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A NOWCASTING MODEL FOR CANADA: DO U.S. VARIABLES MATTER?*

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Abstract

We propose a dynamic factor model for nowcasting the growth rate of quarterly real Canadian gross domestic product. We show that the proposed model produces more accurate nowcasts than those produced by institutional forecasters, like the Bank of Canada, the The Organisation for Economic Co-operation and Development (OECD), and the survey collected by Bloomberg, which reflects the median forecast of market participants. We show that including U.S. data in a nowcasting model for Canada dramatically improves its predictive accuracy, mainly because of the absence of timely production data for Canada. Moreover, Statistics Canada produces a monthly real GDP measure along with the quarterly one, and we show how to modify the state space representation of our model to properly link the monthly GDP with its quarterly counterpart.

JEL Classification: C33, C53, E37.
Keywords: Nowcasting, Updating, Dynamic Factor Model.

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1 Introduction

Policymakers and market participants track the state of the economy on a daily basis, the former to make decisions about the conduct of (conventional and unconventional) monetary policies, macroprudential policies, and fiscal policies, and the latter to make decisions about their investment strategies.

Real gross domestic product (GDP) is one of the most monitored indicators, but it is generally released on a quarterly basis and with a delay that ranges from four weeks (as in the United Kingdom and in the United States) to eight weeks (as in Canada).

Given real GDP's lack of timeliness, policymakers and market participants try to infer current economic conditions by monitoring other indicators that are linked to GDP growth but are released at a higher frequency and in a more timely manner. Statistical offices and central bank release data almost every day that can help infer the level of real GDP.

The fact that variables other than GDP are highly regarded by practitioners may be inferred from global information services, such as Bloomberg and Forex Factory: They not only report a calendar of data releases but also a measure of importance for each, which reflects usage of the data by practitioners. In addition, Bloomberg conducts a survey and collects forecasts from analysts and economists on each release it reports and publishes it the day before the release is disseminated.

The aim of this paper is to propose an econometric model that can give users the ability to infer the state of the economy in terms of real GDP and that can be easily updated whenever new information becomes available. The econometric framework that we propose is based on the seminal paper by Giannone *et al.* (2006), who show how to produce an accurate nowcast of U.S. (quarterly) real GDP using monthly indicators by taking into account their different releasing times and therefore the ragged-edge shape of the data set by using of a dynamic factor model (DFM). In particular, we follow Bańbura and Modugno (2014), who show how to estimate DFM with data released at different frequencies and with different time-span coverage.

DFMs have been successfully applied to various economies, both developed and developing[1]. Although the statistical framework is similar to the one already applied to other economies, each country has its own peculiarities in terms of the relevance that each input series has in tracking real GDP; the timeliness of the releases; and the importance that market participants attribute to production, demand or trade. The aim of country-specific nowcasting models is also to learn about the characteristics of the data, how they interact with real GDP, and, more broadly, how the economy of that specific country works.

To our knowledge, this is the first article in the nowcasting literature to consider the Canadian economy. Canada was the 11th largest economy as of 2015, with a nominal GDP of approximately U.S.$ 1.79 trillion. It is a member of the OECD and the Group of Eight, and is one of the world's top 10 trading nations, with a highly globalized economy. Furthermore, the Toronto Stock Exchange is the 7th largest stock exchange in the world by market capitalization, listing over 1,500 companies with a combined market capitalization of over U.S.$ 2 trillion as of 2015.[2] Tracking the state of the Canadian economy is of interest not only for national policymakers and market participants, but for their international counterparts as well.

Canadian data have several peculiarities that distinguish it from other economies. For example, quarterly GDP is released with eight weeks of delay from the end of the reference period, which is less timely than the United States (four weeks) and the euro area (six weeks). However, Statistics Canada, differently from other countries, also publishes a monthly figure together with quarterly GDP growth eight weeks after the end of the reference period (the monthly real GDP relative to January is available only in March; the quarterly real GDP relative to Q1 is available only in May). Moreover, compared with other countries, Canada lacks some important series linked to production-namely industrial production and capacity utilization-that have been proved to be important in tracking real GDP growth for other economies given their timeliness

[1]The United States (Lahiri and Monokroussos, 2013), the euro area (Angelini *et al.*, 2010; Angelini *et al.*, 2011; and Camacho and Perez-Quiros, 2010), France (Barhoumi *et al.*, 2010), Ireland (D'Agostino *et al.*, 2008; and Liebermann, 2012), the Netherlands (De Winter, 2011), the Czech Republic (Arnostova *et al.*, 2011; and Rusnák, 2013), New Zealand (Matheson, 2010), Norway (Aastveit *et al.*, 2012; and Luciani and Ricci, 2014), Switzerland (Siliverstovs, 2012), China (Yiu and Chow, 2010), Turkey (Modugno *et al.*, 2016), Brazil (Bragoli *et al.*, 2015), Mexico (Caruso, 2015), and Indonesia (Luciani *et al.*, 2015). Moreover, the same framework has been applied to nowcast other variables than real GDP; see, among others D'Agostino *et al.* (2015) for the euro area trade variables and Modugno (2013) for U.S. inflation.

[2]see Fund (2015) and $http://www.tmx.com/resource/en/117$

and their correlation with the target variable.

In order to address these peculiarities, we propose a new modelling strategy that coherently takes into account the relation between quarterly real GDP and its monthly counterpart, and we deal with the lack of timely production data by including some of the most important series of the US economy. The United States is Canada's the first trade partner, with a total trade share of about 70 percent in 2015.[3] U.S. production series, given the strong linkages between the two economies, are crucial to getting an accurate assessment of where the Canadian economy stands. Moreover, given the interconnectedness of the U.S. and Canadian economies, we add two more U.S. series that are particularly relevant for market participants, are among the most timely U.S. series, and have been shown to be crucial to nowcasting the U.S. real GDP: purchasing managers index (PMI) and total non-farm payrolls.[4].

Results show that our model can deliver nowcasts that are at least as accurate as those produced by institutional forecasters such as the Bank of Canada, the OECD, and the Bloomberg survey. This result suggests that model-based forecasts that can quickly incorporate a potentially large set of new information can be a complementary tool to judgmental forecasts for participants assessing the state of the Canadian economy. Moreover, it confirms what has been found in other studies, namely that a linear time-invariant model does a good job, and hence that eventual nonlinearities, time variations, and soft information (such as weather conditions or government decisions) that could be incorporated by judgment, do not provide important new information. According to this last result, the often-cited superiority of professional forecasts (see Ang *et al.*, 2007; Clements and Hendry, 2004; and Jansen *et al.*, 2012) turns out to be weak in our sample, confirming findings in Giannone *et al.* (2006) and Liebermann (2011). Moreover, we show that U.S. data are crucial to obtaining an accurate real GDP nowcast for Canada: The lack of timely production data for the Canadian economy can be compensated for using U.S. data, confirming that the interconnectedness between the two economies can be exploited to produce more precise nowcasts of Canadian real GDP.

The rest of the paper is structured as follows. Section 2 describes the structure of the data

[3] See $http://www.statcan.gc.ca/tables-tableaux/sum-som/l01/cst01/gblec02a-eng.htm$.

[4] See Bańbura *et al.* (2012) and Bańbura *et al.* (2013).

releases in Canada. Section 3 introduces the model and estimation technique. Section 4 describes the Bank of Canada surveys and other benchmarks. Section 5 introduces the empirical analysis and comments on the results. Section 6 concludes.

2 The data set

Canadian real GDP growth is published by the statistical office two months (60 days) after the end of the quarter, which means real GDP growth in, for example, the first quarter (January to March) is disclosed only in May. The delay of real GDP growth data publication in Canada is greater than in most developed countries -that is- four weeks in the case of the United Kingdom and the United States and six weeks for European countries and Japan. Nevertheless, Canada also releases GDP data on a monthly basis about 60 days after month end. The quarterly GDP figure is approximately a summation of the monthly data.[5]

The aim of the statistical model we propose in this paper is to predict GDP before the official figures are published by taking advantage of the flow of other economic data releases that precede GDP publication and that allow us to update our prediction with each successive data release.

We include in our model variables whose headline number is reported by the main statistical sources. In addition, we consider indicators monitored by financial markets and the press. We choose the transformations that guarantee stationarity of the variables (see table 1), which are the same as those reported by the media and Bloomberg, making the comparison easier. We consider only real data and surveys. We disregard prices, financial variables, nominal variables, and sector-specific series. This choice reflects the results of previous research in which the inclusion of these variables does not improve the model's forecasting performance (see Bańbura and Modugno, 2010; and Bańbura and Modugno, 2014).

In the nowcasting model for Canada, we decide to also include some of the U.S. variables; in particular, we focus on the four most timely releases: namely U.S. manufacturing PMI, change

[5]Brazil also releases a nominal monthly GDP series.

in nonfarm employment, industrial production and capacity utilization. One of the aims of this article is to test whether the inclusion of U.S. variables significantly improves the nowcasting performance of our model for Canada.

The target variable is quarterly real GDP growth reported as a quarter-on-quarter (QoQ) transformation, the headline series on which market participants focus their attention. The input series, which are monthly, are reported as month-on-month (MoM) transformations with the exception of PMI manufacturing surveys (both for Canada and the United States), which are in levels but behave like a MoM series because of how they are constructed. U.S. capacity utilization and both U.S. and Canadian employment are reported as a monthly change, and motor vehicle sales, which are not seasonally adjusted, are reported as a year-on-year (YoY) transformation.[6] Linking the QoQ target variable with MoM input series is standard in this literature (see, among others, Mariano and Murasawa, 2003, Camacho and Perez-Quiros, 2010 and Bańbura and Modugno, 2014).

Table 1 reports some details on the selected series, including the timing of the release and the importance that the financial markets attach to the series according to the Bloomberg and Forex Factory indexes. The Bloomberg measure, which is shown as a percentage, reflects usage by Bloomberg subscribers; the Forex Factory measure, which is shown as low/medium/high, reflects Forex Factory subscribers' judgment.

One peculiarity of the Canadian data set is the fact that it includes the monthly real GDP published by Statistics Canada but does not have an index of industrial production, which is one of the most important piece of hard data for other economies given its timeliness (U.S. industrial production index, for example, has a publication lag of only 15 days).

The rest of the variables can be divided into four categories: surveys, labor, domestic demand, and trade indicators. Among surveys, we consider the PMI which is released at the beginning of the following month and rated highly relevant to the market by Forex but relatively unimportant by Bloomberg (15.4 percent). For labor, we include employment, released

[6]To construct the PMI index, respondents are asked whether business conditions for a number of variables have improved, deteriorated, or stayed the same compared with the previous month. Therefore, the index is comparable to a MoM transformation.

one week after month end and rated important by Forex. For domestic demand, we track manufacturing shipments (or sales), manufacturing orders, retail sales and wholesale trade, motor vehicle sales, building permits and dwelling starts. Building permits and retail sales are considered relevant by both Bloomberg and Forex. The trade category includes exports and imports, which have a publication lag of one month and are considered highly important by Forex. Dwelling starts, which are released one week after month end, are considered relevant for market participants by Bloomberg (82.0 per cent)

To conclude, the most timely data in Canada are the PMI, employment and dwelling starts, which are released with a publication lag of one week. Building permits and trade variables (exports and imports) are released five weeks after the end of the reference month. The rest of the hard data (sales and orders) are released with a six - to seven- week lag from the end of the reference month.

If we consider only the Canadian data we immediately realize that there are few timely variable. In the following sections, we will show that the introduction of four of the most timely U.S. variables, which are released at most 15 days after the end of the reference month and are related to the Canadian business cycle, will improve the nowcasting performance of our model for Canada.

Table 1: *Series used in the model*

Name	**Timing**	**Publishing lag**	**Frequency**	**Source**	**Available from**	**Transf.**	**Relevance Forex**	**Relevance Bloomberg**
US Manufacturing PMI	first days	5 days	M	ISM	Jan-48	Levels	H	94.6
US Change in Employment	first days	5 days	M	BLS	Feb-39	Levels	H	99.1
US Industrial Production	middle	15 days	M	FRB	Jan-21	MoM	M	86.6
US Capacity Utilization	middle	15 days	M	FRB	Jan-67	Monthly change	M	60.6
Canada Ivey PMI	first days	5 days	M	IveyUWO	Jan-01	Levels	H	15.4
Canada Building Permits	first week	35 days	M	StatCan	Jan-60	MoM	H	71.8
Canada Employment	first week	8 days	M	StatCan	Jan-66	Monthly change	H	30.8
Canada Dwelling Starts	first week	9 days	M	CMHC	Jan-90	MoM	L	82
Canada Imports of Goods	first days	35 days	M	StatCan	Jan-88	MoM	H	-
Canada Exports of Goods	first days	35 days	M	StatCan	Jan-88	MoM	H	-
Canada Manufacturing Shipments	middle	45 days	M	StatCan	Jan-92	MoM	H	-
Canada Motor Vehicle Sales	middle	45 days	M	StatCan	Jan-46	YoY	-	0
Canada Manufacturing Orders	middle	45 days	M	StatCan	Jan-92	MoM	-	-
Canada Wholesale Trade	20th month	50 days	M	StatCan	Jan-93	MoM	M	51.3
Canada Retail Sales	20th month	50 days	M	StatCan	Jan-91	MoM	M	74.4
Canada Monthly GDP	last days	60 days	M	StatCan	Jan-97	MoM	H	84.6
Canada Real GDP	last days	2 months	Q	StatCan	Q1-81	QoQ	-	92.3

Notes. Timing is approximately the number of days from the end of the reference period. **Frequency** indicates whether the series is monthly (M) or quarterly (Q). **Available from** indicates the starting date of the series. **Sources** are ISM (Institute for Supply Management), BLS (Bureau of Labor Statistics), FRB (Federal Reserve Board), IveyUWO (Richard Ivey School of Business, Univ of W. Ontario), StatCan (Statistics Canada), and CMHC (Canada Mortgage and Housing Corporation). **Bloomberg** reports the market relevance of each variable according to Bloomberg's relevance index, which ranges from 0 to 100. **Forex** reports the market relevance of each variable according to Forex relevance index, i.e., L=Low relevance, M=medium relevance, and H=High relevance.

3 The nowcasting problem and the econometric framework

Nowcasting GDP involves inferring its value after the reference quarters begins but before the official release of GDP data by exploiting information from other, higher-frequency variables [7].

More formally, the nowcast of GDP (y_t^Q) can be defined as the linear projection of y_t^Q on the available information set Ω_v, which contains mixed-frequency variables $(x_{k_j,t_j}, j = 1, ..., J_{v+1})$ and is characterized by a "ragged-edge" structure because the time of the last available information varies from series to series.

Each time new information arrives, a new nowcast is produced. This nowcast can be decomposed as follows:

$$P[y_t^Q|\Omega_{v+1}] = P[y_t^Q|\Omega_v] + P[y_t^Q|I_{v+1}]. \tag{1}$$

The new nowcast, $P[y_t^Q|\Omega_{v+1}]$, is just the sum of the old nowcast, $P[y_t^Q|\Omega_v]$, and the revision, $P[y_t^Q|I_{v+1}]$, where

$$I_{v+1,j} = x_{k_j,t_j} - P[x_{k_j,t_j}|\Omega_v], \tag{2}$$

with $j = 1, ..., J_{v+1}$. This revision $(I_{v+1,j})$ is the linear projection of our target variable on the difference between the actual release of any variable $(x_{k_j,t_j} \in \Omega_{v+1})$ and what our model was predicting for that release $(P[x_{k_j,t_j}|\Omega_v])$: This revision is the only element that leads to a change in the nowcast because it is the "unexpected" (with respect to the model) part of the data release and we call it "news."

As shown by Bańbura and Modugno (2010), the revision can be decomposed as a weighted average of the news in the latest release. We can find a vector, $B_{v+1} = [b_{v+1,1}, ..., b_{v+1,J_{v+1}}]$

[7] In this section, we closely follow Bańbura and Modugno (2010)

such that the following holds:

$$P[y_t^Q|\Omega_{v+1}] - P[y_t^Q|\Omega_v] = B_{v+1}I_{v+1} = \sum_{j=1}^{J_{v+1}} b_{v+1,j}(x_{k_j,t_j} - P[x_{k_j,t_j}|\Omega_v]). \quad (3)$$

The magnitude of the nowcast revision depends on both the size of the news and on its relevance for the target variable, as represented by the associated weight, $b_{v+1,j}$.[8]

Through this mechanism, it is possible to trace the contribution of each series to the revision of the nowcast, in particular by linking the revision of the target variable nowcast with the unexpected developments of the input variables.

The model we use to compute the nowcast and the news is a dynamic factor model (DFM). This model produces a good representation of the data and, at the same time, guarantees parsimony. It exploits the fact that there is a large amount of co-movement among macroeconomic data series and, hence, that relatively few factors can explain the dynamics of many variables (see Sargent and Sims, 1977; Giannone *et al.*, 2005; and Stock and Watson, 2011).

The general representation of a DFM can be written as a system with two types of equations: a measurement equation (equation 4) linking the observed series (that is, GDP and all the indicators listed in table 1) to a latent state process, and the transition equation (equation 5), which describes the state process dynamics. Equations 4 and 5, written in a state space form, allow the use of the Kalman filter to obtain an optimal projection for both the observed and the state variables. The Kalman filter generates projections for all the variables in the model (GDP and all the other data releases).

The DFM is described by the following equations:

$$y_t = \Lambda f_t + e_t, \quad (4)$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + ... + A_p f_{t-p} + u_t \qquad u_t \sim i.i.d.N(0, Q), \quad (5)$$

[8] Equation 3 can be considered a generalization of the Kalman filter update equation to the case in which new data arrive in a non-synchronous manner. See Bańbura and Modugno (2010).

$$e_{i,t} = \rho_i e_{i,t-1} + v_{i,t} \qquad v_{i,t} \sim i.i.d.N(0, \sigma_i^2), \tag{6}$$

where $y_t = [y_{1,t}; y_{2,t}; ...; y_{n,t}]'$ denotes a set of standardized stationary monthly variables, f_t is a vector of r unobserved common factors with zero mean and unit variance, Λ is a matrix of coefficients collecting the factor loadings for the monthly variables, and $e_t = [e_{1,t}; e_{2,t}; ...; e_{n,t}]'$ is an n-dimensional vector of idiosyncratic components uncorrelated with f_t at all leads and lags.

This last assumption, which means that all the joint correlation between observables is explained by the common factors, is strong and unrealistic, however, Doz *et al.* (2006) have shown that the effects of this misspecification on the estimation of the common factors is negligible for a large sample size (T) and the cross-sectional dimension (n).

We consider only one state variable (or factor) and two lags in equation 5 and an AR(1) process for the idiosyncratic components described in equation 6.[9]

In the case of Canada, we depart from the usual DFM representation. As explained earlier, Statistics Canada produces a monthly GDP series. To fully exploit this source of information, we propose a new modelling strategy to incorporate the quarterly GDP series: We impose restrictions on the factor loadings such that the monthly GDP becomes a state variable and the quarterly GDP only loads the monthly GDP through the aggregation proposed by Mariano and Murasawa (2003). The other state variable is instead extracted from all the other series in our data set and interacts with the monthly GDP trough the VAR, helping to forecast the future realizations of the monthly GDP and, therefore, of the quarterly GDP. In practice, our model

[9]We use Bai and Ng (2002) information criteria to select the number of factors in equation 4 and Akaike information criteria to select the lag order of equation 5. See the appendix for details.

has the following state space representation:[10]

$$
\begin{bmatrix} y_t^q \\ y_t^m \\ \mathbf{x_t} \end{bmatrix} = \begin{bmatrix} \lambda_q & 2\lambda_q & 3\lambda_q & 2\lambda_q & \lambda_q & 0 & 0 & .. & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & .. & 0 \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{\Lambda_m} & \mathbf{0} & .. & \mathbf{0} \end{bmatrix} \begin{bmatrix} y_t^m \\ y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \end{bmatrix} + \begin{bmatrix} \epsilon_t^q \\ 0 \\ \mathbf{e_t} \end{bmatrix}, \quad (7)
$$

where y_t^q is the quarterly GDP; y_t^m is the monthly GDP; $\mathbf{x_t}$ are the remaining monthly variables; λ^q is the coefficient that links the quarterly GDP to the monthly GDP through the aggregation proposed by Mariano and Murasawa (2003); Λ^m is the vector of dimension (n-2)x1 of factor loadings connecting the factor to all the monthly variables but the monthly GDP; and $\mathbf{0}$ are vectors of zero of dimension (n-2)x1 where n is the number of variables in our data set. The transition equation is then

[10]For simplicity, we assume here that the idiosyncratic components are i.i.d. white noise. However, our model is estimated assuming that the idiosyncratic components follow an AR(1), though this make the state space representation cumbersome. The state space representation with AR(1) idiosyncratic errors is available in Appendix.

$$
\begin{bmatrix} y_t^m \\ y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 & 0 & a_{13} & a_{14} & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & a_{23} & a_{24} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ y_{t-5}^m \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \end{bmatrix} + \begin{bmatrix} u_t^y \\ 0 \\ 0 \\ 0 \\ 0 \\ u_t^f \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad (8)
$$

where f_t is the common factor to all the variables in the data set but the quarterly and monthly GDP, and $a_{i,j}$ are the VAR(2) coefficients obtained by regressing the monthly GDP and the factor on their own two lags.

4 Institutional benchmarks

To assess the forecasting accuracy of our results, we compare them against two different institutional forecasters: the OECD and the Bank of Canada.

The Bank of Canada's Monetary Policy Report is a quarterly report of the Governing Council presenting the Bank's projections for inflation and growth in the Canadian economy and its assessment of risks. It is published in January, April, July, and October.

The OECD Economic Outlook is the OECD's twice-yearly analysis of major economic trends and prospects for the next two years. Prepared by the OECD Economics Department, the Outlook puts forward a consistent set of projections for output, employment, government spending, prices, and current balances based on a review of each member country and of the induced effect of each of them on international developments. It is published in March and

September.

In addition, the other important benchmark we consider is Bloomberg, which conducts a survey and collects forecasts from analysts and economists to produce predictions for GDP and other market-relevant variables before their release dates. Bloomberg publishes predictions as soon as they have at least three respondents to their questionnaire, which is generally around two weeks before the release of the relevant data series. Thereafter the prediction is continually revised until 24 hours before the release. The final number is usually close to the actual release value.

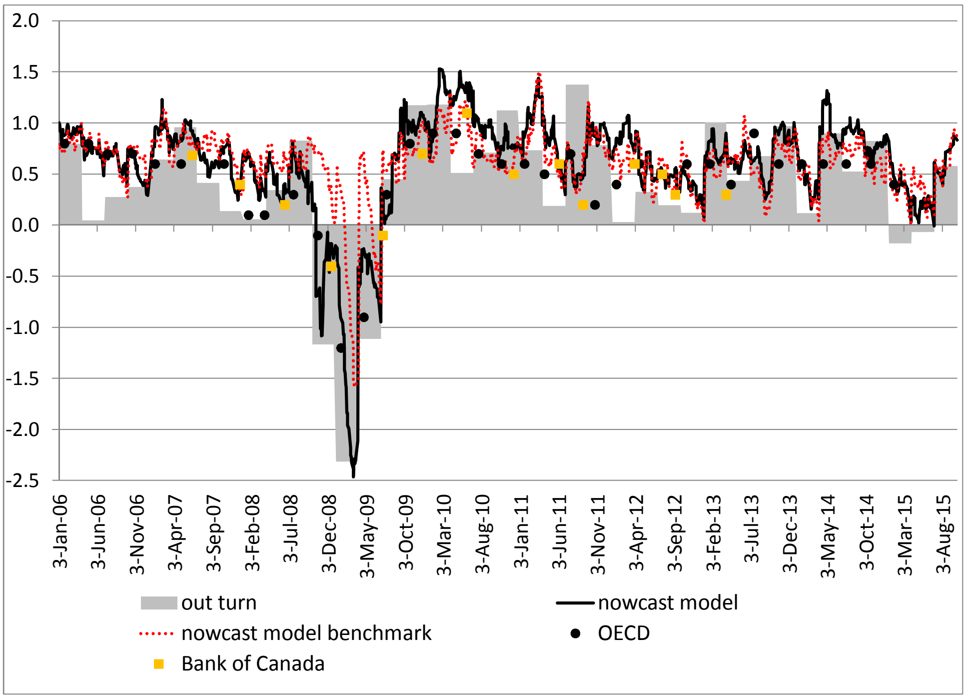
5 Model evaluation

To evaluate the performance of the model, we report a "pseudo real time" historical reconstruction from 2006:Q1 to 2015:Q3. We estimate the model recursively (the estimation period starts in January 1992) and take into account information from each new data release (in real time), but we do not consider revisions (pseudo). This last point can in principle distort the results in favor of the model, given that the Bloomberg survey relies on real-time information. However, given the robustness of factor models to data revision errors (see Giannone *et al.*, 2006; and Bańbura *et al.*, 2013), we expect this not to be the case.

The results of the historical evaluation are reported in figure 1 below. The figure compares the QoQ GDP nowcast with the OECD and Bank of Canada forecasts and with a benchmark nowcasting model that does not include U.S. variables. Figure 1 shows that the nowcasting model mimics the actual realization of GDP very well and that it outperforms the benchmark model. This result implies that the U.S. variables we include in our model improve the forecast performance of the model.

Figure 2 compares the root-mean-squared forecast error (RMSFE) of the model-on average for all of the calendar quarters in the historical reconstruction period- with the benchmark model, the short-term forecasts of the Bank of Canada, and the OECD, Bloomberg's survey of independent forecasters (published the day before the preliminary GDP release), and an auto-

Figure 1: GDP nowcast

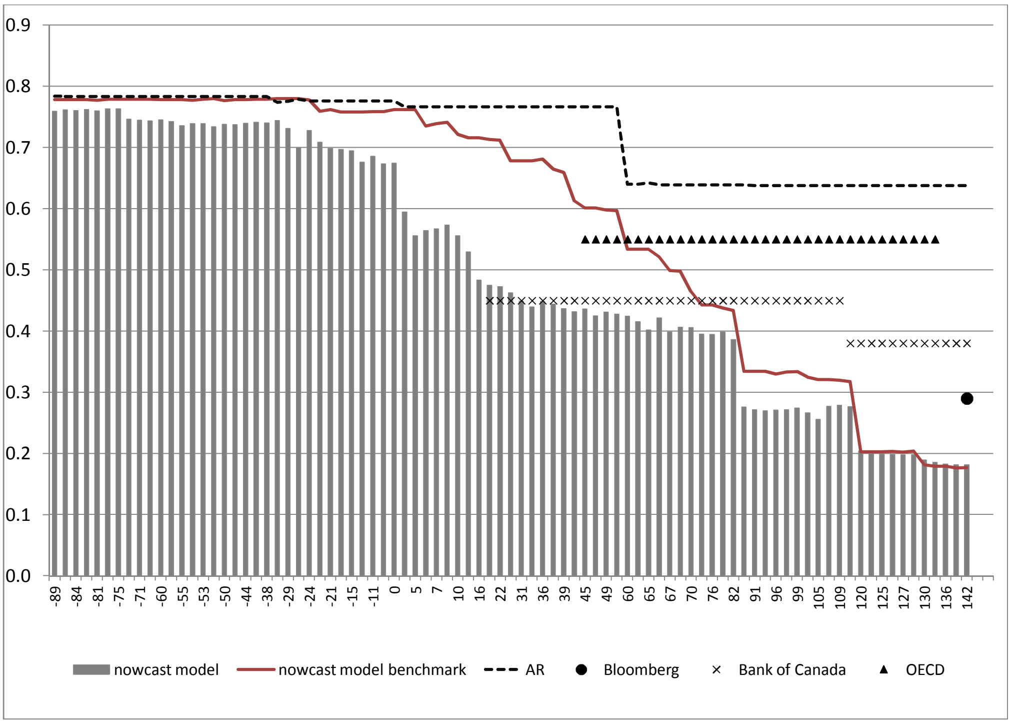


Notes. The graph reports the comparison between a GDP nowcast using U.S. variables (nowcast model), a GDP nowcast without U.S. variables (nowcast model benchmark), the GDP actual value, and OECD and Bank of Canada professional forecasts.

regressive forecast that changes only when GDP is released.

The model's quarterly GDP growth prediction is first made 90 days before the start of a given quarter. It is then updated with each successive data release until the release of preliminary GDP, which takes place 150 days after the start of the calendar quarter. Thus for each calendar quarter, there is a period of 240 days (the "prediction period") over which the prediction is continuously updated. This period is measured by the x axis. The y axis measures the RMSFE for each series of predictions. From figure 2, we can clearly learn two lessons. First, the U.S. data are crucial to obtaining an accurate nowcast of quarterly Canadian GDP growth; indeed, the RMSFE line produced by the model without U.S. data is always above the RMSFE line produced by the model with U.S. data. Second, our mechanical model produces nowcasts that are on average

Figure 2: RMSFE



Notes. The y axis reports the root-mean-squared forecast error (RMSFE) over the period from 2006:Q1 to 2015:Q3. The forecast accuracy is evaluated from the first month of the previous quarter to the time when GDP is released. The x axis reports the distance in days from the beginning of the current quarter.

Table 2: *Average MSFE Reduction by Variable*

	m1	m2	m3
U.S. ISM Manufacturing PMI	4.66	-1.29	-0.48
U.S. Change in Nonfarm Employment	-2.95	-0.02	-0.48
U.S. Industrial Production Index	-6.81	-0.66	-0.17
U.S. Capacity Utilization	-6.81	-0.66	-0.17
Canada Ivey PMI	-0.34	-0.24	0.54
Canada Building Permits	-0.59	0.18	0.21
Canada Employment	0.10	-0.95	-1.42
Canada Dwelling Starts	-0.14	-0.22	-0.20
Canada Imports of Goods	-2.77	-0.24	0.04
Canada Exports of Goods	-2.62	-0.24	0.00
Canada Manufacturing Shipments	-0.11	0.23	-0.72
Canada New Motor Vehicle Sales	-0.70	-0.15	-0.46
Canada New Manufacturing Orders	-0.11	0.23	-0.72
Canada Wholesale Trade	-0.55	0.19	-0.32
Canada Retail Sales Value	-0.18	0.08	-0.38
Canada Monthly GDP	-0.91	-0.57	-7.37
Canada Real GDP		-0.34	

Notes. These results are referred to as the first (m1), second (m2), and third (m3) months of the nowcast period.

more accurate than those produced by institutional forecasters and market participants.

In table 2, we report the RMSFE reduction by release in each of the three months of the reference quarter. From table 2, we notice that U.S. data releases have the biggest effect in improving the accuracy of the model's prediction in the first month. In the second month, Canadian employment, dwellings starts, exports and imports seem to be relevant together with U.S. PMI. In the third month, monthly GDP plays a major role in improving the accuracy of the model's prediction.

5.1 Do U.S. variables matter?

From the previous section, we have shown the role played by U.S. variables in improving the model's nowcasting performance of the model. In this section, we formally test whether the RMSFE of the model that incorporates U.S. variables is statistically different than the RMSFE of the model that only includes Canadian data.

In table 3, we report the Diebold and Mariano (2002) test ("DM test") of equal predictive accuracy to check whether the difference in forecasting performance between models is significant. For each month, we report the sample average of the difference between the squared errors of the AR and the benchmark model forecast, nowcast, and backcast, both with respect to our model and coincident with the first Canadian release (Canada PMI). We report the value of the DM test and its standard deviation estimated using heteroskedasticity and autocorrelation robust standard errors (see appendix A.2 for details). The test confirms that our model performs more accurately than the AR (only in the nowcast and backcast) and slightly more accurate than the benchmark model (only in the nowcast).

From figure 2, we can see that the model's RMSFE declines more or less continuously over the prediction period, which means that new information has a monotonic and negative effect on uncertainty. To formally test the decline in uncertainty, as more data arrive we apply the test for forecast rationality proposed by Patton and Timmermann (2012). Table 4 reports the p-values of three monotonicity tests for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable (see the appendix for a description of the tests). Monotonicity cannot be rejected by any of the three testss confirming the evidence of figure 2 and proving the importance of incorporating new information into the forecast update as it arrives .

Table 3: Diebold-Mariano test of equal forecasting accuracy

	Forecast		Nowcast		Backcast	
	AR	BCB	AR	BCB	AR	BCB
1m	0.03	0.02	0.26	0.22	0.33	0.04
	(0.03)	(0.03)	(0.14)	(0.13)	(0.14)	(0.02)
2m	0.07	0.06	0.39	0.26	0.37	0.00
	(0.07)	(0.07)	(0.22)	(0.15)	(0.15)	(0.01)
3m	0.07	0.08	0.23	0.10		
	(0.08)	(0.10)	(0.14)	(0.06)		

Notes. The table reports the estimated constant and the HAC estimator of its standard error in the first, second, and third month of the forecast, nowcast, and backcast, respectively. The AR and the benchmark are compared against the nowcast model.

Table 4: Monotonicity tests

	$\Delta^e \geq 0$	$\Delta^f \geq 0$	$\Delta^c \geq 0$
nowcast model	0.4977	0.5049	0.5060

Notes. The table reports the p-values of three monotonicity tests for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable.

5.2 The news

The importance of calculating the news is twofold. First, given that the news is defined as the difference between the actual value of the data release and the value predicted by the model, it is possible to check whether the model is well specified in all its dimensions. The average of the news for each release should be close to zero, and the standard deviation should be such that $|mean| < 2$ standard deviations. Table 5 confirms this statement. In addition, the table also compares the model's performance in predicting each of the series with that of the Bloomberg survey. We show that, for most series, the model's predictions are comparable to the Bloomberg survey's predictions. Finally, we include in table 5 the mean and standard deviation of the revisions for each of the series in the data set. As the means of the revisions are close to zero and the standard deviations are such that $|mean| < 2$ standard deviations, this result suggests that the model's relative performance would have been similar in real time.[11]

Table 5: Average news and standard deviation

		Model		Bloomberg		Revisions	
	Units/ Transformation	Mean	StD	Mean	StD	Mean	StD
U.S. ISM Manufacturing PMI	D.I./Levels	-0.21	2.24	0.01	1.82	-0.18	1.86
U.S. Change in Nonfarm Employment	Thous/Levels	-28.87	139.25	7.56	106.34	8.00	63.35
U.S. Industrial Production	Index/MoM	-0.09	0.62	0.12	0.53	0.06	0.42
U.S. Capacity Utilization	Percentage/Diff	0.05	0.48	0.02	0.57	0.05	0.36
Canada Ivey PMI	D.I./Levels	-0.43	7.29	-0.93	6.82	-0.21	3.02
Canada Building Permits	Thous Units/MoM	0.09	11.28	-0.37	10.84	0.00	0.10
Canada Employment	Thous/Diff	-4.34	33.39				
Canada Dwelling Starts	Thous Units/MoM	-0.11	9.52	0.1	12.02	-0.19	4.18
Canada Imports of Goods	Mil.C$/MoM	0.09	2.49				
Canada Exports of Goods	Mil.C$/MoM	-0.05	3.17				
Canada Manufacturing Shipments	Thous.C$/MoM	-0.12	1.75	0.18	1.47	0.04	0.91
Canada Motor Vehicle Sales	Thous/YoY	0.19	6.55				
Canada Manufacturing Orders	Thous.C$/MoM	-0.10	4.83				
Canada Wholesale Trade	Thous.C$/MoM	-0.10	1.20	-0.05	1.17	-0.01	0.86
Canada Retail Sales Value	Thous.C$/MoM	-0.05	0.98	-0.02	0.73	-0.04	0.53
Canada Monthly GDP	Mil.C$/MoM	-0.08	0.25	0.02	0.23	-0.03	0.18
Canada Real GDP	Mil.C$/QoQ	-0.03	0.18	-0.02	0.29	-0.03	1.10

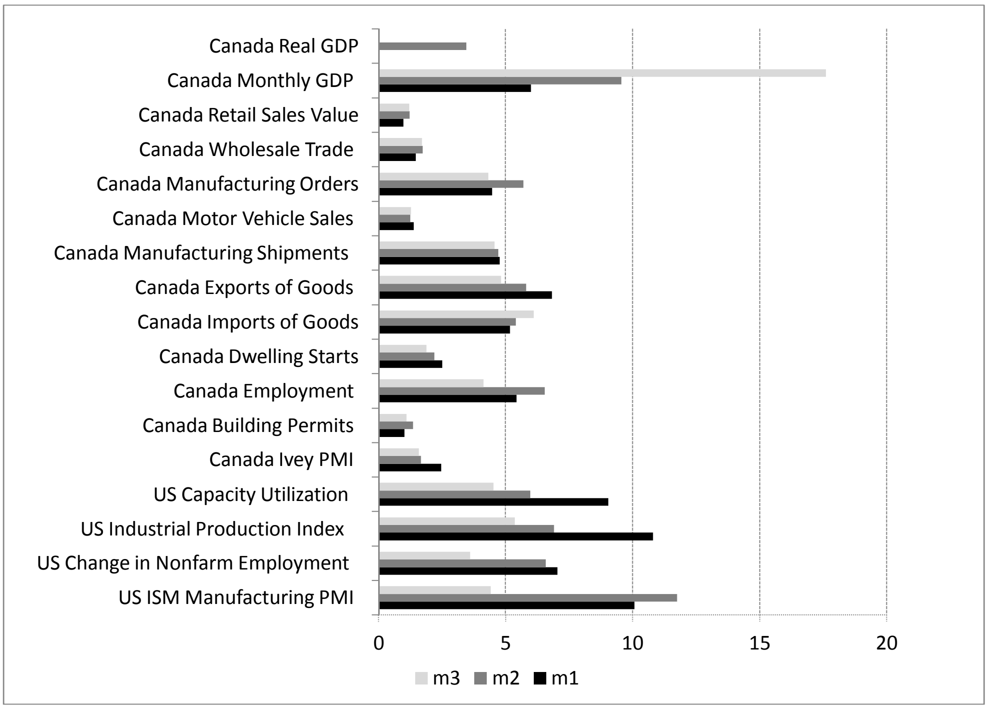
Notes. D.I.= diffusion index; Diff.= differences; Thous. Units = Thousand Units; Mil. C$ = Million Canadian Dollars; MoM=Month on Month; QoQ=Quarter on quarter; YoY=year on year.

The second important feature of the news within a nowcasting framework is that it allows for the interpretation of all the data releases in terms of the signals they give about current

[11] Note that the Bloomberg survey is conducted in real time and the respondents whose forecasts it reflects are attempting to predict the first release of each series, whereas the reconstruction of the model's predictions is based on the last available vintage of data, ignoring revisions.

economic conditions (Bańbura and Modugno, 2010). It is possible, with the use of equation 3, to decompose the forecast revision into contributions from the news in individual series. The impact that a given release has on the GDP nowcast is the product of two variables: the news (or the unexpected component of the release value) and the relevance of the series in relation to GDP, which is expressed as its weight (that is, impact = news standard deviation x weight).[12] Figure 3 shows the average impact of each variable in the first, second, and third months of the quarter. As expected, U.S. variables have a strong impact in the first month, U.S. PMI is also relevant in the second month. Monthly GDP has a relevant contribution only in the third month. See appendix A.4 for the decomposition of the average impact.

Figure 3: Variables' relevance



Notes. Variables' average impact in the first (m1), second (m2), and third (m3) months of the nowcast.

[12]We consider the standard deviation instead of the mean because the latter should be close to zero and also in order to discard the sign.

6 Conclusion

We proposed an econometric framework for inferring the state of the Canadian economy, in terms of real GDP, that can be easily updated any time new information is available. Canadian data are characterized by two peculiarities: the presence of a monthly measure of real GDP other than the quarterly one, and the lack of availability of timely industrial production data. We solve the first challenge by proposing a new modelling strategy that coherently takes into account the relation of the quarterly real GDP and its monthly counterpart. We deal with the lack of timely industrial production data by including in our information set U.S. industrial production data.

Results show that our model can deliver nowcasts that are at least as accurate as those produced by institutional forecasters such as the Bank of Canada, the OECD, and the Bloomberg survey. This result suggests that a model-based nowcast that can quickly incorporate a potentially large set of new information can complement to judgmental nowcast in assessing the state of the Canadian economy. Moreover, we show that U.S. data are crucial to obtaining an accurate real GDP nowcast for Canada; the lack of timely production data for the Canadian economy can be compensated for by using U.S. data, confirming that the interconnectedness between the two economies can be exploited for producing a more precise nowcast of the Canadian real GDP.

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Appendix

A1. Selecting the number of factors and lags

We select the optimal number of factors using an information criteria approach. The idea is to choose the number of factors that maximizes the general fit of the model, using a penalty function to account for the loss in parsimony. Bai and Ng (2002) derive information criteria to determine the number of factors in approximate factor models when the factors are estimated by principal components. They also show that their information criterion (IC) can be applied to any consistent estimator of the factors provided that the penalty function is derived from the correct convergence rate.

Table 6 reports the IC and the sum of the variance of the idiosyncratic components for the different specifications, which allow for a different number of factors. The IC selects the model

Table 6: Model selection (number of factors)

	Sample 1		Sample 2		Sample 3	
	IC	V	IC	V	IC	V
1	0.13	0.84	0.10	0.81	0.04	0.76
2	0.21	0.66	0.19	0.64	0.13	0.61
3	0.34	0.56	0.40	0.58	0.44	0.60
4	0.55	0.50	0.79	0.62	0.59	0.51
T	59		155		272	
N	15		14		14	

Notes. IC stands for information criteria, and V is the sum of the variance of the idiosyncratic component.

with one factor. Given that our data set is unbalanced at the top and some series are more recent than others, we report the test on three different samples. The first (sample 1) considers a balanced panel in the estimation period 2001:Q1 to 2005:Q4 (15 series and 59 observations), the second (sample 2) a restricted balanced panel in which we exclude one of the most recent series (14 series, 155 observations), and the third (sample 3) a balanced panel that incorporates the whole sample (estimation and forecasting period). The choice of one factor is confirmed across the different samples.

To select the number of lags in equation 5 of the model, we report in table 7 the values of the Akaike IC, which selects two lags.

Table 7: Model selection (number of lags)

Number of lags	Akaike information criteria
1	-1.35
2	-1.65
3	-1.60
4	-1.58

Notes. The lag is chosen in correspondence with the minimum AIC value.

A2. Diebold-Mariano test

Denote the loss associated with forecast error e_t as $L(e_t)$ and the time-*t* loss differential between forecasts 1 and 2 as $d_{12t} = L(e_{1t}) - L(e_{2t})$. The Diebold-Mariano (DM) test requires only that the loss differential is covariance stationary:

$$
\begin{aligned}
E(d_{12t}) &= \mu, \forall t \\
cov(d_{12t}, d_{12t-\tau}) &= \gamma(\tau), \forall t \\
0 < var(d_{12t}) &= \sigma_2 < \infty
\end{aligned}
$$

The key hypothesis of equal predictive accuracy (that is, equal expected loss) corresponds to $E(d_{12t}) = 0$, in which case under the maintained assumption DM,

$$DM_{12} = \frac{\bar{d}_{12}}{\hat{\sigma}_{\bar{d}_{12}}} \xrightarrow{d} N(0,1),$$

where $\bar{d}_{12} = \frac{1}{T}\sum_{t=1}^{T} d_{12t}$ is the sample mean loss differential and $\sigma_{\bar{d}_{12}}$ is a consistent estimator of the standard deviation of $\bar{d}_{12}$.

DM is thus an asymptotic $z - test$ of the hypothesis that the mean of a constructed but observed series (the loss differential) is zero. However, forecast errors, and hence loss differential, may be serially correlated for various reasons. In this paper, we calculate the DM statistics by regression of the loss differential on an intercept, using heteroskedasticity and autocorrelation robust standard errors. In a fully articulated econometric model in which we have pseudo out-of-sample forecasts, we follow West (1996) and define the test on the sample mean quadratic loss as follows:

$$\bar{d}_{12} = \frac{\sum_{t=t^*+1}^{T}(e^2_{1,t|t-1} - e^2_{2,t|t-1})}{T - t^*},$$

where $e_{t|t-1}$ is a time-*t* pseudo out-of-sample one-step ahead forecast error. We do not consider a rolling scheme, so results should be taken with caution, as the test ignores estimation uncertainty.

A3. Monotonicity test

We rely on the first three tests of Patton and Timmermann (2012), based on the multivariate inequality tests in regression models of Wolak (1987). We report the p-values for the nowcast model.

Test 1: Monotonicity of the forecast errors

Let us define $\tilde{y}_t = y^k_{t,1}$ and $e_{t|\Omega_v} = \tilde{y}_t - E[\tilde{y}_t|\Omega_v]$ as the forecast error obtained on the basis of the information set corresponding to the data vintage Ω_v, and $e_{t|\Omega_{v+1}}$ as that obtained on the basis of a larger, more recent vintage, $v + 1$ and $v = 1, ..., V$.

The mean squared error (MSE) differential is $\Delta^e_v = E[e^2_{t|\Omega_v}] - E[e^2_{t|\Omega_{v+1}}]$.

The test is H0 : $\Delta^e \geq 0$ vs H1 :$\Delta^e \ngeq 0$, where the $(V - 1) \times 1$ vector of MSE differentials is given by $\Delta^e \equiv (\Delta^e_1, ..., \Delta^e_{V-1})'$.

Test 2: Monotonicity of the mean squared forecast

Define the mean squared forecast (MSF) for a given vintage as $E[\tilde{y}^2_{t|\Omega_v}] = E[E[\tilde{y}^2_t|\Omega_v]]$ and consider the difference, $\Delta^f_v = E[\tilde{y}^2_{t|\Omega_v}] - E[\tilde{y}^2_{t|\Omega_{v+1}}]$, and its associated vector, Δ^f.

The test is H0 : $\Delta^f \leq 0$ vs H1 : $\Delta^f \nleq 0$.

Test 3: Monotonicity of covariance between the forecast and the target variable

Here we consider the covariance between the forecast and the target variable for different vintages, v, and the difference, $\Delta_v^c = E[\tilde{y}_{t|\Omega_v}\tilde{y}_t] - E[\tilde{y}_{t|\Omega_{v+1}}\tilde{y}_t]$. The associated vector is defined as Δ^c and the test is H0 : $\Delta^c \leq 0$ vs H1 : $\Delta^c \nleq 0$.

Wolak (1987) derived a test statistic whose distribution under the null is a weighted sum of chi-squared variables.

A4. Impact of the releases on the nowcast

Table 8: Impact of the releases on the nowcast

	A			B			C		
	m1	m2	m3	m1	m2	m3	m1	m2	m3
U.S. ISM Manufacturing PMI	4.657	4.695	2.105	2.164	2.503	2.096	10.076	11.751	4.412
U.S. Change in Nonfarm Employment	0.047	0.051	0.026	148.212	130.015	136.422	7.035	6.573	3.606
U.S. Industrial Production Index	13.330	14.116	9.933	0.810	0.489	0.540	10.803	6.906	5.359
U.S. Capacity Utilization	14.827	15.658	10.948	0.610	0.381	0.413	9.046	5.965	4.518
Canada Ivey PMI	0.315	0.314	0.202	7.797	5.293	7.849	2.458	1.663	1.585
Canada Building Permits	0.099	0.110	0.106	10.246	12.246	10.365	1.017	1.347	1.096
Canada Employment	0.175	0.182	0.123	30.964	35.993	33.488	5.430	6.538	4.126
Canada Dwelling Starts	0.241	0.256	0.194	10.419	8.562	9.700	2.509	2.190	1.877
Canada Imports of Goods	2.031	2.299	2.322	2.544	2.349	2.628	5.165	5.400	6.104
Canada Exports of Goods	1.732	1.934	1.961	3.936	3.000	2.458	6.818	5.802	4.821
Canada Manufacturing Shipments	2.440	2.876	2.827	1.955	1.640	1.614	4.771	4.716	4.565
Canada New Motor Vehicle Sales	0.187	0.199	0.206	7.347	6.238	6.168	1.374	1.241	1.268
Canada New Manufacturing Orders	0.897	1.058	1.040	4.976	5.383	4.149	4.466	5.697	4.315
Canada Wholesale Trade	1.229	1.371	1.464	1.184	1.262	1.169	1.456	1.730	1.711
Canada Retail Sales Value	1.053	1.158	1.223	0.929	1.052	0.986	0.978	1.218	1.206
Canada Monthly GDP	23.697	36.688	78.031	0.253	0.261	0.226	6.000	9.557	17.609
Canada Real GDP		19.542			0.176			3.446	

Notes. A is the average weight, B is the news standard deviation, and C is the average impact equal to $A \cdot B$.

A5. Complete state space

The exact state space representation of our model for nowcasting Canadian real GDP growth is described in the following two systems of equations where, as in equation 9, y_t^q is the quarterly GDP; y_t^m is the monthly GDP; the vector $\mathbf{x_t}$ contains the remaining $n-2$ (where n is the number of variables in our dataset) monthly variables; λ^q is the coefficient that links the quarterly GDP to the monthly GDP through the aggregation proposed by Mariano and Murasawa (2003); Λ^m is the vector of dimension $n-2$ of factor loadings linking the factor to all the monthly variables but the monthly GDP; $\mathbf{0}$ are vectors of zero of dimension $(n-2)x1$; $\mathbf{I}$ is an identity matrix of dimension $n-2$; f_t is the common factor to all the variables in the data set but the quarterly and monthly real GDP; ϵ_t^q is the idiosyncratic component that enters with its lags, aggregated a la Mariano and Murasawa (2003), in the observation equation for the quarterly GDP; and $\mathbf{e_t}$ is the $(n-2)x1$ vector of the idiosyncratic components of the rest of the monthly variables. In the transition equation 10 we have that $a_{i,j}$ are the VAR(2) coefficients obtained by regressing the monthly GDP and the factor on their own two lags; ρ_q is the autoregressive coefficient of the idiosyncratic components of the quarterly GDP; and $\mathbf{P}$ is a diagonal matrix of dimension $n-2$ containing the autoregressive coefficients for the idiosyncratic components of the remaining $n-2$ variables.

$$\begin{bmatrix} y_t^q \\ y_t^m \\ \mathbf{x_t} \end{bmatrix} = \begin{bmatrix} \lambda_q & 2\lambda_q & 3\lambda_q & 2\lambda_q & \lambda_q & 0 & 0 & .. & 0 & 1 & 2 & 3 & 2 & 1 & 0 & \mathbf{0}' \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & .. & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{\Lambda_m} & \mathbf{0} & .. & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} y_t^m \\ y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^q \\ \epsilon_{t-1}^q \\ \epsilon_{t-2}^q \\ \epsilon_{t-3}^q \\ \epsilon_{t-4}^q \\ 0 \\ \mathbf{e_t} \end{bmatrix} \tag{9}$$

$$
\begin{bmatrix} y_t^m \\ y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^q \\ \epsilon_{t-1}^q \\ \epsilon_{t-2}^q \\ \epsilon_{t-3}^q \\ \epsilon_{t-4}^q \\ 0 \\ \mathbf{e_t} \end{bmatrix}
=
\begin{bmatrix}
a_{11} & a_{12} & 0 & 0 & 0 & a_{13} & a_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
a_{21} & a_{22} & 0 & 0 & 0 & a_{23} & a_{24} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_q & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{P}
\end{bmatrix}
\begin{bmatrix} y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ y_{t-5}^m \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \epsilon_{t-1}^q \\ \epsilon_{t-2}^q \\ \epsilon_{t-3}^q \\ \epsilon_{t-4}^q \\ \epsilon_{t-5}^q \\ 0 \\ \mathbf{e_{t-1}} \end{bmatrix}
+
\begin{bmatrix} u_t^y \\ 0 \\ 0 \\ 0 \\ 0 \\ u_t^f \\ 0 \\ 0 \\ 0 \\ 0 \\ v_t^q \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \mathbf{v_t} \end{bmatrix}
\tag{10}
$$