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Identifying Key Macroeconomic Shocks to Canadian GDP

Jamil Sayeed[*]

Abstract *This paper seeks to identify the largest two shocks that can explain the movement in Canadian GDP for the period 1981Q1 to 2011Q4. I employ a very flexible identification method proposed by Uhlig (2003) that allows us to identify the key shocks from the time series data without imposing any strict identification assumption. The largest two shocks are extracted by maximizing the forecast error variance of GDP for a ten years horizon. Two shocks are sufficient to explain most of the variation in the GDP in Canada. My findings suggest that TFP news shock is the key driver of GDP in the medium run and it creates significant positive co-movements among the aggregate variables at business cycle frequencies. Demand shock dominates in the short run, however, its hard to pin down the exact source of the shock. The findings are robust to alternative SVAR identification strategy and variable specification.*

Keywords*: Macroeconomic Shocks, TFP News Shock, Canadian GDP, Forecast Error Variance*

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1 Introduction

A central question in macroeconomic literature is 'What causes movement in aggregate variables like GDP?'. This query has drawn a significant attention as it has very important policy implication tied to economic prosperity and wellbeing. The standard approach in literature deals this issue by postulating a specific type of fundamental shock as the key driver of GDP and then investigate its potentiality under theoretical framework. Finally, empirical justification is provided by observing the propagation mechanism of the extracted shock from time series data. The key limitation of this approach is that one needs to impose strong identification assumption to identify a specific type of shock. These assumptions are often subject to criticism as they may put strict restrictions on the shock process itself. For example, Beaudry and Portier (2006) used both short run and long run restrictions to identify the TFP news shock. Fisher (2010) pointed out that one of the main limitations of this identification method is that the results are sensitive to the assumed number of common trends among the variables. Moreover, the estimated parameters of MA representation of VAR for a very long horizon are imprecise in finite samples which leads to spurious inference. Barsky and Sims (2011) proposed an alternative identification strategy where they utilized Maximum Forecast Error Variance method to identify the TFP news shock at finite horizon. However, their identification technique relies on a strong assumption that the stochastic process of TFP depends only on two shocks: surprise shock and news shock.

Apart from these limitations, these identification techniques focus on only one shock while in reality more than one shock may be important for the economic fluctuations. Moreover, it is important to identify whether the identified shock is dominant in short run (typically measured as 0 to 4 quarters) or medium run (3 to 5 years). Uhlig (2003) proposed an alternative approach to identify shocks to macroeconomic aggregates without imposing any specific restriction on identification mechanism. This method is purely empirical in nature and so it allows data to reveal the true dynamics of the economy. It can identify few shocks that explain most of the variation in aggregate variables. Its built on the earlier work by Faust (1998). This identification technique has several advantages. First, this approach is very flexible as it does not impose strict restriction on the identification mechanism. Second, this method is particularly useful when more than one shock is important for the economic fluctuations. For example, we can extract largest two shocks instead of focusing on only one shock. Third, it allows to explore which shock dominates in the short run and which one dominates in the medium run. However, once the largest one or two shocks are extracted from the data, the challenge is to ascribe the shock to the specific fundamental source. One needs to use impulse response and variance decomposition to trace out the origin of the shocks.

Uhlig (2003) maximize the forecast error variance to extract the largest one or two shocks to real GNP of US economy. He concluded that two shocks can explain more than 90% of the forecast error variance of real GNP over five-year forecast horizon. He ascribed the largest shock to productivity shock and the second largest to inflationary or wage push shock. Kurmann (2013) utilized Uhlig's (2003) method to identify the largest exogenous shock that contributes to the forecast error variance of slope of term structure in US. He attributes this shock to the news shock about future TFP which can explain more than 50 percent variation of prediction error in the slope of term structure over a ten-year forecast horizon.

This paper aims at identifying the key driver of fluctuations in GDP in Canada using the method proposed by Uhlig (2003) which is a flexible identification scheme. The main goal of this paper is to extract the largest two shocks that can explain the majority of the movement of GDP in Canada. A standard VAR model with seven variables is used to extract the largest two shocks by maximizing the forecast error variance of GDP for a ten-year prediction horizon. By analyzing impulse response functions and variance decomposition, I want to characterize whether the shock is coming from demand side or supply side of the economy. In addition, I try to explore the fundamental source of the shock.

There are three main contribution of this paper. First, to my best knowledge, this is the first study to identify largest two shock to GDP in Canada using a flexible identification method proposed by Uhlig (2003). Second, I isolate short run shock from medium run shock by observing the dynamics of the identified shocks. This helps us to understand whether the shock is prominent in shorter horizon or longer horizon. Thirdly, I show that my result holds under alternative SVAR identification mechanism proposed by Barsky and Sims (2011).

The remainder of the paper is organized as follows. Section 2 describes the econometric strategy. Section 3 provides the variable specification and transformation. Section 4 illustrates the results from different model specification. Robustness tests are provided in section 5. Concluding remarks in section 6.

2 Econometric Strategy

Consider a reduced form VAR

$$y_t \;=\; B_1 y_{t-1} \;+\; B_2 y_{t-2} \quad \dots\dots\dots\dots\dots .. B_p y_{t-p} + u_t \qquad\qquad (1)$$

Where y_t is n x1 vector of variables observed at time t, B_i are n x n matrix of coefficient and u_t is a nx1 vector of one step ahead forecast error with variance covariance matrix $\sum = \mathrm{E}[u_t u'_t]$

We can write (1) more compactly as

$$B(L)y_t = u_t \qquad (2)$$

Where $B(L) = 1 - B_1L - B_1L^2 - \ldots\ldots\ldots. B_PL^P$

Now the vector moving average representation of this reduced form VAR is

$$y_t = C(L)u_t \qquad (3)$$

Where $[B(L)]^{-1} = C(L) = 1 + C_1 L + C_2 L^2 + \ldots\ldots\ldots\ldots\ldots$

To identify mutually orthogonal structural shocks, we need a mapping A between forecast error u_t and shocks e_t. So, we can write

$$u_t = Ae_t \qquad (4)$$

Where A satisfies the restriction

$$\sum = \mathrm{E}[u_t u'_t] = \mathrm{E}[Ae_t e'_t A'] = AE[e_t e'_t]A' = \mathrm{AA}' \qquad (5)$$

Here A shows immediate impact of e_t on all variables. So, the jth column of A represents the immediate impact of jth shock in e_t on all variables. But this restriction is not sufficient to identify A because $\sum = \mathrm{AA}'$ gives us n(n+1)/2 restriction where $\sum$ has nxn unknown. So, we need n(n-1)/2 additional restrictions.

Suppose Ã is Cholesky decomposition of $\sum$ such that $\sum = \tilde{A}\tilde{A}'$. Then there must be an orthonormal matrix Q satisfying $QQ' = I$ such that $A = \tilde{A}Q$ [QR decomposition]. This alternative matrix Ã maps u_t into another vector of mutually orthogonal shocks $\tilde{e}_t$ ie $u_t = \tilde{A}\tilde{e}_t$

Now using (3) and (4) we can write

$$y_t = C(L)Ae_t \;\; = C(L)\tilde{A}Qe_t = \tilde{R}(L)Qe_t \tag{6}$$

Here $\tilde{R}(L)$ shows impulse response ie dynamic impact of e_t on all variables.

Now we can transform the VAR(p) process given in (1) into VAR (1) by using companion matrix F.

$$Y_t = FY_{t-1} + v_t \tag{7}$$

Where $Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ . \\ . \\ y_{t-p+1} \end{bmatrix}$ $\quad v_t = \begin{bmatrix} e_t \\ 0 \\ . \\ . \\ 0 \end{bmatrix}$ $\quad \text{F} = \begin{bmatrix} B_1 & \cdots & B_p \\ I_n & \ddots & \vdots \\ 0 & \cdots I_n & 0 \end{bmatrix}$

By iteration we can get

$$Y_t = \sum_{p=0}^{\infty} F^p \, v_{t-p} = \sum_{p=0}^{\infty} F^p \, Ae_{t-p} = \sum_{p=0}^{\infty} F^p \, \tilde{A}Qe_{t-p} = \sum_{p=0}^{\infty} \tilde{R}_p \, Qe_{t-p} \tag{8}$$

Where we denote $\tilde{R}_p = F^p\tilde{A}$

2.1 Forecast Error Variance

The h step ahead value of Y_{t+h} is

$$Y_{t+h} = \sum_{p=0}^{\infty} \tilde{R}_p \, Qe_{t+h-p} \qquad (9)$$

$$Y_{t+h} = \sum_{p=0}^{h-1} \tilde{R}_p \, Qe_{t+h-p} + \sum_{p=h}^{\infty} \tilde{R}_p \, Qe_{t+h-p} \qquad (10)$$

The 1st term captures the accumulative effect on Y_{t+h} of all the structural shocks that have yet to occur between t+1 and t+h period. So the expected value of this term is zero as we have assumed e~N(0,I).

The 2nd term captures the accumulative effects on Y_{t+h} of all shocks that already occurred between -∞ and t period. This term is predetermined at t. So, the expected value of Y_{t+h} is

$$E_t Y_{t+h} = \sum_{p=h}^{\infty} \tilde{R}_p \, Qe_{t+h-p} \qquad (11)$$

So, the h step ahead forecast error of Y_{t+h} is

$$Y_{t+h} - E_t Y_{t+h} = \sum_{p=0}^{h-1} \tilde{R}_p \, Qe_{t+h-p} \qquad (12)$$

Now the h step ahead forecast error of ith variable in Y_{t+h} is

$$Y_{i,t+h} - E_t Y_{i,t+h} = e'_i \left[\sum_{p=0}^{h-1} \tilde{\mathrm{R}}\, \mathrm{Q} e_{t+h-p} \right] \quad (13)$$

Where e_i is a selection vector with 1 in the ith position and zeros elsewhere. Now variance covariance matrix at horizon h=[$\underline{H}$, $\overline{H}$] is

$$\Omega_i = E\,[(Y_{i,t+h} - E_t Y_{i,t+h})\,(Y_{i,t+h} - E_t Y_{i,t+h})'] = e'_i \left[\sum_{h=\underline{H}}^{\overline{H}} \sum_{p=0}^{h-1} \tilde{\mathrm{R}}_p \mathrm{Q}\, Q'\, \tilde{\mathrm{R}}'_p \right] e_i \quad (14)$$

2.2 Extracting the largest shock

To find the largest shock i.e. q_1 column of Q that explains most of the forecast error variance of variables in Yi we need to solve the following problem

$$q*_1 = argmax\ \ e'_i \left[\sum_{h=\underline{\mathrm{H}}}^{\overline{\mathrm{H}}} \sum_{p=0}^{h-1} \tilde{\mathrm{R}}_p q_1\, q'_1\, \tilde{\mathrm{R}}'_p \right] e_i \quad (15)$$

$$\mathrm{st.}\, q'_1 q_1 = 1 \quad (16)$$

So we need to find a vector q_1 of unit length that maximizes the objective function.

2.3 Implementing Principal Component Analysis

We can write the objective function as

$$e'_i \left[\sum_{h=\underline{H}}^{\bar{H}} \sum_{p=0}^{h-1} \tilde{R}_p q_1 \, q'_1 \, \tilde{R}'_p \right] e_i$$

$$= \sum_{h=\underline{H}}^{\bar{H}} \sum_{p=0}^{h-1} \text{trace} \left[(e'_i \, e_i) \, (\tilde{R}_p q_1) \, (q'_1 \tilde{R}'_p) \right] \tag{17}$$

$$= \sum_{h=\underline{H}}^{\bar{H}} \sum_{p=0}^{h-1} \text{trace} \left[\, (q'_1 \tilde{R}'_p)(e'_i \, e_i)(\tilde{R}_p \, q_1) \, \right] \tag{18}$$

$$= q'_1 \left[\sum_{h=\underline{H}}^{\bar{H}} \sum_{p=0}^{h-1} \tilde{R}'_p E_{ii} \tilde{R}_p \right] q_1 \tag{19}$$

$$= q'_1 M q_1 \tag{20}$$

Where E_{ii} is a selection matrix with 1 in (1x1) position and zeros elsewhere and M is denoted as

$$\mathrm{M} = \sum_{h=\underline{H}}^{\bar{H}} \sum_{p=0}^{h-1} \tilde{R}'_p E_{ii} \tilde{R}_p \tag{21}$$

Now the maximization problem can be written as

$$\mathrm{L}(q_1) = q'_1 M q_1 - \lambda \left(q'_1 q_1 - 1 \right) \tag{22}$$

FOC:

$$M q_1 = \lambda \, q_1 \tag{23}$$

This is the definition of the eigenvalue decomposition. Here the solution q_1 is the eigenvector of M that corresponds to eigenvalue λ.

Now as $q'_1 q_1 = 1$, so we can write

$$q'_1 M q_1 = \lambda \qquad (24)$$

$$\lambda = \Omega_i \, (\underline{H}, \overline{H}, q_1) \qquad (25)$$

So, to maximize the FEV, we need to find the eigenvector q_1 with the maximal eigenvalue λ i.e we need to find the first principal component.

2.4 Calculating Forecast Error Variance and Impulse Response

Total forecast error variance of n variables in Y_{t+h} is

$$\Omega = E\,[(Y_{\,t+h} - E_t Y_{t+h})\,(Y_{t+h} - E_t Y_{t+h})'] = \sum_{i=1}^{n}\sum_{p=0}^{h-1} \tilde{R}_{i,p} Q\, Q'\, \tilde{R}'_{i,p} \qquad (26)$$

Now forecast error variance of n variables for the largest shock (denoted as the 1st column in Q matrix) is

$$\Omega_1 = \sum_{i=1}^{n}\sum_{p=0}^{h-1} \tilde{R}_{i,p}\, q_1\, q'_1\, \tilde{R}'_{i,p} \qquad (27)$$

The fraction of the forecast error variance of variable i due to the largest shock at horizon h is denoted by $\Omega_{i,1}$

$$\Omega_{i,1} = \frac{Diag\ (\Omega_1)}{\mathrm{Diag}\ (\Omega)} \tag{28}$$

$$= \frac{Diag\ (\sum_{i=1}^{n} \sum_{p=0}^{h-1} \tilde{R}_{i,p}\ q_1 q'_1 \tilde{R}'_{i,p})}{Diag\ (\sum_{i=1}^{n} \sum_{p=0}^{h-1} \tilde{R}_{i,p} QQ' \tilde{R}'_{i,p})} \tag{29}$$

The impulse response vector ‘a’ can be written as

$$\mathrm{a} = \tilde{A} q_1 \tag{30}$$

3. Data and Variable Specification

The baseline VAR model has seven variables. The target variable is GDP which is placed at first position in the VAR. The rest of the variables are Total Factor Productivity (TFP), private consumption, private investment, hours worked, inflation, interest rate. Private consumption measured as non-durable and services and private investment measured as non-residential investment. GDP, consumption and investment are in real per capita term.

Total Factor Productivity (TFP) data series is taken from Shutao and Sharon (2015) who constructed the quarterly TFP data for Canada. The limitation of this dataset is that it is not utilization adjusted. inflation rate is measured with CPI inflation and interest rate is measured by 3-month treasury bill rate. Hours worked shows the total number of hours that a person spends working. In the extended VAR model, we used stock price which is measured by Toronto Stock Exchange composite index deflated by CPI.

All variables are standardized by subtracting mean and dividing by standard deviation. This transformation is necessary as we need to conduct Principal Component Analysis (PCA) in our model which requires all variables to be in the same scale.

All data are collected from Statistics Canada website except CPI inflation and TFP which are taken from OECD database and Shutao and Sharon (2015) respectively. The sample period is from 1981Q1 to 2011Q4.

4 Results

I have used OLS to estimate the VAR in levels with 4 lags of each variable and no intercept term. By maximizing the forecast error variable of GDP over a ten-year horizon I have derived the largest eigenvalue i.e. the first principal component which corresponds to the largest shock to GDP. Similarly, the second principal component is associated to the second largest shock. The screen plot illustrates that the first principal component is very larger compared to the other components. The first two principal components can explain almost all the variation of GDP as the rest of the components altogether are very insignificant.

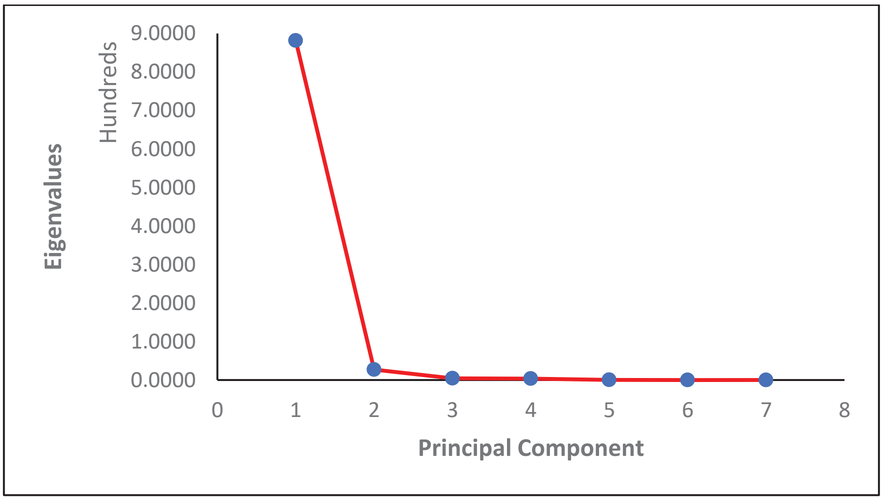

Figure-1: Screen Plot

I examine the impulse responses of all variables to 1 percent shock to GDP. Bootstrapping is used to construct the confidence interval for the impulse responses. The bands used in the impulse responses are the 16th and 84th percentiles of the bootstrapped distributions of the estimates. Therefore, I am using 68% confidence interval for all the impulse responses.

4.1 Largest Shock to GDP

Figure-2 displays the impulse responses to the largest shock to GDP in the Baseline VAR model. The largest shock to GDP is causing strong positive co-movement among the macroeconomic aggregates. GDP increases moderately on impact but then increases gradually over time to a permanent level. This implies that the largest shock to GDP is persistent and mainly dominates in the medium run rather than short run. TFP also increase on impact and then gradually increase before dipping down after 9 quarter. Consumption, investment and hours worked all have positive co-movement which is in line with empirical evidence of business cycle. Both inflation and interest rate fall on impact. Even though inflation returns to its initial level after 15 quarter, interest rate remains below its initial level even after 40 quarters. The fall in nominal interest rate is larger than the fall in inflation implying that the real interest rate had declined on impact.

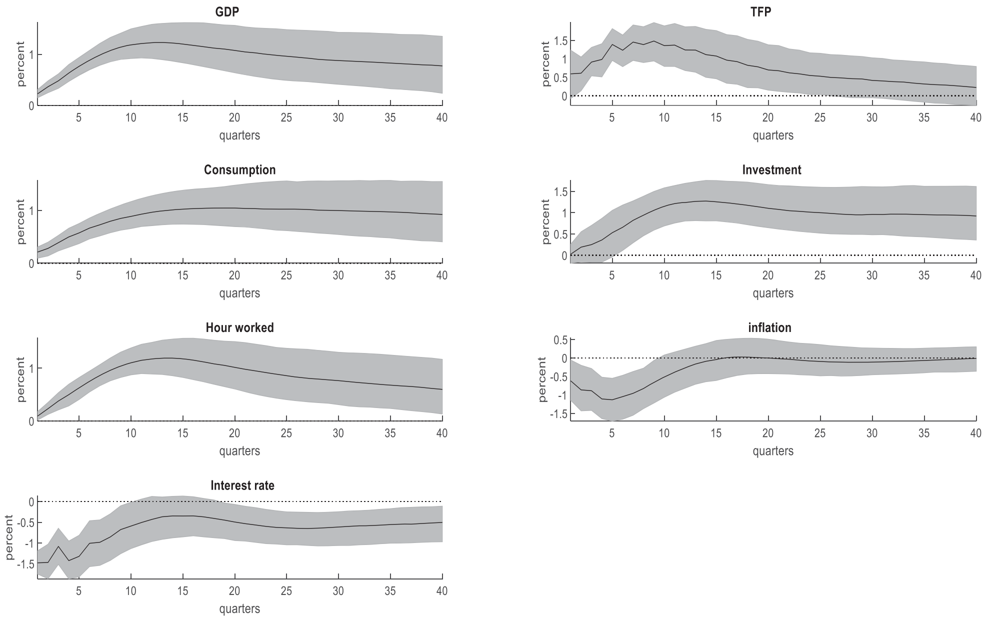

Figure-2: Impulse response to the largest shock to GDP in the Baseline Model
Note: 68 percent confidence interval is used

Now we want to check which prominent macroeconomic shock is consistent with the impulse responses in figure 2. First consider a monetary policy shock. If an exogenous monetary policy shock that reduces the interest rate, inflation rate should increase rather than decrease. Moreover, a monetary policy shock should not have a permanent impact on consumption and TFP (Christiano, Eichenbaum, and Evans 2005). So, the largest shock to GDP is not associated with monetary policy.

Let's consider any kind of demand shock for example preference shock or investment specific shock. Such demand shock also should not have a permanent impact on consumption and TFP. In addition, a fall in inflation in our case for a prolonged period is inconsistent with any conventional demand shock.

So, the response of the aggregate variables to the largest shock to GDP resembles a supply shock as both inflation and interest rates went down on impact and remains below the initial level for a prolonged period. We can eliminate the possibly of a TFP surprise shock which would increase TFP on impact significantly and then TFP would gradually decline. Here we are observing a gradual increase in TFP after the impact. So, the only possible candidate left is a TFP news shock which usually don't affect TFP on impact but causes a gradual increase of TFP over time. A positive TFP news shock is characterized as good news about future productivity which does not affect current productivity but increases future productivity. So, the largest shock to GDP seems like a TFP news shock, except the fact that there is an initial jump on impact. As our TFP data of Canada is not utilization adjusted, so this quarterly estimate of TFP may indeed be influenced by changes in capacity utilization. (Shutao and Sharon, 2015). Moreover, news shocks can change capital utilization, and therefore measured productivity immediately if the productivity data are left unadjusted. (Nam and Wang, 2011). Thus, we suspect that the increase in TFP on impact is arising due to the change in capacity utilization rather than the change in TFP itself. This makes TFP news shock a strong candidate for the largest shock to GDP.

One of the characteristics of TFP news shock is that it affects the forward-looking variables on impact. In the baseline VAR we have inflation which is forward looking. In the New Keynesian framework inflation is defined as the present value of expected real marginal cost. A news about increase in future productivity should reduce the expected future marginal cost and this might lead to a decline in inflation on impact.

In order to find additional evidence in support of TFP news shock as the largest shock to GDP, I extend my VAR model by incorporating stock prices which are considered to be prognostic of future movements in TFP (Beaudry and Portier, 2006). A positive TFP news shock should increase stock price on impact. Figure-3 shows impulse responses for the extended model. We can observe a significant increase in stock price on impact which provides additional support in favor of TFP news shock being the largest shock to GDP.

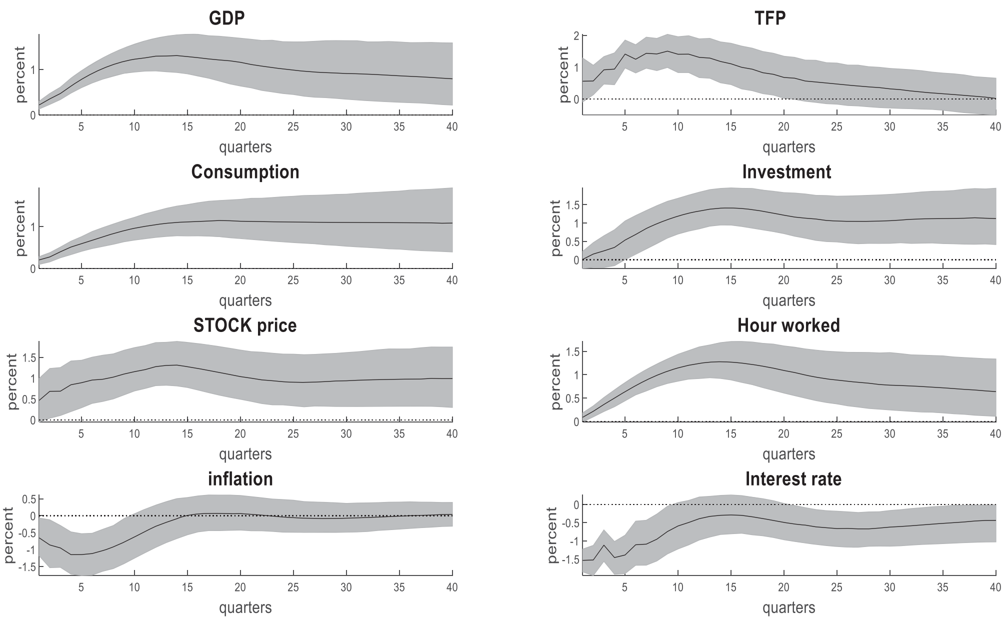

Figure-3: Impulse response for the extended model with stock price
Note: 68 percent confidence interval is used

4.2 Second Largest Shock to GDP

The second largest shock to GDP in Canada corresponds to the second largest eigenvalue i.e. second principal component of our model. Figure-4 displays the impulse response to the second largest shock to GDP. This shock has a transitory effect on all variables. GDP rises on impact and reaches to its peak in 1 year, then become negative after 3 years. This implies that the second largest shock to GDP does not have a permanent impact and it mainly dominates in the short run. TFP increases on impact but then falls gradually. Consumption, investment, stock price and inflation all behave in a similar manner where they rise on impact, reaches to its peak very quickly and then gradually falls to initial level. Hours worked, and interest rate do not change to much on impact but afterwards both rises. Even though interest rate returns to its initial level after 16th quarter, hours worked becomes negative only after 12th quarter.

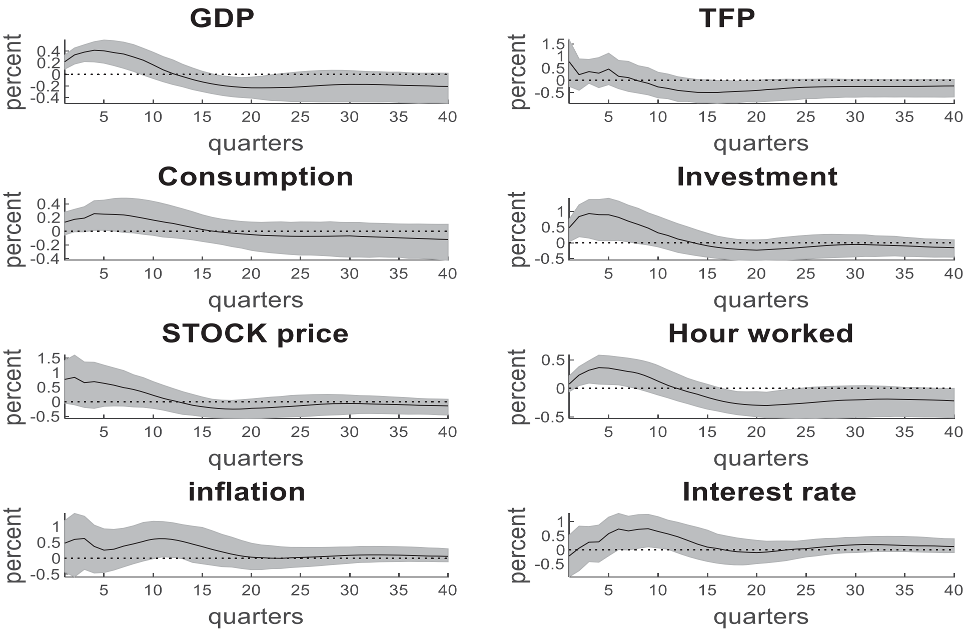

Figure-4: Impulse response to the second largest shock to GDP in the extended Model
Note: 68 percent confidence interval is used

As the inflation is increasing on impact so I can discard the possibility of a supply shock. It seems like the shock is arising from demand side. Two features of the responses to the shock are in favor of this claim. First, inflation is rising on impact which is the typical response of price level due to any demand shock. Second, the shock is not permanent and causes fluctuations to the economic aggregates only in the short run. These are the usual characteristics of a demand shock in the economy. Even though I suspect that the second largest shock to GDP is some type of demand shock, it is not possible to pin down the exact source of the shock. Uhlig (2003) was also unable to identify the short run shock to real GNP accurately as medium run shock contributes a considerable amount of variation at shorter horizons too, which does not allow us to fully disentangle the short run shock from the medium run shock.

4.3 Decomposition of Forecast Error Variance

Figure-5 illustrates fraction of forecast error variance of aggregate variables explained by TFP news shock. TFP news shock can explain more than 50 percent of variation in TFP after 15 quarters. This seems intuitive as most of the variation of TFP in shorter horizon is explained by TFP surprise shock whereas in longer horizon news shock can explain majority of the variation. TFP news shock can explain around 60 percent variation of GDP after 17 quarter, which implies that it is the key driver of GDP in the medium run. TFP news shock also explain significant variation in other aggregate variables too but at a longer horizon.

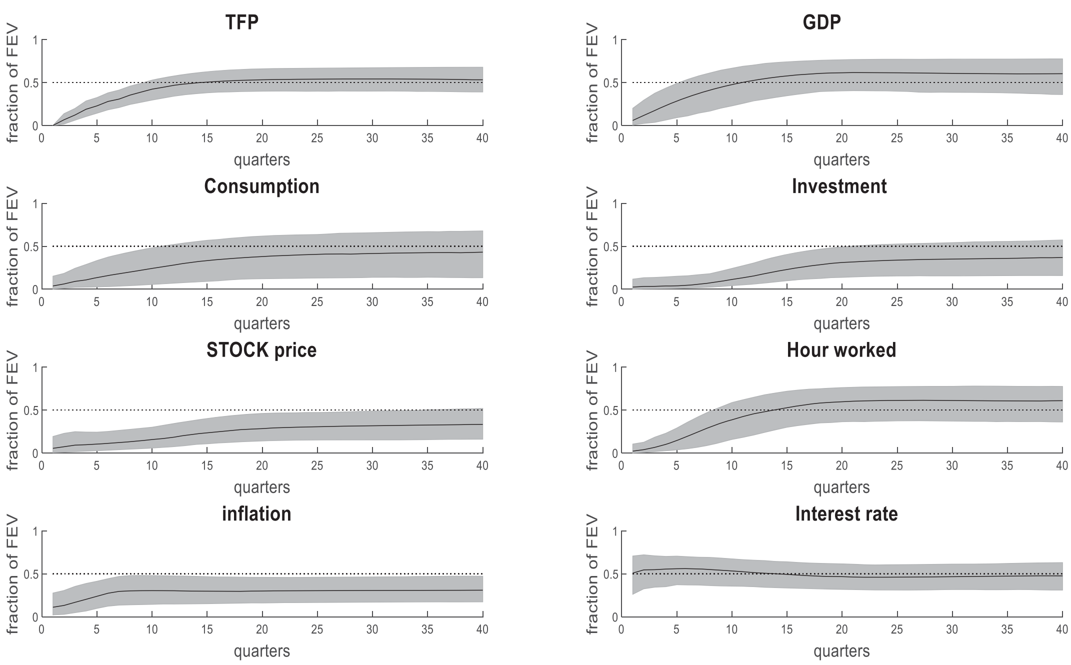

Figure-5: Fraction of FEV explained by TFP news shock
Note: 68 percent confidence interval is used

4.4 Discussion

Since the last decade, expectation driven business cycle hypothesis has become prominent in business cycle literature. Even though this concept was originally pioneered by Pigou (1927), it gained popularity by the work of Beaudry and Portier (2004) who theoretically proved that business cycles might arise on the basis of expectations of future fundamentals. Beaudry and Portier (2006) empirically demonstrated that good news about future productivity can cause positive co-movement among aggregate variables. However, Barsky and Sims (2011) concluded that despite being an important source of output fluctuation at medium frequencies, TFP news shock fail to explain four out of six of the most recent US recessions. Their findings endorse the prediction of neo-classical model where a TFP news shock causes movement in consumption and hours worked in opposite direction. Our findings are more in line with the findings of Beaudry and Portier (2006) as we found significant positive co-movements of all the aggregate variables. Kamber (2017) also found evidence that TFP news shock can generate business cycle in small open economy like Canada.

5 Robustness Check

I carry out some robustness check to ensure that my findings do not alter for different specification of TFP and alternative identification strategy. As my TFP estimate for Canada might be contaminated because it is not utilization adjusted, I am going to use labor productivity as a proxy of TFP for the first robustness check. Also, I am going to verify whether a different identification strategy that identifies TFP news shock can lead to the same conclusion that I made. So, I will use SVAR identification method proposed by Barsky and Sims (2011) to extract the TFP news shock by using the same variable set and check whether this shock can generate the similar fluctuations in the aggregate variables.

5.1 Labor Productivity as a Proxy of TFP

As a robustness check of measurement of TFP, I replace the TFP series in the extended model with labor productivity series in Canada. Labor productivity is measured by output per hour in the non-farm business sector. The unconditional correlation between TFP and labor productivity for Canada is 0.85. So, labor productivity should be a reasonable proxy of TFP. The variable hours worked is removed from the extended model to avoid collinearity, so now I have a seven variable VAR model.

Figure-6 shows the impulse responses when labor productivity is used as a proxy of TFP. The responses of GDP and other aggregate variables to the largest shock is similar to those in the benchmark specification. Labor productivity is increasing on impact and then rises gradually over time to a permanent level. Nam and Wang (2011) noted that the labor productivity may have an initial jump on impact to a news shock as it is not adjusted for capital utilization. So, my findings are robust to a different specification of TFP.

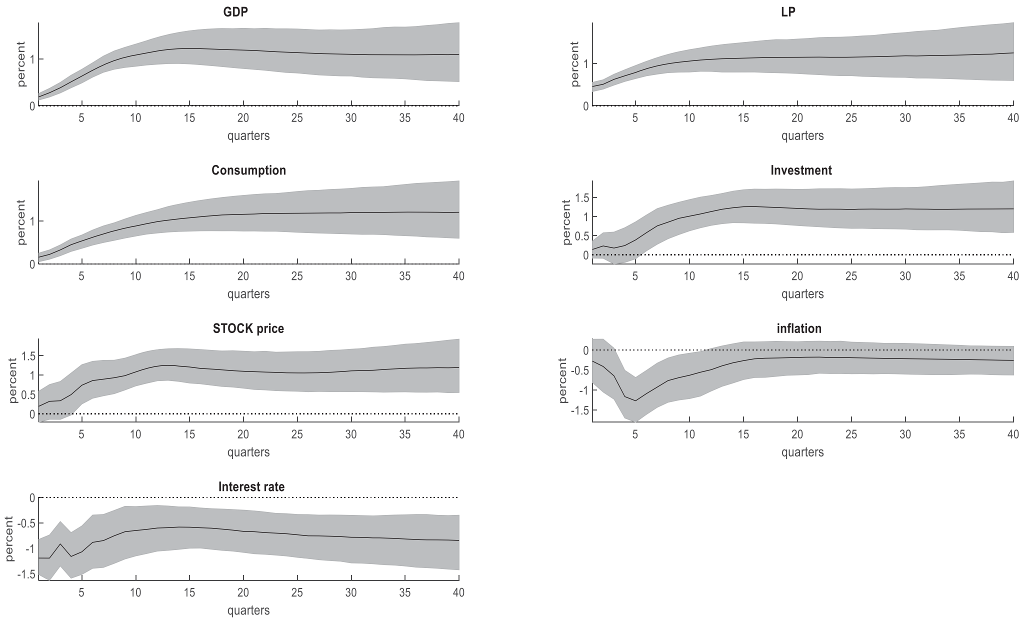

Figure-6: Impulse response to the largest shock to GDP (using labor productivity as a proxy of TFP)
Note: 68 percent confidence interval is used

5.2 Robustness under an Alternative Identification Approach

I want to check whether an alternative identification method that extracts TFP news shock can generate similar findings as mine. For this purpose, I choose Barsky and Sims (2011) identification technique where they employed Maximum Forecast Error Variance method to identify TFP news shock. This identification scheme is built on Francis et al. (2007).

Barsky and Sims (2011) assume that TFP is an stochastic process which is driven by only two shocks: a TFP surprise shock that can affect TFP contemporaneously and a TFP news shock that does not have contemporaneous affect of TFP, instead it impacts TFP in the future. Consider the logarithm of TFP as the following:

$$\ln A_t = g + ln\,A_{t-1} + e_{1,t} + e_{2,t-j}$$

Here A_t denotes TFP, g is the drift term and $e_1$is the surprise TFP shock and e_2 is the TFP news shock. e_2 has no contemporaneous impact on TFP but it affects TFP 'j' periods into the future. In a VAR with TFP ordered first and several forward-looking variables along with macroeconomic aggregates, the surprise shock is identified as the reduced form innovation in TFP. Then the news shock of TFP can be identified as the shock that best explains future movement in TFP not accounted for by its own innovation.

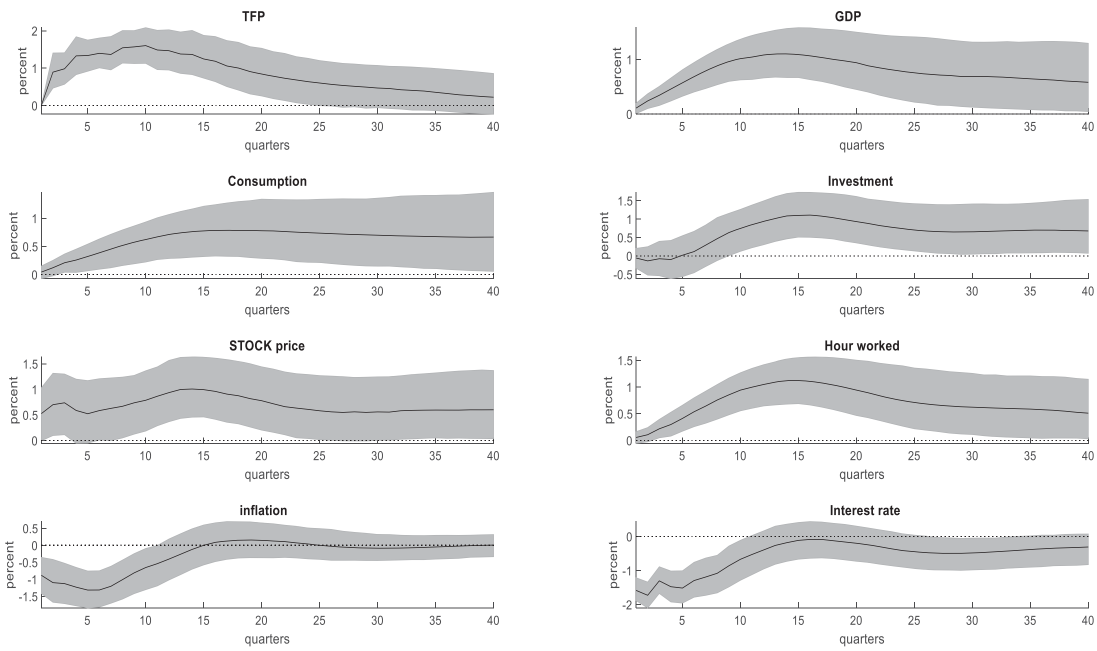

Figure-7: Impulse response to the TFP news shock (Barsky and Sims, 2011 identification method)
Note: 68 percent confidence interval is used

The impulse responses to the TFP news shock illustrate how aggregate variables responds to a news shock. By construction, TFP does not change on impact due to the news shock as we have assumed that news shock to TFP does not have a contemporaneous effect. GDP, consumption and hours worked all have small or no movement on impact but increases gradually afterwards to a permanently higher level. Investment increases with a delay. Stock price increases significantly on impact which is intuitive as stock price should rise in anticipation of good news about future productivity. Both inflation and interest rate drop significantly on impact and remain below the initial level up to 15 quarter. Therefore, comparing figure 3 with figure 7, we can observe that impulse responses of TFP news shock of Canada that is identified with an alternative identification method is very similar to that of my baseline findings. So, my findings are robust for alternative identification strategy.

6 Conclusion

This paper attempts to find the key driver of fluctuations in GDP in Canada for short and medium run. I used a flexible approach to extract the largest two shocks to GDP in Canada without imposing any strong assumption in identification method.

The largest shock to GDP can be characterised as a TFP news shock which is more dominant in medium term and has a permanent effect on GDP and other aggregate variables. My findings are robust under different specification of TFP and alternative identification strategy proposed by Barsky and Sims (2011). A TFP news shock causes positive co-movements in aggregate variables which is consistent with the empirical evidence. It can explain more than 60 percent variation of GDP in longer horizon and has a permanent level effect which implies that this shock is key driver of GDP in Canada.

The second largest shock to GDP has transitory effect on GDP and so I characterize it as a short run shock. Analyzing the responses of aggregate variables, I suspect that this shock is coming from demand side of the economy, but it is difficult to pin down exact fundamental source of the shock.

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