Oil Price Shocks and Canadian Stock Returns: A Structural FAVAR Approach

By

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Abstract

This paper seeks to address the gap in the literature concerning the effects of oil price shocks on stock returns with three contributions. First, it tackles the strength of the widely accepted freight rate index used commonly in structural vector autoregressive (VAR) models of the oil market, by introducing an alternative real economic activity index that also captures global business cycle movements. Second, it adopts a factor-augmented vector autoregressive (FAVAR) model to capture oil market dynamics and its impact on Canadian stock returns. Third, it provides an exclusive focus on the Canadian industry responses to oil price shocks to investigate the behaviour of the Canadian aggregate stock returns. The model of systemically important real sectors (SIRS) is used to identify SIRS sectors, which belong to certain industries, that render these industries highly sensitive to price changes to explain the recessionary impacts of these shocks on the Canadian economy. It finds that the real economic activity index introduced displays similar patterns as that of the freight index; the Canadian aggregate stock returns responses heavily depend on the oil and gas industry responses, given its major role in the Canadian economy; both oil supply disruptions and precautionary demand shocks have recessionary impacts, but it is not clear which is dominant, which contrasts from previous studies that identify the precautionary demand shock to be dominant.

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1 Introduction

In Hamilton's 1983 paper on oil and the macroeconomy, he presents evidence showing a pattern of oil price spikes preceding recessions. Since then, there has been a tremendous number of papers attempting to break down the economic reasoning for this observation (see Lee et al. (1995), Darrat et al. (1996), Hooker (1999), Barsky and Kilian (2004) and Carlstrom and Fuerst (2005) among others). Although significant progress has been made in identifying the possible macroeconomic relationship between oil price movements and economic recessions, there are many issues that either have not been addressed or have been addressed in limited form. After nearly two decades of literature relating oil price movements to macroeconomic activity, Barsky and Kilian (2004) argued for the importance of treating oil prices as endogenous rather than exogenous as was previously assumed. Kilian (2009a) used this as a foundation on which he attempted to disentangle oil price shocks using a structural vector autoregressive model (VAR) showing that the historical decomposition of the oil price movements suggested a larger portion of oil price movements were explained by aggregate demand and oil-market specific shocks. A vector autoregression is a macroeconometric framework and a generalization of the univariate auto-regression (a single-equation, single-variable linear model with its lagged values as regressors). The generalization is in the form of a multivariate auto-regression (a n-equation and n-variable linear model). Each variable is explained by its own lagged values and/or a combination of the remaining $n-1$ variables' current or lagged values providing a way to capture the dynamics in multiple time-series variables.[1] Since then, many others have applied this notion to understand the effect of these shocks—that drive oil prices—to macroeconomic variables. Kilian (2009a) used his progress on decomposing oil price shocks to see the impact on U.S. GDP by observing impulse response functions. However, the problem with this approach is the discrepancy in the frequency of the oil price variable versus the GDP variable in his data. The simpler way to account for this would be to aggregate the data so that all variables are in quarterly frequency. Having said that, creating an analogous structural VAR model where the data is aggregated to quarterly frequency to account for this discrepancy would have discredited

[1]see Stock and Watson (2001) and Kilian and Lütkepohl (2016) for detailed discussion on vector autoregressive analysis.

the identifying assumptions of the model. Therefore, he outlined an alternative method, which did not present as robust a result but was sufficient for his argument, that produced findings suggesting the most significant effects on GDP were due to aggregate demand shocks and precautionary demand shocks. Kilian argued that the precautionary demand shock is oil-demand specific; when an exogenous shock such as political conflict in the middle east hits the market, consumers take precautionary measures to increase their inventory of crude oil raising the price of oil. This would lead to an increase in commodity prices, deceasing the final demand for goods reflected in a decrease in U.S. GDP in the medium and long-term horizons. In contrast, he showed that the aggregate demand shock raises oil prices, but also has only a temporary net positive effect where the stimulating effect of greater demand dominates the growth-inhibiting effect of higher oil prices. However, as the effect of the positive shock stimulus wears out, the negative effect of higher commodity prices triggered by higher price of crude oil makes the effect of the aggregate demand shock recessionary with a delay. Of course, negative oil supply shocks raises the price of oil but to a limited extent and the effect of this shock on U.S. real GDP was only statistically significant and negative in first few periods and became insignificant as the time horizon increased. Many papers have attempted to use this methodology in order to identify any causal relationship that oil price shocks may have on stock markets possibly to progress an understanding of mechanisms that could explain the recessionary effects of oil prices through financial markets. To summarize, research concerning the effects of oil price shocks on macroeconomic aggregates have reached a stale-mate position and little progress has been made beyond this.

The smaller strand of literature builds on the discussion above focusing on the effect of oil prices on stock returns and asset prices and by modeling the indirect relationship between oil prices and financial markets. Kilian and Park (2009) find using a linear model of structural VAR, given the identifying assumptions, helps explain a signification portion of the variation in the aggregate stock returns during 1975-2006. Wang et al. (2013) addressed that the effects of the oil price shocks may be different depending on the net position of the country in the crude oil market so they evaluate this effect using the same model specification as Kilian and Park (2009). In contrast, Fang and You (2014) only focus on making this comparison between Newly Industrialized Economies (NIEs) of

China, India and Russia. Similarly, Güntner (2014) looks at the difference in the effects on major OECD net oil exporters and net oil importers. Although, they find differences between net oil exporters and net oil importers in their stock returns responses to oil price shocks, they also find differences within each group.

Now it is agreeable to say that this literature is not without its limitations. First, the recent progress to understand oil price shocks using the structural VAR methodology suffers from a lack of heterogeneity in the index used for real global economic activity. To my knowledge, almost all the attempts at this question uses the same structural specification. And although Kilian (2009a) specification is received reasonably well in this field, given its ability to treat oil prices as endogenous and addressing the problem of reverse causality in earlier studies, none have attempted at using a separate index for global economic activity[2]. Kilian (2009a) dedicates a sensitivity analysis to point out that an alternative measure of monthly global real economic activity would be world industrial production, which is difficult to find. However, some difference in the index used for global real economic activity in research would help to solidify the results of the impact of aggregate demand shocks if other truly global indices helped provide the same results. Beyond this, the real economic activity index accounts for the cyclical movements of the global economy and the technical drawbacks of using a freight index, which includes the shipping market using bunker fuel as inputs among others, still holds. Second, in contrast to Kilian (2009a) that attempts to provide an economic story of how oil price shocks impact movements of macroeconomic aggregates, Kilian and Park (2009), like many others, does little to disentangle the effect on stock price movements. The primary concern for these papers seems to be addressing the investor's problem to diversify portfolios. The major contribution in this area only addresses the potential differences between net oil exporters and net oil importers and little beyond this. Third, there has been little effort to explain recessionary effects of oil price shocks using stock price responses. This area of research focusing on oil price shocks and stock market returns suggests a strong economic mechanism through which oil prices will affect market

[2] Of course, given the little difference between the historical patterns of different oil price measures up until the financial crisis and between different world oil production measures, testing models where these variables are from different sources are of little interest. It is, however, interesting to see whether the duration and magnitude of oil price shocks still hold when using a different index for real global economic activity. Wang et al. (2013), Fang and You (2014), and Güntner (2014) all use Kilian's monthly index based on bulk dry cargo ocean freight rates.

returns, but steps back to explain the concern for the decisions of investors. The literature seems to have missed the mark not recognizing that oil price shocks can explain recessionary effects if these papers exploited the relevance of stock returns to the macroeconomy. Lastly, there has been little effort to exclusively understand how these shocks play out in the Canadian economy in particular. Since Canada is a net oil exporter, there are anticipated differences in the response of Canadian stock returns that will differentiate Canada from net oil importing economies, but Güntner (2014) found interesting results showing that Canadian stock return responses differentiate it from other net oil exporting countries as well. There has been little investigation into the underlying reason for this finding.

This paper attempts to address these issues in the literature by adapting a similar specification as Kilian and Park (2009). The contribution of this paper will be three-fold. First, I will construct an index for real economic activity by using principal component analysis to extract a latent factor that will be an index for real economic activity. This will replace the real economic activity index Kilian uses, which is based on bulk dry cargo ocean freight rates. The construction of this will allow for comparisons to be made verifying the robustness of Kilian's results. This is significantly important because the real economic activity index captures cyclical movements in the world economy. Incorrectly capturing these effects or not capturing them could drastically affect the way the dynamics of the oil market is modeled. Second, a FAVAR framework will be used to link the relationship between oil price shocks and Canadian stock returns to provide an economic story that agrees with the intuition provided in Kilian and Park (2009). The factor augmented vector autoregressive (FAVAR) model is an extension of the VAR; at least one of the macroeconomic time-series variable will be an unobserved latent factor that is constructed mechanically to capture co-movements of a matrix of column variables. It is used when it is not possible to incorporate all the variables in a given VAR specification due to the large number of column variables.[3] The objective of this will be to use the latent factor in a structural VAR context that respects the integrity of the oil market dynamics. Furthermore, this paper will allow us investigate the relationship linking the oil price shocks to the financial markets and the macroeconomy. The FAVAR framework provides a strong

[3] see Kilian and Lütkepohl (2016) for detailed discussion.

interpretation that accounts for interrelations between variables and this will help to investigate a mechanism where oil prices will affect final demand for commodities, thus impacting market returns depending on the industries affected. Third, I will examine the effect of oil price shocks on particular industries in Canada through examination of their indices in the financial markets to address why Canadian aggregate returns behave the way they do and break down the recessionary effects of oil prices shocks in the Canadian economy. This will take a different approach to Kilian and Park (2009), which aims to identify a potential relationship between stock market returns of sectors where oil price shocks are anticipated to have an effect. This literature seems to have missed the mark by suggesting that investors will need to know this relationship to diversify their portfolios and not recognizing the significant relevance of stock returns to the performance of the macroeconomy. Since the structural VAR specification allows us to model the supply and demand variation and the dynamic interrelations across periods of time I will use a recently developed model of Systemically Important Real Sectors, which allows researchers to improve the ability to anticipate a recession, to hone in on the recessionary effects of oil price shocks by focusing on particular industries. This will address the initial motivation of oil price literature that tackled the reason behind the observations of Hamilton (1983). Through a comprehensive introduction to the Systemically Important Real Sector (SIRS) model by Crean and Milne (2014), I will legitimize the importance of focusing on indexes of particular industries, which the SIRS sectors are apart of, in the financial markets to further investigate why oil price increases could precede a recession by focusing on the recessionary effects of oil price shocks. It is important to mention that for the sake of plausible and meaningful comparison to previous research, the model will be made to replicate Kilian and Park (2009)'s model to preserve the widely accepted dynamics of the model. The differences will lie in the contributions of the paper. The rest of this article will be organized as follows. Section 2 will introduce the data, discuss the methodology adopted for this paper and construct the global economic activity index. Section 3 will present the results of impulse response functions that decomposes the oil price shocks' effects on stock market returns. Section 4 will introduce the SIRS model by Crean and Milne (2014) and link oil price shocks to stock returns of both SIRS industries and industries with SIRS sectors. Lastly, Section 5 will conclude and suggest further areas of research.

2 A Structural FAVAR Model with Canadian Returns

As mentioned, this paper will replicate the structural VAR elements of Kilian and Park (2009)'s model and differences will lie in the contributions of the paper or the factor-augmented aspect of the model. The elements that will be maintained include the identifying assumptions of the model, measures for crude oil price, measure for global crude oil production and interpretations of the shocks affecting the model. The motivation to use a FAVAR specification can be attributed to several reasons. First, the structural VAR aspect of the model has widely accepted features that explain oil price shocks and is consistent with the historical movements of oil prices and their responses to anecdotal shocks (see Kilian (2009a) for a deeper discussion). Second, the structural VAR has a strong ability to take into account dynamic interrelations between variables in the model. Previous models tested the effects of oil prices without taking into account the possible reverse causality, which meant that the cause and effect were not well defined in linear regression models. The implementation of the vector autoregressive model allows for the researcher to use economic intuition to impose identifying assumptions that builds the skeleton of relationships in the model and specify the direction of the cause and effect. Beyond this, impulse response functions allows a researcher to extract the different shocks that could impact how the variables of interest will interact providing a deeper outline of the cause and effect. Third, the factor-augmented aspect of the FAVAR model allows for capturing a co-movement of macroeconomic aggregates of global economic activity in the form of a latent factor while maintaining the integrity of the dynamic interactions of the structural VAR model. This will further the understanding of aggregate demand shocks and its effects by introducing a variable not subject to the limitations of the commonly used bulk dry cargo freight rates (see Section 2.2.1 for further discussion). This section will begin with familiarizing the reader to the data used. Then it will introduce the empirical methodology of the paper and discuss the motivation behind the structure of the model. The discussion on construction of the global economic activity index will follow and will outline the major advantages and features that are not subject to the limitations of the bulk dry cargo freight rate index or GDP/Industrial Production indices for real economic activity. Lastly, the identifying assumptions of the model will be discussed.

2.1 Data

The data includes a measure of the percentage change in world crude oil production, real price of oil, global real economic activity and Canadian stock market variables. All data are monthly and the sample period is 1990.01-2016.12. The data for world crude oil production was obtained from the U.S. Energy Information Administration. This was reported monthly as the average of daily production of crude oil in thousands of barrels per day and was rescaled to represent the monthly average of millions of barrels per day worldwide. This was later transformed into percentage change by taking the logarithm and first-differencing it. The measure for the real price of oil was generated using U.S. refiner's acquisition cost of crude oil, also reported by the U.S. Energy Information Administration. This represents the nominal price of oil, which was first transformed to Canadian dollars using the monthly exchange rate of a U.S. dollar to Canadian dollars, then deflated using the Canadian CPI for all items reported by Statistics Canada. The index for global economic activity was generated using a static factor model to extract a latent factor through principal components from 64 series reported in Appendix A. To construct this index, I used time series variables of industrial production, total exports and total imports of countries and groups of countries detailed in Appendix A. Roughly 16 country series' contained missing observations. To account for this, I employed expectation-maximization (EM) methodology with static factor models to simulate what the values would be using an iteration procedure outlined in Appendix C. The aggregate Canadian stock returns typically used is the S&P/TSX Composite Index. I use the composite index to represent aggregate stock returns and also use a measure for the market excess returns, which is constructed by subtracting the 30 day return on T-bills from the Canadian Financial Markets Research Centre's (CFMRC) value-weighted index. The latter measure is used for verification purposes. The Canadian industry indices used were generated by S&P Dow Jones indices. The S&P/TSX Composite Index, the CFRMC value weighted index, 30 day return on T-bills and the industry indices for each Canadian industry were all obtained from the CFMRC database. The S&P Composite Index is the headline index for the Canadian equity market and is comprised of 248 constituents and is also generated by S&P Dow Jones indices. To transform this into returns, this was first deflated using the Canadian CPI, then the index from the previous period was subtracted from the current period index and the result was divided by the previous period index. Then the logarithm of one plus the returns were taken to get an accurate specification of real returns. This was performed on all Canadian industry indices as well. Finally, the log returns of CFMRC value-weighted index and the 30 day return on T-bills were used to construct market excess returns or the equity premium of investing in the market portfolio.

2.2 Empirical Methodology

The model specification is assumed to be a factor-augmented vector autoregressive (FAVAR) model. Previous efforts to model stock returns and oil prices consisted of two strands of literature. The first strand focused on using oil price volatility to explain asset or portfolio returns. However, this specification is flawed as the stock market returns can reversely impact the oil market. In addition, cyclical movements in the world economy that would typically affect asset returns and oil prices are not captured either. The second strand used structural VAR models to explain the relationship between stock returns and oil prices. In the context of our discussion, research on using oil price volatility as a factor to explain the cross-section of stock returns (and subsequently asset prices) (see Chen and Ross (1986), Casassus and Higuera (2011), Casassus and Higuera (2012) and Christoffersen and Pan (2014) among others) does not analyze knowledge of macroeconomic effects of oil price movements as it only focuses on developing factors to explain stock returns. Our focus, thus, concerns the second strand of literature. Given that the structural VAR methodology addresses the problem of reverse causality and decomposition of oil price shocks, this paper will estimate a FAVAR model. The model was estimated in the following order:

1) The static factor model was used to extract a common factor from a large number of macroeconomic time-series variables. See Appendix B for the estimation algorithm of the static factor model. The static factor model can be represented as:

$$\underset{(T\times N)}{\boldsymbol{X}} = \underset{(T\times r)}{\boldsymbol{F}}\underset{(r\times N)}{\boldsymbol{\Lambda}'} + \underset{(T\times N)}{\boldsymbol{e}} \tag{1}$$

where $\boldsymbol{X}$ characterizes the list of time-series variables including industrial production, export and import variables of 64 countries, regions and groups of countries, $\boldsymbol{F}$ represents the latent factor representing the global economic activity index and $\boldsymbol{\Lambda}'$ is the factor loading. $\boldsymbol{X}$ has dimensions $T \times N$ with T time-series observations and N cross-sectional units and $\boldsymbol{F}$ has dimensions $T \times r$ where r is the number of factors (in our case that is 1). Due to data irregularities and missing values in 16 variables of countries and groups of countries, the method of expectation-maximization (EM) was used to generate values for these observations following an iterative procedure (see Appendix C for details on the EM algorithm based iterative procedure).

2) The VAR specification was then estimated. The model uses 24 lags for the sake of consistency with previous studies. The structural representation of the model is:

$$B_0 z_t = \alpha + B_1 z_{t-1} + \ldots + B_p z_{t-24} + \epsilon_t \tag{2}$$

$$B_0 z_t = \alpha + \sum_{i=1}^{24} B_i z_{t-i} + \epsilon_t \tag{3}$$

where z_t is a $K \times 1$ (K is the number of variables in the model and is 4 in our case) vector time series consisting of the percentage change in world crude oil production, the global economic activity index extracted using the static factor model, the real price of oil and the Canadian real stock returns variable; B_i is a $K \times K$ matrix, the inverse of the structural impact multiplier matrix B_0^{-1} and ϵ_t is a $K \times 1$ vector representing the structural shock. The vector ϵ_t is a white noise variable and its elements are mutually uncorrelated. In other words, the variance-covariance matrix Σ_ϵ is full rank. The model can also be represented in reduced-form:

$$z_t = \underbrace{B_0^{-1}\alpha}_{A_0} + \underbrace{B_0^{-1}B_1}_{A_1} z_{t-1} + \ldots + \underbrace{B_0^{-1}B_{24}}_{A_{24}} z_{t-24} + \underbrace{B_0^{-1}\epsilon_t}_{u_t} \tag{4}$$

The covariance matris of the structural innovations can be seen to be $\mathbb{E}(\epsilon_t \epsilon_t') \equiv \Sigma_\epsilon = I_K = I_4$. Therefore, the reduced form covariance matrix is $\mathbb{E}(u_t u_t') \equiv \Sigma_u = B_0^{-1} B_0^{-1\prime}$ where $u_t =$

$B_0^{-1}\epsilon_t$ showing that the mutually correlated reduced-form error (u_t) can be represented as the weighted averages of the mutually uncorrelated structural innovations (ϵ_t) with the elements of the structural impact multiplier matrix B_0^{-1} serving as the weights. A more detailed analysis can be found in Kilian and Lütkepohl (2016).

This structural representation allows for easier economic interpretation of the dynamics of the model. For example, with the reduced form representation, the vector u_t is mutually correlated and limits interpretation, whereas the ϵ_t is a vector of mutually uncorrelated structural innovations that allows us to break down the shocks affecting the system of equations. This K model variables are driven by K shocks, where K is 4 and each structural shock can be represented by the corresponding element in ϵ_t (see Section 2.2.2 for the break-down of the oil price shocks using recursive identification).

2.2.1 Alternative Index for Global Economic Activity

The rationale for the extensive use of Kilian's index of bulk dry cargo freight rates for real economic activity is justified, given that it addresses the major problems associated with other measures. The lack of heterogeneity in present measures of global activity may be due to these problems. For example, the approach to identify the structural shocks to the real price of oil relies on the delay restrictions that are economically plausible only at the monthly frequency. Using global GDP as a measure for real activity, thus, cannot be feasible in studies using monthly data. However, one can argue the use of quarterly frequency for the global production of oil variable, GDP as a measure of global activity and real price of oil. Since oil supply responses to shocks to global activity and real economic activity responses real price of oil shocks can be argued to display monthly delay, the identifying assumptions may not be valid under quarterly frequency in the data. An alternative measure is often stressed to be a measure of world industrial production. Since this measure does not exist, the closest to this would be the OECD industrial production, which does not account for economies of China and India.[4] Therefore, it is difficult to identify a truly global measure of real activity and the advantages of the bulk dry cargo freight rate index addresses these issues as

[4] Kilian (2009a) argues that the demand for industrial raw materials from these emerging economies "is thought to be fueling the surge in industrial commodity and oil prices especially since 2002".

an economically justified measure. However, the lack of any other measure in this regard tests the credibility of the model's results. Beyond this, this index suffers from other limitations as well. First, this index represents the movement of cargo mostly through sea and ocean routes and does not accurately account for all land movement of commodities especially in countries with shared borders or of close proximity. Second, Kilian (2009a) argues that the ship-building and scrapping cycle may weaken the business cycle link between global commodity market and the freight rate index. Third, one can also expect that this index would exaggerate the expansion in real activity since the index would lag increases in real economic activity as spare capacity in shipping cushions the impact of higher demand on freight rates, and lead decreases in real economic activity as the arrival of new ships slow down the freight rates. The use of a truly global economic activity index that could address all of these problems would be difficult to find. Therefore, I employ a static factor model to extract a latent factor that reflects movements in 64 macroeconomic aggregate time series variables outlined in Appendix A. This index offers clear advantages:

(i) Since the index uses macroeconomic aggregates that are reported monthly, the frequency will be consistent with the frequency required for the validity of the identifying assumptions (see Section 2.2.2).

(ii) This also takes into account emerging economies of Brazil, Russia, India and China (BRIC) to capture the rise in activity in industrial commodity markets since 2002. Therefore, it manages to account for major economic movement induced by BRIC countries.

(iii) The seasonally-adjusted log-differenced measures of macroeconomic aggregates allows it to avoid to avoid seasonal variation and obtain stationary series.

(iv) This index does not fall subject to the technical disadvantages of the freight rate index.

(v) Provides opportunity to challenge or reinforce the credibility of the widely accepted features of Kilian (2009a)'s SVAR model of oil price shocks.

The bottom line of this methodology is that it extracts an unobserved factor that can capture the co-movement of the macroeconomic variables. In traditional data, this is an unobserved variable.

Furthermore, the method of principal components allows researchers to consistently estimate the true factor space (see Bai and Ng (2002) and Bai and Ng (2008) for a more extensive discussion of the technical features of large dimensional factor models and see Appendix B for the estimation procedure).

2.2.2 Oil Price Shocks and Recursive Identification

The structural VAR aspect of the FAVAR model employed was presented in Section 2.2 that displayed the structural shocks. This model imposes a recursive structure on the contemporaneous relationships between reduced-form errors. The order of the variables denote their contemporaneous relationships, with the first variable responding to shocks to following variables with a delay, the second variable responding to shocks to the first variable contemporaneously and shocks to third variable with a delay and so on and so forth:

$$
\begin{aligned}
z_t \equiv \begin{pmatrix} z_{1t}^{\Delta \textit{Oil Production}} \\ z_{2t}^{\textit{Real Activity Index}} \\ z_{3t}^{\textit{Real Price of Oil}} \\ z_{4t}^{\textit{Canadian Stock Returns}} \end{pmatrix} &= A_0 + A_1 \begin{pmatrix} z_{1,t-1}^{\Delta \textit{Oil Production}} \\ z_{2,t-1}^{\textit{Real Activity Index}} \\ z_{3,t-1}^{\textit{Real Price of Oil}} \\ z_{4,t-1}^{\textit{Canadian Stock Returns}} \end{pmatrix} + \dots \\
\dots + A_{24} &\begin{pmatrix} z_{1,t-24}^{\Delta \textit{Oil Production}} \\ z_{2,t-24}^{\textit{Real Activity Index}} \\ z_{3,t-24}^{\textit{Real Price of Oil}} \\ z_{4,t-24}^{\textit{Canadian Stock Returns}} \end{pmatrix} + \underbrace{B_0^{-1} \begin{pmatrix} \epsilon_{1t}^{\textit{Oil Supply Shock}} \\ \epsilon_{2t}^{\textit{Aggregate Demand Shock}} \\ \epsilon_{3t}^{\textit{Oil-Specific Demand Shock}} \\ \epsilon_{4t}^{\textit{Other Stock-Specific Shocks}} \end{pmatrix}}_{u_t}
\end{aligned}
\tag{5}
$$

The vector of structural innovations can be broken down into two blocks, where the first block represents the oil market with the first three variables and the second block consists of the Canadian real stock returns. Since our interest is not in the reduced-form estimates, but in the dynamics of the structural FAVAR and the effect of oil price shocks on the stock returns, I report on the first three structural shocks that drive the real price of oil; these are represented above in the right-most matrix. Here, ϵ_{1t} represents the shocks to the world supply of crude oil or *oil supply shocks*; ϵ_{2t} represents shocks to the demand for crude oil that is induced by real economic activity or *aggregate demand shock*; ϵ_{3t} denotes the shock to the real price of oil induced by demand that is uncorrelated to the global business cycle or *oil-market specific demand shock* or *precautionary demand shock* (following Kilian and Park (2009), these terms will be used interchangeably throughout the paper); ϵ_{4t} captures any remaining shocks of real stock returns that are orthogonal to the shocks above or *other stock-specific shocks*. From Section 2.2, the variance-covariance matrix of the reduced form is $\Sigma_u = B_0^{-1} B_0^{-1\prime}$ and the reduced-from innovations above was represented as $u_t = B_0^{-1}\epsilon_t$. To exactly identify the structural VAR, I impose six restrictions on B_0^{-1}; the recursive ordering imposed on B_0^{-1} allows for the dynamics of the oil-market to function:

$$u_t \equiv \begin{pmatrix} u_t^{\Delta \textit{Oil Production}} \\ u_t^{\textit{Real Activity Index}} \\ u_t^{\textit{Real Price of Oil}} \\ u_t^{\textit{Canadian Stock Returns}} \end{pmatrix} = \underbrace{\begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}}_{B_0^{-1}} \begin{pmatrix} \epsilon_{1t}^{\textit{Oil Supply Shock}} \\ \epsilon_{2t}^{\textit{Aggregate Demand Shock}} \\ \epsilon_{3t}^{\textit{Oil-Specific Demand Shock}} \\ \epsilon_{4t}^{\textit{Other Stock-Specific Shocks}} \end{pmatrix} \tag{6}$$

The recursive identification structure of the structural impact multiplier matrix is based on the real dynamics of the oil market and its interactions with stock returns. First, following existing studies, the recursive identification in row one and columns two and three of (6) postulate that the short-run supply curve of crude oil is vertical; in other words, the disturbances to any other variables do not induce a supply-side response within the same month. This identifying assumption could also be interpreted as a delayed response by oil suppliers to a positive aggregate demand shock or precautionary demand shock due to frictions such as large adjustment costs in changing production levels and uncertainty about whether the increase in price is transitory or permanent.[5]. It is obvious that this variable only responds contemporaneously to an exogenous oil supply shock. Second, the exclusion restriction in the second row and third column follows from the rationale that real economic activity does not respond contemporaneously to changes in the price of oil due to the

[5]This assumption follows from Hamilton (2009) and Kilian (2009a)

"sluggish" response of global real activity after oil price hikes (see Kilian (2009a)). Real economic activity responds contemporaneously to oil supply shocks and aggregate demand shocks, where an aggregate demand shock represents exogenous shocks to the demand for all industrial commodities contributing to the global business cycle. Third, the real price of oil responds contemporaneously to oil supply shocks and aggregate demand shocks within the same month. Furthermore, the structural shock ϵ_{3t} represents shifts in demand that are not explained by the business cycle which this paper will refer to as precautionary demand shock.[6] This demand shock is also orthogonal to shocks to oil supply, aggregate demand, or real stock returns. Lastly, the placement of real stock returns as the final variable implies that the oil market variables (z_{1t}, z_{2t} and z_{3t}) are assumed to be contemporaneously predetermined with respect to Canadian financial markets. Since Canada is a small net exporting economy, this is likely to hold where the oil market variables will not respond to shifts in demand for stocks atleast within the same month. From an empirical perspective, Kilian and Vega (2011) and Lee and Ni (2002) argue that predeterminedness of energy prices, being a common identifying assumption, holds with U.S. macroeconomic aggregates and the West-Texas Intermediate price of crude oil. This identification also implies Canadian real stock returns can respond immediately to oil supply, aggregate demand, and oil-market specific demand shocks, whereas any stock-market specific demand shocks' effects on the oil-market is excluded within the same month. Given the above implications of the identifying assumptions of (6), it follows that a Cholesky decomposition of the reduced-form sample covariance matrix $\Sigma_{\hat{u}_t}$ is possible due to the recursive structure of B_0^{-1}.

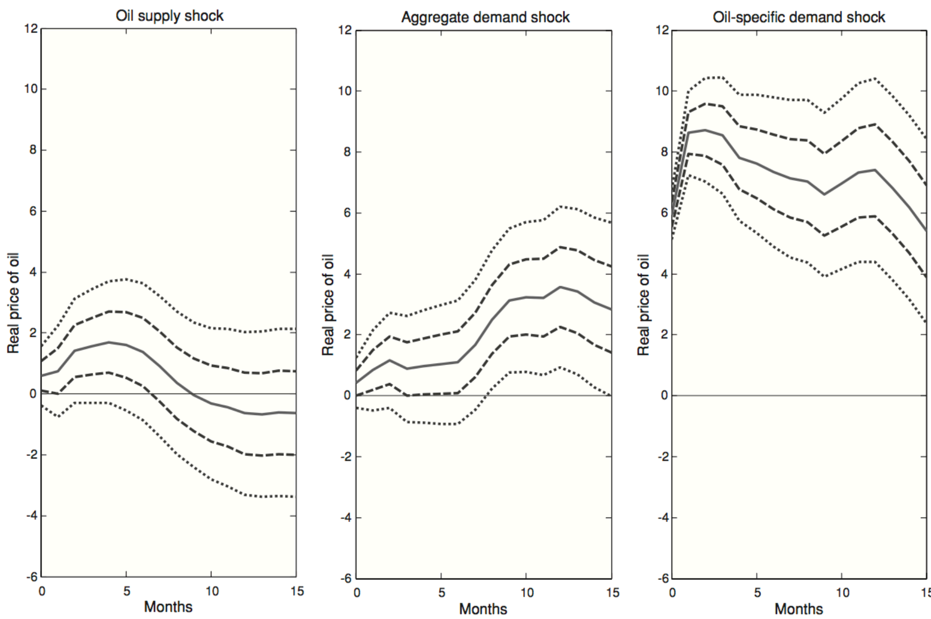
[6] Kilian (2009a) elaborates on the legitimacy of this interpretation. Four points are made: First, there are no other plausible candidates for exogenous oil-market demand shocks and no evidence that the observed oil-specific demand shocks are associated with unexpected weather shocks. Second, the impact of oil-market specific shocks, he argues, "is difficult to reconcile with shocks not driven by expectation shifts". Third, the timing and direction of the shocks effects are consistent with the timing of exogenous events evident through the historical decomposition of the oil price. Fourth, "movements in the price of oil driven by this shock and measures of precautionary demand" based on oil futures prices are correlated up to 80%. This result was shown by Alquist and Kilian (2007).

3 Results

With the model presented, the interest of this paper, next, is to analyze the impulse response functions and plot the responses of particular variables to certain structural shock over time. This section will be organized as follows: First, I will present the consistency of my results to previous findings of Kilian and Park (2009) and Kilian (2009a) with respect to the response of the real price of oil to oil market shocks (or oil price shocks). This response will be interpreted in the context of comparing the index this paper constructed to the freight rate index; the differences and similarities will provide crucial information on the credibility in the use of the freight rate index, while using it as a benchmark to comment on the performance of the latent-factor index. Second, this section will present the impulse response plots of Canadian aggregate stock returns to oil price shocks. This will analyze the implications of the oil price shocks in the movement of Canadian aggregate stock returns. Many researchers suggest that stock market returns are often indicative of the performance of equity markets and an indirect measure of economic performance and growth (see Nguyen and Pham (2014) and Masoud (2013) among others for research on the link between stock market performance and growth and economic growth for Canada). This will also present a comparison of certain shocks and their transmission into the Canadian economy.

3.1 Consistency of Oil Price Shock and Oil Price Responses

Previously reported structural VAR estimates by Kilian (2009a), Kilian and Park (2009), Wang et al. (2013), Fang and You (2014) and Güntner (2014) have shown roughly the same responses of the price of oil to oil supply shocks, aggregate demand shocks and precautionary demand shocks. Of course, it was established earlier that all have used the freight index as a measure of real economic activity. These results will be used as a benchmark to test the effectiveness of the latent-factor index as a measure of real economic activity, but also as a comparative index to infer the robustness of using the freight rate index. The figure below displays Kilian and Park (2009)'s impulse responses for the real price of oil. This result is the same as the findings in Kilian (2009a) and shows that the largest effect on the real price of oil comes from aggregate demand shock and precautionary demand shock. The structural responses were created such that it would induce a positive response in the price of oil.



Notes: *Figure 1 of [Kilian and Park (2009)] showing the response of the real price of oil to the oil price shocks. As can be seen, the most significant responses are to aggregate demand shocks and oil-specific demand shocks.*

Here it is clear that the greatest response is due to an oil-specific demand shock or precautionary demand shock that shows exogenous shocks of rising uncertainty for future oil supply shortfalls contributes to the greatest rise in the real price of oil. Figure 1 below displays the results from our FAVAR specification. Similarly, the shocks were constructed such that they would induce a positive response in the price of oil; a negative oil supply shock, a positive aggregate demand shock or a positive precautionary demand shock all induce a positive real price of oil response. This was to obtain results comparable to previous findings on the responses of the price of crude oil to oil price shocks. It can be seen that our FAVAR model produced similar results; the two technical difference lie in our use of the latent-factor index for real economic activity and in the construction of the confidence intervals using standard residual-based recursive-design bootstrap.[7]. Figure 1 shows three distinct features of the oil market dynamics that is different from the oil market interactions

[7]See Appendix D for discussion on the algorithm used for this.

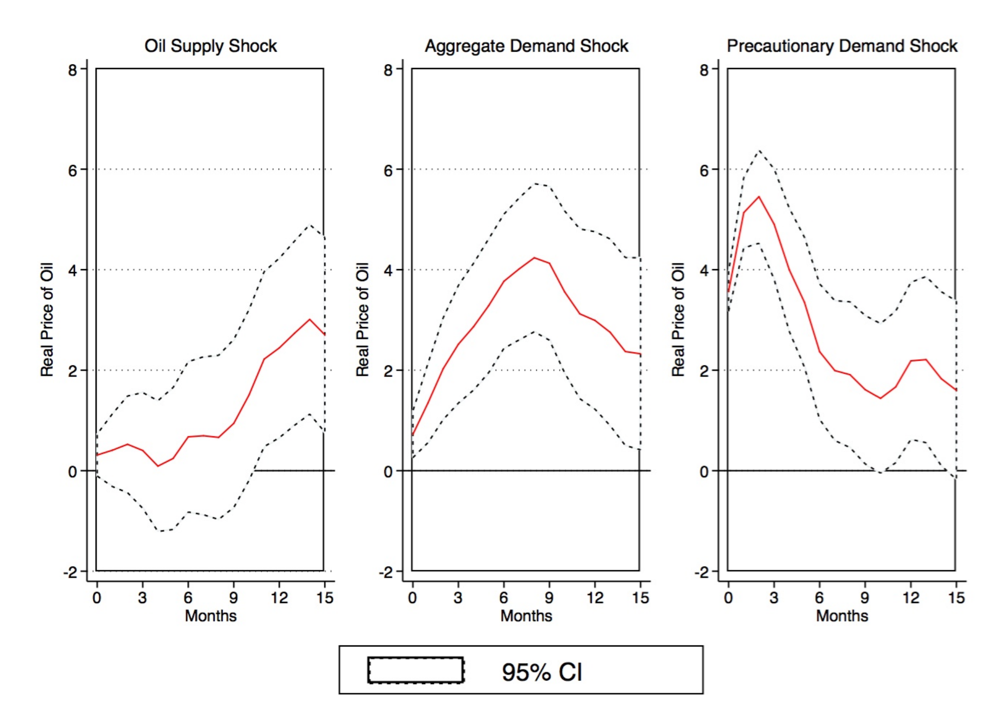


Figure 1: CUMULATIVE REAL OIL PRICE RESPONSES WITH CONFIDENCE INTERVALS CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP.

suggested by Kilian (2009a).

First, with respect to the negative oil supply shock, both figures initially show that the response of the real price of oil is negligible and insignificant, however, our model suggests a delayed, yet significant increase in the real price of oil after 9 months. This distinction could be the result of the 24 lags used; since, the negative supply shock is persistent for 24 lags, the induced response in the price of oil may be due to this persistence, where the model suggests a somewhat significant rise in the price of oil if the negative oil supply shock is persistent. This does not alter the dynamics of the model that is widely accepted and is still consistent with the economics of the oil market. Second, the response to a positive aggregate demand shock in our model is a persistent and more significant increase in the price of oil until 9 months, after which the response is still positive but to a lesser extent and rapidly approaches the steady state level. Although it seems that both of these responses are significantly greater in Figure 1, it can been seen that the scale of Kilian and Park (2009)'s figure's y-axis is somewhat larger and can lead to an exaggerated interpretation of the response of real price of oil in the first and second panel, respectively. Even though this difference is noticeable, it is not a significantly different response from Kilian's model. This suggests our use of the latent-factor index displays the same dynamics of the oil market, but shows a somewhat stronger response of the price of oil. Therefore, it meets the benchmark response of the real price of oil in models using the freight rate index and supports the robustness of the model's dynamics. Finally, the third panel of Figure 1 shows a very similar path of the real price of oil in response to a precautionary demand shock, however, it is not as large as that in Kilian's figure even though the confidence interval is significantly smaller. The reasoning for this may be due to the greater portion of real price movements captured by the aggregate demand shock, however, this cannot be inferred unless the forecast error variance decomposition is analyzed.

3.1.1 Forecast-Error Variance Decomposition of Oil Price Response

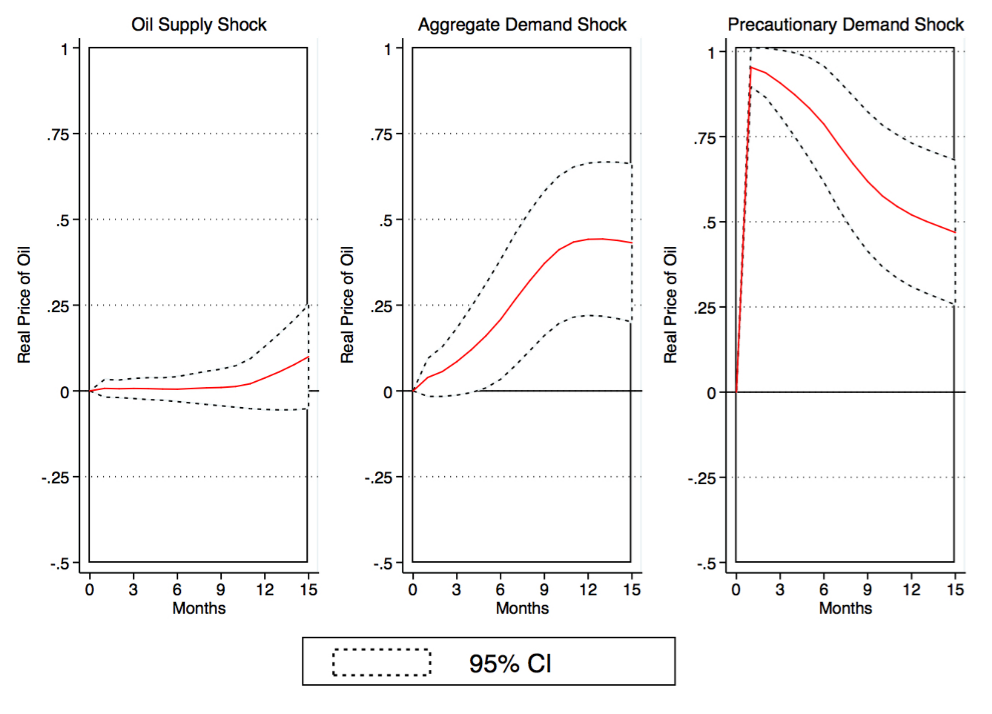


Figure 2: forecast-error variance decomposition of the real price of oil.

The above graph shows that, although precautionary demand shock contributes significantly to the increase in the real price of oil, there is still a significant amount of the prediction mean squared error (MSPE) that is accounted for by real economic activity index. Having interpreted this, it is clear that the oil-specific demand shock contributes significantly to the increase in the price of oil, but not as significantly as argued by Kilian and Park (2009). Given that the above results have indicated that the model has met the dynamical requirements suggested by previous literature, the following section will report on the responses of the Canadian stock returns to oil price shocks addressing the second discrepancy in previous literature after the lack of heterogeneity in using different indices for real economic activity.

3.2 Canadian Stock Return Responses to Oil Price Shocks

Previous literature addressing the relationship between oil market dynamics and stock returns have emphasized the significance of investigating this relationship within the context of investor decisions. Similarly, research has been dedicated to distinguish whether the response of stock returns to oil price shocks will change given the net position of a given country in the oil market. However, existing studies in this regard suffer from two limitations. First, the structural VAR framework used introduced dynamics to explain the transmission of shocks to the stock market, however, the significance of this transmission was not recognized in the context of the country's economic performance. The literature seems to have missed the mark developing the impressive interactions between the oil market and the financial market, but falling short of utilizing the financial market's significance in explaining the macroeconomic performance of a given country. On the contrary, this relationship was briefly mentioned to be important for investors making investment decisions. It should be noted that the global economic activity index used in the model captures global cyclical movements and the aggregate stock returns is argued to be a measure of a country's economic performance. Previous literature does not take advantage of an aggregate stock return index's ability to capture the growth or performance of an economy. Section 4 will discuss the results of industry responses utilizing the industry return index as a measure of the economic performance of that given industry. Second, the literature also analyzes the important differences between the aggregate stock returns' responses of countries with different net positions in the oil market, however, there is little on the effects of these exclusively in a Canadian context, which is arguably attributable to the infancy of this framework to explain the oil market. Therefore, this paper intends to decompose the effects of oil price shocks on Canadian aggregate stock returns to infer the economic consequences of each structural shock. This will be closely related to the work by Masoud (2013) and Nguyen and Pham (2014), which have, among others, suggested a positive relationship between stock markets and economic performance in Canada.

Furthermore, recent research using this structural VAR methodology to address the influence of oil market shocks on the macroeconomy is limited. This is primarily due to the lack of important macroeconomic aggregates (primarily GDP data) in monthly frequency. Even if this methodology was implemented with quarterly data, the result would be flawed as the identifying assumptions would not hold with quarterly measures. Given the convenient representation of stock market performance by the S&P/TSX Composite Index, I investigate the effect of oil price shocks on aggregate stock returns and in turn make careful inferences on the effects of oil price shocks on economic performance. Of course, this does not provide an extensive analysis of the level of variation in Canada's economic performance explained by oil price shocks, however, it does open the door to further research in this area by presenting interesting findings. Now, since our interest lies only in one direction of the interactions between the oil market and the stock returns, this paper will focus primarily on the response of Canadian aggregate stock returns to oil price shocks to infer a potential effect on the economy:

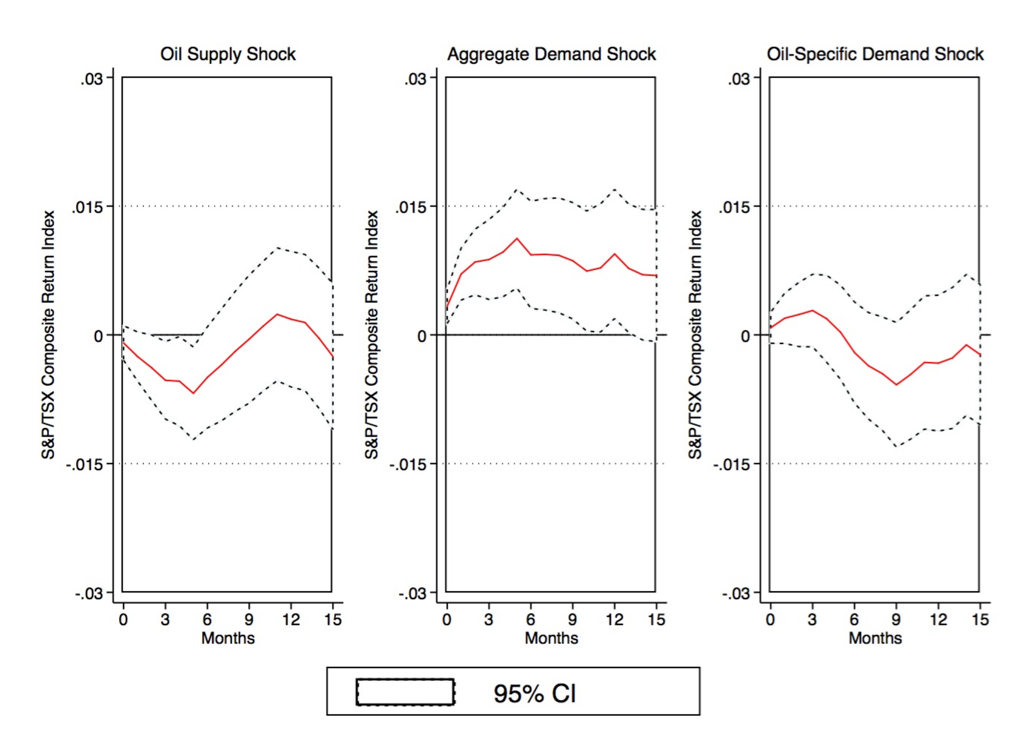


Figure 3: S&P/TSX composite index response to oil price shocks with confidence intervals constructed using standard residual-based recursive-design bootstap

For consistency, the shocks were adjusted based on economic intuition, such that they would induce a positive oil price response. As was mentioned earlier, there is limited exclusive focus on the way Canadian stock returns respond to oil price shocks. A deeper motive of this paper is to focus on attributes of the Canadian economy that would lead to the stock return responses shown in this paper. Given this, an in-depth examination of Figure 3 allows us to make several interesting inferences. Firstly, a negative oil supply seems to have a significant impact on the aggregate stock returns. The response is initially a negative contemporaneous response that persists and is significant for roughly four months between month 2 and month 6. Beyond month 6, the return index for the Canadian equity market approaches the initial steady state level at which point the rest of the path is insignificant. This is an interesting result because of Canada's net position in the oil market. This S&P/TSX Composite Index is constructed by S&P Dow Jones Indices and is composed of roughly 11 industries and 248 constituent companies. Further breakdown of the composition of this index shows the number and the percentage of the index explained by each industry:[8]

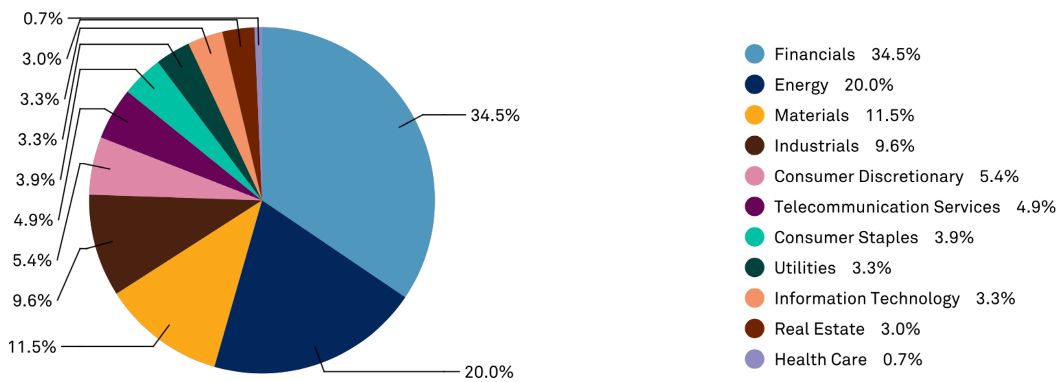


Figure 4: S&P/TSX composite index breakdown of industries. reported by S&P dow jones indices, a division of S&P global and obtained from factsheet of S&P/TSX composite index.

It can be seen above that the financials and energy industries combine to 54.5% of the constituents that comprise the S&P/TSX Composite Index. Thus, the response of the stock return index is not surprising as the energy industry is 20% of the index not accounting for the percentage of constituents with dealings in the energy industry or oil and gas industry (used interchangeably by S&P Dow Jones Indices). Given this and the net position of Canada in the oil market as an exporter of oil, the impulse response for the negative oil supply shock can be rationalized, especially

[8]See S&P Indices website page: `http://ca.spindices.com/indices/equity/sp-tsx-composite-index`

since we concluded that the response of the price of oil to the same negative oil supply shock was insignificant and negligible for the first 9 months. Secondly, the middle panel of Figure 3 shows a positive contemporaneous response to an aggregate demand shock and persistent and significant response. After the first spike, the return seems to decrease before spiking again and approaching the steady state. From an economic standpoint, it surprising to see that the fall in stock returns to an aggregate demand shock is not below the steady state level after the first year as reported by Kilian and Park (2009) to have happened with U.S. aggregate stock returns, since the rise in the price of oil due to the aggregate demand shock acts as a depressant in the economy (by influencing an increase in the price of commodities) offsetting the stimulating effect of economic expansion after one year. However, there seems to be a third effect functioning in the background of this dynamic, which is likely attributable to the net exporting position of Canada. Kilian and Park (2009) and Güntner (2014) both report that after roughly 10 months U.S. stock returns fall below the steady state level and Güntner (2014) shows that this same pattern is also true for Germany and France, which are both net oil importing countries. Thus, it is likely that the absence of a fall in the real aggregate stock returns is due to the net exporting position of Canada channeled through the prominence of the energy industry among industries comprising the composite index. Lastly, the third panel of Figure 3 shows that the stock returns respond positively for the first 4-5 months, after which the stock returns fall below the steady state level insignificantly and maintain this position for the duration of the time horizon. This contrasts insignificantly to the results of Kilian and Park (2009), which shows that the response of the U.S. aggregate stock returns is a negative contemporaneous response that stays negative for the duration of the time horizon. From an economic standpoint, it can be argued that this result may hold due to the fact that the precautionary demand shock initiates a significant and positive response in the price of oil, which leads to greater commodity prices, thus having a growth-inhibiting effect in the economy. However, it is interesting to observe that there is an initial positive response in the stock returns indicating that the energy industry could be performing very well due to higher oil prices induced by greater precautionary demand. Over time, the size of the energy industry may not be large enough or accounted for enough in the index to maintain a positive response the growth-inhibiting effect of higher commodity prices is shown in the fall of the stock return after 6 months. Overall, the above results provide an unseen analysis of the Canadian equity market (to my knowledge) and the interactions that take place with the oil market.

As Kilian and Park (2009), Aloui et al. (2012), Wang et al. (2013) and Güntner (2014) all show their interest in observing this level of interaction of oil market and the financial market from an investor's perspective, this paper also wishes to briefly investigate the effect on the equity premium of investing in the market portfolio. For this, I constructed an equity premium variable using the Canadian Financial Markets Research Centre's (CFMRC) value-weighted index and subtracting the 30-day return on T-bills from it. Before this linear combination was used, each variable was already reported in returns, thus, only a log transformation was needed for each.

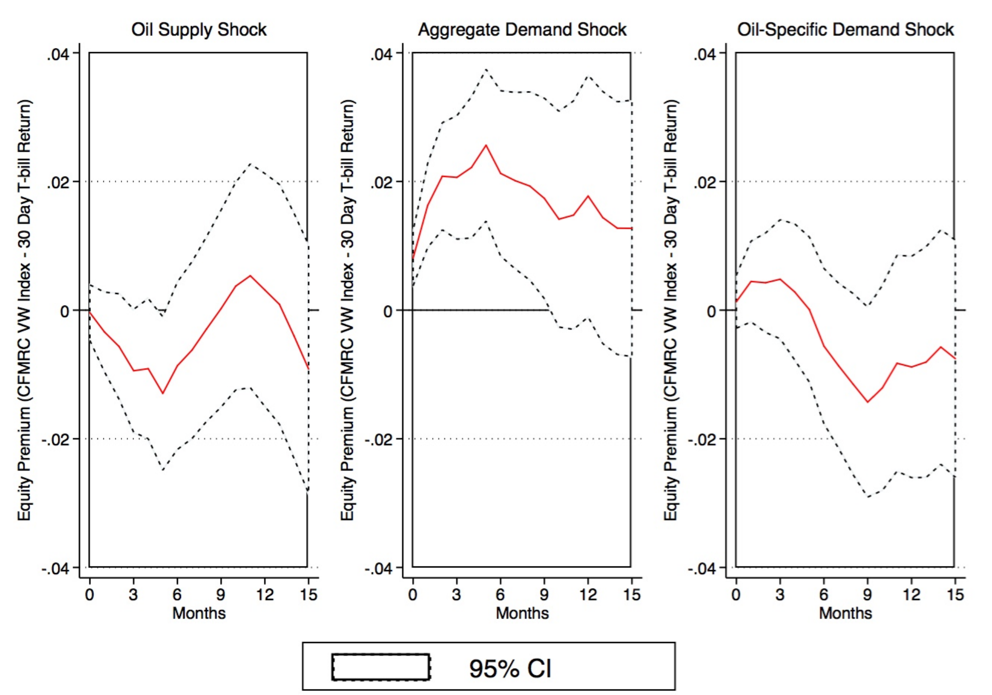


Figure 5: RESPONSE TO OIL MARKET SHOCKS OF EQUITY PREMIUM VARIABLE REPRESENTING INVESTMENT IN A PORTFOLIO REPLICATING THE CFMRC VALUE-WEIGHTED INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP

As expected, this index places similar weights as that of the composite index on particular industries and shows a similar pattern of responses to each shock. However, the major difference to be noted is that the response of the equity premium variable is exaggerated in comparison to that of the S&P/TSX Composite Index. The difference in magnitude may be due to the risk free return being accounted for in Figure 5. Given this, there is little inference to be made beyond that discussed above for the Composite Index as the direction and path of the responses are the same.

4 Dynamics of SIRS Sector Responses to Oil Price Shocks

Canadian aggregate stock returns have been reported by Güntner (2014) to show somewhat different responses from other countries' returns in the sample including net oil exporting countries. Similarly, there were some observations of the Canadian aggregate stock return responses that this paper made:

1) The Composite Index responded to a negative oil supply shock with a fall below the steady state for approximately the first 10 months, after which it briefly rose before falling back down below the steady state level. This is a surprising observation as it was established that oil price response to a negative oil supply shock is almost negligible for the 10 months horizon we are concerned with. Thus, it would imply that this effect could be the result of the oil and gas industry representing a significant chunk of constituents that comprise the Composite Index.

2) The response to an aggregate demand shock seems to be a consistently positive response with no hint of a significant fall back to steady state level; any decreases in the stock return response to this shock is minimal and does not indicate the pattern of significant decrease suggested to be the case for U.S. by Kilian and Park (2009) and Güntner (2014). It was inferred that the significant decrease after the first 10 months was due to the increased oil prices that led to greater commodity prices. In other words, the response of lower stock returns was reflective of the growth-inhibiting effect of greater oil prices dominating the stimulating effect of greater demand (from the shock) after 10 months. Clearly, this pattern was non-existent in the case of Canadian stock returns, which also could be due to the greater influence of the oil and gas industry on aggregate stock returns.

3) It is typically observed that stock return responses would fall below steady state for the duration of a given time horizon; since a precautionary demand shock would raise oil prices, thus, influence an increase in final commodity prices, stock returns would display the growth-deterring effect of greater commodity prices. The above structural impulses shown in panel 3 of Figure 3 indicate stock return responses to increase in precautionary demand not observed previously. It was interpreted that the increase in stock returns above steady state for the first 5-6 months and below steady state for the rest of the time horizon may have again been due to the composition of the composite index. Given Canada's net position in the oil market and the heavy influence of the oil and gas industry, the initial rise in stock return responses may have been due to profits observed in the oil and gas industry dominating the lagged growth-inhibiting effect of higher crude oil prices. After the first 5-6 months, the growth-inhibiting effect may been greater resulting in stock returns below steady state for the duration of the time horizon.

Although the above results were observed, it was not clear what the underlying reason for this pattern is. The industry breakdown indicated that the percentage of constituents in the financials industry and the oil and gas industry accounted for more than 50% of the constituents that comprised the Composite Index. However, a brief look at this breakdown does not provide sufficient information to identify whether the differences is truly due to the oil and gas (or energy) industry. It is, thus, ideal to observe the effects of these shocks on individual industries. A deeper analysis of the oil and gas industry will help identify whether our intuition, on "what likely is the case" with the differences observed in Canadian aggregate return responses, holds. However, it will be difficult to compare and contrast these effects if little is known of the oil price shocks' effects on other industries. It was also observed that the rise in oil prices will lead to decreases in stock returns, which, given the relationship between economic performance and stock returns, could be called recessionary. Thus, we must familiarize with the theoretical aspects of recession and systemic risk using a model that addresses this.

Previous reports on the dynamics of the structural VAR model of the oil market ends at investigating its effects on aggregate stock returns. Beyond this, there has been little progress to address the breakdown of the effects on areas within the economy. Realistically, it is, first, difficult to find macroeconomic aggregates of particular industries or sectors to test what the predictions of the model are with respect to oil price shocks affecting these industries. Second, if this were found, it is challenging to use these measures as economic performance of industries in a meaningful way without consistency across these measures. Since this paper wishes to observe the underlying mechanism that led to the differences in aggregate returns detailed above, a deeper look into the effect of the shocks on industry indices will address these challenges. First, the use of stock returns for industries already takes advantage of the relationship between stock returns and economic performance. Second, all indices used are formulated using the same process and the only major difference lies in that they represent different industries of the economy. Lastly, the relationship between stock returns and economic performance further supports our use of industry indices as artificial measures of performance of industries. Therefore, using these indices provides advantages in this context to explain influences of oil market shocks on industries that combine to comprise the aggregated economy. Although Figure 4 displayed that the composite index is composed of 11 industries, I will be investigating seven of these industries, which include oil & gas, materials, industrials, consumer staples, consumer discretionary, telecommunications and financials. To argue this, I will take advantage of the strong findings of Crean and Milne (2014). Using these results provides two advantages: First, these findings will be used to tie our use of these indices to their abilities to capture recessionary movements in the economy. Second, since data is only available for industry indices, using findings of Crean and Milne (2014) we can narrow down the list of industry indexes to observe by focusing on industries that contain sectors that Crean and Milne (2014) argue to capture recessionary movements. Third, to observe the effects of oil price shocks within the economy, it is beneficial that a theoretical model be used to underpin the importance of certain sectors. Without the necessary theoretical foundation, blindly observing industries will lead to limited meaningful results and more speculation. A blind decomposition of all of the industries will likely lead to less confidence in results observed. A theoretical model also helps to provide a basis to use for comparison of responses across the industries. Furthermore, a breakdown of movements of industry indices will help address the mechanism through which the differences in the responses mentioned in the analysis of aggregate return responses rise. Therefore, the sub-section will begin with familiarizing the model introduced by Crean and Milne (2014). Then it will state why we focus on certain industries using evidence from Crean and Milne (2014). Lastly, it will present the dynamic responses of these industries and interpret them.

4.1 Recession and Systemically Important Real Sectors (SIRS)

The discussion in Section 3 introduced the convenient relationship whereby oil price changes affect stock returns and subsequently the macroeconomy. It also presented the predeterminedness of oil price with respect to macroeconomic aggregates and stock returns allowing researchers to exploit the use of a structural FAVAR to explain the dynamics between the oil market, financial market and the macroeconomy. The focus of this paper has thus far been to understand in what ways are oil price shocks (which are manipulated to raise the real oil price) going to affect the macroeconomy indirectly through the financial markets. It has been widely accepted that rising oil prices influence the macroeconomy by raising the cost of purchasing commodities to consumers (see Hamilton (1983), Lee et al. (1995), Lee and Ni (2002), Hamilton (2009), Kilian (2009a), Kilian (2009b), Charnavoki and Dolado (2014) and Güntner (2014) among others). Given this mechanism, it was shown that the recessionary effects of oil price increases are mostly due to aggregate demand shock and precautionary shock. Implementing this same structural FAVAR model with industry-level indices as the fourth variable in the vector z_t will allow us to understand the recessionary effects of oil price shocks on particular industries and how these will combine to display an aggregated effect on the economy. In order to do so, what must be understood is which industries are likely to capture this recessionary effect. Kilian and Park (2009) is the only attempt at observing sectoral responses. They observe responses of four sectors in the U.S. economy, which are expected to have a response to greater oil prices. These were petroleum and natural gas, automobiles and trucks, retail and precious metals. Of course, their objective was to provide inferences on whether investors should rely on these sectors to diversify their portfolio. Regardless of their objective, there was little *a priori* reasoning as to what the responses should be and found mostly insignificant results. To avoid this problem, this paper uses theoretical findings of Crean and Milne (2014) to provide some foundation as to which industry indices are likely to be affected due to their sensitivity to price changes. Recently, Crean and Milne (2014) introduced a model arguing that systemic risk, which is observed to rise before recessions, is the result of failure of particular industry sectors, where systemic risk is the risk of severe instability in or collapse of an entire financial system and not just the failure of its individual parts. Given the great financial crisis of late 2000's, I decompose the effect of rising oil prices on particular industries, derived from unstable SIRS sectors, which could potentially be contributing to greater systemic risk and the downfall of financial systems.

Crean and Milne (2014) decompose recessions of the past century to show that systemic risk arises in a number of systemically important real sectors (SIRS) and not solely in the financial sector as it is mostly assumed; the general agreement is that systemic risk arises from imbalances in the financial sector. Many models argue that systemic risk is due to an ongoing series of random shocks and assume that financial markets are competitive. Consequently, due to reasons explained by Crean and Milne (2014), these models have failed to identify the recent 2008 financial crisis. Other schools of thought argue that market failures caused in financial crisis.[9] Crean and Milne (2014) argues that systemic risk is found in real sectors and that the financial crisis was caused by collapses in a small number of these key real sectors, which collapsed two or more years before the banking crisis. The bank losses in the U.S. that were consequently realized in major episodes, occurred due to exposures to these key sectors. In Crean and Milne (2014), these are referred to as Systemically Important Real Sectors. A sectoral decomposition of the losses from the past two recessions recessions using data from the Federal Deposit Insurance Corporation (FDIC) and calculations from Standard & Poors *Institutional Loan Default* show that bank losses from SIRS account for 60% of the total losses when these comprise only four of the total 24 industries (see Figure 6). A deeper look at Media, Automotive, Real Estate and Chemicals shows that they account for 60.9% of the bank losses from the early 2000's recession and 80.5% of the bank losses in the recent financial crisis. Moreover, they identified a list of five characteristics that qualify them to be SIRS:

(1) To generate revenues in each sector, firms must maintain large levels of capital. High asset levels are necessary.

[9] see Crean and Milne (2014).

	Two Years November 2000 - October, 2002		Two Years January, 2008 - December 2009		Total Remaining Eleven Years		Total Fifteen Years	
Total Losses, $MM		17,712		62,105		17,382		97,200
Percentage of Total		18.2%		63.9%		17.9%		100.0%
Percentage Distribution								
Media, Total		49.8%		47.3%		10.9%		41.2%
Printing and Publishing	0.0%		23.8%		0.0%		15.2%	
Telecom	43.9%		3.0%		9.0%		11.5%	
Cable	5.9%		0.0%		0.0%		1.1%	
TV	0.0%		0.0%		1.9%		0.3%	
Other	0.0%		20.5%		0.0%		13.1%	
Automotive		4.9%		9.8%		13.2%		9.5%
Real Estate - Total		4.2%		11.2%		3.0%		8.5%
Real Estate	0.0%		4.7%		0.0%		3.0%	
Building Materials	4.2%		3.6%		3.0%		3.6%	
Construction	0.0%		2.9%		0.0%		1.9%	
Chemicals		2.0%		12.2%		1.1%		8.4%
Healthcare		4.4%		0.8%		22.9%		5.4%
Computers and Electronics		7.3%		1.7%		5.4%		3.4%
Gaming and Hotels		1.6%		4.7%		0.0%		3.3%
Metals and Mining		2.6%		1.8%		7.4%		2.9%
Environmental		1.9%		0.0%		8.8%		1.9%
Retail - Total		3.7%		0.5%		4.9%		1.9%
Retail	3.5%		0.5%		3.0%		1.5%	
Food and Drug Chains	0.2%		0.0%		1.9%		0.4%	
Oil and Gas		0.0%		2.5%		0.0%		1.6%
Business Services		0.0%		2.2%		0.0%		1.4%
Forest Products		0.0%		1.8%		1.1%		1.4%
Food and Beverage		1.5%		0.1%		5.3%		1.3%
Transportation		0.6%		1.3%		1.4%		1.2%
Home Furnishings		1.8%		1.0%		0.7%		1.0%
Entertainment and Leisure		2.1%		0.7%		0.9%		1.0%
Airlines		0.0%		0.0%		4.2%		1.0%
Services and Leasing		4.7%		0.0%		0.2%		0.9%
Textile and Apparel		3.6%		0.2%		0.4%		0.9%
Manufacturing and Machinery		2.8%		0.2%		1.1%		0.8%
Professional & Business Svcs		0.3%		0.2%		1.3%		0.7%
Utilities		0.0%		0.1%		5.2%		0.4%
Consumer Non-Durables		0.3%		0.0%		0.0%		0.1%
Aerospace and Defence		0.0%		0.0%		0.7%		0.1%
Total		100.0%		100.0%		100.0%		100.0%

Figure 6: TABLE 2 OF CREAN AND MILNE (2014) SHOWING THE DISTRIBUTION OF LOSS ON RATED LOANS ISSUED PUBLICLY FROM 1995-2009 BY INDUSTRY AND SUB-SECTORS

(2) Capital expenditure on these fixed assets are high.

(3) Assets or capital expenditure are financed by high levels of bank borrowing.

(4) Due high levels of assets financed by high levels of borrowing, Firms experience high fixed costs and low marginal costs.

(5) Markets in which these firms operate are highly competitive.

These five characteristics, Crean and Milne (2014) argue, define a SIRS sector and renders them potentially unstable. The mechanism through which systemic risk causes financial collapse can be summarized as follows. Over certain periods of time, cash flows in these industries are enough to cover both high fixed costs and low marginal costs. However, with excess capital investment, excess capacity can emerge causing pricing to collapse in the industry. Due to high levels of competition, pricing is driven towards marginal costs and subsequently drops cash flows. These firms can no longer service their debts and end up defaulting. The result leads to large amounts of bank losses, causing a large number of small banks with great exposure to these sectors to fail. This leads to larger banks that finance smaller banks to also be affected and experience losses.[10] Using detailed anecdotal evidence, examples of SIRS sectors are introduced and include telecommunications, automotive, printing, commercial real estate, residential real estate, mining and oil among others. Furthermore, their development of a model, which incorporates features of a financial crisis, supports their conclusion of the incredible role these SIRS sectors play in recessions. Given that available data is limited to industry level indices, I will utilize the importance of SIRS sectors, which belong to these industries, to investigate the effect these shocks can have in causing instability in the industries through the SIRS sectors. This can be argued to be the result of SIRS sectors being sensitive to sudden price changes. We cannot explicitly state how much of the responses will be due to these sectors, but we can argue their importance in contributing to the responses of industry stock return indices.

[10] Crean and Milne (2014) build on this model, which was used to justify patterns of growth in an economy dominated by few major sectors, to explain the dynamics of recessions using SIRS. Their model functions with much weaker assumptions, combines it with more modern theory and incorporates divergent expectations to explain the failure of financial systems.

4.2 Sector Responses to Oil Price Shocks

The SIRS sectors which I wish to investigate are the oil and gas, chemical, mining, construction and materials, automobile and parts, printing and publishing, telecommunications and real estate. Table 1 presents the industry level indices that contain these sectors. Using the SIRS sectors serves a great deal of convenience for several reasons. First, the breakdown of oil price shocks on Canadian returns showed significant results; it was concluded that oil price shocks can affect the Canadian economy in a number of ways. The finding that oil price increases can have recessionary effects through increasing commodity prices can be investigated by utilizing the mechanism of SIRS sectors in the background to help explain why the aggregate index responds the way it does. Second, the fact that the oil and gas industry is identified as a SIRS sector provides us the opportunity to compare and contrast the way the oil and gas sector will be affected in comparison to the other SIRS sectors. Third, a SIRS analysis allows us to focus on a number of industries with SIRS sectors that are sensitive to random shocks and make meaningful inferences rather than dissecting the oil price shocks' influences on all industries. Given that the above rationale strengthens the argument to look at SIRS sectors, it should be noted that these inferences will still need to be made carefully as SIRS sectors account for a portion of each industry. Unfortunately, not all SIRS sectors can be investigated alone due to the limited data. After 2002, the previous sector indices, which included sectors of automotive, real estate and telecommunications as separate indices, were discontinued and these industry indices, which are generated for both the Canadian equity market and U.S. equity market by the S&P Dow Jones, remained. As a result, all the SIRS sectors we are interested in are not available as separate indices but are combined with other sectors to create aggregated industry indexes. This is shown in Table 1; the boldened supersectors/sectors/subsectors highlight the sectors this paper will be focusing on. It should be reiterated that this paper will use industry indexes of those in column 1 of Table 1. The boldened supersectors/sectors/subsectors are the SIRS sectors within these industries and they motivate investigation of these industries out of the 11 industry indices available.

Therefore, the rest of this section will be organized such that it analyzes the effect of the oil price shocks on the industries in which each of these sectors belong. There are four industries that

Industry	**Supersector**	**Sector**	**Subsector**
Oil & Gas (Energy) (3)	**Oil & Gas**	*Oil & Gas Producers*	...
		Oil Equipment, Services	
		Alternative Energy	
Materials (1)	Chemicals	**Chemicals**	*Commodity Chemicals*
			Specialty Chemicals
	Basic Resources	*Forestry, Paper*	*Forestry*
			Paper
		Industrial metals	...
		Mining	...
Industrials (2)	Construction	**Construction & Materials**	*Building Materials*
			Heavy Construction
	Industrial Goods	...	...
Consumer Staples (5)	Automobiles & Parts	**Automobile & Parts**	*Automobiles*
			Auto Parts
			Tires
	Food & Beverage	*Beverages*	...
		Food Producers	...
	Personal & Household Goods	...	...
Consumer Discretionary (4)	Retail	*Food& Drug Retailers*	...
		General Retailers	...
	Media	*Media*	*Broadcasting*
			Entertainment
			Media Agencies
			Publishing
	Travel & Leisure	...	...
Telecommunications (4)	**Telecommunications**	*Fixed Line Telecom*	...
		Mobile Telecom	...
Financials (5)	Banks	*Banks*	...
	Insurance	...	...
	Real Estate	*Real Estate Investment*	...
		Real Estate Investment Trusts	...
	Financial Services	...	...
	Investment Instruments	...	...

Table 1: Shortened sector classification table reported by S&P Dow Jones Indices. The "..." represent sectors and sub-sectors which have been omitted as they are irrelevant to this study. (1)-(5) indicates a scale of energy intensiveness based on CANSIM Table 153-0032 and Layzell et al. (2016) with (1) being the most energy intensive industry and (5) being the least. The scale was generated by referencing the full sector classification table reported by S&P Dow Jones Indices based on sector and sub-sector matches.

have not been included in the table and will be omitted from our analysis. The industries will be analyzed in the order they are presented in Table 1. For each industry, the same structural FAVAR specification will be used, where the only difference will be that the fourth variable in the FAVAR will be replaced by each industry index.

For the first industry/sector of oil & gas (or energy), the structural impulse responses that were generated is presented in Figure 7. These show interesting results. First, it is apparent that a

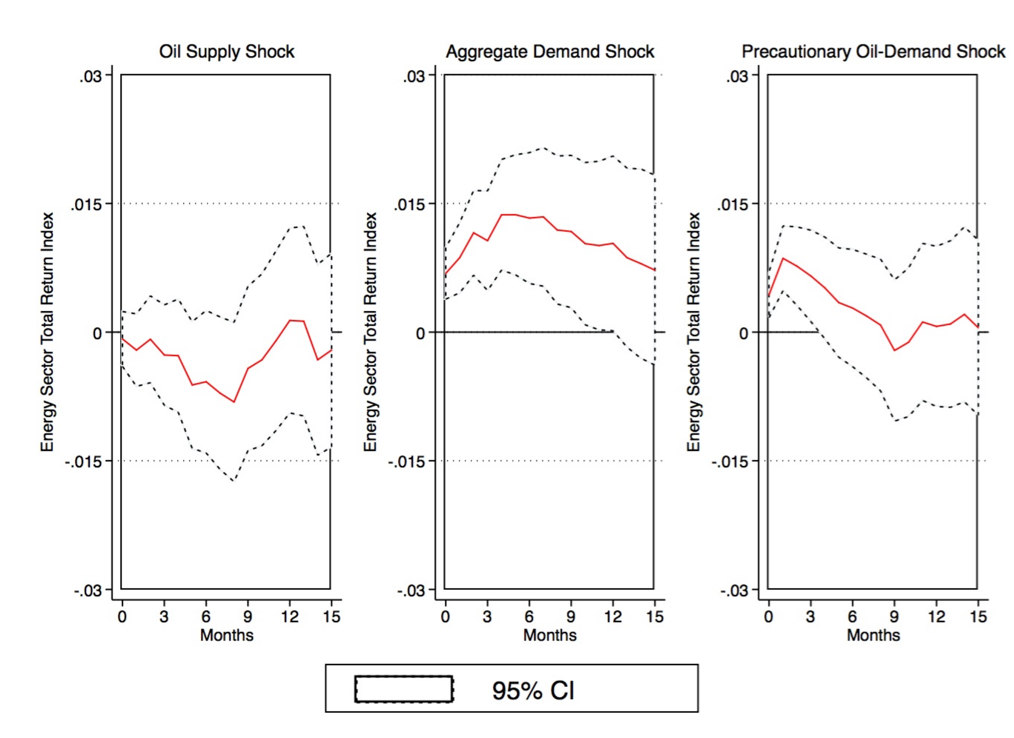


Figure 7: CUMULATIVE RESPONSE TO OIL MARKET SHOCKS OF ENERGY SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

negative oil supply shock induces an insignificant negative response from the energy total return index for the first 9 months, after which it rises towards the steady state. This pattern could be attributed to the fact that the oil supply disruption causes a small stir in the market for crude oil. Prices do not change likely because consumers with immediate oil demands have access to other alternatives and understand that this is a temporary outcome. Given this, the oil and gas sector decreases production to meet the demands of the lowered demands of the market. Oil prices begin to rise after 10 months likely due to the persistence of shock which causes consumers to settle for greater prices and return to initial demand levels. The oil and gas industry begin supplying this demand until the market returns to some equilibrium with the index reflecting greater production by the industry after 9 months. Since the energy sector accounts for roughly 20% of the aggregate index and a significant percentage of the total Canadian economy. This response supports our argument that although oil price changes very little in response to negative oil supply shocks (which should mean that aggregate return responses in general should also display minimal response) the aggregate return index responded with a drop below steady state in the first 9-10 months likely because of the energy sector response. It, thus, provides evidence for the pattern displayed in the composite return index for Canada in its response to the oil supply disruptions. Second, it is also apparent that the largest and most significant response is that of the aggregate demand shock. This also shows that this sector gains significantly from rising oil prices due to aggregate demand shock but this industry is also very energy intensive. It seems that it does seem like it falls subject to the growth-inhibiting effect of costs of energy induced by greater oil prices. Although the return index positive response decreases in magnitude and is not significant after 12 months, it still remains positive and above the steady state at a level higher than even its contemporaneous response level. Lastly, a positive precautionary demand shock generates a significant positive response, but this response dies out and is not as persistent as the aggregate demand shock. Here consumer expectations for future oil supply shortfalls shift and consumers wish to hold inventories of oil causing a significant increase in the index for the oil and gas industry. This response still likely explains the pattern we observed with the aggregate stock return response in Figure 3 panel 3, where the first 5 months saw a positive response to precautionary demand shock when it is expected to generate an overall negative and significant response. As a result of Canada's net oil exporting position, the aggregate return responses can be supported by breaking down the responses of the energy sector or oil and gas sector in Figure 7.

Next, this paper will observe the responses of the materials industry index, which is also an aggregated index of sectors, to understand the overall recessionary impacts of higher oil prices here. Figure 8 below represents the response of the materials industry to oil price shocks. The materials

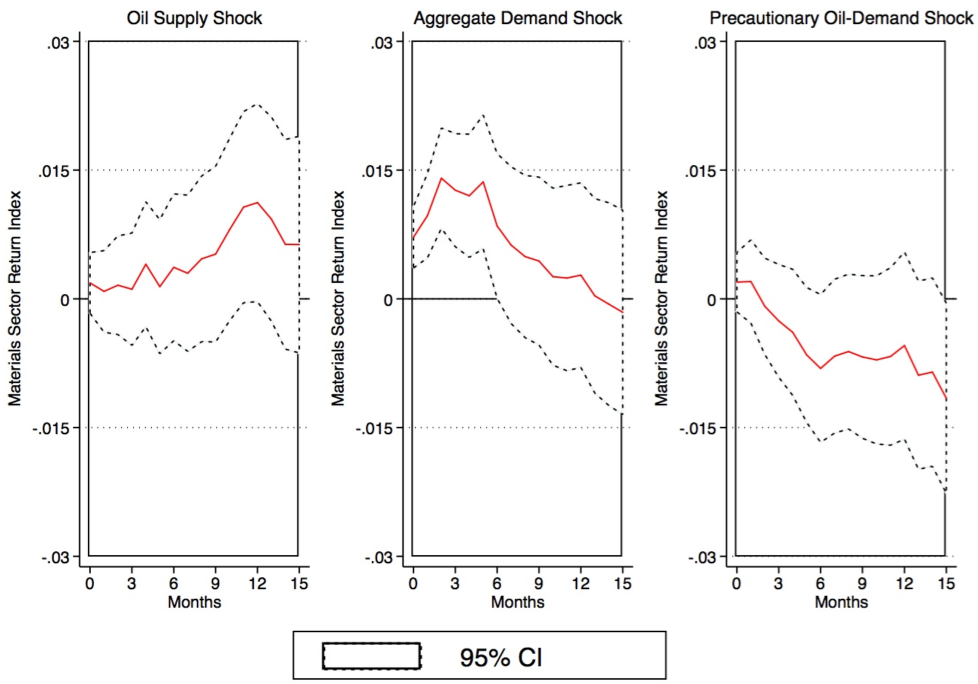


Figure 8: CUMULATIVE IMPULSE RESPONSE TO OIL MARKET SHOCKS OF MATERIALS INDUSTRY/SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

industry contains chemicals as well as mining SIRS sectors both of which are highly energy intensive according to Table 1. A first glance at Figure 8 indicates an unnatural pattern. An oil supply disruption does not have a significant effect on oil prices for the first 9-10 months and raises oil prices significantly due to high levels of persistence after 9 months. Here, it seems that the materials sector is responding positively after 9 months when oil prices begin to rise. The complex composition of this industry which includes various sub-sectors of the mining sector and other basic resources make it difficult to economically reason this response. The anticipated response would be that the chemicals and mining sectors would likely suffer, once oil prices increase, due to increasing costs of inputs that rely on crude oil in order to be produced. This is due to the materials industry ranking the highest in terms of energy intensiveness. However, since the materials industry also includes the entire basic resources sectors as well as power generation sectors from all other sources, that may supply the same consumers that use oil primarily as inputs, may be supplying resources that could be competitive substitutes to oil as inputs. Since the oil supply disruption is also persistent causing incapability to meet immediate oil demands, consumers in these markets with immediate oil demands begin to also face higher oil prices due to short supply after 9 months and thus resort to demanding alternatives and substitutes. This phenomenon would explain the rise of the index between 9-13 months. However, from the perspective of the materials industry, the momentum of rising oil prices at 14-15 months may have made it more costly for the resources sector to maintain higher production levels and have also negatively impacted the mining and chemicals sectors. Due to increasing costs growing faster than the demand the power generation sectors face, the return index drops almost at the same rate as it rose. This explains the interesting response of this sector to oil supply disruptions. The second panel shows that the materials industry responds positively to an aggregate demand shock contemporaneously and this stays positive (and significant) for the first 6 months. The response declines towards the steady state after this. Given that this shock has the greatest positive impact on oil prices which peaks at 6 months and there is no oil supply disruption, we can see support for our hypothesis explaining the effect consumers with immediate oil demands would have when also faced with rising oil prices. Here, greater oil prices due to aggregate demand shock increases the costs of input for the industry but consumers with immediate oil demands are accommodated and the decisions of consumers (in markets where basic resources can substitute oil as inputs) are not altered. Thus, we only observe a recessionary effect dominating the stimulating effect of greater demand after 6 months for this industry. It is also apparent that the decline in the sector index is the greatest out of all the industry by sheer magnitude. This is likely due to the fact that the SIRS characteristics of chemicals and mining are contributing greatly to the sensitivity to greater input costs from higher oil prices. Thus, the growth inhibiting effect is the largest for this sector due to the fact that it is the most energy intensive, but also due to the SIRS sectors' sensitivity to higher costs in this industry. For the third panel, it can be seen that the precautionary demand shock, which raises the real price of oil has a negative effect on the materials industry index. This could be attributed to the recessionary effect of greater input prices. In addition, there is no supply disruption for oil, thus, we observe only a negative response of the materials sector. Given that this industry contains the chemicals and mining SIRS sectors, both of which contribute to the high energy intensive ranking of this industry, the response to a rise in oil prices is the most negative of all the industries. Although it is tough to isolate how much of the response is due to the energy intensiveness of the industry, it can be agreed that the SIRS characteristics of the two sectors are likely not helping to mute the negative response.

The construction and materials SIRS sector belongs in the industrials industry, which also contains the industrial goods sector. Here, observing Figure 9 shows a somewhat different set of responses than what was observed with the materials industry. Here, we observe that a negative oil supply shock leads to a contemporaneous negative response that stays negative for the duration of the horizon. It displays a smoother fluctuating response similar to what was observed with the energy sector. This is likely to be due to the effect of oil supply disruption rather than rising oil prices, since oil prices do not change for the first 9 months. Thus, the fluctuating response indicates the following. Given that the global oil market has been hit with an exogenous shock that disrupts the supply, and this industry is the second most energy intensive industry, this industry is likely composed of sectors with consumers that are a portion of those that rely on immediate supplies of oil as inputs. However, these sectors have access to alternatives. Thus, the persistence of the shock causes the return for this industry to fall below the steady state as they consider alternatives as inputs. This pattern indicates that the sectors in this industry are likely dependent on the production levels of the energy sector, which can be seen from the similarity to the energy response to the same shock. As the energy sector recovers production levels, the immediate oil demands of these consumers are met and they begin to recover following somewhat the same pattern. The response in the second panel displays a pattern that is familiar. In a hypothetical scenario, it could be expected that an aggregate demand shock would stimulate a response by a SIRS sector that is positive and significant in the first several months (based on current results), with a lagged and consistent fall in the return index for the following months indicating the dominant effect of rising costs of inputs. Here, the decrease is not observed, but it is apparent that after the first 8 months the response is insignificant. Regardless, this shows that there could exist a growth-inhibiting effect in this industry, but it is not clear due to the fluctuations near the end of the horizon. Lastly, the third panel shows a general insignificant response all throughout with some fluctuations. Using our intuition on the effect of a

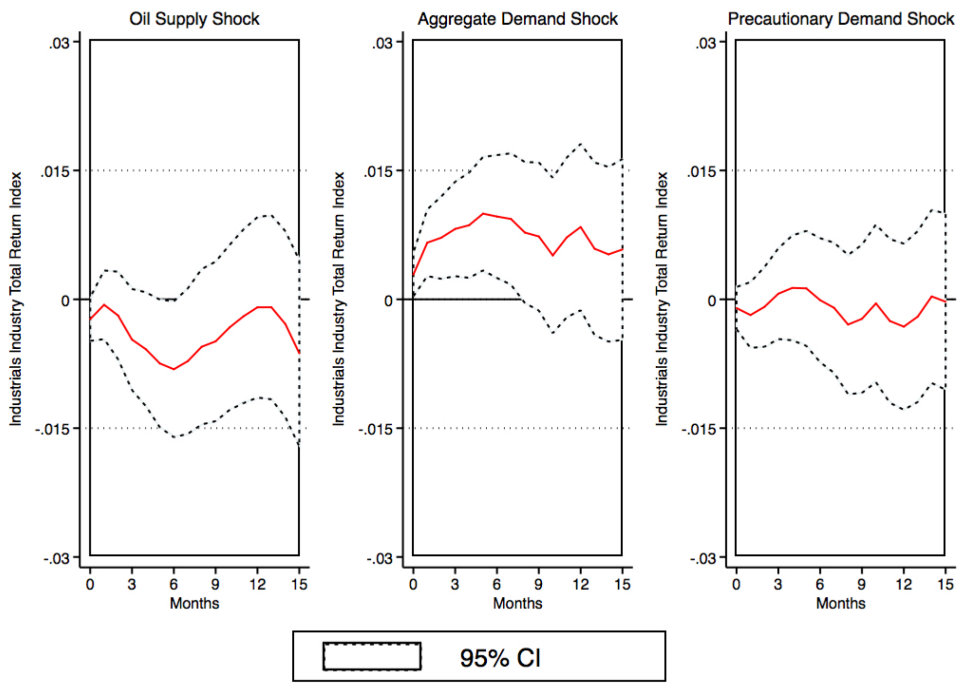


Figure 9: CUMULATIVE IMPULSE RESPONSE OF INDUSTRIALS INDUSTRY/SECTOR INDEX TO OIL MARKET SHOCKS. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

precautionary demand shock, which creates uncertainty in the market regarding future oil supply shortfalls, it can be expected that, since this industry's immediate oil demands are, it can only be subject to rising oil prices given its energy intensiveness. However, they also have alternatives to consider when faced with a rise in oil prices, and, thus, the response fluctuates insignificantly mostly below the steady state level but it does fall below it significantly.

The next set of responses that will be discussed will be that of the consumer staples industry. Here it is observed that the only significant change is due to the negative oil supply shock. There is no response to aggregate demand shock nor any response to precautionary demand shock. Referring to Table 1, it is shown that the SIRS sector accounted for by this index is only the automobile sector. The other sectors include the long list of food and beverage sectors as well as personal and household goods sectors. Since there is no response to aggregate demand shock in this industry, it is likely that this is the result of the goods exchanged in this industry being highly inelastic and that consumer decisions on the quantity of important household goods are not affect by an aggregate demand shock. Observing the consumer staples industry response, there is a similarly no effect of

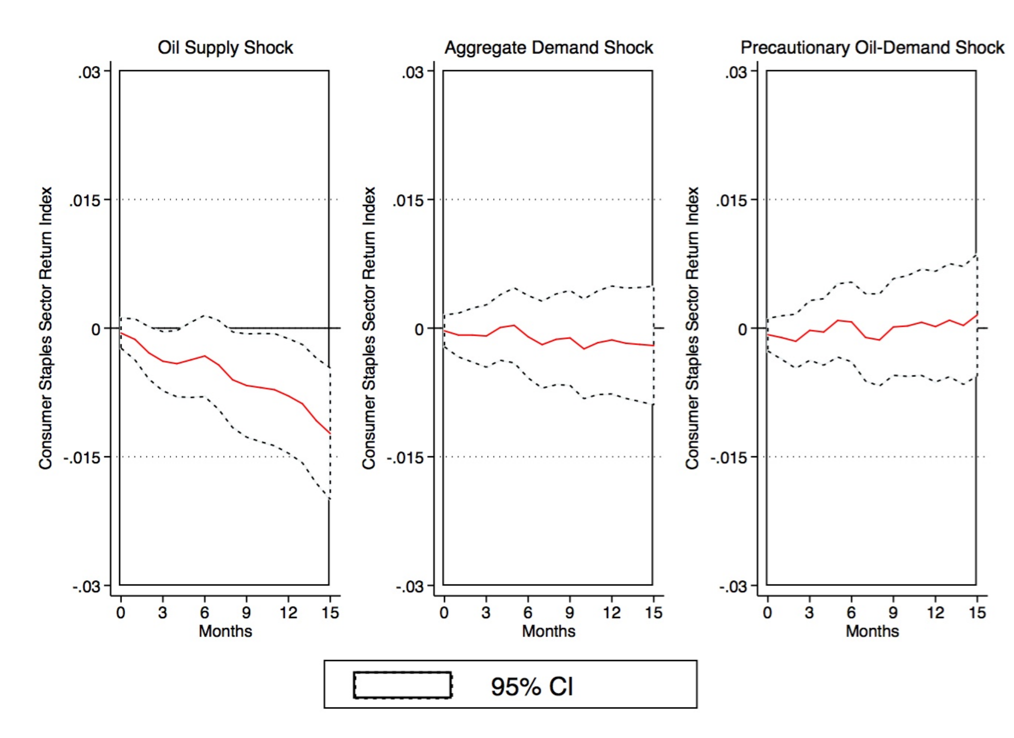


Figure 10: CUMULATIVE IMPULSE RESPONSE TO OIL MARKET SHOCKS OF CONSUMER STAPLES INDUSTRY/SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

precautionary demand shock on the industry. Although the auto sector is included in this industry, it is possible that the auto sector consists of such a small portion of the industry that any effect from aggregate demand shock or precautionary oil-demand shock is negligible. On the contrary, we do observe a response to a negative oil supply shock. This suggests that the industry is affected more by oil supply disruptions and not oil price increases, possibly due to the industry's heavy immediate oil demands. This also hints that sectors in this industry possibly engage in markets where there is little to no substitutes to their use of oil. Given that is industry is ranked last in terms of energy intensiveness, it is possible that their use of crude oil may be for other purposes other than energy, where price changes will not affect their decisions as consumers of their products demand their goods inelastically.

Next we observe the responses of the consumer discretionary industry, which consists of the publishing sector as a SIRS sector. The publishing sector accounts for a small sub-sector of the media sector.

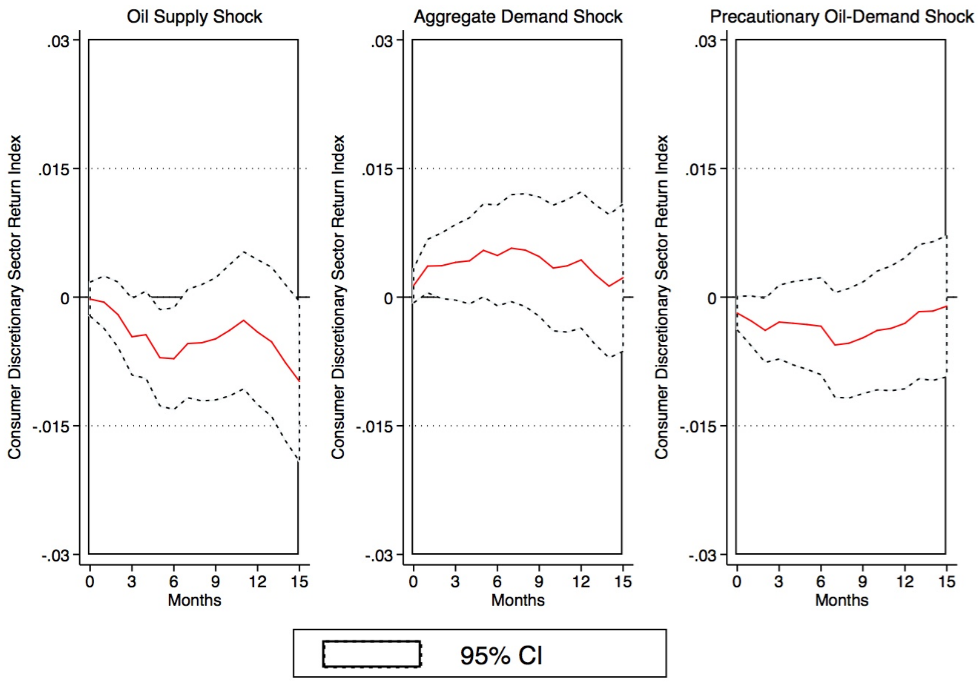


Figure 11: CUMULATIVE IMPULSE RESPONSE TO OIL MARKET SHOCKS OF CONSUMER DISCRETIONARY INDUSTRY/SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

However, looking at the consumer discretionary industry will provide a contrasting perspective from consumer staples. This is because these are responses of an industry with sectors that supply less inelastic consumer goods that are not important for survival. A glance at the responses show that they are consistent with our expectations. First, an oil disruption shock displays a similar response to that which was observed for the consumer staples industry, except that this is somewhat more volatile and contains fluctuations. The contemporaneous response is minimal, insignificant and negative, whereas it becomes significant between months 4-6. Again, this is because the consumer discretionary industry likely contains sectors that have immediate oil demands, where there is some but minimal number of alternatives. This likely produces the negative consistent response with some fluctuations. The middle panel shows that the industry responds positively to an aggregate demand shock but this response is less significant than that of other sectors and more significant than that of the consumer staples sector, which could be due to low levels of price elasticity. Here the response is not as significant due to low elasticity, but not very significant since the aggregate demand shock would only encourage limited demand increase for the goods supplied by this industry. It is also clear that this panel displays the growth-inhibiting effect of greater oil prices with a lag. Observing the final panel shows that the industry responds with lower returns as a result of precautionary demand shock which raises the real price of oil significantly. This suggests that the industry responds to greater real price of oil as an input. Similar to consumer staples, this industry is influenced mostly by oil supply disruptions, but greater oil prices still has some effect which differentiates its responses from that of the consumer staples industry.

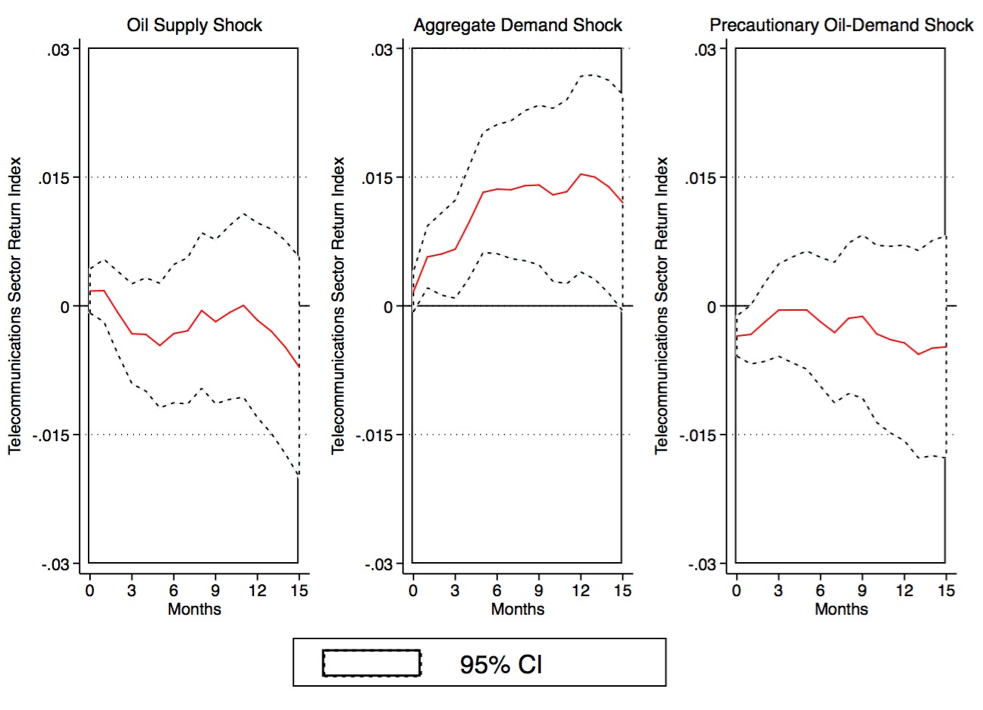


Figure 12: CUMULATIVE IMPULSE RESPONSE TO OIL MARKET SHOCKS OF TELECOMMUNICATIONS INDUSTRY/SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

The sixth industry of telecommunications shows a similar response to that of consumer discretionary industry. First, the response to an oil disruption is mostly a negative response over the entire horizon; the return index displays a negative response even though the real price of oil does not change until the 9th month. Since this response is highly insignificant throughout the horizon, it is difficult to argue what could be the case. However, the pattern it displays could be due to the same explanation provided above that there is some level of immediate oil demands (with minimal input substitutes) in the industry that allows the response to follow the pattern of the energy industry response to the same shock. With respect to the aggregate demand shock, it is clear that the positive response to this is significant for the entire time horizon. There is no sign of a dominating growth-inhibiting effect of greater oil prices here. However, a closer observation of the precautionary demand shock does show that the effect of higher oil prices does cause a negative response, however it is not as significant as one would anticipate. This is likely the reason for the absence of a growth-inhibiting effect in the second panel. For this industry, accommodation of immediate oil demands is likely more important than the rise of oil price since sectors in this industry have access to some substitutes similar to the consumer discretionary industry.

Lastly, we look at the financials industry. Although the financials industry is being investigated since the real estate SIRS sector belongs to this, it should be noted that this industry also contains many firms in financial services, insurance, and banks. The results can be interpreted as follows. First, an oil disruption was previously reported to lead to a negative response in the index for the oil and gas sector. The response of the financials sector seems to be a significant negative response to a negative oil supply shock. This can be attributed to the fact that the banking sector in Canada is possibly heavily invested in the oil and gas industry as it is the second largest industry after financials. This heavy investment follows from the SIRS model that the banking industry is also involved in the SIRS sectors as it finances them. From a SIRS perspective, the banks are likely financing aspects of all industries. Since it was observed that industrials, consumer discretionary and telecommunications industries follow similar response patterns to the energy industry due to their involvement in the domestic market for crude oil, it is also clear that the financials response to the same shock is significant as it reflects their levels of involvement in financing SIRS sectors belonging

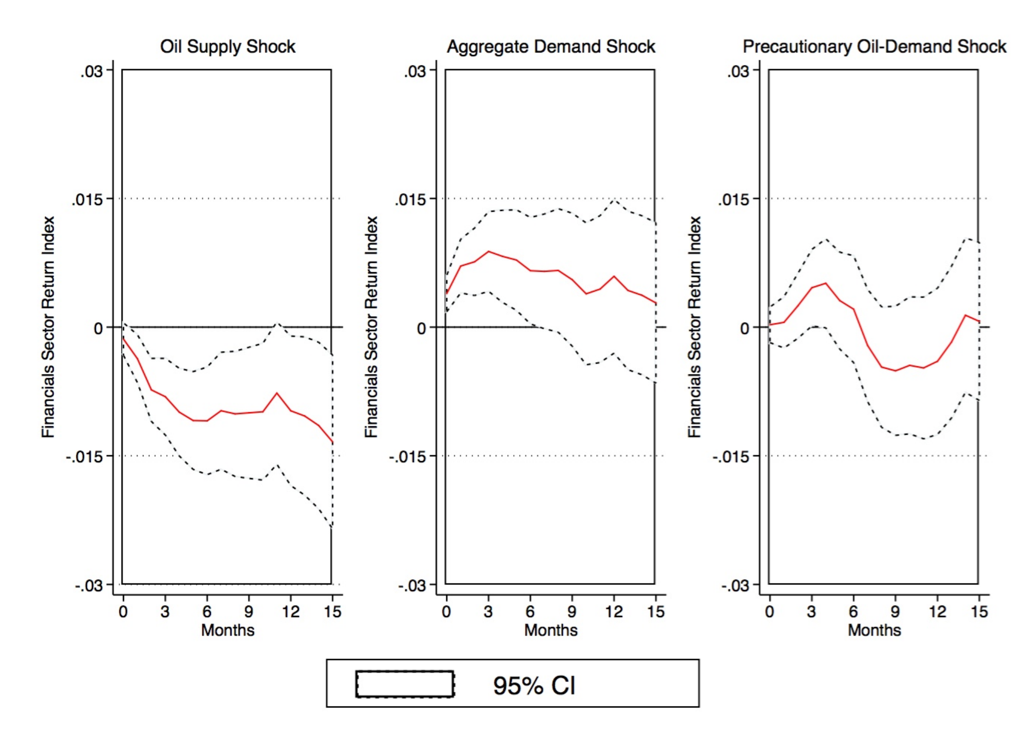


Figure 13: CUMULATIVE IMPULSE RESPONSE TO OIL MARKET SHOCKS OF FINANCIALS INDUSTRY/SECTOR INDEX. CONFIDENCE INTERVALS WERE CONSTRUCTED USING STANDARD RESIDUAL-BASED RECURSIVE-DESIGN BOOTSTRAP; SEE APPENDIX D FOR BOOTSTRAP ALGORITHM.

to each sector. With this in the background and the argument that oil and gas industry is also SIRS industry, the high level of financing by banks is reflected in this negative response of the financials industry due to their exposure to the oil and gas industry as well as the industrials, consumer discretionary and telecommunications industries. From the oil and gas responses, it was seen the oil disruption caused a negative and falling response, which was followed suit by the consumers in the domestic market with immediate oil demands, it can be safely argued that the financials industry's exposure to these industries is reflected above in panel 1. Although real estate sector is part of this industry, the financials industry is dominated by a large number of constituents that are banks. From observing the second panel, it is clear that an aggregate demand shock raises the return for this industry; it is also clear that the declining pattern towards the steady state is indicative of the growth-inhibiting effect of greater oil prices dominating the stimulating effect of an aggregate demand shock. The heavy exposure to all industries is likely the cause of the declining return index we observe above in the second panel. Finally, for the third panel, we observe a fluctuating response with narrow confidence intervals that follows the same pattern as that observed in the composite index response to precautionary demand shock. Here, the first increase in the return is likely because of the gains in the oil and gas industry, followed by the dominating losses in all the other industries that faced greater input costs due to higher oil prices. Observing this industry shows the great dependence of banks and financial markets on the large oil and gas industry as well as the smaller industries that also depend on the oil and gas industry of the Canadian economy.

After noting the responses of all seven industries, it became clear that industry compositions played a huge role in the way oil price shocks affected these indices. The response of the composite index can be supported with a deeper understanding of the dynamics of the industry-to-industry connections. It can be safely reported that observing these sectors easily broke down the questions that were raised regarding the difference in the Canadian aggregate response from other aggregate return responses. The results above showed that the type of consumers each industry contained was crucial to the interpretation of the responses. These consumer types were:

- Type 1: Consumers with immediate oil demands that have access to some substitutes in the market.
- Type 2: Consumers with immediate oil demands that have no access to substitutes in the market.
- Type 3: Consumers with long term oil demands.

A brief summary of the results is as follows. Given this breakdown of the consumers, the results of the impulse responses can be summarized as follows:

(1) The oil and gas industry is third most energy intensive industry. Since the domestic producers of crude oil face decreasing demand from type 1 consumers and type 2 consumers, the industry stock return index captures the decreasing levels of production in response and the overall impact from this shock is negative with some fluctuations in the index. Aggregate demand shock induces a positive and significant effect with hints of growth-inhibiting effect of greater oil prices which is the cause of more costly inputs for this energy intensive industry. Precautionary demand shock raises the returns in this industry since the price of oil has gone up due to greater demand.

(2) The materials industry is the most energy intensive industry and contains sectors that rely heavily on oil as inputs but also power generation sectors that supply resources which act as oil substitutes in some markets. With an oil disruption, consumers in these markets resort to the substitutes supplied by this industry, thus, leading to an overall positive response to the shock. With an aggregate demand shock, there is an initial positive response that is significant. Consumers in the markets with resources as substitutes (type 1) to oil do not alter their behaviour, the rising oil price causes input costs to rise leading to the fall of the return index back to the steady state level. The third shock leads to greater input costs, leading to lower returns by this energy intensive industry.

(3) The industrials industry responds negatively to an oil disruption shock and contains consumers of type 1. Since these consumers also have other substitutes that are limited, the industry index follows the same pattern as the domestic oil and gas industry. The response to an aggregate demand shock is positive and significant and the rise in the price of oil does not affect them as much given their access to substitutes. Similarly, the rise in the price of oil from the third shock does not affect them as negatively as other industries given their access to substitutes.

(4) The consumer staples industry responds only to an oil supply shock and does so negatively. This is argued to be due to the type 2 consumers that do not have access to substitutes. An oil supply shock inhibits the sectors of this industry to produce their goods as effectively. Due to the fact that the products of this industry are products that are essentials, their consumption is not affected by aggregate demand shocks or precautionary demand shocks. This result from the consumers of the products, the fact that this ranks the lowest in terms of energy intensiveness and the idea that oil, although essential, is used as inputs at a very low level such that price changes do not drastically increase input costs. Even though the automobile sector is included, this is likely a small portion of the total industry.

(5) The consumer discretionary industry has the second lowest ranking of energy intensiveness and contains sectors that are consumers of type 1. An oil supply shock affects this industry in the same way the industrials industry is affected. The difference is that these sectors respond to higher prices of oil but the responses are insignificant likely due to low levels of price elasticity. Thus, the response to aggregate demand shock is positive but insignificant and the response to precautionary demand shock is negative and insignificant.

(6) The telecommunications industry seems to also contain consumers of type 1 that have access to substitutes. An oil supply shock causes this industry to follow the returns to the energy sector closely as well but the negative effect is not as significant. The aggregate demand shock response is positive and signficant throughout. The precautionary demand shock response is somewhat negative but insignificant likely because of access to substitutes.

(7) The financials sector captures the responses of all the SIRS sectors in each industry including the oil and gas SIRS industry. The response to an oil supply shock is negative and significant throughout. The response to an aggregate demand shock is positive with hint of the dominating growth inhibiting effect of oil prices. Precautionary demand shock causes positive response in the oil and gas industry which is captured here with a positive initial response that is later dominated by the losses due to higher oil prices leading to a negative response for the remainder of the horizon.

Beyond the general interpretations, it was also found that SIRS sector played a large role especially in industries that were likely to have larger SIRS sectors such as the materials industry and the oil and gas industry itself. Even though the oil and gas industry did not explicitly experience a price reduction in crude oil, the symmetry of the impulse responses can be used to argue that a negative aggregate demand shock will likely affect the oil and gas industry the most as the response from Figure 7 panel 2 shows that this industry responded the most strongly to a positive aggregate demand shock along with telecommunications (which is also a SIRS industry). Using the SIRS model allowed us to narrow down the number of industries that will be affected by oil price shocks and it was clear that four things were crucial for the way each sector responded to the oil price shocks. First, it was important to understand the composition of the sectors in terms of the types of oil consumers which these industries consisted of. Second, it was crucial to understand whether an industry produced goods that were substitutes to oil in a given market. Third, it was imperative to know how energy intensive each industry is. Lastly, knowing the number and gauging the size of the SIRS sectors in non-SIRS industries helps to understand the magnitude of the responses. For example, it was known that the materials industry contained both the chemicals sector as well as the mining sector, which we knew contributed to the sensitivity to rises in input costs. This coupled with the fact that this industry is an energy intensive industry contributed to breaking down why the magnitude of the negative response to precautionary demand shock was so large. Therefore, researchers that wish to understand the relationship of oil price increases preceding recessions must know that this relationship involves understanding a number of moving parts and how they engage with one another. Depending on the dynamics of the industries in a given country, the results found may be entirely different than that of which was found above. Compiling what I believe to be reflective of the Canadian economy, it is clear that the cause of the oil price rise is severely important. In a Canadian context, given the models identifying assumptions and the dynamics of the oil market and its interactions with the Canadian economy, the most likely candidate shock (excluding a negative aggregate demand shock) to cause recessionary movements in the Canadian economy is unclear. This statement can be made for two reasons. First, given the financials industry response, it was clear that an oil disruption shock had a very large effect on the Canadian financial system as it was exposed severely to the oil and gas industry as well the industries that had large immediate oil demands (industrials, consumer discretionary and telecommunications), which followed the pattern of the oil and gas response. In an event with a more severe oil supply disruption shock that is persistent will likely cause multiple industries to collapse. On the contrary, there is argument that a precautionary demand shock would raise the costs of inputs for all sectors which brings us to the next argument. Second, it can also be argued that a more pronounced negative response was not observed since many of the SIRS sectors consisted of a portion of each industry and, thus, it was not clear how drastic the impact was on SIRS sectors and the devastating effect of a larger precautionary demand shock was not realized. Even without the SIRS sectors, it is commonly supported that precautionary demand shock raises the price of oil so significantly that a compilation of responses from a number of countries showed that this has the most recessionary impact (see Güntner (2014)). However, judging from the findings of this paper with Canadian sectors, this may be difficult to argue given the large role the oil and gas industry plays in this economy and the high level of exposure of the financials industry to the oil and gas sector and other industries that depend on it. Therefore, it is unclear which effect would dominate in its recessionary impact on the Canadian economy.

5 Conclusion

Having reviewed the current literature on oil price shocks, this paper aimed to decompose the economic influence of oil price shocks. It made three particular contributions. First, it addressed the lack of heterogeneity in using different indices for real economic activity to capture the cyclical movements of the global economy. It did this by implementing a FAVAR framework to generate a new index that captured co-movements of international macroeconomic variables. Second, it addressed the gap in literature of exclusive focus on the Canadian economy to explain the unconventional responses to oil price shocks. Third, it used the recently developed SIRS model by Crean and Milne (2014) to argue the recessionary impact of oil price shocks on the Canadian economy by breaking down industry responses and interpreting them. In conclusion, it was found that the Canadian economy's interesting industry interactions and its large oil and gas industry explained the behaviour of the aggregate stock return index since aggregate index responses behaved very similarly to the oil and gas industry responses. Each industry response was found to be dependent on the composition of the industry, the types of consumers in its sectors, whether the industry produced goods that were substitutes to oil in certain markets, the energy intensiveness of the industry and the number and potential size of the SIRS sectors in each. These points were crucial to the industry responses and their interpretations. Given these attributes, it was found that the industrials, consumer discretionary and telecommunications industries followed similar response patterns as that of the oil and gas industry. The financials industry was, thus, found to have a significantly negative response to a negative oil supply shock supporting its exposure to these industries in the context of the SIRS model. It is clear that both oil supply shock and precautionary demand shock in the crude oil market contributed to recessionary effects but it was unclear which shock was dominant; it was evident that this industry level dynamics contributed to the obscurity of the answer. Perhaps further research could progress the analysis of using SIRS sectors to explain recessionary movements to oil price shocks. Given the availability of sector-level data, an analysis of a country similar in industry composition and aggregate return responses as Canada can reveal the dominant recessionary effects amongst the oil price shocks.

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Appendices

A Static Factor Model Series and Transformations

All time-series variables used for the construction of the real economic activity index were obtained from OECD Database.[11] The following displays the variables used and the type. All series are monthly series spanning from 1990.01 to 2016.12. All series are first difference of logarithm. The entire data set for constructing the global economic activity index consists of 64 monthly series with missing observations of more than 1 in 16 series and only 1 in 9 series. Appendix C addresses the algorithm used to correct for data irregularities or missing values. The series are ordered such that developed OECD countries are reported in alphabetical order first, following measures for groups of countries belonging to some group and emerging economies reported in alphabetical order at the end.

	Series ID	Title	Data
1	Canada	Industrial Production Canada, Seasonally Adjusted	OECD
2	France	Industrial Production France, Seasonally Adjusted	OECD
3	Germany	Industrial Production Germany, Seasonally Adjusted	OECD
4	Japan	Industrial Production Japan, Seasonally Adjusted	OECD
5	Korea	Industrial Production Korea, Seasonally Adjusted	OECD
6	Mexico	Industrial Production Mexico, Seasonally Adjusted	OECD
7	Netherlands	Industrial Production Netherlands, Seasonally Adjusted	OECD
8	United Kingdom	Industrial Production U.K., Seasonally Adjusted	OECD
9	United States	Industrial Production U.S., Seasonally Adjusted	OECD
10	Euro 19	Industrial Production Euro 19, Seasonally Adjusted	OECD
11	EU 28	Industrial Production European Union, Seasonally Adjusted	OECD
12	G7	Industrial Production G7, Seasonally Adjusted	OECD
13	OECD - EU	Industrial Production OECD Euro, Seasonally Adjusted	OECD
14	OECD - TOT	Industrial Production OECD Total, Seasonally Adjusted	OECD
15	Brazil	Industrial Production Brazil, Seasonally Adjusted	OECD
16	Colombia	Industrial Production Colombia, Seasonally Adjusted	OECD
17	India	Industrial Production India, Seasonally Adjusted	OECD
18	Russia	Industrial Production Russia, Seasonally Adjusted	OECD

Table 2: Industrial Production Series

Of course, due to the quarterly frequency of GDP data, it could not be used without losing the validity of the identifying assumptions of the structural FAVAR aspect of the FAVAR model.

[11] See OECD website for access: `http://stats.oecd.org`

However, to maximize the number of series we use to maintain the asymptotic properties of the static factor model, we used export data and import data, both of which are reported below:

	Series ID	Title	Data
1	Canada	Exports in goods Canada, Seasonally Adjusted	OECD
2	France	Exports in goods France, Seasonally Adjusted	OECD
3	Germany	Exports in goods Germany, Seasonally Adjusted	OECD
4	Japan	Exports in goods Japan, Seasonally Adjusted	OECD
5	Korea	Exports in goods Korea, Seasonally Adjusted	OECD
6	Mexico	Exports in goods Mexico, Seasonally Adjusted	OECD
7	Netherlands	Exports in goods Netherlands, Seasonally Adjusted	OECD
8	United Kingdom	Exports in goods U.K., Seasonally Adjusted	OECD
9	United States	Exports in goods U.S., Seasonally Adjusted	OECD
10	Euro 19	Exports in goods Euro 19, Seasonally Adjusted	OECD
11	EU 28	Exports in goods European Union, Seasonally Adjusted	OECD
12	G7	Exports in goods G7, Seasonally Adjusted	OECD
13	OECD - EU	Exports in goods OECD Euro, Seasonally Adjusted	OECD
14	OECD - TOT	Exports in goods OECD Total, Seasonally Adjusted	OECD
15	Argentina	Exports in goods Argentina, Seasonally Adjusted	OECD
16	Brazil	Exports in goods Brazil, Seasonally Adjusted	OECD
17	China	Exports in goods China, Seasonally Adjusted	OECD
18	Colombia	Exports in goods Colombia, Seasonally Adjusted	OECD
18	Costa Rica	Exports in goods Costa Rica, Seasonally Adjusted	OECD
19	India	Exports in goods India, Seasonally Adjusted	OECD
20	Indonesia	Exports in goods Indonesia, Seasonally Adjusted	OECD
21	Lithuania	Exports in goods Lithuania, Seasonally Adjusted	OECD
22	Russia	Exports in goods Russia, Seasonally Adjusted	OECD
23	South Africa	Exports in goods South Africa, Seasonally Adjusted	OECD

Table 3: Exports in Goods Series Including Emerging Economies

The export table adds a number of series not available in the industrial production table. These series include China, Costa Rica, Lithuania, South Africa and Argentina taking into account trade movements of these countries as well. From Table 1, India and Russia had more than 1 missing values, whereas Colombia had only one missing values. From Table 2, there were European Union, OECD-Total, China, Colombia, Costa Rica, Lithuania and Russia with missing values of more than one, whereas Euro 18, Argentina, India and Indonesia had only one missing value. It was likely that the OECD-Total had a fair share of missing values due to missing values in the beginning of the data set for some of the countries. All missing values for each series started in the beginning of the data set and spanned for some months until these countries began keeping track of these measures. The import table below (Table 4) reported missing values for the same series as in the export table.

It was also likely the case that the countries did not keep track of these measures until the time OECD began their reports.

	Series ID	Title	Data
1	Canada	Imports in goods Canada, Seasonally Adjusted	OECD
2	France	Imports in goods France, Seasonally Adjusted	OECD
3	Germany	Imports in goods Germany, Seasonally Adjusted	OECD
4	Japan	Imports in goods Japan, Seasonally Adjusted	OECD
5	Korea	Imports in goods Korea, Seasonally Adjusted	OECD
6	Mexico	Imports in goods Mexico, Seasonally Adjusted	OECD
7	Netherlands	Imports in goods Netherlands, Seasonally Adjusted	OECD
8	United Kingdom	Imports in goods U.K., Seasonally Adjusted	OECD
9	United States	Imports in goods U.S., Seasonally Adjusted	OECD
10	Euro 19	Imports in goods Euro 19, Seasonally Adjusted	OECD
11	EU 28	Imports in goods European Union, Seasonally Adjusted	OECD
12	G7	Imports in goods G7, Seasonally Adjusted	OECD
13	OECD - EU	Imports in goods OECD Euro, Seasonally Adjusted	OECD
14	OECD - TOT	Imports in goods OECD Total, Seasonally Adjusted	OECD
15	Argentina	Imports in goods Argentina, Seasonally Adjusted	OECD
16	Brazil	Imports in goods Brazil, Seasonally Adjusted	OECD
17	China	Imports in goods China, Seasonally Adjusted	OECD
18	Colombia	Imports in goods Colombia, Seasonally Adjusted	OECD
18	Costa Rica	Imports in goods Costa Rica, Seasonally Adjusted	OECD
19	India	Imports in goods India, Seasonally Adjusted	OECD
20	Indonesia	Imports in goods Indonesia, Seasonally Adjusted	OECD
21	Lithuania	Imports in goods Lithuania, Seasonally Adjusted	OECD
22	Russia	Imports in goods Russia, Seasonally Adjusted	OECD
23	South Africa	Imports in goods South Africa, Seasonally Adjusted	OECD

Table 4: Imports in Goods Series Including Emerging Economies

There was no major difference across the import and export tables. All of the series were seasonally adjusted. To correct for these missing values, the expectation-maximization method was employed accordingly. This is reported in Appendix C.

B Principal Components Estimation of Factor in Static Factor Model

The estimated factors $\tilde{\boldsymbol{F}}$ are given by the eigen-vector corresponding to the r largest eigen-values ($r = 1$) of $\dfrac{\boldsymbol{X}\boldsymbol{X}'}{\boldsymbol{T}\boldsymbol{N}}$ where $\boldsymbol{X}$ is $T \times N$ matrix of all the series. The corresponding factor loadings are given by:

$$\tilde{\boldsymbol{\Lambda}} = \boldsymbol{X}'\tilde{\boldsymbol{F}}(\tilde{\boldsymbol{F}}'\tilde{\boldsymbol{F}})^{-1} = \frac{\boldsymbol{X}'\tilde{\boldsymbol{F}}}{\boldsymbol{T}} \tag{7}$$

The problem with principal component estimation of the factor in a static factor model is that the following two specifications are observationally equivalent. In other words, it is difficult to identify which of these two specifications represent what is being observed:

$$\boldsymbol{X} = \boldsymbol{F}\boldsymbol{\Lambda}' + \boldsymbol{e} \tag{8}$$

$$\boldsymbol{X} = (\boldsymbol{F}\boldsymbol{A}^{-1})(\boldsymbol{A}\boldsymbol{\Lambda}') + \boldsymbol{e} \tag{9}$$

However, it is clear that the following inequality may be the case in certain instances:

$$\boldsymbol{X} = \boldsymbol{F}\boldsymbol{\Lambda}' + \boldsymbol{e} \neq (\boldsymbol{F}\boldsymbol{A}^{-1})(\boldsymbol{A}\boldsymbol{\Lambda}') + \boldsymbol{e} = \boldsymbol{X} \tag{10}$$

Given the identification problem above, it crucial to impose certain restrictions to identify the factors appropriately. Note that we identify the factors using the restriction that $\frac{\boldsymbol{F}'\boldsymbol{F}}{\boldsymbol{T}} = \boldsymbol{I_r}$. Therefore, $\frac{\tilde{\boldsymbol{F}}'\tilde{\boldsymbol{F}}}{\boldsymbol{T}} = \boldsymbol{I_r}$.

C Expectation-Maximization Algorithm for Data Irregularities

Given that there were 16 variables with more than 1 missing values and 9 series with 1 missing value, I employed the EM algorithm to account for these missing values. The following set of steps artificially generates the potential values of those missing. This is an important step as it helps to generate values for emerging economies in the data set that had many missing values.

(1) Find an $T \times N^*$ sub-matrix $\boldsymbol{X^*}$ from the $T \times N$ matrix such that $\boldsymbol{X}^*$ has no missing values. In this case $N^* < N$.

(2) Estimate the number of factors r summarizing the information in $\boldsymbol{X}^*$ (using the procedure in Bai and Ng (2002)) and estimate the corresponding factors $\tilde{\boldsymbol{F}}_{(1)} : T \times r$ and factor loadings $\tilde{\boldsymbol{\Lambda}}_{(1)} : N^* \times r$.

(3) Estimate new factor loadings $\tilde{\boldsymbol{\Lambda}}^*_{(1)} : N \times r$ based on $\boldsymbol{X}_{(1)} : T^* \times N$ (which replace missing values by 0) and $\tilde{\boldsymbol{F}}_{(1)}$. More precisely, we regress $\boldsymbol{X}_{(1)}$ on $\tilde{\boldsymbol{F}}_{(1)}$ to have:

$$\tilde{\boldsymbol{\Lambda}}^*_{(1)} = \boldsymbol{X}'_{(1)}\tilde{\boldsymbol{F}}_{(1)}(\tilde{\boldsymbol{F}}'_{(1)}\tilde{\boldsymbol{F}}_{(1)})^{-1} \tag{11}$$

(4) Obtain the dataset: $\underbrace{\boldsymbol{X}^*_{(1)}}_{T\times N} = \underbrace{\tilde{\boldsymbol{F}}_{(1)}}_{T\times r}\underbrace{\tilde{\boldsymbol{\Lambda}}^{*\prime}_{(1)}}_{r\times N}$. Replace the missing values in $\boldsymbol{X}$ by their estimates from $\boldsymbol{X}^*_{(1)}$ to obtain a new dataset $\boldsymbol{X}_{(2)}$ without any missing values.

(5) Compute estimated factors $\tilde{\boldsymbol{F}}_{(2)}$ and factor loadings $\tilde{\boldsymbol{\Lambda}}_{(2)}$ from $\boldsymbol{X}_{(2)}$ and compute the average of squared idiosyncratic residuals:

$$\tilde{\boldsymbol{V}}_{(2)} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}(X_{(2)ti} - \tilde{F}_{(2)t}\tilde{\Lambda}_{(2)i})^2 \tag{12}$$

(6) Iterate step 4 to 5 until the average sum of squared residuals $\tilde{\boldsymbol{V}}$ converges to its minimum. We identify this minimum when $|\tilde{\boldsymbol{V}}_l - \tilde{\boldsymbol{V}}_{l-1}| < 10^{-6}$, where l is the l^{th} iteration and 10^{-6} is the tolerance level to signal the end of the iterations.

D Standard Residual-Based Recursive-Design Bootstrap Algorithm

For each figure displaying the responses to structural shocks, I employed a standard residual-based recursive-design bootstrap to accurately generate 95% confidence intervals.[12] Bootstrap applications provide several advantages:

(A) Application of bootstrap methods allows researchers to make inferences about smooth differentiable functions $g(\boldsymbol{\alpha}, \boldsymbol{\sigma})$ even when closed-form solutions of the variance of the given estimator is impossible to produce.

(B) This methodology is also much more general than standard asymptotic inference. In some cases where obtaining a closed-form solution of the variance of a structural impulse response estimator relies on the errors being independently and identically distributed with mean zero ($u_t \overset{iid}{\sim} \mathcal{N}(0, 1)$), a standard residual-based recursive-design bootstrap estimator remains valid even under weaker conditions.

(C) Confidence intervals constructed using bootstrap methodology tends to be at least equally accurate in small samples compared to asymptotic approximations.

(D) In other instances, employing bootstrap methods can improve the accuracy of asymptotic approximations.

Given these advantages, we employ the standard residual-based bootstrap for constructing the confidence intervals for the cumulative structural impulse responses in IRF figures above. Let $u_t \overset{iid}{\sim} F$, where F is a given distribution and specify the bootstrap data generating process :

$$z_t^* = \hat{\alpha} + \hat{A}_1 z_{t-1}^* + \ldots + \hat{A}_p z_{t-p}^* + u_t^* \tag{13}$$

where $u_t^* \overset{iid}{\sim} \hat{F}_t$. The parameters above denote least squares estimate of the model parameters conditional on the observed sample $\{z\}_{t=1-p}^{T}$. The distribution $\hat{F}_t$ is an estimate of the error distribution F_t and assume that the $\mathbb{E}(u_t) = 0$ and that u_t has finite moments. We do not impose any parametric

[12] See Kilian and Lütkepohl (2016) chapter 12 for extensive discussion on bootstrap theory and various types typically employed in economic analysis.

assumptions on the estimator $\tilde{F}_t$ (but it can be parametric) because if the parametric assumption is wrong, it reflects on the accuracy of bootstrap inference, whereas making an assumption does not reflect a noticeable efficiency gain. Since we do not know the parametric family of the distribution of the error term $\hat{F}_t$, we draw u_t^* with repalcement from the set of residuals $\{\hat{u}\}_{t-1}^{T}$ where $\hat{u}_t = z_t - \hat{\alpha} - \hat{A}_1 z_{t-1} - \ldots - \hat{A}_p z_{t-p}$ to ensure that $(u_t^*|Data)$ is *iid* and has the same distribution as the empirical distribution of the residuals. A simple procedure is outlined below:

(1) For a univariate AR(p) process, given the *iid* process for u_t, identify $\hat{u}_t$ to be a set of one sample realization of the *iid* process. The objective is to replicate this sampling process conditional on the observed set of residuals. From Kilian and Lütkepohl (2016), consider the vector $\hat{u}$ of residuals $\hat{u}_t$. Specify a uniform distribution over the set of integers $1, ..., T$ in the index (*index*) below to ensure the sample probability $1/T$ of being chosen. A new index is then created for each bootstrap replication $r = 1, ..., R$ of length T ($index^{*r}$) by scaling T draws from a random number generator defined on a given interval (here the interval can be [0,1]) by T and rounding the results to form a column vector. The elements of u^{*r} are elements in $\hat{u}$, where the index provides the row number.

$$index = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{pmatrix}, \hat{u} = \begin{pmatrix} 0.10 \\ -0.22 \\ 0.35 \\ 0.01 \\ -0.40 \end{pmatrix} \Longrightarrow index^{*r} = \begin{pmatrix} 5 \\ 2 \\ 4 \\ 3 \\ 5 \end{pmatrix}, u^{*r} = \begin{pmatrix} -0.40 \\ -0.22 \\ 0.01 \\ 0.35 \\ 0.40 \end{pmatrix}$$

According to Kilian and Lütkepohl (2016), this process should destroy any stochastic dependence among the residuals $\hat{u}_t$ and ensures that u_t^* is *iid* consistent with u_t being *iid*. The objective of drawing for u_t^* is to recreate the process that generated the sample we observe $\{z_t\}_{t=1-p}^{T}$, where the bootstrap DGP is a proxy for the unknown DGP.

(2) To use the standard approach, draw the initial conditions $[z_{1-p}^*, \ldots, z_0^*]$ at random with replacement as a block of $p = 24$ consecutive vector-valued observations from the observed data and for each $r = 1, \ldots, R$, select a new draw for $[z_{1-p}^*, \ldots, z_0^*]$ to ensure that the pre-sample observations are drawn from the same distribution as the rest of the observations without any parametric assumptions made. Due to stationarity, the approximation error declines with T; $p = 24$ and $T = 324$ in our sample.

(3) Given the random draws for u_t^{*r} and the initial conditions $[z_{1-p}^{*r}, \ldots, z_0^{*r}]$, generate as many sequences of bootstrap realizations $\{z_t\}_{t=1-p}^{T}$ as required. Recursively generate for each bootstrap replication $r = 1, \ldots, R$, a sequence of bootstrap realizations $\{z_t^{*r}\}_{t=1-p}^{T}$ as

$$z_1^{*r} = \hat{\alpha} + \hat{A}_1 z_0^{*r} + \ldots + \hat{A}_p z_{1-p}^{*r} + u_1^{*r},$$

$$\vdots$$

$$z_T^{*r} = \hat{\alpha} + \hat{A}_1 z_{T-1}^{*r} + \ldots + \hat{A}_p z_{T-p}^{*r} + u_T^{*r},$$

where r represents the r^{th} bootstrap replication. Since the interest is in the bootstrap estimate of the variance of an estimator. This paper uses 399 replications. Furthermore, R is so large that the approximation error can be safely ignored.

(4) Given the data $\{z_t^{*r}\}_{t=1-p}^{T}$ for $r = 1, \ldots, R$, fit the FAVAR(p) model with intercept and obtain the least squares estimates $[\hat{\alpha}^{*r}, \hat{A}_1^{*r}, \ldots, \hat{A}_p^{*r}]$ and Σ_u^{*r} to construct the bootstrap estimates $\hat{\theta}_{ik,h}^{*r}$ for each replication of the structural impulse responses.

(5) From the bootstrap approximation of the empirical distribution of the structural response estimates $\hat{\theta}_{ik,h}$, construct the confidence intervals. This paper constructs the following 95% confidence interval:

$$[\hat{\theta}_{ik,h,0.025}^{*}, \hat{\theta}_{ik,h,0.975}^{*}]$$

with $\hat{\theta}_{ik,h,0.025}^{*}$ being the lower bound and $\hat{\theta}_{ik,h,0.975}^{*}$ as the upper bound.

E Forecast Error Variance Decomposition of Sector Responses

The interpretations made in the paper on the responses of each industry to the shocks were made using the below forecast error variance decompositions as evidence of the magnitudes of the responses. These provided further support for the inferences made on the significance of each shock. The forecast error variance decomposition displays how much of the prediction mean squared error of each variable at a give horizon is accounted for by each of the structural shocks. To generate these, I referred to Chapter 4 of Kilian and Lütkepohl (2016) text.

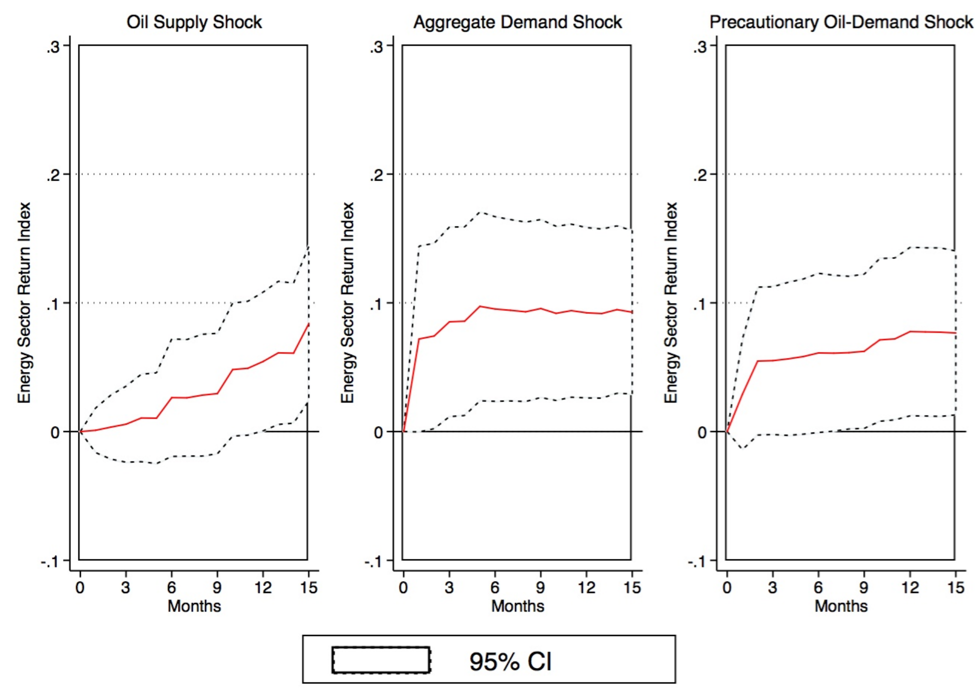

Figure 14: FORECAST ERROR VARIANCE DECOMPOSITION OF ENERGY INDUSTRY/SECTOR INDEX RESPONSES.

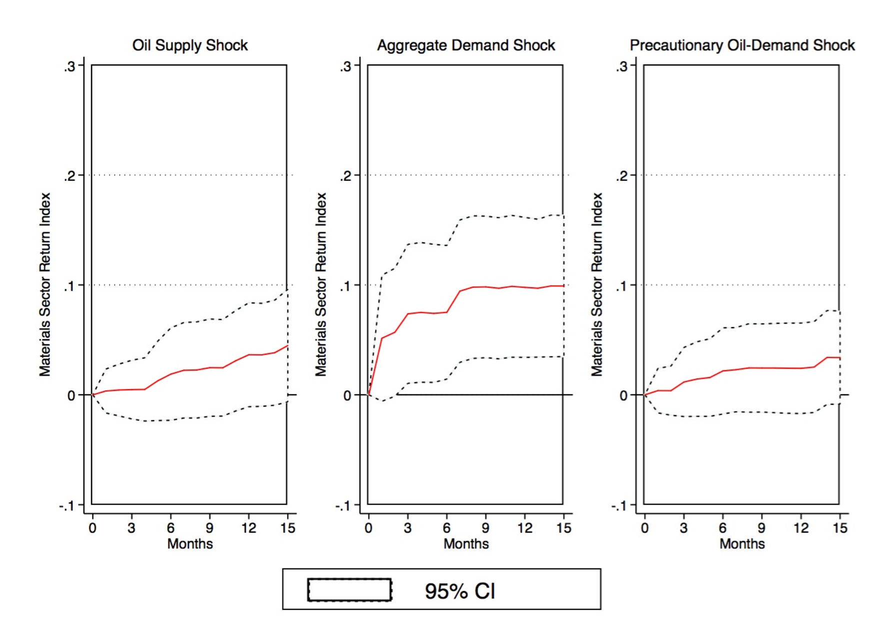

Figure 15: FORECAST ERROR VARIANCE DECOMPOSITION OF MATERIALS INDUSTRY/SECTOR INDEX RESPONSES.

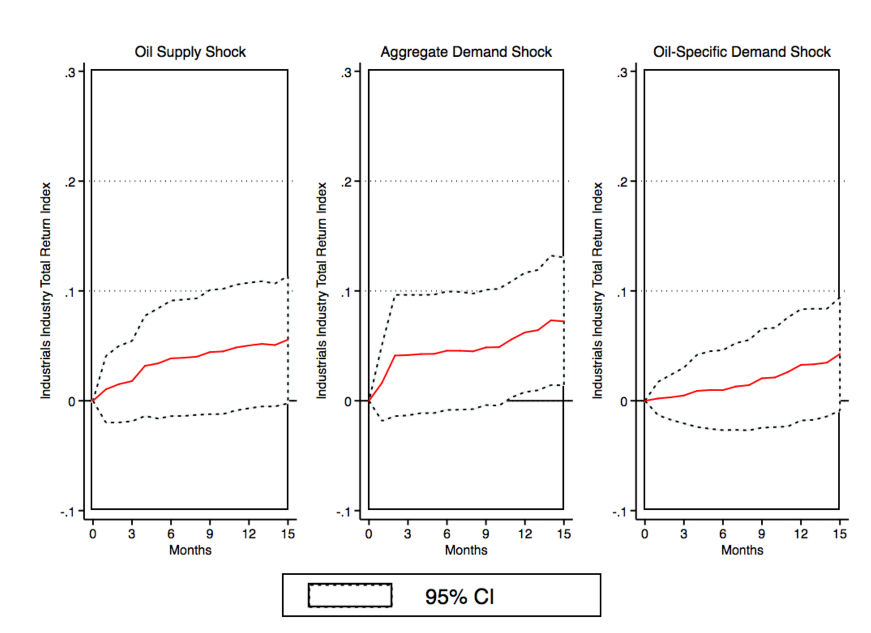

Figure 16: FORECAST ERROR VARIANCE DECOMPOSITION OF INDUSTRIALS INDUSTRY/SECTOR INDEX RESPONSES.

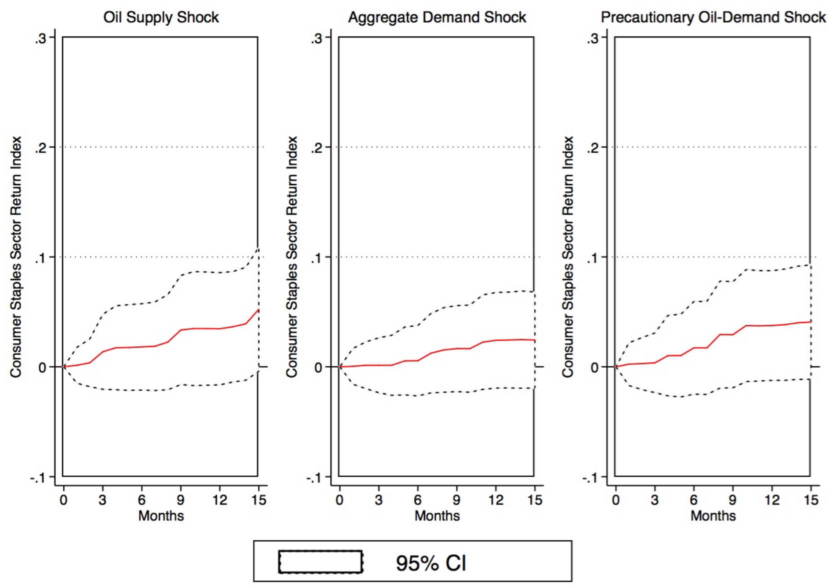

Figure 17: FORECAST ERROR VARIANCE DECOMPOSITION OF CONSUMER STAPLES INDUSTRY/SECTOR INDEX RESPONSES.

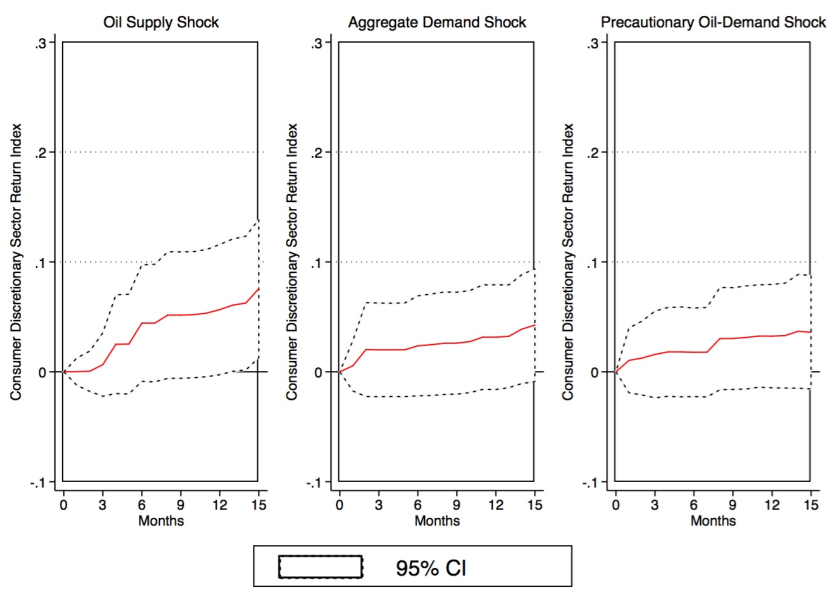

Figure 18: FORECAST ERROR VARIANCE DECOMPOSITION OF CONSUMER DISCRETIONARY INDUSTRY/SECTOR INDEX RESPONSES.

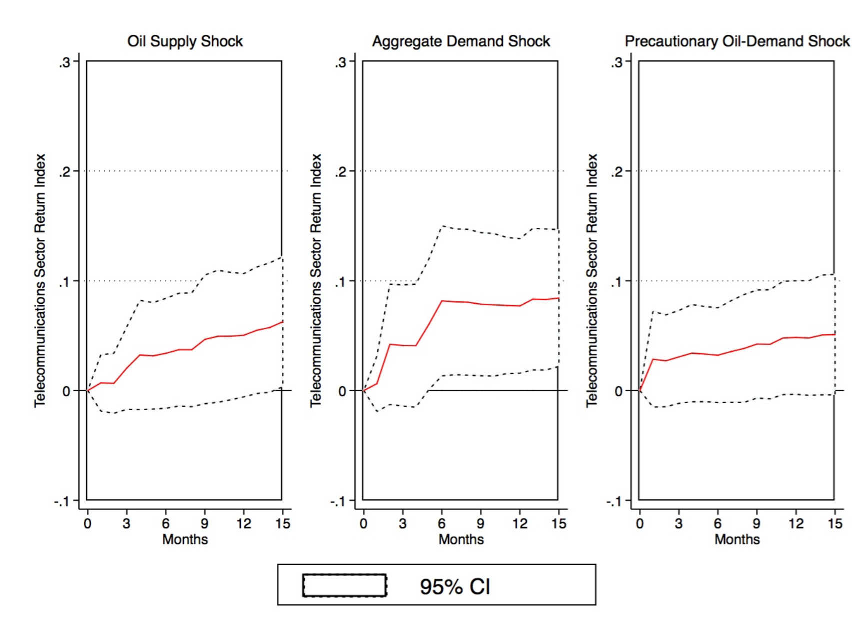

Figure 19: FORECAST ERROR VARIANCE DECOMPOSITION OF TELECOMMUNICATIONS INDUSTRY/SECTOR INDEX RESPONSES.

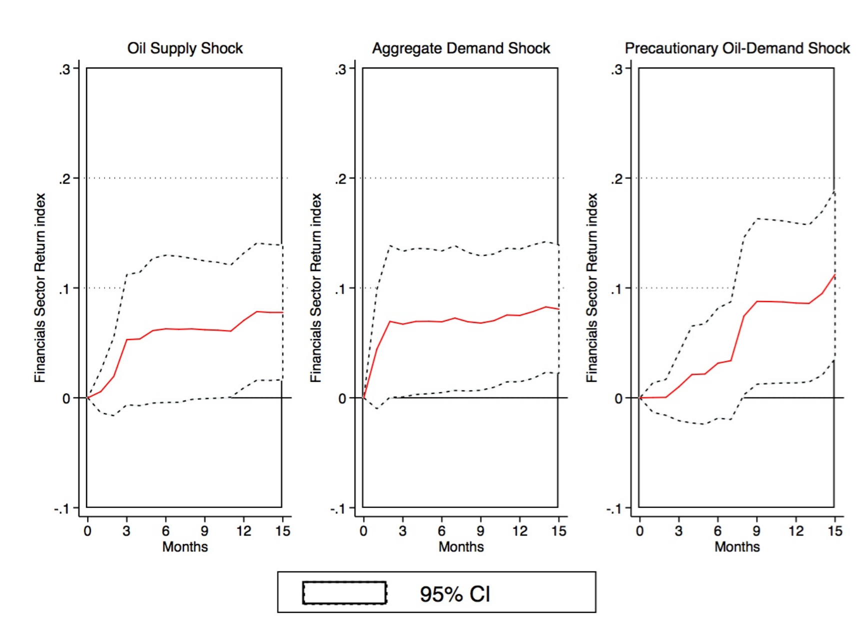

Figure 20: FORECAST ERROR VARIANCE DECOMPOSITION OF FINANCIALS INDUSTRY/SECTOR INDEX RESPONSES.