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MASTER THESIS

"Oil Price Shocks and the Stock Market"

By: Victoria Mørkedal

Master of Science in Business, major in Economics

Supervisor: Jamie L. Cross

June 2022

Table of Contents

Acknowledgement

I would like to thank my family for their patience over my five years of study at BI Norwegian Business School. I would like to express my gratitude to my supervisor, Jamie L. Cross, Postdoctoral Research Fellow at the Centre for Applied Macroeconomics and Commodity Prices (CAMP) at BI Norwegian Business School, for assisting with the formulation of the research question and providing invaluable feedback and suggestions for improvement throughout the work on this thesis. I would also want to thank Lutz Kilian, Senior Economic Policy Adviser at the Federal Reserve Bank of Dallas and architect of the econometric model framework utilized in the thesis, for clarifying model inputs in a way that was quite useful. Lastly, I would like to thank my lecturers at BI during my Bachelor of Finance and Master of Science in Business with a concentration in Economics for providing me with a solid education, especially in the areas of econometrics, finance, and macroeconomics.

Executive Summary

This thesis examines how oil price shocks affect real stock returns in the United States and Norway. I have reproduced and updated the Kilian & Park (2009) study with exclusion restrictions using current data. I have also employed the refined oil market model by Zhou (2020) with narrative and dynamic sign restrictions to study the impact on stock returns for the first time. Furthermore, I have rebuilt the Kilian real economic activity index based on daily shipping rates in order to assess the results' robustness in greater detail.

Oil price shocks are shown to have a significant impact on real stock returns in the United States and Norway. The impact depends on whether they are driven by demand or supply shocks. The investigated shocks pertain to (1) oil supply disruptions, (2) demand for crude oil associated with unexpected fluctuations in the global business cycle, (3) demand for oil inventories arising from forward-looking behavior (speculative demand shock), and (4) other oil-specific demand shocks not otherwise accounted for (such as weather shocks).

Earlier studies demonstrated that a disruption to global oil production has no statistically significant effect on real stock performance. Unanticipated changes in aggregate demand caused by the business cycle have a positive and long-term impact on real stock returns. Both in the United States and in Norway, this study confirms this conclusion. Norwegian stock returns, on average, respond more strongly to these shocks.

In the event of oil-specific demand shocks, such as precautionary inventory demand, Kilian & Park (2009) found that U.S. stock returns were solely negative. With additional data, it is determined that the effect is closer to zero. The refined oil market model verifies that the impact of storage demand and other oil-specific demand shocks on U.S. stock returns is negative but close to zero. Other oil-specific

demand shocks, however, are found to have a positive impact on the stock returns of Norway.

The four structural shocks that drive the global crude oil market account for approximately 24 percent of the variability in U.S. real stock returns and 25 percent of the variability in Norwegian real stock returns over the long term, suggesting that shocks in the global oil markets are an important driver of real stock returns.

Introduction

It is widely known that swings in the price of crude oil are a major element in explaining stock price fluctuations in the U.S. economy; however, less is known about Norway. This thesis seeks to fill this void by investigating how oil price shocks on the global crude oil market affect real stock returns. In order to do so, I will use a structural vector autoregressive (SVAR) model to identify oil market shocks and project these shocks onto real stock returns in the U.S. and Norwegian economies.

The first objective of this thesis is to replicate Kilian & Park's (2009) analysis of the effect of oil price shocks on the U.S. stock market using monthly data on (1) the percentage change in global crude oil production, (2) a measure of global real economic activity, (3) the real price of crude oil, and (4) real stock market returns. 1973:1-2006:12 was the initial sample period. Then, I will extend the data set to 2021:12 and apply the same model to Norwegian stock market data in addition to U.S. stock market data. Furthermore, I will evaluate the outcomes of using the refined oil market models and research methodology of Kilian & Murphy (2014) and Zhou (2020), which employ a structural VAR model with sign restrictions as opposed to the traditional recursive identification utilized by Kilian & Park (2009). As a final robustness check, I will determine if the results change if a modified real economic activity index is utilized.

Using the MATLAB R2022a software release, I perform the empirical work and generate all figures and graphs.

In this thesis, I will specifically address the following question: "What are the dynamic effects of demand and supply shocks from the global crude oil market on stock returns in the United States and Norway?"

Methodology

Structural vector autoregressive (SVAR) models of the oil market have become the standard method for analyzing the evolution of the real price of oil and its effect on the macroeconomy (Kilian & Zhou, 2021).

Consider the example cited by Kilian & Park (2009, p. 1267) to demonstrate why this method is so popular: Given the relationship between economic activity and stock returns, an increase in oil prices caused by a shock to aggregate demand is likely to lead to higher stock prices. Conversely, an increase in oil prices due to a supply shock could potentially lead to lower stock prices (because of for example cost inflation). This means that a (traditional) regression comparing stock returns to changes in the price of oil will be biased toward finding no significant associations.

The SVAR methodology is useful for addressing the issue of the simultaneity of oil prices, stock returns, and the global economy because it allows variables to be determined endogenously within the model. We can also isolate the effects of various market shocks. For example, what impact would a disruption in oil supply have on stock returns? And does the impact differ if there is a shock to aggregate demand?

Kilian (2009) introduced the SVAR model with exclusion restrictions for oil market research. Using this oil market model as a starting point, Kilian & Park (2009) constructed a model that included stock returns.

Using the modified nomenclature used by Zhou (2020), define $y_t = (\Delta q_t, rea_t, p_t, s_t)'$ to be a vector of variables of interest:

1. Δq_t: Global crude oil monthly year-over-year production change

2. rea_t: Real economic activity index, an equal-weighted, detrended indicator of dry bulk freight costs
3. p_t: The real price of oil (U.S. refiners' average acquisition cost), in log terms
4. s_t: Aggregated U.S. stock returns constructed by subtracting the consumer price index (CPI) inflation rate from the log returns on the CSRP value-weighted market portfolio.

Let y_t be generated by the covariance stationary structural VAR(24) process:

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_{24} y_{t-24} + w_t \quad (1)$$

where w_t are the uncorrelated structural shocks. In order to simplify notation, deterministic terms have been excluded. A lag order of 24 months enables the model to capture extended cycles in the real price of oil (Kilian & Lütkepohl, 2016).

u_t are the reduced-form VAR shocks such that $u_t = B_0^{-1} w_t$:

$$u_t = \begin{pmatrix} u_t^{\Delta q} \\ u_t^{rea} \\ u_t^{p} \\ u_t^{s} \end{pmatrix} = B_0^{-1} w_t = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{pmatrix} w_t^{\text{oil supply}} \\ w_t^{\text{aggregate demand}} \\ w_t^{\text{oil-specific demand}} \\ w_t^{\text{other shocks to stock returns}} \end{pmatrix} \quad (2)$$

Identification: Recursive Cholesky decomposition

Kilian (2009) and Kilian & Park (2009) defended the recursive identification of the oil-market block by noting that oil-producing countries are unable to alter oil production with a month's notice, so they assume that oil production does not respond to shocks from global demand or oil prices within a month ($b_{12} = b_{13} = 0$). Second, they assume that it will take longer than one month for a shock to oil prices to affect real economic activity, hence the constraint that real economic activity does not respond to shocks in the real price of oil within one month. ($b_{23} = 0$). Furthermore, exogenous shocks to stock returns will not affect the real price of oil within the same month, but only with a delay ($b_{34} = 0$). This seems to be a plausible assumption, given that the real price of oil is defined as the average acquisition cost for U.S. refiners, that import crude oil over great distances and, thus, over time. This assumption could be controversial if we had instead utilized oil futures prices that may demonstrate co-movement with stock returns.

U.S. stock returns are ordered last since stock return shocks will have no immediate effect on the other oil market variables. In other words, exogenous shocks to stock returns will not affect oil production, oil demand and aggregate demand within the same month, but could have a delayed impact.

Alternative identification: Sign restrictions

Various historical events, according to Kilian & Zhou (2021), appear to violate the zero limits imposed on the structural impact multiplier matrix B_0^{-1}. Instead of applying a constraint of zero, Kilian & Murphy (2012, 2014) investigated alternative identification that restrict the sign of selected impulse responses. One benefit of sign-identified structural VAR models is that they permit the impact price elasticity of oil supply to be close to zero rather than requiring it to be exactly zero (Kilian & Zhou, 2021, p. 5).

Kilian & Murphy (2012) expand on Kilian (2009) by employing sign restrictions. Kilian & Murphy (2014) expand upon Kilian & Murphy (2012) by (1) adding a variable to the SVAR for inventories and (2) adding new identification assumptions. Zhou (2020) further improves the model by Kilian & Murphy (2014) by incorporating narrative sign restrictions into the identification strategy.

To account for storage demand shocks, a new variable, Δinv_t, representing changes in global crude oil stocks has been included to the refined oil market model. Changes in crude oil inventories are assumed to reflect latent expectation shifts regarding future oil market conditions. The model does not differentiate between precautionary and speculative oil demand despite the fact that storage demand reflects both. According to Cross, Nguyen & Tran (2022), who isolate these elements, uncertainty-driven precautionary crude oil demand is, on average, the principal driver of real oil price changes traditionally associated with storage demand shocks.

The refined model renames oil supply and aggregated demand as flow supply shocks and flow demand shocks, respectively. Storage demand shocks include shocks to inventory technology, preferences for holding inventory, speculation, and idiosyncratic shocks from strategic reserve releases (Kilian & Zhou, 2021, p. 9). Other oil demand shocks are categorized as residual without any structural interpretation.

The model imposes a number of inequality constraints on the first-month price elasticities of oil demand and oil supply. In addition, disruptions in the oil supply are believed to increase the real price of oil and reduce world oil production for at least a year. Based on numerous historical events, narrative sign limitations are subsequently added into the sampler algorithm (see Zhou (2020, p. 132) for details).

The Zhou (2020) oil market model including stock returns is as follows:

$$u_t = \begin{pmatrix} u_t^{\Delta q} \\ u_t^{rea} \\ u_t^{p} \\ u_t^{\Delta inv} \\ u_t^{s} \end{pmatrix} = \begin{bmatrix} - & + & + & b_{14}^0 & 0 \\ - & + & - & b_{24}^0 & 0 \\ + & + & + & b_{34}^0 & 0 \\ b_{41}^0 & b_{42}^0 & + & b_{44}^0 & 0 \\ b_{51}^0 & b_{52} & b_{53} & b_{54}^0 & b_{55}^0 \end{bmatrix} \begin{pmatrix} w_t^{\text{flow supply}} \\ w_t^{\text{flow demand}} \\ w_t^{\text{storage demand}} \\ w_t^{\text{other oil demand}} \\ w_t^{\text{other shocks to stock returns}} \end{pmatrix} \quad (3)$$

The refined model includes four variables in the oil market block and one exogenous stock return variable ordered last. The model is block recursive because it imposes zero restrictions for stock return shocks ($b_{15} = b_{25} = b_{35} = b_{45} = 0$).

From (3), we can deduce the following by looking at the sign restrictions: The direction of oil supply shocks is indicated in the first column. An unexpected disruption to flow supply decreases global oil production and real activity while increasing the real price of oil. A positive flow demand shock raises oil output, real economic activity, and the real price of oil, as shown in the second column. Lastly, a positive shock to storage demand leads to an increase in oil inventories, the real price of oil, and global oil output, but a decline in global real activity.

The sign-identified approach differs significantly from the recursive model in that the parameters of the impact multiplier matrix are no longer point identified but set identified (because inequality constraints are imposed). This implies that even with an infinite amount of data, we can only limit the parameters of interest (Kilian & Lütkepohl, 2016, p. 414).

Since sign restrictions provide the researcher with a set of admissible points, further restrictions are required to determine candidate points.

In oil market analysis, elasticity bounds are commonly used to eliminate circumstances in which oil supply shocks create too large oil price responses (Kilian & Lütkepohl, 2016, p. 424). Kilian & Murphy (2012) demonstrate that restricting the impact price elasticity of oil supply to a reasonable magnitude suffices to eliminate structural models from the admissible set that imply large responses of the real price of oil to flow supply shocks and generates results that are much more consistent with those in Kilian (2009).

Bayesian Inference and the Householder Transformation Algorithm

Frequently, SVARs contain more parameters than conventional macroeconomic datasets can accommodate. Therefore, it is improbable that common estimation approaches, such as maximum likelihood, have reasonable features. This is referred to as the over-parameterization issue (Banbura, Giannone, & Reichlin, 2010). The introduction of so-called informative priors that push the coefficient values in the SVAR toward zero, resulting in a system of parsimonious random walks, is therefore necessary to address the over-parameterization issue (Cross, 2020). These priors are known as shrinkage priors, because they reduce parameter uncertainty. In essence, we utilize prior beliefs (usually guided by theoretical models) regarding the expected sign of shocks on endogenous variables. In our context, for instance, we know that an aggregate demand shock should result in an increase in oil output, real economic activity, and oil prices, so we can place a plus sign in the second column.

To accomplish identification, the following three stages must be followed (Cesa-Bianchi, 2021).

1. Consider a random orthonormal matrix Q such that $QQ' = I$
2. Consider the lower triangular B matrix corresponding to the Cholesky factor of the covariance matrix of the reduced-form residuals $\sum_u = PP'$
3. The following equality holds
   $$\sum_u = PP' = PQQ'P' = \underbrace{(PQ)}_{B}\underbrace{(PQ)'}_{B'} = BB'$$

The matrix $B = PQ$ is a valid candidate impact matrix that solves the identification problem. In contrast to P, the matrix PQ is no longer lower triangular. To determine whether $B = PQ$ is a viable solution, we must verify that the shock effects predicted by $B = PQ$ fulfill a set of a priori sign restrictions.

Kilian & Lütkepohl (2016, p. 418) describes the Householder transformation, as first proposed by Rubio-Ramírez, Waggoner & Zha (2010) and also detailed in Arias, Rubio-Ramírez, & Waggoner (2018, Theorem 4, p. 695): Any square matrix can be decomposed as $W = QR$, where Q is an orthogonal matrix, and R is an upper-triangular matrix with the diagonal normalized to be positive. This amounts to drawing Q from a uniform distribution. The algorithm guarantees invertibility.

The QR decomposition can be done in MATLAB using the *qr()* function. This function does not normalize the diagonal of W, and since we are not interested in R, Kilian & Lütkepohl (2016, p. 419) recommend reversing the signs of the ith column of Q if the ith diagonal element of R is negative.

The algorithm is as follows. Perform N replications of the following steps:

1. Draw a random $n \times n$ matrix W with each element having an independent standard normal distribution
2. Perform QR decomposition of W
3. Compute $B = PQ$ where P is the Cholesky decomposition of the reduced form residuals
4. Compute the impact effects of shocks associated with B
5. Are the sign restrictions satisfied?
    a. Yes. Store B and go back to step 1.
    b. No. Discard B and go back to step 1.

This procedure may be repeated for a large number of posterior draws to account for parameter estimation uncertainty (Kilian & Zhou, 2021, p. 19). The algorithm is computationally demanding. In our analysis, we conducted 40,000 posterior draws of W, with 20,000 rotations of matrix Q for each posterior draw. Our desktop computer required 20 days to compute the results.

Data

The reduced form version of the above structural VAR model is estimated with a data set that contains monthly observations on the four fundamental oil market variables and stock returns from 1973:1 to 2021:12. In the original Kilian & Park (2009) study, the data set ended in 2006:12.

Global real activity: Updated index of global real economic activity in industrial commodity markets, as proposed in Kilian (2009), with the correction discussed in Kilian (2019), is updated monthly by the Federal Reserve Bank of Dallas (2021). This business cycle index is reported as a percentage deviation from the trend. It is produced from a panel of dollar-denominated global dry bulk cargo shipping rates and can be interpreted as a proxy for the volume of shipping in global industrial commodity markets.

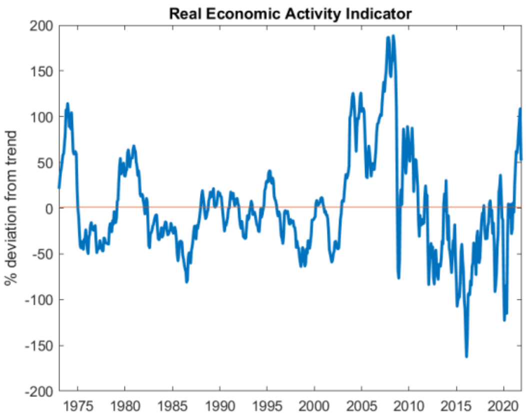


Figure 1: Kilian's Real Economic Activity indicator, monthly percentage deviation from trend.

Global oil production: Data on global crude oil production are available in the Monthly Energy Review of the Energy Information Administration (EIA). These data also include lease condensates, but natural gas plant liquids are excluded. In the model, oil production is expressed as a percentage change.

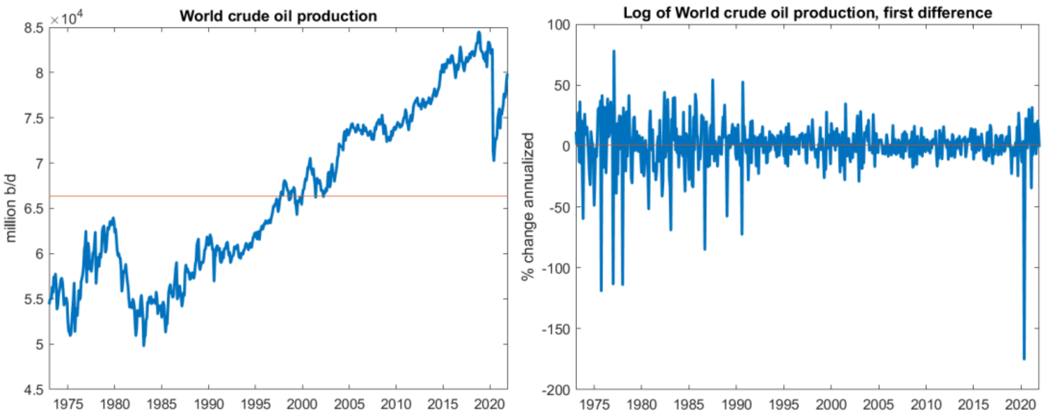


Figure 2: World oil production in 10 million barrels per day (lhs), and log of world oil production, first difference (month-on-month), annualized (rhs).

Real oil prices: The real price of oil is defined as the U.S. refiners' acquisition cost for imported crude oil, as reported by the EIA. The data is deflated by the U.S. consumer price index. The real price of oil is expressed in log-levels.

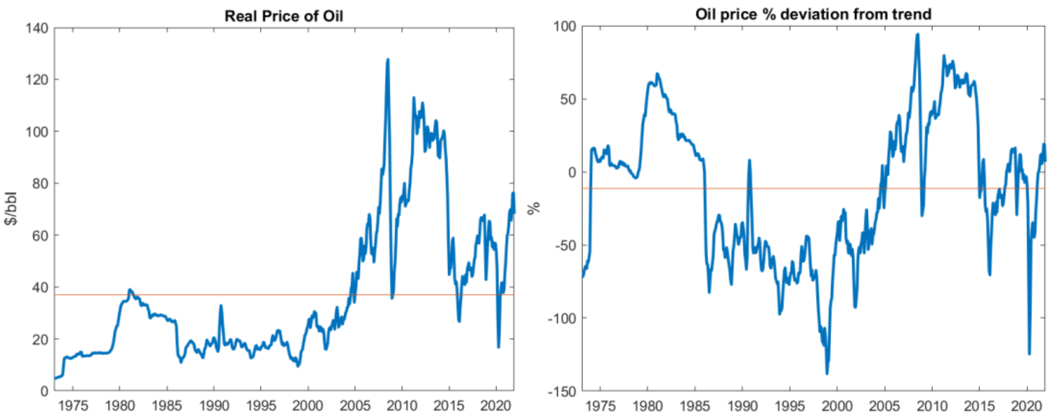


Figure 3: Real price of crude oil in dollar per barrel (lhs), and log of real price of oil in percentage deviation from the log mean (rhs).

Inventories: The EIA provides information on total crude oil stocks in the United States. The ratio of OECD petroleum stockpiles to U.S. petroleum stocks, also acquired from the EIA, is used to scale this statistics. The resultant proxy for global crude oil inventories is expressed in terms of differences as opposed to percentage changes.

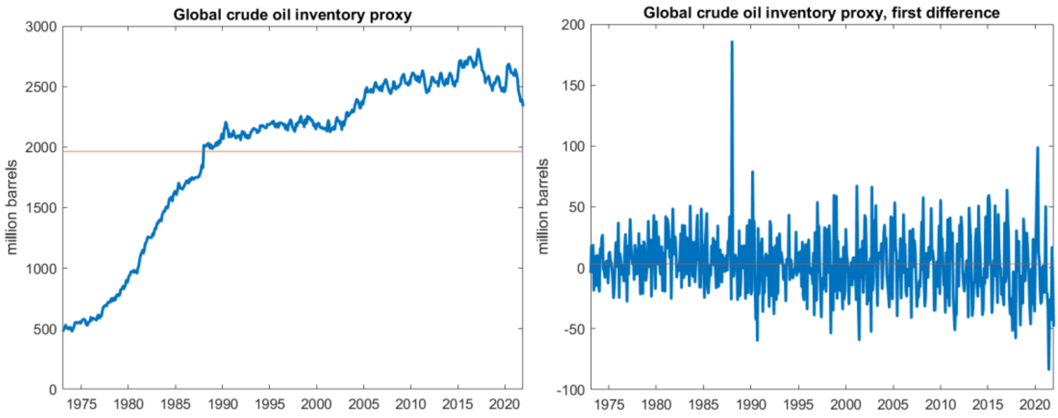


Figure 4: U.S. crude oil inventory in million barrels scaled by a factor of OECD petroleum stocks divided by U.S. petroleum stocks (lhs), and the same time-series expressed in month-on-month difference (rhs)

U.S. stock returns: The aggregate U.S. real stock return is calculated by deducting the consumer price index (CPI) inflation rate from the log returns on the Center for Research in Security Prices (CRSP) value-weighted market portfolio. Data can be obtained from Wharton Research Data Services (2021).

Norwegian stock returns: The stock market information for Norway for the period 1973:1-1999:12 is collected from Klovland (2004). From 2000:1-2021:12 the source is Euronext (2022). The Norwegian stock market index is adjusted for the USD/NOK exchange rate in order to calculate dollar-returns. Contrary to U.S. data, historical stock returns are not based on dividends being reinvested (total return). Arguably, dividends on an aggregated index level are relatively stable, and as a result, the exclusion of dividends should not affect the results in terms of shock processes.

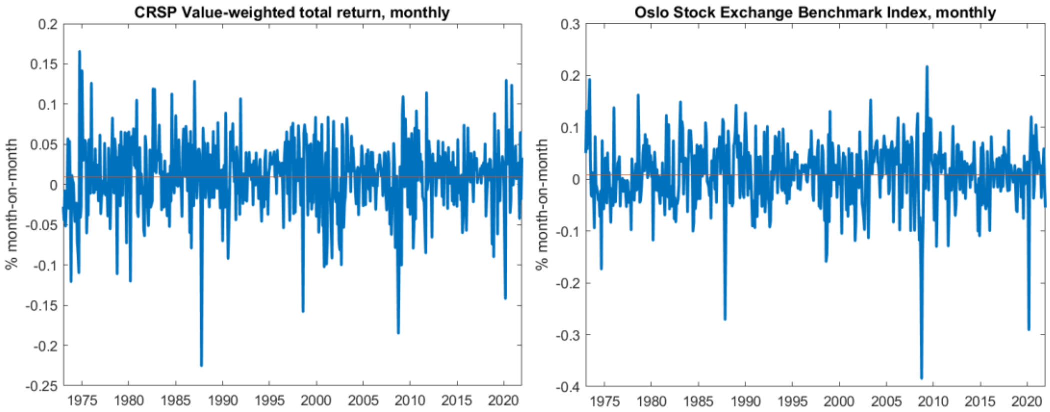


Figure 5: Month-on-month percentage return on the U.S. stock markets aggregate index (lhs), and month-on-month percentage return on the Oslo Stock Exchange Benchmark Index (rhs).

Before estimating the model, we deseasonalized each of these variables, following Zhou (2020).

Kilian's Real Economic Activity Index

All oil market statistics, such as oil prices, global oil output, and inventories, are available monthly. This is advantageous because the exclusion restrictions and elasticity bounds used for identification are more credible at monthly frequency than at quarterly or annual frequency (Kilian & Zhou, 2021, p. 15). However, typical aggregate demand indicators, such as global GDP growth, are only available on a quarterly or even annual basis. Kilian (2009) made a significant contribution with the real economic activity index, a monthly business cycle measure. The indicator is based on a proxy for the volume of industrial raw material shipping.

Shipping volumes have high correlation with world economic activity (Clarksons Research, 2022):

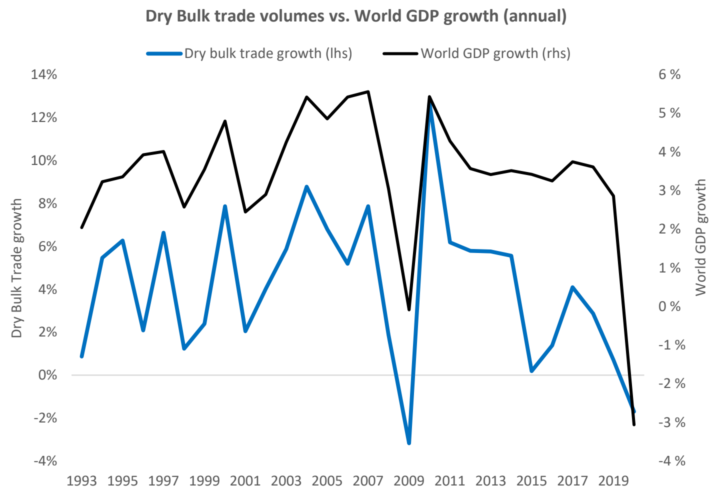


Figure 5: Annual world seaborne dry bulk commodities trade growth (lhs), and world GDP growth (rhs).

The Kilian index is based on freight rates as opposed to shipping volume. Freight rates are determined by the availability and demand for ships. With monthly data, it is argued that the supply of ships cannot respond to a demand shock within a month because it takes years to construct new vessels. However, according to Stopford (2009, p. 187), the speed of vessels determines the short-run supply curve for shipping:

$$\text{speed} = \sqrt{\frac{\text{freight rate}}{\text{fuel price} \times \text{distance} \times \text{constant}}} \tag{4}$$

If a vessel increases its speed, it can achieve quicker turnaround times and transport more cargo every period. This potentially boosts the supply of vessels within a month. Equation (4) states that, everything else being equal, increased freight rates will increase speed. If all else remains constant, a decrease in the price of fuel will result in an increase in speed.

Thus, the use of freight rates as a measure of aggregate demand is not without issues. In light of the preceding, it is evident that freight rates may be affected by supply factors within a given month if speed increases. This might occur if there is an increase in freight rates and if oil prices decline, reducing the cost of speeding.

Instead, Hamilton (2019) suggests that the computations could be based on the daily frequency of freight rates. It seems unlikely that the speed and supply of vessels will matter within a day.

The relationship between freight rates and oil prices is a second concern. This is due to the fact that bunker fuel (which is derived mostly from crude oil prices) is passed on to the ship's charterers in the form of a higher gross rate per ton (Evans & Marlow, 1990, pp. 96-100). In freight rate negotiation, ship owners are only concerned with their net revenues once fuel costs are deducted. Daily net revenue is computed as:

$$\text{net revenue \$ per day} = \frac{\text{freight rate}\frac{\$}{ton}\times\text{cargo } tons - \text{fuel costs} - \text{other voyage costs}}{\text{voyage days}} \quad (5)$$

Consider the following numerical illustration: A large ship transporting iron ore from Brazil to China is rented for \$20 per ton of cargo. The vessel has a cargo capacity of 170,000 tons. Therefore, the shipowner's gross revenue is \$3.4 million. The owner is responsible for fuel and port fees during the voyage. If, say, fuel prices increase by 10 percent, a (different) owner would want a gross freight rate per ton that compensates for the increase. Similarly, if the cost of fuel decreases by 10 percent, a charterer would request a reduction in the gross freight rate.

Assuming unchanged market balance for ships, if fuel prices increase, the freight rate in dollars per ton will likewise increase to maintain daily net revenue levels. This suggests that if Kilian's index is based on dollar-per-ton freight rates, there is a direct correlation between crude oil prices and the index. According to Hamilton (2019), from 1968 to 2008, Kilian used gross freight rates per ton of cargo. The index has been based on the Baltic Dry Index since 2008. According to the website of the Baltic Exchange, the Baltic Dry Index (BDI) went into effect on November 1, 1999, and is updated daily. It replaced the Baltic Freight Index which was updated daily since January 1, 1987. Since 1999, the index has been based on both dollar-per-ton freight rates and daily net revenues (also called timecharter averages). The indicator has been a composite of only dry bulk timecharter averages since 1 July 2009. In other words, the Baltic Dry Index is no longer directly connected with the price of oil as of the middle of 2009. There is however underlying data available to extend this data set back to January 1, 2006. A shipping index based on net revenues per day, and thus unaffected by confounding oil prices, is therefore available beginning on the same day.

As a robustness check, I will follow Hamilton's recommendation and recalculate the Kilian index using daily freight rate observations from January 1, 2006 to determine whether the results are meaningfully different from the results using the official Kilian index.

Real Economic Activity Index using daily freight rates

In contrast to Kilian's index, which is based on monthly averages, the Baltic Dry Index is available on a daily basis. In a daily window, it is improbable that vessel supply can respond to demand shocks; hence, the Baltic Dry Index is likely a more accurate gauge of global real economic activity at a daily frequency.

According to Hamilton (2019), in order to obtain stationary series, differencing is preferred over regression on a time trend. Hamilton suggests that the two-year difference is often a robust method for isolating the cyclical component. As such, a daily indicator of the cyclical component could be obtained from:

$$c_t = \log\left(\frac{\mathrm{BDI}_t}{\mathrm{CPI}_t}\right) - \log\left(\frac{\mathrm{BDI}_{t-2*247}}{\mathrm{CPI}_{t-2*247}}\right) \qquad (6)$$

where t is daily data with 247 the number of business days in a year. CPI_t is value for the consumer price index associated with day t. However, CPI data is only provided on a monthly basis. Hamilton suggests that using a linear interpolation between monthly data, this issue can be resolved. Although we have accounted for inflation, it may be argued that this step can be skipped because dollar-per-day freight rates are stationary around their mean.

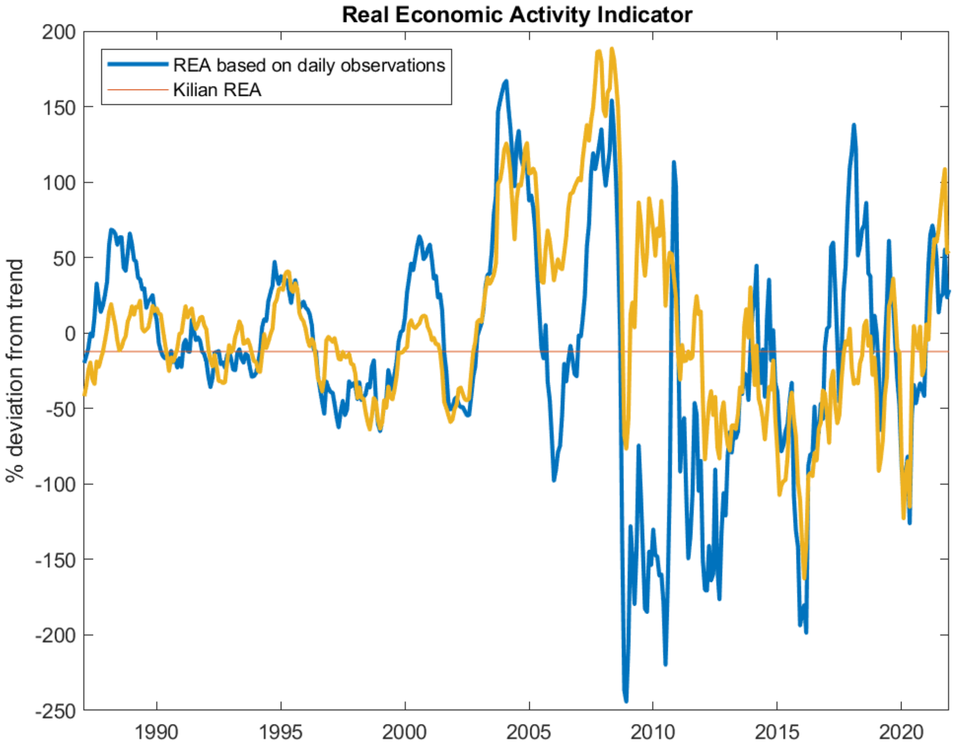


Figure 6: Real Economic Activity Index. Blue line is a new series based on daily observations of the Baltic Dry Index, yellow line is the official Kilian index based on monthly data.

The recalculated activity index in blue, which is based on daily observations of the shipping index, is deviating from the official index, which is based on monthly data. The daily index captures the 2008-2009 financial crisis more accurately.

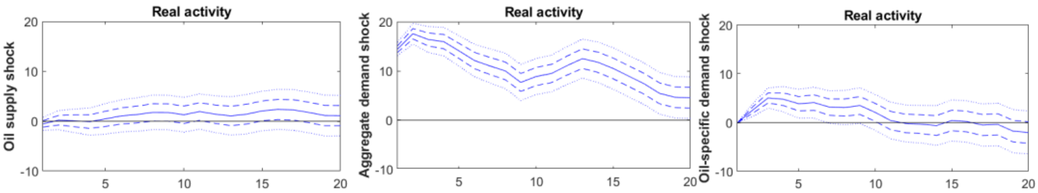
Main results

Replicating and expanding Kilian & Park’s study of U.S. stock returns

My initial task was to replicate Kilian & Park's (2009) research with U.S. stock returns from 1973:1 to 2006:12, and then to extend the data set until 2021:12.

A fundamental finding of Kilian (2009) and Kilian & Park (2009) is that the effect on the economy, the real price of oil, and real stock returns, will vary depending on whether shocks in the crude oil market are driven by supply, aggregate demand, or oil-specific demand.

Extended data set (1973:1-2021:12)



Original data set (1973:1-2006:12)

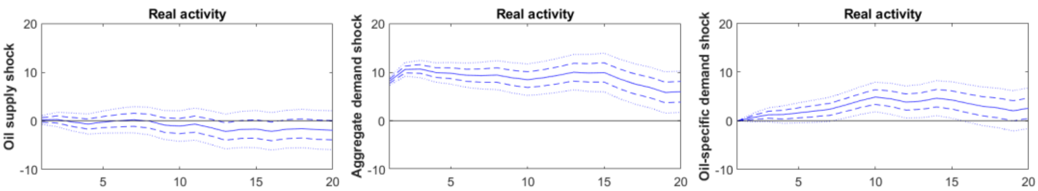
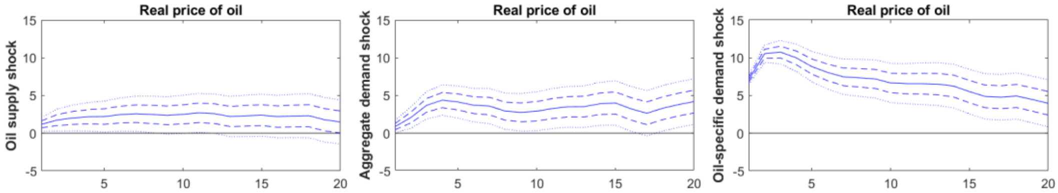


Figure 7: Impulse response functions of real economic activity to one-standard deviation demand and supply shocks in the global market for crude oil. Thick line is mean response, dash line is one-standard deviation confidence band and dotted line is two-standard deviation confidence band.

According to Kilian (2009, p. 1062), an unexpected disruption in the oil supply (normalized to one standard deviation) results in a short decline in real economic activity (left charts above). However, with the extended data set, we observe a more positive trend. We can see that zero is included within the confidence intervals; hence, neither result differs significantly from zero. In other words, oil supply disruptions have little effect on real economic activity.

An unanticipated aggregate demand expansion, however, is very persistent and quite significant (charts in the middle of the preceding image), with a real activity gain of approximately 10-15 percent. We observe that the influence appears to have grown with the addition of data from 2006 to 2021. An unexpected oil market-specific shock has also a temporary increase in real economic activity (right hand chart on the previous page).

Extended data set (1973:1-2021:12)



Original data set (1973:1-2006:12)

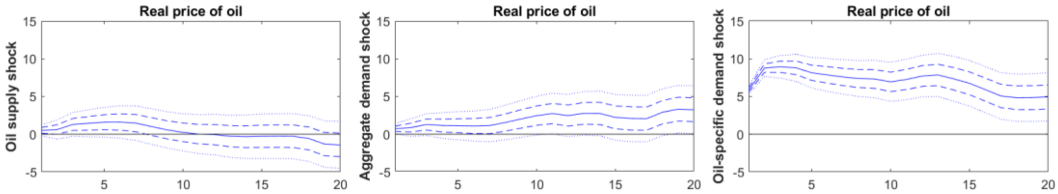


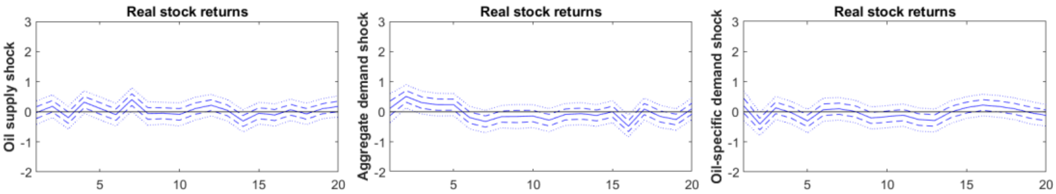
Figure 8: Impulse response functions of the real price of oil to one-standard deviation demand and supply shocks in the global market for crude oil. Thick line is mean response, dash line is one-standard deviation confidence band and dotted line is two-standard deviation confidence band.

In terms of oil prices, oil supply shocks in the original data until 2006:12 cause a small, transitory and partially statistically significant increase in the real price of oil (left charts above). With the increased data set until 2021:12, the oil price increase appears to be more significant and long-lasting.

Aggregate demand expansions cause a large, persistent, and statistically significant increase in the real price of oil (middle charts above). With the revised data sets, the beneficial effect on oil prices appears to arrive earlier and lead to higher percentage increase to oil prices.

Unanticipated oil market specific demand increases have an immediate, large, and persistent positive effect on the real price of oil that is highly statistically significant (right hand charts on the previous page). The differences between the original Kilian 2009 study and our updated data set appear to be minimal.

Extended data set (1973:1-2021:12)



Original data set (1973:1-2006:12)

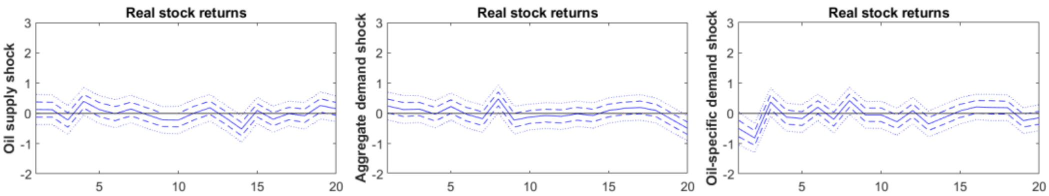


Figure 9: Impulse response functions of U.S. real stock returns to one-standard deviation demand and supply shocks in the global market for crude oil. Thick line is mean response, dash line is one-standard deviation confidence band and dotted line is two-standard deviation confidence band.

The impulse response functions for real stock returns to each of the three demand and supply shocks in the crude oil market are depicted in Figure 9. In both the original analysis and the extended data set, it is evident that oil supply shocks have no significant effect on stock returns (zero is within the confidence interval).

In contrast, aggregate demand shocks result in a sustained boost in U.S. stock returns for at least five months. The expanded data set reveals a larger and more significant effect.

Lastly, an unanticipated increase in other (precautionary) demand for oil would result in negative stock returns, although with the newer data set, that are still near to zero.

Kilian & Park's (2009) conclusions for stock returns are that only when there is an oil-market specific demand shock, stock returns become negative. In contrast, crude oil production disruptions have no significant effect on cumulative stock returns. Finally, higher oil prices driven by unanticipated economic expansion have positive persistent effect on cumulative stock returns. The original analysis is broadly supported by our new data sets, albeit with a lesser negative impact from precautionary demand shocks.

Robustness check: Using Daily Real Economic Activity Index

A Real Economic Activity Index based on daily updates of shipping rates is anticipated to more properly reflect the business cycle, as detailed on page 19. I also wish to prevent the direct correlation between oil prices and dollar-per-ton freight rates. As a result, I rerun the preceding study using the daily measure of the business cycle beginning at the moment where we have freight rates quoted in dollars per day, net of fuel costs.

Daily frequency of the business cycle

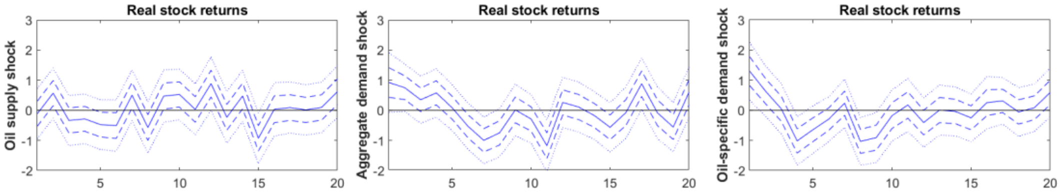


Figure 10: Impulse response functions of U.S. real stock returns to one-standard deviation demand and supply shocks in the global market for crude oil. Thick line is mean response, dash line is one-standard deviation confidence band and dotted line is two-standard deviation confidence band.

With 16 years of monthly data as opposed to 49 years for the original index, confidence intervals are widened. Compared to Figure 9, which is based on the official Killian index, we notice that oil supply shocks are still not statistically distinct from zero. It appears that aggregate demand shocks have a greater positive impact but which turns negative after period 5. The impact of oil-specific demand shocks on U.S. stock returns, which was plainly negative in the initial analysis and closer to zero in the extended study, is now instantaneously positive, but turns negative after a few months.

Jiang, Skoulakis, & Xue (2018), albeit using a different research methodology, also discovered that oil price fluctuations had a negative predictive slope for stock returns until the middle of the 2000s, but that the slope seems to have reversed since then.

Based on the Kilian & Park (2009) model, we can conclude that oil supply shocks and aggregate demand shocks have the same effect on U.S. stock returns across all three studies. However, oil-specific demand shocks have an unclear effect on U.S. real stock returns in the three studies, and Zhou's (2020) revised model is required for future investigation.

Brief comment on efficient markets

According to financial theory, only systematic risk, or risk that cannot be eliminated through diversification, is the source of long-term returns. In an early study conducted by Chen, Roll, & Ross (1986), it was shown that oil price risk was not separately rewarded in the stock market. That study, however, investigated the effect of an exogenous oil price component on stock returns. As previously noted on page 8, such studies will have a tendency of finding no statistical relationships. However, Kilian & Park's (2009) research analyzes an endogenous relationship between oil market variables which exert influence on systematic risk (the risk premium), and thus stock returns.

The fact that stock returns drift upwards for several months (in the event of an aggregate demand shock) may appear to contradict the efficient market hypothesis, which states that stock markets will quickly reprice to reflect new information. However, Kilian & Park (2009, p. 1279) note that the outcome is consistent with modern models of time-varying expected returns. Since the value of equities is the present value of expected future cash flows (dividends), the impact response of stock returns to a particular oil demand or oil supply shock must be attributable to updated predictions of future cash flows (dividends) and/or revised estimates about future discount rates (the risk premium). Kilian & Park (2009, p. 1281) suggest that fluctuations in the risk premium (time-varying discount rates) are an important transmission mechanism for the responses of real stock returns to oil demand and oil supply shocks. According to Fama & French (1989), the fluctuation in the risk premium over time is dependent on business conditions. When economic conditions are good, (prospective) stock returns are lower, and when economic conditions are bad, stock returns are higher. This is based on the assumption that, during prosperous times, stock prices have already risen. Consequently, future stock gains are often modest. In poor times, stock prices often decline significantly, and as a result, future return potential is increased, assuming an economic and stock price recovery.

Norwegian stock returns with the Kilian & Park model

The oil and gas industry accounts for 8 percent of the U.S. gross domestic product (American Petroleum Institute, 2018), with a general upward trend over the last decade due to the shale oil and gas revolution. Comparatively, the industry accounts for approximately 18 percent of the Norwegian GDP based on five-year average statistics (Norwegian Petroleum, 2022). Given Norway's greater reliance on oil and energy, it is not a big surprise to notice a greater influence on stock returns.

Norwegian data from 1973:1-2021:12

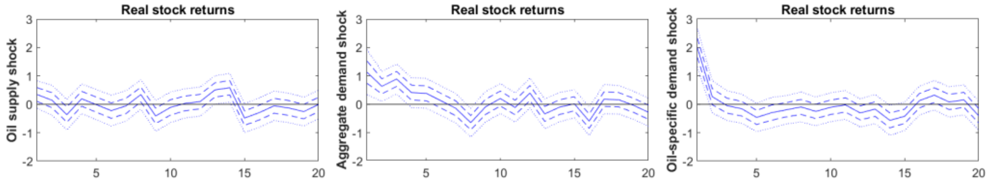


Figure 11: Impulse response functions of Norwegian real stock returns to one-standard deviation demand and supply shocks in the global market for crude oil. Thick line is mean response, dash line is one-standard deviation confidence band and dotted line is two-standard deviation confidence band.

We observe that although U.S. stock returns were negative in response to oil-specific demand shocks, Norwegian stock returns have a substantial, instantaneous positive reaction to a precautionary oil demand shock. We can only assume, but with the oil and gas major Equinor being the largest firm on the Oslo Stock Exchange, and a number of oil service companies also listed on the exchange, an oil-specific demand shock leading to stockpiling might be advantageous for oil producers and associated service companies. However, the effect is rather short-lived and becomes negative after three or four periods.

Similarly, we can observe that aggregate demand shocks have a greater impact on Norwegian stock returns than on U.S. stock returns. Lastly, oil supply disruptions have a small positive impact on Norwegian stock returns whereas U.S. stock returns were zero. Foreign supply disruptions, such as those in the Middle East, could be advantageous for Norwegian oil producers.

In general, it can be stated that Norway is a small and open economy where the impact of oil shocks is expected to have a greater influence on the economy and stock returns than in the United States, which is a key economy and returns driver for most of the world.

Stock return IRFs using the refined oil market SVAR with sign restrictions

On the following pages, all impulse response functions for oil production, real economic growth, the real price of oil, inventories, and U.S. stock returns based on data from 1973:1 to 2021:12 are displayed. Compared to the SVAR model with exclusion restrictions, the impulse response functions exhibit only minor differences.

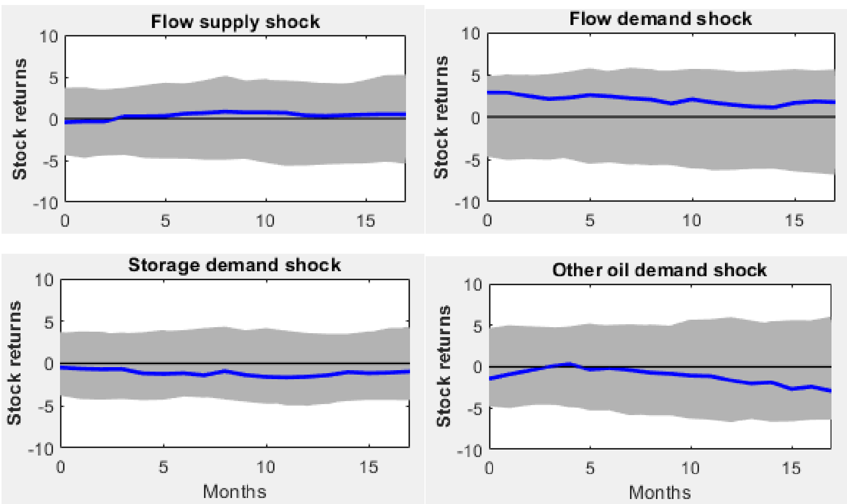


Figure 12: Impulse response functions for U.S. stock returns. The response in blue represents the most likely structural model and the remaining responses are from the 68 percent joint credible set obtained from the posterior distribution of structural models.

Taking a closer look at U.S. stock returns, Figure 12 reveals that the impulse response functions for flow supply and flow demand shocks follow the same trajectory as the model of Kilian and Park (2009), see Figure 9.

There are two types of oil-specific shocks in the Zhou (2020) model: storage demand and other oil demand shocks. The impact of these shocks on U.S. stock returns appears akin to the model developed by Kilian & Park (2009), with stock returns being somewhat negative but close to zero.

As stated on page 26, in regard to the Kilian & Park (2009) model, the effect of oil-specific demand shocks on U.S. real stock returns is uncertain. In the original Kilian & Park (2009) analysis based on data through the end of 2006, the impact response was immediately negative, whereas with expanded data through the end of 2021, the outcome was close to zero. The preceding results from Zhou's (2020) model demonstrate a similar relationship. Nonetheless, as mentioned on page 27, the conclusion altered when the revised economic activity index based on daily shipping rates was utilized, resulting in a more favorable outcome for U.S. stock returns. We have not incorporated the modified business activity index into the Zhou (2020) model due to time limitations (running the Matlab scripts takes 20 days), but this could be useful for future research.

Turning our attention to Norwegian stock returns, Figure 13 demonstrates that flow demand shocks have a greater and longer-lasting impact on Norwegian stock returns than on U.S. stock returns. Flow supply shocks have a somewhat similar direction, but a little larger influence on Norwegian stock returns. Storage demand shocks have a slightly positive, but near-zero, immediate impact on Norwegian stock returns, but a negative tendency over time. Other oil demand shocks appear to have a positive influence on Norwegian stock returns, although U.S. market evidence suggests the opposite. It confirms the findings of Kilian & Park's (2009) model applied to Norwegian stock data (see page 22), with a strong, instantaneous response to a precautionary oil demand shock.

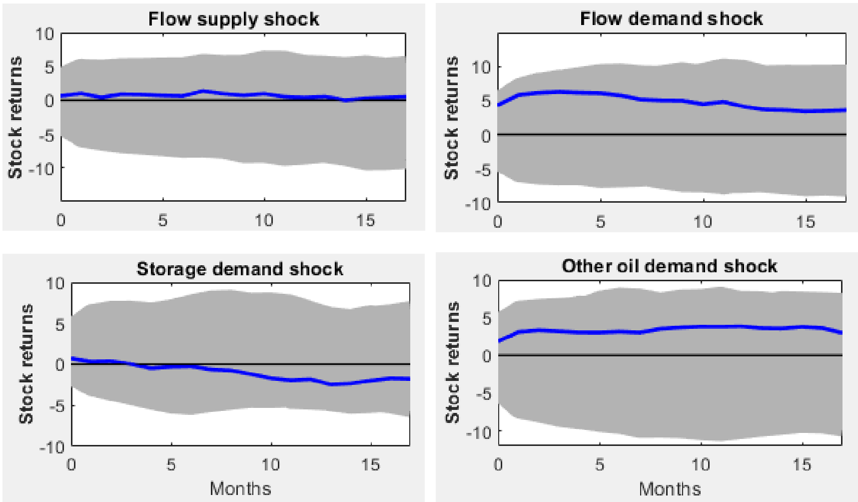


Figure 13: Impulse response functions for Norwegian stock returns. The response in blue represents the most likely structural model and the remaining responses are from the 68 percent joint credible set obtained from the posterior distribution of structural models.

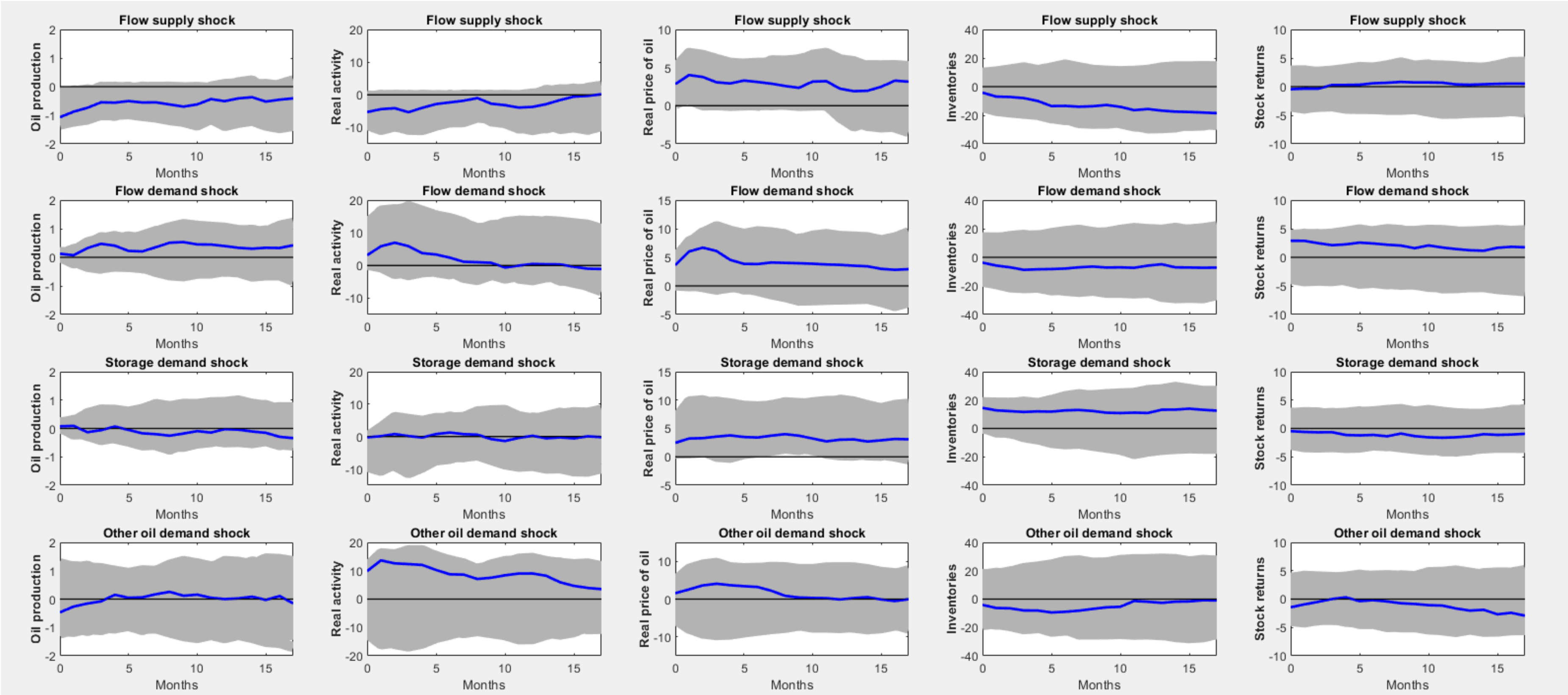


Figure 14: Impulse response functions for oil production, real economic activity, the real price of oil, inventories and U.S. stock returns. The response in blue represents the most likely structural model and the remaining responses are from the 68 percent joint credible set obtained from the posterior distribution of structural models.

Structural Forecast Error Variance Decomposition

A variance decomposition based on the refined oil market model with narrative and dynamic sign restrictions reveals that 24 percent of cumulative U.S. stock returns can be explained by oil shocks. This is slightly greater than the 22 percent identified by Kilian & Park in their 2009 study. Given the rise of the U.S. shale oil sector over the past decade, it is reasonable to anticipate that the demand and supply shocks driving the global crude oil market will collectively account for a bigger proportion of the variation in real U.S. stock returns over the long run.

Flow demand shocks, as indicated in Figure 15, are the most significant structural contributors to return variability.

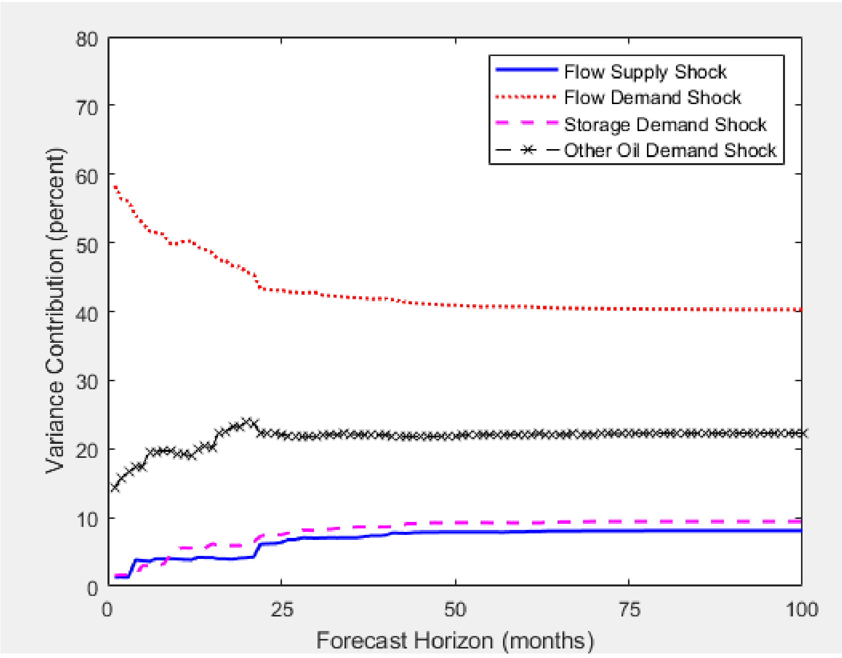


Figure 15: Variance decomposition of U.S. real stock returns to each of the demand and supply shocks in the crude oil market.

A variance decomposition of Norwegian real stock returns reveals that oil demand and supply factors account for 25 percent of cumulative Norwegian stock returns. Figure 16 indicates, similar to the U.S. experience, that flow demand shocks, or aggregate demand, have the greatest impact on return variability.

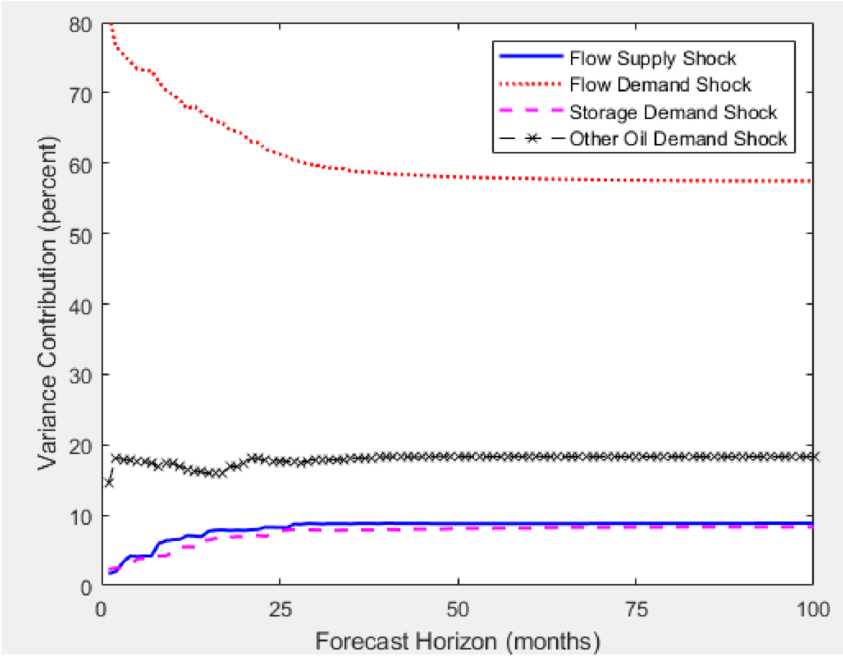


Figure 16: Variance decomposition of Norwegian real stock returns to each of the demand and supply shocks in the crude oil market.

Conclusions

This thesis examined the impact response of oil shocks on stock market returns. Using a structural vector autoregressive model, we are able to differentiate between the effects of various oil market shocks, whether they are caused by a disruption in global oil production, changes in aggregate demand related to the business cycle, altered preference for holding oil inventories, or other oil demand shocks.

I have reproduced and updated the Kilian & Park (2009) model with exclusion restrictions using current data. I have also employed the refined oil market model by Zhou (2020) with narrative and dynamic sign restrictions to study the impact on stock returns for the first time. Furthermore, I have rebuilt the Kilian real economic activity index based on daily shipping rates in order to assess the results' robustness in greater detail.

According to the findings of Kilian & Park (2009), stock returns become negative only when there is an oil-specific demand shock. In contrast, disruptions in crude oil supply have no major impact on cumulative stock returns. Higher oil prices brought on by unanticipated economic expansion have a favorable, long-lasting impact on cumulative stock returns. Our extended data sets mostly confirm the previous study, albeit with a less negative impact from precautionary demand shocks.

Using the real economic activity index based on daily shipping rates, we confirmed that the impulse response to oil supply shocks is statistically indistinguishable from zero. Aggregate demand shocks have a greater positive impact while the impact of oil-specific demand shocks on U.S. stock returns, which was plainly negative in the initial analysis and closer to zero in the extended study, is now instantaneously positive, but turns negative after a few months.

Using the same model framework with Norwegian stock market data, we discovered that oil supply disruptions had a small, favorable effect on Norwegian stock returns, whereas they have no effect on U.S. stock returns. The impact of aggregate demand shocks on Norwegian stock returns is stronger than on U.S. stock returns. In contrast to the initial study on U.S. stock returns, Norwegian stock returns had a strong, instantaneous positive reaction to a precautionary oil demand shock, which is more in line with the results obtained when utilizing the alternative real economic activity index.

Comparing the refined SVAR model to the original model with exclusion restrictions, we discovered that impulse response functions display only minor differences. The impulse response to shocks in flow supply and flow demand follows the same path as the model of Kilian & Park (2009). Storage demand and other oil demand shocks are the two categories of oil-specific shocks. In the Zhou (2020) model, the impact of these shocks on U.S. stock returns is comparable to the model by Kilian & Park (2009).

Using Norwegian data and the model refined by Zhou (2020), flow demand shocks have a higher and longer-lasting effect on Norwegian stock returns than on U.S. stock returns. Flow supply shocks effect Norwegian stock returns in a similar manner as U.S. stock returns, but slightly more positive. Similar to U.S. data, storage demand shocks have a negligible impact on stock returns in Norway. Other oil demand shocks, on the other hand, tend to have a distinctly positive impact on Norwegian stock returns, although evidence from the U.S. market indicates the opposite.

In summary, oil price shocks are shown to have a significant impact on real stock returns in the United States and Norway. The impact depends on whether they are driven by demand or supply shocks. The four structural shocks that drive the global crude oil market account for approximately 24 percent of the variability in U.S. real stock returns and 25 percent of the variability in Norwegian real stock returns over the long term, suggesting that shocks in the global oil markets are an important driver of real stock returns.

Robustness Check and Future Work

All the data series are stationary by construct. To be certain, I ran an Augmented Dickey Fuller test of unit roots. However, evaluating the VAR's stability is far more important. This may be accomplished by calculating the eigenvalues of the companion form matrix. Because all eigenvalues are less than one in absolute value (they lie within the unit circle), the VAR(24) is stable.

As future study, I would recommend to investigate the impact of incorporating the adjusted real business cycle indicator based on daily freight rates into the refined oil market model. As indicated on page 27, employing the index based on daily shipping rates within the framework of Kilian & Park (2009) resulted in a favorable impact of oil-specific demand shocks on U.S. stock returns. It would be intriguing to learn if the Zhou (2020) model confirms this.

The impact response to an oil-specific demand shock is a significant difference between this study and the original study by Kilian & Park (2009). Although we did incorporate storage demand as a specific shock, a potential extension of this work would be to analyze Cross, Nguyen, & Tran's (2022) model, which extended Zhou's (2020) model by adding a real oil price uncertainty indicator to differentiate precautionary and speculative demand shocks. This may offer further light on the factors influencing U.S. and Norwegian stock returns.

According to Hamilton (2019), global industrial production may be a more accurate indicator of economic activity than shipping freight rates. Baumeister & Hamilton (2019) assert that the advantage of using the OECD's index of monthly industrial production in the OECD and six major other countries (Brazil, China, India, Indonesia, Russia, and South Africa) is that it permits us to draw directly on information on income elasticities from previous studies. Therefore, the next step would be to analyze the effects of using industrial production as an indicator of economic activity.

Moreover, Baumeister & Hamilton (2019) propose a generalization based on Bayesian inference that makes use of a larger set of prior information that extends beyond the data being analyzed, while also relaxing some of the rigid priors implied in conventional identification. Despite the fact that Baumeister & Hamilton (2019) discovered that their alternative model matches the findings of Kilian & Murphy (2014), future research could evaluate the results of assessing stock returns using their framework.

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