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Shocks and stocks:
An examination of stock market returns and -volatility in relation to changes in the oil market

Written by: Christina Lindstad & Nina Emelie Lyford

Master of Science in Business, Economics

Supervisor: Dr. Jamie L. Cross

BI Norwegian Business School

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The process of writing this thesis has been characterized by discovery, learning and enjoyment. We are grateful for the opportunity to delve into the complexities of oil price dynamics and how it relates to the stock markets of the United States and Norway.

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Abstract

This paper reexamines the dynamic relationship of the oil- and stock markets by extending the original Structural vector autoregressive model (SVAR) for oil market shocks, proposed by Kilian (2009), to include two separate measures for the stock market, returns and volatility. This facilitates a deeper dive into the distribution of the stock market, in addition to an exploration of the relationship between stock returns and -volatility in response to changes in the oil market. We apply our SVAR to both U.S. and Norwegian stock price data for a further investigation of the structural differences between oil importers and -exporters.

Using traditional zero short-run restrictions, we find that the global oil price disruptions decomposed by Kilian (2009) are remarkably robust. Further, we show that inclusion of several measures representing the U.S. stock price alter the responses of the stock market dynamics. Specifically, even though returns often are considered the preferable measure for the stock price, volatility is equally important, and oil market disruptions are responsible for a greater part of the variability of volatility than returns.

Next, an analysis of the Norwegian stock market dynamics unveil different responses than those of the U.S., suggesting structural differences between the two countries. Oil market disruptions have overall greater explanatory power for the movements of the Norwegian stock market. Concretely, we find a large part of the variability of Norwegian returns to be caused by oil supply shocks. Conversely, oil-specific demand shocks play a larger role for the U.S. stock market than that of Norway. We postulate that economic structures, including net-imports of oil, and sector-focus in the stock market, significantly affects the dynamics of the oil-stock price relationship in a country.

Keywords: Structural VAR, Oil Market, Stock market, Stock Returns, Realized Volatility, Norway, U.S.

1 Introduction

The beginning of the 21st century has been impacted by substantial global events resulting in an economic landscape characterized by high uncertainty and volatile market movements, impacting both international stock markets and the price of crude oil, e.g. the great recession of 2008 (Norges Bank, 2022). The majority of later research based on Kilian's (2009) Structural Vector Autoregressive model (SVAR) has focused on stock returns and -volatility responses in isolation, subjected to the underlying oil price shock. Conversely, a stylized fact within financial literature is asymmetric volatility, meaning stock returns are negatively correlated with stock volatility (Bae et al., 2007). This suggests that examining an isolated time series might not represent the full complexities of the stock market. Given this insight, we are motivated to contribute to the macroeconomic research on oil price dynamics by facilitating a deeper understanding of the stock market distribution, and how this relates to the dynamics of the oil-stock price relationship.

Hence, the primary goal of this thesis is to estimate and analyze the effects of oil price shocks on stock market returns and -volatility, while accounting for the aforementioned returns-volatility relationship. To this end, we build on the existing research papers by Kilian and Park (2009) and Bastianin and Manera (2018), which examine the impact of oil price shocks on stock market returns and -volatility, respectively. The first objective of this thesis is therefore to reexamine the above mentioned research papers by separately replicating their SVARs. Secondly, we continue by investigating the responses in a combined model that accounts for the relationship between stock returns and -volatility. Third, we will apply the combined model to Norway, in order to explore how the oil- and stock market dynamics are affected in an oil-exporting nation. Thus, this thesis will specifically address the following research question [1]:

"How do stock returns and volatility respond to oil price shocks in the United States and Norway?"

[1] Analysis of exogenous stock market shocks, their effects on the oil market and the economy at large, lie outside the scope of this thesis.

2 Literature review

2.1 Oil market literature

Since the 1980s, a comprehensive body of research related to oil price shocks and the responses of macroeconomic variables have been conducted. Early studies on oil price shocks, e.g. Hamilton (1983), used regressions to research the effects, treating the price of oil as exogenous while underlying causes of the shocks were unidentified.

2.1.1 Kilian (2009)

The ceteris parabus assumption that one can vary the oil price while holding other variables fixed has later been challenged. Kilian (2009) address two complications with previous work relying on this assumption:

- Cause and effect are not clearly defined when relating changes in the price of oil to other macroeconomic variables, resulting in possible reverse causality, i.e. a simultaneity problem.
- The oil price is driven by structural demand- and supply shocks who provide different dynamics, creating both direct and indirect effects.

As a response, Kilian (2009) proposed a structural vector autoregressive model, where he decomposed the oil price fluctuations into three underlying causes. The first component being oil supply shocks, which are shocks to the current physical availability of crude oil and can be defined as unpredictable innovations to global oil production. Second, he defines shocks to aggregate demand as shocks to the current demand for crude oil driven by real business cycle fluctuations. These are fluctuations derived from innovations to global real economic activity. Finally, Kilian (2009) introduced oil-specific demand shocks as shocks to the precautionary oil demand, capturing market concerns and expectations about the future availability of oil supply.

By introducing the underlying causes of oil price disruptions, Kilian (2009) was able to estimate the dynamics of the contributions from each shock to the real price of oil. He found demand shocks to play a key role when analyzing effects from shocks to the price of oil. Moreover, his work contributed to a renewal of existing approaches on modeling oil price shocks, leading successor researchers to adapt his new model when investigating stock returns, volatility and other macroeconomic variable responses, e.g Kilian and Park (2009) and Bastianin and Manera (2018).

2.1.2 Kilian and Park (2009)

An important contribution to the research followed by Kilian (2009) was introduced by Kilian and Park (2009). By relating U.S. stock returns to a variety of fundamental supply and demand shocks instead of focusing on the average effects, they were able to investigate if stock returns are impacted differently depending on the underlying cause of the unanticipated oil price change. Kilian and Park (2009) applied the method from Kilian (2009) using a SVAR including the three types of oil price shocks. They added a fourth variable representing U.S. real stock returns, enabling the authors to examine the effects of the oil price shocks on U.S. stock returns and dividend growth.

This led the researchers to conclude that the three shocks jointly explain one fifth of the long run variation in U.S. stock returns. Moreover, the response depended on what shocks the returns were exposed to, where they found that supply shocks had a lesser effect than aggregate and precautionary demand shocks (Kilian & Park, 2009). Further they agree with previous research that most of the asset returns and price variation come from fluctuations in the risk premia, not variation in the expected cash flows (Kilian & Park, 2009). This implies that it would be relevant to examine returns together with volatility, rather than dividend growth.

2.1.3 Bastianin and Manera (2018)

Bastianin and Manera (2018) investigated the response of stock price volatility related to oil price shocks. A common assumption among researchers at the time was that unexpected oil price changes led to negative asset returns and increased volatility (Bastianin & Manera, 2018). Bastianin and Manera (2018) sought to investigate whether this assumption holds when treating the oil price as endogenous. Following Kilian's (2009) methodology, they added a fourth augmented variable, realized volatility, as a proxy representing the variability in the U.S. stock market. This enabled them to investigate stock volatility fluctuations in response to oil market dynamics.

Bastianin and Manera (2018) were able to prove that stock volatility reacts differently when exposed to different oil price shocks. One of their key findings was that the U.S. stock market volatility is negligible to oil supply disruptions, while volatility responds significantly to demand shocks. Aggregate demand fluctuations cause an immediate reaction in volatility lasting for about six months, while oil-specific demand affects the volatility with a periodic delay (Bastianin & Manera, 2018). Their study is therefore another important contribution to the research by Kilian (2009) and Kilian and Park (2009) on the link between oil price shocks and the stock market.

2.2 Financial literature

Through the capital asset pricing model, Merton (1980) found a relationship between expected return and expected volatility of the aggregate stock market. Later evidence from financial literature solidifies this link between stock returns and volatility (Aït-Sahalia et al., 2013), signifying a negative correlation between the variables where low average returns are associated with high volatility and opposite. Bae et al. (2007) propose two explanations for this asymmetric relationship:

1. The leverage effect: When equity value drops, companies become more leveraged since the relative value of their debt increases compared to their equity. This leads to a riskier stock, implying increased volatility.
2. The feedback effect: When an increase in volatility raises the expected future volatility and thereby decreases stock returns. This effect results in the same asymmetric relationship as the leverage effect, however the causal relationship is reversed (Bae et al., 2007).

Although the financial literature is broadly in agreement that an asymmetric relationship should be expected when estimating the correlation between returns and volatility (Bae et al., 2007), it appears that this does not apply to all empirical findings. Epps (1979), suggested that high frequency observations tend to weaken the empirical correlation between stock returns due to noise that can be incorporated in the asset prices. This happens due to inconsistencies over time during the trading process of assets or when experiencing limited liquidity Aït-Sahalia et al. (2013). The correlation between asset returns and volatility can therefore become close to zero, instead of the negative relationship that is expected from the financial theory (Chang et al., 2020). To circumvent the potential influence from the Epps effect when using observations of high frequencies, researchers have attempted to estimate the correlation using data for volatility and returns of the same asset (Aït-Sahalia et al., 2013). The observations are by construction synchrone and can be used to further the empirical research on the correlation between oil market shocks and the stock market.

2.3 Other related literature

From an empirical perspective, research on the relationship between expected stock returns and volatility in the context of oil market SVARs is relatively sparse. Jung and Park (2011) published a closely related paper to our thesis, also extending on the research of Kilian and Park (2009). Their paper investigates returns and volatility of the stock market when exposed to oil price shocks, examining Norway as an oil exporter and South Korea as an oil importer. Still, their research differs from ours as they do not consider simultaneous reactions of stock returns and volatility in a combined SVAR, but rather investigate the measures separately before analyzing a conditional covariance measure to determine if the responses can be explained by a risk-return tradeoff (Jung & Park, 2011).

Their findings imply that shocks to aggregate demand have more persistent effects on Norway than South Korea, both when examining returns and volatility. This is explained by the increased oil price leading to higher production costs, while also increasing oil investments. For Norway as an oil exporter, the latter effect leads to economic stimulus which dominates the first effect eliciting the greater response. Oil-specific demand shocks lead to increased stock returns on impact for an oil exporter, but the effect becomes insignificant after only one month. Volatility shows no statistically significant responses. However, oil importers experience positive and persistent effects for volatility when exposed to the same speculative shock, along with a negative response for stock returns. When analyzing the conditional covariance measure for the stock market variables, Jung and Park (2011) finds no evidence of a risk-return tradeoff, i.e. there are no indications of positive comovements appearing in their data.

Further, Degiannakis et al. (2014) investigated the response of volatility subject to structural oil market shocks based on three measures from the European stock market index; realized, conditional and implied volatility. Their results underpinned that stock market volatility responded to shocks in aggregate demand. However, unlike Jung and Park (2011) they could not find any responses to oil-specific demand shocks. Possible explanations could be that their dataset was based on an index for the European stock market containing both oil exporters and importers, or the limited period of available EU data extracted between 1999-2010 (Degiannakis et al., 2014). Given their differing results, this highlights the need for sufficient time series lengths, in addition to clearly defining and controlling for the different moments of the stock market distribution when examining its response to oil market shocks.

3 Methodology

The structural vector autoregressive model by Kilian (2009) is based on the original vector autoregressive model initially introduced by Sims (1980), and has since its development been used in a wide range of empirical research focusing on the dynamic relationships of macroeconomic variables (Kilian & Zhou, 2023).

3.1 The general SVAR with short-run recursive identification

This thesis combines the SVARs of Kilian and Park (2009) and Bastianin and Manera (2018) to construct a vector of variables of interest, y_t. This vector will include the following variables:

Oil market variables, from Kilian (2009)):

- Global crude oil production
- Real economic activity
- The real price of oil

Stock market variables:

- Real stock returns, from Kilian and Park (2009)

- Realized volatility, from Bastianin and Manera (2018)

Using this vector, we generate the following SVAR(24) process using monthly data:

$$B_0 y_t = \mu + B_1 y_{t-1} + \ldots + B_{24} y_{t-24} + \varepsilon_t, \tag{1}$$

Here, B_0 is the matrix of impact responses, μ represents the mean of the processes for each variable and ε represents the structural shocks in period t. These are, by construction, identically, independently distributed with mean, 0 and variance, 1, resulting in a variance-covariance matrix given by the identity matrix of order k:

$$\sum\nolimits_{\varepsilon} = I_k, \tag{2}$$

Direct estimation of *(1)* is not possible due to simultaneity problems. Hence, it is common to invert B_0 and estimate the resulting reduced form VAR.

$$k^2 - \frac{k(k+1)}{2} = \frac{2k^2 - k(k+1)}{2} = \frac{2k^2 - k^2 - k}{2} = \frac{k^2 - k}{2} = \frac{k(k-1)}{2} \tag{3}$$

$$B_0^{-1} B_0 y_t = B_0^{-1} B_1 y_{t-1} + ... + B_0^{-1} B_{24} y_{t-24} + B_0^{-1} \varepsilon_t, \tag{4}$$

The impact matrix has k^2 unknown parameters, while the reduced from error covariance matrix, $\sum_e$ only contains $k(k+1)/2$ unique parameters, since the off diagonal elements are identical by symmetry of the covariance matrix. To solve the resulting identification problem, we therefore need to restrict exactly $k(k-1)/2$ parameters to zero. Identification allows for obtaining the impact matrix, by calculating the reduced form VAR model and finding the covariance matrix for the reduced form shocks,

$$I_k y_t = A_1 y_{t-1} + ... + A_{24} y_{24-1} + e_t, \tag{5}$$

where I_k refers to the identity matrix of order k and e_t now becomes a weighted average of the structural shocks. Here $Cov(e) = \Sigma_e$ is the reduced from covariance matrix.

3.1.1 Identification

In order to estimate a model that is uniquely identified and stationary, with the purpose of performing statistical analysis as well as meaningful policy analysis, it must satisfy two important conditions, the order- and rank conditions:

1. The order condition requires that the number of structural shocks is less or equal to the number of time series variables included in the system (Kilian & Lütkepohl, 2017, pp. 218–219). Satisfying this, yields a covariance matrix of the structural shocks that is invertible.
2. The rank condition requires that the matrix defining the structural system is of full rank, meaning all columns of the impact matrix must be linearly independent. This ensures the uniqueness of the solution to the system (Kilian & Lütkepohl, 2017, pp. 218–219).

If both conditions are satisfied, we are able to uniquely identify the system and use it for economic analysis. There are several methods for satisfying these restrictions. This paper imposes short-run zero restrictions through Cholesky decomposition as means for structural identification. The Cholesky decomposition is a mathematical result in matrix algebra, stating that any positive definite symmetric matrix can be written in terms of the product of a lower triangular matrix with positive diagonal elements and its conjugate transpose. If $\sum_e = PP$', the lower triangular matrix P is the Cholesky decomposition of the positive definite symmetric matrix $\sum_e$, which is the covariance matrix of the reduced form errors (Kilian & Lütkepohl, 2017, p. 219). The reduced from errors are given by

$$\begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{pro} \\ e_t^{r} \\ e_t^{RV} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil\ specific\ demand\ shock} \\ \varepsilon_t^{other\ shocks\ to\ stock\ returns} \\ \varepsilon_t^{other\ shocks\ to\ RV} \end{pmatrix}$$

$$e_t = B_0^{-1}\varepsilon_t, \qquad (6)$$

accompanied by the variance-covariance matrix,

$$\sum_e = \mathbb{E}(e_t e_t^T) = \mathbb{E}(B_0^{-1}\varepsilon_t\varepsilon_t^T B_0^{-1T}) = B_0^{-1}\mathbb{E}(\varepsilon_t\varepsilon_t^T)B_0^{-1T}$$

$$= B_0^{-1}\sum_\varepsilon B_0^{-1T} = B_0^{-1}I_k B_0^{-1T} = B_0^{-1}B_0^{-1T}. \tag{7}$$

If the shocks can be made orthogonal to each other, i.e. mutually uncorrelated, we can identify the impact matrix. Hence, by applying the Cholesky decomposition and $P = B_0^{-1}$, we find the lower triangular Cholesky factor, which is the impact matrix. This transformation allows for conversion of the reduced form covariance matrix into a fully, uniquely, identified system of equations of contemporaneous effects (Kilian & Lütkepohl, 2017, pp. 218–219).

3.1.2 Stability and stationarity

In addition to the order- and rank conditions discussed above, the model has to be stable in order to estimate interpretable results and use them for statistical analysis. Lack of stability may lead to misleading results, e.g. impulse responses that show spurious cycles or never revert to its mean (Bjørnland & Thorsrud, 2015, p. 117). We can inspect the stationarity of the individual time series, x_t, by use of the Augmented Dickey-Fuller test (see appendix A). Stationarity requires a time invariant series (Kilian & Lütkepohl, 2017, p. 19), i.e. constant mean, constant variance and a first order autocorrelation of the system that is independent of time, however the autocorrelation can still depend on the lag length:

$$\mathbb{E}(x_t) = \mu \tag{8}$$

$$var(x_t) = \sigma^2 \tag{9}$$

$$cov(x_t, x_{t+h}) = cov(x_t, x_{t-h}) = \gamma_h. \tag{10}$$

Stationary time series are advantageous for valid inferences in time series analysis. Nevertheless, a stable model is also necessary, and stationarity of the individual time series does not guarantee a well behaved dynamic system. Conversely, the SVAR model can be stable even if all time series are not individually stationary (Kilian & Lütkepohl, 2017, p. 25). The process is stable if all the roots of the determinantal polynomial of the VAR operator are outside the complex unit circle. By construction, the eigenvalues of the companion form matrix are the reciprocals of the roots of the

VAR lag polynomial. This is equivalent to all the eigenvalues staying below 1 in absolute value (see Appendix A). Then the system will be mean-reverting, i.e. stable (Kilian & Lütkepohl, 2017, p. 25).

3.1.3 Imposed ordering

As a consequence of the impact matrix being lower triangular, it limits how the variables affect each other contemporaneously (Kilian & Lütkepohl, 2017, p. 220). Variables above can affect those below in the impact period of a shock, but the variables below can not affect those above contemporaneously. Still, all variables can affect each other with a lag, here we place no restrictions. It is important to appreciate the fact that this selected ordering means that we are trying to solve a system by imposing a solution on the system. The order in which we place the variables therefore ends up being paramount to the relationships we estimate. It is therefore necessary to have plausible economic justifications for any ordering imposed in order to use the estimates for economic analysis.

With the intent of staying consistent with the literature our research is building on, we have opted for the same ordering that was used by both Kilian and Park (2009) and Bastianin and Manera (2018) for the oil variables and will place those above the variables representing the stock market. Hence, the only consideration to be made with respect to ordering is regarding the two variables representing the stock market. We derive the stock returns and -volatility from the same initial time series, stock prices, making the variables by constriction synchrone and they should therefore be close to interchangeable. Returns represent overall market performance, while volatility can be defined as the price movements of the stock market investments, and interpreted as the dispersion in the returns themselves (Hillier et al., 2016, p. 241). The volatility is therefore placed at the very bottom. The ordering of our five variables of interest is as follows:

$$y_t = \begin{pmatrix} \textit{Oil production} \\ \textit{Real economic activity} \\ \textit{Real price of oil} \\ \textit{Real stock returns} \\ \textit{Realized volatility} \end{pmatrix} \tag{11}$$

4 Data

To estimate the structural relationships of the SVAR, careful decisions must be made when collecting time series for the vector of interest, y_t. Historical data on oil prices can be traced back to january 1947, yet there have been substantial changes in the regulation of the oil price since then. E.g, the Texas Railroad Commision previously set production limits in the U.S., leading to fixed nominal oil prices for long time periods (Alsalman & Herrera, 2015). Kilian and Park (2009) and Bastianin and Manera (2018) both extracted samples beginning in february 1973, presumably as oil production heavily increased and oil prices started to fluctuate at this time. When collecting data, we were unable to access the first year, and our full time series therefore spans 1974:2-2021:12.

4.1 International oil market variables

The foundation of the oil market variables is based on Kilian's (2009) seminal paper "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market".

4.1.1 Global oil production

Monthly time series for the global crude oil production were retrieved from the International Energy Statistics published by the U.S. Energy Information Administration (EIA, 2023a). Global crude oil production reported in 10 million barrels per day is a common measure of oil supply for time series analysis. By including lease condensate, a light liquid hydrocarbon often added into crude oil after production (EIA, 2013), the series provides a comprehensive measure of the overall oil market. Further, the data is processed by calculating the logarithmic values and the first difference, expressing the data as percentage change from previous period.

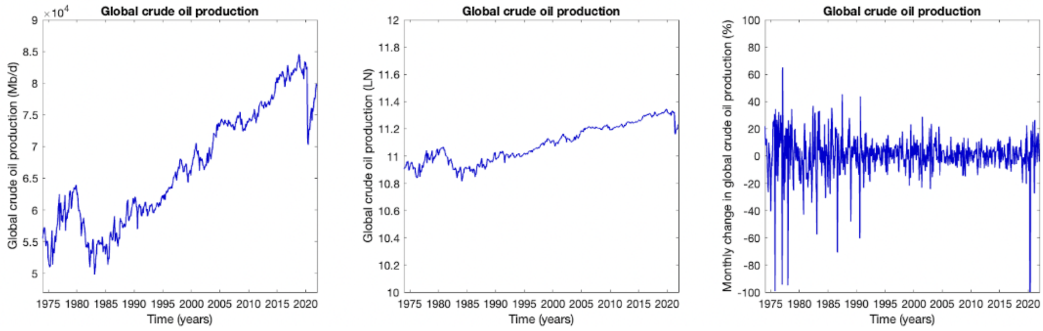


Figure 4.1: *Global crude oil production including lease condensate (LTR), expressed in 10 million barrels per day, logarithmic values and percent change from previous month.*

4.1.2 Real economic activity

The index of global real economic activity is a measure for the volume of shipping designed to capture shifts in demand for industrial commodities in global markets. The index was first proposed by Kilian (2009), and later updated in Kilian (2019). Kilian derived the time series from a panel of dollar-denominated global bulk dry cargo shipping rates by computing the average growth rate of the series, removal of inflation using U.S. CPI, and linearly detrending the real freight rate index. The resulting index is expressed in percent deviations from trend, and monthly updates can now be collected from the Federal Reserve Bank of St. Louis (FRED, 2023).

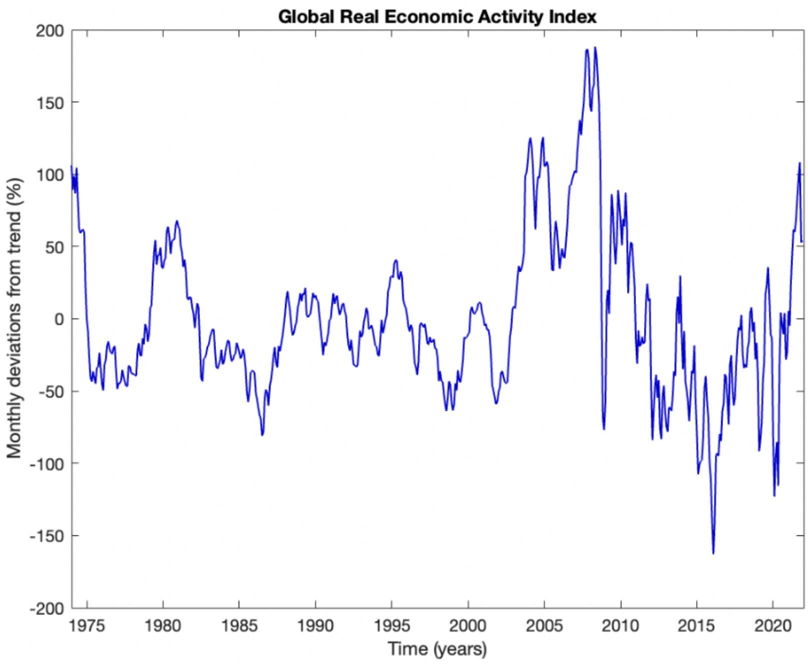


Figure 4.2: *Index of global real economic activity in industrial commodity markets (Kilian Index, 2019 version), expressed in monthly percent deviations from trend.*

4.1.3 *Real price of oil*

The crude oil imported acquisition cost by refiners is given in U.S. dollars and can be used as a measure for the real price of oil. Monthly prices in dollars per barrel are provided by EIA (EIA, 2023b). The time series is deflated using the U.S. CPI, and further calculated to its logarithmic value. This enables estimation of percentage deviation from the average logarithmic oil price.

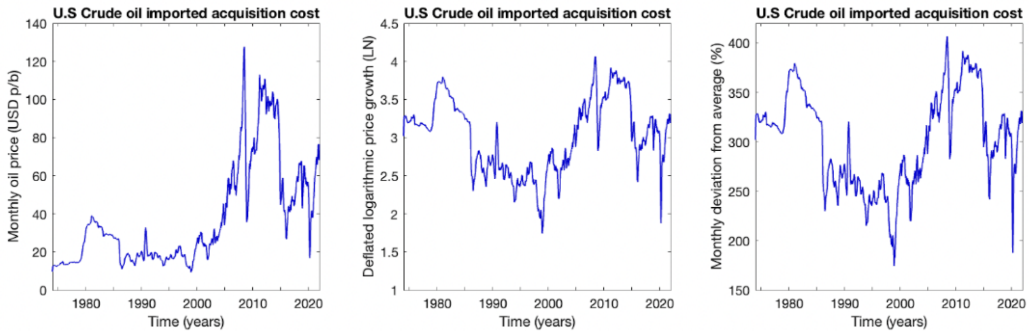


Figure 4.3: *U.S. Crude oil imported acquisition cost (LTR), expressed in dollars per barrel, deflated with U.S. CPI in logarithmic values and in percentage deviation from average.*

4.2 U.S. Stock market variables

Kilian and Park (2009)) utilized the value-weighted market portfolio from the Center for Research in Security Prices (CRSP) as measure for their stock market variable. The index reflects the performance of the entire U.S. stock market including large-, mid-, and small-CAP stocks (Zoll, 2013). On the other hand, Bastianin and Manera (2018) computed a monthly measure for realized volatility using daily closing prices for the Standard and Poor's 500 index (S&P 500), which tracks the 500 largest U.S. companies listed on the stock exchange (Zoll, 2013). To omit unnecessary white noise, this thesis uses one time series for both stock market variables, which have been downloaded from the Bloomberg terminal.

80% of the variation in the CRSP equals the entire S&P 500, while the remaining variations are caused by mid- and small-CAP stocks (Dong, 2022). The CRSP is slightly more volatile than the S&P 500 as small and mid-CAP stocks usually experience more price fluctuations than large companies (Zoll, 2013), however we were unable to access high frequency (daily) data for the CRSP. The differences between the estimates are minimal, and with the intent of capturing the synchrone effects in the stock market, the thesis will proceed using the S&P 500.

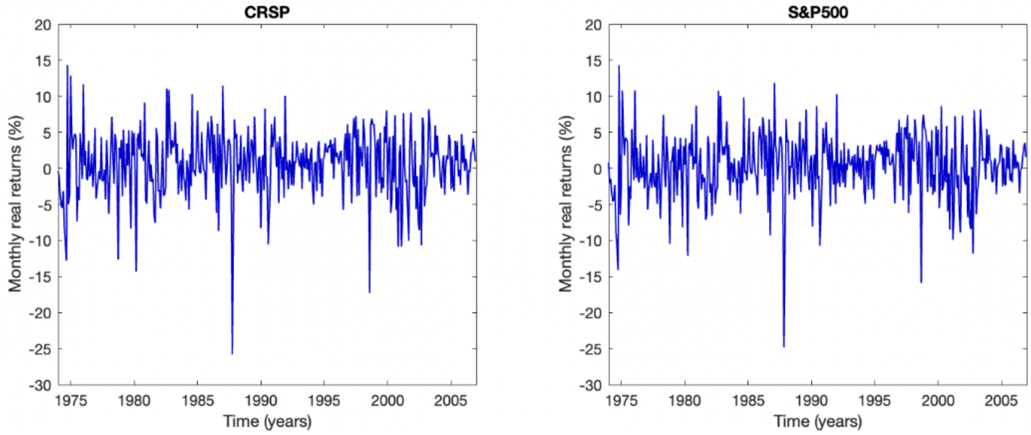


Figure 4.4: *(LTR) CRSP index and S&P 500 index, expressed in real returns.*

4.2.1 U.S. Real stock returns

From the S&P 500 monthly closing price, we remove inflation with the U.S. CPI and calculate the logarithmic values of the deseasonalized series. Lastly, the real returns are computed as the percent change in monthly returns.

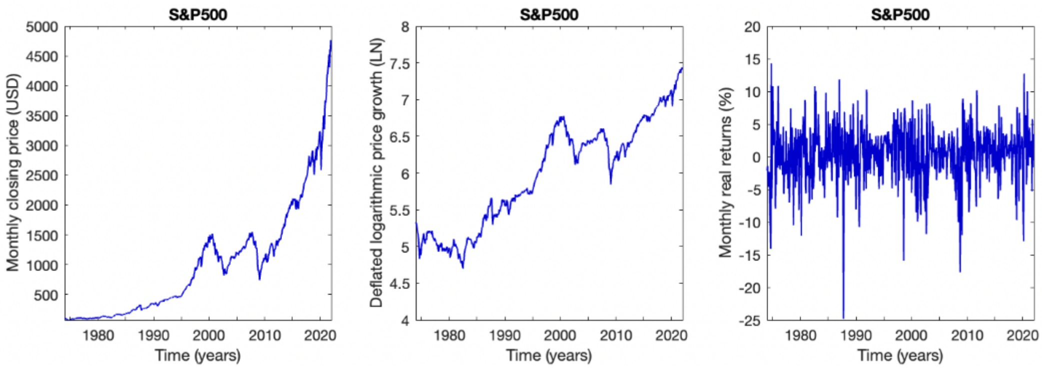


Figure 4.5: *S&P 500 (LTR), expressed in monthly closing price, deflated with U.S. CPI in logarithmic values and in real returns.*

4.2.2 U.S. Realized volatility

To explore the relationship between stock price volatility and oil price disruptions, there is a wide variety of volatility measures available. Since this paper is dealing with high frequency data, to circumvent the aforementioned potential Epps effect, we intend to estimate the returns and volatility from the same asset. The true volatility is latent, and we therefore need to estimate it by proxy (Aït-Sahalia et al., 2013). With the intent of staying consistent with the research of Bastianin and Manera (2018), we construct a historical measure for the realized volatility representing the S&P 500 variability. The proxy is estimated from the same index as for stock returns, resulting in the two sets of observations being syncrone by construction. It is worth noting that we have been careful during the computation process to limit potential microstructure noise as the realized volatility estimator would then overestimate the volatility, resulting in weaker correlation with returns (Chang et al., 2020). Following Schwert (1989), we have computed the realized volatility as the sum of squares of daily logarithmic returns based on daily closing prices for the S&P 500 composite portfolio as follows,

$$RV_t = \sum_{j=1}^{N_t} r_{j:t}^2, \qquad (12)$$

where r is the daily real logarithmic returns, N_t is the number of days in the month, j is the number of business days the stock exchange is open for trading and t is the respective month the observation is belonging to. The resulting proxy is a strictly positive and stationary monthly time series reflecting the volatility of the U.S. stock market.

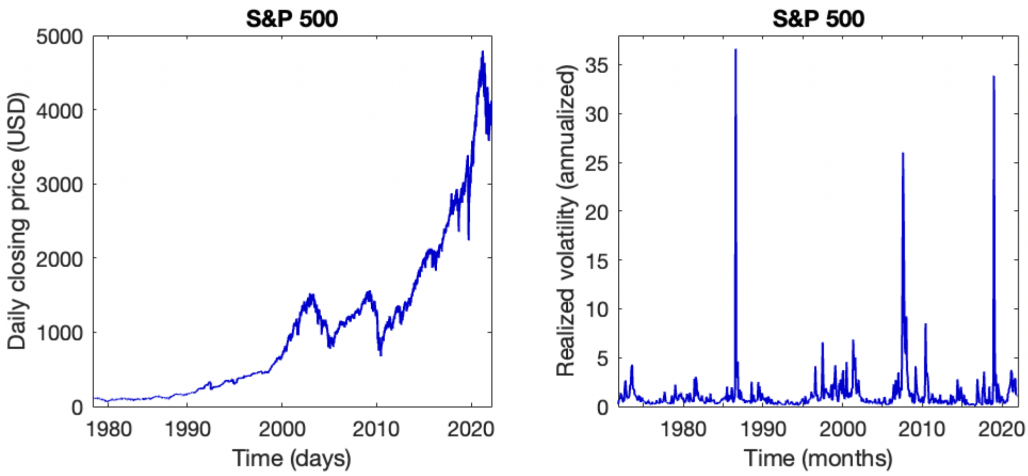


Figure 4.6: *S&P 500 (LTR), expressed in daily USD closing prices and in realized volatility.*

4.3 Norwegian stock market variables

For the Norwegian time series, we have used the Oslo Børs Benchmark Index (OSEBX) monthly closing prices for both the real returns and realized volatility estimates. In contrast to the S&P 500, the OSEBX index contains a selection of listed firms on Oslo Stock Exchange, consisting of a varying number of between 50 to 70 representative companies (Euronext, 2023). Both daily and monthly data for the index can be accessed through the Bloomberg terminal. The Norwegian real stock returns are estimated using the same method as described above. As the OSEBX is given in Norwegian kroner, we have used the Norwegian CPI for deflation of the series.

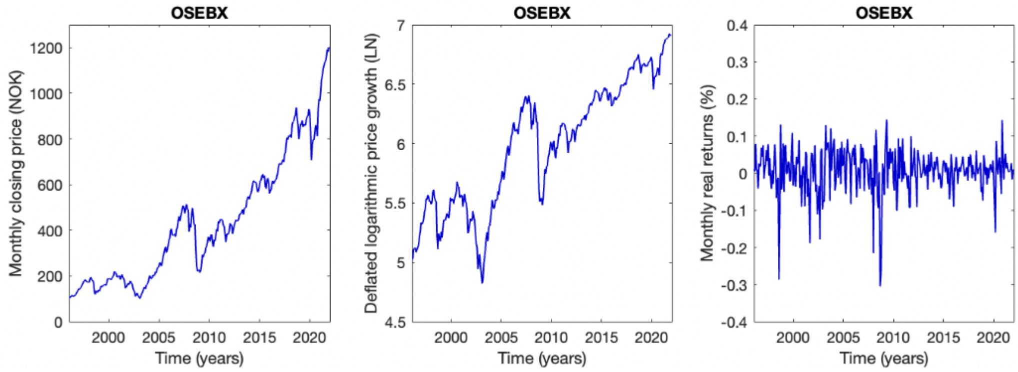


Figure 4.7: *OSEBX (LTR), expressed in monthly NOK closing prices, deflated with Norwegian CPI in logarithmic values and in real returns.*

Using daily closing prices for the OSEBX, the Norwegian realized volatility is estimated in the same manner as for the U.S. volatility.

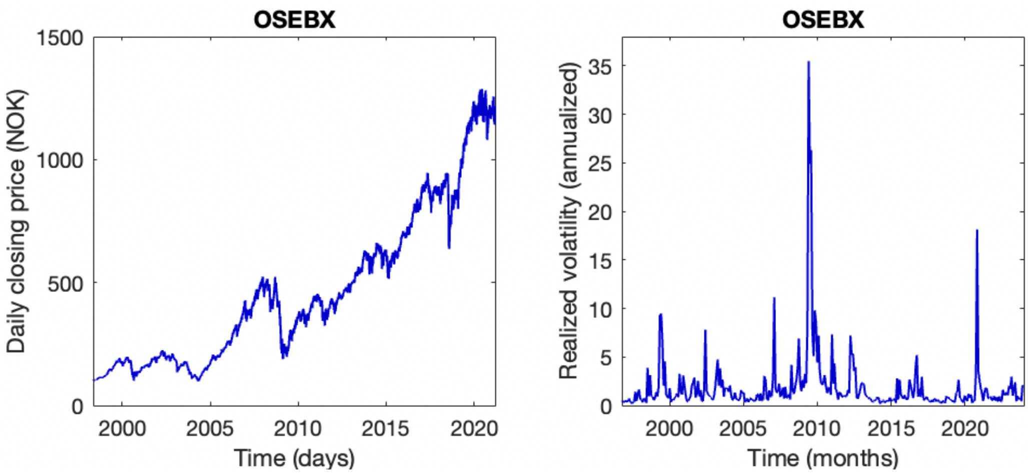


Figure 4.8: *OSEBX (LTR), expressed in daily NOK closing prices and in realized volatility.*

5 Analysis

Reiterating the objectives of this thesis, with the intent of answering the aforementioned research question, the analysis reports, firstly, replications of the main literature this research is building on. Secondly, a combined model for joint empirical and economic analysis of real stock returns and realized volatility using U.S. stock market data. Finally, an application of the model using Norwegian stock market data, accompanied by comparable estimates from the U.S. for empirical end economic analysis on how stock returns and -volatility are affected by underlying oil price shocks.

5.1 Replication models

To ensure a stable and robust extension of the existing literature on oil- and stock market shocks, before estimating a combined model, we first replicate the findings of Kilian and Park (2009) and Bastianin and Manera (2018) separately. To examine the average responses of each variable to the three fundamental oil market shocks, we inspect the cumulative impulse responses of the variables.

5.1.1 Replication of Kilian & Park (2009)

To ensure robustness when extending on the research of Kilian and Park (2009), we first replicate their model. The responses of their oil market variables are in line with the findings of Kilian (2009), where the price of oil was negligible to supply side shocks, while demand shocks elicited significant responses. Further, Kilian and Park (2009) argues that the global oil market is an important fundament for the U.S. stock market and that the responses of real stock returns may differ significantly depending on the underlying cause.

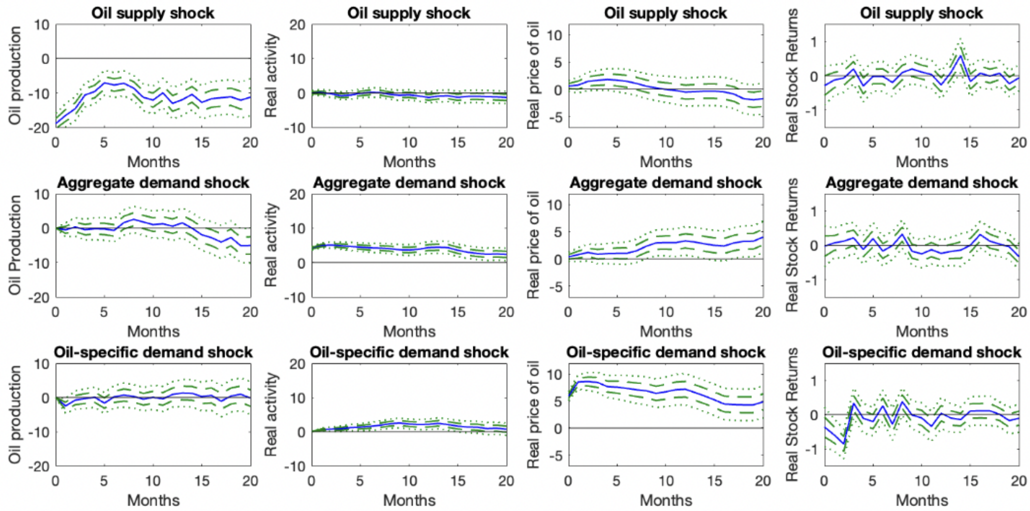


Figure 5.1: *Kilian and Park (2009) replication. Cumulative impulse response functions (blue) of global oil production, real economic activity, the real oil price and real stock returns to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2006:12.*

Our replication is consistent with the findings of Kilian and Park (2009), confirming that the estimated impulse response functions (IRF) using the S&P 500 index in place of the CRSP will not affect the trajectory of the impulse responses. The findings show that unexpected structural shocks to oil supply have no significant effect on the cumulative real stock returns, which can be seen from the stationary level lying within the bootstrap standard deviation error bands. An unexpected increase in aggregate demand motivates an instantaneous, albeit insignificant, increase in stock returns, which persists for around a quarter. Finally, an unexpected positive precautionary demand shock yields an instant decrease in the real stock returns which is undoubtedly significant for 3 months[2].

5.1.2 Replication of Bastianin & Manera (2018)

With the intent of estimating sound results, we next replicate the SVAR of Bastianin and Manera (2018). The responses in their oil market variables also corroborate the seminal findings of Kilian (2009). Further, their key findings are firstly, that volatility of stock prices in the U.S. are unresponsive to unexpected disruptions in oil production. Furthermore, the effects from the demand side of the oil market induces significant responses in volatility.

[2]For replication of Kilian and Park (2009) using CRSP, see appendix C

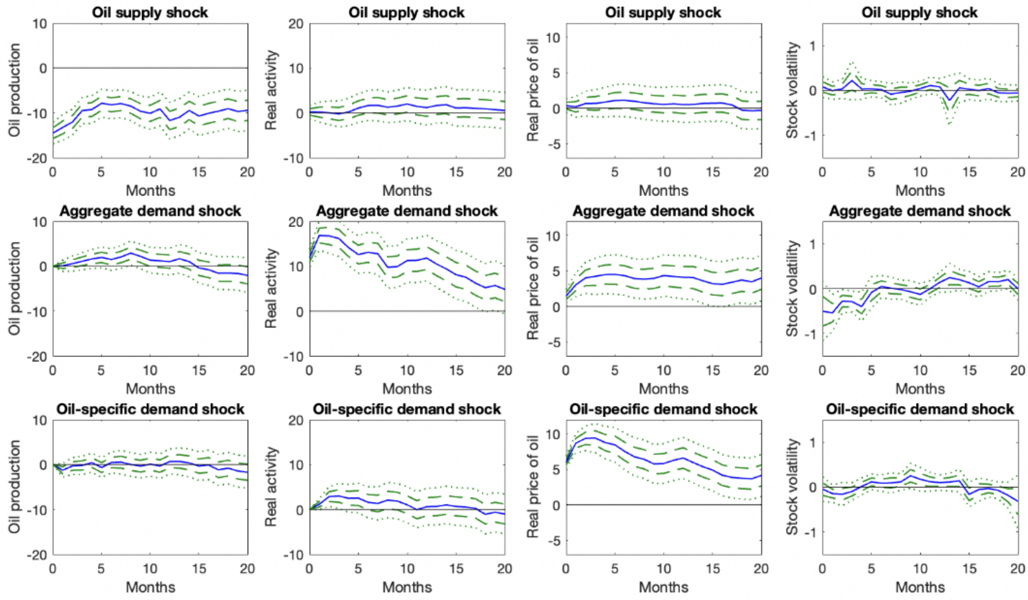


Figure 5.2: *Bastianin and Manera (2018) replication. Cumulative impulse response functions (blue) of global oil production, real economic activity, the real oil price and realized volatility to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2013:12.*

In our replication model, the results reflect only minor differences compared to the original paper. When examining the effects of U.S. stock volatility to an oil supply shock there are no significant effects at the 1 standard deviation level. An unexpected increase in the aggregate demand for industrial commodities leads to an evident negative response in volatility until it turns statistically indistinguishable from zero after about six periods. After a year, the volatility increases, and stays positive for the rest of the horizon. For a 1 standard deviation error band, the response of volatility to an oil-specific demand shock is negative on impact, before increasing to a positive level after six months, lasting for about a year[3].

5.2 Combination of models

5.2.1 Combined model U.S. data

To examine the responses of stock returns and volatility to oil market dynamics, we merge the replications of Kilian and Park (2009) and Bastianin and Manera (2018) into a combined model. This model is regressed on two sets of different time series. The first from 1974:2 until 2006:12 with the intent of examining how the variables change when controlling for each other, and further an extended time series ending in 2021:12. This allows for inclusion of more information in the model, and the

[3]For replication of Bastianin and Manera ending in 2006:12, see appendix C

estimates will depict more accurate structures for the current oil-and stock market dynamics. In the following sections we interpret the estimates through empirical and economic analysis of impulse response functions and forecast error variance decompositions[4].

5.2.1.1 Fundamental oil market shocks

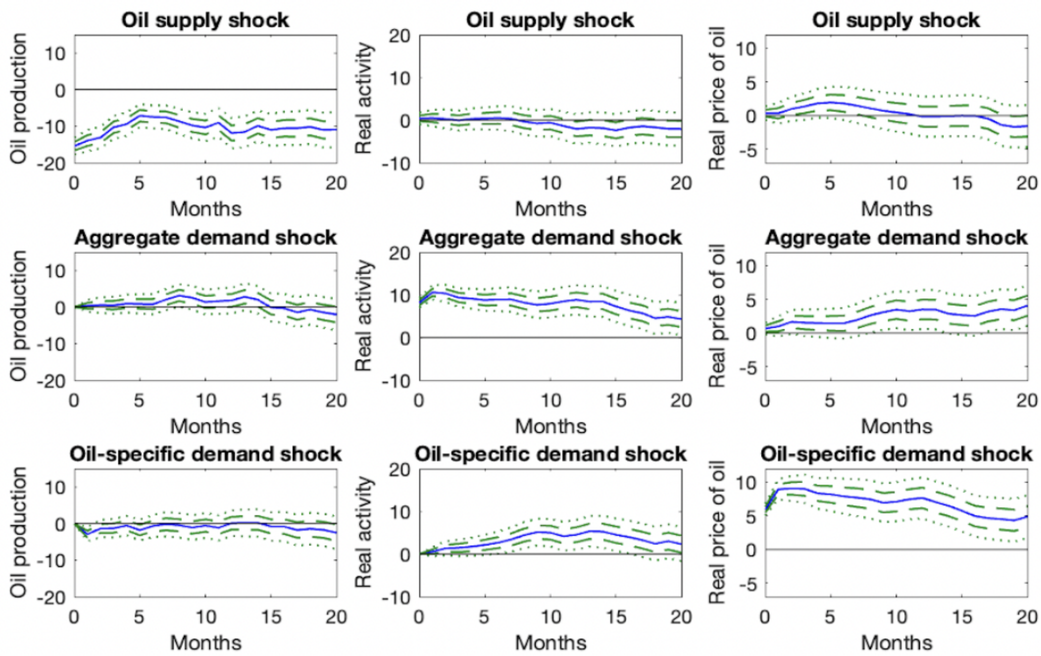
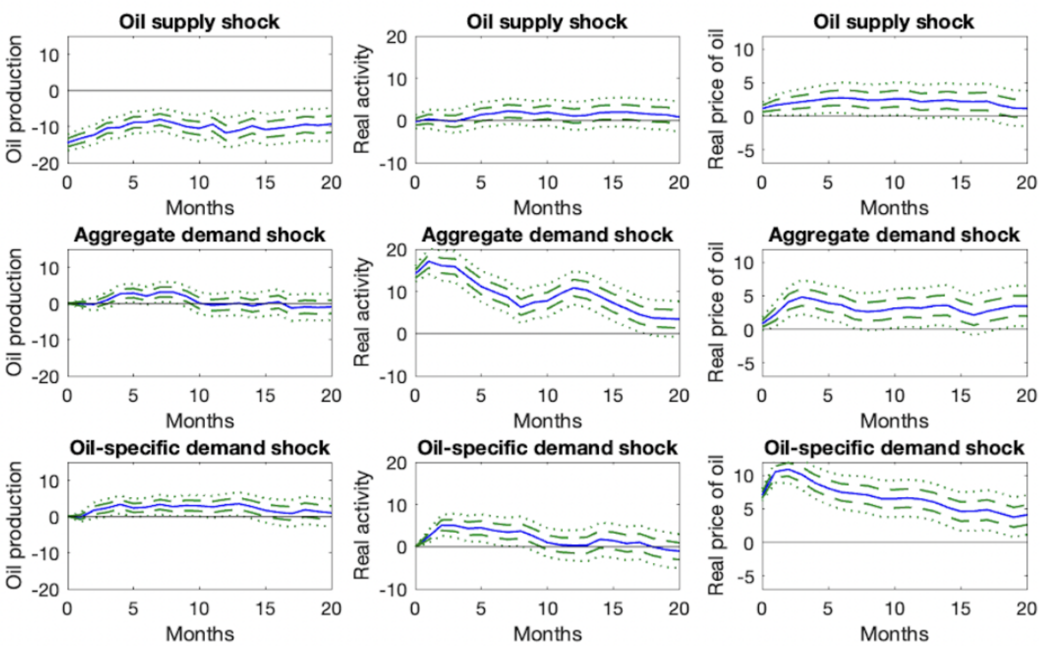


Figure 5.3: *Cumulative impulse response functions (blue) of global oil production, real economic activity and the real oil price to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2006:12.*



[4] For combined model with time series ending in 2019:12, see appendix C

Figure 5.4: *Cumulative impulse response functions (blue) of global oil production, real economic activity and the real oil price to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2021:12.*

In the primary sample, the alterations in the oil market variables are minor, indicating that the fundamental oil market shocks are robust. When extending the dataset until the end of 2021, the shock to aggregate demand is larger. Recalling the index for global real economic activity (see section 4.1.2 Real Economic Activity), the extended sample is visually more volatile. It is therefore plausible that increased global economic unrest in recent years can explain this larger aggregate demand shock.

5.2.1.2 Oil supply shock to U.S. stock market

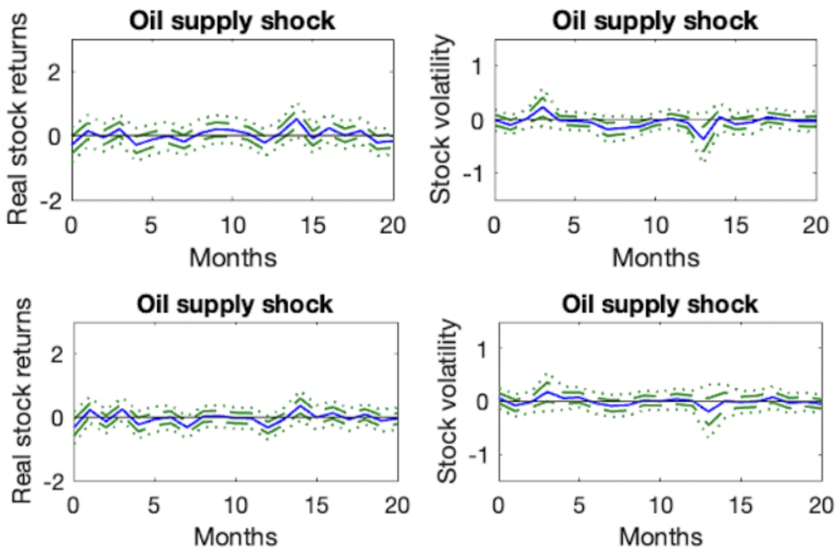


Figure 5.5: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized oil supply shock. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2006:12 (top row) and 1974:2-2021:12 (bottom row).*

Examining the IRFs of the stock market variables subject to an unanticipated decrease in oil production shows insignificant responses regardless of sample length. Unsurprisingly, this mirrors the replications above, strengthening the existing belief of stock market variables being negligible to oil supply shocks (Kilian & Park, 2009). Nonetheless, there seems to be tendencies of an inverse relationship between the responses of returns and volatility in parts of the sample. The responses, albeit insignificant, are anticipated due to existing financial literature, suggesting structural stock market effects that imply an asymmetric link between the variables (Bae et al., 2007). This is worth further exploration.

5.2.1.3 Aggregate demand shock to U.S. stock market

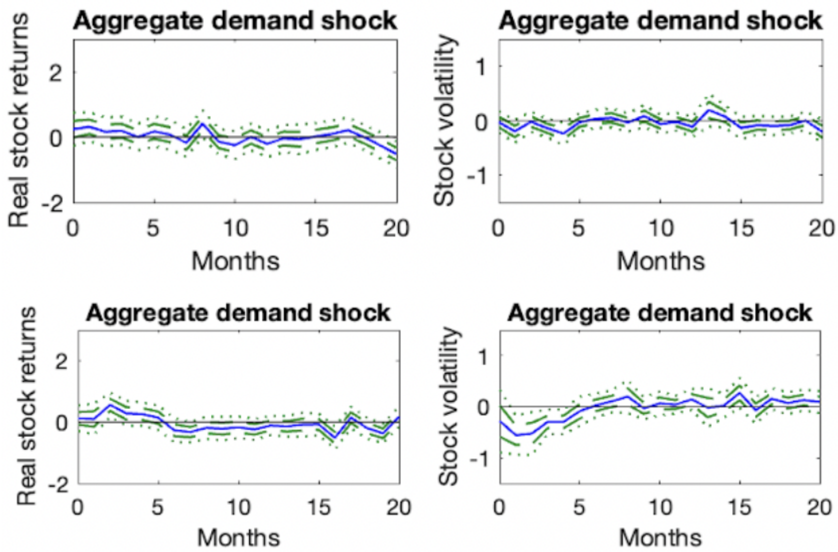


Figure 5.6: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized aggregate demand shock. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2006:12 (top row) and 1974:2-2021:12 (bottom row).*

When controlling for returns and volatility jointly in the primary sample, subjected to an aggregate demand shock, it is prevalent that the trajectories of the impulses are similar in trend to the separate analysis of the variables. Nonetheless, the reaction of volatility when controlling for returns are minuscule compared to the replication above, indicating that the effects on volatility might be less prevalent than previously assumed by Bastianin and Manera (2018).

An extension of the series results in responses larger in magnitude, which can suggest unequal variance in the time series, indicating a greater importance of global real activity dynamics. Kilian and Park (2009) terminated their sample before the great recession in 2008, excluding more recent and severe distress to the finance- and oil markets. This crisis is endogenous to the financial system and therefore reflects the underlying structures of the stock market. Hence, it is reasonable to presume the extended model as a more accurate reflection of the structural dynamics of the financial sector today.

An unanticipated boost to global real activity generates an instantaneous increase in real stock returns, lasting for about six months, before turning negative and statistically significant at the 1 standard deviation level, persisting to the end of the horizon. Simultaneously, stock volatility decreases for the first half year, until it turns positive for the rest of the horizon, mirroring the trajectory of returns. Increases in aggregate demand can create two simultaneous effects; firstly, an immediate stimulus to the economy through improved business conditions, and secondly a later increase in the real price of oil that counteracts the first effect by slowing down the economy (Kilian & Park, 2009). This can be observed in our impulses where an economic stimulus increases returns immediately (decreases volatility), while an oil-price increase leads to decreased returns (increased volatility) later on.

To further explore this asymmetric relationship of returns and volatility, we recall that increased economic activity boosts firms profits, making them less leveraged, subsequently decreasing systematic risk and volatility instantaneously in response to the shock (Bae et al., 2007). Opposite effects occur when the oil price increases later. The IRFs also imply that returns turn negative before volatility turns positive, suggesting the primary cause of the correlating movement here to be the leverage effect.

5.2.1.4 *Oil-specific demand shock to U.S. stock market*

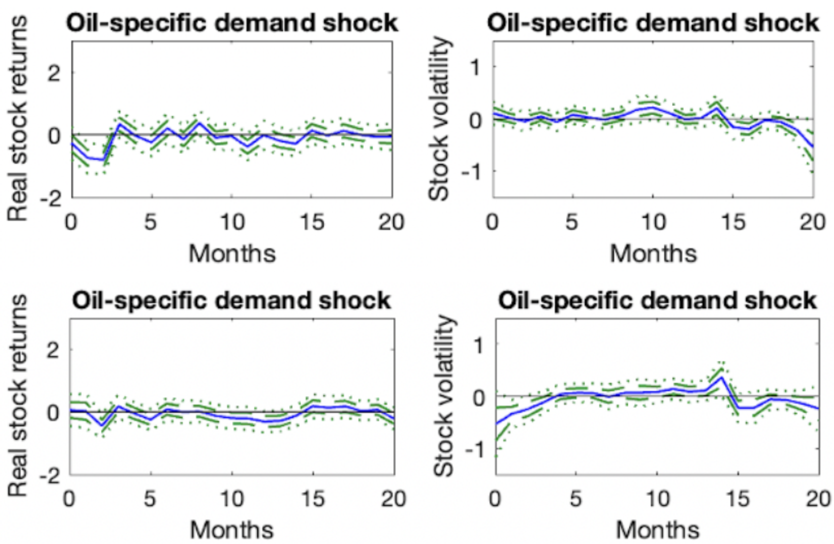


Figure 5.7: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized oil-specific demand shock. 1 and 2 standard deviation error bands (green). Monthly data from 1974:2 to 2006:12 (top row) and 1974:2-2021:12 (bottom row).*

Next, reporting the results of a precautionary demand shock on the stock market, we notice an instant decline in stock returns on impact for the primary sample length, corroborating the findings of Kilian and Park (2009). While there are visible changes in the response of volatility compared to the replication above, the replication falls in line with the combined model when excluding the financial crisis from Bastianin and Manera's (2018) results (see appendix C). For an extended sample examination, the IRFs of volatility is more similar to their results, moreover, the extended data elicits a volatility response even greater in magnitude than the replication. Additionally, the instantaneous decline in stock returns is now minuscule compared to the original sample.

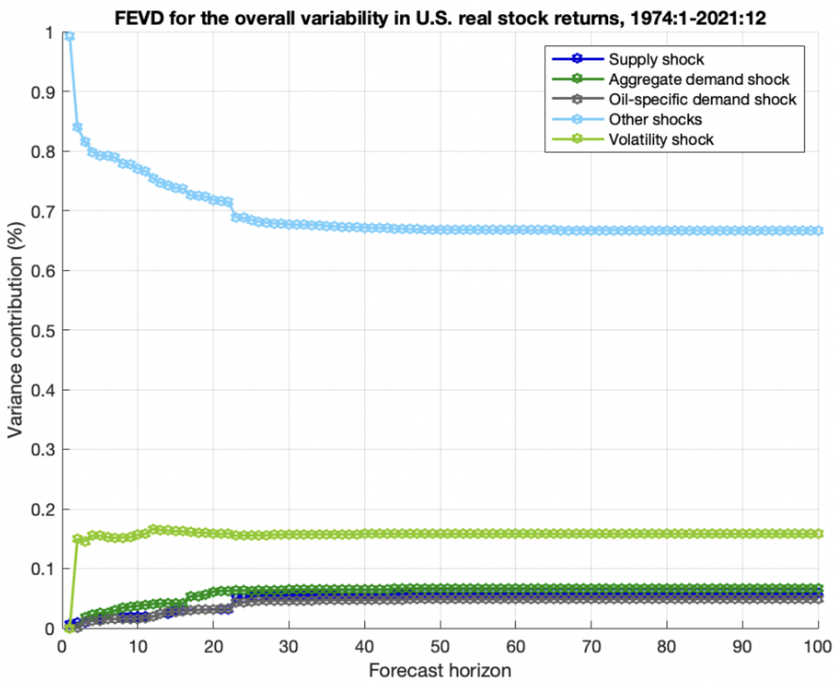
The extension of the information included in the SVAR yields a reversal of the signs for the stock market variables, where volatility becomes negative, and returns turn less negative. This suggests that the asymmetric relationship of the variables still exists, however, elicits opposite reactions for both. A possible explanation for this result is innovations, specifically more advanced technological equipment for oil extraction, joined by discovery of oil reserves, enabling the U.S. to export more oil (EIA, 2023c), which has later been coined the "shale oil revolution" (Zhou, 2020). The impulses could therefore suggest underlying structural changes to the oil- and stock market dynamics, where the net positive returns from firms invested in oil outweighs the net negative returns from the remaining stock market. Alternatively, we postulate that the dynamic shifts can be reflections of more recent distress in the finance- and oil market sectors as explained from the real economic activity shock. Hence, more fluctuations in the recent sample is inducing the shifts visible in the IRFs, which is also observable in real activity response elicited by the shock to precautionary demand. This deserves further exploration by use of more elegant identifying restrictions and advanced models, for instance time-varying VARs (see section 7 Future work).

Reporting the extended results, stock returns are negligible to oil-specific demand on impact. There are slight movements in the first few months, but they are for the most part economically ambiguous. Further, there seems to be a negative effect around 8 months after the shock. This effect is significant until the end of the first year followed by a positive increase in the subsequent months. When inspecting the response of volatility on impact, a large negative effect is observed, which persists for the first 4 months. Subsequently, the IRF hoovers above its stationary level, and is significant in some parts of the horizon, indicating a delayed boosting effect. A larger spike occurs around period 13, albeit short lived.

Bastinain and Manera's (2018) following interpretation corroborates this discovery; Given that the precautionary demand shock in essence is a shock to the expectations of future oil supply shortfalls, this delayed positive volatility reaction could reflect higher macroeconomic uncertainty, thus a more volatile stock market. The feedback effects suggest that the increased volatility further induces even higher expectations for future volatility, and thereby decreases stock returns (Bae et al., 2007). This can be observed from the positive volatility occurring around period 4, while stock returns only stabilize below its stationary level around period 6. Thus, our results are in line with the financial theory regarding the asymmetric relationship of returns and volatility.

5.2.1.5 Forecast error variance decompositions for extended U.S. data

To deepen our understanding of the results presented so far, this paper estimates forecast error variance decompositions (FEVD) for the extended data (for FEVD of original time series, see appendix B). The estimates reveal how much of the variability of stock returns and volatility, respectively, is accounted for by each of the exogenous shocks included.



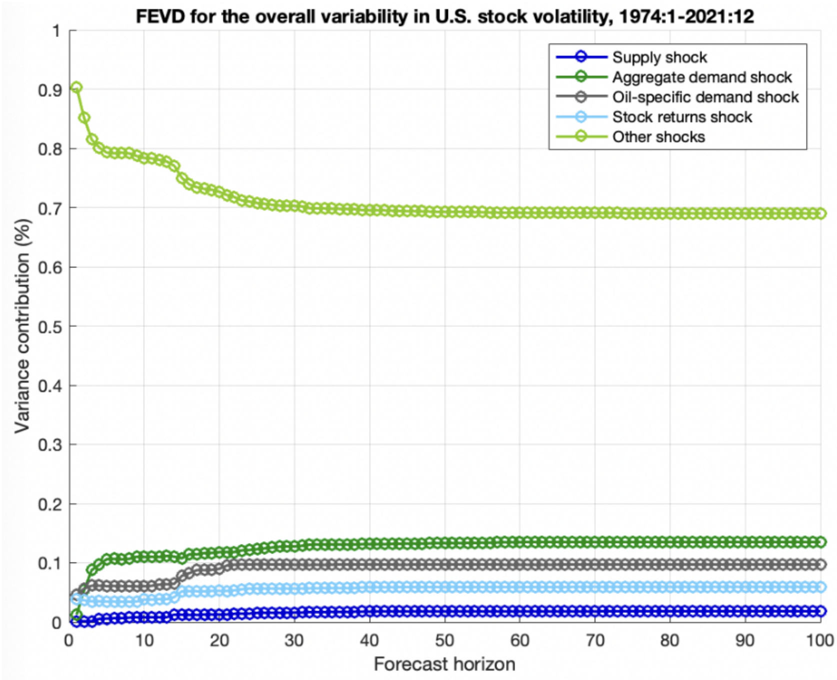


Figure 5.9: *Forecast error variance decompositions for the overall variability of U.S. real stock returns (top) and U.S. realized volatility (bottom). Variance contribution measured in decimals and sum to 1 at every horizon. Monthly data from 1974:2 to 2021:12.*

Jointly, the oil market shocks explain 17,5% of the long run variation in stock returns. Similar, but slightly less than the 22% previously found by Kilian and Park (2009). Recalling that their model only contained four variables, there might be some variation caused by volatility not accounted for, which is why their estimate might be slightly higher. Other possible explanations could be the shift in the composition of the stock market index, where there is an increasing focus on technology stocks relative to energy stocks (Crowley, 2023). Alternatively, recent years have seen more global movements caused by endogenous financial market disruptions (Norges Bank, 2022). Further, all three oil market shocks have similar explanatory powers, although aggregate demand shocks accounts for slightly more of the variability of returns, 6,7%. Real activity disruptions directly affect all aspects of the economy, not only the oil price, and it is therefore reasonable for it to explain more of the overall variability for all sectors of the stock market.

Oil market disruptions explain about 25% of the long run variation in U.S. stock volatility. Demand shocks have significantly more influence, as the oil supply shocks only account for 2% of the variability, underpinning our above mentioned results of stock market variables as negligible to oil supply shocks. Shocks to aggregate demand creates the most substantial effects, and can be linked to unrest in global real activity dynamics as a large contributor to stock market uncertainty. Oil-specific demand shocks essentially induce fear for future oil price increases and therefore connects directly to stock market volatility, increasing its explanatory power over the long run (Bastianin & Manera, 2018).

Noticeably, shocks to realized volatility explains almost as much of the variation in returns as the three oil market shocks combined. Nevertheless, the aforementioned research question relates to how oil market shocks affect the stock market, and examinations of exogenous stock market shocks therefore lie outside the scope of this thesis. Conclusively, we defer this to later research.

5.2.2 Combined model Norwegian data

With the intent of examining how stock returns and volatility responds to oil market disruptions in Norway, we regress our model on Norwegian stock market data for the time frame 1996:1-2021:12. To unify the new result with the U.S. findings, it is prudent to also make a comparable sample from the U.S. starting in 1996. Exclusion is a necessity for separating the differences caused by the shorter sample length from those due to structural characteristics of the Norwegian and U.S. stock markets. Notice that excluding information from the model involves removing the energy crisis of the late 1970s in addition to several other economic events taking place in the previous millennia (Blanchard & Gali, 2007). Caution has therefore been taken when interpreting results. Further, we provide an analysis of how the Norwegian stock market variables are affected compared to those of the U.S. by exploring impulse response functions and forecast error variance decompositions produced from the SVAR model.

5.2.2.1 Informative summary on Norwegian and U.S. markets

In the interest of fostering a deeper understanding how the market dynamics in Norway and the U.S. has evolved over time, and their contra-distinctive features, this paper briefly presents some of the distinct factual differences between the countries. The U.S. is a major world economy, and has historically been an oil importer, but due to the shale oil revolution, they have recently increased their exports of oil. Net imports for oil peaked in 2005, and have since decreased rapidly, reaching an all time low with negative net imports in 2020 (EIA, 2022).

The oil sector, as part of the total value of S&P 500, has been persistently decreasing in favor of other sectors, e.g technology, today making up only 5,3% of the index's total value (Crowley, 2023). Norway is a small, open economy, who's main export is oil, making up 60% of total Norwegian exports in 2021 (Norsk Petroleum, 2023a) and 21,3% of total GDP for the same year (Norsk Petroleum, 2023b). This is mirrored in the main stock return index, OSEBX, which is made up of approximately 20% oil, while other sectors account for the remaining 80% (Johansen, 2020). Although oil is a relatively larger part of the Norwegian stock market, the index is measured in NOK, which often acts as a dampening mechanism for the oil price, measured in USD. Conversely, the U.S. does not have any currency softening effects, and is therefore fully exposed to the price changes.

5.2.2.2 *Fundamental oil market shocks*

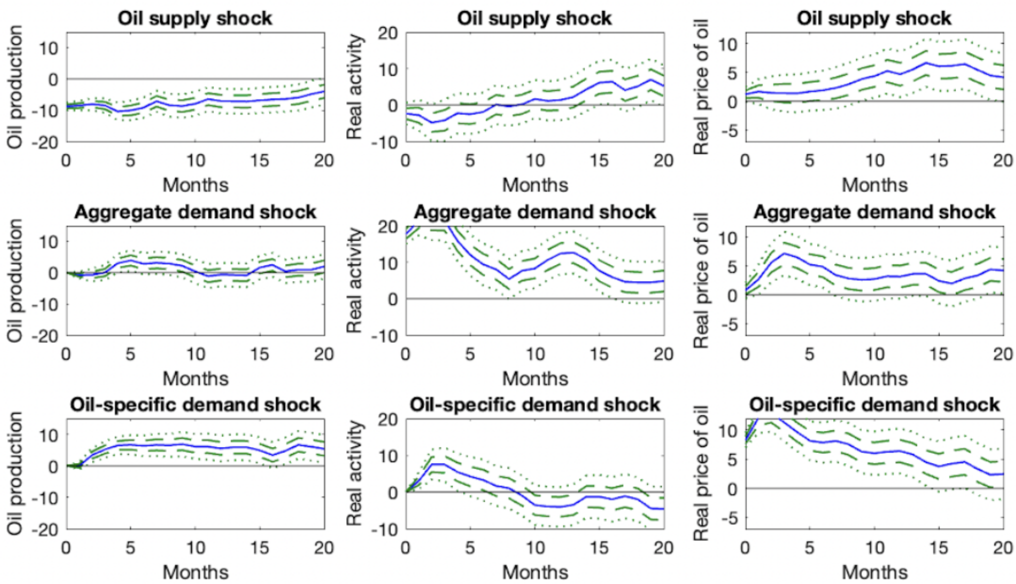


Figure 5.10: *Cumulative impulse response functions (blue) of global oil production, real economic activity, and the real oil price to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). U.S. monthly data from 1996:1 to 2021:12.*

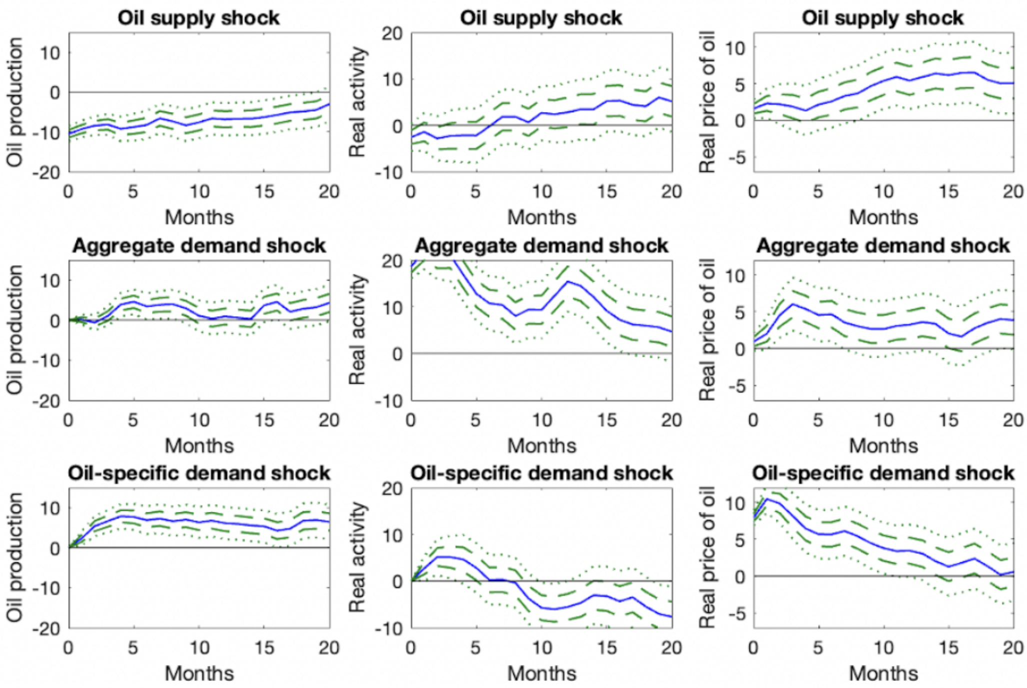


Figure 5.11: *Cumulative impulse response functions (blue) of global oil production, real economic activity, and the real oil price to 1-standard deviation sized structural shocks. 1 and 2 standard deviation error bands (green). Norwegian monthly data from 1996:1 to 2021:12.*

Reporting the IRFs for the global oil market variables, it is prevalent that the responses subject to structural demand shocks are similar to those previously presented. However, subjecting the variables to an unexpected oil supply disruption now yields significant responses, unlike before. The real price of oil is persistently increased, and real activity simultaneously reacts negatively before increasing and staying significantly positive towards the end of the horizon. Nonetheless, a common change for all responses is the increased width of their error bands, an unsurprising result as excluding information elicits higher uncertainty. Reporting the differences between the responses of the U.S. and Norway, there are no significant deviations, indicating that the global oil market variables exhibit equal importance when examining both stock markets. In accordance, the behavior of the oil market variables can be interpreted as a result of their structural dynamics.

5.2.2.3 Oil supply shock to U.S. and Norwegian stock market

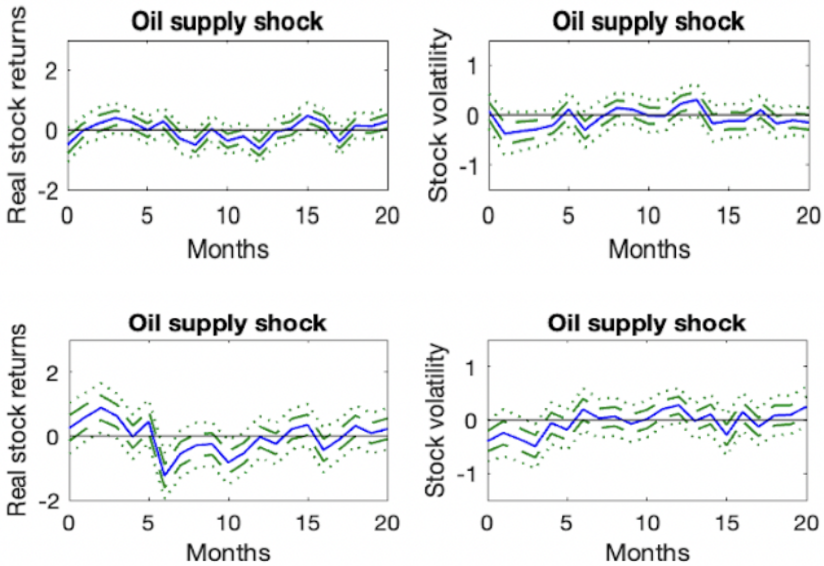


Figure 5.12: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized oil supply shock. 1 and 2 standard deviation error bands (green). Monthly data from 1996:1 to 2021:12 for the U.S. (top row) and Norway (bottom row).*

Investigating the effects from the unexpected decline in the international production of oil, there are noticeable differences compared to the earlier time frame. The stock markets now respond significantly both in the U.S. and Norway, positing an increased importance of supply disruptions in more recent years. This is contradictory to the findings of Kilian (2009), where he suggests that oil price disruptions historically have been driven solely by demand shocks when decomposing the fluctuations. Moreover, recalling the significant response displayed by the real price of oil subject to supply shortfalls, this can further manifest through an immediate decline and persistent response for stock returns due to higher production costs. In line with existing financial theory on market dynamics (Bae et al., 2007), volatility exhibits an inversely correlated response for the extent of the horizon. This further supports the argument of increased supply disruption effects.

Taking a closer look at the impulse responses for the U.S. stock market, the returns display a negative reaction on impact, lasting only two months, followed by a period of positive, statistically significant returns. However, this response is also short lived as the impulse quickly declines to a negative level for the remaining first year. Further, the inverse relationship with volatility is visible throughout the response horizon. The Norwegian stock market, unlike the U.S., responds with an immediate increase in returns, and an inversely related negative volatility. This persists for six months, after which, like in the U.S., the returns decrease and stay negative for the remaining first year. Simultaneously with the decrease in Norwegian stock returns, volatility increases and hoovers right above the steady state, but is not statistically significant at the 1-standard deviation level.

Further, examining the economic interpretation for the immediate positive response of Norwegian returns, a sudden supply shortfall indicates a decline in the international availability of oil. Norway, as an oil exporter, will plausibly become a relatively larger market player and can reap the benefit of this advantageous position. In essence, oil invested firms listed on the Norwegian stock exchange, e.g Equinor, could experience increased market capitalization, transmitting to the immediate increased returns referred to in the empirical analysis.

An economic interpretation of the instantaneous drop of stock returns should take into account the dynamic changes the U.S. oil- and stock market sectors have seen over the previous decades. From increased exportation of oil, we would expect higher returns as seen in Norway, however, the U.S. impulse responses tell another story. While exports have increased since 2005 (EIA, 2022), the technology sector has seen a greater surge of investment, making up 27,1% of the S&P 500's market value (Crowley, 2023), making the relative importance of the energy sector smaller compared to other sectors on the stock market. Recalling the increased price of oil and the lower aggregate demand that oil supply shortfalls now induce, the variation in the stock market can be a result of increased production costs and lower sales in other sectors e.g technology, that manifest itself through lower profits and then also decreased returns.

Following the first six months with varying responses for Norway and the U.S., a period of negative returns can be observed for both countries. Recalling the trajectory of the price of oil in response to the unanticipated supply disruption, there is a delayed, persistent increase after about six months, much larger in size than the initial reaction. One possible explanation is the example where higher production costs affect the U.S. returns negatively. The delayed effect seems to be of a size substantial enough to also yield a net negative effect for Norwegian returns, accompanied by persistent positive volatility.

The possible explanations presented so far, speak in favor of an equity value drop, i.e. firms become more leveraged, and as a result more risky. Therefore, the theory supports these results of a dominant leverage effect at play in the market dynamics. Further, this can also be observed visually in the IRFs, where volatility reacts one period later than returns throughout most of the impulse horizon. Conclusively, returns is the causal driver for the stock market relationship with volatility in response to supply shortfalls for both the Norwegian and U.S. stock markets.

Given the degree in which the results presented in this section deviate from the existing literature e.g. Kilian and Park (2009) and Bastianin and Manera (2018), we hesitate to draw a final conclusion on the effect of supply shortfalls, but refer to future research with more advanced models for further exploration (see section 7 Future work).

5.2.2.4 Aggregate demand shock to U.S. and Norwegian stock market

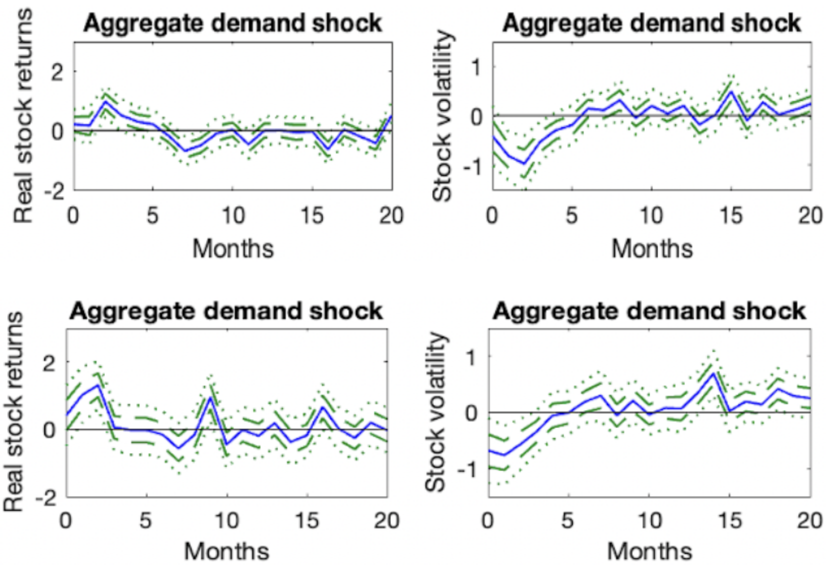


Figure 5.13: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized aggregate demand shock. 1 and 2 standard deviation error bands (green). Monthly data from 1996:1 to 2021:12 for the U.S. (top row) and Norway (bottom row).*

Earlier, we experienced that newer time series increased the effects on U.S. stock returns and volatility when exposed to a shock to aggregate demand. Examining the impulse responses for a sample containing data spanning 1996:1-2021:12, the increased effects now seem even more vast. Appreciating the fact that IRFs essentially provides the average effects, it is unsurprising to see responses of a greater magnitude when only using the latter part of the sample, which visually contains more movements, reiterating our suspicions of unequal variance.

Reporting the U.S. stock returns response subject to an aggregate demand shock, an immediate positive effect can be observed, persisting for approximately six months. Norway displays a similar trajectory, albeit larger in size and shorter lasting. Similar responses continue throughout the impulse horizon where the tendencies of the responses are the same. Following the initial positive effect, both countries display an extended period of negative returns for most of the remaining horizon, albeit often insignificant. Further, volatility of stock prices show an inverse relationship to the returns for both countries.

From an economic interpretation of the empirical results, the initial increase occurring in both U.S. and Norwegian data can be explained by the two effects induced by aggregate demand shocks. Immediately, increased profits as a result of improved business conditions. Later, the increased real activity causes a higher oil price, which translates to a delayed increase in production costs (Kilian & Park, 2009). This results in lower profitability, and more leveraged firms, i.e. lower returns. Noticeably the delayed effect seems smaller in Norway, as it is hovering around the steady state, being insignificant for most of the response horizon. The occurrence of the latter effect can yield positive returns for the oil sector, while higher production costs for other sectors yield lower returns. The two dynamic structures seem to compete, and might cancel each other out. Thus, Norway's heavy investment in oil (Johansen, 2020) can be inducing the insignificant response, and also explain why the U.S. sees a more negative response throughout.

5.2.2.5 Oil-specific demand shock to U.S. and Norwegian stock market

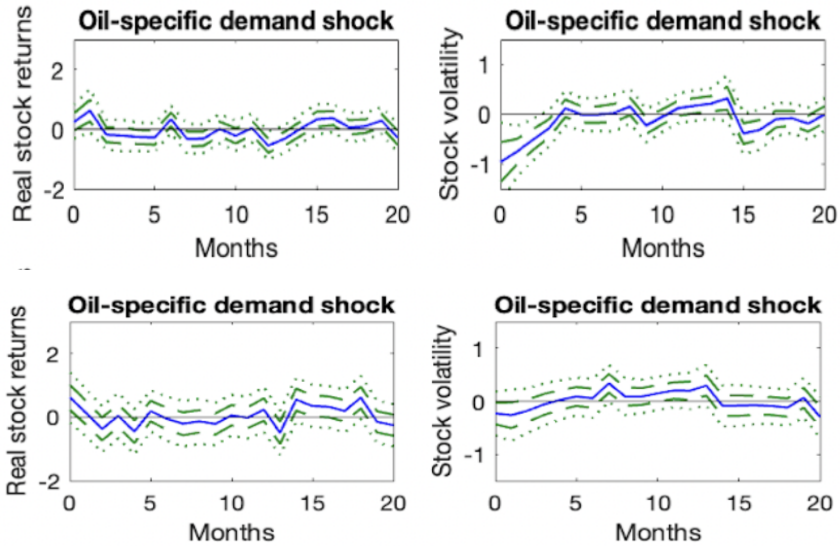


Figure 5.14: *Cumulative impulse response functions (blue) of real stock returns and realized volatility subject to a 1-standard deviation sized oil-specific demand shock. 1 and 2 standard deviation error bands (green). Monthly data from 1996:1 to 2021:12 for the U.S. (top row) and Norway (bottom row).*

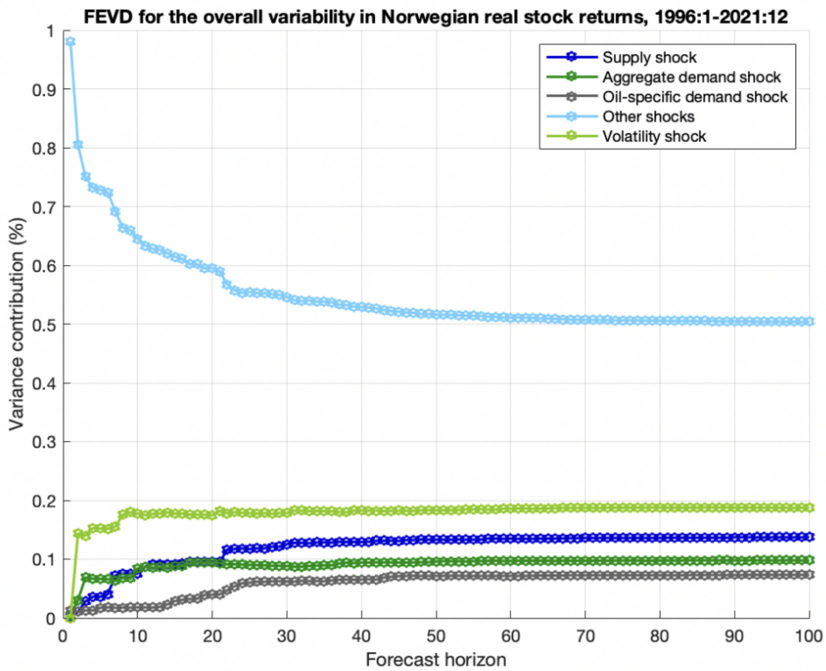
In light of the results provided earlier of U.S. stock returns and volatility subject to a precautionary demand shock, the results using a shorter data length are unsurprising. The trend of stock returns moving in a positive direction in the extended sample is also visible when examining the latest IRF, as the immediate reaction is now positive and clearly statistically different from zero. The volatility of stock prices is asymmetrically related, reacting negatively on impact and persisting for approximately four months. Further, the response of stock returns shifts between statistically positive and negative results throughout the remaining horizon. Inspecting the empirical results of the Norwegian model, stock return responses follow a similar trajectory to that of the U.S., albeit smaller in magnitude. Nonetheless, returns are only significantly positive at the 1 standard deviation level for one period, fading into insignificance for the remaining response horizon. Volatility is still negatively correlated, but significant at the 1 standard deviation level for the first three months.

Economically interpreting the Norwegian stock market dynamics, an increased oil price will instantaneously generate positive returns in the oil sector, inducing increased wealth in the Norwegian economy given their role as an oil exporter. Further, other sectors experience negative consequences from a price increase, decreasing their profits and canceling out the initial wealth effect (Jung & Park, 2011). The

Norwegian responses are corroborated by Jung and Park's (2011) findings, suggesting positive initial effects for an oil-exporter, later offset by increased production costs. The Newer U.S. time series also suggests tendencies of a positive initial response, previously explained by increased oil-exports, consequently likening their responses more to those of Norway in recent years.

Remembering that the precautionary demand shock can be interpreted as an increase in the expectation of future supply shortfalls, the shock essentially creates fear (Bastianin & Manera, 2018). This also elicits a persistent negative response for real activity six months after the occurrence of the initial precautionary demand shock. Norway is a small open economy, and unlike the U.S., does not possess the same market power as larger countries. They are therefore more exposed to global business cycles (Jung & Park, 2011), which can be seen in the increased volatility from the fourth period, albeit insignificant. Global effects therefore seem to cancel out the negative response, explaining why the initial effect is so short lived.

5.2.2.6 Forecast error variance decompositions for Norwegian data



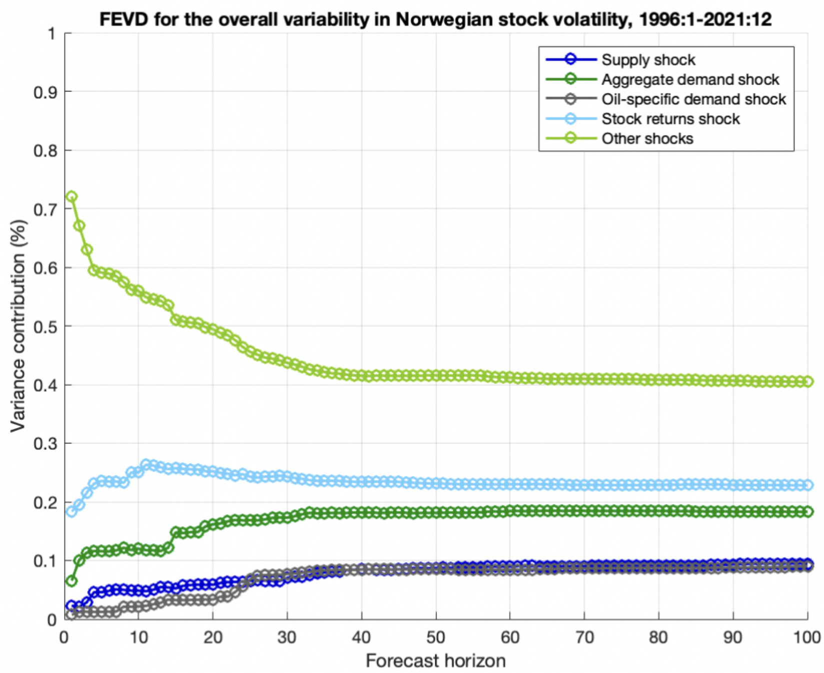


Figure 5.16: *Forecast error variance decompositions for the overall variability of Norwegian real stock returns (top) and Norwegian realized volatility (bottom). Variance contribution measured in decimals and sum to 1 at every horizon. Monthly data from 1996:1 to 2021:12.*

Exploring the overall variability in the Norwegian data, the three oil price shocks account for approximately 30% of stock returns in the long run. Supply shocks account for 13,7% of the variation in the Norwegian stock returns. The importance of the shock has also increased in the newer U.S. time series to 12,97% at the infinite horizon (see appendix B). The results corroborate our analysis, indicating higher importance of global oil supply shortfalls to stock market variables in later years. Shocks to aggregate demand have also increased as an explanatory factor for the long run variability in Norwegian stock returns, now by a representative 9,7%. Recalling the assumption that increased profits as a result of improved business conditions in the oil sector largely affects the Norwegian economy, the results seem reasonable.

Jointly, the oil market shocks explain 36,8% of the variation in the volatility of Norwegian stock prices, distinctly larger than previously accounted for in the U.S. The dominating oil market shock is that of aggregate demand, initially accounting for 6,6% of the variability, moreover increasing to 18,3% in the long run. Initially, supply shocks explain a larger portion of the variability than oil-specific demand shocks, however as the abovementioned, delayed uncertainty effect commences in full, they end up accounting for about the same amount of variability, 9% each.

In total, the oil market accounts for a larger portion of the Norwegian stock market than that of the U.S., insinuating that Norway's vulnerability to oil market disruptions is of a higher degree. Conclusively, exogenous shocks to returns and volatility have greatest explanatory powers for each other. This is deferred for future research as it is outside the scope of this thesis.

6 Conclusion

The objective of this thesis has been to investigate how stock returns and volatility responds to oil price shocks in the United States and Norway. Inclusively, we shed light on the relationship between oil and stock market dynamics, by controlling for the relations between stock returns and volatility. For examination, we have adapted the structural vector autoregressive model introduced by Kilian (2009), that allows for disentangling the fundamental oil price disruptions. Additionally, we have extended the model by including two variables representing the dynamics of the stock market; real stock returns, and realized volatility. Our approach builds on replicating the existing research papers presented by Kilian and Park (2009) and Bastianin and Manera (2018), who examine how isolated returns- and volatility responses are impacted by oil price shocks. Following our replications, we have merged the model structures into one combined model, enabling an analysis accounting for the effects on both returns and volatility.

Application of the combined model on U.S. data from 1974:2 to 2021:12 allowed for a detailed examination of how the stock market reacted to different oil market disruptions while also including the structural dynamics of the markets today. Corroborated by Kilian and Park (2009) and Bastianin and Manera (2018), subject to an unexpected supply shortfall, the findings presented show no significant responses of neither returns nor volatility, and have minuscule explanatory powers for the variability of the stock market variables.

Conversely, shocks to aggregate demand have the greatest explanatory power, accounting for 6,7% and 13,5% of the long run variation of returns and volatility, respectively. In response to an unanticipated shock, volatility decreases while both oil price and U.S. returns instantly increase as a result of improved business conditions.

However, a delayed cost increase from the oil price, decreases returns. A lower equity value results in more systematic risk and leveraged firms (Bae et al., 2007). Consequently, the leverage effect motivates a simultaneous upswing in volatility.

In contradistinction to Kilian and Park's (2009) findings, this thesis does not report an immediate decrease in stock returns subject to an oil-specific demand shock when examining the extended model. On the contrary, it is insignificant, while the volatility responds in a clearly negative manner on impact. A possible explanation is the enablement of oil exportation, brought on by the shale oil revolution (Zhou, 2020), allowing for U.S. oil-invested firms to capture the benefits of a higher oil price. Our findings are further vindicated by Bastianin and Manera (2018) who find similar tendencies, albeit smaller in size. In line with their interpretation, we postulate that the shock to expectations of future supply shortfalls further spawn fear, inducing a delayed increase in volatility, visible from around 4 months. The feedback effects transmit the reaction back to returns, which is significantly negative after 8 months. We postulate that volatility is the driver for the movements of the stock markets in the U.S. subject to oil-specific demand shocks, rather than returns, as presumed by Kilian and Park (2009).

Our investigation of the oil-stock price nexus in the U.S. shows that for the most part, oil market dynamics are very robust, where demand shocks affect both the oil price and stock price significantly, while supply shocks were considered negligible. Still, we challenge this assumption with our findings when only examining the recent years. Concerning the link between returns and volatility, when controlling for the variables, they significantly alter their movements in response to the oil market shocks. Returns have long been a commonly used measure when examining the oil and stock market structures e.g. Kilian and Park (2009) and Alsalman and Herrera (2015), but our findings indicate that volatility also plays a significant part when examining the oil-stock price relationship.

We next applied our extension to Norwegian stock market data, and examined the response based on monthly information in the interval 1996:1-2021:12. The most unexpected result presented in this thesis is derived from subjecting Norwegian returns and volatility to an international oil supply shortfall. Supply shocks have substantially higher explanatory powers for the stock market variability, accounting for 13,7% and 9,5%, respectively. This thesis reported an immediate positive reaction in stock market returns, accompanied by negative volatility. We propose the movements to be a result of Norway's role as an oil exporter. In essence, a lower international availability of oil increases the exporters relative market power, and Norwegian oil invested firms therefore increase their market capitalization. Increased equity value suggests the leverage effect as the dominating transmission mechanism for the stock market variables in response to the shock (Bae et al., 2007). This persists for six months, after which the impulse responses shift to the opposite reaction, depicting a delayed effect. Our results are distinctly different from most existing research. Considering we utilized a shorter datasample, we hesitate to draw a final conclusion, but defer to future work examining the responses for the Norwegian stock market.

Further enhancing the tendencies of the extended model when subjecting stock market variables to aggregate demand shocks, Norwegian stock returns react positively on impact and volatility, negatively. The same initial boosting effect described above applies in this instance, moreover, the aforementioned delayed cost increase brought on by the shock, has a dual effect, where it increases returns for the oil sector, while simultaneously decreasing returns for other sectors, justifying why the negative returns are not statistically significant. Aggregate demand shocks have greater explanatory powers for both returns and volatility relative to the other oil market shocks in the initial periods, however, it is not the main driver for the long run variability of stock returns.

Oil-specific demand shocks explain the least amount of variability in the Norwegian stock market variables at every horizon. Volatility reacts negatively in the first three months, following a period of positive response from the variable. Returns are inversely related. The shock symbolized increased fear for the future, so although we observe an initial wealth effect for the oil-focused sector, this is quickly suppressed by increasing uncertainty affecting all sectors of the stock market (Jung & Park, 2011).

When examining the Norwegian oil- and stock market dynamics, we find significant changes compared to the U.S., specifically, larger responses when subject to aggregate demand and oil supply disruptions. Conversely, the Norwegian stock price does not react as much as the U.S. to an oil-specific demand shock and it has little explanatory powers for the movements in Norway. Considering that Norway is an oil exporter, with heavy oil investments, these results are expected. Our findings should serve as a reminder that the U.S., although a major player in the world economy, is not representative of the structural dynamics of all countries in the world when examining the complex relationships of the oil- and stock prices.

This thesis is a contribution to the debate surrounding oil price shocks, while at the same time unifying perspectives from financial literature with macroeconomic research. Investigating the relations between stock returns and volatility allow for deeper exploration of the stock market dynamics in response to oil market disruptions. The current global economic landscape is heavily influenced by financial distress, both in the oil- and stock markets. This paper attempts to provide a greater perception on how the dynamic relationships behave relative to each other, by quantifying the fluctuations we observe today. Hopefully, our thesis can motivate future research on this topic, generating even broader understanding for the underlying oil- and stock market structures.

7 Future Work

A closely related exploration of the stock market dynamics to our contribution, is application of alternative proxies for the underlying volatility of the stock market, such as conditional or implied volatility. For instance, implied volatility is forward looking, and could provide a deeper understanding of the expectation aspect of the current oil price (Aït-Sahalia et al., 2013). Inclusion of an alternative measure in our model could facilitate a broader examination of how oil price shocks impact stock volatility. Degiannakis et al. (2014) utilized these measures to estimate the volatility of the European stock market and applied the time series to a SVAR model subject to oil market shocks. Separation of the moments of the stock market distribution in a SVAR using these volatility measures could be interesting to examine for a more comprehensive understanding of stock returns and volatility subject to oil market disruptions.

An alternative avenue for further extension of our research, is to analyze the responses of the variables we have defined, using alternative methods for identification, e.g. sign restrictions as described by Kilian and Murphy (2012). We propose controlling for both returns and volatility, as it will provide a more complete picture of the stock market dynamics in response to oil market shocks, without the imposed immediate restriction our model employs.

Alternatively, inclusion of both the first and second moments of the stock market price in a Time-Varying VAR approach is interesting given the recent increase in the variance of the aggregate demand time series. As the approach allows for the coefficients of the VAR equations to change over time (Kilian & Lütkepohl, 2017, p. 630), this could clarify whether the changes we found in the newest sample are a result of structural changes to the global economy. If the latter is correct, application of alternative representative series for aggregate demand to our approach, like the measure developed by Hamilton (2021), is appropriate.

Going even further, Bjørnland et al. (2023) examined the complete stock market distribution subjected to oil market shocks by examining the responses of mean, variance, skewness and kurtosis of the S&P 500. The authors developed a Mixed

VAR model that allows for examination of both functional and aggregate time series jointly subject to both conventional and distributional shocks (Bjørnland et al., 2023). Application of this model to Norwegian data could be interesting for further delving into how the stock market dynamics differs based on whether the nation is an exporter or importer of oil.

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Appendices

Appendix A:

Stationarity, stability and lag order selection

Information Criteria

The Akaike information criterion (AIC) and the Schwarz information criterion, also known as the Bayesian information criterion (BIC), are two different methods for determining the lag order selection for a vector autoregressive model. Including too few lags will omit valuable information and result in residual autocorrelation, while including too many lags can cause unreliable parameter estimates. The intuition behind information criteria tests are as follows; we seek to minimize the estimate, the first term of the measurement contains the residual covariance matrix estimator and rewards us for including extra information (see equation 1 and 2 below). Conversely, the second term penalizes larger lag orders to avoid over-fitting (Kilian & Lütkepohl, 2017, pp. 54–55). As seen from our estimates below, the BIC generally penalizes increased lag orders more than the AIC. We present both tests for the replications and main models presented in our thesis.

$$AIC(m) = \ln(det(\widetilde{\Sigma}_e(m))) + \frac{2}{T}(mK^2 + K) \tag{A.1}$$

$$BIC(m) = \ln(det(\widetilde{\Sigma}_e(m))) + \frac{\log(T)}{T}(mK^2 + K) \tag{A.2}$$

These measures, although common, are usually considered too simplistic for analyzing the oil market as it fails to capture the rewards of delayed effects of the shocks to the economy. It is therefore standard practice to select either 12 or 24 lags when working with monthly data (Kilian & Lütkepohl, 2017, p. 56). This paper reassesses and extends upon the research of Kilian and Park (2009) and Bastianin and Manera (2018), who both opted for a 24 lag order. Hence, we have done the same.

Table A.1: AIC and BIC test - Replication models

	Kilian & Park (2009)		Bastianin & Manera (2018)	
Lags	AIC	BIC	AIC	BIC
1	16.1263	16.2656	16.3577	16.497
2	15.8007	**16.0798**	15.9616	**16.2407**
3	**15.7808**	16.2002	15.9154	16.3348
4	15.8106	16.3707	**15.8256**	16.3857
5	15.8156	16.5168	15.8349	16.5361
6	15.8514	16.6942	15.8504	16.6932
7	15.8773	16.8621	15.8757	16.8606
8	15.9199	17.0473	15.919	17.0463
9	15.9361	17.2064	15.9453	17.2155
10	15.9666	17.3803	15.9683	17.382
11	15.9865	17.5441	15.9776	17.5352
12	15.9895	17.6914	16.0173	17.7193
13	15.989	17.8358	16.0117	17.8585
14	16.015	18.0071	16.0051	17.998
15	16.0264	18.1642	16.0345	18.1723
16	16.065	18.349	16.0569	18.341
17	16.1158	18.5466	16.1035	18.5343
18	16.146	18.724	16.1321	18.7101
19	16.1833	18.909	16.1468	18.8725
20	16.1828	19.0567	16.1737	19.0476
21	16.1635	19.186	16.1503	19.1729
22	16.1435	19.3152	16.1466	19.3184
23	16.1746	19.496	16.1866	19.508
24	16.2396	19.7112	16.2448	19.7164

AIC and BIC tests (LTR), Kilian and Park replication, Bastianin and Manera replication

Table A.2: AIC and BIC tests - U.S. combined models

	U.S. 1974:2-2006:12		U.S. 1974:2-2021:12	
Lags	AIC	BIC	AIC	BIC
1	16.9619	17.1231	18.1989	18.3201
2	**16.6436**	**16.9665**	17.8854	**18.1281**
3	16.6584	17.1438	**17.8361**	18.2006
4	16.7098	17.3581	17.8688	18.3555
5	16.7147	17.5267	17.8561	18.4652
6	16.7423	17.7185	17.8728	18.6047
7	16.7362	17.8774	17.8867	18.7417
8	16.779	18.0857	17.9012	18.8797
9	16.8187	18.2916	17.9171	19.0194
10	16.8438	18.4835	17.9346	19.1611
11	16.8414	18.6486	17.9454	19.2964
12	16.818	18.7933	17.9087	19.3845
13	16.8443	18.9884	17.9376	19.5385
14	16.8447	19.1583	17.9573	19.6837
15	16.858	19.3416	17.9696	19.8219
16	16.8703	19.5247	17.999	19.9775
17	16.9245	19.7504	18.029	20.1341
18	16.9649	19.9629	18.049	20.2809
19	17.0128	20.1837	18.0711	20.4302
20	17.0265	20.3708	18.1024	20.5892
21	17.0336	20.5521	18.1317	20.7464
22	16.9272	20.6206	18.0691	20.8121
23	16.9439	20.8129	18.0858	20.9575
24	16.9169	20.9622	18.1144	21.1152

AIC and BIC tests (LTR), U.S. combined model 1974:2-2006:12, U.S. combined model 1974:2-2021:12

Table A.3: AIC and BIC tests - U.S. and Norway Combined models

	U.S. 1996:1-1996:12		Norway 1996:1-2021:12	
Lags	AIC	BIC	AIC	BIC
1	19.6803	19.9809	20.2665	**20.5679**
2	19.1345	**19.7372**	19.9937	20.5978
3	**19.0742**	19.9804	**19.9455**	20.8538
4	19.1368	20.3479	20.0204	21.2344
5	19.0965	20.6139	19.9663	21.4874
6	19.1079	20.9332	19.9795	21.8092
7	19.1701	21.3047	20.0917	22.2314
8	19.2191	21.6646	20.0684	22.5198
9	19.3253	22.083	20.1302	22.8945
10	19.4105	22.4821	20.2187	23.2977
11	19.5021	22.889	20.3122	23.7073
12	19.5243	23.2281	20.3763	24.0891
13	19.6279	23.6501	20.4824	24.5145
14	19.6683	24.0105	20.5433	24.8962
15	19.7314	24.3952	20.6177	25.293
16	19.7172	24.7042	20.6355	25.6348
17	19.7832	25.095	20.7571	26.082
18	19.8273	25.4654	20.8516	26.5037
19	19.871	25.8372	20.8639	26.8449
20	19.9266	26.2225	20.9804	27.292
21	20.0011	26.6282	20.9654	27.6091
22	19.9745	26.9346	21.0626	28.0402
23	20.0069	27.3017	21.1671	28.4803
24	20.0168	27.6479	21.1937	28.8442

AIC and BIC tests (LTR), U.S. combined model 1996:1-2021:12, Norwegian combined model 1996:1-2021:12

Augmented Dickey-Fuller Tests

The Augmented Dickey-Fuller test is a one tailed test for examining whether the time series included, have unit roots. Without unit roots, the data can be made stationary and used for autoregressive analysis (Bjørnland & Thorsrud, 2015, p. 118). We therefore perform ADF tests for all time series used in the thesis. The interpretation is as follows; If the bar is below the stippled line, we can reject the null hypothesis of the existence of unit roots in the time series at the critical level the line signifies (Bjørnland & Thorsrud, 2015, pp. 118–119). We recognize that not all our time series are stationary. Nevertheless, this is not detrimental to the model stability, as described in the next section.

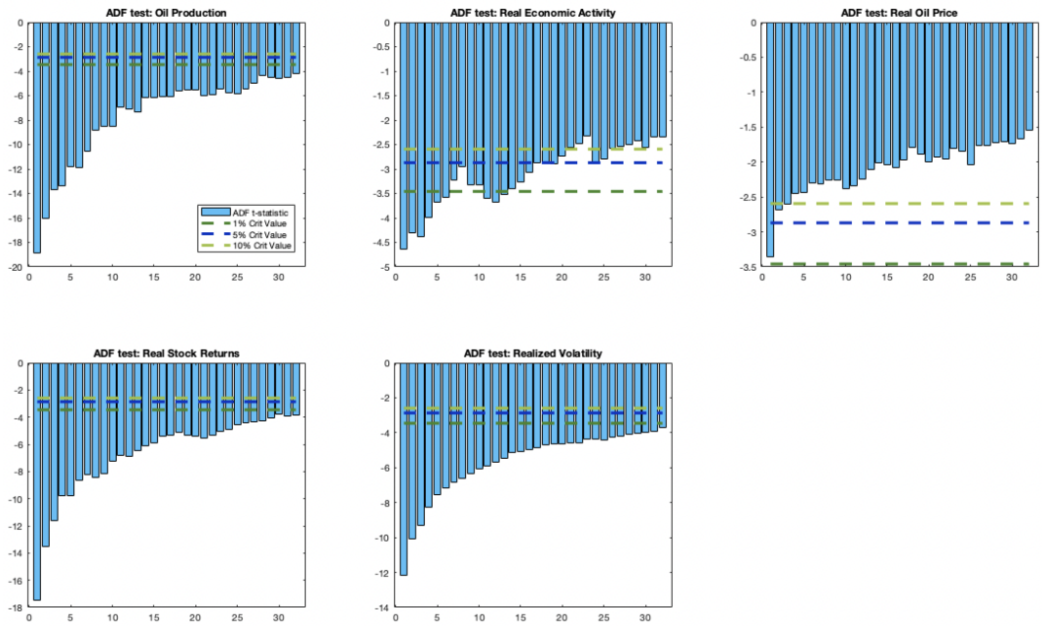

Figure A.1: *ADF tests, U.S. combined model 1974:2-2006:12*

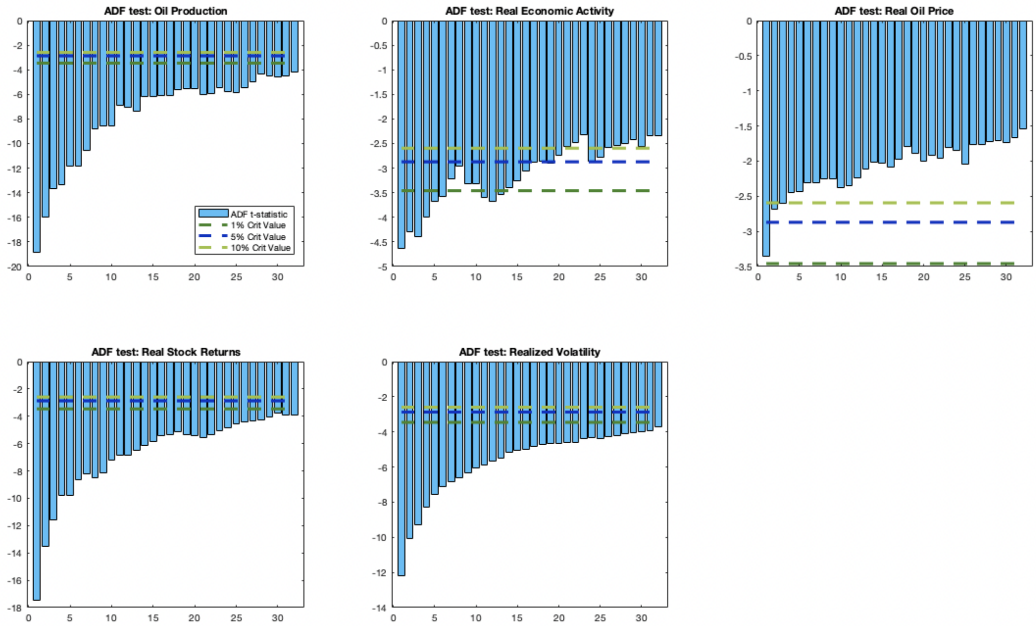

Figure A.2: *ADF tests, U.S. combined model 1974:2-2021:12*

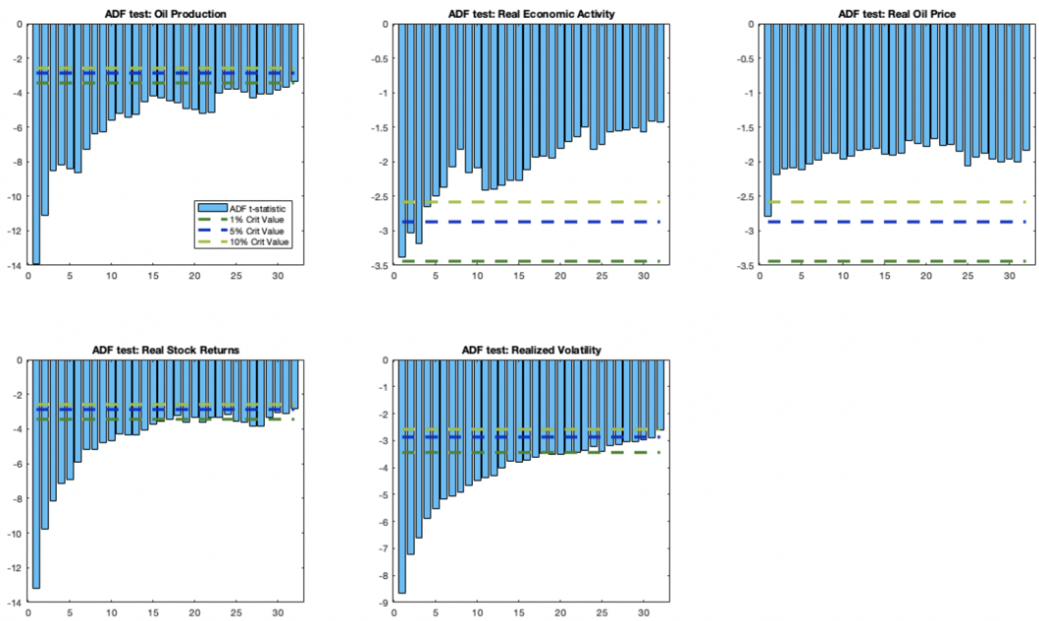

Figure A.3: *ADF tests, U.S. combined model 1996:1-2021:12*

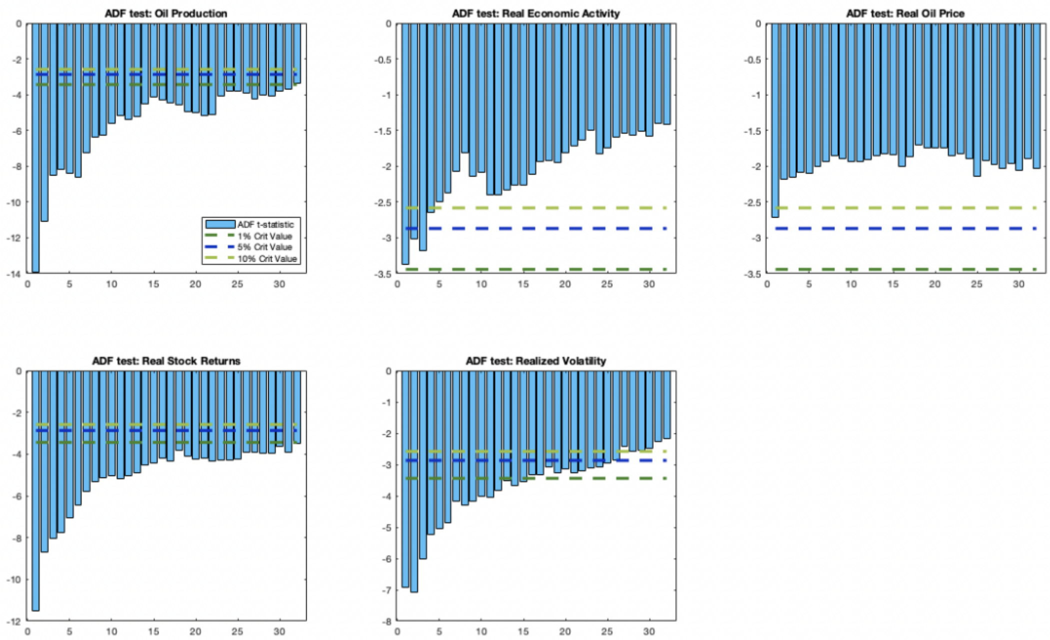

Figure A.4: *ADF tests, Norwegian combined model 1996:1-2021:12*

Maximum eigenvalue of the companion form matrices

Even though ADF tests are useful for examining the singular variables for unit roots at different lag orders, it is not strictly necessary for ensuring model stability. As described in the thesis (see section 3 Methodology), we can ensure a stable model, even in the presence of unit roots, so long as the all eigenvalues of the model's companion form matrix have an absolute value less than one. We therefore present the stability examination for all SVARs reported in the thesis:

Table A.4: Maximum Eigenvalue of Companion Form Matrices

SVAR	Max value
Replication of Kilian & Park (2009) 1974:2-2006:12	0.986472
Replication of Bastianin & Manera (2018) 1974:2-2013:12	0.993824
U.S. Combined model 1974:2-2006:12	0.988897
U.S. Combined model 1974:2-2021:12	0.982205
U.S. Combined model 1996:1-2021:12	0.988932
Norwegian Combined model 1996:1-2021:12	0.988858

All models used in thesis are stable and appropriate to use for economic analysis

Appendix B:

Additional analytical tools for models presented in the thesis

Historical decompositions of the shocks

This thesis is mainly focused on interpreting IRFs and FEVDs, which both describe the average movements in the data, representing the unconditional expectations (Kilian & Lütkepohl, 2017, p. 116). For quantifying the historical fluctuations, historical decompositions describe the cumulative effect of a given structural shock on each variable at a given point in time. It can be a useful analytical tool for examinations of which shocks caused most of the responses of the variables included in the system during specific historical periods (Kilian & Lütkepohl, 2017, p. 116).

A noticeable response from the historical decompositions we have created, is that in the combined model, aggregate demand shocks have a significantly negative effect on U.S. stock returns (and positive effect on volatility) around 2008. This implies, not surprisingly, that aggregate demand was the main driver behind the movements of stock returns during the great recession. Further, the underlying oil market disruptions have historically had a larger impact on the Norwegian stock market movements than those of the U.S. More surprisingly, the oil price drop of 2014 did not significantly affect the overall stock market in Norway, even though this was the general opinion of the public at the time.

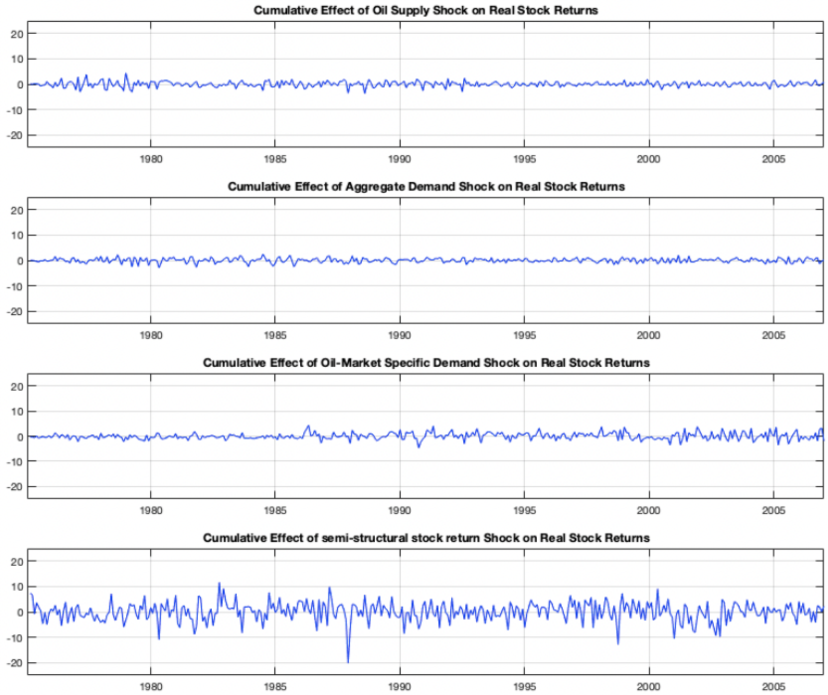

Figure B.1: *Historical decompositions of the shocks, Kilian and Park with S&P 500 index, 1974:2-2006:12*

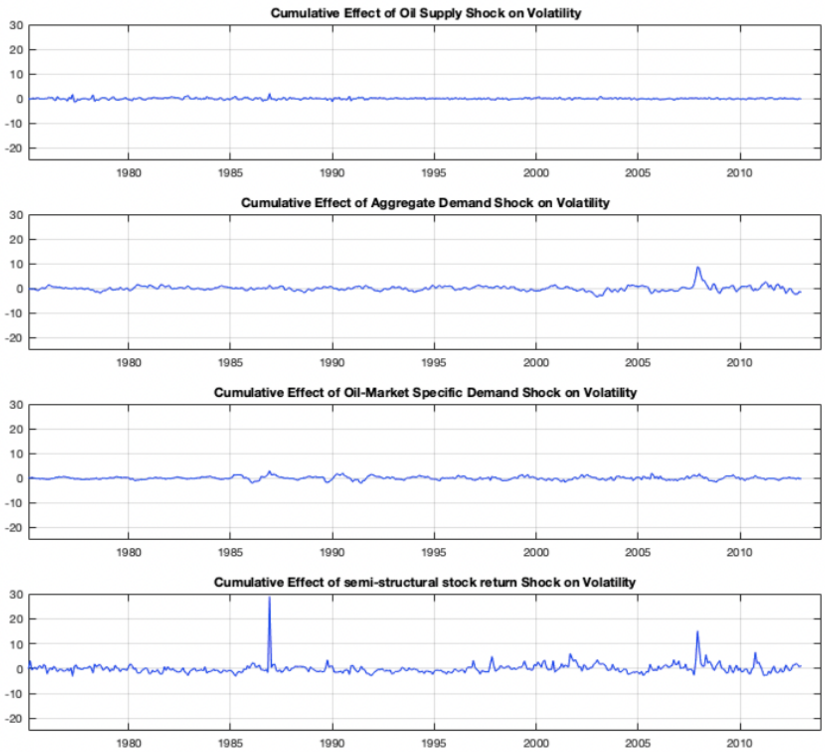

Figure B.2: *Historical decompositions of the shocks, Bastianin and Manera replication, 1974:2-2013:12*

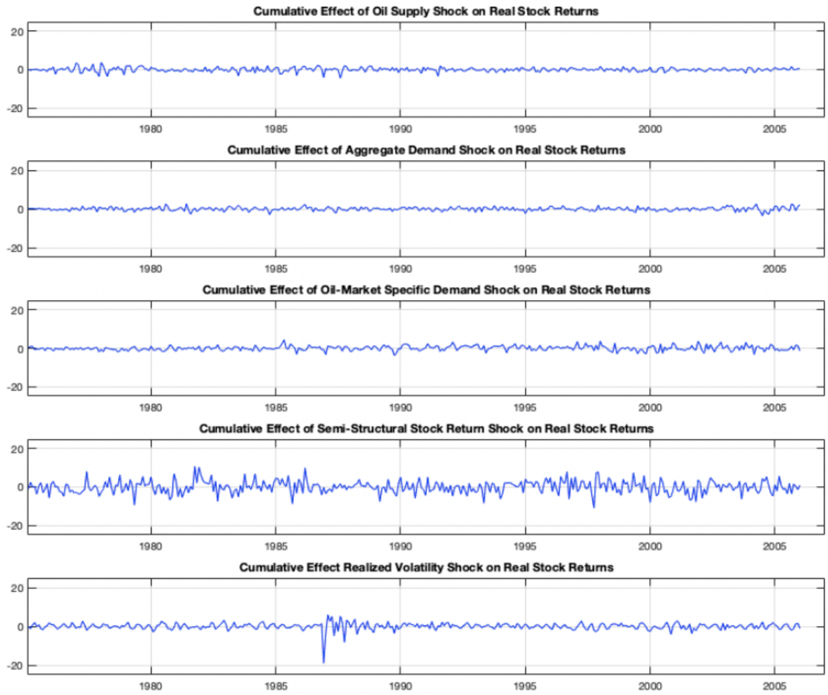

Figure B.3: *Historical decompositions of the shocks, combined model for the U.S. stock returns, 1974:2-2006:12*

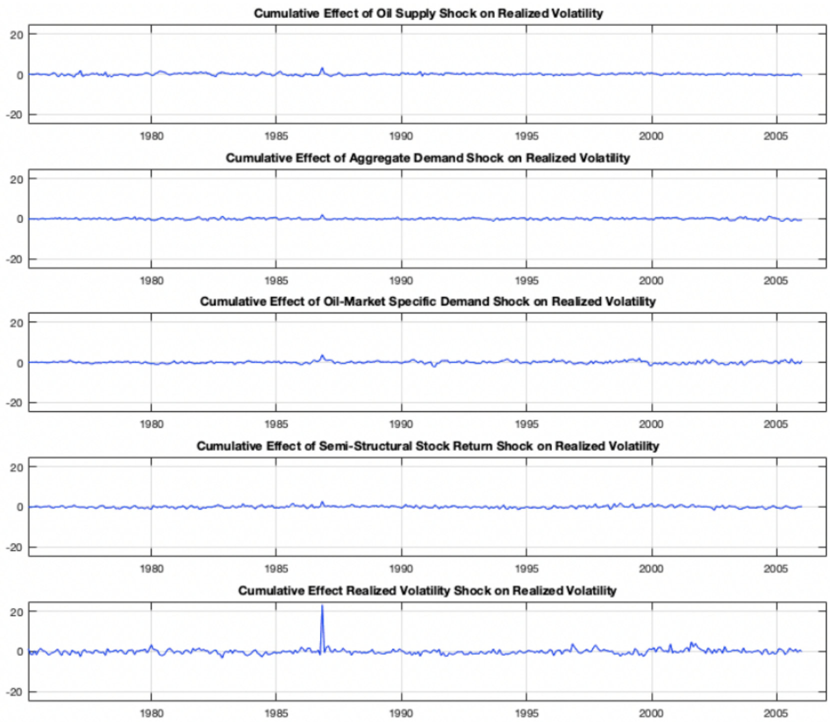

Figure B.4: *Historical decompositions of the shocks, combined model for the U.S. realized volatility, 1974:2-2006:12*

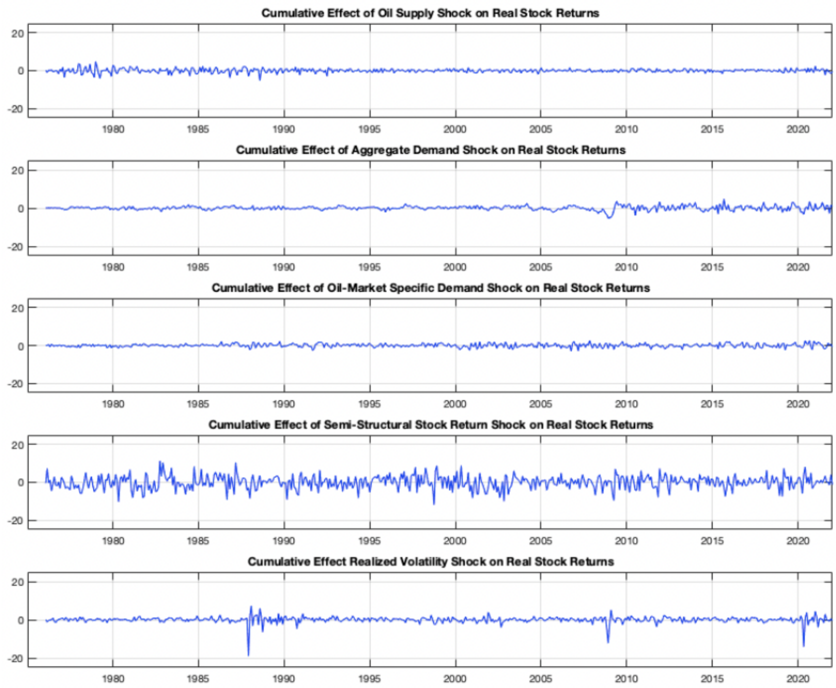

Figure B.5: *Historical decompositions of the shocks, combined model for the U.S. stock returns, 1974:2-2021:12*

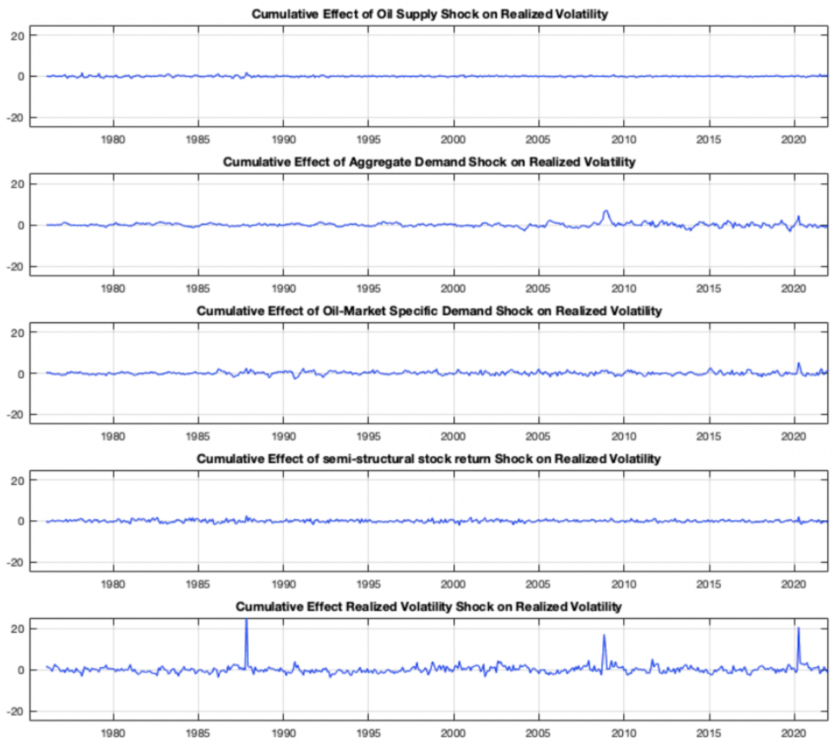

Figure B.6: *Historical decompositions of the shocks, combined model for the U.S. realized volatility, 1974:2-2021:12*

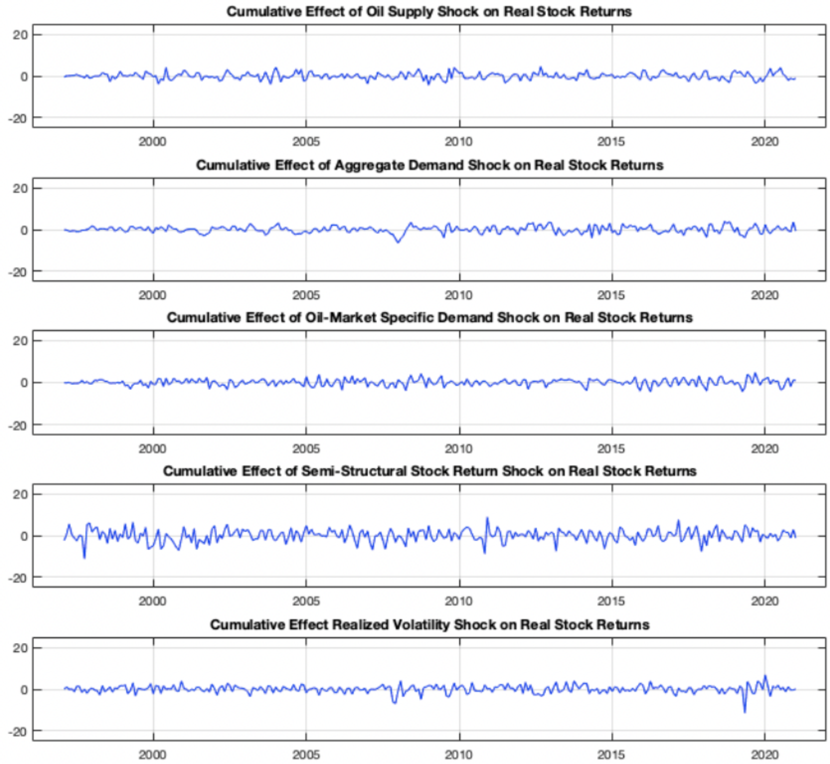

Figure B.7: *Historical decompositions of the shocks, combined model for the U.S. stock returns, 1996:1-2021:12*

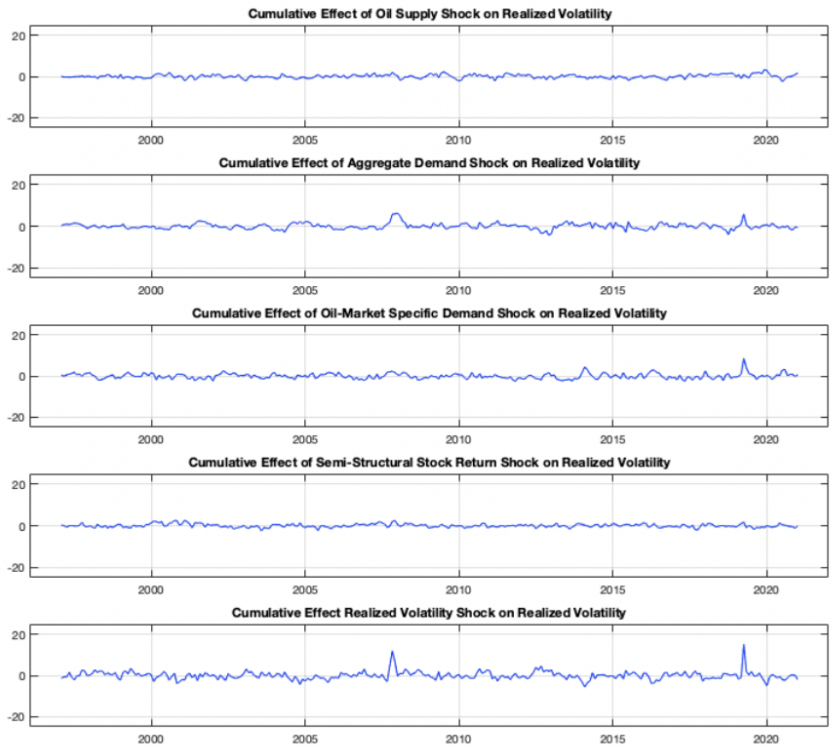

Figure B.8: *Historical decompositions of the shocks, combined model for the U.S. realized volatility, 1996:1-2021:12*

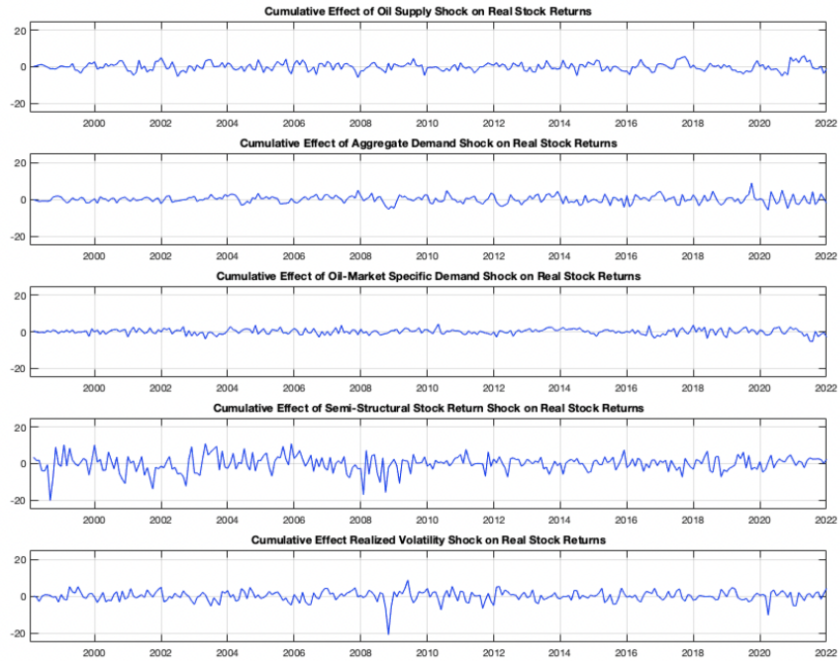

Figure B.9: *Historical decompositions of the shocks, combined model for Norwegian real stock returns, 1996:1-2021:12*

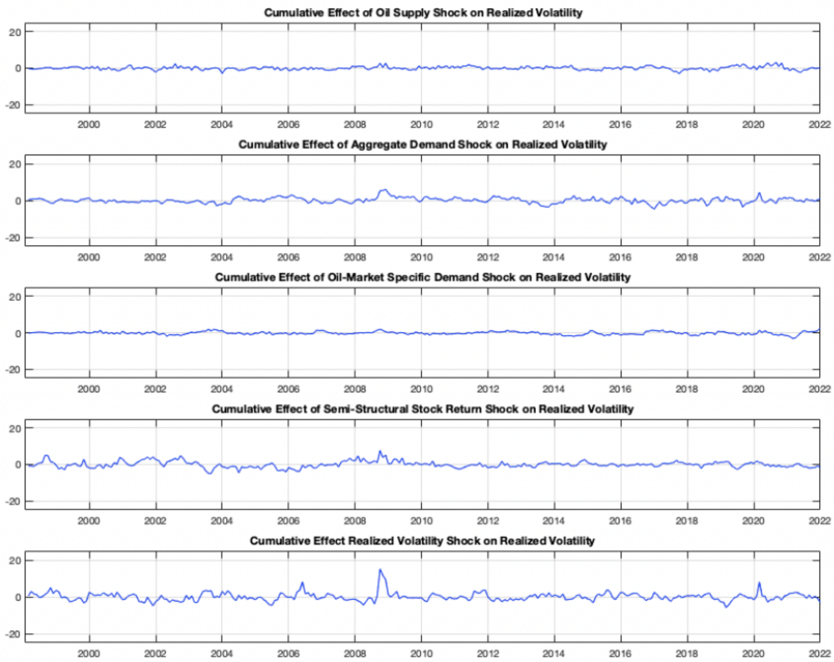

Figure B.10: *Historical decompositions of the shocks, combined model for Norwegian realized volatility, 1996:1-2021:12*

Forecast Error Variance Decompositions

We present forecast error variance decompositions, as described in section 5.2.1.4. The rows in the tables below describe the FEVD for horizons 1, 2, 3, 12 and infinity, respectively, and are measured in decimals that sum to 1 at every horizon.

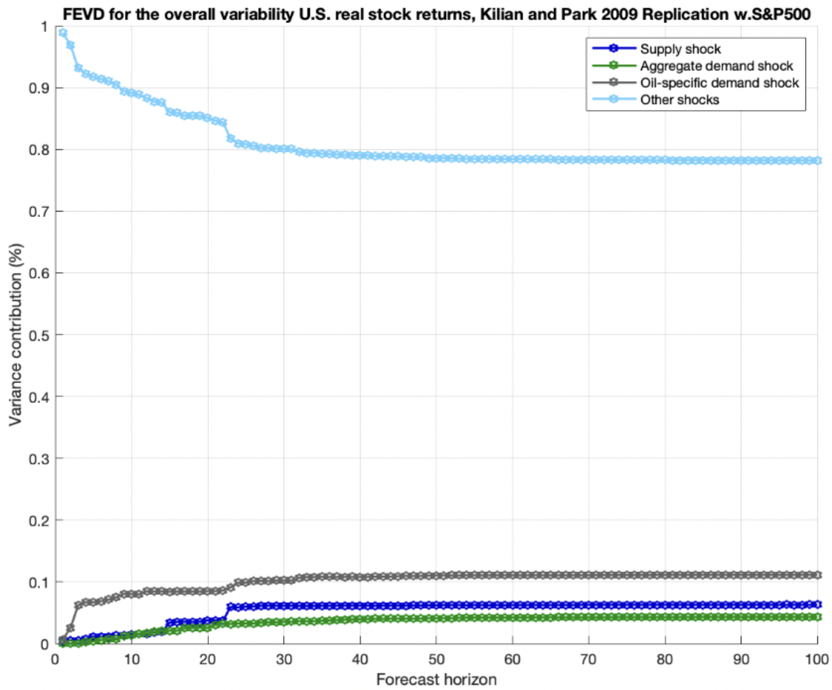

Figure B.11: *FEVD, Kilian & Park replication with S&P 500, 1974:2-2021:12*

Table B.1: FEVD for the overall variability of U.S. real stock returns, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:				
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks
1	0.0045813	0.00004327	0.0071133	0.98826
2	0.0053612	0.00028659	0.025722	0.96863
3	0.0053649	0.0010165	0.062463	0.93116
12	0.015537	0.016837	0.085089	0.88254
∞	0.063033	0.043495	0.11153	0.781194

FEVD,for U.S. real stock returns derived from S&P 500, 1974:2-2006:12

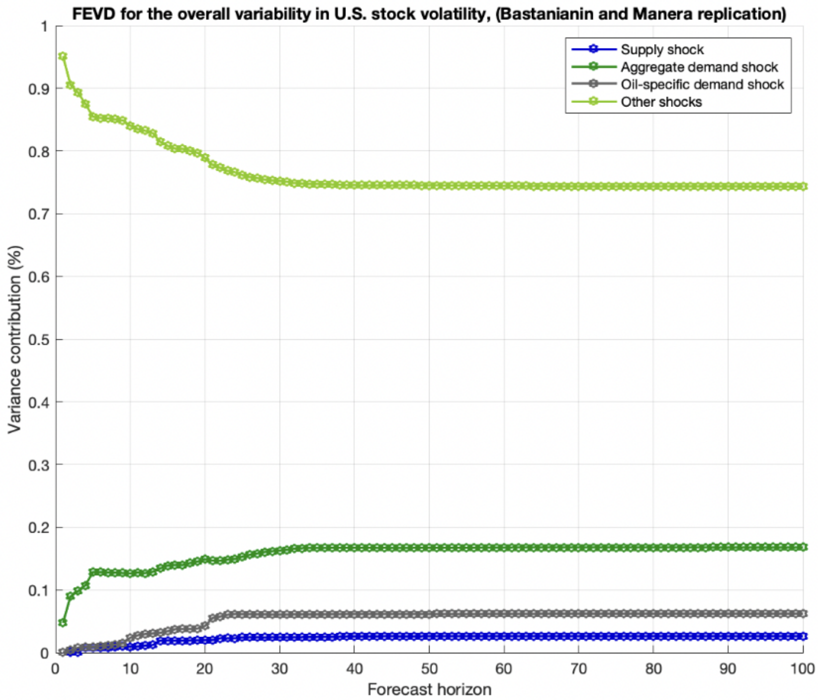

Figure B.12: *FEVD, Bastanin & Manera replication, 1974:2-2013:12*

Table B.2: FEVD for the overall variability of U.S. stock volatility, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:				
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks
1	0.0010669	0.047406	0.0004142	0.95111
2	0.00094487	0.089576	0.0039059	0.90557
3	0.0010501	0.097984	0.0078975	0.89307
12	0.01138	0.12679	0.029518	0.83232
∞	0.02625	0.16797	0.062342	0.74344

FEVD, U.S. stock volatility, 1974:2-2013:12

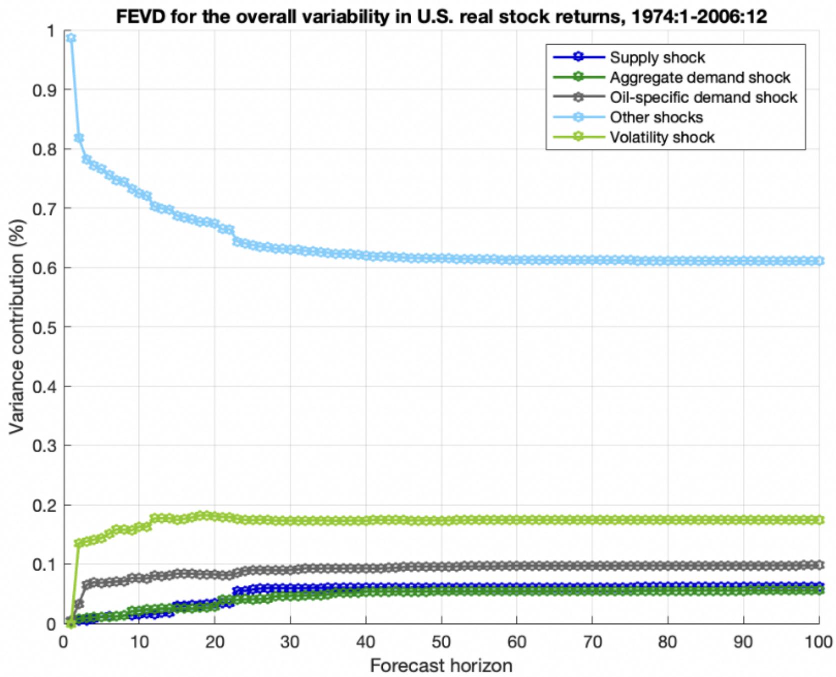

Figure B.13: *FEVD, U.S. stock returns, 1974:2-2006:12*

Table B.3: FEVD for the overall variability of U.S. stock returns, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks	Volatility shock
1	0.0054336	0.0035565	0.0047363	0.98627	0
2	0.0055571	0.0080808	0.033298	0.81763	0.13544
3	0.005518	0.008981	0.064867	0.78248	0.13815
12	0.016041	0.023413	0.080583	0.70295	0.17701
∞	0.061442	0.055541	0.097858	0.6106	0.17456

FEVD, combined model for U.S. real stock returns, 1974:2-2006:12

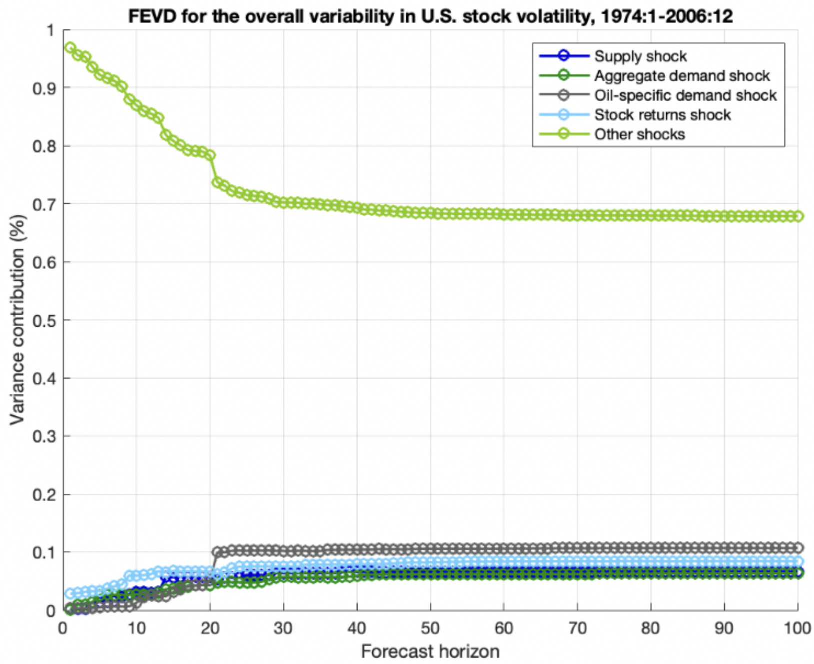

Figure B.14: *FEVD, combined model U.S. volatility, 1974:2-2006:12*

Table B.4: FEVD for the overall variability of U.S. stock volatility, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Stock return shocks	Other shock
1	0.000021771	0.00013992	0.0031198	0.028229	0.96849
2	0.0026388	0.0097008	0.0031885	0.029296	0.95518
3	0.0025992	0.0095206	0.0036604	0.031544	0.95268
12	0.030601	0.027442	0.024892	0.062366	0.8547
∞	0.066805	0.063593	0.107	0.084301	0.6783

FEVD, combined model for U.S. realized volatility, 1974:2-2006:12

Table B.5: FEVD for the overall variability of U.S. stock returns, 1974:2-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks	Volatility shock
1	0.007224	0.00094448	0.00024365	0.99159	0
2	0.0090139	0.0013476	0.00024053	0.83986	0.14
3	0.0097181	0.018151	0.010838	0.81545	0.14954
12	0.019469	0.040825	0.019163	0.75431	0.16623
∞	0.059228	0.06711	0.0488	0.66685	0.15802

FEVD, combined model for U.S. real stock returns, 1974:2-2021:12

Table B.6: FEVD for the overall variability of U.S. stock volatility, 1974:2-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Stock return shocks	Other shock
1	0.00063214	0.012516	0.045949	0.038556	0.90235
2	0.0013912	0.054083	0.056392	0.036852	0.85128
3	0.0013418	0.087628	0.061358	0.034985	0.81469
12	0.0081393	0.10968	0.063286	0.03867	0.78022
∞	0.018117	0.13508	0.097198	0.059572	0.69004

FEVD, combined model for U.S. realized volatility, 1974:2-2021:12

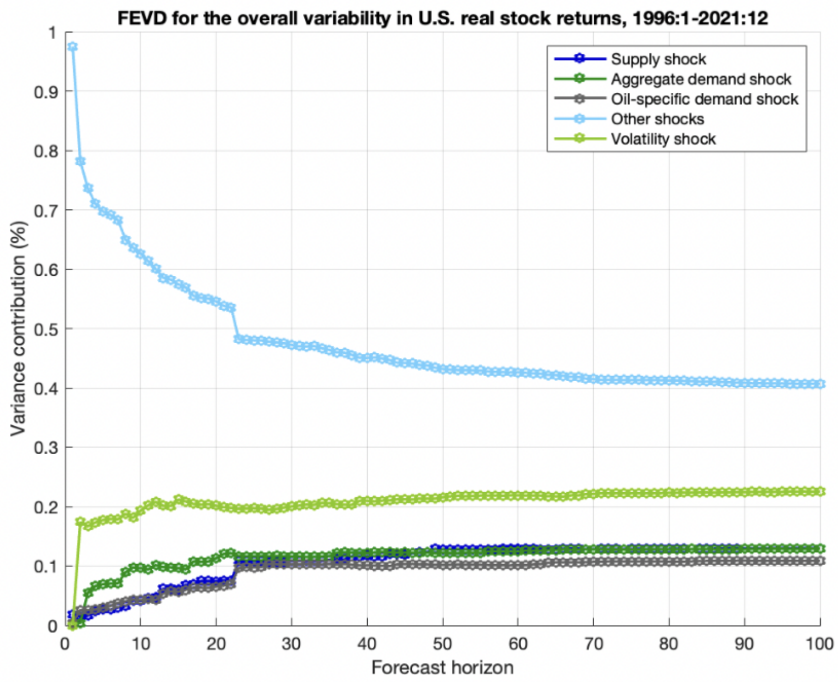

Figure B.15: *FEVD, combined model U.S. stock returns, 1996:1-2021:12*

Table B.7: FEVD for the overall variability of U.S. stock returns, 1996:1-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks	Volatility shock
1	0.017973	0.0031462	0.0041832	0.9747	0
2	0.01441	0.0039456	0.025708	0.78215	0.17379
3	0.016162	0.054965	0.025552	0.73628	0.163704
12	0.04713	0.10145	0.042962	0.60047	0.20799
∞	0.12974	0.12938	0.10874	0.40676	0.22539

FEVD, combined model for U.S. real stock returns, 1996:1-2021:12

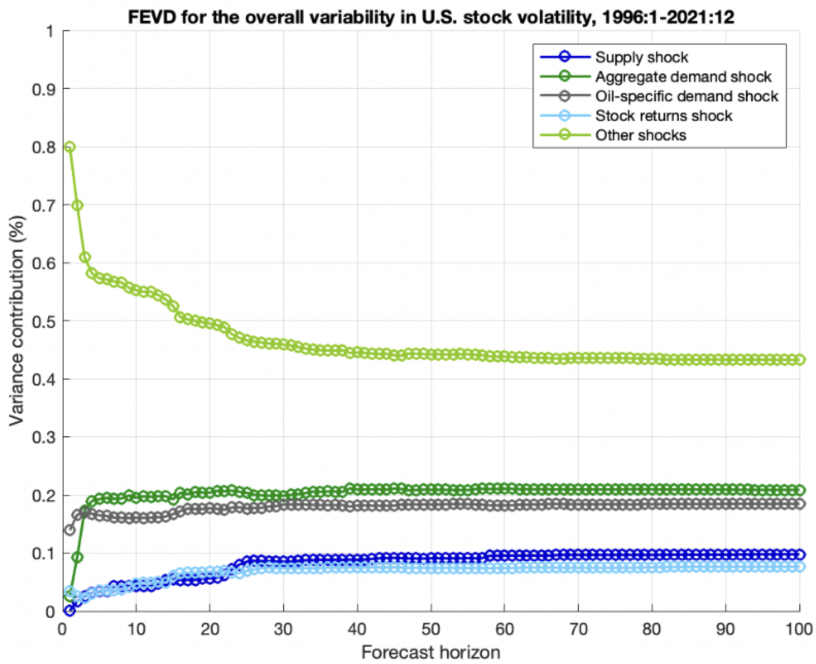

Figure B.16: *FEVD, combined model U.S. stock volatility, 1974:2-2021:12*

Table B.8: FEVD for the overall variability of U.S. stock volatility, 1996:1-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Stock return shocks	Other shock
1	0.0010092	0.025698	0.13944	0.034896	0.79896
2	0.016647	0.093348	0.1659	0.026048	0.69806
3	0.024872	0.17333	0.16944	0.023275	0.60988
12	0.043081	0.19657	0.16888	0.049585	0.54988
∞	0.097752	0.20863	0.18452	0.076452	0.43265

FEVD, combined model for U.S. realized volatility, 1996:1-2021:12

Table B.9: FEVD for the overall variability of Norwegian stock returns, 1996:1-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks	Volatility shock
1	0.0018726	0.0050633	0.012277	0.98079	0
2	0.010268	0.030386	0.010423	0.80503	0.14397
3	0.027909	0.068716	0.012959	0.75045	0.13997
12	0.091826	0.085742	0.017616	0.62799	0.17682
∞	0.13748	0.097957	0.073489	0.50372	0.18736

FEVD, combined model for Norwegian stock returns, 1996:1-2021:12

Table B.10: FEVD for the overall variability of Norwegian stock volatility, 1996:1-2021:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Stock return shocks	Other shock
1	0.022792	0.065526	0.007608	0.18368	0.7284
2	0.020934	0.1007	0.01186	0.19535	0.67116
3	0.028457	0.11334	0.012761	0.21524	0.6382
12	0.0502	0.11727	0.02544	0.26177	0.54532
∞	0.094731	0.18278	0.090159	0.22791	0.40442

FEVD, combined model for Norwegian realized volatility, 1996:1-2021:12

Appendix C:

Application of alternative time series

Replication of Kilian and Park with CRSP

Kilian and Park (2009) estimates real stock returns using the monthly CRSP data. However, to be consistent during our thesis by the use of only one price index, we have used the S&P 500 to represent the stock market in all models. To ensure robustness when changing the measurement, we therefore replicated the methodology from Kilian and Park (2009) using both indices. Comparing the two shows only minor differences.

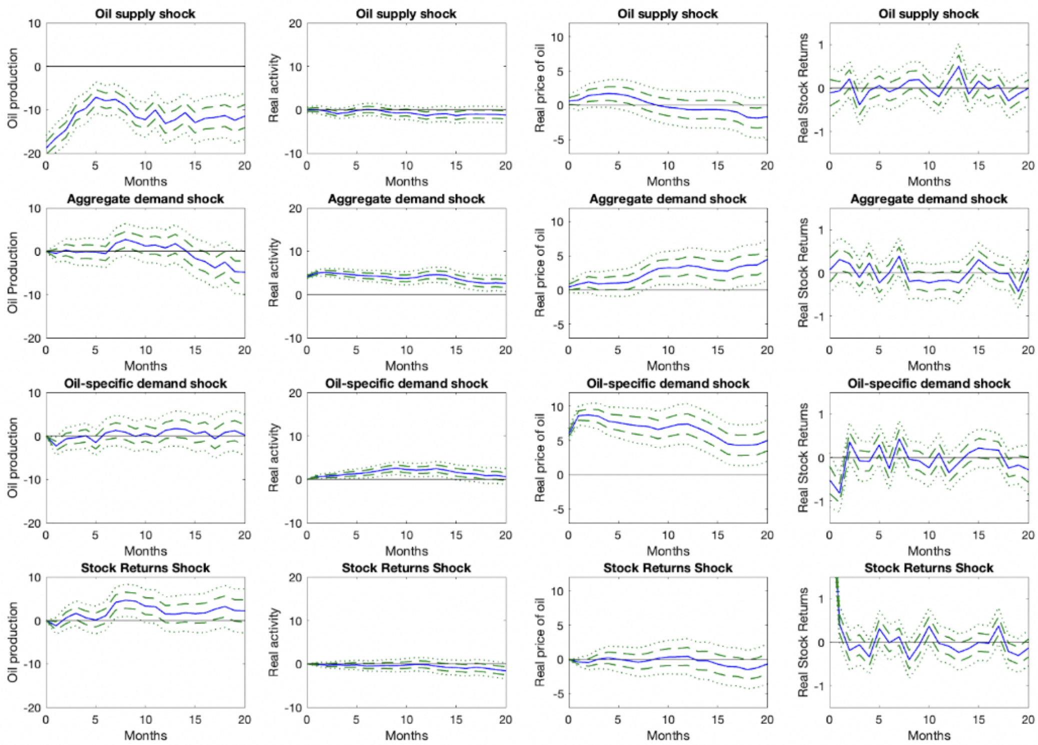

Figure C.1: *Impulse response functions, Kilian & Park replication with CRSP, 1974:2-2006:12*

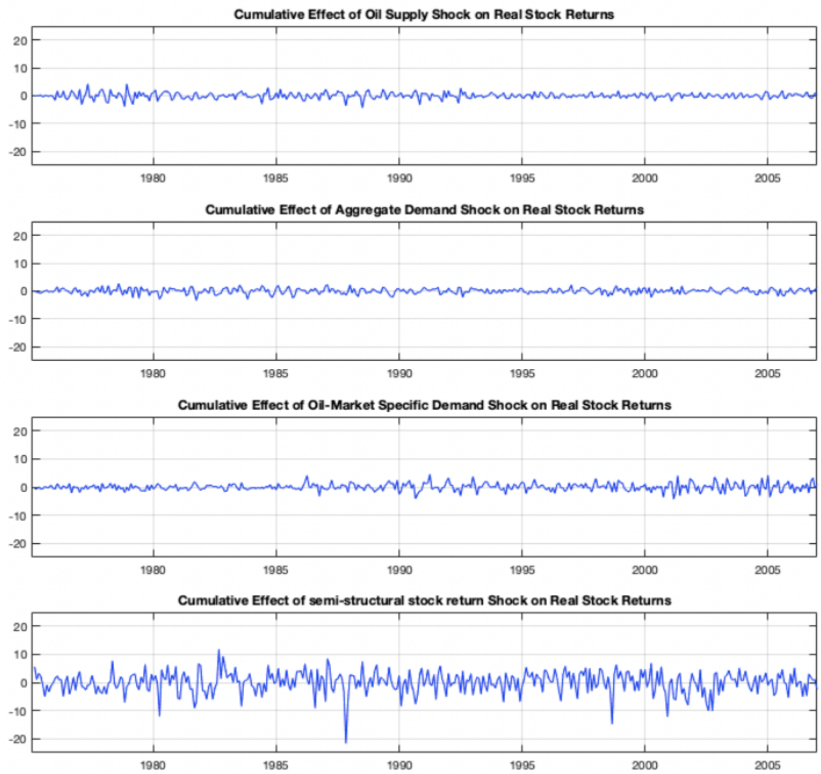

Figure C.2: *Historical decompositions, Kilian & Park replication with CRSP, 1974:2-2006:12*

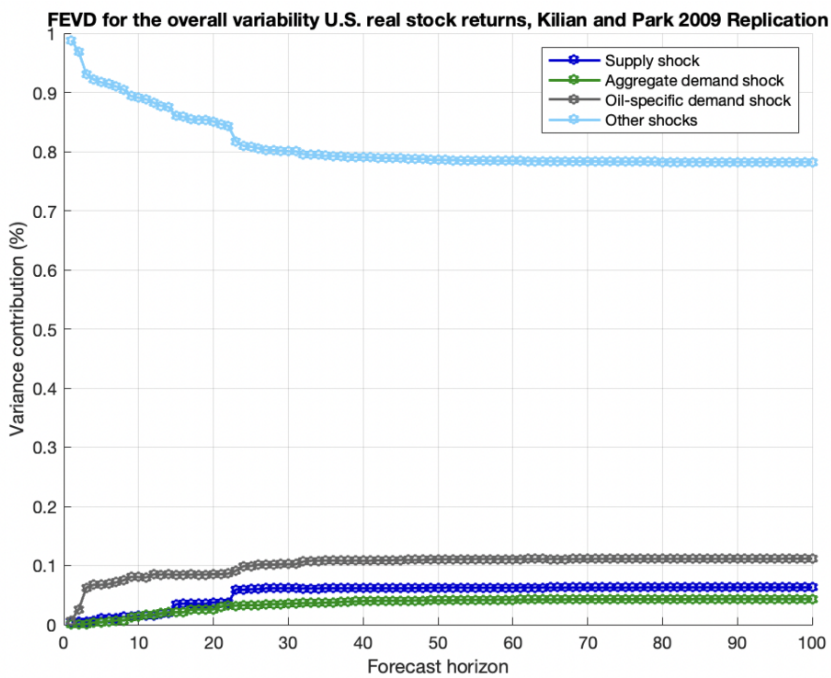

Figure C.3: *FEVD, Kilian & Park replication with CRSP, 1974:2-2006:12*

Table C.1: FEVD for the overall variability of real stock returns, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:				
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks
1	0.0064856	0.00020957	0.013691	0.98545
2	0.00083093	0.0049703	0.046625	0.904757
3	0.0030442	0.0072286	0.052577	0.93715
12	0.015279	0.026003	0.068054	0.89066
∞	0.06391	0.051209	0.10507	0.777981

FEVD, U.S. real stock returns derived from CRSP, 1974:2-2006:12

Bastianin and Manera replication ending in 2006

Bastianin and Manera (2018) used a sample containing data from 1973 lasting until the end of 2013. In addition to replicating their paper using the original datasample, we have also estimated an SVAR model containing data only until 2006. The reason behind this is to enable us to compare the model with that of Kilian and Park (2009), who only samples data until 2006. With this model we can detect whether differences in the oil market variables between the two models, are due to the different stock variables or simply the unequal data samples.

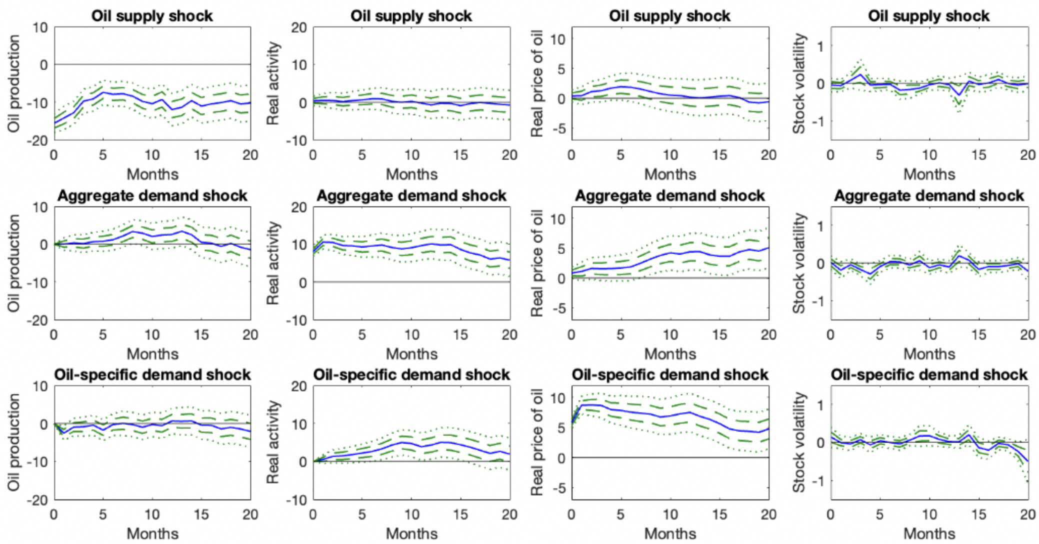

Figure C.4: *Impulse response functions, Bastianin and Manera replication ending in 2006, 1974:2-2006:12*

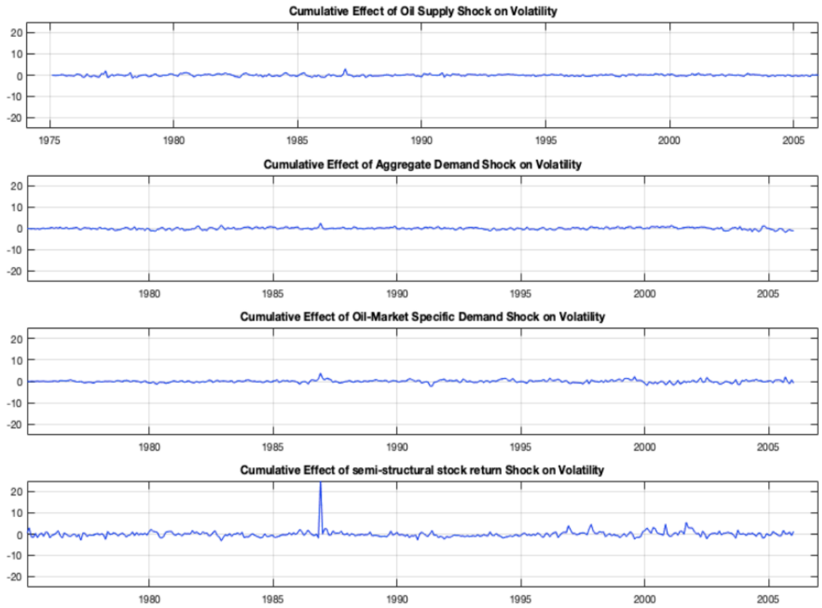

Figure C.5: *Historical decompositions, Bastianin and Manera replication ending in 2006, 1974:2-2006:12*

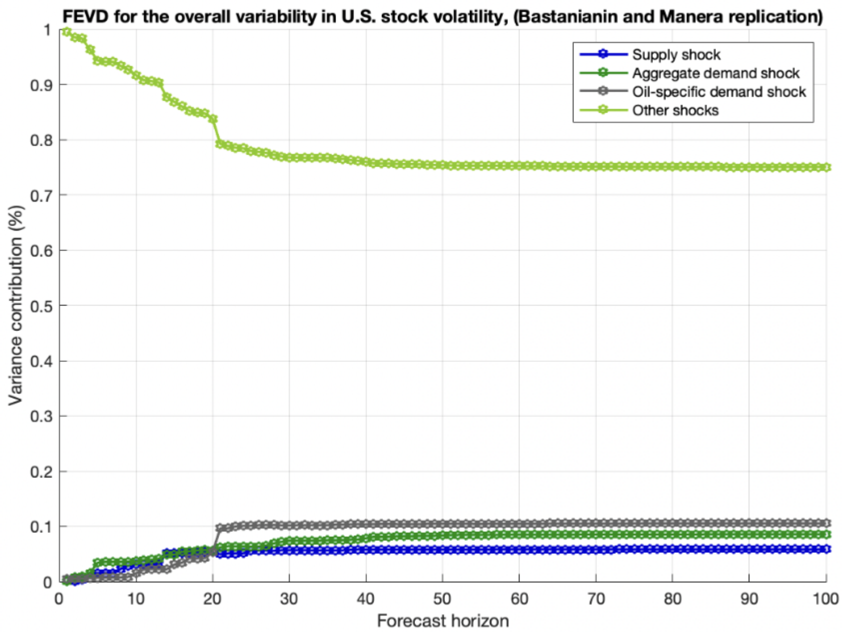

Figure C.6: *FEVD, Bastianin and Manera replication ending in 2006, 1974:2-2006:12*

Table C.2: FEVD for the overall variability of stock volatility, 1974:2-2006:12

Percent of h-step ahead forecast error variance explained by:				
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks
1	0.0010669	0.047406	0.0004142	0.95111
2	0.00094487	0.089576	0.0039059	0.90557
3	0.0010501	0.097984	0.0078975	0.89307
12	0.01138	0.12679	0.029518	0.83232
∞	0.02625	0.16797	0.062342	0.74344

FEVD, combined model for U.S. realized volatility ending in 2006, 1974:2-2006:12

Combined model excluding COVID-19

The COVID-19 pandemic was a large exogenous shock that affected the global economy because governments decided to decrease activity. The shock resulted in changes in some empirical time series analysis, and to ensure that this is not the case for our model, we differentiate the effects from the irregular, artificial shock that coronavirus created, to the other shocks included in our data. This, by estimating a model based on time series ending in december 2019. From this, we found that this model is not substantially different from the extended model included in the thesis, insinuating that the large, global shock did not create instabilities in our data.

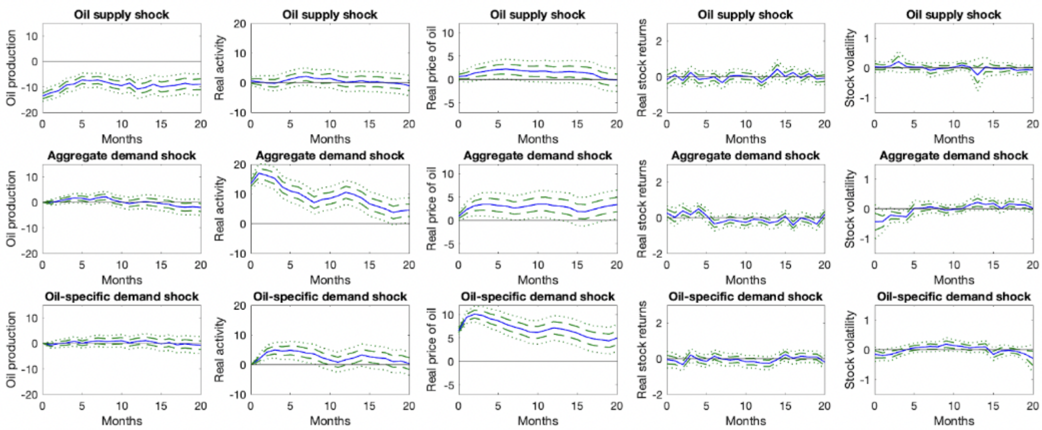

Figure C.7: *Impulse response functions, combined model U.S. data without COVID-19, 1974:2-2019:12*

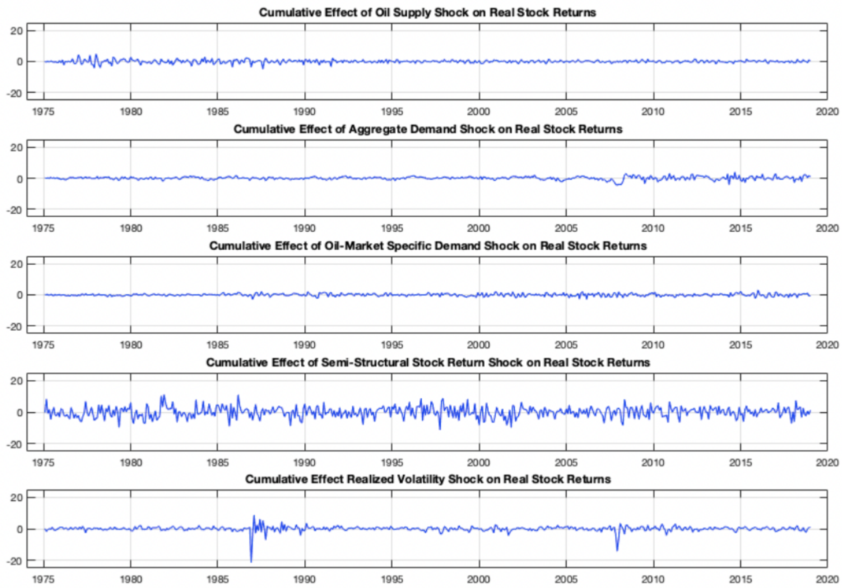

Figure C.8: *Historical decompositions, combined model for U.S. stock returns without COVID-19, 1974:2-2019:12*

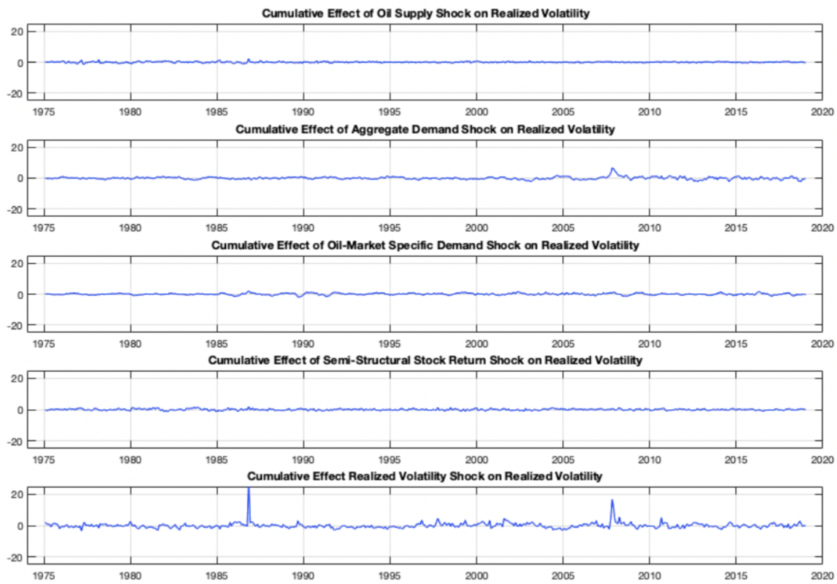

Figure C.9: *Historical decompositions, combined model for U.S. stock volatility without COVID-19, 1974:2-2019:12*

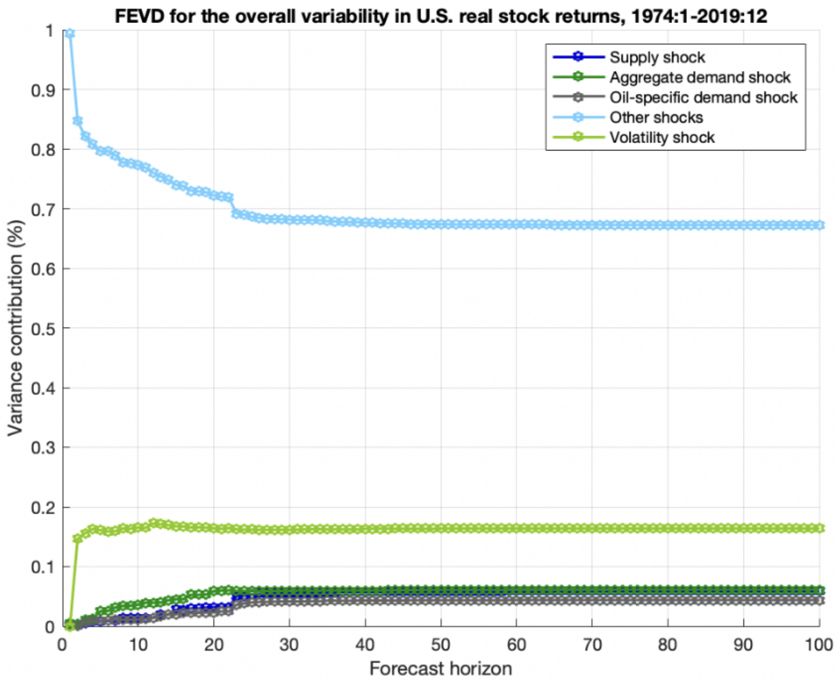

Figure C.10: *FEVD, combined model for U.S. real stock returns without COVID-19, 1974:2-2019:12*

Table C.3: FEVD for the overall variability of stock returns, 1974:2-2019:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Other shocks	Volatility shock
1	0.0016289	0.0045285	0.00019351	0.99365	0
2	0.0020636	0.0038744	0.00096331	0.84693	0.14617
3	0.0045907	0.011485	0.0070145	0.82107	0.15584
12	0.014326	0.03931	0.013902	0.76004	0.17243
∞	0.058622	0.061168	0.043731	0.67269	0.16379

FEVD, combined model for U.S. real stock returns without COVID-19, 1974:2-2019:12

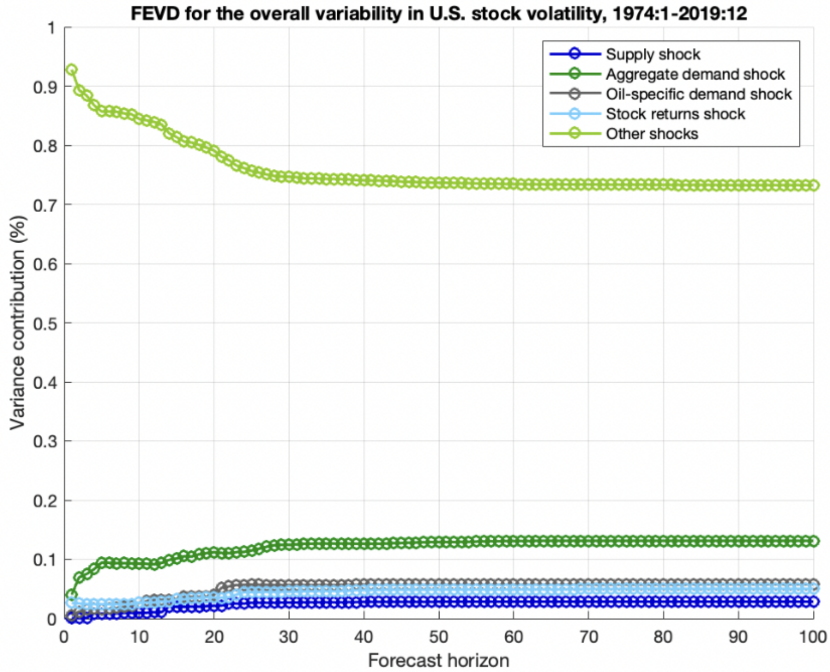

Figure C.11: *FEVD, combined model for U.S. stock volatility without COVID-19, 1974:2-2019:12*

Table C.4: FEVD for the overall variability of stock volatility, 1974:2-2019:12

Percent of h-step ahead forecast error variance explained by:					
Horizon	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Stock return shocks	Other shock
1	0.00028941	0.040398	0.00516	0.026457	0.9277
2	0.00030009	0.069745	0.011479	0.02543	0.89305
3	0.00095266	0.075201	0.015594	0.024396	0.88386
12	0.010721	0.091709	0.0310131	0.027123	0.83942
∞	0.028389	0.13135	0.057812	0.050009	0.73244

FEVD, combined model for U.S. realized volatility without COVID-19, 1974:2-2019:12