ABSTRACT

OIL PRICE AND THE STOCK MARKET: A STRUCTURAL VAR MODEL IDENTIFIED WITH AN EXTERNAL INSTRUMENT

by Tomas Rene Perez

This paper studies the relationship between oil prices and United States stock market from January 1987 to May 2020. It has been documented in previous studies that oil prices cannot be taken as strictly exogenous. Stock market returns and oil prices are endogenously determined. To address this issue, the use of a Structural Vector Autoregression is employed where the target shock is identified using an external instrument. Impulse responses are obtained and disaggregated between the total U.S. market and 11 chosen sectors. The results of the SVAR-IV model are compared with results from a standard SVAR where shocks are identified with Cholesky decomposition. Cumulative impulse responses are taken to illustrate the change in stock market responses over time. The results show that oil prices generally don't have a strong impact on the U.S. stock market. This paper also illustrates the importance of having current data observing the dramatic changes occurring in the U.S. oil market.

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Chapter 1

Introduction

Since the emergence of the Organization of Petroleum Exporting Countries in the 1960s and the stagflation of the U.S. in the 1970s, many economists have studied the changing relationship between energy, primarily oil, and economic factors. Today, there exists a large body of research on the subject in both macroeconomic and microeconomic studies. A majority of the results point towards a clear correlation between energy prices and various economics indicators including aggregate output [1][2], employment and wages [3], industrial and firm-level production [4], and stock market returns[5][6][7].

The abundance of research in this area does not diminish the importance of repeated studies on these relationships. The relationships between oil markets and macroeconomic variables change dramatically over time. Blanchard and Gali (2009), and Blanchard and Riggi (2013) study how this relationship has changed, finding that the effects of oil demand shocks on industrialized economies have become more mild over time. However, developing countries and purely importing countries are more susceptible to disruptions in oil prices. Thus, the relevance of these studies and contribution to the area is still intact.

Contributions to the literature involving oil markets come in two flavors: 1) repeated studies measuring how the relationships continuously change over time, and 2) introducing new methodologies to test and better understand said relationships. Coincidentally, the abundance of data and previous studies provide an ideal testing ground for new statistical methods as well. The results of this paper can be easily compared for robustness. This paper focuses on contributing to the literature in the latter avenue, introducing a new statistical method in the form of a Structural Vector Autoregression with external instruments, or SVAR-IV.

Identifying causal relationships in empirical macroeconomics is a challenge. The simultaneous co-movements between macroeconomic variables can make isolating exogenous variation incredibly difficult. Since the seminal work of Sims (1980), the estimation of dynamic effects of structural shocks in vector autoregressions (VARs) has been an important part of macroeconomics research. The use of VARs has expanded into numerous variations of the model. Most recently, an increasingly important area of research is the use of structural vector autoregressions (SVARs) where variables not included in the system (external instruments) are used to identify the dynamic causal effects, known as "structural impulse response functions". These models are sometimes referred to as Proxy-SVARs, SVAR with external instruments, or simply SVAR-IV as is the case with this paper.

Chapter 2

Literature Review

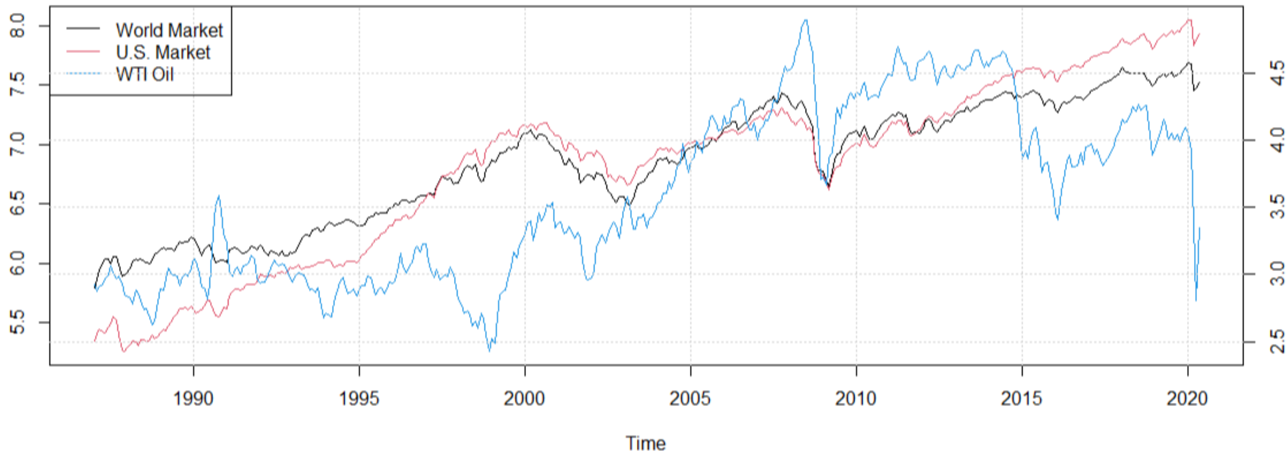
As noted before, literature concerning the effects of oil shocks on economic factors is extensive. Hamilton (1983) published an key paper finding that an oil price increase preceded all but one recession in the United States following World War II. Following this study, numerous other papers such as Gisser and Goodwin (1986) have generated similar results that reinforce Hamilton's findings. A majority of studies find that oil prices have an inverse relationship with many important economic variables (output, stock return, employment, etc.), meaning that increases in oil prices are associated with decreases in output, etc.. However, this relationship appears to have weakened over time. Blanchard and Gali (2009) find smaller effects on macroeconomic variables of the 2000s compared to previous years.

2.1 Oil Price and Stock Markets

Following Hamilton's seminal work in 1983, the relationships between macroeconomic indicators and oil-specific shocks have been extensively studied. Two papers written in 1996 provided an interesting conflict in results. Huang et al. (1996) test the effects of oil price returns on 3 levels (composite, sectoral, and individual firms) of the U.S. financial market. They find that shocks to oil prices have no greater impact on the U.S. market, and only impact sectors and firms related to energy. While not entirely disputing Huang, Kual and Jones (1996) find that changes in oil prices appear to cause larger changes in stock returns in post-war U.S., Canada, U.K., and Japan. Over time, subsequent studies tend to align with Kaul and Jones's findings. More specifically, oil price changes often have a negative relationship with stock markets as noted by Park and Ratti (2008).

More recent evidence has shown that in the United States this relationship is weakening over time. Blanchard and Gali (2009) investigate four hypotheses for the mild effects from recent oil price increases. They find that the reduction of oil in production, more flexible labor markets, changes in monetary policy, and a lack of concurrent adverse shocks all lower the impact of oil price changes compared to the 1970s and 1980s. Hooker (1996) provides several potential explanations for this including sample stability issues, oil prices becoming endogenous, and that linear and symmetrical

Figure 2.1: Market Indexes and WTI Oil Price



Note: Figure 1 shows log-market indexes (indexed on the left vertical axis) and log-WTI oil prices (indexed on the right vertical axis).

specifications misrepresent the true form of the relationship.

The nonlinear specification of the relationship and the endogeneity issue are key points when studying the effect of oil prices on the macroeconomy. Several studies, including papers from Ratti et al. (1995), Mork (1989), and Hamilton (1996), suggest that the relation between oil prices and economic activity are nonlinear. A particularly important paper for this study comes from Ciner (2001). Using data from Huang et al. (1996), Ciner tests for nonlinear causality and concludes that the effect is in fact nonlinear. Ciner claims that the reason Huang did not find a relation between oil price and the stock market is because he used a linear approximation. Ciner's study also notes that oil prices cannot be taken as exogenous since stock index returns also impact oil futures. Hamilton (2003) and Yin et al. (2009) both compare the result of nonlinear specifications and instrument variable regressions as tools to deal with the endogenous effects from oil prices. Both studies find that either method produces similar results.

2.2 Structural Vector Autoregression with External Instruments

Structural Vector-Autoregressions are used extensively in macroeconomic time series. The goal of SVAR models is to estimate the dynamic causal effects of structural shocks on macroeconomic outcomes through a system of simultaneous equations. Compared to a standard VAR, the SVAR allows for variables to have a contemporaneous effect on other variables in the regression, an important feature when working with low-frequency data. Identification in standard SVAR or VAR models can be classified as internal - the variables (instruments) used for identification are internal to the system.

Modern microeconometric techniques use external sources of variation to identify causal effects. The instrumental variable approach as proven to be remarkably useful in quasi-experimental studies. In macroeconometrics, an increasingly prevalent method of identification comes from using external variables to identify dynamic causal effects in a system. Identification in these models can be classified as external. The use of "external instruments" in SVARs is similar to the microeconometric instrument variable approach. The goal of using this external instrument approach is to find a variable external to the system that is correlated with the shock of interest, but uncorrelated with other potential shocks in the system, in order to capture exogenous variation in the shock of interest. For brevity, this method is often referred to as SVAR-IV or proxy-SVAR.

Prior to the development of the SVAR-IV approach, Romer and Romer (1989) used what they called, a "narrative approach" to argue for the exogeneity of their monetary shocks. This non-statistical method of identification has carried through to numerous subsequent papers. Hamilton (2003) is a notable example of the use on external instruments in a single equation distributed-lag model. Hamilton uses the external instrument method to compare results with the nonlinear method in estimating the impact of changes in oil price on GDP growth. Stock (2008) introduced how these external instruments can be used to identify structural shocks in the impulse responses of an SVAR. Use cases of SVAR-IV methodology can be seen in Stock and Watson (2012), Mertens and Olea (2018), and Mertens and Ravn (2013).

Chapter 3

Empirical Methodology

3.1 Data

The sample of data in this study spans from January 1987 to May 2020. The analysis is based on monthly average returns of the United States stock market at two levels: total market-wide index, and sector-level indexes. The 11 sectors accounted for in this study are Consumer Discretionary, Consumer Staples, Energy, Financial, Utilities, Healthcare, Information Technology, Real Estate, Industrial, Materials, and Telecommunications. Datastream U.S. indexes are used for these 12 variables of interest. Our key regressor is oil price return. Here we use West Texas Intermediate (WTI) spot prices also taken from Datastream. Our primary objective is to measure the effect that oil price returns have on total stock market returns and through which sectors these effects traverse. Thus, our market index returns and oil price returns are calculated as the log-difference of monthly average prices.

With return as a primary dependent variable, it is important to distinguish between idiosyncratic and systematic risk. Idiosyncratic, or unsystematic, risk is generally referred to as the inherent risk in an asset. These risks are typically dealt with by diversification in a portfolio and therefore often uncorrelated with aggregate market returns. Systematic risks are broader trends that affect the market as a whole and cannot be mitigated through diversification. As our dependent variables are stock market indexes, much of the idiosyncratic risk is dealt with via diversification. Therefore, we require systematic variables to be included in our analysis. Common systematic variables include world market return, industrial production, interest rates, inflation rates, money supply, and energy prices [8][9]. In this study we include world market returns, U.S. industrial production growth rate, inflation rate, and the U.S. 10-year treasury rate as controls. All data is gathered through Thomson Reuters Datastream. Table 3.1 provides descriptive statistics for all variables used in the study.

Table 3.1: Summary Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
U.S. Total Market	0.7	3.5	−23.6	−0.9	2.8	11.3
Consumer Discretionary	0.7	3.9	−23.1	−0.7	2.9	13.1
Consumer Stationary	0.8	3.3	−15.5	−1.0	2.8	11.5
Energy	0.5	4.4	−27.9	−1.9	3.5	11.8
Financial	0.6	4.7	−24.1	−1.2	3.2	20.7
Healthcare	0.8	3.5	−15.8	−1.2	3.2	12.0
Industrials	0.8	4.4	−28.7	−1.1	3.2	16.1
Information Technology	0.9	5.7	−23.4	−1.9	4.1	18.6
Materials	0.5	5.1	−42.0	−1.8	3.4	15.3
Real Estate	0.4	5.0	−32.4	−1.9	3.1	19.1
Telecommunications	0.3	4.2	−21.5	−1.9	2.9	15.9
Utilities	0.4	3.5	−20.9	−1.5	2.5	10.0
WTI Crude Oil	0.3	8.2	−33.8	−4.7	5.6	39.2
No.2 Heating Oil	0.3	8.3	−27.6	−4.5	5.3	35.4
Industrial Production	0.2	0.6	−4.4	−0.2	0.6	2.0
Inflation Rate	0.2	0.3	−1.8	0.1	0.3	1.4
World Total Market	0.5	3.8	−27.0	−1.3	2.7	12.3
10-Year Treasury Rate	−0.3	5.9	−37.8	−3.5	3.0	20.0

All variables are calculated as the monthly percentage change.

The choice of external instrument is an important one. The variable should be correlated with crude oil prices, but uncorrelated with stock market performance. Stock (2008) adapts standard IV conditions to SVAR-IV methodology and notes two key identifying assumptions to be met by the external instrument. If Z_t is an instrument variable, it must satisfy the following:

$$E(Z_t \varepsilon_{1t}) = \alpha \neq 0$$

$$E(Z_t \varepsilon_{jt}) = 0, j \neq 1$$

The first equation is our relevance condition; Z_t must be correlated with the shock of interest. The second equation is our exogeneity condition; Z_t must be uncorrelated with other current shocks.

The choice of external instrument comes from Ciner (2001). In his study he notes that crude oil futures have an effect on stock market returns, but heating oil futures do not. Heating oil is used as fuel for furnaces and boilers in buildings, particularly in the Northeast region of the United States. According to the Energy Information Administration, from one 42-gallon barrel of crude oil, approximately 11-12 gallons of distillate fuel is refined. This distillate fuel is sold as diesel fuel and heating oil. In this study, U.S. No.2 Heating Oil is used as our external instrument. Theoretically, heating oil should satisfy the conditions for a suitable instrument as it is highly correlated with crude oil prices, buy uncorrelated with stock market returns. Tables 6.1 - 6.3 show the first-stage regression and instrument variable tests.

Our estimate of the first-stage regression finds an F-statistic greater than the Staiger-Stock value of 10 for our instrument and therefore we assume that the external instrument is not weak.

3.2 Model and Identification

For the purposes of this paper, we employ a version of the SVAR-IV methodology pioneered by Stock and Watson (2012), and Mertens and Ravn (2013). The SVAR-IV identifies contemporaneous effects by using external instruments that are not included in the set of endogenous variables.

Y_{it} $(i = 1, ..., 12)$ is our vector of endogenous variables. In this paper there exist 12 different sets of variables, each with a different primary variable of interest represented by the subscript i (i.e. the market indexes). Each Y_{it} contains 6 variables represented by the subscript j $((j = 1, ..., 6))$. Let OIL_t be our endogenous regressor of interest, that is oil price returns. No.2 heating oil (Z_t) is our chosen instrumental variable. Let C_{jt} be our selected control variables (Industrial Production, Inflation Rate, World Market Return, and 10-Year Treasury Rate). Y_{it} can be written as:

$$Y_{it} = [INDEX_{it}, OIL_t, C_{1t}, C_{2t}, C_{3t}, C_{4t}] \tag{3.1}$$

The Structural VAR representation is,

$$AY_{it} = \sum_{p=1}^{n} \alpha_p Y_{i,t-p} + \varepsilon_{it} \tag{3.2}$$

where ε_{it} is a vector of serially and mutually uncorrelated structural disturbances. The latent variables of ε_{it} are estimated on the basis of the prediction errors of Y_{it} conditional on the information contained in the vector of lagged dependent variables $X_{it} = [Y^{'}_{i,t-1}, ..., Y^{'}_{i,t-p}]^{'}$. A is a 6×6 matrix of contemporaneous coefficients and α_p are 6×6 coefficient matrices. The reduced-form VAR model is obtained by multiplying both sides of Equation (3.2) by A^{-1}. The reduced-form error term can be written as $\eta_{it} = B\varepsilon_{it}$, where $B = A^{-1}$.

The requirement $E[\eta_{it}\eta^{'}_{it}] = BB^{'}$ imposes $j(j-1)/2 = 30$ identifying restrictions, but we require additional identifying restrictions for the elements of the last column of B. Consider the partition of the structural shocks $\varepsilon_{it} = [\varepsilon^{j-1}_{it}, \varepsilon^{oil}_{it}]$, where ε^{oil}_{it} is the shock of interest and ε^{j-1}_{it} is a $(j-1) \times 1$ vector containing all other $(j-1)$ shocks.

Following Mertens and Ravn (2013), we use covariance restrictions obtained from the proxy for the latent shocks. These are our key identifying assumptions and an additional condition:

(3.3) $$E[Z_t \varepsilon_{it}^{oil}] = \alpha \neq 0$$

(3.4) $$E[Z_t \varepsilon_{it}^{j-1}] = 0$$

(3.5) $$E[Z_t X_{it}^{'}] = 0$$

The third condition requires that the instrument be orthogonal to the history of Y_{it}, however this assumption can be relaxed. The external instrument can be used for identification of the elements B as long as Equation (3.3) and Equation (3.4) are satisfied. Consider the partition of B for a single VAR(p) system of Y_{it}:

$$B = \begin{bmatrix} \beta_1 & \beta_2 \\ (6 \times 1) & (6 \times 5) \end{bmatrix}, \beta_1 = \begin{bmatrix} \beta_{11}^{'} & \beta_{21}^{'} \\ (1 \times 1) & (1 \times 5) \end{bmatrix}^{'}, \beta_2 = \begin{bmatrix} \beta_{12}^{'} & \beta_{22}^{'} \\ (5 \times 1) & (5 \times 5) \end{bmatrix}^{'}$$

Equations (3.2) - (3.5) imply that

(3.6) $$\alpha \beta_1^{'} = \Theta_{Z_t, \eta'} \equiv E[Z_t \eta^{'}]$$

Further partitioning of $\Theta_{Z_t, \eta'}$ gives,

$$\Theta_{Z_t, \eta'} = \begin{bmatrix} \Theta_{Z_t, \eta_1^{'}} & \Theta_{Z_t, \eta_2^{'}} \\ (1 \times 1) & (1 \times 5) \end{bmatrix}$$

These restrictions therefore give the following:

(3.7) $$\beta_{21} = (\Theta^{-1}_{Z_t, \eta_1^{'}} \Theta_{Z_t, \eta_2^{'}})^{'} \beta_{11}$$

The SVAR-IV identification process for B in this study is as follows[1]:

Step 1: Estimate the reduced-form VAR(p) using p-lagged values of Y_{it} as controls and obtain the residuals η_{it}.
Step 2: Estimate $\Theta^{-1}_{Z_t, \eta_1^{'}} \Theta_{Z_t, \eta_2^{'}}$ from the regressions of η_{it} on Z_t.
Step 3: Impose the restrictions in Equation (3.6) and estimate the dynamic causal effects of ε_{it}^{j}, specifically ε_{it}^{oil}.

[1]For a generalized approach not restricted to one external instrument, see Mertens and Ravn (2013). Ramey (2016) offers another, potentially more intuitive, explanation of the SVAR-IV process used by Mertens and Ravn (2013).

Chapter 4

Empirical Results

4.1 Impulse Responses to Oil Demand Structural Shocks

Figure 6.1 shows the impulse response functions of the returns on U.S. stock market indexes to one-standard deviation structural oil demand shocks over a horizon of 12 months. Following the advice of Kilian and Ivanov (2005), Akaike Information Criteria (AIC) is used to determine our lag order selection of p=1. Note, however, Schwarz Information Criteria (SIC) also suggests the use 1 lags. Bootstrapped 95% confidence bands over 100 runs are included.

Overall, the responses to an unexpected shock of oil demand are minor, indicating that for most stock market sectors, oil prices don't influence market returns in a large way. The results show that an unexpected increase in oil price returns is associated with a negative impact on stock market returns in the immediately following period for 4 of the 11 sectors of the U.S. stock market and the total U.S. market sees an overall positive return of 0.337%. Energy and Materials sectors stand out by having a statistically significant positive response to an oil price increase. In the first period following a oil demand shock, the energy sector sees a 2.898% return and the materials sector sees a 1.1% return. The second month following an oil demand shock has all but 2 sectors facing a decrease in monthly return from the previous month. By the third month, 10 of 11 sectors and the U.S. total market see negative market returns. Responses stabilize around the sixth month following the shock, and the impact is virtually gone by the eighth month.

These results are semi-consistent with previous studies stating that oil price increases generally result in negative impacts to the United States stock market. The overall positive impact found in the first period differs from most prior studies. It is not until the third period that most sectors see negative returns. Compared to previous studies, the results show an overall lesser impact on the U.S. stock market. These discrepancies can be explained by two features that differentiate this study from prior work: 1) the use of an external instrument, and 2) the use of data that captures recent changes in the U.S. oil market.

The use of an external instrument will produce different results. Stock et al. (2018) find differing results between Cholesky-identified shocks and external-instrument identified shocks in a reexamination of Kilian (2009). Another explanation comes from the sample of data. The data used in these models extends from January 1987 to May 2020. Studies have shown that the impact of oil shocks on markets has changed over time. With new trends in the world oil market, a full-sample evaluation with current data will produce results that indicate a lesser impact, or potentially an opposite impact, than results obtained with older data. Kilian and Park (2009) show that a one standard deviation shock to oil-market specific demand has a statistically significant negative effect on U.S. stock returns. However, that study uses data from January 1973 to December 2006. In a revisit of the study, with included data up to December 2014, W. Kang et al. find a continued negative response, but at a reduced level. This paper will review structural changes in the U.S. that developed after the Great Recession, and discuss current events with the ongoing COVID-19 pandemic.

4.2 Comparison with Cholesky-Identified SVAR

First we compare the results to a base standard SVAR model where the shocks are identified via Cholesky decomposition. This base model contains the same vector of endogenous variables and the same lag order of p=1 suggested by AIC, but the shocks are no longer identified by our external instrument, No.2 Heating Oil. Figure 6.2 shows the impulse response functions of the returns on U.S. stock market indexes to one-standard deviation structural oil demand shocks over a horizon of 12 months.

There are several notable differences between the results of the two SVAR models. Overall, the results are more depressed in the Cholesky-identified SVAR compared to the SVAR-IV model, with the exception of the materials and utilities sectors. This is consistent with the findings by Stock et al. (2018) where the Cholesky-identified results in Kilian (2009) were lesser than the responses from the SVAR-IV reevaluation. In some cases the the initial market response is in the opposite direction. In the SVAR-IV model, the total U.S. market index has a positive reaction of 0.377% in the first month following an oil demand shock. The total U.S. market index from the standard SVAR model sees a -0.268% reaction in the first month following an oil demand shock, a decrease of 0.645% compared to the SVAR-IV result. Energy and materials sectors still see a statistically significant positive response in the first period, but while the energy sector sees a lower return in the standard SVAR model the materials sector's response is more than twice as large as in the SVAR-IV model.

4.3 Market Responses Over Time

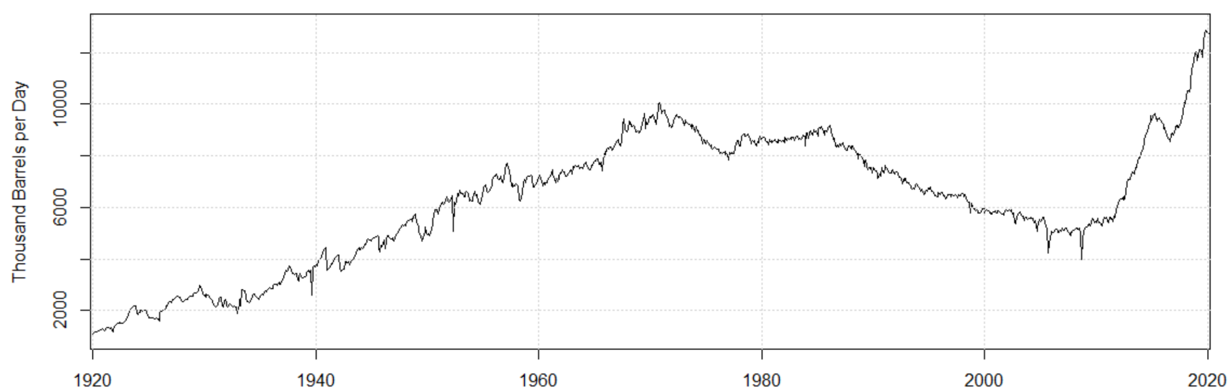
Figure 6.5 shows the SVAR-IV cumulative impulse response functions of U.S. stock market returns using an 8-year rolling window. The first period observed is January 1995. Most sectors face negative, or near-zero, returns with the exceptions of the energy sector which maintains positive returns over the entire sample period. Following the Great Recession in 2008, the responses of stock markets to an oil demand shock generally increase across all sectors and most sectors see positive returns. By 2012 all sectors see positive cumulative returns in response to an oil demand shock.

The impulse responses of U.S. stock market returns to an oil demand shock from the period of 1987:01 to 2007:12

are shown in Figure 6.3. The data is truncated to December 2007 in order to capture the effects prior to the Great Recession in the United States[1]. Comparing the impulse responses from the truncated sample (1987:01-2007:12) with the full sample (1987:01-2020:05), the U.S. stock market faced dramatically different responses prior to the structural changes that occurred after 2007. Monthly returns were substantially lower following an oil demand shock and overwhelmingly negative, with the exception of the Energy and Utilities sectors. The energy sector once again sees positive returns following an oil demand shock, albeit at a lower level than in the full sample test, and the utilities sector response is insignificantly close to zero.

Figure 4.1 illustrates monthly oil production in the United States over the course of the past century, from January 1920 to May 2020. U.S. oil production peaked at 10 million barrels per day in 1970 and eventually slumped to the lowest recorded value since 1943 of approximately 4 million barrels per day in 2008. After decades of low U.S. oil production, innovations in the extraction of crude oil have resulted in substantial growth in U.S. oil production. In 2018, U.S. oil production reached a new high surpassing the 1970 total. In 2019, the United States produced approximately 12 million barrels per day and exported more crude oil and petroleum products than it imported for the first time in 75 years. The EIA projects that the U.S. will continue to be a net oil exporter until 2050. As of 2020, the U.S. oil production is nearing 13 million barrels per day.

Figure 4.1: U.S. Oil Production



Over the past decade, recent structural innovations point towards new trends in the U.S. oil market. These significant changes suggest that empirical research observing data prior to 2010 may not provide an accurate representation of how the economy will react to oil-specific shocks. Many influential studies, that are still referenced today, were performed prior to the significant market changes of the past ten years. The findings in this section bring attention to the importance of performing repeat studies with updated data, and investigating the new dynamics within the energy

[1]According to the National Bureau of Economic Research (NBER), the recession began in December 2007 and continued until June 2009.

economy.

4.4 A Note on the COVID-19 Pandemic

The coronavirus disease 2019 (COVID-19) pandemic is an ongoing global pandemic that was first identified in Wuhan, China, December 2019. In January 2020, the virus was declared an international public emergency by the World Health Organization and subsequently declared a global pandemic two months later in March 2020. As of July 2020, there are over 12 million confirmed cases, and and estimated 556,000 deaths. With nearly 3.1 million confirmed cases and over 132,000 deaths, the United States accounts for approximately a quarter of the world's coronavirus cases and deaths. Efforts to mitigate the outbreak in the U.S. have been ineffective, and the number of cases continue to rise. At the time of writing this paper, the Centers for Disease Control and Prevention are recording around 60,000 daily cases.

The COVID-19 outbreak has had a sharp impact on the U.S. entered a nationwide quarantine. U.S. GDP fell by 4.8% in the first quarter of 2020, putting an end to the longest period of expansion in U.S. history. The unemployment rate in April reached an all time high of 14.7%, an increase of 10.3% from the 4.4% number recorded just one month earlier. On April 20th, 2020, the price of U.S. oil turned negative for the first time in history. WTI Crude Oil reached a price of $-\$36.96$ per barrel as demand for petroleum products fell with lockdowns occurring across the world.

Table 4.1: Raw Data Values 2019:12 - 2020:05

	Dec 19	Jan 20	Feb 20	Mar 20	Apr 20	May 20
U.S. Total Market	3031.80	3127.66	3138.55	2156.69	2617.30	2784.81
World Total Market	2113.67	2188.76	2159.00	1728.07	1758.99	1849.14
WTI Crude Oil	59.88	57.52	50.54	29.21	16.55	28.56
No.2 Heating Oil	1.97	1.84	1.59	1.16	0.86	0.85
Industrial Production	109.43	109.13	109.26	104.33	92.59	92.55
Consumer Price Index	258.44	258.82	259.05	257.95	255.90	255.77
10-Year Treasury Rate	1.86	1.77	1.43	0.87	0.63	0.64

All values are recorded as the monthly average.

The sample period for this paper was originally supposed to cover the time from January 1987 to December 2019. However, with the events that have occurred in the past six months it was decided to extend the sample to May 2020. Table 4.1 shows some of the raw data values used in this study from December 2019 to May 2020, illustrating the impact of the COVID-19 pandemic in the first half of 2020. The sudden impact of the pandemic is apparent in some of the graphs included in this paper including the graphs of the Market Indexes and WTI Oil Price (Figure 2.1) and cumulative impulse responses (Figure 6.5). Figure 6.4 shows the SVAR-IV analysis with the sample period ending in December 2019. The results are similar to the full-sample analysis and the magnitude of the impacts remain small in size. Despite this, the differences are still worth noting and the degree to which including the additional 5 periods impacts the market responses is surprising.

Chapter 5

Conclusion

In this paper, the impact of oil prices on the U.S. stock market is evaluated using the novel method of SVAR-IV. Influenced by the narrative approach pioneered by Romer and Romer (1989), the contemporaneous effects in a SVAR are identified using data that is external to the model. No.2 Heating Oil is chosen as the external instrument and is taken to be correlated with the target shock, a positive oil price shock, and uncorrelated with other shocks in the model. It is believed that the choice of external instrument in this study provides sufficient exogenous variation to identify the dynamic causal effects of an oil demand shock. The results show that U.S. stock market returns generally do not respond in a large way to oil market shocks, with the exception of the energy and materials sectors. Furthermore, the existing significant effects are relatively small in magnitude. These results are semi-consistent with previous studies on the subject area. The differences in results are explained by two differentiating factors: 1) the use of in external instrument, and 2) the use of data that captures significant structural changes over the past decade.

When implementing the relatively new statistical technique of including external instruments in a vector autoregressive model, it is necessary to compare the results with the results of a standard SVAR model. This paper finds that SVAR-IV estimates are generally larger in magnitude than estimates from a Cholesky-identified SVAR. However, the magnitude of the market responses to an oil price shock remain small even in the Cholesky-identified SVAR.

Changes in U.S. oil market are also considered. This paper illustrates that recent innovations in the U.S. oil industry will produce dramatically different results in new studies compared to studies performed even less than a decade ago. Market responses to oil price shocks overall changed from negative to positive after 2008 in a majority of sectors. The ongoing COVID-19 pandemic has also complicated matters, causing a larger than expected change in market responses over the course of only a few months.

5.1 Concluding Remarks

This paper benefits greatly from having a strong instrument, avoiding the complications that come with the use of weak instruments in the SVAR-IV methodology. Having an instrument that is highly correlated with the target shock suggests that the SVAR parameter estimators are approximately normally distributed and the confidence sets are reasonably precise [10]. Thus, the estimates gathered in this study and the concluding results are believed to be sufficiently accurate. However, there are key elements not included that would greatly expand the findings from this paper. A deeper investigation of instrument variable tests and inference on variance decomposition [11] would provide additional insight. As SVAR-IV methodology is developed further, the techniques used in this paper may require reevaluation.

Chapter 6

Appendix

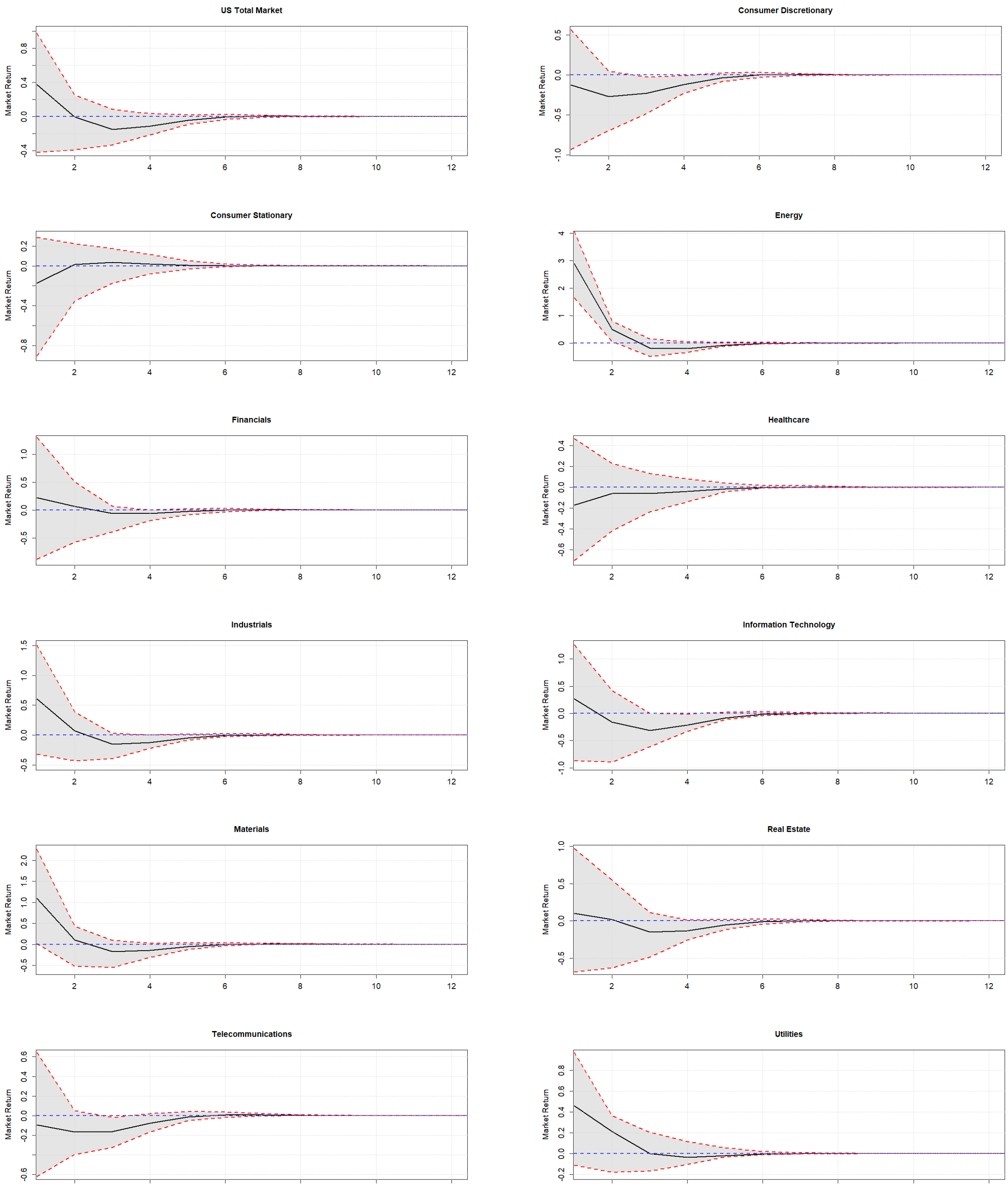


Figure 6.1: Orthogonal Impulse Responses to Oil Price Shock (SVAR-IV)
1987:01-2020:05

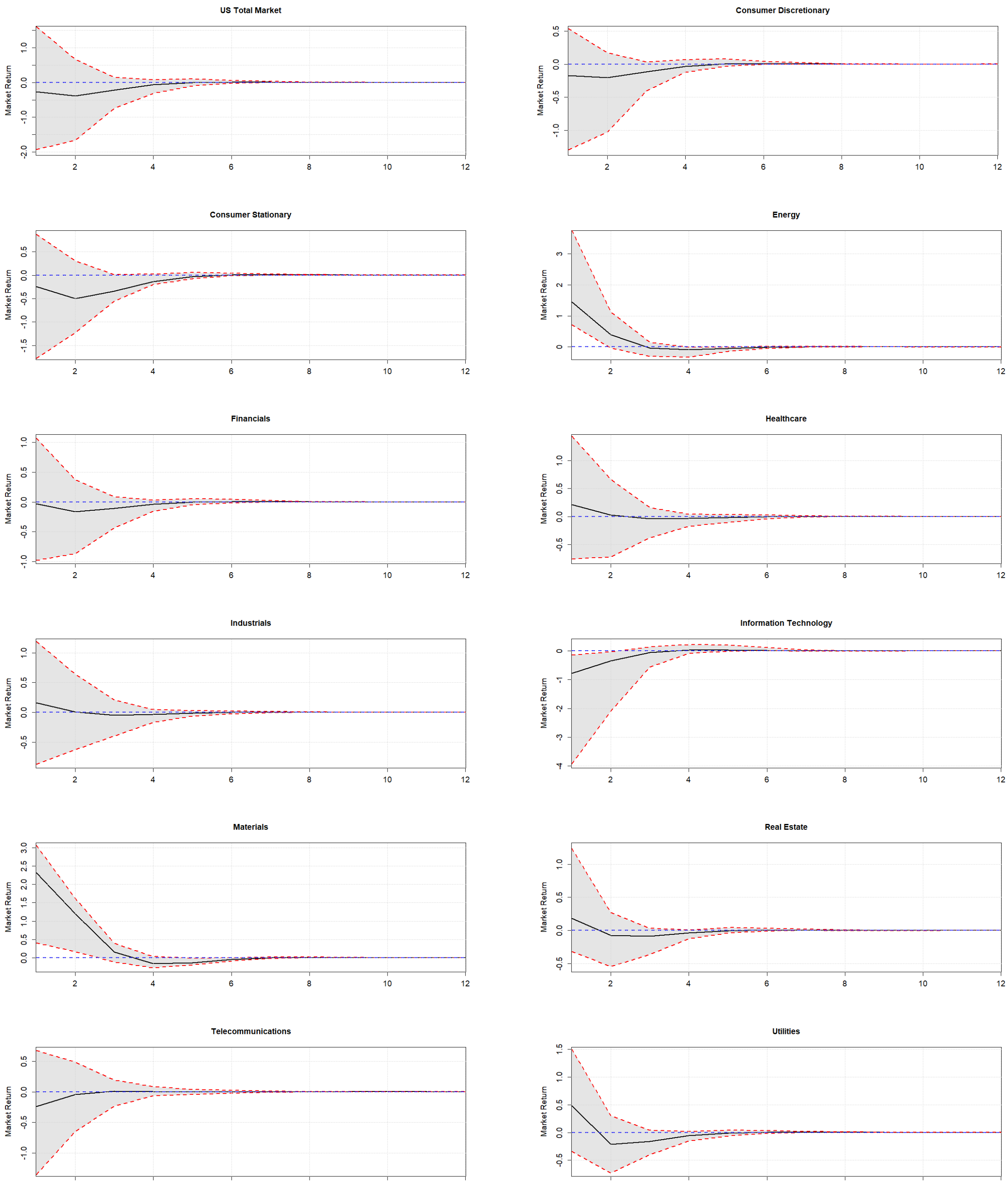


Figure 6.2: Orthogonal Impulse Responses to Oil Price Shock (Standard SVAR)
1987:01-2020:05

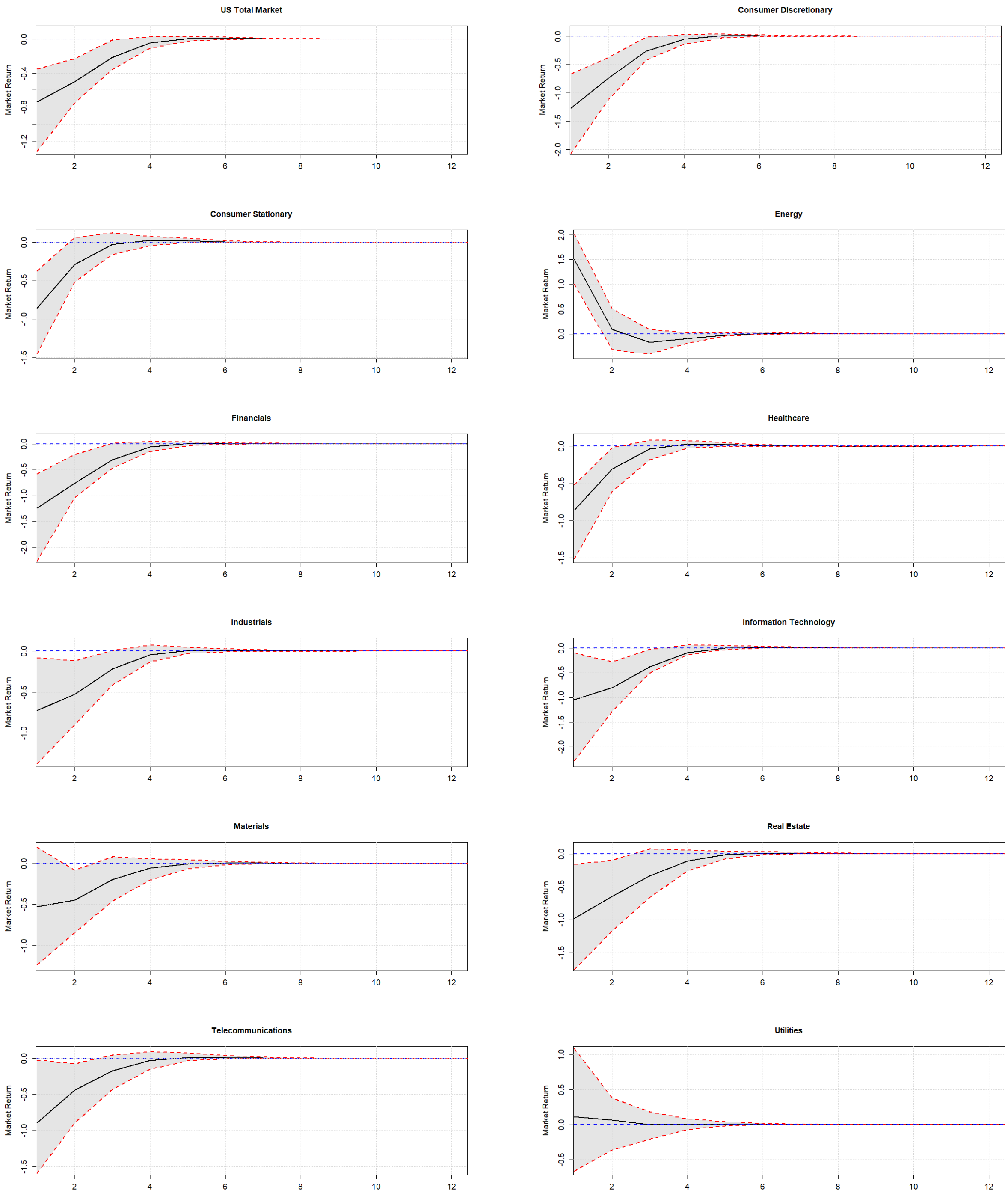


Figure 6.3: Orthogonal Impulse Responses to Oil Price Shock (SVAR-IV)
1987:01-2007:12

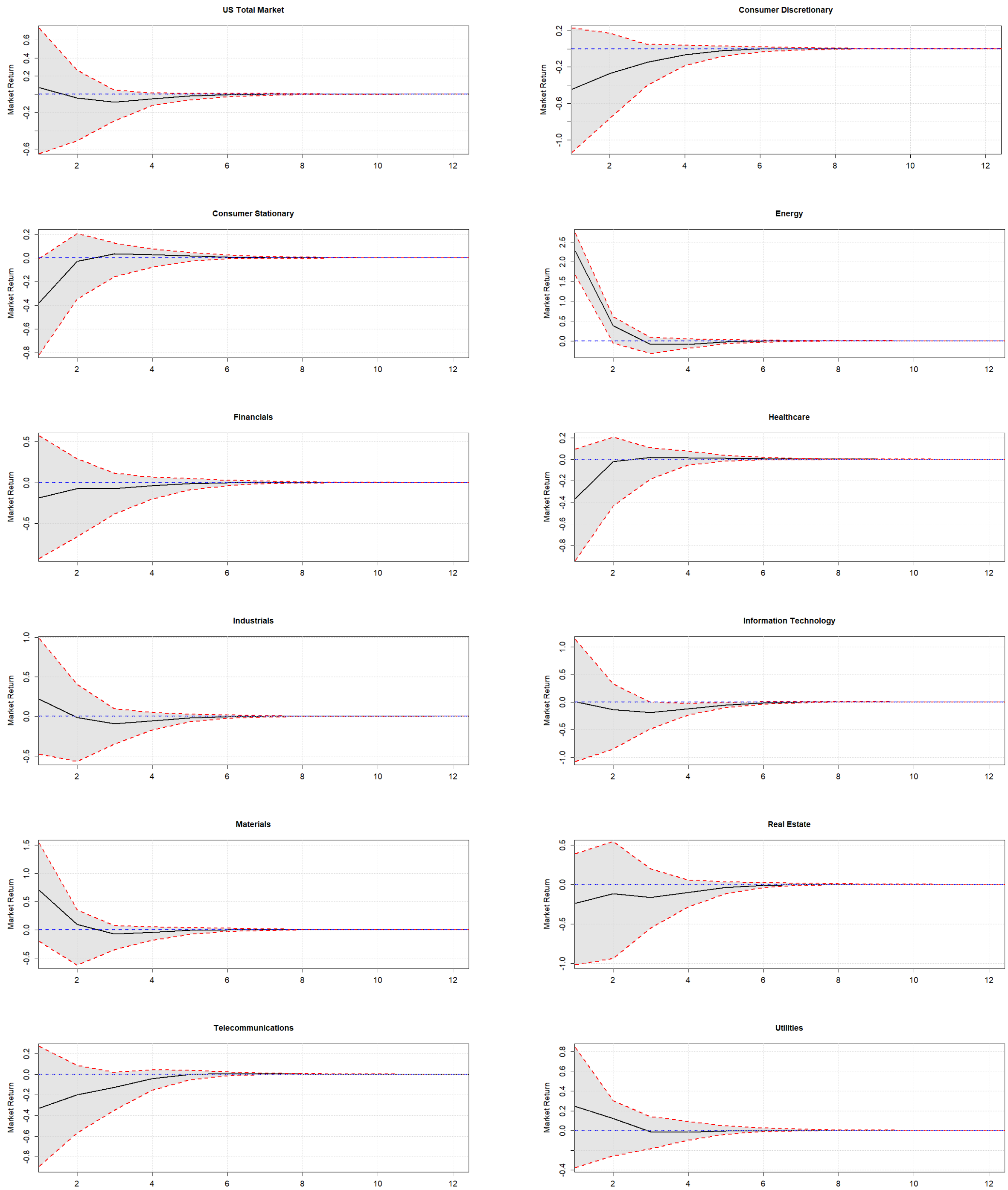


Figure 6.4: Orthogonal Impulse Responses to Oil Price Shock (SVAR-IV)
1987:01-2019:12

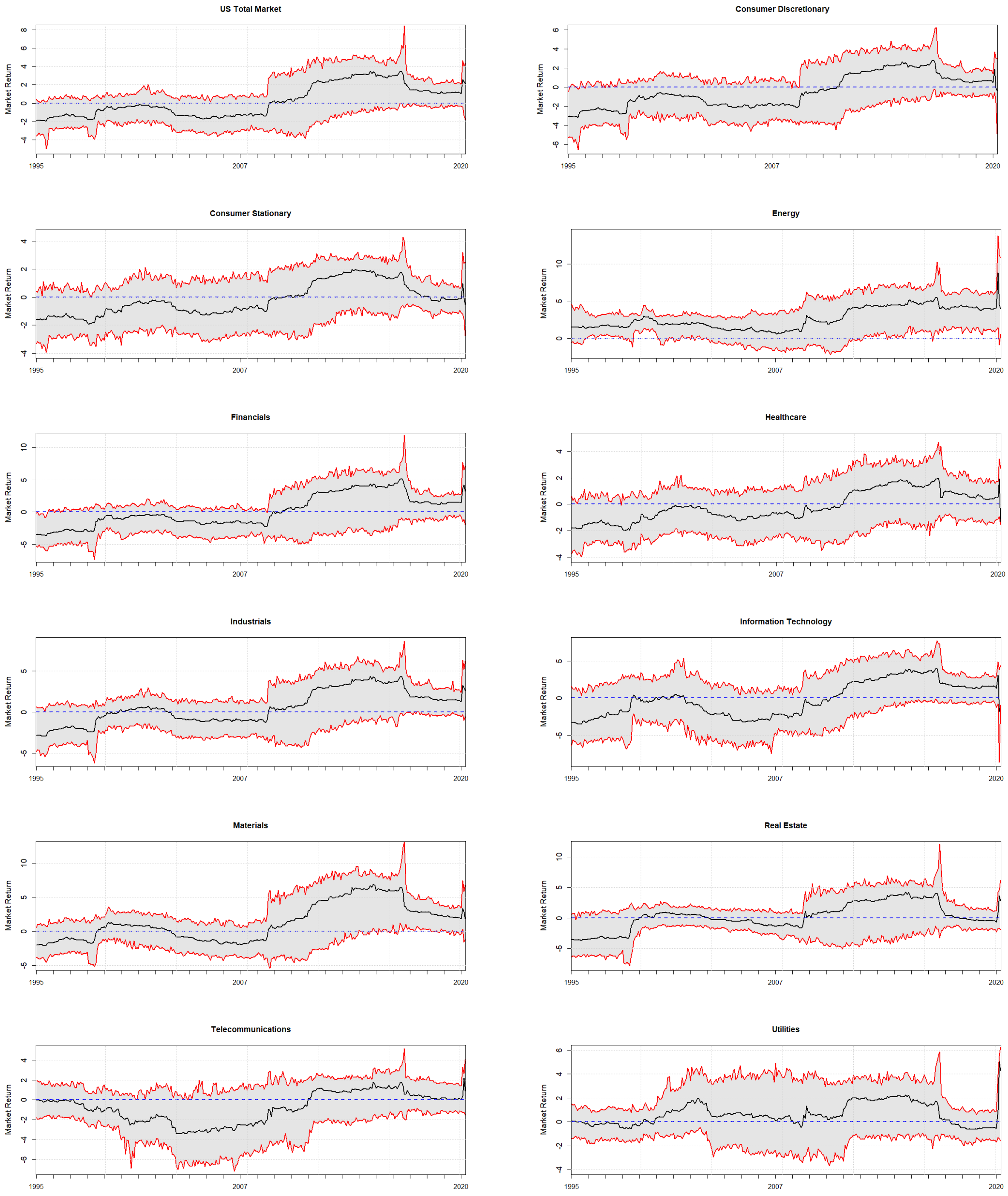


Figure 6.5: Cumulative SVAR-IV Impulse Responses to Oil Price Shock, 8-year Rolling Window

Table 6.1: First-Stage Regression

	Dependent variable:
	OIL_t
OIL_{t-1}	−0.006
	(0.055)
$Heating\ Oil_t$	0.709^{***}
	(0.036)
$Heating\ Oil_{t-1}$	0.030
	(0.053)
IP_t	1.935^{***}
	(0.342)
IP_{t-1}	-2.262^{***}
	(0.326)
CPI_t	6.806^{***}
	(1.388)
CPI_{t-1}	-3.172^{**}
	(1.266)
$WMKT_t$	0.200^{***}
	(0.073)
$WMKT_{t-1}$	−0.066
	(0.077)
TEN_t	0.144^{***}
	(0.046)
TEN_{t-1}	0.048
	(0.048)
Constant	−0.006
	(0.004)
Observations	399
R^2	0.718
Adjusted R^2	0.710
Residual Std. Error	0.051 (df = 387)
F Statistic	89.740^{***} (df = 11; 387)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6.2: First-Stage F-test for No.2 Heating Oil

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	388.000	1.414	387	387.5	388.5	389
RSS	2	1.529	0.722	1.019	1.274	1.784	2.040
Df	1	2.000		2.000	2.000	2.000	2.000
Sum of Sq	1	1.021		1.021	1.021	1.021	1.021
F	1	193.856		193.856	193.856	193.856	193.856
Pr(>F)	1	0.000		0.000	0.000	0.000	0.000

Table 6.3: Wu-Hausman Diagnostic Tests

Market Index	F-Stat	Pr(>F)
U.S.Total Market	5.812	0.016^{**}
Consumer Disc.	10.163	0.002^{***}
Consumer Stat.	0.466	0.495
Energy	6.157	0.015^{**}
Financials	3.872	0.049^{**}
Healthcare	0.184	0.668
Industrials	0.129	0.735
Info. Tech.	4.213	0.041^{**}
Materials	0.151	0.697
Real Estate	0.125	0.723
Telecom.	5.046	0.025^{**}
Utilities	2.385	0.123

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Chapter 7

R Codes

Much of the code required to perform the SVAR-IV analysis was constructed using processes gathered from the packages listed below.

Information on Packages Used

AER: `https://cran.r-project.org/web/packages/AER/AER.pdf`

stargazer: `https://cran.r-project.org/web/packages/stargazer/vignettes/stargazer.pdf`

tseries: `https://cran.r-project.org/web/packages/tseries/tseries.pdf`

moments: `https://cran.r-project.org/web/packages/moments/moments.pdf`

vars: `https://cran.r-project.org/web/packages/vars/vars.pdf`

svars: `https://cran.r-project.org/web/packages/svars/svars.pdf`

xtable: `https://cran.r-project.org/web/packages/xtable/xtable.pdf`

reshape2: `https://cran.r-project.org/web/packages/reshape2/reshape2.pdf`

boot: `https://cran.r-project.org/web/packages/boot/boot.pdf`

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