Term paper EC7415: Uncertainty shocks and unemployment dynamics in Canada

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January 9, 2023

1 Introduction

This term paper investigates the effect of uncertainty shocks on unemployment dynamics in Canada. The primary aim of this study is to gain more insight on the role of macroeconomic uncertainty in causing and amplifying fluctuations in unemployment. As shown in Figure 1, when the Canadian economy is in recession, the unemployment rate increases drastically in a very short time, accompanied by a similar sharp decline in job finding probability[1]; whereas when the economy is in an expansionary phrase, these two variables change more slowly. Such non-linear behaviour motivates the use of a regime-switching model for analysis. As suggested by Caggiano et al. (2014), a smooth-transition VAR model (STVAR) would be a suitable candidate for this task.

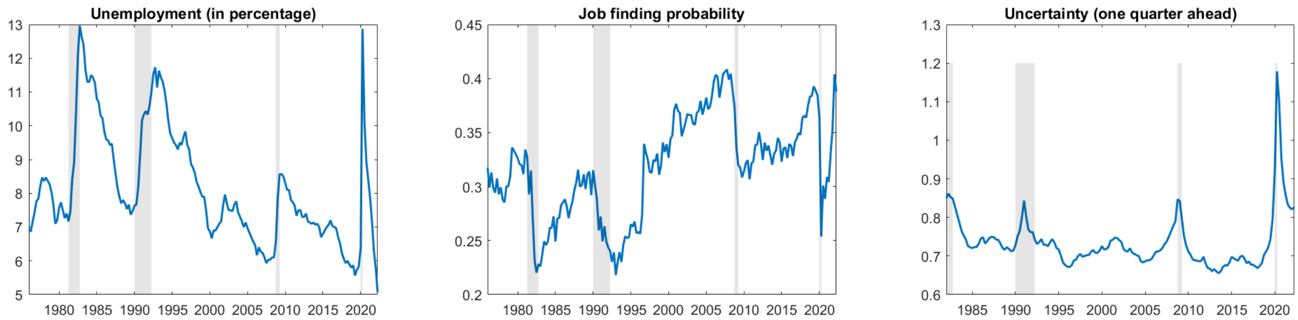

Figure 1: *The movement of Canadian unemployment rate in percentage term, job finding probability, and one-quarter-ahead Canadian macroeconomic uncertainty index. Shaded regions indicate recession periods dated by C.D. Howe Institute Business Cycle Council.*

2 Theory

Although there are many types of shock that could contribute to fluctuations in unemployment, in this study, I chose to focus on one particular type of shock: *uncertainty*. As indicated by the rightmost panel of Figure 1, spikes of uncertainty tend to occur during recessions, periods in which unemployment is also high. Leduc and Liu (2016) suggested that uncertainty may affect unemployment through aggregate demand: an increase in uncertainty induces consumers to make precautionary savings, thereby lower the aggregated demand. As demand falls, firms earn less profit and the value of a job match decreases. Hence, firms will respond to an uncertainty shock by posting fewer vacancies, leading to a decline in the job finding probability and an increase in the unemployment rate. In the following sections, we will see whether this theory is supported by the data.

3 Data

It is common in existing literature to use an uncertainty index, such as the VIX index (Leduc and Liu, 2016) and the Economic Policy Uncertainty (EPU) index (Caggiano et al., 2020), as a proxy for economic uncertainty. In this paper, I followed the example made by Moran et al. (2022) and used two uncertainty

[1]That is, the outflow rate from unemployment. Section 4.2 explains in detail how job finding probability is calculated.

indices to capture the overall uncertainties in the Canadian economy: the Total Macroeconomic Uncertainty Index developed by Jurado et al. (2015), which provides estimates of the uncertainties in the US economy, and the Canadian Macroeconomic Uncertainty Index developed by Moran et al. (2022), which can be treated as the Canadian counterpart of the former[2].

The macroeconomic variables used in this paper come from various sources. Quarterly data on Canadian real GDP level, Consumer Price Index (CPI), and unemployment rate were downloaded from the FRED database. Monthly data on unemployment durations, which is essential for the calculation of job finding probability, were retrieved from Statistics Canada (StatCan)[3].

Notice that this study is based on quarterly data, as the transition variable used (discussed below) is given at quarterly level. The period of study is 1982Q2–2020Q1. The sampled period covers, according to the C.D. Howe Institute[4], three recession periods in Canadian macroeconomic history: (i) 1981Q2–1982Q4, (ii) 1990Q1–1992Q2, (iii) 2008Q3–2009Q2. The choice of starting date is based upon the fact that the Canadian Macroeconomic Uncertainty Index starts from 1982Q1. And as a result of the log-difference transformation, which is performed on nearly all variables to ensure stationarity, the 1982Q1 is omitted, making 1982Q2 my starting date. Notice also that I omitted from the sample observations after the Covid-19 outbreak. This is mainly because of the extreme variations in data since the outbreak in March 2020 (or 2020Q1) could, according to Lenza and Primiceri (2022), influence the parameter estimates substantially and thereby making the estimates heavily dependent on observations in the end of the sample[5]. As the purpose of this study is to understand Canadian unemployment dynamics and not to make forecast, it is therefore reasonable to exclude observations after 2020Q1 from the sample (Lenza and Primiceri, 2022). Nevertheless, the 2020Q1 data is included because, as suggested by Moran et al. (2022), the drastic increase in uncertainty during this particular quarter represents the Covid-19 shock, which is informative for a study investigating the macroeconomic effect of uncertainty.

As mentioned above, nearly all variables in my data were transformed. Monthly data such as the unemployment duration and the US uncertainty index were transformed into quarterly data through quarterly averaging. To ensure stationarity, which is required for VAR estimation, different transformation strategies were implemented. Log-diff transformations are applied to the real GDP level, CPI, unemployment rate, and job finding probability[6]. The US and the Canadian uncertainty indices were transformed into percentualised quarter-to-quarter growth rate.

4 Empircal strategy

4.1 Smooth-transition VAR

As noted above, Figure 1 shows a clear non-linear, state-dependent pattern of the Canadian unemployment rate and job finding probability. Modelling these variables using a linear VAR could be misleading, as the structural impulse responses estimated from a linear VAR are invariant to the state of the economy in which the shocks occurred (Kilian and Lütkepohl, 2017). A non-linear VAR such as STVAR addresses

[2]The US uncertainty index by Jurado et al. (2015) can be downloaded from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes, while the Canadian version by Moran et al. (2022) from https://chairemacro.esg.uqam.ca/previsions-et-mesures-macroeconomiques/mesure-dincertitude/.

[3]More specifically, data that were downloaded from FRED are: seasonally adjusted real GDP levels for Canada (NGDPRSAXDCCAQ), unadjusted CPI on all items for Canada (CANCPIALLQINMEI), and unemployment rate for all Canadians aged 15 or above (LRUNTTTTCAQ156S). And from StatCan: duration of unemployment, monthly and seasonally adjusted (Table: 14-10-0342-01).

[4]C.D. Howe Institute Business Cycle Council is the Canadian equivalent to the NBER Business Cycle Dating Committee in the US. The council's recession dating can be accessed from its website https://www.cdhowe.org/council/business-cycle-council.

[5]In my opinion, this dependency will only exacerbate given the events occurred during 2022, such as the Russian invasion of Ukraine. It would therefore be reasonable to disregard observation 2020Q2–2022Q2 entirely.

[6]The job finding probability was rescaled to 1-100 before transformation.

these issues by using a linear combination of m estimated linear VARs to describe the endogenous variables, where m is the number of states or regimes (Caggiano et al., 2014). In this paper, I consider the case that the economy is either in expansion or in recession ($m = 2$). The STVAR used in this paper can be described as followed

$$\mathbf{X}_t = (1 - F(z_{t-1}))\,\mathbf{\Pi}_E(L)\,\mathbf{X}_t + F(z_{t-1})\,\mathbf{\Pi}_R(L)\,\mathbf{X}_t + \mathbf{u}_t \tag{1}$$

$$\mathbf{u}_t \sim N(0, \mathbf{\Omega}_t) \tag{2}$$

$$\mathbf{\Omega}_t = (1 - F(z_{t-1}))\,\mathbf{\Omega}_E + F(z_{t-1})\,\mathbf{\Omega}_R \tag{3}$$

$$F(z_t) = \frac{\exp(-\gamma z_t)}{1 + \exp(-\gamma z_t)}, \quad \gamma > 0, \quad E[z_t] = 0, \quad V(z_t) = 1 \tag{4}$$

where $\mathbf{X}_t$ in Eq.(1) is the set of endogenous variables included in the model. $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_R$ are both matrices of estimated VAR coefficients, which capture the *dynamic* effects of a given structural shock. Notice that we have here two sets of dynamic effects: $\mathbf{\Pi}_E$ captures the dynamic effects during the expansion regime, whereas $\mathbf{\Pi}_R$ captures that of the recession. $F(z_{t-1})$ is the transition function, in this case, it is the probability of being in a recession. Eq.(4) shows that the transition function depends on z_t, the transition variable, and on a parameter γ, which governs the "smoothness" of the transition from expansion to recession. A high value of γ implies that the regime transition becomes more sudden. Notice that $F(z_t)$ in Eq.(4) takes the shape of a logistic function, and that in Eq.(1), the transition variable z_t is lagged by one period[7]. Finally, the term $\mathbf{u}_t$ in Eq.(1) is the reduced-form residuals resulted from VAR estimation. As indicated by Eq.(2), $\mathbf{u}_t$ is normally distributed with zero mean and a variance-covariance matrix $\mathbf{\Omega}_t$. Eq.(3) shows that $\mathbf{\Omega}_t$ can also be decomposed into two parts: $\mathbf{\Omega}_E$ for expansion and $\mathbf{\Omega}_R$ for recession. It is worth noting that, in contrast to $\mathbf{\Pi}_E$ and $\mathbf{\Pi}_R$, $\mathbf{\Omega}_E$ and $\mathbf{\Omega}_R$ are both matrices whose elements capture the *contemporaneous* effects of a given structural shock. This implies that, in a STVAR, both the dynamic and the contemporaneous relationship of the economic system might differ from one regime to another: whereas $\mathbf{\Pi}_R(L)$ and $\mathbf{\Omega}_R$ describes the behaviour of endogenous variables in the recession phrase, the behaviour of the same set of variables in an expansion is described by $\mathbf{\Pi}_E(L)$ and $\mathbf{\Omega}_E$ instead (Auerbach and Gorodnichenko, 2012).

4.2 Model specification

My baseline analysis is based upon a set of five endogenous variables

$$\mathbf{X}_t = \left[\Delta\mathcal{U}_t^{US} \;\; \dot{y}_t \;\; \dot{u}_t \;\; \pi_t \;\; \Delta\mathcal{U}_t^{CAN}\right]' \tag{5}$$

where $\Delta\mathcal{U}_t^{US}$ and $\Delta\mathcal{U}_t^{CAN}$ are the *quarter-to-quarter* percentage change of the *one-quarter-ahead* macroeconomic uncertainty in the US and Canada, respectively; $\dot{y}_t$ and $\dot{u}_t$ denotes the *continuously compounded* percentage growth of Canadian real GDP and unemployment rate, respectively; and finally, π_t is the inflation, defined as the log-difference of the quarterly CPI for all items.

Additionally, I also estimate the following model, in which the percentage change in unemployment rate, $\dot{u}_t$, is replaced by the same change in job finding probability, $\dot{\Phi}_t$.

$$\mathbf{X}_t = \left[\Delta\mathcal{U}_t^{US} \;\; \dot{y}_t \;\; \dot{\Phi}_t \;\; \pi_t \;\; \Delta\mathcal{U}_t^{CAN}\right]' \tag{6}$$

where the level of job finding probability Φ_t is calculated using the following formula suggested by Rogerson and Shimer (2011)

$$\Phi_t = 1 - \frac{U_{t+1} - U_{t+1}^{<1}}{U_t} \tag{7}$$

[7] This is because the transition variable chosen (see discussion below) is itself an endogenous variable. In this case, the economy could be in a recession either because of a shock in the endogenous variable or because of the assignment through the transition function. Lagging the transition variable by one period prevents us from mixing up the these two causes (Auerbach and Gorodnichenko, 2012).

where U_t in Eq.(7) above denotes the total *number* of unemployed in month t, while $U^{<1}_{t+1}$ is the number of unemployed with unemployment duration less than one month. So $U_{t+1} - U^{<1}_{t+1}$ will be the number of unemployed at month $t+1$ who have waited more than one month to find a job. Thus, the fraction at the RHS of Eq.(7) is the share of the unemployed who failed to find a job at month t, and one minus that fraction is defined as the probability of finding a job within one month.

4.2.1 Identification

Following previous research such as Caggiano et al. (2014), I applied short-run restriction (i.e., Cholesky decomposition) for identification[8]. Using this identification strategy requires careful motivation of how the endogenous variables are ordered. In fact, the ordering of the endogenous variables, as shown in Eq.(5) and (6), resembles that of Moran et al. (2022). The US macroeconomic uncertainty, which is unlikely to be affected by fluctuations in the Canadian economy, is ordered first[9]. Among the macroeconomic variables, the growth rate of real output is ordered second, followed by changes in unemployment/job finding probability and in inflation. This ordering rules out any contemporaneous effect of an unemployment shock on real output and of a price shock on unemployment (or job finding probability)[10].

Concerning the ordering of Canadian macroeconomic uncertainty, two different views were offered in Moran et al. (2022). The first is to order the Canadian uncertainty last, treating the Canadian uncertainty as an outcome endogenous to changes in the Canadian economy. The second view is to treat uncertainty as exogenous, and domestic macroeconomic variables have zero contemporaneous impact on the uncertainty level of the domestic economy. This view suggests that we should order the Canadian uncertainty second – after the US uncertainty. My baseline specifications, as outlined in Eq.(5) and (6), follow the first view. Since the first view implies that Canadian uncertainty shock will only have a modest effect, one can interpret my baseline estimates as the lower bounds of the impact of Canadian uncertainty shock on unemployment/job finding probability. The second view will serve as a robustness check for my baseline results.

4.2.2 The transition function

In choosing the transition variable z_t, I followed the example made by Auerbach and Gorodnichenko (2012) and selected the seven-quarters backward moving average of the *quarter-on-quarter* real GDP growth rate[11]. The main reason for this choice is that data on real GDP is readily available, something that allowed me to use a sample starting from the earliest record of the Canadian macroeconomic index[12]. As indicated in the left panel of Figure 2, the troughs of the non-standardised $MA(7)$ of real GDP growth overlap with recession periods quite well.

In choosing the appropriate value for the smoothness parameter γ in the transition function, as specified in Eq.(4), I again followed existing research (Auerbach and Gorodnichenko, 2012; Caggiano et al., 2015) and performed a grid search to find a value of γ that matches the frequency of recession periods observed in the data. The share of recession periods in my sample is 10.53 % (9 out of 152 quarters), hence is the

[8] This means to decompose the variance-covariance matrices of reduced-form residuals in Eq.(3), $\mathbf{\Omega}_R$ and $\mathbf{\Omega}_E$, as the product of a lower triangular matrix and its transpose. The lower triangular matrix found in this way – the so-called short-run impact matrix – can be used to obtain the structural shocks and the generalised impulse response function for each regime.

[9] In addition, considering the fact that the US economy is ten times larger than the Canadian one and the degree of economic integration between the two countries, it is also reasonable to assume that the US uncertainty has a contemporaneous effect on all Canadian macroeconomic variables included in the model.

[10] It is more likely that the unemployment rate responds to a demand shock within a quarter than the reverse case. And firms are unlikely to make a contemporaneous response to an inflation shock because of nominal rigidities in wages.

[11] This means that z_t is based on real GDP growth in discrete time, which is slightly different from the endogenous variable $\dot{y}_t$, which is the growth rate in continuous time.

[12] I have also considered using the Canadian capacity utilisation rate as z_t. However, the earliest available record of capacity utilisation rate on StatCan is 1987Q1. Using capacity utilisation rate would mean that I have to omit the recession 1981Q2–1982Q4 from my sample, something I am unwilling to do.

recession defined as $F(z_t) \geq 1 - 0.1053 = 0.8947$. Matching γ with the frequency of recessions means, therefore, to find a γ such that $Pr(F(z_t) \geq 0.8947) \approx 0.1053$. This yields $\gamma = 1.3164$. The resulted transition function is shown in the right panel of Figure 2.

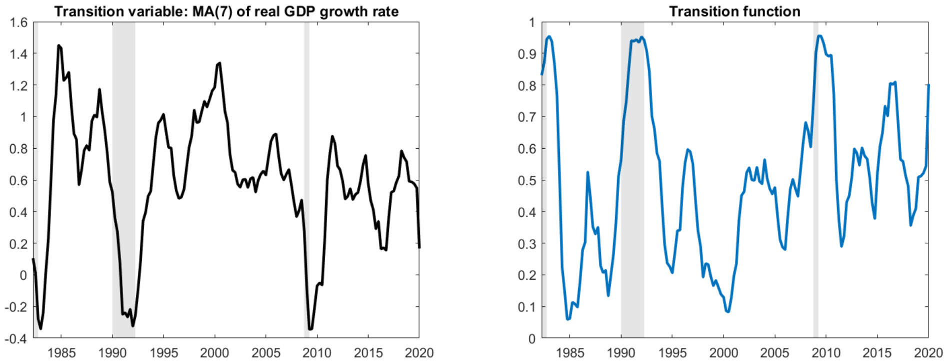

Figure 2: *Left panel: Non-standardised seven-quarter backward moving average of real GDP growth in percentage. Right panel: the transition function $F(z_t)$ computed from the normalised transition variable and the smoothness parameter $\gamma = 1.3164$. The shaded regions are recession periods*

4.2.3 Non-linearity test

In order to provide more support for the choice of modelling unemployment and uncertainty with a STVAR, I performed the Lagrange multiplier test of linearity developed by Teräsvirta and Yang (2014). The idea is to compare the residual sum of squares (RSS) of a linear VAR with that of a STVAR[13]. The linear VAR is the restricted model in this case, hence is linearity the null hypothesis of the test. The test statistics is

$$LM_{TR2} = T\left(p - \mathrm{tr}\left(\left(\tilde{\mathbf{E}}'\tilde{\mathbf{E}}\right)^{-1}\tilde{\mathbf{\Xi}}'\tilde{\mathbf{\Xi}}\right)\right) \tag{8}$$

where T is the number of periods in the sample, p is the number of endogenous variables, $\tilde{\mathbf{\Xi}}'\tilde{\mathbf{\Xi}}$ and $\tilde{\mathbf{E}}'\tilde{\mathbf{E}}$ are matrices of RSS from the linear VAR and the STVAR, respectively. The LM statistics of my baseline specifications Eq.(5) and (6) are $LM^{u}_{TR2} = 98.4791$ (p-value $= 0.000$) and $LM^{\Phi}_{TR2} = 80.2851$ (p-value $= 0.000$), respectively. The null hypothesis of linearity is therefore rejected.

4.2.4 Selection of lags, stationarity test, and estimation

The number of lags chosen for my STVAR is one lag for both model in Eq.(5) and that in Eq.(6). The decision is based on Akaike's Information criterion (AIC). In addition to AIC, I also computed the Bayesian information criterion (BIC) and the Hannan–Quinn information criterion (HQC). As indicated in Table 1, all three information criteria agreed on selecting only one lag for both models.

A vital assumption for VAR and STVAR is that the endogenous variables and the transition variable are stationary. Most of the series used in this study are non-stationary at levels and therefore must be transformed. Using the lag length selected previously, I performed an Augmented Dickey-Fuller (ADF) test with drift and trend, and a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, to check whether the transformed variables were stationary. The results are shown in Table 2. The ADF test rejects the null-hypothesis of unit root for all variables used in this study, while the KPSS test shows that while five of seven variables are trend stationary, two are not: the difference in logs of the CPI and the $MA(7)$ of

[13]More specifically, the STVAR tested here uses a logistic transition function approximated by an n-th order Taylor expansion. For the technical details of the test, see the online appendix of Caggiano et al. (2020) and Teräsvirta and Yang (2014). The MATLAB code is written by myself based on (or "translated" from) the R code written by Bucci et al. (2022).

quarter-to-quarter real GDP growth[14]. Nevertheless, since the ADF test rejects unit root for both these two variables, and the fact this study focuses more on uncertainty and unemployment, rather than on inflation, I decided to proceed with both variables included, while acknowledging the non-stationarity of these variables could imply some stability issue of the VARs.

	Model in Eq.(5)			Model in Eq.(6)		
Lags	AIC	BIC	HQC	AIC	BIC	HQC
1	**3.5932***	**3.8356**	**4.1900**	**4.4310***	**4.6734**	**5.0278**
2	3.6165	4.0610	4.7106	4.4847	4.9292	5.5789
3	3.6461	4.2927	5.2377	4.4918	5.1383	6.0833
4	3.6766	4.5252	5.7655	4.5326	5.3811	6.6214
5	3.7654	4.8161	6.3517	4.6521	5.7027	7.2383
6	3.9265	5.1791	7.0100	4.7861	6.0387	7.8696
7	4.0281	5.4828	7.6090	4.9384	6.3931	8.5193
8	4.1459	5.8026	8.2241	5.0688	6.7255	9.1470

Table 1: *Information criteria for the selection of lags. The lowest value of each information criterion in boldface. The lowest value among all three information criteria is marked by assterisk.*

	ADF test		KPSS test	
Variables	Test statistics	p-value	Test statistics	p-value
$\Delta\mathcal{U}_t^{US}$	-6.2712	0.0010	0.0718	0.1000
$\dot{y}_t$	-6.2121	0.0010	0.0896	0.1000
$\dot{u}_t$	-6.9007	0.0010	0.0650	0.1000
$\dot{\Phi}$	-9.0086	0.0010	0.0528	0.1000
π_t	-10.6062	0.0010	0.2748	0.0100
$\Delta\mathcal{U}_t^{CAN}$	-4.2094	0.0058	0.1202	0.0979
z_t	-3.9624	0.0122	0.2077	0.0131
Critical value:	-3.4407		0.1460	

Table 2: *Results from stationarity tests using the conventional level of* $\alpha = 0.05$.

The estimation of STVAR is done in MATLAB, using the *macrometrics* toolbox written by Gabriel Züllig[15]. The STVAR estimation function in his codes is based on that of Auerbach and Gorodnichenko (2012), who used a Monte Carlo Markov Chain (MCMC) for estimation. The number of MCMC draws is set to 30,000, while 20 % of them will be discarded as burn-in sample[16]. The confidence band for the impulse response function (IRF) is set to 90 %. In addition to a STVAR, a linear VAR will also be estimated for the purpose of comparison.

[14]Concerning the log-difference of CPI, graphical examination revealed that there might be a structural break in the variable around 1991. Perhaps this is the reason for the rejection of trend stationarity. Although the non-stationarity of π_t might not necessarily invalidate the results of this study, caution must still be taken, as the results of ADF test might be biassed towards non-rejection if structural break is present (Enders, 2015).

[15]This MATLAB toolbox can be downloaded from here: `https://gabrielzuellig.ch/macrometrics/`.

[16]In Bayesian statistics, inference is based on the posterior distribution of parameters. However, for various reasons, such as non-linearity in the parameters, the posterior distribution might not be available in close form. In cases like this, we have to rely on numerical methods such as the MCMC to approximate the posterior. MCMC does that by generating a long sample of the parameter vector, whose distribution converges to the posterior distribution of parameters if the Markov chain is sufficiently long. However, draws from this parameter vector are not independent. So to ensure a precise approximation of the posterior distribution, some initial sample values are discarded, these are the so-called burn-in sample (Kilian and Lütkepohl, 2017).

5 Results

5.1 Impulse response functions

5.1.1 US Uncertainty shock

Figures 3 and 4 show the IRFs of a one standard deviation shock in one-quarter-ahead US uncertainty. It is clear that US uncertainty shocks have significant impacts on Canadian macroeconomic uncertainty, real output, unemployment, and job finding probability within the first four to six quarters. The movements of the macroeconomic variables after an unexpected rise in uncertainty (i.e., fall in real output and job finding probability, and rise in unemployment rate) shown in Figure 3 and 4 also provide tentative empirical support to the theory presented by Leduc and Liu (2016).

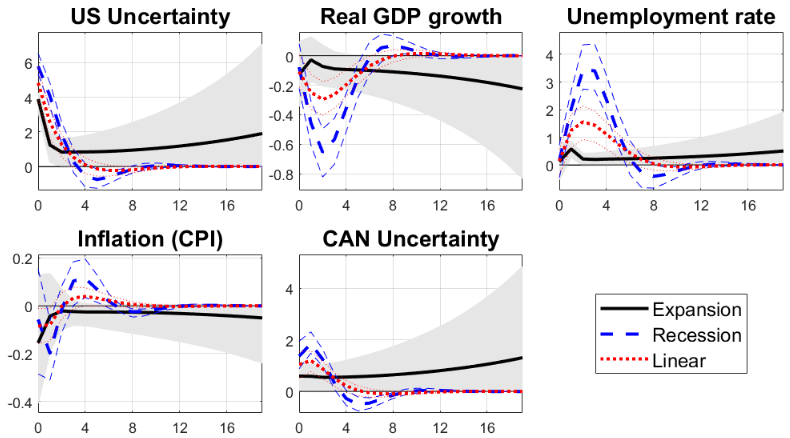

Figure 3: *IRF of one standard deviation shock in US uncertainty, baseline model in Eq.(5)*

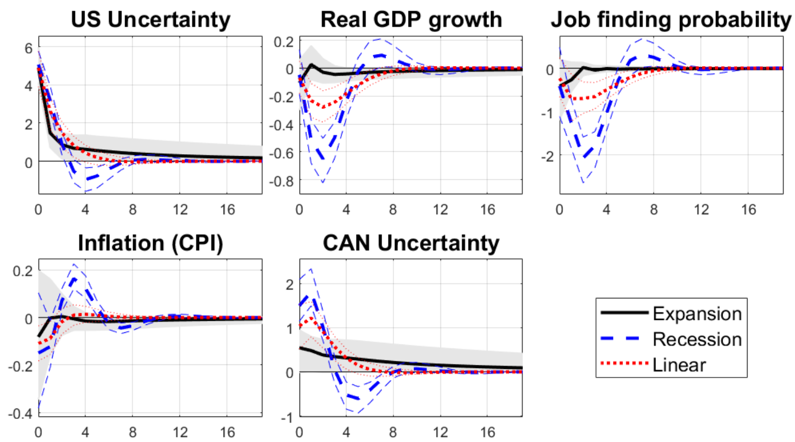

Figure 4: *IRF of one standard deviation shock in US uncertainty, baseline model in Eq.(6)*

As expected, a US uncertainty shock has a larger impact on the Canadian unemployment rate and job finding probability during recessions than during expansions. Under the recession regime, the STVAR estimated the effect of a one standard deviation-shock in US uncertainty to unemployment and job finding probability to peak about three quarters after the shock, leading to a roughly 3.43 % increase in the unemployment rate and a 1.96 % decrease in job finding probability. Both these estimates are higher than those estimated by a linear VAR (1.56 % increase and 0.7 % decrease, respectively). These two patterns corroborate with those found by Caggiano et al. (2014, 2020).

5.1.2 Canadian uncertainty shock

As shown in Figures 5 and 6, the effect of a one standard deviation shock in Canadian uncertainty is relatively moderate compared to its US counterpart. This is partly because of the "late" ordering of the Canadian uncertainty measure. Nevertheless, as in the US case, the STVAR estimated a larger effect of the Canadian uncertainty shock on the unemployment rate during recessions than during expansions. Its effect on job finding probability is less clear, probably not statistically significant.

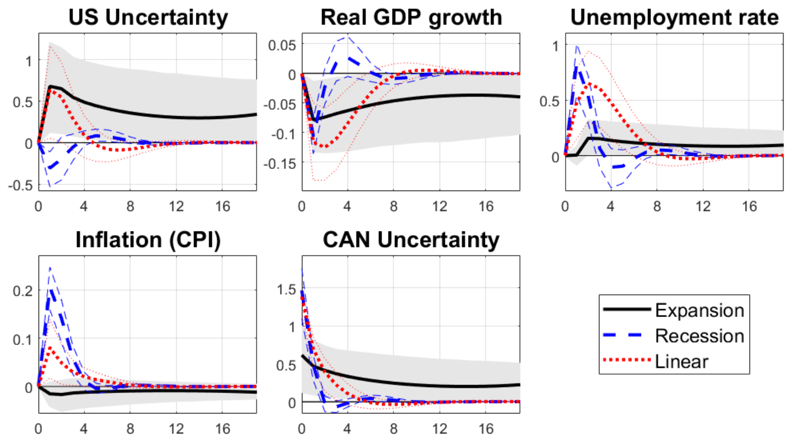

Figure 5: *IRF of one standard deviation shock in Canadian uncertainty, baseline model in Eq.(5)*

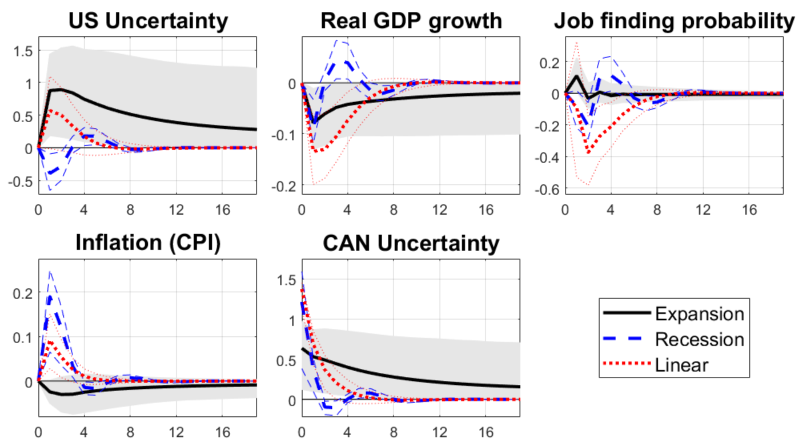

Figure 6: *IRF of one standard deviation shock in Canadian uncertainty, baseline model in Eq.(6)*

5.2 Robustness check

5.2.1 Alternative ordering

As mentioned previously, we can also treat Canadian uncertainty as exogenous to macroeconomic activities, and place it right after the US uncertainty, that is

$$\mathbf{X}_t = \left[\Delta\mathcal{U}_t^{US} \;\; \Delta\mathcal{U}_t^{CAN} \;\; \dot{y}_t \;\; \dot{u}_t \;\; \pi_t\right]' \quad \text{and} \quad \mathbf{X}_t = \left[\Delta\mathcal{U}_t^{US} \;\; \Delta\mathcal{U}_t^{CAN} \;\; \dot{y}_t \;\; \dot{\Phi}_t \;\; \pi_t\right]'$$

My focus in this alternative setting is on the effect of a Canadian uncertainty shock. The IRFs are shown in Figure 7 and 8. Clearly, by treating Canadian uncertainty as exogenous, its impact on the unemployment rate and job finding probability is larger than that in my baseline specifications. During recessions, an unexpected rise in Canadian uncertainty by one-standard deviation will increase the unemployment rate by 1.09 % and decrease job finding probability by 0.78 %[17] after two quarters compared to the baseline estimates of 0.75 % and 0.23 %, respectively[18].

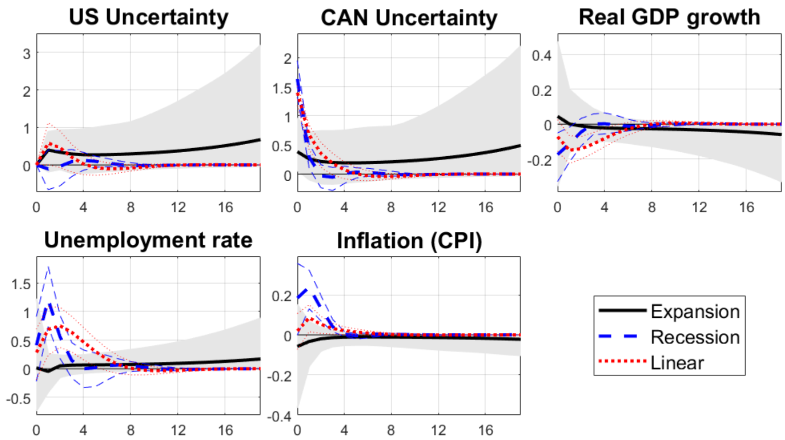

Figure 7: *IRF of one standard deviation shock in Canadian uncertainty, alternative ordering that corresponds to Eq.(5)*

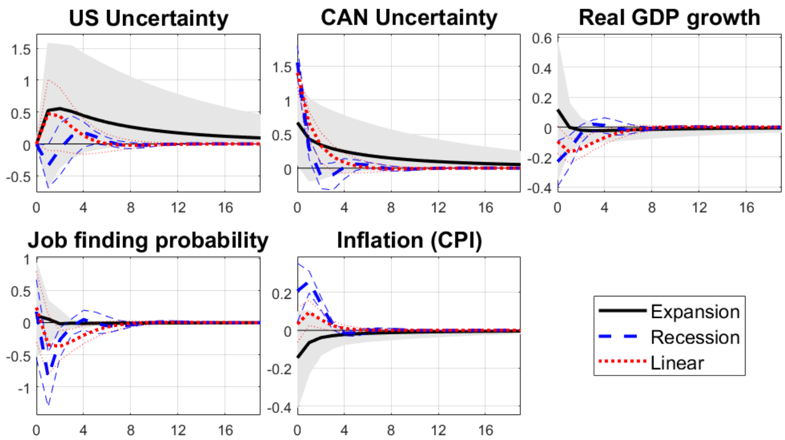

Figure 8: *IRF of one standard deviation shock in Canadian uncertainty, alternative ordering that corresponds to Eq.(6)*

5.2.2 Other robustness checks

Two other robustness checks were performed. The first one is to change the uncertainty measures from *one-quarter-ahead* macroeconomic uncertainty to *one-year-ahead*. The IRFs for expansions, produced by STVARs using this alternative uncertainty measure, rise wildly as the number of horizons increases. It appears, therefore, that the STVARs presented in this study are sensitive to alternative choices of uncertainty measure. The second one is to change the transition variable to an $MA(4)$ of quarter-to-

[17]Notice that this effect is statistically significant as the 90% error bands do not include zero.

[18]Notice that in the baseline specification, the 0.75% increase in unemployment rate comes two quarters after the shock, while the 0.23 % decrease in job finding probability (and probably not statistically significant) comes after three quarters.

quarter real GDP growth rate. Contrary to the robustness check with alternative uncertainty measure, in this case the IRFs are quite similar to that produced from STVARs using the $MA(7)$ version. This provided some evidence for the robustness of my results to changes in the transitional variable.

6 Conclusion

Using a STVAR, I investigated the role of macroeconomic uncertainty in Canadian unemployment dynamics. My results show that, in general, uncertainty has a much larger effect on unemployment rate and job finding probability during recessions than expansions. In fact, US and Canadian uncertainty shocks both have a limited, if not zero, effect on unemployment and job finding probability during expansions. Additionally, my results show that the Canadian macroeconomic uncertainty has a relatively smaller impact on the country's unemployment dynamics than does the US uncertainty.

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