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A now-casting model for Canada: Do U.S. variables matter?

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ABSTRACT

We propose a dynamic factor model for now-casting the growth rate of the quarterly real Canadian gross domestic product. We select a set of variables that are monitored by market participants, track their release calendar, and use vintages of real-time data to reproduce the information sets that were available at the time when the forecasts would have been made. The accuracy of the forecasts produced by the model is comparable to those of the forecasts made by the market participants and institutional forecasters. We show that including U.S. data in a now-casting model for Canada improves its predictive accuracy dramatically, 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 the state space representation of our model can be modified to link the monthly GDP properly with its quarterly counterpart.

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1. Introduction

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

The real gross domestic product (GDP) is one of the most heavily monitored indicators because it provides a summary of the health of an economy. It is generally released on a quarterly basis and with a delay of between four (as in the United Kingdom and in the United States) and eight (as in Canada) weeks.

Given the real GDP's lack of timeliness, policymakers and market participants also try to infer current economic conditions by monitoring other indicators, linked to GDP growth, that are released at a higher frequency and in a more timely manner. Statistical offices and central banks release data almost every day that may be useful for predicting real GDP growth in real-time.

The list of variables, other than GDP, that are regarded highly by practitioners may be inferred from global information services, such as Bloomberg and Forex Factory, which report a calendar of data releases and also a measure of variables' importance, which reflects practitioners' usage of the data. In addition, Bloomberg also conducts a survey and collects forecasts from analysts and economists in order to produce predictions for GDP and other market-relevant indicators before their release dates.

The aim of this paper is to propose a model that can help users to infer the state of the economy in terms of real GDP, while still being easy to update whenever new information becomes available. The econometric framework we propose is based on the seminal paper by Giannone, Reichlin, and Small (2008), who show how an accurate now-cast of U.S. (quarterly) real GDP can be produced by means of a dynamic factor model (DFM), using

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monthly indicators and taking into account their different release times.

By tracking the release calendar and using vintages of real-time data where available, we reconstruct almost exactly the information set that would have been available at the time when the forecasts would have been made, and we mimic the output that the model would have produced had it been used continuously over a historical period of 10 years (2006–2016).

DFMs have been applied successfully to various economies, both developed and developing, small open economies and large economies.[1] Although the statistical framework is similar to those already applied to other economies, each country has its own peculiarities in terms of the relevance of each input series for 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 now-casting models is also to learn about the characteristics of the data and the way in which they interact with real GDP, and, more broadly, how the economy of that specific country works.

Canadian data have several peculiarities that distinguish them from those of other economies. For example, unlike other countries, Statistics Canada also publishes a monthly GDP eight weeks after the end of the reference period (the monthly real GDP relative to January is not available until March), in addition to the quarterly GDP. 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 for tracking real GDP growth in other economies, given their timeliness and their correlation with the target variable.

We deal with these peculiarities by proposing a new modeling strategy that takes into account the relationship between quarterly real GDP and its monthly counterpart coherently, and we deal with the lack of timely production data by including some of the most important series from the U.S. economy. The United States is Canada's first trade partner, with a total trade share of about 70% in 2015.[2] The U.S. variables that we choose are particularly relevant for market participants: they are among the most timely U.S. series, and have been shown to be crucial for now-casting the U.S. real GDP.[3]

We are not the first to propose a model for forecasting real GDP growth in Canada; for example, the Bank of Canada is using a range of models to produce short term forecasts of real GDP: some very simple and others more complex, some built for forecasting quarterly GDP growth over the very short term and others designed for producing more accurate forecasts at longer horizons (see Granziera, Luu, & St-Amant, 2013). The closest model to the one that we propose in this paper is that described by Binette and Chang (2013), namely a factor model that produces daily updates of real GDP growth, accounting for mixed frequencies and the ragged-edge shape of the data.

Also, the Organisation for Economic Co-operation and Development (OECD) developed a short-term indicator-based model for predicting the quarterly GDP in Canada by exploiting all available monthly information (Mourougane, 2006).

In accordance with our choice, both studies introduce a short list of U.S. economic indicators as input variables, including industrial production, retail sales, motor vehicle sales and housing starts. Mourougane (2006) included only U.S. PMI.

The numbers of variables considered in these other papers are rather large, and the variables are not well rationalized. In this paper, we choose to collect 'market moving' variables, identifying those that are relevant for decision makers, rather than providing an *ad hoc* list of indicators. Decision makers can be viewed as now-casters, and are the final users of GDP predictions.

This paper also provides some insights as to the forecast performance of each input variable and its impact on the accuracy of the model's predictions. In fact, the model we present not only updates the forecast of real GDP, but also calculates the 'news', the surprise relative to the model's expectation, for each input variable release.

Our results show that this model can deliver now-casts that are at least as accurate as those produced by institutional forecasters such as the Bank of Canada (which publishes quarterly forecasts of real GDP growth), the Organisation for Economic Co-operation and Development (OECD), and the Bloomberg survey. Thus, model-based forecasts that can incorporate a potentially large set of new information quickly can be seen by participants assessing the state of the Canadian economy as a tool that is complementary to judgmental forecasts. This finding confirms the point that has been highlighted in other studies, namely that a linear time-invariant model does a good job, and hence that eventual non-linearities, time variations, and soft information (such as weather conditions or government decisions) that can be incorporated using judgment do not provide important new information. This last result indicates that the oft-cited superiority of professional forecasts (see Ang, Bekaert, & Wei, 2007; Clements & Hendry, 2004; Jansen, Jin, & de Winter, 2012) is weak in our sample, confirming the findings of Giannone et al. (2008) and Liebermann (2014).

Moreover, we show that U.S. data are crucial for obtaining accurate real GDP now-casts for Canada, as U.S. data can compensate for the lack of timely production data for the Canadian economy. This confirms that the interconnectedness between the two economies can be

[1] Examples include the United States (Lahiri & Monokroussos, 2013), the euro area (Angelini, Bańbura, & Rünstler, 2010; Angelini, Camba-Méndez, Giannone, Reichlin, & Rünstler, 2011; Camacho & Perez-Quiros, 2010), Belgium (de Antonio Liedo, 2014), France (Barhoumi, Darné, & Ferrara, 2010), Ireland (D'Agostino, McQuinn, & O'Brien, 2008; Liebermann, 2012), the Netherlands (De Winter, 2011), the Czech Republic (Arnostova, Havrlant, Ruzicka, & Toth, 2011); and Rusnák, 2013, New Zealand (Matheson, 2010), Norway (Aastveit, Gerdrup, Jore, & Thorsrud, 2012; Luciani & Ricci, 2014), Switzerland (Siliverstovs, 2012), Japan (Bragoli, 2017), China (Yiu & Chow, 2010), Turkey (Modugno, Soybilgen, & Yazgan, 2016), Brazil (Bragoli, Metelli, & Modugno, 2015), Mexico (Caruso, 2015), and Indonesia (Luciani, Pundit, Ramayandi, & Veronese, 2015). Moreover, the same framework has also been used to now-cast variables other than real GDP; see for example D'Agostino, Osbat, and Modugno (2015) for the euro area trade variables and Modugno (2013) for U.S. inflation, among others.

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

[3] See Bańbura, Giannone, Modugno, and Reichlin (2013) and Bańbura, Giannone, and Reichlin (2012).

exploited to produce more precise now-casts of Canadian real GDP.

The rest of the paper is structured as follows. Section 2 describes the structure of Canadian data releases. Section 3 introduces the model and the 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

Data on the Canadian real GDP are published by Statistics Canada two months (60 days) after the end of the quarter, which means that, for example, the level of real GDP in the first quarter (January to March) is not disclosed until May. This delay is greater than those experienced in most developed countries; for example, four weeks in the case of the United Kingdom and the United States and six weeks for most of the European countries and Japan.

Unlike statistical agencies in the United States and some other countries, which publish preliminary and advance estimates of the quarterly real GDP, Statistics Canada provides monthly GDP figures around 60 days after the month ends. Although monthly and quarterly GDP are not identical conceptually — the monthly figures are published at basic prices whereas the quarterly figures are at market prices, accounting for net taxes on products — the growth rates of the two measures often exhibit similar dynamics at a quarterly frequency. One of the peculiarities of the model that we present is that it makes use of this information, which characterizes Canadian data.[4]

The aim of the statistical model that we propose in this paper is to predict GDP before the publication of the official figures, 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.

Our model includes variables whose headline numbers are reported by national statistical offices, central banks and local newspapers; however, most importantly, following Bańbura et al. (2013), we consider only indicators that are monitored by financial markets. The reason for this decision is the fact that market participants can be viewed as now-casters. Given that they monitor macroeconomic data when forming their expectations about the state of the economy in order to allocate their investments, we believe that they have the knowledge and experience to know which series is relevant to monitor. We estimate the model on a small data set, consisting only of real data and surveys, and disregarding prices, financial variables, nominal variables, and sector-specific series. This choice reflects the results of previous research which has found that the inclusion of these variables does not improve the model's forecasting performance (see Bańbura & Modugno, 2014; Luciani, 2014).[5]

In addition, given the absence of some important and in some cases timely series, such as industrial production and capacity utilization, on the one hand, and the interconnectedness of the Canadian and U.S. economies on the other, we decided to include a small set of U.S. indicators as well, in accordance with the literature.[6,7] The selection of these variables is driven by the same principles as are used to select the Canadian series; i.e., the variables have to be relevant for the markets. In addition, we also focus on the four most timely releases: U.S. manufacturing PMI, change 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 improves the now-casting performance of our model for Canada significantly.

Table 1 describes the data characteristics (i.e., publication lag, frequency, source, starting date and transformations), as well as the importance that financial markets assign to the series according to the Bloomberg and Forex Factory indexes. The Bloomberg measure, which is shown as a percentage, reflects the series' usage by Bloomberg subscribers; the Forex Factory measure, which is shown as low/medium/high (L/M/H), reflects Forex Factory subscribers' judgment.

The target variable is quarterly real GDP growth, the headline series on which market participants focus their attention. The input series, which are monthly, can be divided into four categories: surveys, labor, domestic demand, trade indicators and monthly GDP.

The survey that we consider is 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%). For labor, we include employment, released one week after the month ends and rated important by Forex. For domestic demand, we track manufacturing shipments (or sales), manufacturing orders, retail sales, wholesale trade, motor vehicle sales, building permits and dwelling starts. Building permits and retail sales are considered relevant by both Bloomberg (around 71.8% and 74.4%, respectively) and Forex. Dwelling starts, which is released one week after the month ends, is also considered relevant for market participants by Bloomberg (82.0%). The trade category includes exports and imports, which both have publication lags of one month and are considered highly important by Forex.

We chose the transformations that guaranteed stationarity of the variables, which are the same as those reported by the media and Bloomberg, making the comparison easier. The target variable is reported as a quarter-on-quarter (QoQ) growth rate, while the monthly variables are reported as either monthly changes, such as capacity utilization and employment, or month-on-month (MoM) growth rates, with the exception of motor vehicle sales (which are

4 Brazil also releases a nominal monthly GDP series.

5 The literature has shown that small-scale DFM models perform as well as large-scale models (Bańbura et al., 2012; Barhoumi et al., 2010).

6 Industrial production is one of the most important piece of hard data for other economies, given its timeliness. In the U.S., the index has a publication lag of only 15 days.

7 The decision to include U.S. variables turns out to be important for Mexico as well (Caruso, 2015), as it is another economy that is characterized by a high level of interconnectedness with the U.S. economy.

Table 1
Series used in the model. .

Name	Now-cast model with US	Benchmark model	RT	Day	Month	Frequency	Source	Available from	Units	Transformation	Relevance Forex	Relevance Bloomberg
US manufacturing PMI	X			5	1	M	ISM	Jan-48	Diffusion index	Levels	H	94.6
US change in employment	X		X	5	1	M	BLS	Feb-39	Thous.	Levels	H	99.1
US industrial production	X		X	15	1	M	FRB	Jan-21	Index	Δ ln (MoM)	M	86.6
US capacity utilization	X			15	1	M	FRB	Jan-67	Percentage	Δ	M	60.6
Canada Ivey PMI	X	X		5	1	M	IveyUWO	Jan-01	Diffusion index	Levels	H	15.4
Canada building permits	X	X		5	2	M	StatCan	Jan-60	Thous. units	Δ ln (MoM)	H	71.8
Canada employment	X	X	X	8	1	M	StatCan	Jan-66	Thous.	Δ	H	30.8
Canada dwelling starts	X	X		9	1	M	CMHC	Jan-90	Thous. units	Δ ln (MoM)	L	82.0
Canada imports of goods	X	X	X	5	2	M	StatCan	Jan-88	Mil. Canadian $	Δ ln (MoM)	H	–
Canada exports of goods	X	X	X	5	2	M	StatCan	Jan-88	Mil. Canadian $	Δ ln (MoM)	H	–
Canada manufacturing shipments	X	X		15	2	M	StatCan	Jan-92	Thous. Canadian $	Δ ln (MoM)	H	–
Canada motor vehicle sales	X	X		15	2	M	StatCan	Jan-46	Thous.	Δ ln (YoY)	–	0.0
Canada manufacturing orders	X	X		15	2	M	StatCan	Jan-92	Thous. Canadian $	Δ ln (MoM)	–	–
Canada wholesale trade	X	X		20	2	M	StatCan	Jan-93	Thous. Canadian $	Δ ln (MoM)	M	51.3
Canada retail sales	X	X	X	20	2	M	StatCan	Jan-91	Thous. Canadian $	Δ ln (MoM)	M	74.4
Canada monthly GDP	X	X		28	2	M	StatCan	Jan-97	Mil. Canadian $	Δ ln (MoM)	H	84.6
Canada real GDP	X	X	X	28	2	Q	StatCan	Q1-81	Mil. Canadian $	Δ ln (QoQ)	–	92.3

Notes. *Now-cast model with US:* reports the list of variables in the model including U.S. indicators; *Benchmark model:* reports the list of variables in the model excluding U.S. indicators; *RT:* reports the list of series available in the OECD real-time data and revision database; *Day:* reports the approximate day of release of each variable; *Month:* indicates the number of months after the end of the reference period that the data are released; *Frequency:* indicates whether the series is monthly (M) or quarterly (Q); *Source:* 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); *Available from:* indicates the starting date of the series; *Units:* reports the units of measure of each series; *Transformation:* specifies whether the variables have been transformed to month-on-month (MoM), quarter-on-quarter (QoQ), year-on-year (YoY) growth rates (Δ ln) or differences (Δ), or are considered in levels; *Relevance 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); and *Relevance Bloomberg* reports the market relevance of each variable according to Bloomberg's relevance index, which ranges from 0 to 100.

reported as year-on-year (YoY) growth rates),[8] and PMI manufacturing surveys, for both Canada and the United States (which are reported in levels).[9] Linking the QoQ target variable with MoM input series is standard in this literature (see, among others, Bańbura & Modugno, 2014; Camacho & Perez-Quiros, 2010; Mariano & Murasawa, 2003).

Figs. 4–6 in the Appendix, compare the input series with the GDP realizations. We compare the two series effectively by centering both variables and aggregating the monthly series in order to obtain their quarterly counterpart. It is also possible to see from the graphs how the transformations used seem to be working well for obtaining stationary data.

To conclude, the most timely data in Canada are employment, dwelling starts, and PMI, which are released with publication lags 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 realize immediately that there are few timely variables. The discussion that follows shows that the introduction of four of the most timely U.S. variables, which are released a maximum of 15 days after the end of the reference month and are related to the Canadian business cycle, improves the now-casting performance of our model for Canada.

3. The econometric framework

The model that we use to compute now-casts is a dynamic factor model (DFM). This model produces a good representation of the data, while at the same time guaranteeing parsimony. It exploits the fact that there is considerable co-movement among macroeconomic data series, and hence that relatively few factors are needed to explain the dynamics of many variables (see Giannone, Reichlin, & Sala, 2005; Sargent & Sims, 1977; Stock & Watson, 2011).

The general representation of a DFM can be written as a system with two types of equations: a measurement equation (Eq. (1)) linking the observed series (that is, GDP and all of the indicators listed in Table 1) to latent state variables, and the transition equation (Eqs. (2) and (3)), which describes the state variables dynamics. (1)–(3), written in a state space form, allow the use of the Kalman filter to obtain optimal projections for both the observed and state variables. The Kalman filter generates projections for all of the variables in the model (GDP and all the other data releases).

The DFM is described by the following equations:

$$y_t = \Lambda f_t + e_t, \tag{1}$$

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

$$e_{i,t} = \rho_i e_{i,t-1} + v_{i,t}$$
$$v_{i,t} \sim i.i.d.N(0, \sigma_i^2), \tag{3}$$

where $y_t = [y_{1,t}; y_{2,t}; \ldots; y_{n,t}]'$ 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; u_t is a vector of common shocks; $e_t = [e_{1,t}; e_{2,t}; \ldots; e_{n,t}]'$ is an n-dimensional vector of idiosyncratic components; and v_t is a vector of idiosyncratic shocks. The common and idiosyncratic shocks are assumed to be uncorrelated at all leads and lags, whereas the idiosyncratic shocks are allowed to be cross-sectionally correlated, but only by a limited amount.[10]

We estimate the model using quasi maximum likelihood through the expectation–maximization (EM) algorithm, as proposed by Bańbura and Modugno (2014) for dealing with missing data.[11]

We consider only one state variable (or factor) and two lags in Eq. (2), and an AR(1) process for the idiosyncratic components described in Eq. (3).[12]

In the case of Canada, we depart from the usual DFM representation. As was explained earlier, Statistics Canada produces a monthly GDP series. We exploit this source of information fully by proposing a new modeling strategy for incorporating 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, on the other hand, is extracted from all of the other series in our data set, and interacts with the monthly GDP through the VAR, helping to forecast the future realizations of the monthly GDP, and therefore of the quarterly GDP (see Appendix A.3 for technical details).

Having described the econometric framework, the now-casting of GDP involves inferring its value after the

8 The motor vehicle sales series is not seasonally adjusted, and therefore we consider the YoY transformation in order to clean the variable from seasonality.

9 The index in levels is actually comparable to a MoM transformation, given that respondents to the survey are asked whether business conditions for a number of variables have improved, deteriorated, or stayed the same compared with the previous month; see http://iveypmi.uwo.ca/about/ for Canada.

10 This is the model studied by Doz, Giannone, and Reichlin (2011, 2012), which is a special case of the model studied by Forni, Giannone, Lippi, and Reichlin (2009).

11 Watson and Engle (1983) introduced the use of the EM algorithm for estimating dynamic factor models, while Doz et al. (2012) showed that this procedure is suitable for estimating dynamic factor models using large datasets. Bańbura and Modugno (2014) adapted this procedure for dealing with missing data. All of the parameters are initialized with the ordinary least squares (OLS) estimates, obtained using the principal components estimates of the factors as initial guesses. Given the initial parameters, a new set of factors is obtained using the Kalman smoother (a two-step procedure introduced by Giannone et al., 2008 and studied by Doz et al., 2011). Maximum likelihood estimates are obtained by iterating these two steps until convergence, provided that the OLS regressions are modified to take into account the fact that the common factors are estimated.

12 We select the number of factors in Eq. (1) using the Bai and Ng (2002) information criterion and the lag order of Eq. (2) using the Akaike information criterion. See the Appendix for details.

reference quarter begins but before the official release of GDP data by exploiting information from other, higher-frequency variables.

More formally, the now-cast 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 ($x_{k_j,t_j}, j = 1, \ldots, J_{v+1}$) and is characterized by a 'ragged-edge' structure, because the time of the last available information varies from series to series.

A new now-cast is produced each time new information arrives. This now-cast can be decomposed as follows:

$$P[y_t^Q|\Omega_{v+1}] = P[y_t^Q|\Omega_v] + P[y_t^Q|I_{v+1}]. \tag{4}$$

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

$$I_{v+1,j} = x_{k_j,t_j} - P[x_{k_j,t_j}|\Omega_v], \tag{5}$$

with $j = 1, \ldots, J_{v+1}$. 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 ($P[x_{k_j,t_j}|\Omega_v]$). It is the only element that leads to a change in the now-cast because it is the 'unexpected' (with respect to the model) part of the data release, and is referred to here as 'news'.

As was 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 $B_{v+1} = [b_{v+1,1}, \ldots, b_{v+1,J_{v+1}}]$ such that the following holds:

$$P[y_t^Q|\Omega_{v+1}] - P[y_t^Q|\Omega_v] = B_{v+1}I_{v+1}$$
$$= \sum_{j=1}^{J_{v+1}} b_{v+1,j}(x_{k_j,t_j} - P[x_{k_j,t_j}|\Omega_v]). \tag{6}$$

The magnitude of the now-cast revision depends on both the size of the news and its relevance for the target variable, as represented by the associated weight $b_{v+1,j}$.[13]

This mechanism allows us to trace the contribution of each series to the revision of the now-cast, in particular by linking the revision of the target variable now-cast with the unexpected developments of the input variables.

4. Benchmarks

We assess the accuracy of our forecasts by comparing 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 by 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 over 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.

The other important benchmark that we consider is Bloomberg, which conducts a survey and collects forecasts from analysts and economists in order 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. The prediction is then revised continually until 24 h before the release. The final number is usually close to the actual release value.

The last benchmark that we use for comparison is a bridge equation that forecasts the quarterly GDP using the monthly GDP. In practice, this benchmark is generated using two regression models. The first is a regression of the quarterly GDP on the monthly GDP aggregated to a quarterly frequency (note that, as was explained in Section 2, the monthly figures are published at basic prices whereas the quarterly figures are published at market prices; thus, the monthly GDP aggregated to a quarterly frequency differs from the quarterly GDP). The second regression model is an AR process for the monthly GDP. We use the latter to forecast the missing months in the quarter (if our monthly GDP data are available until January, we forecast February and March using the AR parameters), then aggregate them to a quarterly frequency. We then use the parameters of the first regression model to convert the aggregated monthly GDP (realizations and forecasts) into quarterly GDP forecasts.

5. Model evaluation

We evaluate the performance of the model by constructing a real-time dataset from 2006:Q1 to 2016:Q3, where available. We estimate the model recursively (the estimation period starts in January 1992) and use only the data that were available when the forecast was meant to have been produced.

The real-time dataset is gathered from the OECD Real-Time Data and Revisions Database. Table 1 lists all of the series for which we have gathered this information. Given that the Canadian PMI is not revised, we can rely on eight real-time variables and nine variables for which we consider the last vintage of data, not accounting for data revisions.

The results of the historical evaluation are reported in Fig. 1. The figure compares the QoQ GDP now-casts obtained with and without U.S. variables with the now-casts produced by the OECD and the Bank of Canada, and the actual realization. Fig. 1 shows that the now-casting model with U.S. variables mimics the actual realization of GDP very well, outperforming the model without U.S. variables, especially during the 'Great Recession'.

Fig. 2 compares the root mean squared forecast errors (RMSFE), on average over all of the calendar quarters in

[13] Eq. (6) can be considered as a generalization of the Kalman filter update equation to the case in which new data arrive in a non-synchronous manner.

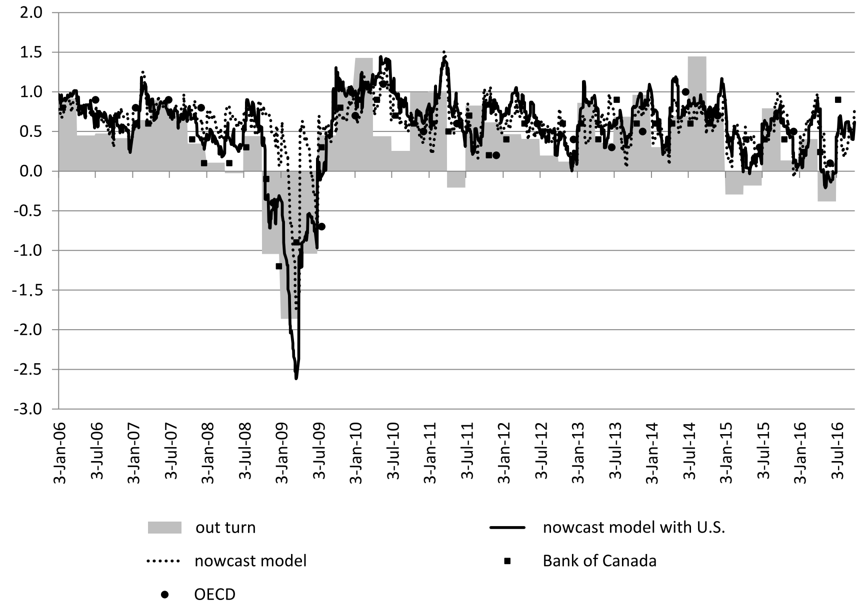

Fig. 1. GDP now-casts. *Notes.* The graph reports a comparison between a GDP now-cast using U.S. variables (now-cast model with U.S.), a GDP now-cast without U.S. variables (now-cast model), the GDP actual value (out turn), and the OECD and Bank of Canada now-casts.

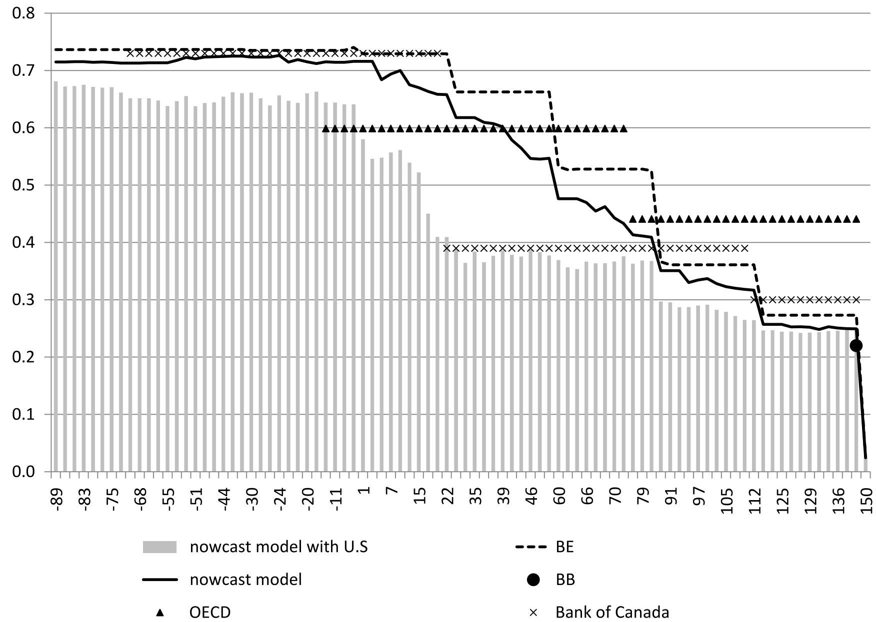

Fig. 2. Root mean squared forecast errors. *Notes.* The *y*-axis reports the average root mean squared forecast errors (RMSFE) over the period from 2006:Q1 to 2016:Q3. The forecast accuracy is evaluated from the first month of the previous quarter to the time when the GDP is released. The *x*-axis reports the distance in days from the beginning of the current quarter. BE: bridge equation.

the historical reconstruction period, for the two now-cast models, 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 the bridge equation (BE) that changes each time the monthly GDP is released.

Our initial quarterly GDP growth prediction is made 90 days before the start of a given quarter, then updated with each successive data release until the release of the GDP, which takes place 150 days after the start of the calendar quarter. Thus, there is a period of 240 days (the 'prediction period') for each calendar quarter over which the prediction is updated continuously. This period is measured by the *x*-axis, while the *y*-axis measures the RMSFEs for each series of predictions. We can learn two clear lessons from Fig. 2. First, U.S. data are crucial for obtaining accurate now-casts of quarterly Canadian GDP growth: the RMSFEs produced by the model without U.S. data are always above those produced by the model with U.S. data. Second, our mechanical model produces

Table 2
Diebold–Mariano test of equal forecasting accuracy.

	Forecast		Now-cast		Back-cast	
	BE	Now-cast model	BE	Now-cast model	BE	Now-cast model
1m	0.08	0.05	0.24	0.18	0.04	0.03
	(0.06)	(0.05)	(0.15)	(0.12)	(0.03)	(0.02)
2m	0.13	0.10	**0.30**	**0.24**	**0.01**	0.00
	(0.11)	(0.10)	(0.15)	(0.12)	(0.01)	(0.00)
3m	0.11	0.10	**0.14**	**0.09**		
	(0.14)	(0.12)	(0.08)	(0.05)		

Notes. The table reports the estimated constant and the HAC estimator of its standard errors in the first, second, and third months of the forecast, now-cast, and back-cast, respectively, in coincidence with the first Canadian release manufacturing PMI. A positive sign on the estimated constant shows that the model with U.S. variables outperforms the two benchmarks, namely the BE and the model without U.S. variables. Significant values of the test are reported in bold.

Table 3
Monotonicity tests.

	$\Delta^e \geq 0$	$\Delta^f \geq 0$	$\Delta^c \geq 0$
Now-cast model	0.5006	0.4957	0.4974

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

now-casts that are as accurate as those produced by institutional forecasters and market participants, on average.

5.1. Do U.S. variables matter?

The previous section showed the role played by U.S. variables in improving the model's now-casting performance. This section formally tests whether the RMSFEs of the model that incorporates U.S. variables are statistically different from those of the model that includes only Canadian data.

Table 2 reports the results of the Diebold and Mariano (2002) test ('DM test') of equal predictive accuracy in order to check whether the differences in forecasting performances between models are significant. For each month, we report the sample average of the difference between the squared errors of the BE and of our model without US variables for forecasts, now-casts and back-casts, each with respect to our model with U.S. variables on the day of first data release (Canada PMI). Both the value of the DM test and its standard deviations are estimated using heteroskedasticity and autocorrelation robust standard errors. If the value of the DM test has a positive sign, the benchmark's loss (BE or our model without U.S. variables) is higher than that of our model (with U.S. variables), and vice versa. The test confirms that our model is more accurate than either the BE or the model without U.S. variables, especially for the now-cast.

We can see from Fig. 2 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. We test this decline in uncertainty as more data become available formally by applying the test for forecast rationality proposed by Patton and Timmermann (2012). Table 3 reports the *p*-values of three monotonicity tests for the forecast errors (Δ^e), the mean squared forecast (Δ^f), and the covariance (Δ^c) between the forecast and the target variable, respectively. Monotonicity cannot be rejected for either the mean squared forecast or the covariance between the forecast and the target variable.

Table 4
Average news and standard deviations.

	Units/transformation	RT	Model		Bloomberg		Revisions	
			Mean	StD	Mean	StD	Mean	StD
U.S. ISM manufacturing PMI	D.I./levels		−0.182	1.865	0.026	1.755	0.028	0.386
U.S. change in nonfarm employment	Thous/levels	x	−24.862	259.530	7.977	101.579		
U.S. industrial production	Index/MoM	x	−0.001	0.008	0.120	0.516		
U.S. capacity utilization	Percentage/diff		0.024	0.544	0.043	0.613	0.017	0.441
Canada Ivey PMI	D.I./levels		−0.459	7.117	−0.892	6.753	0.000	0.000
Canada building permits	Thous. units/MoM		−0.184	9.584	−0.700	8.820	0.198	9.749
Canada employment	Thous/diff	x	−4.902	40.220				
Canada dwelling starts	Thous. units/MoM		−0.248	9.754	−0.528	12.171	−0.019	3.951
Canada imports of goods	Mil. C$/MoM	x	0.000	0.025				
Canada exports of goods	Mil. C$/MoM	x	0.000	0.038				
Canada manufacturing shipments	Thous. C$/MoM		−0.121	1.939	0.133	1.427	0.051	0.945
Canada motor vehicle sales	Thous./YoY		0.376	6.393				
Canada manufacturing orders	Thous. C$/MoM		−0.093	4.958				
Canada wholesale trade	Thous. C$/MoM		−0.103	1.197	−0.065	1.117	−0.008	0.852
Canada retail sales value	Thous. C$/MoM	x	0.000	0.010	−0.003	0.734		
Canada monthly GDP	Mil. C$/MoM		−0.065	0.256	0.012	0.225	−0.024	0.172
Canada real GDP	Mil. C$/QoQ	x	0.000	0.002	−0.019	0.117		

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.

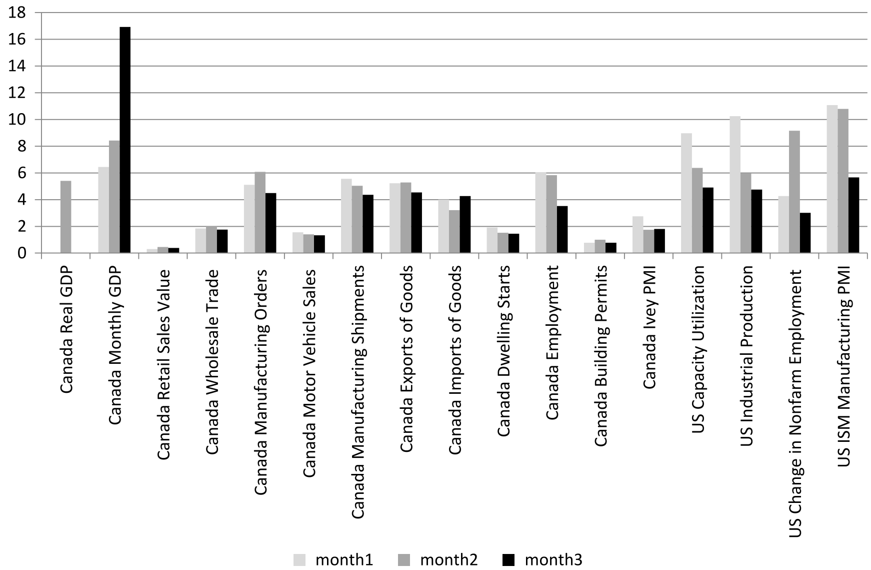

Fig. 3. Relevance of the variables. *Notes.* Average impact of each variable in the first (m1), second (m2), and third (m3) months of the now-cast.

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 specified well in all of 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 4 confirms this statement. In addition, the table also compares the model's performance for predicting each of the series with that of the Bloomberg survey. We show that the model's predictions are comparable to the Bloomberg survey's predictions for most series. Finally, Table 4 includes the mean and standard deviation of the revisions for only those series for which no real-time information is available.[14]

The second important feature of the news within a now-casting framework is that it allows all of the data releases to be interpreted in terms of the signals that they give about current economic conditions. Using Eq. (8) (Box I), it is possible to decompose the forecast revision into contributions from the news in individual series. The impact of a given release on the GDP now-cast is the product of two variables: the news (the unexpected component of the release value) and the relevance of the series to GDP, which is expressed as its weight (that is, impact $=$ news standard deviation $\times$ weight).[15] Fig. 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, and the U.S. PMI is also relevant in the second month. The monthly GDP only makes a relevant contribution in the third month. See Appendix A.2 for the decomposition of the average impacts.

6. Conclusion

This article proposes a formal econometric framework for the real-time monitoring of economic conditions in Canada in terms of real GDP. The model forecasts are updated automatically as new information becomes available. Over a historical period of 10 years, we reconstruct almost exactly the same information set that was available at the time when the forecasts were made. Canadian data are characterized by two peculiarities: the presence of a monthly measure of real GDP in addition to the quarterly one, and the lack of availability of timely industrial production data. We solve the first challenge by proposing a new modeling strategy that coherently takes into account the relationship between the quarterly real GDP and its monthly counterpart. We deal with the lack of timely production data by including the four more timely U.S. series in our information set.

Our results show that this model can deliver now-casts 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 suggests that a model-based now-cast that can incorporate a potentially large set of new information quickly can complement judgmental now-casts in assessing the state of the Canadian economy. Moreover, we show that U.S. data are crucial for obtaining accurate real GDP now-casts for Canada; the lack of timely production data for the Canadian economy can be compensated for through the use of U.S. data, confirming that the interconnectedness between the two economies can be exploited in order to produce more precise now-casts of Canadian real GDP.

[14] 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 for some variables the reconstruction of the model's predictions is based on the last available vintage of data, ignoring revisions.

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

Acknowledgments

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Appendix

A.1. Selecting the number of factors and lags

We select the optimal number of factors using an information criterion 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 of parsimony. Bai and Ng (2002) derive an information criterion for determining 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 5 reports the IC and the sum of the variance of the idiosyncratic components for the different specifications, which allow for different numbers of factors. The IC selects the model with one factor. Given that our data set is unbalanced at the top and some series are more recent than others, we report the results of running the test on three different samples. The first (sample 1) considers a balanced panel over the estimation period 2001:Q1 to 2005:Q4 (15 series, 59 observations), the second (sample 2) a restricted balanced panel in which we exclude one of the most recent series (14 series, 15 observations), and the third (sample 3) a balanced panel that incorporates the whole sample (both estimation and forecasting periods). The choice of one factor is confirmed across the different samples.

We select the number of lags in Eq. (2) of the model based on the values of the Akaike IC, reported in Table 6, which selects two lags.

Table 5
Model selection (number of factors).

	Sample 1		Sample 2		Sample 3	
	IC	V	IC	V	IC	V
1	0.15	0.84	0.18	0.87	0.13	0.82
2	0.24	0.67	0.33	0.73	0.25	0.68
3	0.43	0.59	0.56	0.67	0.46	0.61
4	0.58	0.49	0.77	0.60	0.68	0.55
T	59		156		285	
N	15		14		14	

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

Table 6
Model selection (number of lags).

Number of lags	Akaike information criterion
1	−1.55
2	−1.98
3	−1.84
4	−1.95

Notes. The lag is chosen based on the minimum AIC value.

A.2. Impact of the releases on the nowcast

See Table 7.

A.3. 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 Eq. (7) (Box I), 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

Table 7
Impact of the releases on the nowcast.

	A			B			C		
	m1	m2	m3	m1	m2	m3	m1	m2	m3
U.S. ISM manufacturing PMI	0.060	0.056	0.030	1.837	1.920	1.874	0.111	0.108	0.057
U.S. change in nonfarm employment	0.000	0.000	0.000	177.094	377.298	175.511	0.043	0.092	0.030
U.S. industrial production index	9.814	9.693	7.327	0.010	0.006	0.006	0.102	0.060	0.048
U.S. capacity utilization	0.136	0.134	0.102	0.661	0.476	0.482	0.090	0.064	0.049
Canada Ivey PMI	0.004	0.003	0.002	7.803	5.157	7.465	0.028	0.017	0.018
Canada building permits	0.001	0.001	0.001	8.847	10.591	8.911	0.008	0.010	0.008
Canada employment	0.001	0.001	0.001	43.715	42.529	34.537	0.061	0.058	0.035
Canada dwelling starts	0.002	0.002	0.001	10.635	8.450	10.192	0.019	0.015	0.014
Canada imports of goods	1.469	1.597	1.528	0.027	0.020	0.028	0.040	0.032	0.043
Canada exports of goods	1.279	1.391	1.333	0.041	0.038	0.034	0.052	0.053	0.045
Canada manufacturing shipments	0.024	0.028	0.026	2.276	1.817	1.672	0.056	0.050	0.044
Canada New Motor Vehicle Sales	0.002	0.002	0.002	7.065	6.124	6.084	0.016	0.014	0.013
Canada new manufacturing orders	0.010	0.011	0.011	5.214	5.445	4.247	0.051	0.061	0.045
Canada wholesale trade	0.015	0.016	0.016	1.250	1.244	1.109	0.018	0.020	0.018
Canada retail sales value	0.337	0.393	0.386	0.009	0.011	0.010	0.003	0.005	0.004
Canada monthly GDP	0.236	0.319	0.721	0.273	0.264	0.235	0.064	0.084	0.169
Canada real GDP		21.820			0.002			0.054	

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

$$
\begin{bmatrix} y_t^q \\ y_t^m \\ \mathbf{x_t} \end{bmatrix} = \begin{bmatrix} \lambda_q & 2\lambda_q & 3\lambda_q & 2\lambda_q & \lambda_q & 0 & 0 & \cdots & 0 & 1 & 2 & 3 & 2 & 1 & 0 & \mathbf{0}' \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{\Lambda}_m & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} y_t^m \\ y_{t-1}^m \\ y_{t-2}^m \\ y_{t-3}^m \\ y_{t-4}^m \\ f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^q \\ \epsilon_{t-1}^q \\ \epsilon_{t-2}^q \\ \epsilon_{t-3}^q \\ \epsilon_{t-4}^q \\ 0 \\ \mathbf{e_t} \end{bmatrix} \tag{7}
$$

$$
\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{8}
$$

Box I.

factor loadings that links the factor to all of the monthly variables except for 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 of the variables in the data set except for the quarterly and monthly real GDP; ϵ_t^q is the idiosyncratic component that enters the observation equation for the quarterly GDP, along with its lags, aggregated as per Mariano and Murasawa (2003); 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 (Eq. (8) in Box I), $a_{i,j}$ are the VAR(2) coefficients that link the monthly GDP and the factor to 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 $n-2$ that contains the autoregressive coefficients for the idiosyncratic components of the remaining $n-2$ variables. We estimate the model using quasi maximum likelihood through the expectation–maximization (EM) algorithm, as proposed by Bańbura and Modugno (2014), in order to deal with missing data.

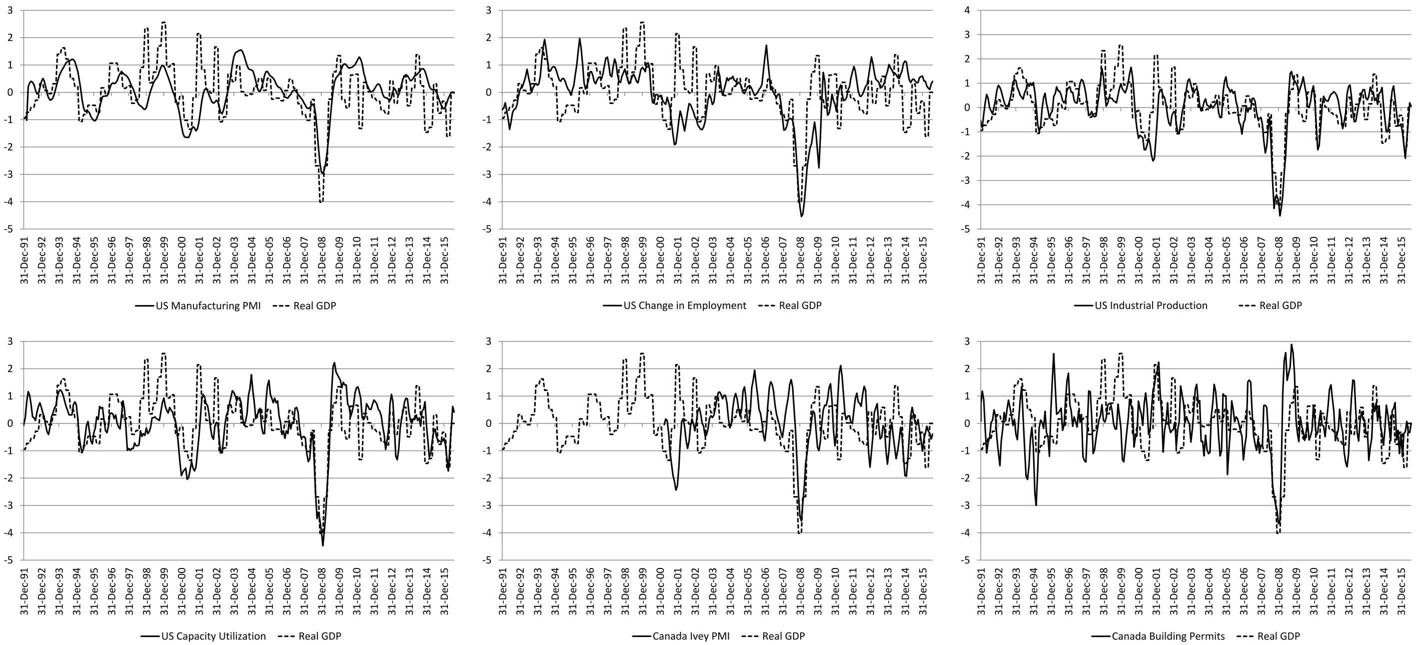

Fig. 4. Input variables against real GDP. *Notes:* All input variables are transformed as follows: US manufacturing PMI (levels), US change in employment (monthly change), US industrial production (month on month growth rates), US capacity utilization (monthly change), Canada Ivey PMI (in levels), and Canada building permits (month on month growth rates). The input variables are filtered and centered to enable comparison with real GDP (quarter on quarter growth rates).

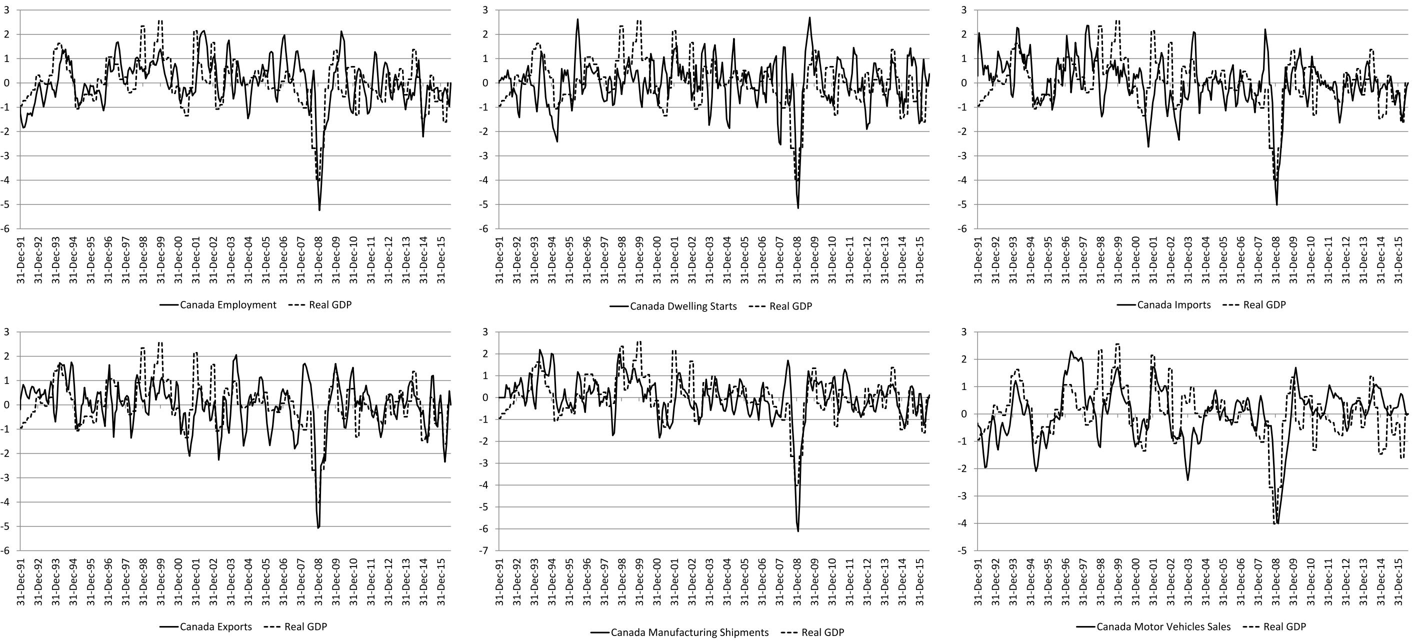

Fig. 5. Input variables against real GDP. *Notes:* All input variables are transformed as follows: Canada employment (monthly change), Canada dwelling starts (month on month growth rates), Canada imports (month on month growth rates), Canada exports (month on month growth rates), Canada manufacturing shipments (month on month growth rates), and Canada motor vehicles sales (year on year growth rates). The input variables are filtered and centered to enable comparison with real GDP (quarter on quarter growth rates).

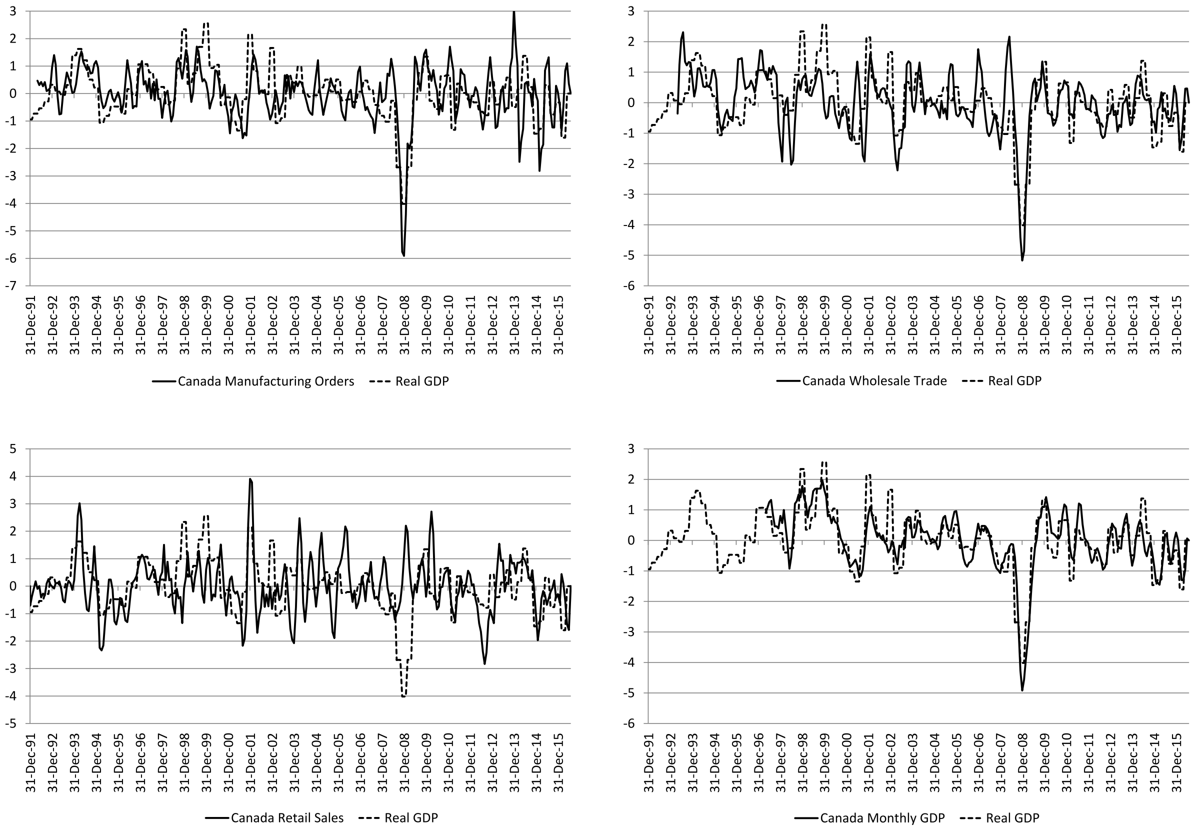

Fig. 6. Input variables against real GDP. *Notes:* All input variables are transformed as follows: Canada manufacturing orders (month on month growth rates), Canada wholesale trade (month on month growth rates), Canada retail sales (month on month growth rates), and Canada monthly GDP (month on month growth rates). The input variables are filtered and centered to enable comparison with real GDP (quarter on quarter growth rates).

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