An empirical study of credit shock transmission in a small open economy*

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Abstract

In this paper we identify and estimate the dynamic effects of foreign (US) and national (Canadian) credit shocks in a small open economy. We use standard credit spreads as proxies to the external finance premium. Our first result suggests that the US and Canadian credit spreads contain substantial forecasting power for several measures of the Canadian real economic activity, especially during the recent financial crisis and its aftermath. Secondly, an adverse US credit shock generates a significant and persistent economic slowdown in Canada: the national external finance premium rises immediately while interest rates, credit aggregates, output, and employment indicators decline. Variance decomposition reveals that credit shocks have a sizeable effect on real activity measures, leading indicators, and credit spreads. On the other hand, the unexpected shocks in domestic credit spreads are not able to generate any significant dynamic response of the real activity once we control for the US credit market conditions.

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1 Introduction

The Great Recession episode suggests the existence of information in the financial sector that has not been fully integrated into our understanding of macroeconomics. Studies by Stock and Watson (1989, 2003), Estrella and Hadrouvelis (1991), Gertler and Lown (1999), Diebold et al. (2006), Mueller (2007), and Gilchrist, Yankov, and Zakrajsek (2009) have shown that financial series have some significant predictive content. The results in Forni et al. (2003) show that financial variables are important when forecasting inflation rates, but do not help in predicting industrial production, which is also confirmed in Espinoza et al. (2009). In an early contribution, Williamson (1987) shows that, through a credit supply mechanism, financial intermediation is important for real business cycles. Here, we propose to empirically measure the impact of credit shocks in Canada, the standard example of a small open economy, given its great openness and small economic size compared to the U.S.

In order to incorporate the information from a large number of economic and financial indicators, we apply the factor analysis approach similar to Bernanke et al. (2005), Marcellino and Kapetainous (2005), and Stock and Watson (2005)[1]. In particular, we adopt the factor-augmented VARMA (FAVARMA) model proposed by Dufour and Stevanovic (2013). This is a theoretically coherent approach that combines two-dimension reduction techniques: factor analysis and VARMA modeling. The identification of structural shocks is achieved by imposing a recursive ordering on the impact matrix of the structural MA representation of observable variables.

Similar studies have been done by Gilchrist, Yankov, and Zakrajsek (2009), and Boivin, Giannoni, and Stevanovic (2013) for the U.S. economy . They find that credit shocks have wide effects on the real activity and produce a significant economic slowdown. Pesaran et al. (2006) use the global VAR model to link the firm-specific changes in the credit portfolio to macroeconomic business cycles, while Eickmeier and Ng (2011) use the same model to investigate the international propagation of credit supply shocks. Safei and Cameron (2010) and Atta-Mensah and Dib (2008) have studied the dynamics of the Canadian credit market, the former employing a structural VAR approach, the latter using the dynamic stochastic general equilibrium model. Their results are conditional on treating Canada as a closed economy. In contrast, the FAVARMA methodology allows to include more relevant information about the global financial markets, and to simulate shocks from outside Canada.

Our results can be summarized as follows. First, we find that US and Canadian credit spreads have some significant predicting power for Canadian economic activity. The in-

[1] Remark that Bayesian VAR with a large number of variables is an alternative, see Banbura et al. (2010).

sample and out-of-sample forecasting exercises show that including credit spreads as predictors improve on competing models, such as diffusion indices of Stock and Watson (2002), in terms of the mean squared predictive error. In particular, they are especially good in predicting the industrial production and employment growth during the recent financial crisis and its aftermath.

Second, we find strong evidence that an unexpected increase in the US external finance premium generates a significant and persistent economic slowdown in Canada: Canadian credit spreads rise immediately, while interest rates, credit, and real activity measures decline. The variance decomposition analysis reveals that the credit shock has an important effect on several economic and financial measures. On the other hand, the results suggest that there is no significant effect of domestic credit shocks in Canada; the unexpected changes in domestic measures of credit spreads are not able to generate any significant dynamic response of the real activity once we control for the US credit market conditions. Hence, our paper suggests that the US credit shock could have generated the economic downturn of 2008-09 in Canada.

The theoretical framework in which the credit shocks are studied has been very popular in the last decade. Bernanke et al. (1999) (BGG hereafter) introduce the idea of a financial accelerator working through the external finance premium and the net worth of potential borrowers, which is used to measure the collateral that firms are able to offer to obtain credit. The financial accelerator mechanism works as follows: a fall in net worth raises the acquisition capital cost, and hence the external finance premium, pushing firms to invest a sub-optimal quantity of capital and creating a persistent effect from the original crisis. Building on BGG, Gilchrist, Ortiz, and Zakrajsek (2009) aim to quantify the role of financial frictions in generating business cycle fluctuations. They augment a standard DSGE model with the financial accelerator mechanism, which links the conditions in the credit market to the real economy through the external finance premium. Two financial shocks are introduced: a financial disturbance shock, which affects the external finance premium, and a net worth shock affecting the balance sheet of a firm. The first shock is presented as a credit supply shock, which Christiano et al. (2009) interpret as an increase in the agency costs due to a higher variance of idiosyncratic shocks affecting the firm's profitability. The second shock can be viewed as a credit demand shock. Their effect will depend on the degree of frictions in the financial market. After estimating the structural model, the authors find that both financial shocks cause an increase in the external finance premium, which, through the financial accelerator, implies a slowdown in economic activity.[2]

[2]Moreover, there is a growing literature modelling the banking sector within macroeconomic DSGE models

In what follows, we first present the econometric framework in a data-rich environment and discuss the estimation and identification issues. The data are discussed in Section 3. The exploration of the predictive power of credit spreads is presented in Section 4, followed by the presentation of impulse responses from VAR models. The FAVARMA results are analyzed in Section 6. The Appendix contains the explanation of the bootstrap procedure and the data description. Additional results are available in the online-not-for-publication appendix.

2 Econometric framework in data-rich environment

The importance of large data sets and factor analysis is well documented in both forecasting macroeconomic aggregates and structural analysis. Boivin et al. (2009) have shown that incorporating information through a small number of factors corrects for several empirical puzzles when estimating the effect of monetary policy shocks in a small open economy. However, Dufour and Stevanovic (2013) argue that in general, multivariate series and their associated factors do not both follow a finite order VAR process. Hence, they propose a FAVARMA framework that combines two parsimonious methods to represent the dynamic interactions between a large number of time series: factor analysis and VARMA modeling. Their results suggest that adding the MA component helps in forecasting several US and Canadian macroeconomic aggregates. In addition, their very parsimonious structural FAVARMA model on US data identifies the monetary policy shock and precisely estimates the effects and transmission of monetary policy. For instance, only 84 VARMA coefficients had to be estimated while the Bernanke et al. (2005) FAVAR approach requested estimation of 510 VAR parameters.

The VARMA modeling might sound unusual, but that class of models has several advantages over the finite VAR approach. VARMA models are closed under marginalization and linear transformations in contrast to VAR processes [Lutkepohl (1984)]. This is of particular interest within factor-augmented frameworks. Even in case where factors follow a finite-order VAR process, if their number is under-estimated, the subset of factors will have a VARMA representation. They are also able to produce accurate forecasts, since they are very parsimonious [Lutkepohl (1987), Athanasopoulos and Vahid (2012)]. Finally, the first order approximation of the equilibrium conditions of standard dynamic stochastic general equilibrium models generally implies a VARMA representation on the observable endogenous

and showing its impact on the transmission mechanism of real and financial shocks to economic activity [see Dib (2010), Meh and Moran (2010) among others].

variables [Ravenna (2006), Fernandez-Villaverde et al. (2007), Komunjer and Ng (2011), Poskitt (2011)].

2.1 Factor-augmented VARMA model

Following the notation from Dufour and Stevanovic (2013), the Factor-augmented VARMA (FAVARMA) model can be stated as follows:

$$X_t = \Lambda F_t + u_t, \tag{1}$$
$$F_t = \Phi(L)F_{t-1} + \Theta(L)\eta_t. \tag{2}$$

where X_t are N observable time series, F_t consists of K latent factors, Λ is an $N \times K$ matrix of factor loadings, u_t and η_t are N-dimensional and K-dimensional white noise processes respectively. By assumption, $\mathrm{E}(u_{it}u_{jt}) = 0$ and $\mathrm{E}(u_{it}\eta_{kt}) = 0$ for all $i \neq j$ and for all $i = 1, \ldots, N$ and $k = 1, \ldots, K$. As is standard in approximate factor model literature, we assume that the correlation across elements in X_t is sufficiently pervasive to distinguish the common factors from the idiosyncratic component[3].

The VARMA(p,q) process in (2) is assumed stable and invertible with $\Phi(L) = [\Phi_1 L + \ldots + \Phi_p L^p]$ and $\Theta(L) = [1 + \Theta_1 L + \ldots + \Theta_q L^q]$, where the lag orders p and q are all finite. It is well known that the VARMA process is not identified in general and one must impose an estimable representation. Several identified specification are available such as the echelon, final and diagonal forms [Dufour and Pelletier (2008)]. We choose the diagonal moving average representation that is presented in its generic form in Definition 1.

Definition 1 (Diagonal MA equation form) *Suppose a K-dimensional stochastic process F_t has the following VARMA representation:*

$$A(L)F_t = B\eta_t$$

This VARMA representation is said to be in diagonal MA equation form if $B(L) = \mathrm{diag}[b_{ii}(L)] = I_N - B_1 L - \cdots - B_q L^q$ where $b_{ii}(L) = 1 - b_{ii,1}L - \cdots - b_{ii,q_i}L^{q_i}$, $b_{ii,q_i} \neq 0$, and $q = \max_{1\leq i\leq K}(q_i)$.

[3]Mathematically, assume that the q largest eigenvalues of the spectral density matrix of X are unique and diverge as $N \to \infty$, that the largest eigenvalues of the spectral matrix of idiosyncratic components are bounded [see Stock and Watson (2002), Bai and Ng (2006) for details]. This assumption is important when estimating the common factors by principal components of X_t.

From the point of view of practitioners, this form is very appealing since adding lags of η_{it} to the i^{th} equation is a natural extension of the VAR model. Thus, the dynamic correlations between macroeconomic series, or fundamentals, as approximated by the common factors, are captured mainly by the autoregressive part, while this simple MA structure could avoid the use of very long VAR orders. Hence, it is more intuitive than the echelon and final forms, and it has the advantage of giving a simple structure to the MA polynomials, the part which complicates the estimation.

Note that several assumptions have been implicitly imposed in the representation (1)-(2), compared to the dynamic factor model with VARMA factors in Dufour and Stevanovic (2013). First, we do not model explicitly a possible serial correlation in the idiosyncratic component, hence there is no autoregressive part in the observational equation (1). This is not very restrictive since the principal component estimates of F_t are consistent even in presence of some serial correlation within u_{it} [Stock and Watson (2002)].[4] Second, we assume the same number of *dynamic* and *static* common shocks. Recall that the so-called 'dynamic' and 'static' versions of the latent factor model are equivalent representations of data [Stock and Watson (2005), Bai and Ng (2007)]. Working with dynamic factors could be more efficient since a smaller number of common shocks is assumed, but this comes with a cost in terms of estimability of the model since it is not obvious how to distinguish the lag polynomials in the observation and the state equations. Third, these assumptions make the identification of structural shocks easier and more transparent, as discussed below. Lastly, we want to stay as close as possible to the previous applications of FAVAR models that in general impose the same restrictions [Bernanke, Boivin and Eliasz (2005), Gilchrist, Zakrajsek and Yankov (2009), Boivin, Giannoni and Stevanovic (2013), among others].

2.2 Estimation

To estimate the model (1)-(2), we use the two-step approach from Dufour and Stevanovic (2013). In the first step, $\hat{F}_t$ are computed as K principal components of X_t. More details about the estimation of the common latent factors within approximate factor models are in Stock and Watson (2002) and Bai and Ng (2006). In the second step, we estimate the VARMA representation (2) on $\hat{F}_t$ by the GLS method proposed in Dufour and Pelletier (2008): (i) we first approximate the VARMA errors by estimating a long VAR; (ii) the residuals are then used as observed and both the VAR and MA coefficients are estimated by GLS (see Dufour and Pelletier (2008) for theoretical results on this estimation procedure).

[4] Otherwise, the Iterative Principal Component method in Stock and Watson (2005) can be used.

The main advantage of this two-step method is its simplicity and possibly the robustness: (i) standard estimation of VARMA models relies on highly nonlinear algorithms and can be very unstable; (ii) estimating common factors by maximum likelihood is very hard and imposes a large number of strong restrictions. Hence, we believe our approach is more interesting for practitioners.

Since the unobserved factors are estimated and then included as regressors in the FAVARMA model, the two-step approach suffers from the "generated regressors" problem. To get an accurate statistical inference on the impulse response functions that accounts for uncertainty associated with factors estimation, we implement a bootstrap procedure inspired on Yamamoto (2009). The details of the bootstrap procedure are presented in the Appendix.

2.3 Identification of structural shocks

To identify the structural shocks, we adopt the contemporaneous timing restrictions framework proposed in Stock and Watson (2005). After inverting the VARMA process of factors in (2) and plugging into (1), we obtain the VMA(∞) representation of X_t:

$$\begin{aligned} X_t &= \Lambda[I - \Phi(L)L]^{-1}\Theta(L)\eta_t + u_t, \\ &= B(L)\eta_t + u_t. \end{aligned} \tag{3}$$

We assume that residuals in (2) are linear combinations of structural shocks ε_t

$$\varepsilon_t = H\eta_t, \tag{4}$$

where H is a nonsingular square matrix and $\mathrm{E}[\varepsilon_t\varepsilon_t'] = I$. Replacing (4) in (3) gives the structural impulse response functions of X_t:

$$\begin{aligned} X_t &= \Lambda[I - \Phi(L)L]^{-1}\Theta(L)H^{-1}\varepsilon_t + u_t, \\ &= B^*(L)\varepsilon_t + u_t. \end{aligned} \tag{5}$$

To achieve the identification of shocks in ε_t, the contemporaneous timing restrictions are imposed on the impact matrix in (5)

$$B_0^* \equiv B^*(0) = \begin{bmatrix} x & 0 & \cdots & 0 \\ x & x & \ddots & 0 \\ x & x & \ddots & 0 \\ x & x & \cdots & x \\ \vdots & \vdots & \vdots & \vdots \\ x & x & \cdots & x \end{bmatrix}. \tag{6}$$

Let $B_{0:K}^* = B_{0:K}H^{-1}$ be a $K \times K$ lower triangular matrix, where $B_{0:K}$ contains the first K rows of B_0. Then, H is obtained as

$$H = [\text{Chol}(B_{0:K}\Sigma_e B_{0:K}')]^{-1}\Lambda_K, \tag{7}$$

where Σ_η is the covariance matrix of η_t and Λ_K is a $K \times K$ matrix of the first K rows of Λ. To estimate H, we plug in the estimates of $B_{0:K}$, Σ_e and Λ_K. Hence, the impulse responses to any shock in ε_t are obtained using (5). To just-identify the K structural shocks, we need to impose $K(K-1)/2$ restrictions. Imposing them in a recursive way eases the estimation of the rotation matrix H. Contrary to other identification strategies in the FAVAR literature, we do not need to impose any observed factors or rely on the interpretation of a particular latent factor: the restrictions are imposed directly on the MA representation of observables.

This procedure is similar to the standard Choleski identification in VAR models. However, the difference is that imposing a recursive structure on VARMA process (2) alone is not sufficient: one must also constrain some factor loadings to be zero. Let $L = 0$ in equation (5) and assume $K = 2$ for simplicity. Then, the impact MA representation of first two series in X_t is

$$\begin{pmatrix} X_{1t} \\ X_{2t} \end{pmatrix} = \begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{pmatrix} \begin{pmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{pmatrix}^{-1}.$$

If the factors in VAR(MA) equation (2) were observed, setting $h_{12} = 0$ would be sufficient to identify the structural shocks and the impulse responses. But this is not the case in general and an additional restriction must be imposed: $\lambda_{12} = 0$.

Note that we follow the strategy to impose the minimum number of restriction by choosing the impact response of only K variables. Since there are many series in X_t, another possibility is to over-identify the model by imposing zero restrictions on more than K series. In that case, B^* would be block lower triangular.[5]

3 Data

The data consists of 124 monthly series that synthesize real and financial Canadian activity. It also includes important foreign variables for a small open economy as Canada: exchange rates, world commodity prices and some US series. The time span is from January 1981 to February 2012.[6] All series have been transformed to induce stationarity. They are described in Appendix B.

The series of particular interest are the credit spreads (CS). Canadian CS correspond to variables 112-117, while the series 118-119 are the usual US spreads used in Boivin et al. (2013). They are constructed as the difference between the actuarial rate of a firm bond and the actuarial rate of a risk-free product (typically a treasury bond), see the Appendix B. The Figure 1 shows all the spreads, including the short term yields that we not consider further in the paper since they start only from 1986.[7]

3.1 Exploring the factor structure

This section performs a preliminary analysis on the Canadian data set: (i) documents the strength of the factor structures; (ii) investigates potential numbers of common factors using tests and information criteria. The Figure 2 plots the largest eigenvalues of the correlation matrix of data (scree plot), and the proportion of the variance explained by consecutive factors (trace test). As is often the case within the large macroeconomic data sets, the eigenvalues die out slowly and is hard to determine the number of common factors by examining the scree plot and trace visually.[8] In addition, we used several most recent and most popular

[5]Let X_{it} and X_{jt} be two series of the same type, and a restriction is imposed on X_{it} only. Constraining the response of X_{jt} may be of interest if this variable loads on the corresponding factor in the same way as X_{it}, i.e. $\lambda_{i2} \simeq \lambda_{j2}$. We adopt the less restrictive scheme and do not impose equality between factors loadings within a group of series.

[6]We must end our data set on February 2012 because the actual tables from StatCan start only from 1997, and we prefer to have a longer sample. Moreover, the financial crisis was already finished in 2012.

[7]Other measures of US credit spreads have been produced by Gilchrist, Yankov and Zakrajsek (2009) but they do not change the identification nor the impact of credit shocks compared to publicly available 10-Year B spread.

[8]See Onatski (2012) for more details on factor models with potentially weakly influential factors.

selection procedures.[9] Bai and Ng (2002) suggest 8 static factors, Alessi et al. (2010) find 9, while Onatski (2009) test does not reject 6 and 10 factors at 5% and 10% level respectively. The estimates of the number of dynamic factors vary from 1 to 10 according to Amengual and Watson (2007), Bai and Ng (2007), Hallin and Liska (2007), Onatski (2010) and Ahn and Horenstein (2013).

The first factor is related to interest rates (CA and US) and to some housing series. The second explains a sizeable part of variance of output, employment and Canadian credit spreads. The third is clearly a price factor, while the forth seems related to stock market, exchange rates and credit measures. Explanatory power of subsequent factors is less and less by definition, but they are still important for some groups of series. For example, the eight explains movements in net exports. The Figures are available in the online appendix.

In following sections, and before estimating the FAVARMA model, we will: (i) examine the predictive power credit spreads on important real activity measures in both in- and out-of-sample; (ii) estimate the dynamic effects of credit shocks using several small-scale recursive VAR models in order to investigate the identification restrictions that will be used in the factor model framework.

4 Predictive power of credit spreads

In this section we explore the forecasting power of Canadian and US credit spreads both in-sample and out-of-sample. Let Y_t define a measure of economic activity. We consider 12 (sectoral) GDP indices as well as 11 (sectoral) employment variables. They correspond to series 23-34 and 92-101, respectively, in Appendix B. The quantity of interest is the average annualized monthly growth:

$$y_{t+h}^{h} = (1200/h)\ln(Y_{t+h}/Y(t)).$$

The horizons of interest are 1, 3, 6 and 12 months ahead. The forecasting power of four credit spreads will be evaluated separately: BBB Long, AA+ Long, BAA and AAA. They differ in 2 ways: (i) first two are Canadian and last two are US credit spreads; (ii) the second and the fourth are constructed with the less risky corporate bonds. The objective is thus to verify which information is more relevant for Canadian economic activity in terms of prediction.[10]

[9]See Mao Takongmo and Stevanovic (2014) for the review and their relative performance.

[10]Zhang (2002) also studies the predictive content of credit spreads. However, the author verifies only the impact of US credit spreads on the aggregate employment growth over a very short out-of-sample, 1998-2002.

4.1 In-sample analysis

The in-sample analysis is based on 3 models:

Model 1 Simple predictive regression:

$$y_{t+h}^h = \alpha^h + \beta^h(L)CS_t + e_{t+h} \tag{8}$$

where CS_t is one of the four credit spreads.

Model 2 Autoregressive distributed lag:

$$y_{t+h}^h = \alpha^h + \rho^h(L)y_t + \beta^h(L)CS_t + e_{t+h} \tag{9}$$

where $y_t = \ln(Y_t/Y_{t-1})$.

Model 3 Autoregressive diffusion index:

$$y_{t+h}^h = \alpha^h + \rho^h(L)y_t + \gamma^h(L)\hat{f}_t + \beta^h(L)CS_t + e_{t+h} \tag{10}$$

where $\hat{f}_t$ are K estimated factors from the subset of large macroeconomic data X_t. It contains first 111 series in Appendix B (excluding the variable to forecast). We fix the number of factors to 6, as suggested by the IC_{p2} criteria of Bai and Ng (2002). The model (10) is a version of the autoregressive diffusion index model considered in Stock and Watson (2002), augmented by the credit spread.

In all models the quantities of interest are the finite order polynomial coefficients $\beta^h(L)$, as well as the adjusted R^2. The polynomial orders are simultaneously determined by BIC. However, the minimal model always contains the value at time t of each predictor. The models are estimated through the complete time span: 1981M01 - 2012M02. For sake of space, we only present the results for two economic activity measures: industrial production (IP) and the total employment (EMP) and for forecasting horizons of 3 and 12 months. The supplementary material contains the results for all 23 series. Table 2 present the p-values of the test $\beta^h(L) = 0$ as well as the adjusted R^2 for each model. In case of Model 1, data suggest that Canadian AA+ and US BAA spreads have a good explanatory power for both IP and EMP 3- and 12- months ahead: e.g. BAA alone explains 20% of variability in the

Canadian industrial production growth. $\beta^h(L) = 0$ is rejected for other credit spreads in most of the cases but the adjusted R^2s are small. The results are similar in Model 2 when the autoregressive part is included. Finally, the most difficult case for credit spreads is the autoregressive diffusion index model where, in addition to autoregressive part, a number of estimated factors is included as predictors. At horizon $h = 3$, all credit spreads coefficients are significant except for AAA in case of employment. At one year horizon, both B-rated spreads are important for industrial production, while the employment growth can be predicted only by the Canadian spreads. An interesting evidence is that the explanatory power of the Model 3 for IP is stronger at horizon $h = 12$ than $h = 3$.

4.2 Out-of-sample analysis

In this section we evaluate the predictive content of credit spreads in an out-of-sample exercice. Two models are added to those used in the previous section: (i) autoregressive direct model (Model 2 above without CS); (ii) autoregressive diffusion index (Model 3 above without CS). The out-of-sample period is 1995M01 - 2012M02. We use the rolling window approach. The lag orders in each model are estimated by BIC recursively for each forecasting horizon. For example, in Model 3, the orders of $\rho^h(L)$, $\gamma^h(L)$ and $\beta^h(L)$, as well as the number of factors in f_t are estimated by BIC for every period in the out-of-sample and for every forecasting horizon. The Table 3 contains mean squared predictive errors (MSPE) of the Model 2 (AR + CS), the Model 3 (AR-DI + CS) and the diffusion index model without CS (AR-DI) relative to the MSPE of the autoregressive direct model. If the value is smaller than 1, the corresponding model produces smaller squared predictive errors. The bold characters correspond to best model and they are all significant at 5% level according to Diebold-Mariano test.

At 3-month horizon, the best model for IP is the AR-DI augmented with BBB credit spread that reduces the MSPE by 16% upon the autoregressive model. But compared to AR-DI model, adding the Canadian BBB spread improves the forecasting power by only 2%. For employment growth, the best model is AR-DI augmented by the Canadian AA+. In this case, adding the credit spread improves the prediction by 13% upon the diffusion index model. The predictive content of credit spreads is much smaller at 12-month horizon: the best model for IP is the AR-DI model while the employment is best predicted by the autoregressive model. The supplementary material contains the results for all 23 sectoral series.

The Table 4 present the same relative MSPE but for the period 2007M01-2009M12 that covers both recent Canadian and US recessions (according to C.D. Howe Institute and NBER respectively). Several remarks can be made. First, the forecasting performance against the AR direct model explodes during that period compared to the entire out-of-sample. Second, the best models for both real activity series and all horizons contain one of the credit spreads, and in particular the Canadian AA+ long spread. Hence, the predictive content of credit spreads is particularly strong during the financial crisis and its aftermath.

5 Evidence from VAR model

The most popular way to measure the effects of a structural shock is to estimate a standard VAR model and identify the shock, and the corresponding impulse response functions, by Choleski decomposition. Our benchmark model consists of two blocks: US, containing CPI inflation (US-CPI), Industrial production growth (US-IP), Federal funds rate (US-R), Business loans growth (BUSLOADS) and BAA credit spread (US-CS); and Canadian block which includes same but Canadian series (CPI, IP, R, CREDIT, CA-CS), where R is the 3-month T-bill, CREDIT business credit growth and CA-CS is the Canadian BBB Long credit spread. The US block is placed first in the VAR ordering. Many other VAR specifications have been examined and are included in the supplementary material, but the main results are robust.

Figures 3 and 4 plot dynamic responses to a positive shock on US and Canadian credit spreads respectively. The VAR lag order is set to 2 (estimated by BIC). The 90% confidence bands are generated by the standard bootstrap procedure. The US credit shock generates important and significant effects on US economic activity: industrial production, business loans and prices decline, followed by a drop in Federal funds rate as a reaction to recessionary behaviour. These are similar to Mueler (2007) since he used a very similar VAR specification, and are consistent with Gilchrist et al. (2009) and Boivin et al. (2013). The effects on Canadian series are similar: a 25 basic points increase in US credit spread raises the Canadian credit spread by 7 basic points and generates significant declines in industrial production and business credit. The responses of CPI inflation and the short term interest rate are barely significant. On the other hand, the Canadian credit shock does produce a significant and persistent increase in Canadian credit spread, but no significant effect on other variables in the system.

The Figure 5 shows the impulse responses to a shock on Canadian credit spread in a VAR system that does not include the US block of series. The response of the credit spread is still significant and persistent, but now it generates some significant contractionary movement in economy: industrial production decreases during 8 months, while the effect on credit last much longer, as well as for the short term rate. Hence, this suggest that the Canadian credit shock is not well identified when we do not control for US credit shock or at least for US business cycle movements. The findings in Figures 3 and 4 seem not be a consequence of using a large number of series (10) in the VAR. The same evidence is obtained from an 8-variable VAR that does not include business loans and credit series, see the supplementary material.

6 Evidence from FAVARMA model

The goal of this paper is to measure the dynamic effects of credit shocks on economic activity in Canada. Since we are looking at a small open economy it is important to control for any global influence on financial markets when identifying the credit shock effects. In previous studies, authors have considered Canada to be a closed economy, but the VAR empirical evidence above suggests this could be misleading. In what follows, we show that the effect of a credit shock is essentially driven by foreign financial conditions, i.e. by U.S. credit markets.

To identify the credit shock, we restrict the impact response of K variables as in equation (6). The choice of the series to include and their number is motivated mainly by the VAR evidence but one must keep in mind the estimation of the number of factors. Recall from section 4.1 that several selection procedures suggested between 6 and 10 static factors and 1-10 dynamic components. We choose to estimate 10 static factors and impose the same recursive ordering as in the VAR analysis: [US-CPI, US-IP, US-R, US-LOANS, US-CS, CPI, IP, R, CREDIT, CS]. Adding the MA part to factors dynamics prevents from parameters proliferation so we can model a large number of factors without being forced to estimate hundreds of VAR coefficients. The objective is to identify two unexpected disturbances: US and Canadian credit shocks that correspond to fourth and last element in the recursion.[11] The information criteria from Dufour and Pelletier (2008) suggests a VARMA(1,1) process for the extracted factors. The 90% confidence bands are constructed using bootstrap procedure

[11] It has been shown in Boivin et al. (2013) that the US credit shock is well identified within a small-scale VAR, which is the US block in the recursive ordering. An alternative would be to fully specify a joint factor model for both US and Canada. While this could potentially improve on efficiency of the impulse response coefficients estimates, it comes also with a large number of additional restrictions that are not necessarily true and easy to verify (number of joint and/or country-specific factors, restrictions on factor loadings and/or on their dynamic processes, etc.). In this standard efficiency vs robustness trade-off, we choose the more robust approach.

explained in the Appendix A.

Figure 6 shows the dynamic responses of many series of interest to a 25 basis points US credit shock. The panels on the first line represent impulse responses of US series. These are coherent with previous studies and show strong recessionary impact of the credit market disturbances. The second line is for Canadian series included in the recursive structure. The Canadian BBB credit spreads reacts positively on impact while the business credit growth as well as the short interest rate decline significantly for 3 years after the shock. The industrial production does not react a lot: a slight increase on impact followed by a significant, but short, decline around 4 months after the shock. These findings are similar to the VAR evidence. An advantage of the factor model framework is the ability to verify the impact of a shock to a large number of indicators. The rest of panels in Figure 6 show dynamic responses of several important macroeconomic and financial series. The decline in US economy caused by the credit shock has an important effect on Canadian labor market indicators as well as on new orders and business loans. The net exports to US decline significantly for few months after the shock while the increase of CAN/US exchange rate (which means a depreciation of the $CA) is barely statistically different from zero. The Canadian yield curve (here only the 10-year treasury bond) follows the behaviour of the short term, while the stock market declines. The AA+ Canadian credit spread simply mimics the response of the BBB spread.

The impulse responses to the Canadian credit shock are depicted in Figure 7. The point estimates of impulse response coefficients of many indicators are qualitatively in line with those after the US credit shock, but they are almost never significant. Moreover, they are quantitatively much smaller. Hence, once we have controlled for the US credit markets, the Canadian credit shocks do not generate any significant movements in economic activity.

Table 5 shows the variance decomposition of US and Canadian credit shocks, at different horizons, as well as the explanatory power of the common component (10 factors). The US credit shock is an important ingredient of the forecast error of many Canadian series. For instance, it explains 11% after 3 months and 17% after 6 months of the variance of business credit. It also generates lot of variation in real activity measures such as average work hours and employment, and, as expected, in financial series. On the hand, the Canadian credit shock does not have a large explanatory power except for business loans. To complete, since we are using a factor model, the natural question is how well the extracted factors explain the variability in the observable series. The last column shows that the common component explains a sizeable fraction of the variability in these variables. This means that these factors do capture some important dimensions of the business cycle movements.

In addition, we tested the Granger causality between the US and Canadian credit spreads.

The results are reported in Table 6. We did the exercise for both categories of corporate bonds as well as for BIC and AIC selected number of lags. According to p-values: (i) the hypothesis that the US credit spread does not cause the Canadian credit spread is strongly rejected; (ii) no strong evidence to reject the hypothesis that the Canadian credit spread does not Granger cause the US spread. Hence, these results confirm our intuition and suggest that the effects of credit shocks in Canada are essentially caused by unexpected changes in foreign credit market conditions.

It is important to note that we do not focus on the 2007-09 financial crisis in this paper. As observed by Porter (2010), Canada was the only G7 country that did not have to engage in a large-scale bank bailout, and the Canadian banks remained relatively profitable through the crisis. However, the Canadian economy was in recession from 2008Q3 to 2009Q2, according to Bergevin and Cross (2012), and the Canadian corporate credit spreads widened during 2008. What our results suggest, at least for the latest crisis, is that this correlation between the movements of Canadian credit spreads and real activity is not able to generate significant dynamic responses of domestic variables once we control for the US credit market conditions. In contrast, our paper suggests that the US credit shock could have generated the economic downturn of 2008-09 in Canada.

6.1 Robustness analysis

In the robustness analysis, available in the supplementary material, we repeated the same exercise but with the less risky category corporate bonds: AAA for US and AA+ for Canada. The results are very similar, hence the credit shock seems not be rooted in the very risky projects but comes from the credit sector as a whole. Moreover, we repeated the exercise using BAA - AAA spread to explore the extent to which the results are driven by the liquidity premium (even though during the last recession some of the AAA bonds were not very liquid). The results, available in the supplementary material, show that BAA-AAA spread shock generates similar qualitative impulse responses but the variance decomposition reveals some quantitative differences: for most of the series the the BAA-AAA explains less variance than the benchmark BAA-10y spread. In addition, the ordering between the Federal funds rate and the credit spread does not change the results substantially. The dynamic responses from the model where the Federal funds rate can react on impact to the credit shock are presented in the online appendix.

Finally, we estimated the impulses responses to both US and Canadian credit shocks using a FAVAR model with the same identification scheme as in the benchmark FAVARMA specification. For the seek of space, we just summarize the results here while the details are available in the online appendix. The dynamic responses from the FAVAR model are qualitatively similar to those from the FAVARMA, except for the industrial production, employment and new orders where the FAVAR mode implies an overshooting 1-2 years after the shock. However, quantitatively, the FAVARMA estimated larger maximum responses of most of the series.

7 Conclusion

In this paper we attempted to measure the impact of a credit shocks in Canada. We have considered both small-scale and high- dimensional data models. In order to incorporate information from a large number of economic and financial indicators, we used a factor-augmented VARMA (FAVARMA) model. The structural shocks were identified by imposing a recursive structure on the impact matrix of the structural MA representation of observable variables.

We found that the credit spreads, both US and Canadian, have some significant predicting power for Canadian economic activity. The forecasting exercise has revealed that including credit spreads as predictors improve on competing models, such as diffusion indices of Stock and Watson (2002) in terms of the mean squared predictive error. In particular, we find they are especially good in predicting the industrial production and employment growth during the recent financial crisis and its aftermath.

Using both VAR and FAVARMA models, we found strong evidence that an unexpected increase in the US external finance premium generates a significant and persistent economic slowdown in Canada: Canadian credit spreads rise immediately, while interest rates, credit, and real activity measures decline. From the variance decomposition analysis, we observe that the credit shock has an important effect on several economic and financial measures. According to the R^2 results, the common component captures an important dimension of the business cycle movements. In contrast, a shock to the Canadian credit spread does not provoque any significant reaction in the Canadian economic activity.

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Appendix A: Bootstrap procedure

The goal is to obtain confidence bands for impulse responses to structural shocks in representation (1-2) with assumption (4).

- **Step 1**
  Shuffle the time periods, with replacement, of the residuals in (2), and resample static factors using the estimates of the VARMA coefficients:
  $$\tilde{F}_t = \hat{\Phi}(L)\tilde{F}_{t-1} + \hat{\Theta}\tilde{\eta}_t$$

- **Step 2**
  Shuffle the time periods, with replacement, of the residuals in (1), and resample the observable series using new factors obtained from the previous step and the estimated loadings:
  $$\tilde{X}_t = \hat{\Lambda}\tilde{F}_t + \tilde{u}_t$$

- **Step 3**
  Estimate the FAVARMA model on $\tilde{X}_t$, identify the structural shock and produce impulse responses.

As it was pointed out in Dufour and Stevanovic (2013), having a good approximation of the true factor process can be important in order to get valid bootstrap procedure. If the finite-order VAR approximation is far away from the truth, and if the finite-order VARMA representation does much better, allowing for the MA part should provide a more reliable inference.

Appendix B: Data description

The transformation codes (labeled T-Code) are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm.

No	Series and group	Source	T-Code
Prices (PRI)			
1	CPI: All-items	StatCan	5
2	CPI: All-items excluding eight of the most volatile components	StatCan	5
3	CPI: All-items excluding food	StatCan	5
4	CPI: All-items excluding energy	StatCan	5
5	CPI: Food and energy	StatCan	5
6	CPI: Energy	StatCan	5
7	CPI: Housing	StatCan	5
8	CPI: Goods	StatCan	5
9	CPI: Durable goods	StatCan	5
10	CPI: Non-durable goods	StatCan	5
11	CPI: Services	StatCan	5
12	CPI: Services excluding shelter services	StatCan	5
Housing (HOUS)			
13	Building Permits: Total residential and non-residential	StatCan	4
14	Building Permits: Seasonally adjusted; Residential	StatCan	4
15	Building Permits: Industrial	StatCan	4
16	Building Permits: Commercial	StatCan	4
17	Housing starts: Total units	StatCan	4
Leading indicators (LEAD)			
18	Average work week, manufacturing (Hours)	StatCan	1
19	Housing index	StatCan	5
20	New orders, durable goods	StatCan	5
21	Retail trade, furniture and appliances	StatCan	5
22	Shipment to inventory ratio, finished products	StatCan	5
Output (OUT)			
23	GDP at Basic Prices: All industries	StatCan	5
24	GDP at Basic Prices: Business sector industries	StatCan	5
25	GDP at Basic Prices: Non-business sector industries	StatCan	5
26	GDP at Basic Prices: Goods-producing industries	StatCan	5
27	GDP at Basic Prices: Service-producing industries	StatCan	5
28	GDP at Basic Prices: Industrial production	StatCan	5
29	GDP at Basic Prices: Durable manufacturing industries	StatCan	5
30	GDP at Basic Prices: Mining and oil and gas extraction	StatCan	5
31	GDP at Basic Prices: Construction	StatCan	5
32	GDP at Basic Prices: Manufacturing	StatCan	5
33	GDP at Basic Prices: Wholesale trade	StatCan	5
34	GDP at Basic Prices: Finance, insurance, real estate, rental and leasing	StatCan	5
Industrial prices (IPRI)			
35	IPI: All manufacturing	StatCan	5
36	IPI: Total excluding food and beverage manufacturing	StatCan	5
37	IPI: Basic manufacturing industries	StatCan	5
38	IPI: Non-food (excluding basic manufacturing industries) manufacturing	StatCan	5
39	IPI: Primary metal manufacturing excluding precious metals	StatCan	5
Commodity prices (CPRI)			
40	CommPI: Total, all commodities	StatCan	5

41	CommPI: Energy	StatCan	5
42	CommPI: Metals and Minerals	StatCan	5
43	CommPI: Forestry	StatCan	5
Stock market (STOCK)			
44	Toronto Stock Exchange, value of shares traded	StatCan	5
45	Toronto Stock Exchange, volume of shares traded	StatCan	5
46	United States common stocks, Dow-Jones industrials, high	StatCan	5
47	United States common stocks, Dow-Jones industrials, low	StatCan	5
48	United States common stocks, Dow-Jones industrials, close	StatCan	5
49	New York Stock Exchange, customers debit balances	StatCan	5
50	New York Stock Exchange, customers free credit balance	StatCan	5
51	Standard and Poor s/Toronto Stock Exchange Composite Index, close	StatCan	5
52	Toronto Stock Exchange, stock dividend yields (composite), closing quotations	StatCan	1
Exchange rates (FX)			
53	FX: United States dollar, noon spot rate, average	StatCan	5
54	FX: United States dollar, 30-day forward closing rate	StatCan	5
55	FX: United States dollar, 180-day forward closing rate	StatCan	5
56	FX: United States dollar, 1-year forward closing rate	StatCan	5
57	FX: United Kingdom pound sterling, noon spot rate, average	StatCan	5
58	FX: United Kingdom pound sterling, 90-day forward noon rate	StatCan	5
59	FX: Swedish krona, noon spot rate, average	StatCan	5
60	FX: Swiss franc, noon spot rate, average	StatCan	5
61	FX: Japanese yen, noon spot rate, average	StatCan	5
Interest rates (INT)			
62	Bank rate	StatCan	1
63	Forward premium or discount (-), United States dollar in Canada: 3 month	StatCan	1
64	Prime corporate paper rate: 1 month	StatCan	1
65	Prime corporate paper rate: 2 month	StatCan	1
66	Prime corporate paper rate: 3 month	StatCan	1
67	Government of Canada marketable bonds, average yield: 1-3 year	StatCan	1
68	Government of Canada marketable bonds, average yield: 3-5 year	StatCan	1
69	Government of Canada marketable bonds, average yield: 5-10 year	StatCan	1
70	Government of Canada marketable bonds, average yield: over 10 years	StatCan	1
71	Treasury bill auction - average yields: 3 month	StatCan	1
72	Treasury bill auction - average yields: 6 month	StatCan	1
73	Average residential mortgage lending rate: 5 year	StatCan	1
Credit (CREDIT)			
74	Total, Canada s official international reserves	StatCan	5
75	Convertible foreign currencies, United States dollars	StatCan	5
76	Total business and household credit; Seasonally adjusted	StatCan	5
77	Household credit; Seasonally adjusted	StatCan	5
78	Residential mortgage credit; Seasonally adjusted	StatCan	5
79	Consumer credit; Seasonally adjusted	StatCan	5
80	Business credit; Seasonally adjusted	StatCan	5
81	Short-term business credit; Seasonally adjusted	StatCan	5
Loans and monetary aggregates (MON)			
82	Canadian dollar assets, total loans	StatCan	5
83	Total personal loans	StatCan	5
84	Business loans	StatCan	5
85	M1B (gross)	StatCan	5
86	Residential mortgages	StatCan	5
87	M2+ (gross)	StatCan	5

88	Chartered bank deposits, personal, term	StatCan	5
89	Bankers acceptances	StatCan	5
Employment (EMP)			
90	Unemployment rate (Rate); Both sexes; 15 years and over	StatCan	1
91	Total employed, all industries	StatCan	5
92	EMP: Goods-producing sector	StatCan	5
93	EMP: Utilities	StatCan	5
94	EMP: Construction	StatCan	5
95	EMP: Manufacturing	StatCan	5
96	EMP: Services-producing sector	StatCan	5
97	EMP: Trade	StatCan	5
98	EMP: Transportation and warehousing	StatCan	5
99	EMP: Finance, insurance, real estate and leasing	StatCan	5
100	EMP: Professional, scientific and technical services	StatCan	5
101	EMP: Business, building and other support services	StatCan	5
Net exports (NEXP)			
102	Net Exports, United States	StatCan	2
103	Net Exports, United Kingdom	StatCan	2
104	Net Exports, European Union excluding the United Kingdom	StatCan	2
105	Net Exports, Japan	StatCan	2
106	Net Exports, total of all merchandise	StatCan	2
107	Net Exports, Sector 2 Energy products	StatCan	2
108	Net Exports, Sector 3 Forestry products	StatCan	2
109	Net Exports, Sector 4 Industrial goods and materials	StatCan	2
110	Net Exports, Sector 5 Machinery and equipment	StatCan	2
111	Net Exports, Sector 6 Automotive products	StatCan	2
Canadian credit spreads (CS)			
112	BBB CS: Long	Datastream	1
113	BBB CS: Mid	Datastream	1
114	A CS: Long	Datastream	1
115	A CS: Mid	Datastream	1
116	AA+ CS: Long	Datastream	1
117	AA+ CS: Mid	Datastream	1
US series (US)			
118	BAA10YM	FRED	1
119	AAA10YM	FRED	1
120	UNRATE	FRED	1
121	INDPRO	FRED	5
122	CPIAUCSL	FRED	5
123	FEDFUNDS	FRED	1
124	BUSLOANS	FRED	5

The Canadian credit spreads, series no 112-117, are constructed as difference between the FTSM TMX corporate bonds yields, downloaded from Datastream, and Government of Canada marketable bonds yields: 3-5 years and over 10 years for Mid and Long respectively. The US credit spreads, series no 118-119, are constructed as difference between the Moodys BAA or AAA corporate bonds and the 10-year US Treasury bond (all downloaded from FRED database).

Table 2: Predictive content of credit spreads: in-sample analysis

	Model 1: simple regression							
	Forecast horizon $h = 3$ (months)				Forecast horizon $h = 12$ (months)			
	IP		EMP		IP		EMP	
	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$
BBB	0.005	0.019	0.000	0.043	0.000	0.046	0.071	0.006
AA+	0.000	0.169	0.000	0.175	0.000	0.124	0.000	0.082
BAA	0.000	0.200	0.000	0.105	0.000	0.141	0.004	0.025
AAA	0.000	0.058	0.011	0.019	0.000	0.045	0.049	0.008
	Model 2: Autoregressive distributed lag							
	Forecast horizon $h = 3$ (months)				Forecast horizon $h = 12$ (months)			
	IP		EMP		IP		EMP	
	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$
BBB	0.000	0.237	0.001	0.376	0.000	0.123	0.025	0.156
AA+	0.000	0.290	0.000	0.435	0.000	0.151	0.000	0.228
BAA	0.000	0.272	0.000	0.411	0.000	0.172	0.002	0.170
AAA	0.000	0.234	0.000	0.377	0.002	0.097	0.756	0.143
	Model 3: Autoregressive diffusion index							
	Forecast horizon $h = 3$ (months)				Forecast horizon $h = 12$ (months)			
	IP		EMP		IP		EMP	
	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$	p-value	$\bar{R}^2$
BBB	0.006	0.385	0.003	0.485	0.013	0.497	0.000	0.367
AA+	0.000	0.400	0.000	0.519	0.239	0.490	0.000	0.367
BAA	0.000	0.401	0.000	0.498	0.000	0.515	0.092	0.267
AAA	0.004	0.389	0.245	0.474	0.514	0.488	0.669	0.261

This Table presents the in-sample results of the performance of credit spreads to predict the Canadian economic activity in terms of industrial production growth (IP) and employment growth (EMP). BBB and AA+ are the Canadian credit spreads (long) while BAA and AAA are the US counterparts. The p-value is for the test of the null hypothesis that coefficient on credit spread is equal to zero. $\bar{R}^2$ *is the adjusted R squared of the regression. Models 1-3 correspond to (8)-(10) respectively.*

Table 3: Predictive content of credit spreads: out-of-sample analysis

	Forecast horizon $h = 3$ (months)					
		IP			EMP	
	AR + CS	AR-DI	AR-DI + CS	AR + CS	AR-DI	AR-DI + CS
BBB	0.9662	.	**0.8377**	0.9074	.	0.9143
AA+	0.9979	.	0.9520	0.8626	.	**0.8383**
BAA	1.0212	.	0.8752	0.9572	.	1.0154
AAA	1.0764	.	0.8813	0.9475	.	1.0104
		0.8538			0.9677	
	Forecast horizon $h = 12$ (months)					
		IP			EMP	
	AR + CS	AR-DI	AR-DI + CS	AR + CS	AR-DI	AR-DI + CS
BBB	1.1170	.	0.8780	1.1611	.	1.3322
AA+	1.7101	.	1.3315	1.4039	.	1.3521
BAA	1.1786	.	0.9376	1.0986	.	1.4476
AAA	1.5632	.	0.9651	1.0542	.	1.3160
		0.7929			1.2192	

This Table presents the out-of-sample results of the performance of credit spreads to predict the Canadian economic activity in terms of industrial production growth (IP) and employment growth (EMP). The number represent the MSPE of each model relative to AR direct benchmark. BBB and AA+ are the Canadian credit spreads (long) while BAA and AAA are the US counterparts.

Table 4: Predictive content of credit spreads during 2007M01-2009M12: OOS analysis

	Forecast horizon $h = 3$ (months)					
		IP			EMP	
	AR + CS	AR-DI	AR-DI +CS	AR + CS	AR-DI	AR-DI +CS
BBB	0,8902	.	0,5381	0,8198	.	0,8556
AA+	0,8637	.	0,7327	0,6023	.	**0,5548**
BAA	0,8148	.	**0,4850**	0,8947	.	0,8657
AAA	0,8336	.	0,5023	0,8416	.	0,8427
		0,5431			0,9467	
	Forecast horizon $h = 12$ (months)					
		IP			EMP	
	AR + CS	AR-DI	AR-DI +CS	AR + CS	AR-DI	AR-DI +CS
BBB	1,1764	.	0,6858	1,1224	.	1,1479
AA+	0,6069	.	**0,4072**	**0,6082**	.	0,6325
BAA	0,9503	.	0,5326	1,0023	.	0,9448
AAA	1,0700	.	0,5989	0,9662	.	0,8444
		0,5634			0,9731	

This Table presents the out-of-sample (OOS) results of the performance of credit spreads to predict the Canadian economic activity in terms of industrial production growth (IP) and employment growth (EMP) during the period 2007M01 - 2009M12. The number represent the MSPE of each model relative to AR direct benchmark. BBB and AA+ are the Canadian credit spreads (long) while BAA and AAA are the US counterparts.

Table 5: Variance decomposition and explanatory power of the common component

Variables	US credit shock			CA credit shock			
	$h = 3$	$h = 6$	$h = 36$	$h = 3$	$h = 6$	$h = 36$	R^2
US-CPI	4,15	4,74	4,76	0,83	0,86	0,86	0,59
US-IP	14,23	14,71	14,71	0,42	0,40	0,40	0,42
US-R	5,13	12,21	12,54	0,39	0,48	0,47	0,90
US-LOANS	21,71	26,81	26,81	2,94	2,92	2,91	0,36
US-CS	69,19	60,55	60,52	2,96	2,37	2,37	0,72
CPI	6,88	6,88	6,90	0,53	0,52	0,52	0,91
IP	7,51	7,60	7,60	0,18	0,18	0,18	0,80
R	0,63	4,85	5,43	0,10	0,18	0,17	0,97
CREDIT	11,46	17,06	17,08	4,17	4,35	4,35	0,61
CS	28,92	31,59	31,57	20,75	18,04	17,99	0,56
AVERAGE WORK WEEK	59,43	54,46	54,45	8,00	6,15	6,15	0,49
NEW ORDERS	14,09	14,93	14,93	1,32	1,23	1,23	0,32
EMPLOYMENT	17,57	18,61	18,61	6,74	6,35	6,34	0,54
HOUSING INDEX	7,24	7,20	7,21	0,06	0,09	0,09	0,26
NET EXPORTS: US	4,02	4,05	4,05	5,97	5,96	5,96	0,60
SP500-TSX	22,57	22,49	22,49	0,15	0,20	0,20	0,49
FX: CA/US	19,27	19,27	19,27	0,37	0,37	0,37	0,68
T-BOND 10Y	2,37	5,46	6,20	0,55	0,40	0,38	0,96
LOANS	3,61	4,94	4,94	28,09	27,34	27,34	0,51
AA+ CS: LONG	62,35	55,00	54,96	2,67	2,09	2,09	0,83

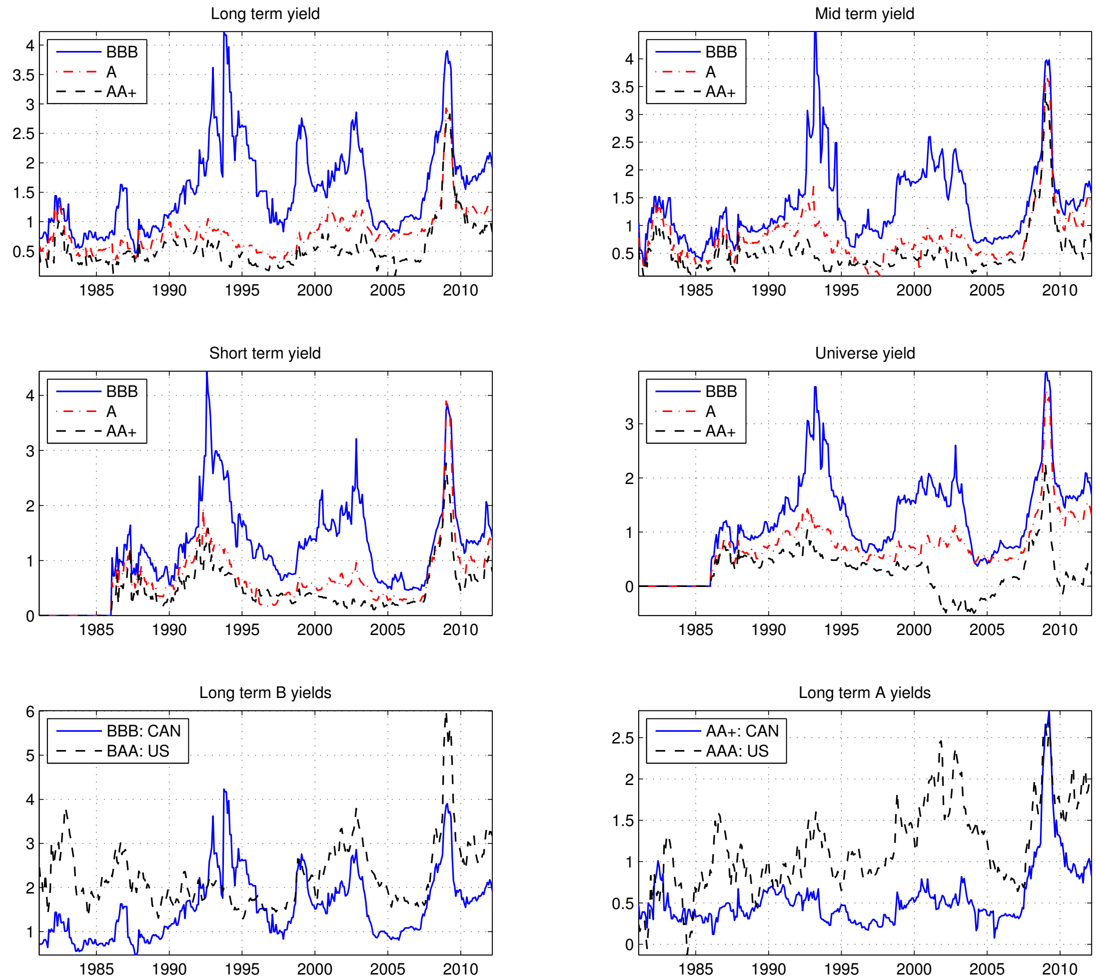
This Table presents the variance decomposition (in %) of the series of interest to US and Canadian credit shocks respectively. The last column shows the R^2 of the common component for each series.

Table 6: Granger causality probabilities between US and Canadian credit spreads

	BBB vs BAA		AA+ vs AAA	
H_0	BIC (2)	AIC (9)	BIC (2)	AIC (4)
US does not Granger cause CA	0.01	0	0.02	0.01
CA does not Granger cause US	0.37	0.64	0.19	0.09

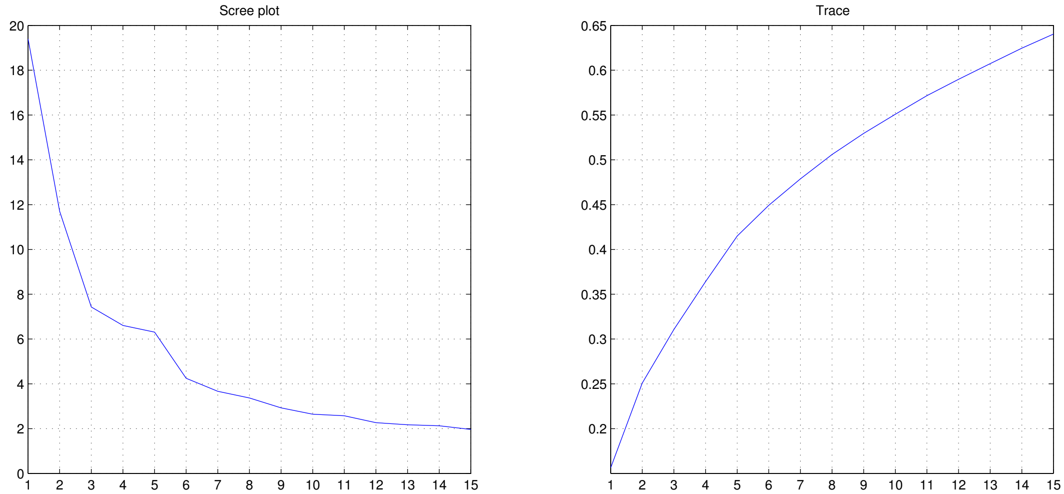
This Table presents the p-values for Granger causality testing between US and Canadian credit spreads. The BIC (2) means that 2 lags in the bivariate VAR have been suggested by BIC criterion. The same goes for AIC.

Figure 1: Credit spreads



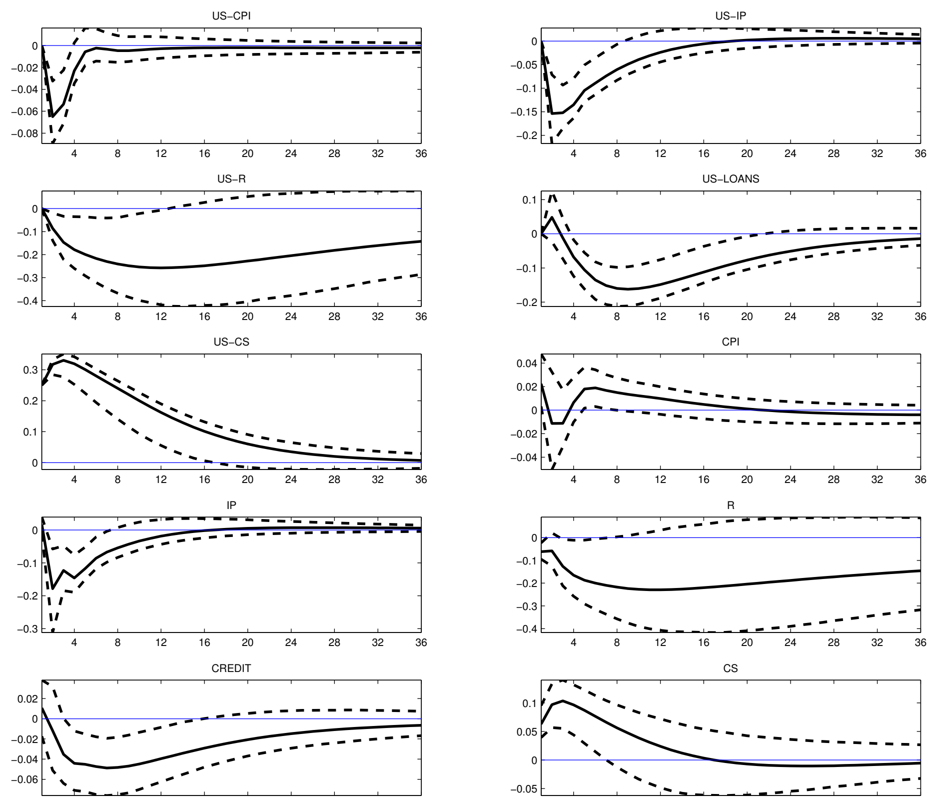
This Figure plots Canadian (BBB, A, AA+) and US (BAA, AAA) credit spreads constructed as described in data description Appendix.

Figure 2: Factor structure in data set: visual approach



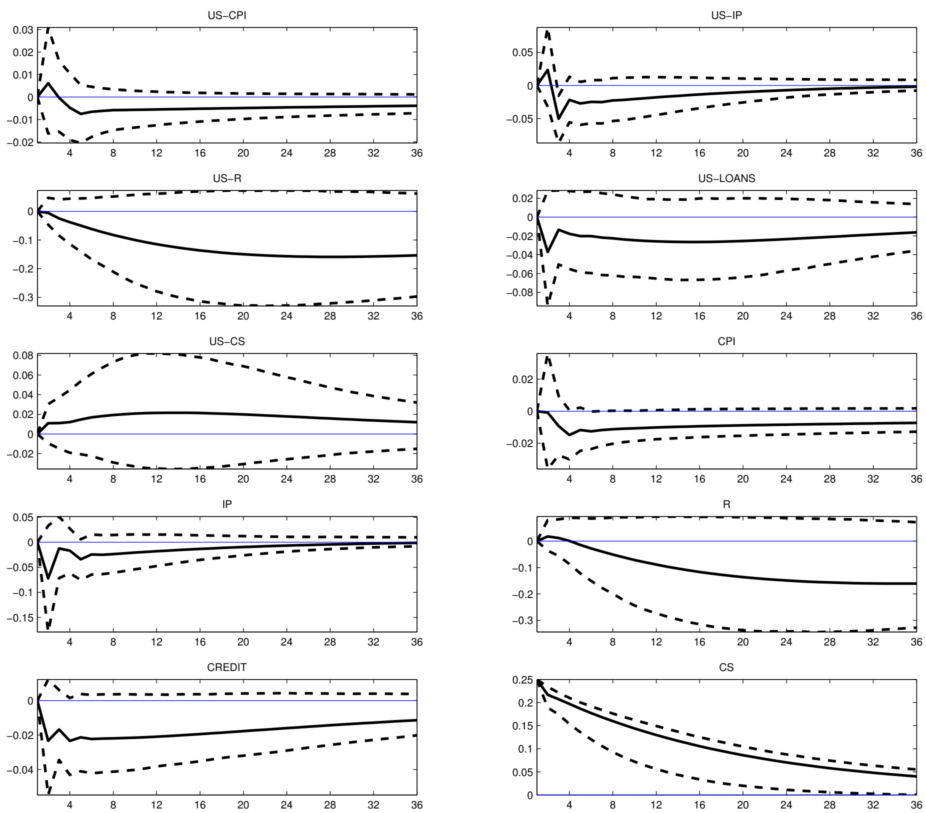
This Figure presents sorted eigenvalues of the correlation matrix of data (scree plot), and the proportion of the variance explained by consecutive factors (trace test).

Figure 3: SVAR evidence: dynamic response to US credit shock



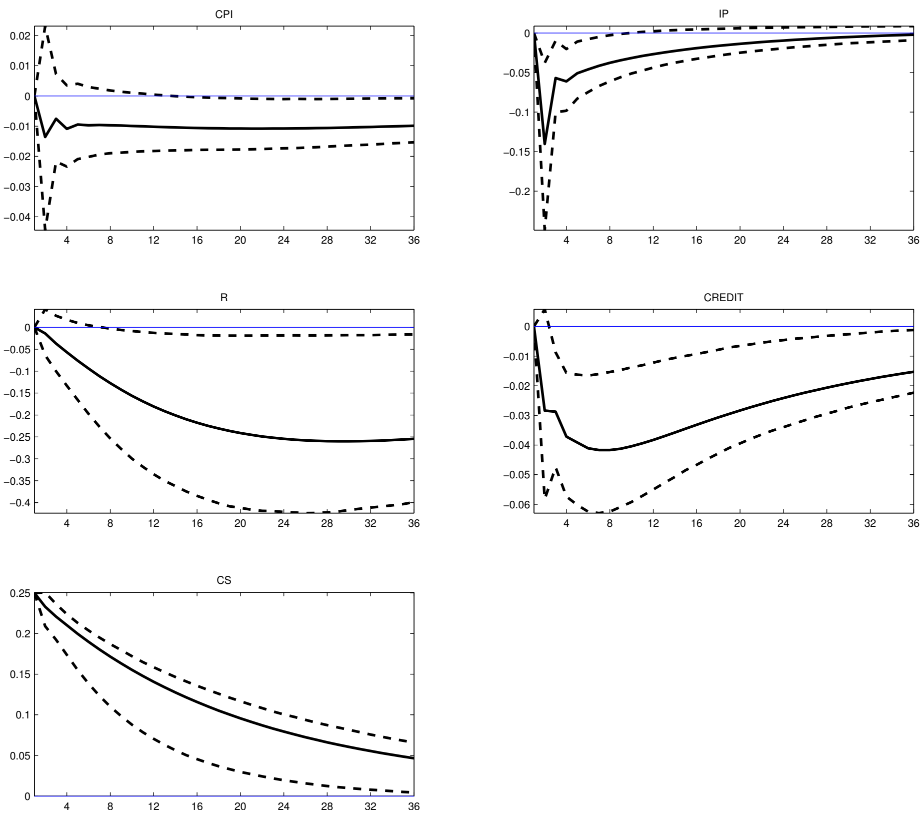
This Figure shows impulse response functions to the positive US credit shock estimated from the benchmark recursive VAR model. The dotted lines present 90% confidence bands constructed after 5000 bootstrap replications.

Figure 4: SVAR evidence: dynamic response to CA credit shock



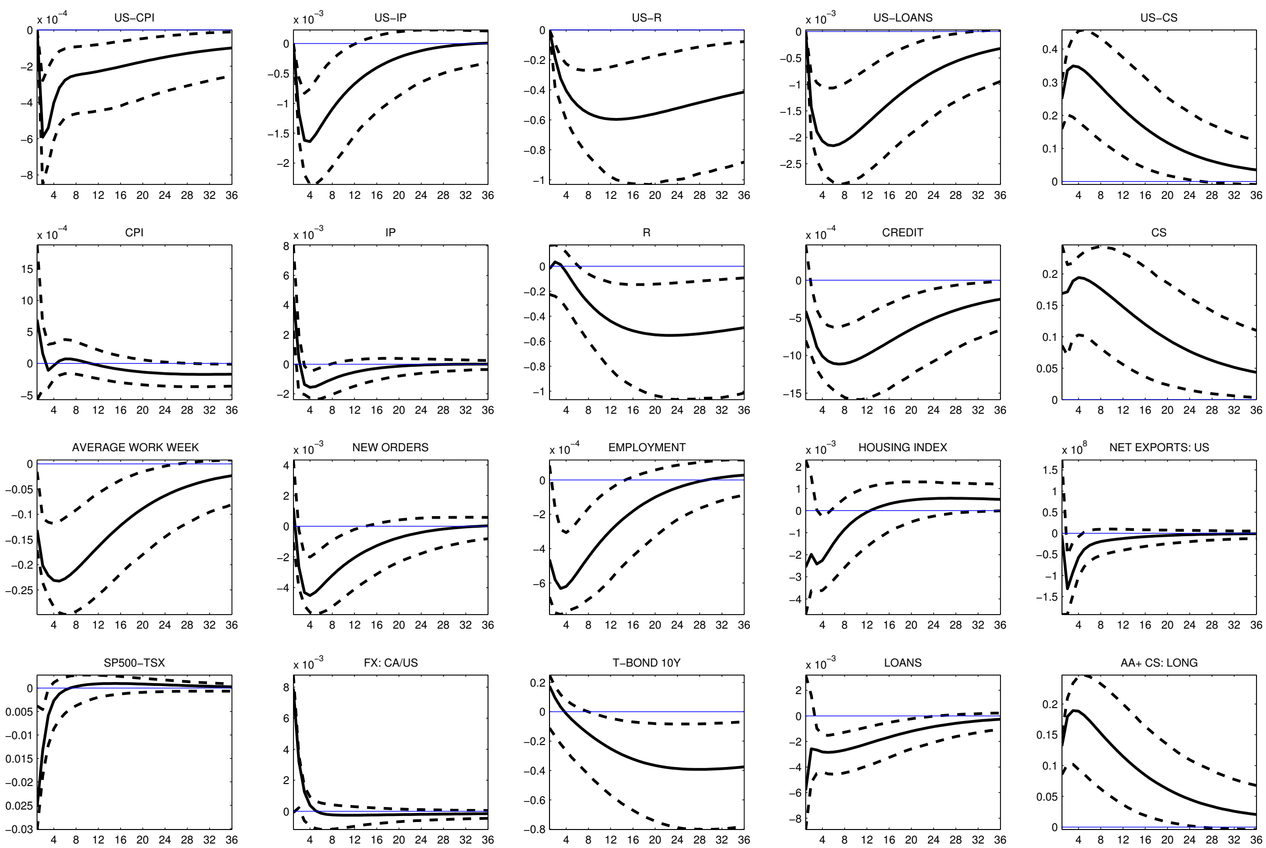
This Figure shows impulse response functions to the positive Canadian credit shock estimated from the benchmark recursive VAR model. The dotted lines present 90% *confidence bands constructed after 5000 bootstrap replications.*

Figure 5: SVAR evidence: dynamic response to CA credit shock without US information



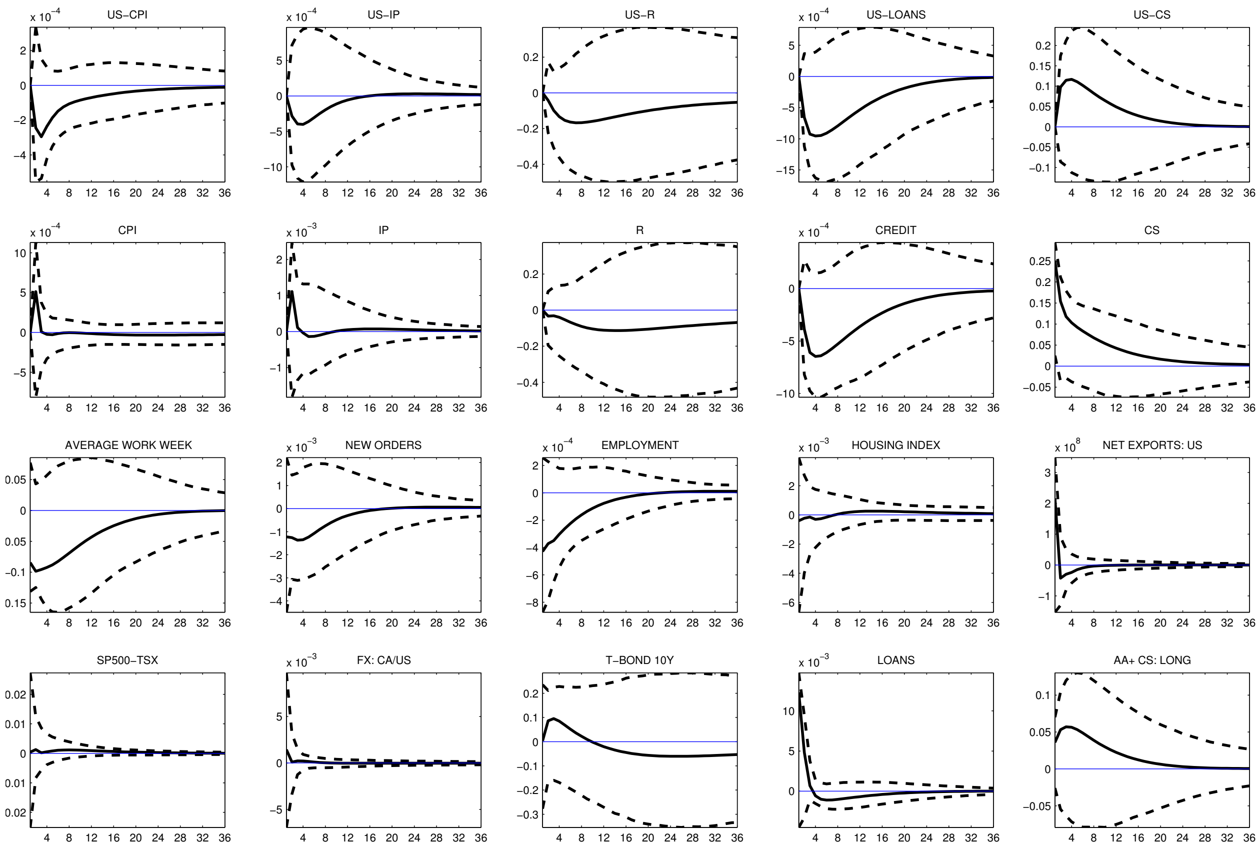
This Figure shows impulse response functions to the Canadian US credit shock estimated from the recursive VAR model that does not contain any US series. The dotted lines present 90% *confidence bands constructed after 5000 bootstrap replications.*

Figure 6: FAVARMA evidence: dynamic response to US credit shock



This Figure shows impulse response functions to the positive US credit shock estimated from the benchmark FAVARMA model. The dotted lines present 90% *confidence bands constructed after 5000 bootstrap replications.*

Figure 7: FAVARMA evidence: dynamic response to CA credit shock



This Figure shows impulse response functions to the positive Canadian credit shock estimated from the benchmark FAVARMA model. The dotted lines present 90% *confidence bands constructed after 5000 bootstrap replications.*