THE INFLUENCE OF OIL PRICE SHOCK ON THE CANADIAN STOCK MARKET

by

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Abstract

This paper conducts an empirical study on the influence of international oil price volatility on the Canadian stock market. Additionally, it addresses the influences of oil price shock vary among stocks in different sectors and stocks with different size of the market value.

By using the SVAR model, we conduct model stationary test, lag period selection, impulse response analysis to give the empirical results. We conclude from the results that oil price shock has a positive impact on the overall stock market in Canada. Moreover, we find that the influence of oil price shock has the similar pattern on both stocks with large market value and small market value, but stocks with small market value are more responsive to the oil price shock. We also find the oil price shock had a major influence in the stock price on the energy sector in Canada, but the influence only lasted for one month according to our study. There was a non-negligible effect on the stock price in material sectors, and the influence lasted for four months. For other sectors, we do not find great influences.

Key words: Oil price shock, Canadian stock market, SVAR, IRF

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1. Introduction

Over the past decade and more, global oil consumption has been increasing, and the international oil market environment has become more complex and volatile. The price level of Brent crude, for example, which plays an important role in global oil pricing, has fluctuated sharply between $34.7 and $125.89 for the recent ten years. As one of the most crucial sources of energy, crude oil has the dual role as production factors and consumer goods. The dramatic uncertainty in oil prices have also brought uncertainty to the entire oil market and the major economics worldwide, which further leads the financial markets to react to the change. Existing literatures has been long contributed to investigate the oil prices change and the macroeconomics of the country. For example, Hamilton (1983) explored the relationship using the data of the United States from 1949 to 1972, and found that 7 of the 8 economic recessions experienced by U.S. were accompanied with the oil prices rising, highlighting the importance of oil prices change to the country's macro economy. Researchers have done a lot on the investigation of oil price changes on macroeconomic variables in various countries and regions.

However, unlike a large number of literatures that focus on the impact on macroeconomic, analyses about the impact on the performance of stock market are still growing, and the conclusion of these studies is still controversial. Also, most of the literatures investigate in the impact on big oil importers, such as US and China, little can be found for oil exporters. Furthermore, few researchers study on the differences of influence on different sectors.

Hamid Sakaki (2019) use the data of US to do empirical study about the influence of oil price shock on stock returns, and also check the impact on returns of different sectors.

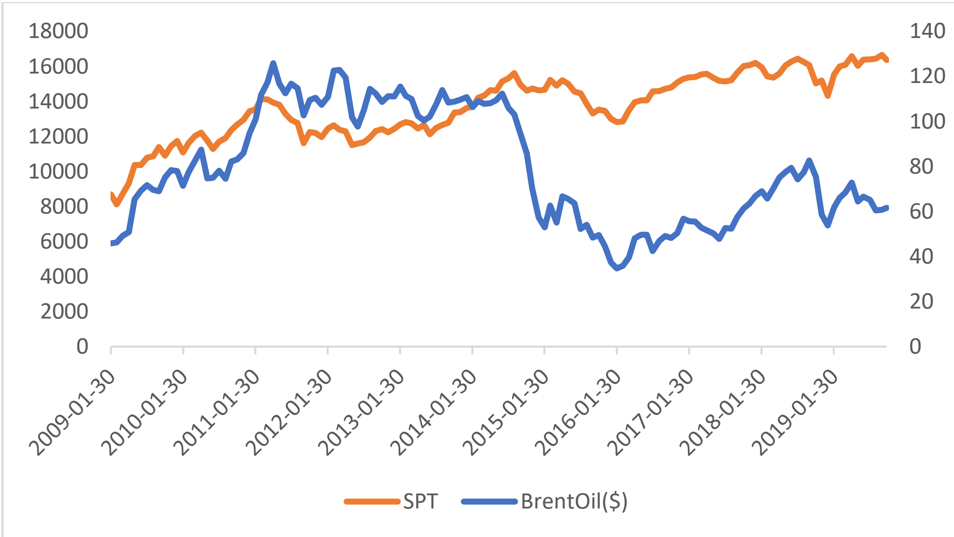
Our paper is a supplement in exist literature by extending empirical research done by Hamid Sakaki to the financial market of Canada, the net oil exporter country. Also, we further contribute to the exist literature by disaggregating the market's reaction into different sectors and size of market value, analyzing and comparing the effect on each segment's return with the data of the Canadian stock market. To address the dynamic relationship between stock performance and oil prices, we use SVAR model, which is widely agreed to be more accurate than VAR model in shock and impact analysis. Then we do impulse response analysis to estimate the shock to different sectors.

2. Description of oil price change and stock market

From the performance of the oil market during this period, we can see that the price of crude oil was quite low in January 2009 due to the financial crisis in 2008. Then, when OPEC members implemented the agreement to reduce production, the market began to recover and the oil price gradually increased. Until May 2011, the oil price increased to $125.89. In this period, the Toronto composite index also shows the same pattern, which moved the same direction as the oil price. During the mid of 2011 to July 2014, the oil price fluctuated between $101.87 and $122.8. Meanwhile, the stock also fluctuated around 12000, showing no significant correlation with the oil price. Later in 2014, the crude oil market was under the influence of the economic downturn, and the demand was insufficient, thus the price dropped sharply. At that time, the stock market also shows a downtrend, which is not so dramatic but still move together with the oil price change. In recent five years, the change of crude oil price and stock prices almost show the same pattern.

From the fluctuation trend of crude oil price and stock price, we can see that there are a certain relationship and an interactive influence between the two.

Figure1. *Brent crude oil price and Toronto composite index change chart*



3. Literature Review

3.1 Evidence of the influence of oil prices change on stock markets

Many researchers think there is a significant influence of oil price shock on stock market performance. For example, Jone & Kaul (1996) analyzed the influence of oil price shock on stock market in several countries. Finally, the author finds that this effect exists in the US and Canadian markets. Also, Sadorsky (1999) drew conclusion that both oil price and its volatility had significant influences on the stock market by using data of the American market with the VAR model. Ciner (2001) reached the same conclusion through the test of causality and further found the existence of nonlinear correlation. Park & Ratti (2008) extended the research to countries in Europe using the data from 1986 to 2005. This study verified the significant influence on the stock returns of the current month and one month after the lag.

However, there are also a few scholars' researches show that the influence is small or insignificant. Apergis & Miller (2009) used the data of eight developed countries and found that although there was an influence of oil on the equity market, the influence was relatively small. Miller & Ratti (2009) analyzed the relationship through a long-term perspective and concluded that before 1999, the oil price shock had a significant negative effect on the stock market, but this effect no longer existed after 1999.

3.2 Evidence of the influence on oil-exporting and importing countries

There are two potential channels how the oil price shock affects the stock market. First, we know from the asset pricing theory that the price of one stock is the sum of the discounted future cash flows. Since oil is a vital input of enterprises, once the oil price rises, it can lead the costs to increase, thus the profit will decrease, which affecting future cash flow and causing changes in stock price (Jones and Kaul, 1996; Sadorsky, 1999). Second, the theory of wealth transfer is another possible way to explain the influence. It shows that the increase of oil prices will lead to a transfer of wealth from people in oil importers to people in oil exporters (Fried & Schulze, 1975; Dohner,1981).

So, rising oil prices are expected to have a positive influence on oil exporters as the country's wealth increases (Bjornland, 2009). Higher incomes are expected to result in higher spending and investment, thereby there would be a positive reaction in the equity market. For those oil importers, any increase of oil prices would have the opposite effect. Higher oil prices will raise costs for businesses and pass them on to consumers. Lower consumption further leads to lower production and higher unemployment, so the stock market will react negatively (Lardic and Mignon, 2006).

3.3 Evidence of the influence of oil prices changes on sectoral stock markets

Some scholars have explored the relationship between the stock market and the shock of oil price from the perspective of industries. Based on existing researches, changes of oil prices have different effects on stocks in different industries. Specifically, Faff & Brailsford(1999) did research on the relationship between oil prices and stocks of different industries in Australia and proved the differences of influence, among which there was a positive influence on stocks of energy-related companies, and a negative influence on banking, paper and packaging, and transportation sector. Sadorsky (2001 and 2003) examined the influence on sector-level stocks in Canada and the US respectively, concluding that the oil price shock has a great effect on the stock returns of

Canadian oil and gas industry. For the US market, the correlation between the price of oil and technology stocks between 1986 and 1999 was found to be significant. Boyer & Filion (2007) also did the same research on the Canadian stock market using the multi-factor model, they found that the increase of oil prices had a positive influence on the stocks in energy industry. Most recent researches like Hamid Sakaki (2019) found that all sectors are negatively affected by oil prices changes, even the oil-related and oil substitutes sectors.

4. Specify the model

Structural VAR (SVAR) model is chosen as the optimal underlying model to conduct our research because the oil price and stock price interact with each other. The stock price can be affected by its momentum as well as the contemporaneous and lagged terms of oil price. On the other side, stock price can have a noticeable impact on the economy and, therefore, affects oil demand and price. Thus, it is hard to solely separate oil price as an endogenous variable. Classic multivariable regression requires strict endogenous variables, if not, the result would be misleading.

By using SVAR model, variables and dependent variables are input into a dynamic system where both independent and dependent variables can be treated as endogenous variables. Besides, the impact of oil price shock can be captured by SVAR model, through which the impact can be identified both in magnitude and steps by using impact response function (IRF).

4.1 Background information about SVAR model

VARs model was popularized in econometrics by Christopher A. Sims in "Macroeconomics and Reality" (1980), where he presented an alternative regression model described as a "multi-variables dynamic system" and latterly recognized as VARs model. A typical VAR model has the following structure:

$$y_t = A_0 + A_1 y_{t-1} + \cdots + A_k y_{t-k} + e_t \qquad E(e_t e_t') = \Sigma \tag{1}$$

where y_t is a vector of variables, $A_k$is coefficient matrix, k is the lag in the model, e_t contains error terms, and Σ is the covariance matrix of errors.

The simple VAR provides a compact summary of second-order moments of the data. However, the VAR model is unsatisfactory that it only estimates predetermined lags, not contemporaneous impact. According to economic theories, price indexes are often connected contemporaneously. A VAR allows the contemporaneous impact is written as follows:

$$Ay_t = C_0 + C_1 y_{t-1} + \cdots + C_k y_{t-k} + e_t \qquad (2)$$

where A is one of the boundary matrices that captures the contemporaneous relationship, and coefficient matrices C are generated from the A_k in the reduced form VAR.

However, this model is still unsatisfactory because its error terms are correlated. In order to solve this problem, we can write the error term as a linear combination of underlying structural shocks u_t , which can decompose these error terms into mutually orthogonal shocks. So we can get:

$$e_t = Bu_t \qquad (3)$$

So, the estimation of VAR now is extended to Structural VAR, which includes the contemporaneous impact and removes the impact of related error:

$$Ay_t = C_0 + C_1 y_{t-1} + \cdots + C_k y_{t-k} + Bu_t \qquad (4)$$

In order to construct a SVAR model, we need to estimate A, B, and C_i separately.

4.2 The advantages and application of SVAR

SVAR model is widely agreed to be more accurate than the VAR model in shock and impact analysis, given the follow reasons.

Upon introducing contemporaneous terms to the VARs model, SVAR can embody the simultaneous impact and lagged impact together; therefore, it can build up a more accurate multivariate dynamic system. On the contrary, the VAR model is unsatisfactory that it only estimates predetermined lags, not contemporaneous impact. Variables are often connected contemporaneously; thus, SVAR would lead to a better model to estimate the relationship between different variables.

The second advantage of SVAR lies in the most criticized part of the VAR model that it assumes the interaction between variables is theoretically meaningful in the economy. Ground theoretical information is needed to construct a SVAR model. Moreover, there are two boundary matrices in SVAR, one for the contemporaneous terms and the other one orthogonalize the error terms. Researchers can decide the boundary matrices based on economic theorem and, therefore, the SVAR model can be more theoretically permissible.

The third improvement by the SVAR model is that its error terms are uncorrelated. Uncorrelated error terms are extremely important in IRF analysis. When analyzing shock behavior, researchers cannot determine a valid relationship if the shock to one equation is associated with the shock in another equation.

SVAR has been a popular multivariate modeling tool since it was introduced to econometrics analysis. Some scholars applied SVAR to analyze the impact of government policy on economic behavior. For example, Olivier Blanchard and Roberto Perotti (2002) studied the effects of shocks in government spending and taxation on US economic activity level by using mixed SVAR. In recent years, more scholars are focusing on explaining shocks in the stock market, especially the impact of oil price shock. Lutz Kilian and Cheolbeom Park (2007) wrote a paper on the oil shock in the US stock market prior to the Financial Crisis. The two scholars used SVAR model to build the relationship between supply, demand, and price of oil. Xuhui Ding and Liuyuan Wang (2017) reapplied the SVAR model on an emerging market to study oil price and stock price fluctuation. Hamid Sakaki (2019) constructed the SVAR model on oil price and stock index in the US.

5. Data

Based on different analyses we proposed, our data are sorted into two parts. The first part aims at studying the influence of oil shock on stocks with different market size. We use monthly data covering 2009 to 2019, including the Brent oil price, S&P Toronto Stock Exchange Index (SPT), and S&P Toronto Stock Exchange Small Market Value Stock Index (SPTSXS). The second part involves sector analysis which studies the impact of the oil shock in different industries. The data set contains monthly data from 2009 to 2019, including energy sector (SPTSEN), industry sector (SPTSIN), utility sector (SPTSUT), material sector (SPTSMT), communication service sector (SPTSTS), information technology sector (SPTSIT), real estate sector (SPTSRE), and financial service sector (SPTSFN). We divided these sectors into two large categories, service group and production group. And inside the production group, we classified the data as upstream, midstream and downstream sectors according to the dependence on crude oil. A more visualized classification is shown in the following chart.

Table1. *Sector Classification Overlook*

	Upstream	**Midstream**	**Downstream**
Production	Energy	Industry Material	Real estate
Service	Utility Financial Service	Communication Service Information Technology	

All the data are sourced from Bloomberg. The motivation for choosing data from 2009 to 2019 is that most of the existed studies focus on crisis time and few pay attention to the post-crisis period. Moreover, we prefer to analyze the oil shock and stock price in a relatively stable period, thus other exogenous factors, like the impact from Financial

Crisis, can not interfere with our study result, and we could draw a generalized conclusion on oil shock and stock price.

6. Applying SVAR to estimate oil price shock

6.1 Check stationarity and cointegration

The first step to build a valid model is transforming non-stationary data to stationary data with constant mean. Apparently, the price index is a trend index, and its mean can change over time. A common way to deal with the stationarity problem is to take the first difference after which the price index will be transformed into return index. Then by applying the augmented Dickey-Fuller test (ADF), it can be determined whether the time series is stationary. The null hypothesis is that a unit root exists and the alternative hypothesis is stationarity. The results shown in Table 2 are extracted from the MATLABS scripts. It can be interpreted from the results that the time series become stationary after applying the first difference.

Table 2. *ADF Test Results*

Return Series	T-statistic	5% C-Value	Hypothesis Test	Conclusion
Brent Oil	9.465	1.943	Rejected	Stationary
SPT	10.829	1.943	Rejected	Stationary
Small Stock	9.657	1.943	Rejected	Stationary
Energy	9.615	1.943	Rejected	Stationary
Industry	10.756	1.943	Rejected	Stationary
Utility	12.738	1.943	Rejected	Stationary
Material	12.958	1.943	Rejected	Stationary
Communication	11.585	1.943	Rejected	Stationary
Information Tech.	11.145	1.943	Rejected	Stationary
Real Estate	9.939	1.943	Rejected	Stationary
Financial Service	10.900	1.943	Rejected	Stationary

Next, we applied the cointegration test to the return series. The process of first difference creates a new and stationary series, however original characters and information carried by the former time series may be erased by the process of stationarity. A cointegration test studies whether there is a stable long-term relationship after the time series is processed by linear regression models. A typical method to test the cointegration is the Johansen Co-integration test. The null hypothesis of a Johansen test is that the number of cointegration vectors is *r* which ranges from 0 to one less than the input vectors. If all the Johansen tests are rejected, then the only option left is that all the input vectors are cointegrated. The results of the cointegration test are shown in Table 3. The test results show that the first difference of original time series still possess original features in both the short and long run.

Table 3. *Johansen Cointegration Test*

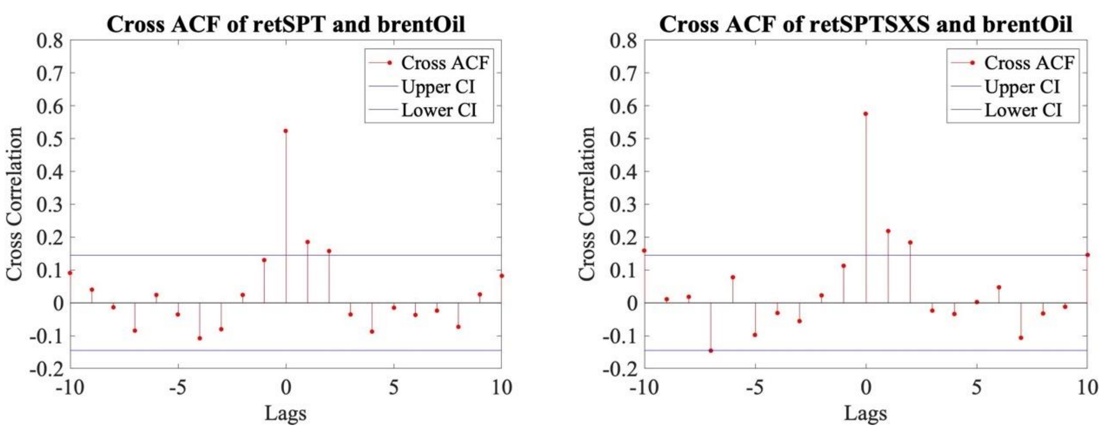
Sectors	No. of Vectors	Trace T-statistic	5% C-value	H_0	Cointegration
SPT	0	179.300	15.495	Rejected	Y
	1	66.501	3.842		
SPTSXS	0	156.616	15.495	Rejected	Y
	1	65.110	3.842		
SPTSEN	0	163.736	15.495	Rejected	Y
	1	68.343	3.842		
SPTSIN	0	177.890	15.495	Rejected	Y
	1	61.536	3.842		
SPTSUT	0	177.001	15.495	Rejected	Y
	1	65.431	3.842		
SPTSMT	0	178.284	15.495	Rejected	Y
	1	67.957	3.842		
SPTSTS	0	170.094	15.495	Rejected	Y
	1	69.009	3.842		
SPTSIT	0	167.876	15.495	Rejected	Y
	1	66.361	3.842		
SPTSRE	0	158.561	15.495	Rejected	Y
	1	61.993	3.842		
SPTSFN	0	179.080	15.495	Rejected	Y
	1	65.877	3.842		

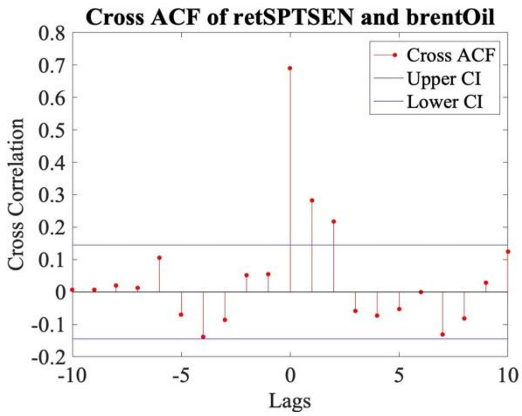
6.2 Determine optimal lags in SVAR model

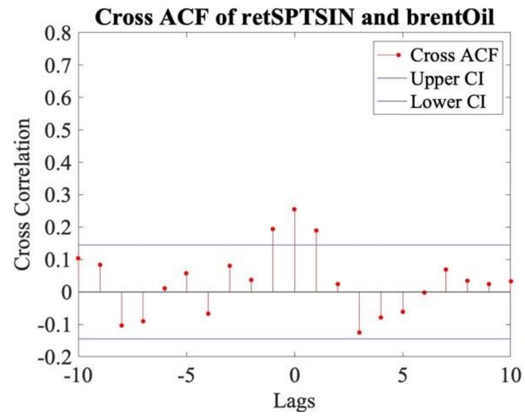
As in most of the former studies on the SVAR model, like Liuyuan Wang (2017) and Hamid Sakaki (2019), they applied Akaike Information Criteria and Bayesian Information Criteria to determine the optimal lags. Information criteria can be of great use and convenient if they give the same conclusion on the preferred lags. However, it becomes hard to handle when the results from two information criteria disagree with each other. In our study, we came across this particular situation, and thus, we decided to use the cross-autocorrelation function (Cross ACF) graph instead.

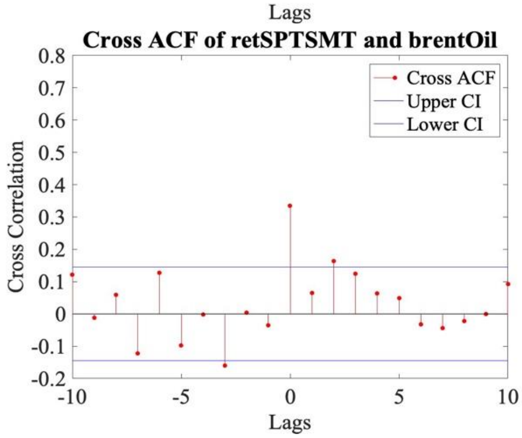
Cross ACF can capture the correlation between the contemporaneous term of one variable array and the lagged terms of both itself and the other variable array. If it shows a significant correlation between the current term and previous terms, then the SVAR model should include that lag. We did Cross ACF figures of all the ten pairs of return series through the MATLABS and the results are shown below in Figure 2.

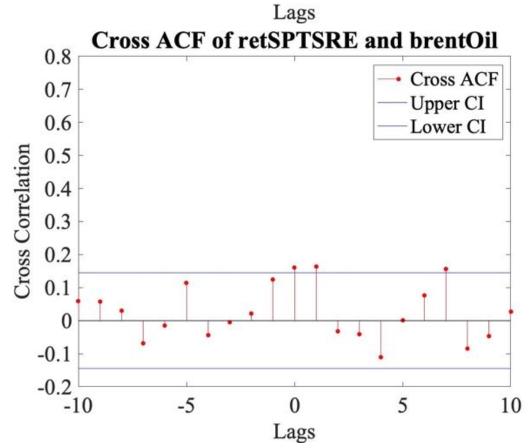
Figure 2. *Cross Autocorrelation Figures for Different Sectors*

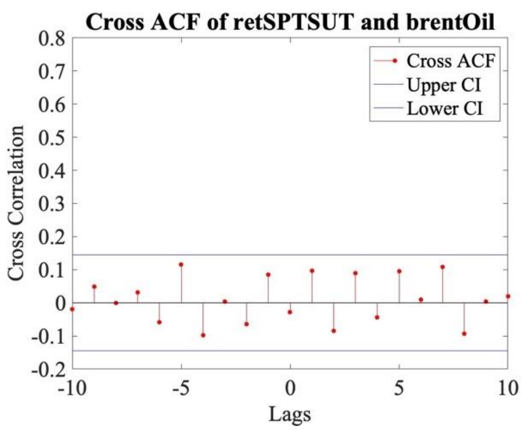


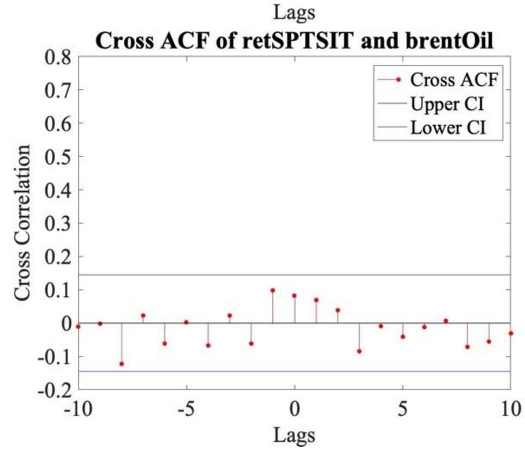

Cross ACF of retSPTSEN and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags

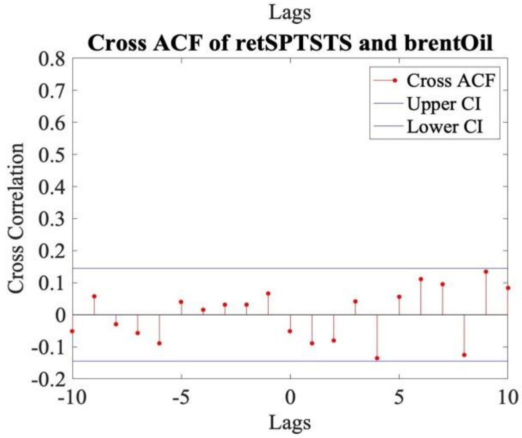

Cross ACF of retSPTSIN and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags

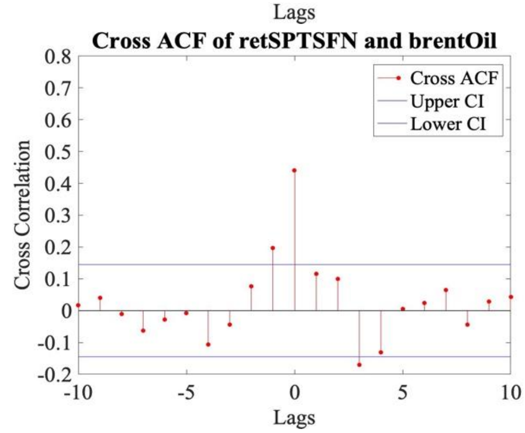

Cross ACF of retSPTSMT and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags


Cross ACF of retSPTSRE and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags


Cross ACF of retSPTSUT and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags


Cross ACF of retSPTSIT and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags


Cross ACF of retSPTSTS and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags


Cross ACF of retSPTSFN and brentOil
Cross ACF
Upper CI
Lower CI
Cross Correlation
Lags

The cross-autocorrelation graph shows the current term is significantly correlated with the lagged term if the red line exceeds the blue boundary given a 95% confidence interval. However, there are three sectors, communication sector, information technology and utility, show no correlation between the contemporaneous term and their lagged terms. The indication of this would be discussed in the latter part and we applied the SVAR (1) model for these sectors to further proceed our study. The following chart shows the optimal lags for the SVAR model.

Table4. *Optimal lags determined by the Cross-autocorrelation Function*

Sector	**Lag(s)**	**Sector**	**lag(s)**
Large Cap.	2	Small Cap.	2
Energy	2	Industry	1
Material	3	Real Estate	1
Utility	-	Information Tech.	-
Communication	-	Finance Service	3

6.3 Estimate SVAR model

A common way to establish the SVAR model is the AB-matrices approach. The first step is to construct reduced-from VAR. Then determine the matrix ordering. Different orderings in variables can imply different economic meanings. The last step is applying limitations to those boundary matrices according to underlying financial theory. The most common limitation applied to the matrix A is upper triangle matrix or lower triangle matrix. The matrix A contains the information of contemporaneous term while the matrix B decomposes the error term in reduced-form VAR to mutually orthogonal shocks. The matrix B can be generated by carrying out Cholesky decomposition to the covariance matrix of original reduced-form VAR.

6.3.1 Reduced-form VAR to SVAR model

There are two input variables in each of our SVAR model. One is the Brent oil price index after applying first difference. The other is different stock price index after applying first difference. First, by using the lags determined previously, we can easily construct reduced-VAR models through MATLAB:

$$\begin{bmatrix} Oil_t \\ Stock_t \end{bmatrix} = \alpha_0 + \alpha_1 \begin{bmatrix} Oil_{t-1} \\ Stock_{t-1} \end{bmatrix} + \dots + \alpha_k \begin{bmatrix} Oil_{t-k} \\ Stock_{t-k} \end{bmatrix} + e_t \quad E(e_t e_t') = \Sigma \qquad (5)$$

where Oil_t and $Stock_t$ are returns after stationary processing. The coefficients of the VAR model in the reduced form are essential to determine the coefficients in the final SVAR model. Besides, the covariance matrix of the error terms is also generated from the reduced-VAR model, and it is used in the latter step to generate mutual orthogonal shocks.

The SVAR model would look like the following structure:

$$A \begin{bmatrix} Oil_t \\ Stock_t \end{bmatrix} = C_0 + C_1 \begin{bmatrix} Oil_{t-1} \\ Stock_{t-1} \end{bmatrix} + \dots + C_k \begin{bmatrix} Oil_{t-k} \\ Stock_{t-k} \end{bmatrix} + Bu_t \qquad (6)$$

where C_n is a 2 by 2 matrix which contains two sets of the coefficient in lagged oil return and lagged stock return.

By multiplying A^{-1} on both side of equation (6), the model can be written as:

$$\begin{bmatrix} Oil_t \\ Stock_t \end{bmatrix} = c_0 + A^{-1}C_1 \begin{bmatrix} Oil_{t-1} \\ Stock_{t-1} \end{bmatrix} + \dots + A^{-1}C_k \begin{bmatrix} Oil_{t-k} \\ Stock_{t-k} \end{bmatrix} + A^{-1}Bu_t \qquad (7)$$

The relationship between the coefficients in reduced-form VAR and SVAR is shown as the following equation:

$$A^{-1}C_i = \alpha_i$$

$$A^{-1}BB^{'}A^{-1\prime} = \Sigma$$

Then the Cholesky decomposition of Σ can give results to $A^{-1}B$.

6.3.2 Estimation of SVAR

If we could estimate A and B matrix, the calculation of C matrix will be quite straightforward. In order to solve the matrix A and matrix B, we need to set up constrains in those matrices. According to Cholesky identification, there are two methods to deal with matrix A and B. The most common one is to set matrix A as an identity matrix and set matrix B to be a lower-triangular matrix, placing zeros on all entries above the diagonal. Another equivalent method is to set A as a lower triangular and let B an identity matrix. Both of the two methods are used to determine the matrix ordering. In our SVAR model, the matrix A and matrix B are set as follow:

$$A = \begin{bmatrix} 1 & 0 \\ A_{21} & 1 \end{bmatrix}, \quad B = \begin{bmatrix} B_{11} & 0 \\ 0 & B_{22} \end{bmatrix}$$

With the help of Cholesky decomposition, the matrix A and B can be calculated respectively. Then by reapplying the matrix A and B to the reduced-form VAR, the final SVAR model can be estimated.

The coefficients of estimated SVAR models are listed below in the matrix form.

Table 5. *SVAR estimated Coefficients*

	Matrix A		Oil τ-1	Stock τ-1	Oil τ-2	Stock τ-2	Oil τ-3	Stock τ-3
BrentOil	1	0	0.0541	0.4906	-0.0862	0.4974		
STP	-0.1917	1	0.0480	0.1172	-0.0466	0.2563		
	Matrix A		Oil τ-1	Stock τ-1	Oil τ-2	Stock τ-2		
BrentOil	1	0	0.0288	0.3585	-0.1023	0.3781		
SPTSXS	-0.3145	1	0.0139	0.2675	-0.0647	0.2279		
	Matrix A		Oil τ-1	Stock τ-1	Oil τ-2	Stock τ-2		
BrentOil	1	0	-0.1174	0.4477	-0.1807	0.4505		
SPTSEN	-0.5159	1	-0.1737	0.4744	-0.1309	0.4014		
	Matrix A		Oil τ-1	Stock τ-1				
BrentOil	1	0	0.1322	0.3280				
SPTSIN	-0.1160	1	0.1129	-0.0082				
	Matrix A		Oil τ-1	Stock τ-1	Oil τ-2	Stock τ-2	Oil τ-3	Stock τ-3
BrentOil	1	0	0.1297	0.0301	-0.0159	0.2179	-0.1987	0.2349
SPTSMT	-0.2769	1	0.0404	-0.1165	-0.0050	0.1417	-0.2043	0.1256
	Matrix A		Oil τ-1	Stock τ-1				
BrentOil	1	0	0.1491	0.3619				
SPTSRE	-0.0548	1	0.0527	0.0849				
	Matrix A		Oil τ-1	Stock τ-1				
BrentOil	1	0	0.1749	0.2672				
SPTSUT	0.0114	1	0.0291	-0.1385				
	Matrix A		Oil τ-1	Stock τ-1				
BrentOil	1	0	0.1680	-0.2454				
SPTSTS	0.0239	1	0.0172	-0.0775				
	Matrix A		Oil τ-1	Stock τ-1				
BrentOil	1	0	0.1674	0.0908				
SPTSIT	-0.0445	1	0.0696	-0.0308				
	Matrix A		Oil τ-1	Stock τ-1	Oil τ-2	Stock τ-2	Oil τ-3	Stock τ-3
BrentOil	1	0	0.1420	0.1599	-0.0163	0.2627	-0.1087	-0.2969
SPTSFN	-0.2016	1	0.1259	-0.0514	0.0050	0.1709	-0.0594	-0.0550

The table above can exhibit a general overview on the observable relationship of the stock price in different sectors in Canada. The matrix A indicates the contemporaneous term of the stock price. Stocks of both big and small market value are correlated with the oil price at the contemporaneous term in the model. In the production industries, the stock price has a positive relationship with the oil price at time-0. However, in the services industry, the relationship becomes rather vague. The communication service sector and the information technology sector are negatively correlated with the contemporaneous term of the oil price, while the stock returns in the finance service sector and utility sector correlate positively with the contemporaneous term of the oil return. In general, most of the returns across different sectors have a positive relationship with the contemporaneous term of oil return.

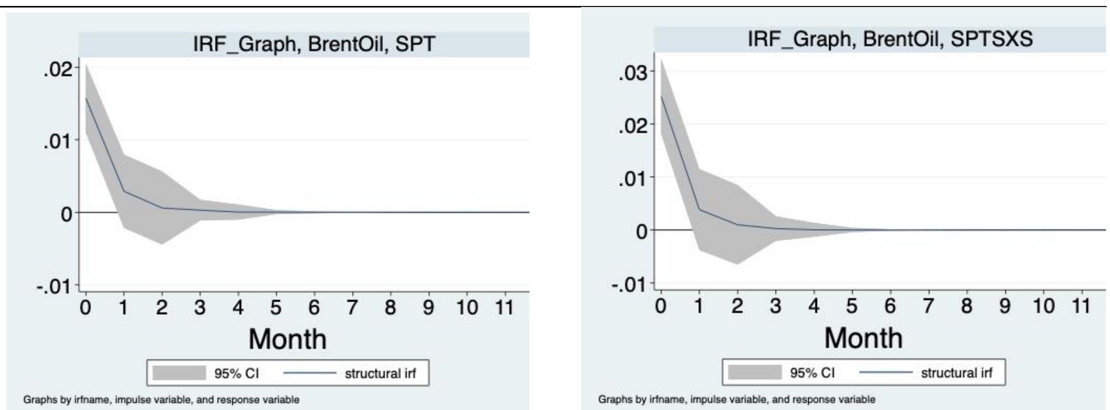
6.4 Impulse Response Function

Impulse Response Function (IRF) describes the cascade impact of a standard shock on the response variable at the spot time. The IRF graph can present a clear view on the impact of oil shock.

6.4.1 Size of stock market value

The following exhibit shows the IRF graph of the SPT index and the small cap index.

Figure3. IRF Graph of Oil Shock on Different Size of Market Value



Large market value Index | Small market value Index

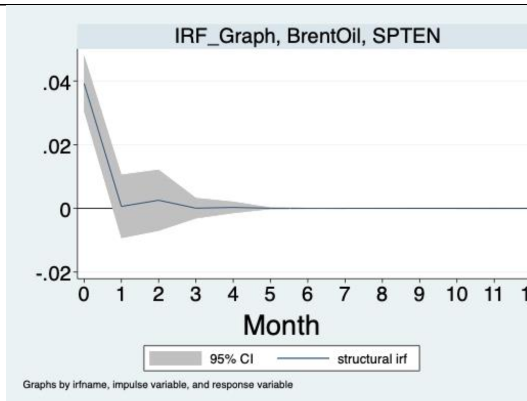
The influence of oil price shock has a similar pattern on both stocks with large market value and small market value. Given a 95% confidence interval, the oil shock has a positive influence in the first month, then there is a shrinking positive influence on average in the second month. Finally, the oil shock would have a minor influence on the stock price after the second month, and the impact of oil shock would totally fade out after six months. In comparison between large cap and small cap, stocks with small market value have a greater response to the oil shock at the beginning. At the spot of the shock, an oil shock with one standard deviation can cause a 0.16% increase in the large market value stock return, while a 0.25% increase in the stock return of small market value.

In summary, the oil shock would have a significant positive impact on the stock returns in the first month and the return of stock with smaller market value reacts more violently on the oil price shock.

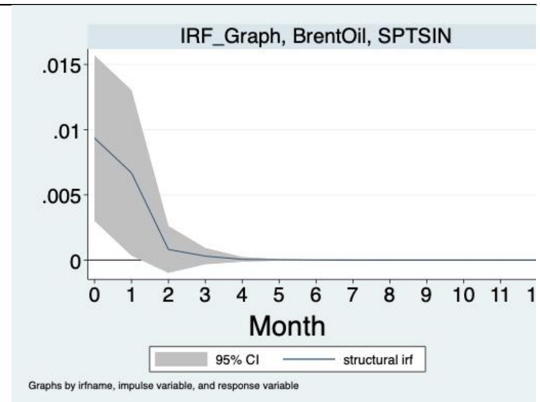
6.4.2 Different Sectors

The following exhibit shows the IRF graphs of different sectors in traditional production industry.

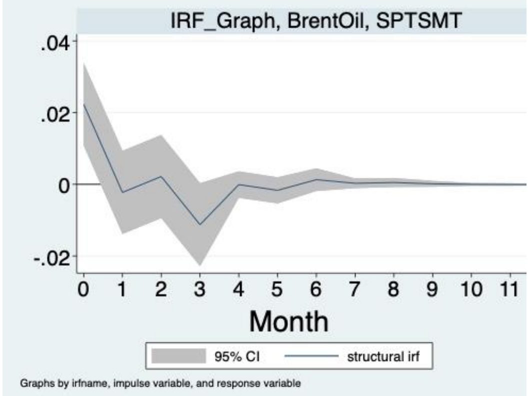
Figure 4. *IRF Graph of Oil Price Shock of Different Sectors (Production Industry)*



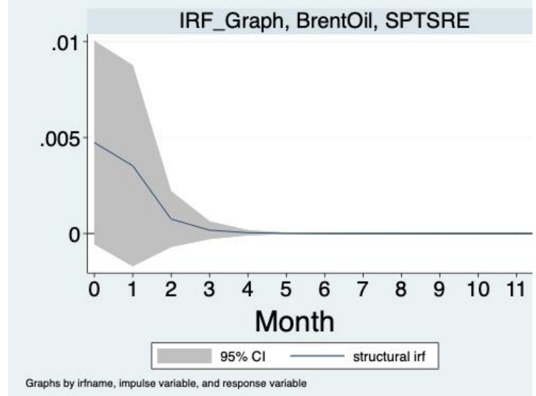
Energy Sector



Industry Sector



Material Sector



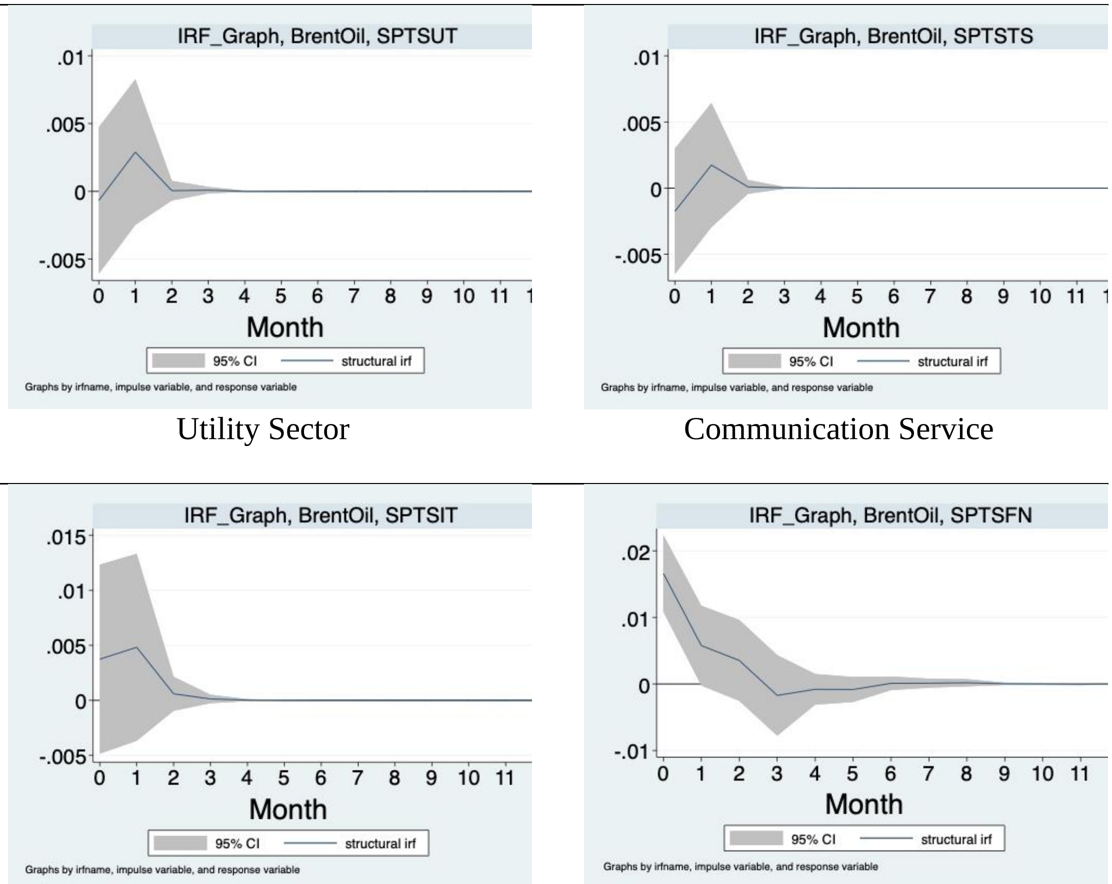
Real Estate Sector

Upon imposing a positive one standard derivation of oil price shock to the stock return, energy sector has the most positive return increase. Although the pattern of IRF is similar in the industry sector and real estate sector, the impulse on real estate sector is minor in comparison. The energy sector, one of the upstream sectors, has a significant increase in the return of 0.04% in return and the impulse diminishes quickly in one month, then the effect dissipates after three months. The average of the oil price shock drops to zero after the first month; and therefore, the oil price shock has no obvious positive or negative influence on the stock price, instead the shock is more similar to a white noise process.

In terms of midstream sectors, including industry and material sector, their patterns are different in scale and pace. Though they had significant increases of stock returns in the starting month when the oil shock takes place, the increase of return in material sector shrinks in the first month and turns into negative from the second month to forth month, then the effect of oil shock dissipates after the tenth month. On the contrary, the average effect of oil price shock on the industry sector return keeps positive and it dissipates in a shorter time, four months. The stock return of material sector in Canada adjusts slower than other production sectors. An upraise in crude oil price will increase the cost of products in the material sector and then cost the future profit to decrease. In the first month of oil shock, the increasing effect of oil shock prevails the decreasing effect in the material sector. As the increase effect diminishes after the second month, the netted effect of the oil shock in material sector is negative.

The following exhibit shows the IRF graph on different service sectors.

Figure 5. *IRF Graph of Oil Price Shock of Different Sectors (Service Sector)*



Utility Sector

Communication Service

Information Technology

Finance Service

As we estimated the lags of the SVAR model in the utility, communication, and information technology sectors in the previous part, we found that the cross ACF cannot give a valid implication of the lags in these three sectors. The IRF of the SVAR (1) model also suggests there is little deterministic impact of oil price shock on these sectors and the impact is similar to a white noise process. The average of the effect on stock return was lower than 0.005. And the confidence interval exhibits the effect of oil price shock is more like a stochastic drift.

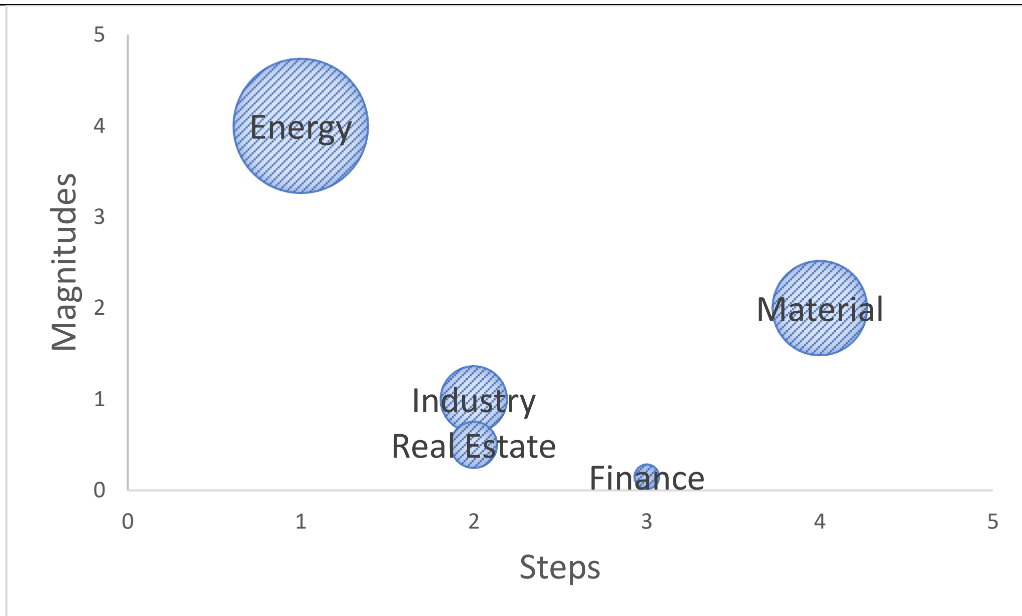
The IRF graph of the finance service sector shows a positive effect for three months, given a positive one standard deviation of oil price shock. Then the impact turns to slightly negative and hovers around zero for eight months before it dissipates at last. The maximum impact is experienced at the spot of oil price shock, about 0.017 increase of return on average.

7. Conclusion

Based on the results from our model, oil price shock has an influence on the overall stock markets in Canada. Unlike the US stock market, the oil price has a positive influence on Canada stock market. The positive influence verified by this paper is the same as the conclusion we draw from previous description and the existing literatures for oil-exporting countries. Canada is the world's 4th largest oil exporter, constitutes 7% of world total oil export. The oil price shock has a huge impact on Canada oil export; however, Canada has a diversified market and the impact of oil shock does not last long, as suggested by our study results.

We provided several essays from other scholars to suggest that there are structural changes and asymmetric effects in the stock market as a result of the oil shock. We also verified those asymmetric effects in the impact response functions. Compared with stocks with large market value, the stock price of small market value tended to fluctuate more violently from 2009 to 2019. Different sectors also reacted differently, as shown in the bubble chart below, we sorted the response of the sector stock price by the length and magnitude.

Figure 6. *The Bubble Chart of Response in Different Sectors*



The oil price shock had a major influence on the stock price in the energy sector in Canada, but the influence only lasted for one month according to our study. There was a non-negligible effect on the stock price in material sectors, and the influence lasted for four months. In comparison, the influence on the industry, real estate and financial service is comparatively small. The industry sector and real estate sector are not the upstream sectors, so their stock prices are not entirely depending on the oil price. In terms of the financial service sector, including hedge funds and investment banks, it has a certain proportion of its portfolio invested in energy and industry sectors. A rise and drop in oil price can affect the performance of the finance sector. However, the impact brought to the financial sector would be minimized due to the diversified portfolio investment.

Based on our study, not all the sectors were influenced by oil price shock. Utility, information technology, and communication service sectors neither responded to the oil shock, nor influenced the oil supply or demand inversely. The oil price is not a significant daily input in the production activity for those sectors, so the oil price shock cannot influence their stock price directly. Indirect influence, such as the export volume only had a minor influence which was too little to be detected.

Through our study, we applied the SVAR model and verified the influence of oil price shock on stock returns. We also contributed to the study carried out by Hamid Sakaki (2019) and Killian (2007) in the field of detecting oil price shock. By applying the SVAR-based oil shock analysis, we generalized their findings to oil-exporting country, Canada, and we enhanced their conclusion about the influence of the oil price on different stock market. We conclude that the oil shock can be an important influence on stock price, and the influence varies in length and magnitudes in different sectors in Canada.

8. Future Work

Our paper does an empirical research on the influence of oil price changes on the Canadian stock market and tries to differentiate those influences from perspective of different sectors and size of market value, finally we get some meaningful conclusions from our study. However, there are still some limitations in our paper. First, we put more emphasis on the empirical study but less on the theoretical analysis of the relationship between these two. We might improve this in further study of this topic. Second, we only investigate the period of post-crisis. If we want to have a deeper understanding of the oil price shock and its influences on stocks, the research period should be extended. By comparing the influence in different period, we can get a more accurate result. Third, we think it will be more meaningful if we can compare results of the oil importers and exporters by using the same research method. The results can be a good guidance for the development of industry in different countries.

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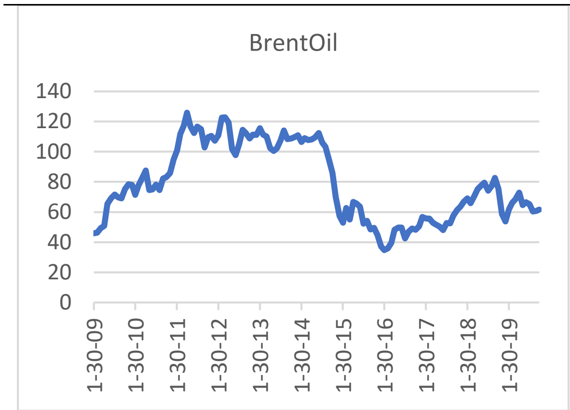
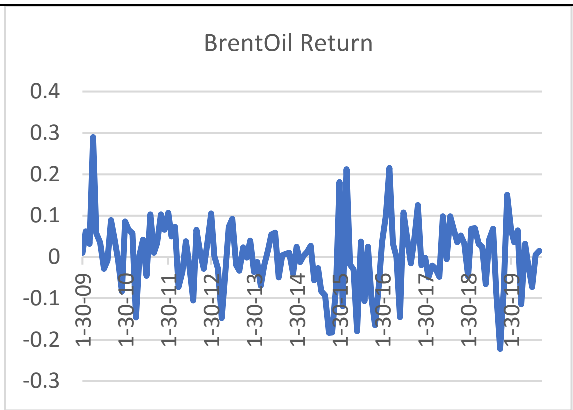
10.**Appendix**

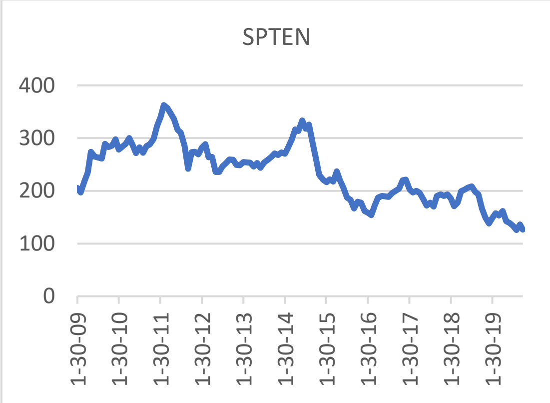
Appendix 1 Price and return graphs.

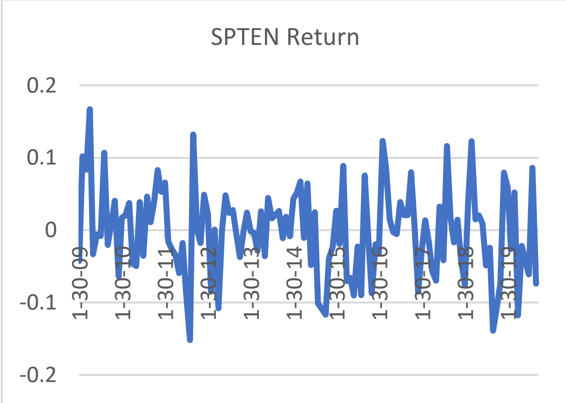
Appendix 1.1 Brent Oil Price and Return Graph



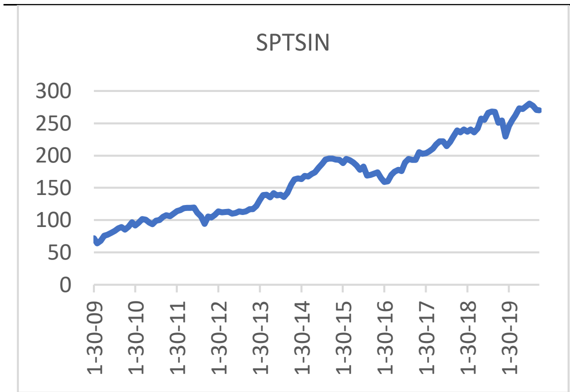


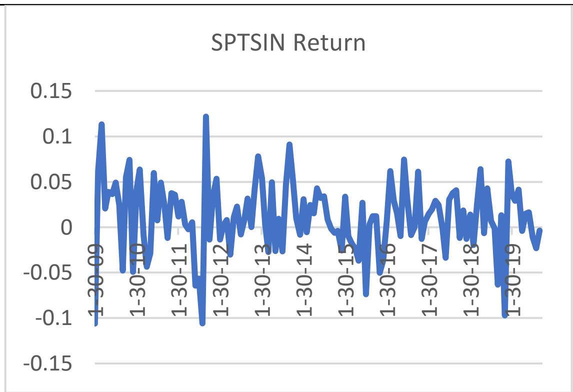
Appendix 1.2 Energy Sector Stock Price and Return Graph



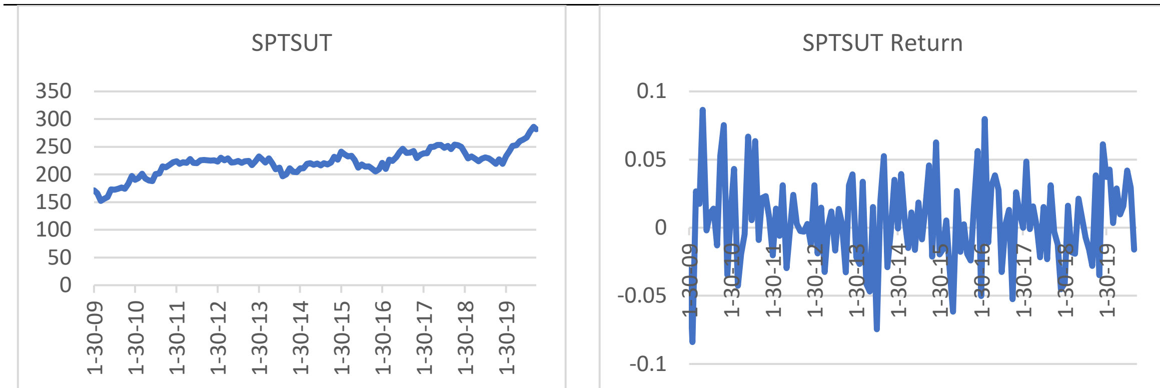


Appendix 1.3 Industry Sector Stock Price and Return Graph

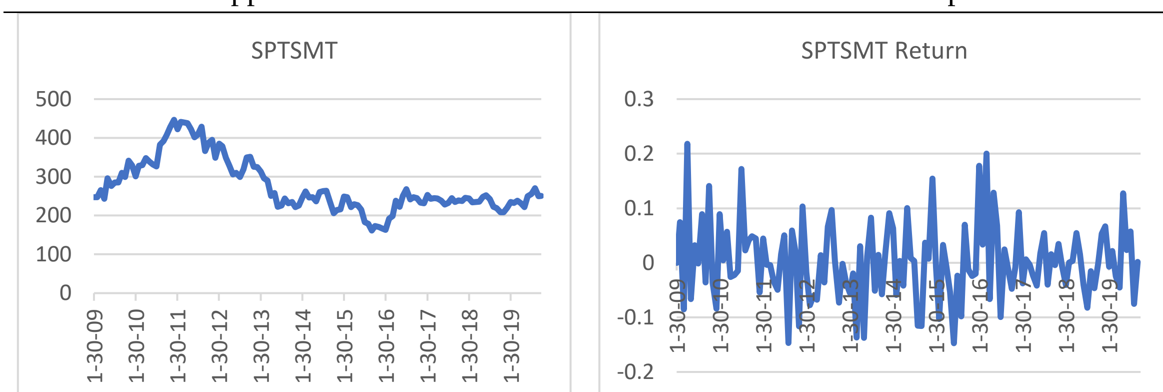




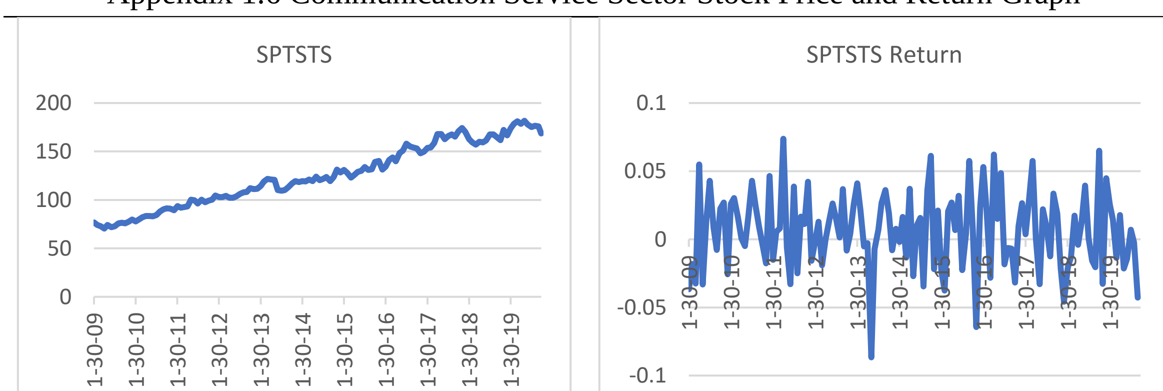
Appendix 1.4 Utility Sector Stock Price and Return Graph



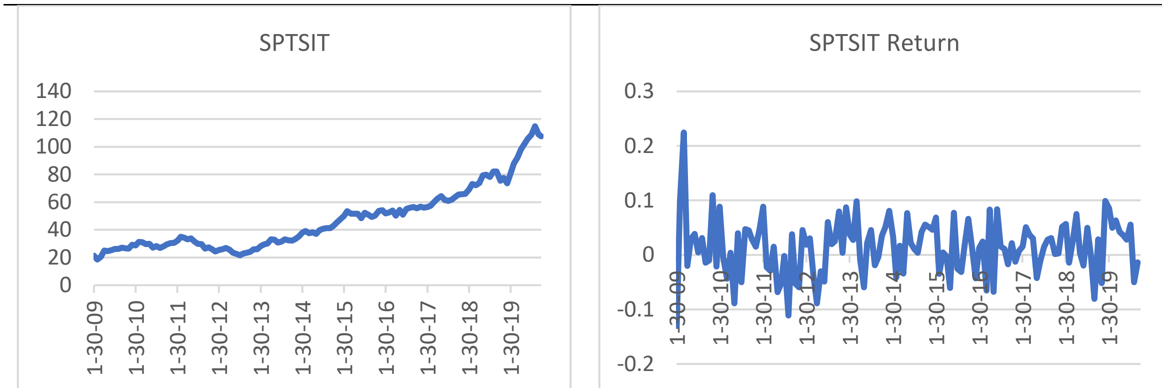
Appendix 1.5 Material Sector Stock Price and Return Graph



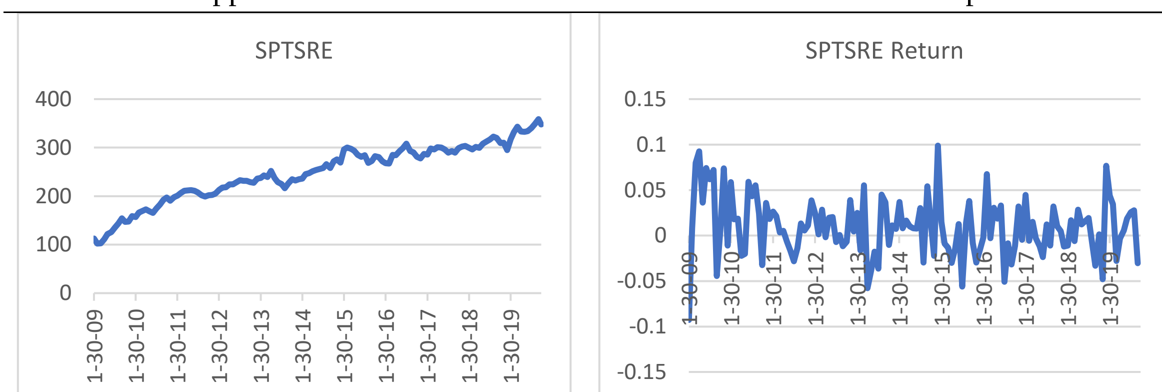
Appendix 1.6 Communication Service Sector Stock Price and Return Graph



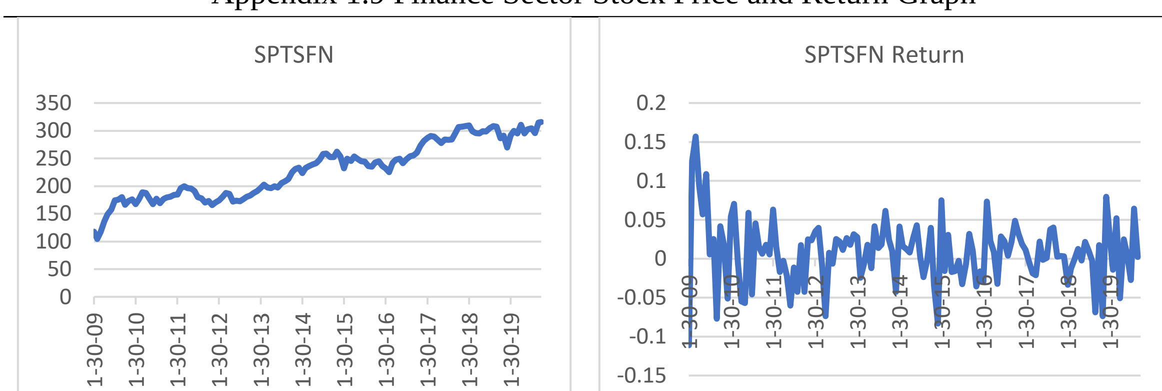
Appendix 1.7 Information Technology Sector Price and Return Graph



Appendix 1.8 Real Estate Sector Stock Price and Return Graph



Appendix 1.9 Finance Sector Stock Price and Return Graph



Appendix 2 The coefficients in Reduced-VAR Model

'Reduced-VAR Model for retSPT and brentOil' VAR(2) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	-0.00342	0.00729	-0.46919	0.63894
Constant (2)	0.00401	0.00269	1.4854	0.13743
AR {1} (1,1)	0.05414	0.10341	0.52354	0.60062
AR {1} (2,1)	0.03763	0.03821	2.9848	0.04247
AR {1} (1,2)	0.49058	0.27768	1.7667	0.07728
AR {1} (2,2)	0.02313	0.10259	2.2255	0.04715
AR {2} (1,1)	-0.08621	0.10122	-0.8517	0.39438
AR {2} (2,1)	-0.03003	0.03739	-2.80295	0.04220
AR {2} (1,2)	0.49742	0.27020	1.8409	0.06563
AR {2} (2,2)	0.16094	0.09982	1.6122	0.10691

Innovations Covariance Matrix:

0.0062	0.0012
0.0012	0.0009

'Reduced-VAR Model for retSPTSXS and brentOil' VAR(2) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	-0.00087	0.00702	-0.12496	0.90055
Constant (2)	0.00256	0.00392	0.65310	0.51369
AR {1} (1,1)	0.02876	0.10618	0.27085	0.78651
AR {1} (2,1)	0.00488	0.05941	2.08210	0.04945
AR {1} (1,2)	0.35849	0.19252	1.86210	0.06259
AR {1} (2,2)	0.15473	0.10771	2.43660	0.04083
AR {2} (1,1)	-0.10225	0.10415	-0.98177	0.32621
AR {2} (2,1)	-0.03251	0.05826	-2.55787	0.04769
AR {2} (1,2)	0.37815	0.19146	1.97510	0.04825
AR {2} (2,2)	0.10896	0.10711	1.01720	0.30904

Innovations Covariance Matrix:

0.0062	0.0019
0.0019	0.0019

'Reduced-VAR Model for retSPTSEN and brentOil' VAR(2) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00545	0.00684	0.79628	0.42587
Constant (2)	-0.00257	0.00521	-0.49301	0.62200
AR {1} (1,1)	-0.11742	0.11829	-0.99261	0.32090
AR {1} (2,1)	-0.11311	0.09006	-2.25600	0.04791
AR {1} (1,2)	0.44770	0.15850	2.82470	0.00473
AR {1} (2,2)	0.24346	0.12067	2.01760	0.04963
AR {2} (1,1)	-0.18069	0.11585	-1.55960	0.11885
AR {2} (2,1)	-0.03773	0.08820	-0.42775	0.66883
AR {2} (1,2)	0.45050	0.16410	2.74530	0.00604
AR{2}(2,2)	0.16898	0.12494	1.3525	0.17620

Innovations Covariance Matrix:

0.0058	0.0030
0.0030	0.0034

'Reduced-VAR Model for retSPTSIN and brentOil' VAR(1) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	-0.00146	0.00729	-0.20058	0.84102
Constant (2)	0.01149	0.00334	3.4354	0.00059
AR {1} (1,1)	0.13216	0.08902	1.4846	0.13764
AR {1} (2,1)	0.09754	0.04080	2.3904	0.01683
AR {1} (1,2)	0.32802	0.18751	1.7493	0.08024
AR {1} (2,2)	-0.04620	0.08594	-0.5376	0.59085

Innovations Covariance Matrix:

0.0064	0.0007
0.0007	0.0013

'Reduced-VAR Model for retSPTSUT and brentOil' VAR(1) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00077	0.00715	0.10878	0.91338
Constant (2)	0.00459	0.00275	1.66690	0.09554
AR {1} (1,1)	0.17493	0.08663	2.01910	0.04347
AR {1} (2,1)	0.03105	0.03335	1.93109	0.51181
AR {1} (1,2)	0.26723	0.22593	1.18280	0.23689
AR {1} (2,2)	-0.13547	0.08699	-2.55730	0.03193

Innovations Covariance Matrix:

0.0064	-0.0001
-0.0001	0.0010

'Reduced-VAR Model for retSPTSMT and brentOil' VAR(3) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00171	0.00694	0.24578	0.80586
Constant (2)	0.00051	0.00594	0.08648	0.93108
AR {1} (1,1)	0.12972	0.09213	1.40800	0.15914
AR {1} (2,1)	0.00448	0.07882	2.05690	0.04546
AR {1} (1,2)	0.03013	0.10852	0.27765	0.78128
AR {1} (2,2)	-0.12482	0.09283	-1.34450	0.17879
AR {2} (1,1)	-0.01592	0.09235	-0.17238	0.86314
AR {2} (2,1)	-0.00056	0.07901	-0.00713	0.99430
AR {2} (1,2)	0.21791	0.10990	1.98280	0.04738
AR {2} (2,2)	0.08134	0.09401	2.86520	0.03869
AR {3} (1,1)	-0.19869	0.09132	-2.17560	0.02958
AR {3} (2,1)	-0.14929	0.07812	-2.01090	0.04801
AR {3} (1,2)	0.23492	0.11019	2.13190	0.03301
AR {3} (2,2)	0.06054	0.09426	0.64226	0.52071

Innovations Covariance Matrix:

0.0061	0.0017
0.0017	0.0044

'Reduced-VAR Model for retSPTSTS and brentOil' VAR(1) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00344	0.00730	0.47212	0.63684
Constant (2)	0.00690	0.00249	2.76820	0.00563
AR {1} (1,1)	0.16800	0.08687	1.93380	0.05313
AR {1} (2,1)	0.02119	0.02967	0.71442	0.47497
AR {1} (1,2)	-0.24543	0.25845	-0.94961	0.34231
AR {1} (2,2)	-0.08338	0.08826	-0.94467	0.34483

Innovations Covariance Matrix:

0.0065	-0.0002
-0.0002	0.0008

'Reduced-VAR Model for retSPTSIT and brentOil' VAR(1) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00070	0.00734	0.09617	0.92338
Constant (2)	0.01403	0.00441	3.18270	0.00145
AR {1} (1,1)	0.16741	0.08723	1.91900	0.05498
AR {1} (2,1)	0.06216	0.05240	1.18630	0.23550
AR {1} (1,2)	0.09075	0.14160	0.64091	0.52158
AR {1} (2,2)	-0.03480	0.08506	-0.40922	0.68238

Innovations Covariance Matrix:

0.0065	0.0003
0.0003	0.0023

'Reduced-VAR Model for retSPTSRE and brentOil' VAR(1) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	-0.00137	0.00734	-0.18663	0.85195
Constant (2)	0.00888	0.00278	3.19390	0.00140
AR {1} (1,1)	0.14906	0.08738	2.00580	0.04804
AR {1} (2,1)	0.04451	0.03310	2.34480	0.03786
AR {1} (1,2)	0.36185	0.22495	1.60860	0.10770
AR {1} (2,2)	0.06506	0.08521	0.76357	0.44512

Innovations Covariance Matrix:

0.0064	0.0003
0.0003	0.0009

'Reduced-VAR Model for retSPTSFN and brentOil' VAR(3) Model

	Value	StandardError	TStatistic	PValue
Constant (1)	0.00045	0.00753	0.06085	0.95147
Constant (2)	0.00624	0.00330	1.89120	0.05859
AR {1} (1,1)	0.14198	0.09702	1.46330	0.14338
AR {1} (2,1)	0.09726	0.04255	2.28570	0.04227
AR {1} (1,2)	0.15986	0.21205	0.75387	0.45093
AR {1} (2,2)	-0.08357	0.09299	-2.89880	0.03688
AR {2} (1,1)	-0.01634	0.09816	-0.16653	0.86774
AR {2} (2,1)	0.00831	0.04304	2.19330	0.04584
AR {2} (1,2)	0.26269	0.20844	1.26030	0.20757
AR {2} (2,2)	0.11799	0.09141	1.29080	0.19678
AR {3} (1,1)	-0.10870	0.09770	-1.11250	0.26591
AR {3} (2,1)	-0.03748	0.04284	-0.87485	0.38166
AR {3} (1,2)	-0.29686	0.19630	-1.51230	0.13045
AR {3} (2,2)	0.00481	0.08608	2.05590	0.04854

Innovations Covariance Matrix:

0.0062	0.0012
0.0012	0.0012