.112
	(-1.787).	(0.232)	(0.354)	(-0.980)
$dWOP_{t-7}$	-0.074	-60.77	-0.937	-2.644
	(-0.561)	(-0.121)	(-0.490)	(-2.994)**
$dGIP_{t-7}$	0	-0.082	0.001	0.001
	(-1.345)	(-0.491)	(1.361)	(2.776)**
dOP_{t-7}	0.005	103.5	0.095	-0.087
	(0.438)	(2.469)*	(0.599)	(-1.175)
$dAgr_{t-7}$	0.018	-69.73	-0.111	0.023
	(1.080)	(-1.114)	(-0.468)	(0.212)
$dWOP_{t-8}$	-0.097	-561.5	-0.01	-0.593
	(-0.687)	(-1.046)	(-0.005)	(-0.629)
$dGIP_{t-8}$	0	-0.027	0	-0.001
	(-1.401)	(-0.148)	(-0.070)	(-2.429)*
dOP_{t-8}	0.006	-81.02	-0.101	0.099
	(0.574)	(-1.929).	(-0.631)	(1.346)
$dAgr_{t-8}$	0.015	-41.29	-0.284	0.076
	(0.995)	(-0.721)	(-1.306)	(0.758)
$dWOP_{t-9}$	-0.186	85.94	1.399	-0.197
	(-1.431)	(0.174)	(0.744)	(-0.227)
$dGIP_{t-9}$	0	-0.025	0	0
	(-0.693)	(-0.140)	(-0.440)	(0.177)
dOP_{t-9}	0.007	11.87	-0.092	0.084
	(0.657)	(0.281)	(-0.571)	(1.127)
$dAgr_{t-9}$	-0.006	52.95	0.214	0.24
	(-0.418)	(0.958)	(1.018)	(2.479)*
$dWOP_{t-10}$	-0.11	162.5	-2.01	-4.483
	(-0.875)	(0.340)	(-1.107)	(-5.343)***

$dGIP_{t-10}$	0	-0.169	0.001	0
	(-2.554)*	(-1.011)	(1.169)	(1.688).
dOP_{t-10}	-0.006	68.24	-0.04	-0.099
	(-0.536)	(1.688).	(-0.262)	(-1.396)
$dAgr_{t-10}$	-0.013	-6.596	-0.107	-0.176
	(-0.878)	(-0.116)	(-0.495)	(-1.759).
$dWOP_{t-11}$	0.101	343	0.636	-0.03
	(0.691)	(0.617)	(0.301)	(-0.031)
$dGIP_{t-11}$	0	-0.095	0.001	-0.001
	(-2.627)*	(-0.494)	(1.864).	(-2.670)*
dOP_{t-11}	-0.001	13.22	0.059	0.08
	(-0.110)	(0.316)	(0.369)	(1.085)
$dAgr_{t-11}$	0.014	-40.99	0.173	-0.047
	(1.035)	(-0.814)	(0.903)	(-0.533)
$dWOP_{t-12}$	0.175	519.6	-2.29	0.257
	(1.307)	(1.020)	(-1.183)	(0.287)
$dGIP_{t-12}$	0	-0.218	0.001	0
	(-0.214)	(-1.084)	(1.309)	(-0.659)
dOP_{t-12}	0.019	-10.03	0.012	0.127
	(1.914).	(-0.270)	(0.088)	(1.949).
$dAgr_{t-12}$	-0.011	-0.568	-0.101	-0.17
	(-0.752)	(-0.011)	(-0.500)	(-1.819).
constant	0.001	-2.817	0.012	0.015
	(1.018)	(-0.916)	(1.028)	(2.696)**
Observations	95	95	95	95
R2	0.6169	0.4261	0.5704	0.7715
F statistic	1.543	0.7114	1.273	3.236

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 15 Parameters Estimates of Reduced Form VAR Model with Telecom Sector

	dWOP	dGIP	dOP	dTel
$dWOP_{t-1}$	0.04	-73.831	0.542	-0.237
	(0.271)	(-0.145)	(0.276)	(-0.185)
$dGIP_{t-1}$	0	-0.188	0.001	0
	(-1.694).	(-1.259)	(0.928)	(-0.316)
dOP_{t-1}	0.017	98.939	0.089	0.318
	(1.400)	(2.312)*	(0.540)	(2.951)**
$dTel_{t-1}$	0.014	35.764	0.394	-0.061
	(0.781)	(0.590)	(1.686).	(-0.400)
$dWOP_{t-2}$	-0.186	-623.235	-2.473	-1.056
	(-1.284)	(-1.255)	(-1.292)	(-0.844)
$dGIP_{t-2}$	0	-0.042	0	0
	(-1.814).	(-0.287)	(0.714)	(1.133)
dOP_{t-2}	-0.018	-27.946	-0.001	-0.042
	(-1.424)	(-0.630)	(-0.007)	(-0.373)
$dTel_{t-2}$	0.011	82.078	-0.424	-0.232
	(0.636)	(1.421)	(-1.905).	(-1.595)
$dWOP_{t-3}$	-0.156	-236.014	2.893	2.853
	(-1.041)	(-0.458)	(1.455)	(2.196)*
$dGIP_{t-3}$	0	-0.246	0	0.001
	(-0.112)	(-1.683).	(0.123)	(3.528)***
dOP_{t-3}	0.007	13.724	-0.066	-0.121
	(0.541)	(0.320)	(-0.401)	(-1.123)
$dTel_{t-3}$	0.022	79.353	0.003	-0.035
	(1.400)	(1.476)	(0.012)	(-0.258)
$dWOP_{t-4}$	-0.058	-211.627	-1.405	-0.722
	(-0.361)	(-0.386)	(-0.665)	(-0.523)
$dGIP_{t-4}$	0	-0.109	0	0.001
	(-2.257)*	(-0.626)	(0.293)	(2.325)*
dOP_{t-4}	0.013	27.253	-0.085	-0.169
	(1.150)	(0.683)	(-0.554)	(-1.686).
$dTel_{t-4}$	0.011	10.847	-0.173	-0.117
	(0.771)	(0.212)	(-0.876)	(-0.909)
$dWOP_{t-5}$	-0.249	437.412	0.497	0.746
	(-1.657)	(0.849)	(0.250)	(0.575)
$dGIP_{t-5}$	0	-0.209	0.002	0.001
	(-0.410)	(-1.081)	(2.543)*	(1.500)

dOP_{t-5}	0.004	52.977	0.058	0.122
	(0.366)	(1.284)	(0.364)	(1.179)
$dTel_{t-5}$	-0.003	0.29	-0.004	0.029
	(-0.205)	(0.006)	(-0.020)	(0.224)
$dWOP_{t-6}$	-0.161	-886.712	-0.165	2.676
	(-1.152)	(-1.847).	(-0.089)	(2.213)*
$dGIP_{t-6}$	0	-0.325	0	0
	(-0.884)	(-1.685).	(-0.539)	(0.749)
dOP_{t-6}	0.005	18.138	-0.273	-0.029
	(0.432)	(0.447)	(-1.746).	(-0.282)
$dTel_{t-6}$	0.008	-29.096	0.147	-0.243
	(0.508)	(-0.573)	(0.752)	(-1.899).
$dWOP_{t-7}$	-0.106	-256.268	-0.757	-0.169
	(-0.676)	(-0.474)	(-0.363)	(-0.124)
$dGIP_{t-7}$	0	-0.187	0.001	0.001
	(-2.320)*	(-1.036)	(1.751).	(2.931)**
dOP_{t-7}	0.009	85.451	0.054	-0.065
	(0.792)	(2.153)*	(0.354)	(-0.649)
$dTel_{t-7}$	0.021	-63.196	-0.313	-0.158
	(1.339)	(-1.193)	(-1.533)	(-1.185)
$dWOP_{t-8}$	-0.191	-722.815	-0.562	1.089
	(-1.313)	(-1.447)	(-0.292)	(0.865)
$dGIP_{t-8}$	0	-0.28	0	0
	(-0.723)	(-1.343)	(-0.002)	(0.370)
dOP_{t-8}	0.003	-45.425	-0.056	-0.03
	(0.231)	(-1.112)	(-0.352)	(-0.296)
$dTel_{t-8}$	0.015	3.499	-0.044	0.178
	(0.933)	(0.063)	(-0.208)	(1.276)
$dWOP_{t-9}$	-0.255	-289.391	1.091	1.071
	(-1.824).	(-0.603)	(0.590)	(0.886)
$dGIP_{t-9}$	0	-0.011	-0.001	0
	(-1.717).	(-0.053)	(-0.806)	(0.884)
dOP_{t-9}	0.011	30.475	0.043	-0.057
	(0.977)	(0.761)	(0.278)	(-0.568)
$dTel_{t-9}$	0.003	-8.587	-0.089	0.296
	(0.217)	(-0.165)	(-0.440)	(2.255)*
$dWOP_{t-10}$	-0.266	-177.176	-1.104	-3.351
	(-1.880).	(-0.365)	(-0.590)	(-2.742)**

$dGIP_{t-10}$	0	-0.206	0.001	0.001
	(-2.167)*	(-1.051)	(1.599)	(2.562)*
dOP_{t-10}	0.007	63.253	-0.1	-0.197
	(0.568)	(1.555)	(-0.641)	(-1.924).
$dTel_{t-10}$	-0.018	-42.806	-0.195	-0.064
	(-1.246)	(-0.865)	(-1.020)	(-0.510)
$dWOP_{t-11}$	-0.056	295.496	-0.561	-1.673
	(-0.379)	(0.587)	(-0.289)	(-1.319)
$dGIP_{t-11}$	0	-0.27	0.001	-0.001
	(-2.136)*	(-1.152)	(1.390)	(-0.950)
dOP_{t-11}	0.001	38.733	-0.003	-0.032
	(0.087)	(0.885)	(-0.018)	(-0.292)
$dTel_{t-11}$	0	-50.96	0.235	0.219
	(-0.029)	(-1.136)	(1.358)	(1.941).
$dWOP_{t-12}$	0.178	562.69	-1.209	0.488
	(1.329)	(1.225)	(-0.683)	(0.422)
$dGIP_{t-12}$	0	-0.185	0.001	0
	(-1.222)	(-0.837)	(1.502)	(-0.151)
dOP_{t-12}	0.022	1.417	0.074	0.098
	(2.050)*	(0.038)	(0.517)	(1.051)
$dTel_{t-12}$	-0.013	6.756	-0.06	0.038
	(-0.883)	(0.137)	(-0.318)	(0.306)
constant	0.001	-2.217	0.014	0.008
	(1.631)	(-0.786)	(1.311)	(1.142)
Observations	95	95	95	95
R2	0.5346	0.4325	0.5628	0.6837
F statistic	1.101	0.7303	1.234	2.072

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 16 Parameters Estimates of Reduced Form VAR Model with Multi-investment Sector

	dWOP	dGIP	dOP	dMinv
$dWOP_{t-1}$	0.072	403.336	1.093	-1.434
	(0.506)	(0.791)	(0.540)	(-0.878)
$dGIP_{t-1}$	0	-0.1	0	0
	(-1.054)	(-0.664)	(0.502)	(-0.809)
dOP_{t-1}	0.009	89.998	0.063	0.383
	(0.851)	(2.281)*	(0.403)	(3.034)**
$dMinv_{t-1}$	0.009	33.066	0.219	-0.024
	(0.730)	(0.723)	(1.210)	(-0.161)
$dWOP_{t-2}$	-0.175	-521.699	-1.438	-1.282
	(-1.221)	(-1.011)	(-0.703)	(-0.777)
$dGIP_{t-2}$	0	-0.012	0.001	0
	(-1.998).	(-0.083)	(1.250)	(0.456)
dOP_{t-2}	-0.021	-25.273	0.052	0.053
	(-1.831).	(-0.611)	(0.315)	(0.402)
$dMinv_{t-2}$	-0.003	15.776	-0.013	0.062
	(-0.227)	(0.374)	(-0.075)	(0.457)
$dWOP_{t-3}$	-0.094	92.538	2.436	3.381
	(-0.645)	(0.178)	(1.178)	(2.027)*
$dGIP_{t-3}$	0	-0.205	0	0
	(0.840)	(-1.442)	(0.282)	(0.379)
dOP_{t-3}	0.02	26.644	-0.128	-0.146
	(1.833).	(0.669)	(-0.813)	(-1.143)
$dMinv_{t-3}$	0.019	42.85	-0.141	-0.181
	(1.878).	(1.155)	(-0.960)	(-1.526)
$dWOP_{t-4}$	-0.074	-251.038	-0.788	-0.78
	(-0.512)	(-0.485)	(-0.384)	(-0.471)
$dGIP_{t-4}$	0	-0.096	0	0.001
	(-1.481)	(-0.657)	(0.342)	(1.283)
dOP_{t-4}	0.004	28.446	-0.103	-0.155
	(0.392)	(0.752)	(-0.689)	(-1.284)
$dMinv_{t-4}$	-0.002	-43.378	-0.055	0.114
	(-0.165)	(-1.163)	(-0.372)	(0.956)
$dWOP_{t-5}$	-0.15	878.817	1.159	0.401
	(-1.071)	(1.749).	(0.581)	(0.250)
$dGIP_{t-5}$	0	-0.053	0.001	0
	(0.127)	(-0.353)	(2.271)*	(-0.428)

dOP_{t-5}	-0.001	44.888	0.15	0.17
	(-0.066)	(1.167)	(0.982)	(1.384)
$dMinv_{t-5}$	-0.005	19.463	-0.088	0.224
	(-0.533)	(0.535)	(-0.607)	(1.920).
$dWOP_{t-6}$	-0.23	-786.563	1.652	1.668
	(-1.743).	(-1.654)	(0.875)	(1.096)
$dGIP_{t-6}$	0	-0.16	0	-0.001
	(0.074)	(-1.030)	(-0.168)	(-1.480)
dOP_{t-6}	0.004	-19.799	-0.198	-0.157
	(0.420)	(-0.529)	(-1.332)	(-1.308)
$dMinv_{t-6}$	-0.01	-12.842	0.131	-0.075
	(-0.988)	(-0.347)	(0.891)	(-0.633)
$dWOP_{t-7}$	0.008	79.252	-2.093	-4.248
	(0.056)	(0.158)	(-1.049)	(-2.640)*
$dGIP_{t-7}$	0	-0.091	0.001	0.001
	(-1.740).	(-0.582)	(1.729).	(1.925).
dOP_{t-7}	0.009	95.401	-0.003	-0.066
	(0.879)	(2.547)*	(-0.019)	(-0.548)
$dMinv_{t-7}$	0.02	-23.808	-0.238	-0.167
	(1.959).	(-0.661)	(-1.668)	(-1.450)
$dWOP_{t-8}$	-0.189	-315.048	0.553	-2.987
	(-1.288)	(-0.597)	(0.264)	(-1.767).
$dGIP_{t-8}$	0	-0.126	0	-0.001
	(-0.487)	(-0.762)	(-0.424)	(-1.495)
dOP_{t-8}	-0.006	-50.839	0.047	0.168
	(-0.502)	(-1.268)	(0.293)	(1.308)
$dMinv_{t-8}$	0.009	-52.713	-0.185	0.139
	(0.835)	(-1.412)	(-1.249)	(1.161)
$dWOP_{t-9}$	-0.215	361.036	1.946	0.363
	(-1.508)	(0.706)	(0.959)	(0.222)
$dGIP_{t-9}$	0	0.073	0	-0.001
	(-0.733)	(0.429)	(-0.696)	(-1.421)
dOP_{t-9}	0.013	39.02	-0.117	-0.094
	(1.227)	(1.005)	(-0.758)	(-0.760)
$dMinv_{t-9}$	-0.004	12.224	0.058	0.349
	(-0.381)	(0.326)	(0.386)	(2.905)**
$dWOP_{t-10}$	-0.172	292.395	-0.475	-5.565
	(-1.257)	(0.594)	(-0.243)	(-3.531)***

$dGIP_{t-10}$	0	-0.156	0.001	0.001
	(-2.151)*	(-0.942)	(1.598)	(2.118)*
dOP_{t-10}	-0.007	49.07	-0.018	0.068
	(-0.616)	(1.214)	(-0.111)	(0.527)
$dMinv_{t-10}$	0.004	-64.466	-0.044	-0.048
	(0.392)	(-1.652)	(-0.285)	(-0.384)
$dWOP_{t-11}$	0.06	804.025	-1.181	-3.031
	(0.411)	(1.541)	(-0.571)	(-1.816).
$dGIP_{t-11}$	0	-0.142	0.001	-0.001
	(-1.675)	(-0.803)	(1.581)	(-1.116)
dOP_{t-11}	-0.009	34.682	0.003	0.137
	(-0.780)	(0.850)	(0.021)	(1.049)
$dMinv_{t-11}$	0.016	-43.297	-0.098	0.053
	(1.693).	(-1.251)	(-0.716)	(0.480)
$dWOP_{t-12}$	0.067	450.426	-0.076	1.919
	(0.501)	(0.934)	(-0.040)	(1.244)
$dGIP_{t-12}$	0	-0.068	0.001	-0.001
	(0.021)	(-0.367)	(1.316)	(-1.255)
dOP_{t-12}	0.02	-27.51	0.097	-0.012
	(2.086)*	(-0.786)	(0.695)	(-0.103)
$dMinv_{t-12}$	-0.011	-7.218	-0.035	-0.05
	(-1.032)	(-0.194)	(-0.240)	(-0.417)
constant	0.002	-4.464	0.007	0.013
	(1.886).	(-1.460)	(0.606)	(1.300)
Observations	95	95	95	95
R2	0.5848	0.4445	0.5467	0.6612
F statistic	1.35	0.7667	1.156	1.87

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 17 Parameters Estimates of Reduced Form VAR Model with Building Sector

	dWOP	dGIP	dOP	dBui
$dWOP_{t-1}$	0.009	505.48	1.382	-0.239
	(0.065)	(1.002)	(0.685)	(-0.156)
$dGIP_{t-1}$	0	-0.154	0	0
	(-0.916)	(-1.045)	(0.186)	(-0.369)
dOP_{t-1}	0.017	86.323	0.068	0.281
	(1.299)	(1.960).	(0.387)	(2.105)*
$dBui_{t-1}$	-0.006	53.087	0.266	-0.096
	(-0.361)	(0.957)	(1.196)	(-0.569)
$dWOP_{t-2}$	-0.19	-432.332	-1.145	-1.877
	(-1.323)	(-0.869)	(-0.575)	(-1.244)
$dGIP_{t-2}$	0	0.039	0.001	0
	(-2.148)*	(0.283)	(1.191)	(0.136)
dOP_{t-2}	-0.001	-59.114	-0.125	0.169
	(-0.083)	(-1.289)	(-0.679)	(1.214)
$dBui_{t-2}$	-0.023	56.349	0.003	-0.193
	(-1.565)	(1.107)	(0.013)	(-1.247)
$dWOP_{t-3}$	-0.249	268.18	3.231	1.809
	(-1.732).	(0.540)	(1.626)	(1.201)
$dGIP_{t-3}$	0	-0.17	0	0
	(0.405)	(-1.182)	(0.431)	(0.543)
dOP_{t-3}	0.025	-9.757	-0.202	-0.077
	(1.832).	(-0.209)	(-1.083)	(-0.545)
$dBui_{t-3}$	-0.004	88.355	0.02	-0.099
	(-0.287)	(1.921).	(0.111)	(-0.707)
$dWOP_{t-4}$	-0.07	218.614	-0.113	-1.367
	(-0.477)	(0.433)	(-0.056)	(-0.892)
$dGIP_{t-4}$	0	-0.1	0	0.001
	(-1.581)	(-0.709)	(0.641)	(1.707).
dOP_{t-4}	0.009	19.836	-0.155	-0.293
	(0.752)	(0.474)	(-0.925)	(-2.306)*
$dBui_{t-4}$	-0.001	-19.747	0.104	0.026
	(-0.111)	(-0.496)	(0.652)	(0.218)
$dWOP_{t-5}$	-0.197	862.175	1.056	0.361
	(-1.413)	(1.792).	(0.548)	(0.247)
$dGIP_{t-5}$	0	-0.081	0.001	0
	(0.590)	(-0.551)	(1.968).	(-0.754)

dOP_{t-5}	-0.001	49.647	0.104	0.051
	(-0.114)	(1.158)	(0.606)	(0.394)
$dBui_{t-5}$	-0.003	-9.837	-0.155	0.386
	(-0.257)	(-0.254)	(-1.003)	(3.284)**
$dWOP_{t-6}$	-0.258	-447.054	1.755	1.719
	(-1.885).	(-0.944)	(0.926)	(1.196)
$dGIP_{t-6}$	0	-0.196	0	0
	(0.601)	(-1.219)	(-0.315)	(0.205)
dOP_{t-6}	-0.006	12.576	-0.173	-0.13
	(-0.481)	(0.306)	(-1.050)	(-1.040)
$dBui_{t-6}$	0.004	-52.186	0.1	0.087
	(0.306)	(-1.140)	(0.544)	(0.628)
$dWOP_{t-7}$	-0.001	-45.667	-1.947	-2.625
	(-0.006)	(-0.094)	(-0.998)	(-1.775).
$dGIP_{t-7}$	0	-0.177	0.001	0.001
	(-1.983).	(-1.121)	(1.263)	(2.264)*
dOP_{t-7}	-0.001	128.159	0.097	-0.251
	(-0.124)	(3.195)**	(0.604)	(-2.059)*
$dBui_{t-7}$	0.033	-88.774	-0.376	0.056
	(2.580)*	(-2.032)*	(-2.149)*	(0.421)
$dWOP_{t-8}$	-0.2	-334.44	0.399	-0.528
	(-1.441)	(-0.696)	(0.208)	(-0.362)
$dGIP_{t-8}$	0	-0.158	-0.001	0
	(0.096)	(-0.933)	(-0.925)	(-0.572)
dOP_{t-8}	-0.009	-25.957	0.166	0.094
	(-0.764)	(-0.615)	(0.986)	(0.737)
$dBui_{t-8}$	0.022	-91.122	-0.232	0.071
	(1.637)	(-1.963).	(-1.249)	(0.502)
$dWOP_{t-9}$	-0.263	281.787	1.707	0.759
	(-1.953).	(0.605)	(0.915)	(0.536)
$dGIP_{t-9}$	0	-0.039	0	0
	(-0.379)	(-0.233)	(-0.583)	(-0.252)
dOP_{t-9}	-0.001	54.817	-0.016	0.078
	(-0.117)	(1.362)	(-0.102)	(0.642)
$dBui_{t-9}$	0.009	-26.836	-0.182	0.268
	(0.737)	(-0.616)	(-1.044)	(2.030)*
$dWOP_{t-10}$	-0.176	108.027	-1.324	-5.384
	(-1.332)	(0.236)	(-0.723)	(-3.883)***

$dGIP_{t-10}$	0	-0.211	0	0.001
	(-1.881).	(-1.296)	(0.741)	(2.637)*
dOP_{t-10}	-0.01	79.92	0.083	-0.156
	(-0.847)	(1.913).	(0.496)	(-1.234)
$dBui_{t-10}$	0.022	-85.319	-0.218	-0.099
	(1.637)	(-1.797).	(-1.146)	(-0.687)
$dWOP_{t-11}$	-0.062	747.213	-0.52	-2.318
	(-0.414)	(1.450)	(-0.252)	(-1.483)
$dGIP_{t-11}$	0	-0.268	0.001	0
	(-0.930)	(-1.452)	(1.035)	(-0.621)
dOP_{t-11}	-0.005	39.614	0.085	0.095
	(-0.453)	(0.944)	(0.505)	(0.749)
$dBui_{t-11}$	0.015	-71.801	-0.161	-0.058
	(1.199)	(-1.704).	(-0.955)	(-0.456)
$dWOP_{t-12}$	-0.025	823.778	-0.162	-0.361
	(-0.182)	(1.763).	(-0.087)	(-0.255)
$dGIP_{t-12}$	0	-0.193	0.001	0.001
	(-0.003)	(-1.045)	(0.919)	(0.985)
dOP_{t-12}	0.016	-15.697	0.126	0.144
	(1.578)	(-0.441)	(0.885)	(1.339)
$dBui_{t-12}$	-0.002	-4.348	-0.137	-0.001
	(-0.205)	(-0.110)	(-0.861)	(-0.010)
constant	0.003	-8.883	-0.007	0.012
	(2.857)**	(-2.413)*	(-0.446)	(1.106)
Observations	95	95	95	95
R2	0.5808	0.4819	0.5697	0.7183
F statistic	1.328	0.8914	1.269	2.443

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 18 Parameters Estimates of Reduced Form VAR Model with Energy Sector

	dWOP	dGIP	dOP	dEne
$dWOP_{t-1}$	0.045	227.486	-0.054	1
	(0.305)	(0.434)	(-0.024)	(0.631)
$dGIP_{t-1}$	0	-0.256	0	0
	(-1.003)	(-1.708).	(0.519)	(0.374)
dOP_{t-1}	0.008	106.906	0.022	-0.016
	(0.706)	(2.760)**	(0.130)	(-0.139)
$dEne_{t-1}$	0.019	-28.708	0.253	-0.21
	(1.213)	(-0.530)	(1.075)	(-1.283)
$dWOP_{t-2}$	-0.229	-132.147	-1.87	-1.658
	(-1.605)	(-0.263)	(-0.856)	(-1.089)
$dGIP_{t-2}$	0	-0.125	0	0
	(-1.394)	(-0.848)	(0.291)	(0.294)
dOP_{t-2}	-0.016	15.697	0.062	0.039
	(-1.444)	(0.393)	(0.359)	(0.319)
$dEne_{t-2}$	-0.002	-31.139	-0.01	0.023
	(-0.121)	(-0.538)	(-0.039)	(0.131)
$dWOP_{t-3}$	-0.174	-19.174	2.879	2.065
	(-1.207)	(-0.038)	(1.298)	(1.337)
$dGIP_{t-3}$	0	-0.216	0	0.001
	(-0.028)	(-1.544)	(0.558)	(1.359)
dOP_{t-3}	0.01	51.898	-0.169	0.063
	(0.909)	(1.325)	(-0.996)	(0.529)
$dEne_{t-3}$	0.014	-54.261	0.004	-0.103
	(0.836)	(-0.918)	(0.016)	(-0.576)
$dWOP_{t-4}$	-0.086	191.853	-1.847	-0.471
	(-0.578)	(0.364)	(-0.807)	(-0.296)
$dGIP_{t-4}$	0	-0.075	0	0
	(-1.398)	(-0.508)	(0.724)	(0.132)
dOP_{t-4}	0	43.42	-0.197	-0.209
	(0.027)	(1.096)	(-1.144)	(-1.748).
$dEne_{t-4}$	0.022	-32.031	0.087	-0.065
	(1.316)	(-0.542)	(0.337)	(-0.362)
$dWOP_{t-5}$	-0.17	1154.87	0.621	0.407
	(-1.173)	(2.257)*	(0.280)	(0.263)
$dGIP_{t-5}$	0	-0.06	0.001	0
	(0.751)	(-0.406)	(2.252)*	(0.171)

dOP_{t-5}	0	57.263	0.123	0.021
	(-0.018)	(1.407)	(0.695)	(0.167)
$dEne_{t-5}$	0.016	-52.737	0.03	0.164
	(0.950)	(-0.894)	(0.118)	(0.919)
$dWOP_{t-6}$	-0.22	-133.468	0.854	-1.027
	(-1.495)	(-0.257)	(0.379)	(-0.654)
$dGIP_{t-6}$	0	-0.145	0	-0.001
	(0.823)	(-0.949)	(-0.630)	(-2.599)*
dOP_{t-6}	-0.007	26.806	-0.215	0.049
	(-0.632)	(0.652)	(-1.203)	(0.396)
$dEne_{t-6}$	0.008	-86.488	0.151	0.083
	(0.524)	(-1.530)	(0.614)	(0.485)
$dWOP_{t-7}$	0.012	292.184	-0.928	-0.256
	(0.084)	(0.580)	(-0.425)	(-0.168)
$dGIP_{t-7}$	0	-0.156	0.001	0.001
	(-1.742).	(-0.931)	(1.788).	(1.103)
dOP_{t-7}	0.009	87.1	-0.013	-0.052
	(0.760)	(2.076)*	(-0.071)	(-0.413)
$dEne_{t-7}$	0.035	-129.681	-0.123	-0.167
	(1.924).	(-2.041)*	(-0.444)	(-0.871)
$dWOP_{t-8}$	-0.181	-128.142	-0.512	-1.351
	(-1.349)	(-0.270)	(-0.249)	(-0.942)
$dGIP_{t-8}$	0	-0.251	0	0
	(-0.461)	(-1.463)	(-0.170)	(-0.658)
dOP_{t-8}	0.013	-27.871	-0.054	-0.035
	(1.128)	(-0.702)	(-0.314)	(-0.288)
$dEne_{t-8}$	-0.007	-99.565	0	0.165
	(-0.360)	(-1.480)	(-0.001)	(0.811)
$dWOP_{t-9}$	-0.193	194.262	0.337	-0.769
	(-1.433)	(0.408)	(0.163)	(-0.535)
$dGIP_{t-9}$	0	-0.055	0	0
	(-0.339)	(-0.297)	(-0.466)	(-0.625)
dOP_{t-9}	0.007	46.878	-0.053	0.095
	(0.652)	(1.212)	(-0.313)	(0.813)
$dEne_{t-9}$	-0.009	-127.687	-0.108	0.189
	(-0.530)	(-2.144)*	(-0.416)	(1.051)
$dWOP_{t-10}$	-0.219	370.306	-0.962	-2.506
	(-1.716).	(0.819)	(-0.490)	(-1.833)

$dGIP_{t-10}$	0	-0.296	0.001	0.001
	(-1.492)	(-1.715).	(1.135)	(2.173)*
dOP_{t-10}	-0.007	52.396	-0.089	-0.073
	(-0.681)	(1.370)	(-0.534)	(-0.630)
$dEne_{t-10}$	-0.002	-129.904	0.029	0.173
	(-0.138)	(-2.169)*	(0.110)	(0.953)
$dWOP_{t-11}$	-0.104	757.441	-1.217	-0.133
	(-0.799)	(1.638)	(-0.606)	(-0.095)
$dGIP_{t-11}$	0	-0.276	0.001	0
	(-1.253)	(-1.464)	(0.682)	(0.556)
dOP_{t-11}	-0.011	35.27	0.058	-0.038
	(-0.985)	(0.919)	(0.350)	(-0.329)
$dEne_{t-11}$	0.026	-109.762	-0.112	0.049
	(1.620)	(-1.907).	(-0.447)	(0.283)
$dWOP_{t-12}$	0.079	710.796	-0.438	-0.845
	(0.619)	(1.575)	(-0.223)	(-0.620)
$dGIP_{t-12}$	0	-0.154	0.001	0
	(-0.249)	(-0.821)	(1.240)	(0.444)
dOP_{t-12}	0.018	-1.795	0.118	0.036
	(1.888).	(-0.053)	(0.798)	(0.348)
$dEne_{t-12}$	-0.006	-35.299	-0.17	0.047
	(-0.381)	(-0.653)	(-0.726)	(0.290)
constant	0.001	-3.051	0.01	0.015
	(1.776).	(-1.053)	(0.794)	(1.749).
Observations	95	95	95	95
R2	0.5769	0.4535	0.4663	0.4958
F statistic	1.307	0.7953	0.8375	0.9423

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 19 Parameters Estimates of Reduced Form VAR Model with Industrial Investment Sector

	dWOP	dGIP	dOP	dInd
$dWOP_{t-1}$	0.051	298.3	0.018	0.027
	(0.352)	(0.618)	(0.010)	(0.021)
$dGIP_{t-1}$	0	-0.173	0	0
	(-0.919)	(-1.126)	(0.067)	(0.048)
dOP_{t-1}	0.011	92.07	0.11	0.152
	(0.867)	(2.143)*	(0.680)	(1.337)
$dInd_{t-1}$	0	12.74	0.156	0.051
	(-0.023)	(0.214)	(0.693)	(0.323)
$dWOP_{t-2}$	-0.206	-232.2	-1.329	-0.81
	(-1.411)	(-0.479)	(-0.729)	(-0.632)
$dGIP_{t-2}$	0	-0.025	0	0
	(-1.684).	(-0.177)	(0.738)	(-0.591)
dOP_{t-2}	-0.013	-31.22	-0.14	0.066
	(-1.015)	(-0.723)	(-0.861)	(0.579)
$dInd_{t-2}$	-0.006	18.57	0.011	-0.225
	(-0.373)	(0.346)	(0.056)	(-1.584)
$dWOP_{t-3}$	-0.194	18.63	3.612	2.305
	(-1.294)	(0.037)	(1.928).	(1.748).
$dGIP_{t-3}$	0	-0.168	0	0.001
	(0.575)	(-1.171)	(0.572)	(1.853).
dOP_{t-3}	0.009	35.7	-0.188	-0.183
	(0.729)	(0.850)	(-1.189)	(-1.648)
$dInd_{t-3}$	0.013	33.57	0.029	0.015
	(0.952)	(0.719)	(0.166)	(0.125)
$dWOP_{t-4}$	-0.017	46.89	-1.646	-0.735
	(-0.113)	(0.093)	(-0.863)	(-0.548)
$dGIP_{t-4}$	0	-0.053	0.001	0.001
	(-1.737).	(-0.358)	(1.191)	(1.448)
dOP_{t-4}	0.006	34.57	-0.186	-0.19
	(0.462)	(0.809)	(-1.159)	(-1.679).
$dInd_{t-4}$	0.007	-53.83	0.098	-0.037
	(0.504)	(-1.169)	(0.568)	(-0.303)
$dWOP_{t-5}$	-0.218	845.8	1.527	1.326
	(-1.480)	(1.727).	(0.828)	(1.022)
$dGIP_{t-5}$	0	-0.082	0.002	0
	(0.725)	(-0.532)	(2.797)**	(-0.877)

dOP_{t-5}	-0.007	59.36	-0.007	0.026
	(-0.538)	(1.358)	(-0.045)	(0.221)
$dInd_{t-5}$	0.004	-27.06	0.063	0.29
	(0.280)	(-0.589)	(0.364)	(2.380)*
$dWOP_{t-6}$	-0.158	-576.5	0.957	0.971
	(-1.105)	(-1.219)	(0.537)	(0.775)
$dGIP_{t-6}$	0	-0.188	0	0
	(0.505)	(-1.081)	(-0.520)	(-0.621)
dOP_{t-6}	-0.004	26.51	-0.134	-0.039
	(-0.303)	(0.638)	(-0.857)	(-0.352)
$dInd_{t-6}$	0.007	-73.86	0.067	-0.205
	(0.515)	(-1.593)	(0.386)	(-1.670)
$dWOP_{t-7}$	-0.035	100.5	-1.609	-0.183
	(-0.245)	(0.213)	(-0.905)	(-0.146)
$dGIP_{t-7}$	0	-0.14	0.001	0.001
	(-1.693).	(-0.840)	(1.968).	(2.219)*
dOP_{t-7}	0.004	114.9	0.088	0.116
	(0.297)	(2.867)**	(0.581)	(1.089)
$dInd_{t-7}$	0.027	-77.99	-0.35	-0.045
	(1.846).	(-1.597)	(-1.903).	(-0.348)
$dWOP_{t-8}$	-0.183	-384.3	-0.147	-0.871
	(-1.301)	(-0.822)	(-0.084)	(-0.703)
$dGIP_{t-8}$	0	-0.2	-0.001	-0.001
	(0.142)	(-1.139)	(-1.022)	(-1.814).
dOP_{t-8}	0	-22.28	0.062	0.059
	(-0.035)	(-0.536)	(0.396)	(0.531)
$dInd_{t-8}$	0.004	-82.44	-0.146	-0.207
	(0.272)	(-1.763).	(-0.829)	(-1.672)
$dWOP_{t-9}$	-0.202	109.9	0.856	1.227
	(-1.426)	(0.234)	(0.483)	(0.984)
$dGIP_{t-9}$	0	-0.008	0	0
	(-0.745)	(-0.044)	(-0.604)	(-0.292)
dOP_{t-9}	0.006	62.5	0.146	0.083
	(0.516)	(1.547)	(0.960)	(0.772)
$dInd_{t-9}$	0.008	-70.33	-0.214	0.141
	(0.544)	(-1.476)	(-1.190)	(1.120)
$dWOP_{t-10}$	-0.216	137.3	-1.946	-5.331
	(-1.549)	(0.297)	(-1.119)	(-4.356)***

$dGIP_{t-10}$	0	-0.291	0.001	0.001
	(-1.708).	(-1.703).	(1.234)	(3.173)**
dOP_{t-10}	-0.005	67.59	0.072	-0.136
	(-0.397)	(1.637)	(0.466)	(-1.247)
$dInd_{t-10}$	0.006	-88.63	-0.433	-0.231
	(0.380)	(-1.789).	(-2.322)*	(-1.758).
$dWOP_{t-11}$	-0.09	791.3	-0.895	-0.702
	(-0.550)	(1.464)	(-0.440)	(-0.490)
$dGIP_{t-11}$	0	-0.256	0	-0.001
	(-1.079)	(-1.278)	(0.254)	(-1.325)
dOP_{t-11}	-0.006	57.05	0.115	0.096
	(-0.487)	(1.374)	(0.734)	(0.874)
$dInd_{t-11}$	0.007	-56.4	-0.083	0.047
	(0.544)	(-1.315)	(-0.512)	(0.411)
$dWOP_{t-12}$	0.051	589.8	-0.021	-0.802
	(0.350)	(1.213)	(-0.011)	(-0.623)
$dGIP_{t-12}$	0	-0.199	0.001	0.001
	(-0.091)	(-1.002)	(0.716)	(1.039)
dOP_{t-12}	0.017	-3.489	0.166	0.051
	(1.613)	(-0.101)	(1.273)	(0.556)
$dInd_{t-12}$	-0.001	-40.06	-0.336	-0.061
	(-0.060)	(-0.882)	(-1.963).	(-0.508)
constant	0.002	-2.905	0.015	0.016
	(1.975).	(-1.008)	(1.342)	(2.050)*
Observations	95	95	95	95
R2	0.52	0.4532	0.5982	0.726
F statistic	1.038	0.7944	1.427	2.54

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 20 Parameters Estimates of Reduced Form VAR Model with Hotel Sector

	dWOP	dGIP	dOP	dHot
$dWOP_{t-1}$	0.057	388.6	-0.194	1.002
	(0.390)	(0.742)	(-0.097)	(0.549)
$dGIP_{t-1}$	0	-0.041	0	-0.001
	(-0.888)	(-0.269)	(0.719)	(-0.937)
dOP_{t-1}	0.013	80.46	0.04	0.317
	(1.088)	(1.899).	(0.250)	(2.151)*
$dHot_{t-1}$	-0.009	35.68	-0.112	-0.029
	(-0.845)	(0.884)	(-0.731)	(-0.204)
$dWOP_{t-2}$	-0.129	-524	-2.352	-2.396
	(-0.862)	(-0.976)	(-1.152)	(-1.282)
$dGIP_{t-2}$	0	-0.031	0	0
	(-1.450)	(-0.212)	(0.629)	(-0.117)
dOP_{t-2}	-0.015	-11.31	0.057	0.074
	(-1.308)	(-0.271)	(0.357)	(0.508)
$dHot_{t-2}$	-0.005	-14.75	-0.088	-0.067
	(-0.477)	(-0.372)	(-0.585)	(-0.489)
$dWOP_{t-3}$	-0.207	89.74	1.712	4.219
	(-1.359)	(0.164)	(0.821)	(2.210)*
$dGIP_{t-3}$	0	-0.198	0	0.001
	(0.244)	(-1.388)	(0.291)	(1.859).
dOP_{t-3}	0.015	36.82	-0.113	-0.071
	(1.383)	(0.947)	(-0.767)	(-0.526)
$dHot_{t-3}$	0.013	51.12	-0.06	0.197
	(1.389)	(1.531)	(-0.473)	(1.697).
$dWOP_{t-4}$	-0.05	-102.9	0.69	-1.108
	(-0.318)	(-0.183)	(0.322)	(-0.565)
$dGIP_{t-4}$	0	-0.043	0.001	0
	(-1.445)	(-0.288)	(1.157)	(0.580)
dOP_{t-4}	0.009	10.99	-0.231	-0.436
	(0.887)	(0.286)	(-1.583)	(-3.261)**
$dHot_{t-4}$	-0.003	-31.05	0.154	0.254
	(-0.341)	(-0.921)	(1.201)	(2.162)*
$dWOP_{t-5}$	-0.162	1051	1.164	1.607
	(-1.074)	(1.941).	(0.565)	(0.852)
$dGIP_{t-5}$	0	-0.067	0.002	-0.001
	(0.866)	(-0.439)	(2.635)*	(-1.385)

dOP_{t-5}	-0.006	51.3	-0.053	0.105
	(-0.536)	(1.207)	(-0.326)	(0.713)
$dHot_{t-5}$	-0.003	6.816	0.124	0.428
	(-0.348)	(0.196)	(0.937)	(3.539)***
$dWOP_{t-6}$	-0.169	-1062	0.284	-2.589
	(-1.226)	(-2.144)*	(0.151)	(-1.501)
$dGIP_{t-6}$	0	-0.122	-0.001	0
	(-0.051)	(-0.748)	(-0.831)	(-0.426)
dOP_{t-6}	0	-24.22	-0.151	-0.122
	(-0.015)	(-0.583)	(-0.953)	(-0.845)
$dHot_{t-6}$	0.008	-45.74	0.235	-0.113
	(0.729)	(-1.204)	(1.630)	(-0.857)
$dWOP_{t-7}$	-0.04	392.2	-1.698	-0.516
	(-0.285)	(0.775)	(-0.882)	(-0.293)
$dGIP_{t-7}$	0	-0.133	0.001	0
	(-2.175)*	(-0.836)	(1.519)	(-0.053)
dOP_{t-7}	0.012	97.85	-0.035	0.274
	(1.108)	(2.474)*	(-0.234)	(1.990).
$dHot_{t-7}$	0.014	-8.327	-0.272	-0.011
	(1.239)	(-0.209)	(-1.798).	(-0.081)
$dWOP_{t-8}$	-0.192	-622.1	-0.395	-4.075
	(-1.345)	(-1.213)	(-0.202)	(-2.282)*
$dGIP_{t-8}$	0	-0.042	0	-0.001
	(-0.013)	(-0.243)	(-0.486)	(-1.555)
dOP_{t-8}	0.005	-83.77	0.003	0.066
	(0.423)	(-2.031)*	(0.021)	(0.456)
$dHot_{t-8}$	-0.002	-59.23	-0.085	0
	(-0.174)	(-1.690).	(-0.636)	(-0.004)
$dWOP_{t-9}$	-0.194	406.1	-0.367	2.456
	(-1.289)	(0.750)	(-0.178)	(1.303)
$dGIP_{t-9}$	0	0.083	-0.001	0
	(-1.270)	(0.469)	(-0.896)	(0.536)
dOP_{t-9}	0.01	38.57	0.084	0.194
	(0.860)	(0.913)	(0.524)	(1.321)
$dHot_{t-9}$	-0.002	22.28	-0.06	-0.078
	(-0.245)	(0.667)	(-0.472)	(-0.667)
$dWOP_{t-10}$	-0.208	-86.02	-0.362	-5.567
	(-1.490)	(-0.172)	(-0.190)	(-3.193)**

$dGIP_{t-10}$	0	-0.177	0.001	0.001
	(-2.132)*	(-1.011)	(1.149)	(1.239)
dOP_{t-10}	-0.004	8.747	0.067	-0.152
	(-0.327)	(0.203)	(0.408)	(-1.012)
$dHot_{t-10}$	0.006	-20.07	-0.121	-0.096
	(0.684)	(-0.617)	(-0.976)	(-0.843)
$dWOP_{t-11}$	-0.077	997.4	-2.802	-0.339
	(-0.504)	(1.814).	(-1.340)	(-0.177)
$dGIP_{t-11}$	0	-0.058	0.001	0
	(-1.146)	(-0.305)	(1.806).	(-0.351)
dOP_{t-11}	-0.004	33.72	-0.087	0.093
	(-0.314)	(0.764)	(-0.516)	(0.603)
$dHot_{t-11}$	0.004	-8.021	-0.125	0.013
	(0.392)	(-0.246)	(-1.003)	(0.118)
$dWOP_{t-12}$	0.045	67.87	-0.909	1.63
	(0.314)	(0.132)	(-0.463)	(0.907)
$dGIP_{t-12}$	0	-0.084	0.001	0
	(-0.367)	(-0.442)	(1.142)	(0.500)
dOP_{t-12}	0.02	-36.24	0.08	0.02
	(1.985).	(-1.012)	(0.587)	(0.161)
$dHot_{t-12}$	-0.003	17.03	-0.007	0.002
	(-0.321)	(0.443)	(-0.047)	(0.017)
constant	0.002	-3.363	0.018	0.01
	(2.016)*	(-1.044)	(1.506)	(0.866)
Observations	95	95	95	95
R2	0.5574	0.4093	0.557	0.6879
F statistic	1.207	0.6639	1.205	2.112

Note: Coefficients are reported with t-tests in brackets; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.