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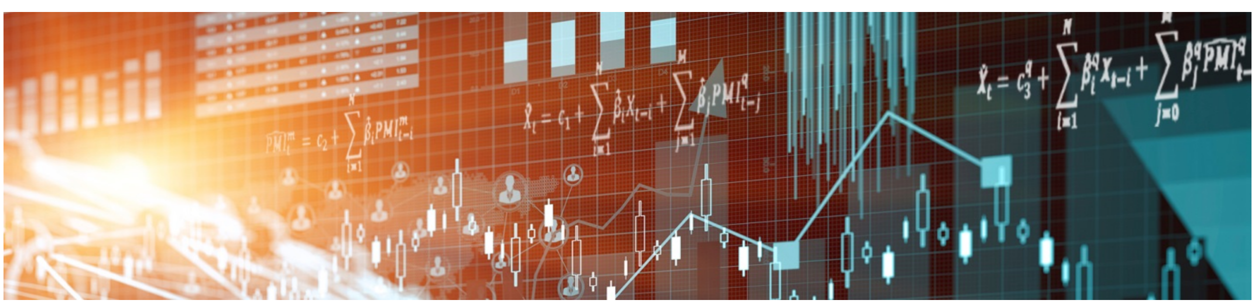
Nowcasting Canadian Economic Activity in an Uncertain Environment



by Tony Chernis and Rodrigo Sekkel

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Nowcasting Canadian Economic Activity in an Uncertain Environment

by

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Abstract

This paper studies short-term forecasting of Canadian real GDP and its expenditure components using combinations of nowcasts from different models. Starting with a medium-sized data set, we use a suite of common nowcasting tools for quarterly real GDP and its expenditure components. Using a two-step combination procedure, the nowcasts are first combined within model classes and then merged into a single point forecast using simple performance-based weighting methods. We find that no single model clearly dominates over all forecast horizons, subsamples and target variables. This highlights that when operating in an uncertain environment, where the choice of model is not clear, combining forecasts is a prudent strategy.

Bank topics: Econometric and statistical methods
JEL codes: C53, E52, E37

Résumé

Dans cette étude, nous examinons la prévision à court terme du produit intérieur brut (PIB) réel du Canada et de ses composantes de dépenses en combinant les prévisions pour la période en cours tirées de différents modèles. Nous appliquons une suite d'outils de prévision à un ensemble de données de taille moyenne afin de prévoir l'évolution du PIB réel trimestriel et de ses composantes de dépenses. À l'aide d'une méthode en deux étapes, nous combinons d'abord les prévisions effectuées pour le trimestre en cours avec des modèles d'une même catégorie, puis les prévisions combinées des différentes catégories pour aboutir à une seule prévision. Aux fins de combinaison, nous faisons appel à des méthodes simples de pondération selon l'exactitude antérieure des modèles. Nous constatons qu'aucun modèle particulier n'est nettement supérieur aux autres pour tous les horizons de prévision, toutes les sous-périodes et toutes les variables cibles. En conclusion, il est prudent de combiner les prévisions dans un contexte d'incertitude où le choix de modèle n'est pas évident.

Sujets : Méthodes économétriques et statistiques
Codes JEL : C53, E52, E37

Non-technical summary

The conduct of monetary policy requires knowledge of the current state of the economy. The current state of the economy, however, is difficult to assess, considering that most macroeconomic indicators are released with a substantial delay. As a result, a number of simple forecasting models have been developed to predict the current state of the economy as well as the recent past. This process is commonly called *nowcasting.*

This paper presents our study of nowcasting in Canada with forecast combinations. While this is not the first paper to examine nowcasting in Canada, to the best of our knowledge it is one of the most comprehensive. Relative to previous work, we study all the major classes of nowcasting models, use a larger set of data, and make predictions not just for GDP but for all of its major expenditure components. We use traditional and recently developed classes of models from the nowcasting literature: autoregressions (AR), leading indicators (LI), dynamic factor models (DFMs), Bayesian vector autoregressions (BVARs) and mixed data sampling (MIDAS) models. Predictions from these models are then combined using various methods, some of which consider the models' past performance. The combination weights are also allowed to vary over time as they are updated every quarter, and can vary over forecast horizons. Finally, this set of models can be an important tool for monitoring the current state of the economy, as the models can be updated daily as new data arrive.

Our results confirm many findings in the nowcasting and forecasting combination literature. We find that the performance of the models and combinations improves steadily as new information arrives. The weight attached to different models changes throughout the quarter in response to the flow of data, showing that the combinations adaptively attach higher weight to models with new and more relevant information. As in the existing literature, we find that combining forecasts from the different model classes (encompassing over 100 models) results in a consistently accurate forecast. We find that the combinations are always among the best performing forecasts, but are not always the best. Since the forecast performance of individual models varies across time, forecast horizon and target variable, a forecast combination allows forecasters to hedge their bets on the best model at any given point in time. Finally, while no model clearly dominates, one model class stands out and consistently performs well: the dynamic factor model. However, the existence of a preeminent model class does not undermine the conclusion that different models perform better at different time horizons and over various time periods. We find many occasions where models other than the dynamic factor model were the best choice—making the choice of model, *ex ante*, uncertain. Since the *ex-ante* choice of the best model is not always clear, combining nowcasts is a robust approach in an uncertain environment.

Introduction

During the second half of 2014, West Texas Intermediate (WTI) per-barrel oil prices declined from around US$100 in July to about US$50 by December. Given Canada's role as a net oil exporter that had benefitted from high oil prices for over a decade, such a shock was "unambiguously negative for the Canadian economy" (Poloz 2015). By early 2015, the outstanding question was just how negative the collapse in oil prices would be for the Canadian economy. It was expected to have a significant negative impact by the first quarter of 2015; however, the data to assess the impact would not be released until the end of May, two months after the end of the quarter. Policy makers working in real time cannot afford to wait for data to become available and instead rely on their own assessment of the current state of the economy, which is informed by several factors, including forecasting models. As a result, in January 2015 the Bank of Canada lowered its overnight rate by 25 basis points (bps) to 0.75 per cent, more than four months before the release of the gross domestic product (GDP) data for the first quarter of 2015 confirmed the scale of the shock. If policy makers had waited for the release of the GDP data, the Canadian economy would have already contracted by around 1 per cent and the required stimulus would have arrived four months later than it did. To deal with situations like these, policy institutions have traditionally used simple forecasting models to "predict" the current state of the economy and assess the very recent past. This process is commonly called *nowcasting.*

Nowcasting has a unique set of challenges. Macroeconomic data, such as GDP, can come with significant lags, and some statistics are released earlier than others. In other words, the data have ragged edges. Furthermore, some indicators of economic activity are released monthly while others are released quarterly. Finally, there is a large amount of data to parse that can exhibit conflicting signals and may be subject to substantial revisions.

This paper presents our study of nowcasting in Canada with model combinations. While this is not the first paper to examine nowcasting in Canada, to the best of our knowledge it is one of the most comprehensive. Relative to previous work, we study all the major classes of nowcasting models, use a larger set of data, and make predictions not just for GDP but for all of its major expenditure components.

The literature on nowcasting is relatively new, but has grown rapidly. Some highlights include the seminal papers of Evans (2005) and Giannone, Reichlin and Small (2008). The paper by Bańbura et al. (2013) provides a survey of recent nowcasting models. The most commonly used models include dynamic factor models (DFMs),[1] mixed data sampling (MIDAS),[2] Bayesian vector autoregressions (BVARs),[3] and bridge models[4] (otherwise known as leading indicator [LI] models). There are many studies that compare the forecast accuracy of these types of models for different countries and sample periods, including for

[1] Camacho and Perez-Quiros 2010; Bańbura and Modugno 2014; and Luciani and Ricci 2014
[2] Ghysels, Santa Clara and Valkanov 2004; Andreou, Ghysels and Kourtellos 2013; Guérin and Marcellino 2013; Barnett and Guérin 2013
[3] McCracken, Owyang and Sekhposyan 2015; Schorfheide and Song 2015
[4] See Baffigi, Golinelli and Parigi 2004; Foroni and Marcellino 2013; and Schumacher 2016.

example, Camacho, Perez-Quiros and Poncela (2013); Kuzin, Marcellino and Schumacher (2011); Kuzin, Marcellino and Schumacher (2013); and Foroni and Marcellino (2013), among many others.

In contrast, the literature on nowcasting in Canada is more sparse. One of the first examples is Binette and Chang (2013), who apply a DFM similar to the EURO-STING model to Canada. Bragoli and Modugno (2017) and Chernis and Sekkel (2017) estimate DFMs for Canada. The former paper compares the DFM forecasts against institutional benchmarks,[5] while the latter finds that DFM nowcasts outperform nowcasts of other model types, such as leading indicators and MIDAS. Finally, both find that US variables are important for nowcasting Canadian GDP growth. Chernis, Cheung and Velasco (2017) nowcast provincial GDP using a three-frequency DFM and find evidence that international and national variables improve the nowcasts of provincial GDP for only a few provinces. Galbraith and Tkacz (2018) study the use of payments system data to nowcast GDP and retail sales growth with leading indicator models. Finally, Granziera, Luu and St-Amant (2013) examine whether combinations of forecasts can improve nowcasts of real GDP, also in the context of simple leading indicator models.

In general, the nowcasting and forecasting literature finds that no model class emerges as a clear favourite. That is, different models provide better nowcasts at different points in time, across different nowcasting horizons, and for different variables. This result makes it unclear which model a practitioner should choose at any given point in time. Because of this uncertain environment, central banks—and policy institutions in general—rarely rely on a single model. Instead, they use a myriad of models for forecasting and policy analysis. This is discussed in detail by Coletti and Murchison (2002), albeit in a broader monetary policy context. The same principles apply in a nowcasting framework: by considering a range of possible models, one mitigates the risk surrounding the choice of a single model.

The decision of which model to use can be thought of as a portfolio diversification problem. In this case the forecaster “hedges” (Timmermann 2006) by combining a large set of models to produce a single nowcast. The motivation is that if each forecast contains some unique information that, for example, could originate from the underlying data or specification, then there are gains to pooling the forecasts. A large amount of literature (Clemen 1989; Bates and Granger 1969; Timmermann 2006; Clark and McCracken 2010; Bjørnland et al. 2012; Granziera, Luu and St-Amant 2013; and many others), both theoretical and empirical, supports the finding that averaging forecasts usually results in better forecasts (i.e., lower root mean forecast error). Furthermore, forecast combinations are commonly used in policy institutions, such as the Bank of England[6] and the Norwegian Central Bank,[7] among others.

This paper expands on previous literature by presenting a comprehensive study of nowcasting in Canada. We construct predictions for the near future, current state and recent past of GDP. And contrary to other studies, we do the same for the main expenditure components of GDP (consumption, investment, housing, exports and imports). We use traditional and recently developed classes of models from the nowcasting literature: autoregressions (AR), LIs, DFMs, BVARs, and MIDAS models. The scale of this

[5] To be specific, the OECD and the Bank of Canada.
[6] See Burgess et al. 2013.
[7] See Aastveit, Gerdrup and Jore (2011) for a description of the Norwegian System for Averaging Models.

project is novel for Canada, since in total we consider over a thousand models from a representative set of model classes. These forecasts are then combined using various methods, some of which consider the models' differing performance. The combination weights can vary over time as they are updated every quarter, and can vary over forecast horizons. Finally, this set of models can be an important tool for monitoring the state of the macroeconomy, as the models can easily be updated on a daily basis as new data arrive.

We confirm many findings in the nowcasting and forecast combination literature. We find that the performance of the models and combinations improves steadily as new information arrives. The weight attached to different models changes throughout the quarter in response to the flow of data, showing that the combinations adaptively attach higher weight to models with new and more relevant information. As with the existing literature, we find that forecasts generated by combining different model classes (encompassing over 100 models) are always among the best performing forecasts, but not always the best. Since the forecast performance of individual models varies across time, forecast horizon and target variable, a forecast combination allows nowcasters to hedge their bets on the best model at any time. Finally, while no model clearly dominates, one model class is prominent and consistently performs well: the dynamic factor model.[8]

The paper proceeds as follows. First, we describe the data used in the exercise for predicting GDP and some of its major components. Next, we discuss the econometric methodology, which starts with an overview of the model classes followed by a description of the combination methods. We then discuss the results and provide a conclusion.

Data

The choice of variables starts with the data set used by Binette and Chang (2013) in their Canadian short-term indicator (CSI) model. This set of 32 variables covers "soft" and "hard" indicators. Most of these indicators are well-known statistics for Canada, including retail trade, merchandise exports, housing starts and consumer confidence, among others. We expand on Binette and Chang's data set using the following criteria for variable selection: (i) the variables should be directly related to the Canadian economy, (ii) the variables should be updated frequently (monthly), and (iii) the variables should be released before GDP with very little publication delay.

We start with a core data set for total GDP and tailor it for each target (forecast) variable. The data set includes a mix of hard and soft indicators and a high proportion of foreign variables. The hard indicators include commonly used statistics, such as retail trade, manufacturing sales and housing starts. There is also a sizeable number of soft indicators including consumer confidence, US Purchasing Managers Index, US Consumer Sentiment, World PMI and several variables from the Bank of Canada's *Business Outlook*

[8] This is a similar result as in Eickmeier and Ziegler (2008).

Survey.[9] The foreign data are for several countries but focus on US variables because of Canada's close trading relationship with the United States. In fact, during 2016, 72 per cent of Canadian exports were sent to the United States, while 64 per cent of Canada's imports originated from the United States.

Tailoring data sets to each component naturally affects the concentration of variables in each set. For example, the investment component has a higher share of financial variables than others, while components such as exports would contain a much higher share of international variables. The size of the variable set varies by component because of data availability, with the largest sets belonging to exports and housing. Appendix D lists the variables we use for each target.

There are two notable features in the Canadian macroeconomic data: first, the data are released with a larger delay relative to other developed economies, and second, Canada has a monthly GDP indicator. The quarterly Canadian System of National Accounts data are released two months after the end of the reference quarter. This means that GDP for the first quarter of the year is released at the end of May. The monthly GDP data, denoted "GDP at basic prices" (GDPBP), has a similar lag, such that January's monthly GDP would be released at the end of March. This is quite different from other developed countries such as the United States and the United Kingdom, for example, which release their first estimates of GDP four weeks after the reference period. Other European countries and Japan release their real GDP figures with a delay of only six weeks. Furthermore, many of the most commonly used and timely international leading indicators, such as industrial production, are not available in as timely a manner for Canada as for other countries. In the United States, industrial production is available within two weeks of the reference period, while in Canada it is reported with, and as a special aggregation of, monthly real GDP data 60 days after the reference period.[10] In general, there is a trade-off between timeliness and accuracy for the first release of data; in theory, the relatively slow release of data should result in a higher quality statistic.

The monthly GDP at basic prices series and the quarterly GDP at market prices are distinct measures that can have, at times, quite different growth rates—sometimes greater than 1 percentage point (p.p.) in absolute value. In principle, the difference lies in the treatment of taxes and subsidies on the products.[11] While production at basic prices excludes taxes and subsidies, GDP at market prices includes them. However, it takes several years for the two measures of GDP to be reconciled to the point where the effects of taxes and subsidies are the only difference (on an annual and nominal basis). Since the reconciliation is done on an annual and nominal basis, the data on a quarterly and real basis could potentially exhibit other differences stemming from deflators, or seasonal adjustment. In real time, differences can stem from variations in methodology, source data or simple measurement error. Nonetheless, monthly GDP at basic prices is a very important predictor of quarterly GDP.

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[9] We loosely follow the guidance presented in the following paper for selecting the appropriate *Business Outlook Survey* variables: Pichette, L. and L. Rennison, "Extracting Information from the *Business Outlook Survey*: A Principal-Component Approach," *Bank of Canada Review* (Autumn 2011): 21–28.

[10] Canadian monthly real GDP is compiled on a by-industry basis and industrial production is an aggregation of mining, quarrying and oil and gas extraction, utilities, manufacturing, and waste management services.

[11] Examples of taxes and subsidies are sales taxes, fuel taxes, duties and taxes on imports, excise taxes on tobacco and alcohol products and subsidies paid on agricultural commodities, transportation services and energy.

There is another point that warrants discussion. GDP at basic prices is on a by-industry basis, which means it provides details on many industries but is difficult to translate into an expenditure GDP framework as is commonly used for macroeconomic analysis.[12] For example, GDP at basic prices reports the value-added production of the manufacturing industry, but it is difficult to determine if this production will be exported, used for investment of machinery and equipment, or stored as inventories. This limits its usefulness in a nowcasting model for the components of GDP. For most of the expenditures components, no monthly analogue is available. Unlike the United States, Canada does not have a monthly personal consumption expenditures series. However, there is a monthly goods exports and imports series released with a one-month lag (the same timing as the United States).

We transform the data to be stationary. Appendix D lists the transformations. Publishing agencies have rebased or made minor definitional changes to some series, which makes finding series with sufficient history difficult. For those series, we splice the most recent series with the corresponding older ones. Otherwise, series that do not have sufficient history are added to the models once a set number of observations are available.

Methodology

Model set

The forecasts we produce are combinations of point forecasts from a set of commonly used nowcasting tools. Econometric models can vary widely, but what makes a nowcasting model is that it solves two unique problems:

(i) Jagged edges: Macroeconomic data are released with lags, with different announcement dates for each variable. This results in unbalanced data sets that nowcasting models must be able to process to create a prediction.

(ii) Mixed frequencies: Most variables of interest, such as National Accounts data, are released at a quarterly frequency, while many, but not all, economic indicators (retail sales and consumer confidence, for example) that would be used for nowcasting are released on a monthly (or higher) frequency. This frequency mismatch is a problem for most models.

There are many classes of models that solve the problems noted above. We choose the suite of models, from which we combine forecasts in an attempt include a broad representation of the most commonly used model classes, subject to constraints on computational burden. The following section briefly describes the model classes and some of the specifics of our implementation. For a more detailed exposition of the models, see Chernis and Sekkel (2017).

[12] Since the measures are reconciled after several years, it is theoretically possible to back out expenditure-side measures of GDP components, but since the reconciliation is valid for only the reference year and done on an annual basis, it does not help us in our nowcasting objective.

Autoregressive (AR) models: This is the first and simplest class of model used. The dependent variable is forecast using only its past values as predictors.[13] There are two specifications of AR models: monthly and quarterly. We use monthly AR models for the trade variables based on the monthly merchandise trade release, and aggregate monthly forecasts to a quarterly frequency. In all other cases, we use a model estimated on a quarterly frequency. The models used in this class vary by the number of lags we use.

Leading indicator (LI) models: This class is similar to the AR model. The model is an auto-regressive term plus an additional indicator. Ragged edges for the leading indicator are filled in by an auxiliary AR(2) model. When our dependent variable has a monthly analogue (GDP, or trade) the model is constructed at monthly frequency in a similar manner to the AR models. When there is no monthly analogue the model is built on a quarterly frequency by aggregating the leading indicator to a quarterly frequency after the ragged edges are filled in, and then estimating the model. Bridge models have been used extensively at central banks (Angelini et al. 2011; Deutsche Bundesbank 2013; and Bell at al. 2014), and although they are relatively simple they have demonstrated good forecasting performance. There is one model for each selected[14] monthly predictor.

Dynamic factor models (DFMs): Factor models have become popular among central banks, as they have useful properties for nowcasting (Giannone, Reichlin and Small 2008). They utilize the co-movement of a large set of indicators to estimate common factors, which in turn represent the underlying dynamic of that set of variables. We use two factor models in our combination method. The first is Binette and Chang's (2013) CSI model and the second is that used by Chernis and Sekkel (2017). CSI is used exclusively for GDP while the Chernis and Sekkel model is used for GDP and all of its components. This is because Chernis and Sekkel's model, which borrows from Bańbura and Modugno (2014), can effectively consider a large number of predictors and flexibly handle a number of data irregularities. We vary the specifications of the DFMs by the number of factors extracted from the data set. Mixed frequencies are modelled using the technique from Mariano and Murasawa (2003).

Mixed data sampling (MIDAS) models: MIDAS models are a popular class of models whose main feature is the ability to estimate using mixed frequency data (see Ghysels, Santa-Clara and Valkanov 2004). The MIDAS regression reduces the number of parameters to be estimated by assuming that the lag coefficients on the high frequency variables can be approximated by a distribution. The distributional assumption reduces the number of parameters to be estimated to only those characterizing the weighting function of the distribution. In our application, we use a beta distribution. We also include a lagged low frequency quarterly autoregressive term. For GDP and the trade variables, we use a bivariate MIDAS that includes the monthly proxy as an additional high-frequency regressor. The same variables are used in the MIDAS class as in the leading indicators model class.

[13] We found that autoregressive models did not add much to the forecasts of total GDP and thus were excluded. However, these models are used to nowcast the *components* of GDP.

[14] We found some gains from trimming the worst performing models, so not all variables are included in this class.

Bayesian vector autoregressions (BVARs): Vector autoregressions and BVARs are among the most common models used by policy makers for forecasting and economic analysis because of their simplicity and good forecasting performance. The BVAR differs from a VAR in that it uses prior assumptions on the parameters to reduce the problem of parameter proliferation. We use the standard Minnesota prior (see Koop and Korobilis 2010). This class is used only to predict total GDP, and includes 10 models with the set of variables always following the convention: monthly GDP (GDPBP), financial variable, another domestic real activity measure and a foreign activity variable.

As mentioned above, there is a large set of possible specifications for each model. We address the consequent "specification uncertainty" by systematically varying the models along a given dimension (lag length, data sample, variables to include, etc.). In addition, there may be structural changes in the time series, so for all model classes we use both rolling and recursive estimation schemes. This results in approximately 100 different models for nowcasting Canadian GDP, and in the largest case upwards of 250 models for residential investment.

Combination methods

We use a two-step procedure for combining forecasts, similar to the Norges Bank (Aastveit, Gerdrup and Jore 2011). We first combine the predictions of models within each class by simple average.[15] This effectively makes our combined forecast more robust to misspecification and instabilities within each model class. It also means the combined forecasts are no longer influenced by the number of models in each class. In the second step, class level forecasts are combined using various weighting schemes to make a single point forecast.

While many different weighting schemes have been proposed in the literature, we focus on three that are commonly used: (i) equal weights or simple average, (ii) inverse root mean squared error (RMSE) weights, and (iii) constrained ordinary least squares (OLS) weights.

(i) Surprisingly, research shows that simple average weights are a very hard benchmark to outperform. While a simple average does not consider any information regarding previous forecasting performance, it avoids parameter estimation uncertainty by simply fixing the weights to be equal.

(ii) Inverse RMSE weights consider the out-of-sample forecasting performance of each class. Model classes with historically lower RMSE are assigned a higher weight than models with poorer performance. This method does not take into account the covariance between the model classes' forecasts. It is a generalization of Bates and Granger (1969) with no correlation across models,

[15] There are two main reasons why we use only simple averaging when combining the models within each class: (i) first, the correlation between the models in most classes is relatively high, diminishing the benefit of more sophisticated averaging schemes; and (ii) more importantly, we would also need another out-of-sample training sample to estimate the inverse RMSE and OLS weights within each class, which would reduce the out-of-sample evaluation window.

which several studies have shown performs well (Bjørnland et al. 2012; Granziera, Luu and St-Amant 2013).

(iii) The last method, constrained OLS weights, considers the performance of *and* covariance between the out-of-sample forecasts. Theoretically, these weights should be optimal (Granger and Ramanathan 1984), but in practice they may not work well because of estimation uncertainty in small samples (Timmermann 2006). The weights are constrained to be between zero and one, and sum to unity. This constraint behaves as a type of shrinkage, and in other applications has been shown to have reasonable out-of-sample performance (Conflitti, De Mol and Giannone 2015).

Table 1: Combination methods

Simple average	$w_{i,h}^{SA} = \frac{1}{N}$
Inverse RMSE	$w_{i,h}^{INV} = \frac{(1/RMSE_{i,h})}{\sum_{i=1}^{N}(1/RMSE_{i,h})}$
Constrained OLS weights	$w^{OLS} = \min_{w} \sum_{t=1}^{T-h} \left(y_{t+h} - w'\hat{y}_{t+h\mid t}\right)^2$ $subject\ to \sum_{i=1}^{N} w_i = 1\ and\ w_i \geq 0$

Note: N is the number of models, i is the model index, h is the forecast horizon, y is the target variable, $\hat{y}$ is the model forecast and t is the time period.

Out-of-sample exercise

The forecasting performance of the combinations and model classes is evaluated using a pseudo real-time exercise. The pseudo real-time exercise aims to recreate the historical flow of data so that we can simulate what the forecasts would have been. This is done by grouping the variables in roughly two-week release blocks so that variables released at similar times throughout the month are grouped together. With each successive forecast the models and combination weights are re-estimated. The exercise remains a *pseudo* out-of-sample exercise because we use final revised data, and therefore do not consider data revisions. While this is less than ideal (see Croushore and Stark 2003; Stark and Croushore 2002; and Orphanides (2001)), we do not have real-time data for all the variables in the model.

Figure 1: Overview of forecast cycle

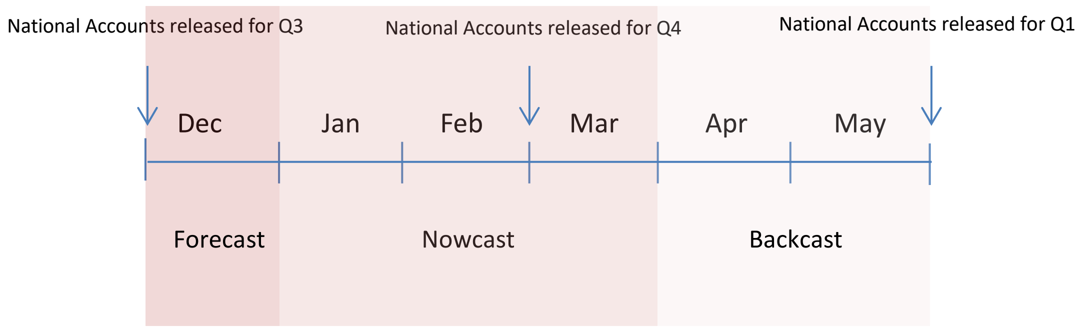


Figure 1 illustrates the timing of releases throughout the six-month forecast cycle. The model's performance is assessed 12 times over the six months, representing a prediction *roughly* every two weeks. This example shows a forecast cycle starting in December after the release of the Q3 National Accounts data targeting the Q1 figures for the upcoming year. This exercise is designed to replicate the forecast cycle faced by a practitioner. The cycle starts in December, when the analyst is *forecasting* the Q1 figures. Throughout Q1, the analyst is in the *nowcast* phase, and from April through to the May National Accounts data release, the analyst is *backcasting* the Q1 figures while awaiting publication of the official figures.

For example, the first forecast made in a month includes all data released in the first two weeks of that month, and the second forecast includes the rest of the data released in that month up to the release of GDP at basic prices. To better illustrate this example, consider a forecast being made in March. The first biweekly block in March includes merchandise trade data for January and GDP at basic prices data for December. The second block also includes retail trade, manufacturing sales and wholesale trade for January.

The first in-sample period in our exercise—used to estimate the models—starts in 1980Q2 and ends in 1995Q3. Subsequently, we use an expanding five-year training sample to estimate the inverse RMSE and OLS weights. Hence the first combined forecast is for 2000Q2 onwards. The pseudo out-of-sample performance is then evaluated from 2000Q2 to 2016Q3.

Results

In this section, we analyze the performance of the forecast combinations and model classes.

First, we discuss the results for GDP. The starting point is the forecast accuracy of the final combinations; within that exercise, we examine the weights each combination places on different model classes, and the behaviour of the model classes themselves. In the interest of brevity, we provide a summary of the results for each of the components of GDP with more details in the appendix. It is worth mentioning that we forecast the components[16] of GDP independently, and do not impose a requirement that the components' weighted growth rates must sum to total GDP growth.

Overall, we show that while the forecast combinations do not always provide the most accurate forecast, they are always among the best forecasts and, on average, outperform the individual models. Furthermore, no model is clearly superior in all circumstances, with the relative performance of the models varying across forecast horizons, sub-samples and target variables.

Real GDP

Figure 2 and **Figure 3** show the RMSE of forecasting the annualized percentage change in GDP. The horizontal axis refers to the number of weeks between when the prediction is made and when the Canadian System of National Accounts data are released. First, it is comforting that the combinations outperform the unconditional mean as a forecasting model (standard deviation) over all horizons

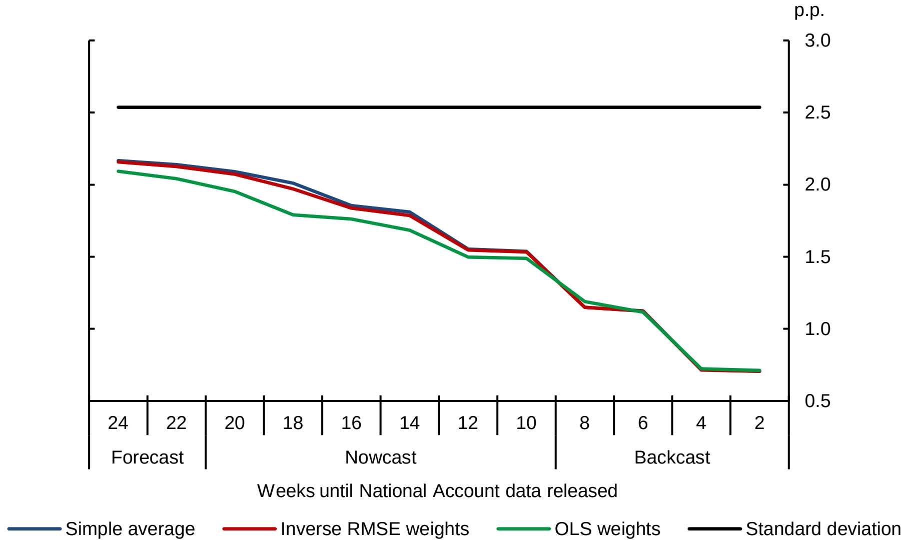
[16] We do not forecast all the components of GDP—we exclude inventory investment and government expenditures.

(**Figure 2**). Second, the performance improves as more data arrive, which signals that the models are processing and integrating new information effectively.

Over the forecast and nowcast periods, the OLS weights perform the best by a small margin that narrows towards the end of the nowcast horizons. During the backcast periods (the final eight weeks before the National Accounts data arrive), the different forecast combination methods perform similarly well, and all improve in almost discrete steps coinciding with the release of monthly GDP.

Figure 2: RMSE: Gross domestic product

Different combination methods, 2000Q2 to 2016Q4

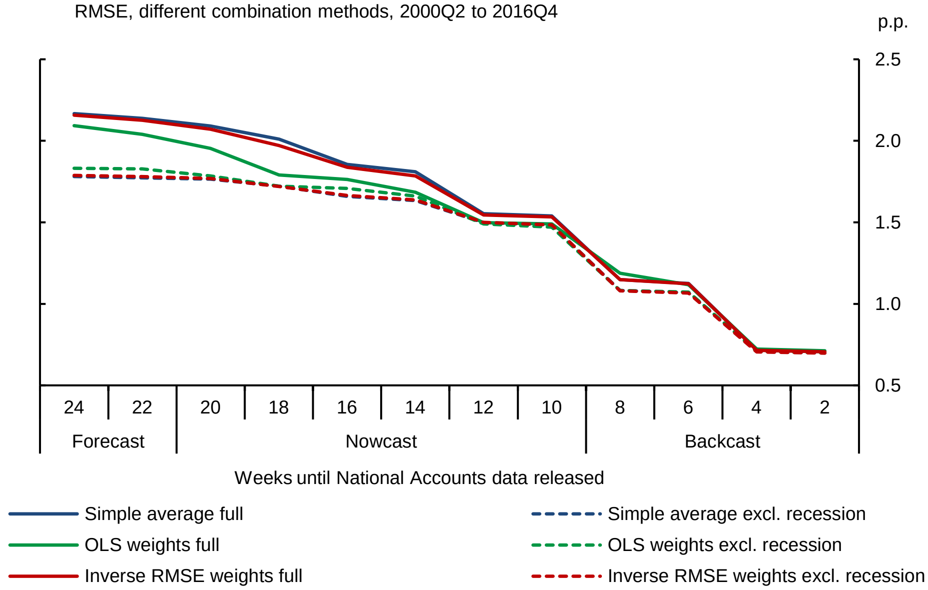


Note: p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

At first, the fact that OLS outperforms equal weights until the backcast period might seem surprising, since the literature shows equal weights are a hard combination method to beat. Upon closer inspection, the superior performance of the OLS weights is rooted in a single, short period: the great financial crisis. **Figure 3** shows the RMSE of the three combination methods excluding the recession period (2008–10): the performances of the three combination methods are much closer together during this period, which suggests the recessionary period is supporting the performance of the OLS combination.

Figure 3: RMSE: Gross domestic product, excluding recession period

RMSE, different combination methods, 2000Q2 to 2016Q4

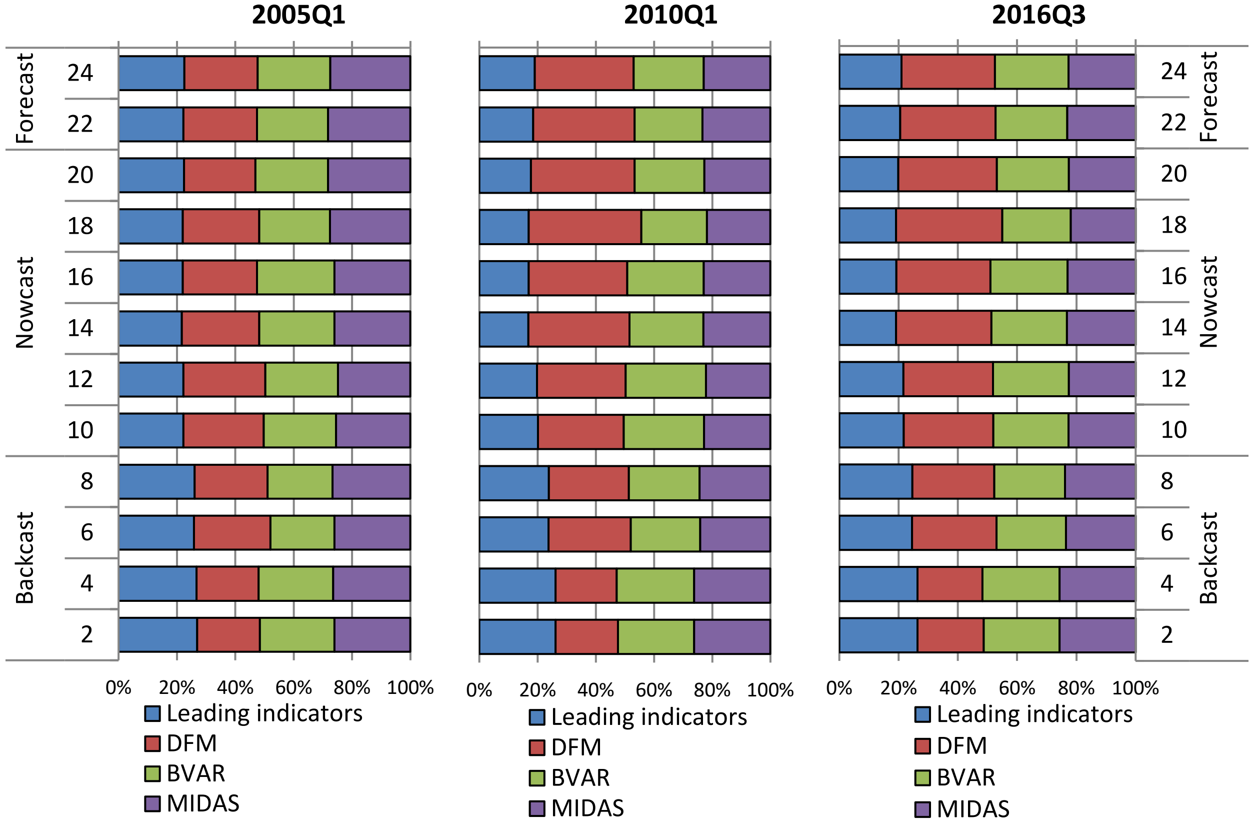


Note: Recession dates include 2008Q1 to 2010Q4; p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

Inspecting the weights of the combination methods can help explain why the OLS combination method performs better in the great recession. **Figure 4** and **Figure 5** show the estimated combination weights on each model class for the inverse RMSE weights and OLS weights respectively.

The inverse RMSE weights are quite stable, and do not deviate much from equal weights (around +/-10 p.p. from equal weights). But they do vary over time and forecast horizon. Between 2005Q1 and 2010Q1 the weights on DFM increased, suggesting relatively better performance during the intervening years, while between 2010Q1 and the end of the sample (2016Q3), the weight on the DFM decreased slightly. At the same time, the weights for the different models change over the forecast horizons. The weight on the DFM tends to be higher during the forecast and nowcast periods (up to 39 per cent), and gradually gives way to the other models during the backcast period (as low as 21 per cent).

Figure 4: **Estimated inverse RMSE weights**



Note: DFM is dynamic factor model, BVAR is Bayesian vector autoregression and MIDAS is mixed data sampling.

The OLS weights show a similar, albeit more exaggerated, pattern. The OLS weights vary over forecast horizon and time. For example, in 2005Q1 MIDAS models have most of the weight over most the forecast horizons. The DFM has substantial weight throughout the forecast and nowcast horizons, and even more so in the last month of nowcasts. Finally, in the backcast the MIDAS and leading indicator models gain the most amount of weight. This is an example of slight differences in performance causing the OLS weights to shift dramatically. This pattern changes over time as more forecasts are made and the models are reassessed. A particularly dramatic example is after the financial crisis: examining the weights in 2010Q1 shows that most of the weight has shifted towards the DFM class, suggesting that this model class performed well during that period. Over almost all forecast horizons the DFM class receives most of the weight. This pattern largely continues until the end of the sample.

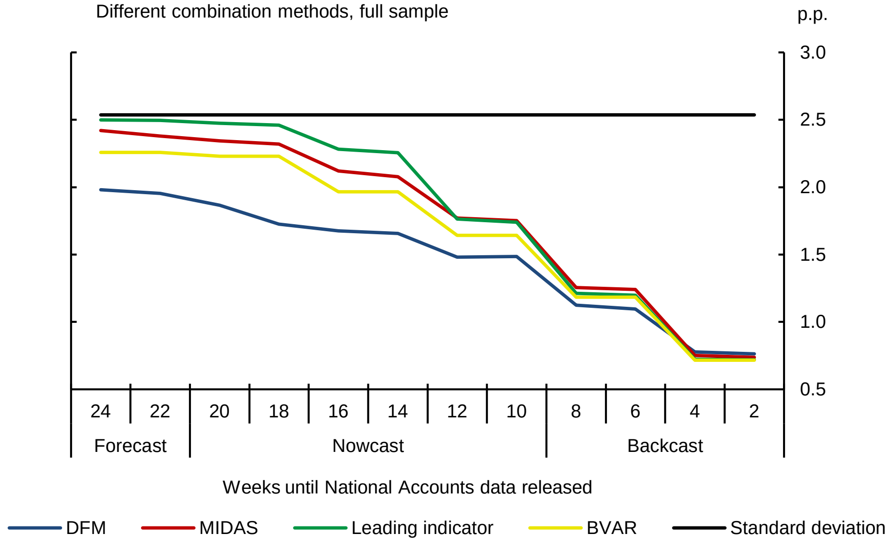
Figure 5: Estimated OLS weights

Note: DFM is dynamic factor model, BVAR is Bayesian vector autoregression and MIDAS is mixed data sampling.

Next, we discuss the model classes' performance. The first thing to notice in **Figure 6** is that the models perform better than using the unconditional mean model (standard deviation from 2000 to 2016). Second, the DFM model performs very well over the full sample. The performance difference between the DFM and the other models narrows as the models enter the backcasting period. As shown by Chernis and Sekkel (2017), the first month of GDP at basic prices for each quarter has, on average, the largest impact on the forecasting models, and tends to diminish the contribution of the remaining data to the forecast.

Figure 6: RMSE: Gross domestic product by model class

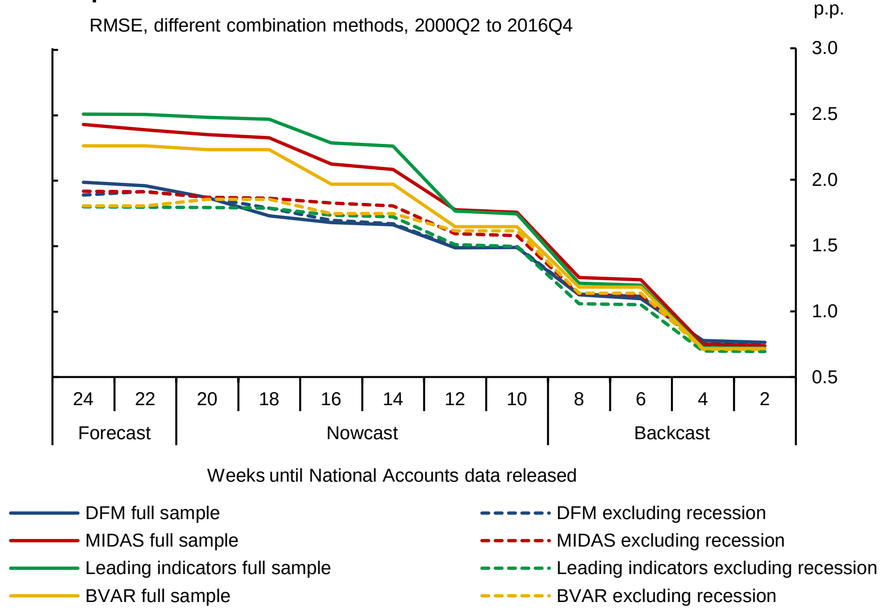
Different combination methods, full sample



Note: p.p. is percentage points, DFM is dynamic factor model, MIDAS is mixed data sampling and BVAR is Bayesian vector autoregression.

Figure 7 shows the pseudo real-time RMSE for the model classes including and excluding the recession. Excluding the recession from the RMSE calculations, the forecast performance of the models becomes much more similar. While the differences between models are small, those differences vary across forecast horizons. It appears as if the DFM model class full sample performance is driven by its success during the financial crisis. There are two likely explanations for this. First, the class level predictions are an average of the component models, and since there are relatively fewer models in the DFM class the prediction will react more to changes in the individual model predictions. Second, the DFM models the co-movement in panels of data, and the broad coordinated movements seen in the data during the great recession are exactly the phenomena the models were designed to capture.

Figure 7: RMSE: Gross domestic product by model class, excluding recession period



Note: Recession dates include 2008Q1 to 2010Q4. p.p. is percentage points, DFM is dynamic factor model, MIDAS is mixed data sampling and BVAR is Bayesian vector autoregression.

Overall, the preceding results show that the combination forecasts perform well. The inverse RMSE and simple average weights have almost the same performance, while the OLS method outperforms them during the forecasting and nowcasting horizons. The successes of the OLS combination weights are due to its ability quickly reassign weight during the great recession to the DFM model class. However, outside of this period the simple average and inverse RMSE combinations are more competitive with the OLS combination methods. The DFM class performed very well during the recession, but outside of this period the other models are more competitive. To summarize, we find that the combinations perform well at predicting GDP due to their ability to shift weight to the best performing models, models whose relative performance changes across time periods and forecast horizons.

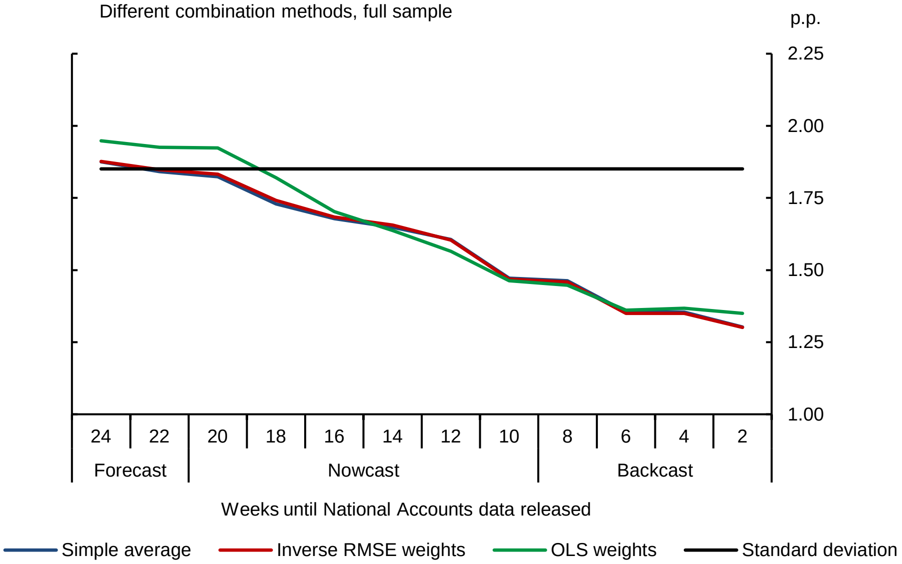
Consumption

This section discusses the results for consumption. Overall, the combinations beat the unconditional mean model (standard deviation), and improve steadily as more data arrive (**Figure 8**). Improvements are especially noticeable with the release of retail trade. This is because retail trade is the most relevant piece of information available, and is always included as an explanatory variable in the models.

However, during the forecast periods it is difficult for the combinations to outperform the unconditional mean model. That changes within the nowcast horizons, when the inverse RMSE weights and simple average weights outperform the unconditional mean, though it takes until the 18-week horizon for the OLS weights to beat this benchmark. The inverse RMSE and simple average weights perform the best until the middle of the nowcast periods, after which the OLS weights perform slightly better for a month. In the backcast periods all combinations perform similarly until the last two weeks, when the OLS weights perform slightly worse.

Figure 8: RMSE: Consumption

Different combination methods, full sample

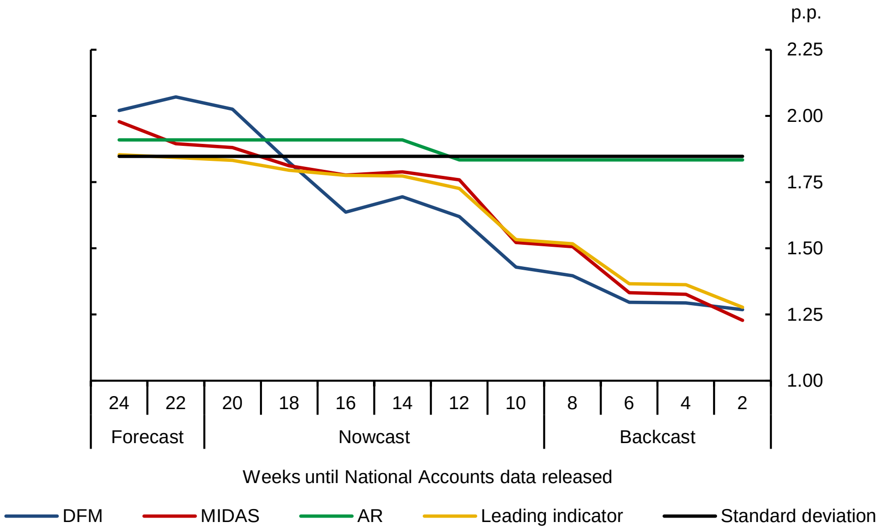


Note: p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

Examining the model classes, we can see that the models' performance changes across forecast horizons (**Figure 9**). For example, the AR and leading indicator models perform the best during the forecast period, but during the nowcast and backcast periods the DFM outperforms the other models. However, when examining the models' performance during different subsamples, the relative rankings change, as reflected in significant changes in the combination weights. Please see the appendix for detailed graphs and tables of the weights and performance over different subsamples.

Figure 9: RMSE: Consumption by model class

Different combination methods, 2000Q2 to 2016Q4



Note: p.p. is percentage points, DFM is dynamic factor model, MIDAS is mixed data sampling and AR is autoregression.

Trade: Exports and imports

Trade variables are some of the more challenging components of GDP to forecast. The total exports series is volatile and it is common to see large positive growth rates followed by immediate contractions. Fortunately, there are monthly merchandise trade statistics to help forecast exports and imports. However, the trade-off for timeliness is that these figures can potentially suffer from large revisions.

Figure 10 and **Figure 11** show the results of the combination forecasts for exports and imports. For both variables the results are similar. Throughout the nowcast periods, as new information arrives the combinations' performance improves. However, for exports it is difficult to beat the unconditional mean model at the forecast horizons. For both variables, the OLS combination performs the best throughout this period because it can more heavily weight better performing models. Like the other components of GDP, the relatively strong performance of the OLS weights is driven by the great recession. Once the merchandise trade data for the target quarter are available, the gap between combination methods narrows. This is because the monthly exports and imports figures become the most informative piece of information.

Figure 10: **RMSE: Exports**

RMSE of different combination methods, 2000Q2 to 2016Q4

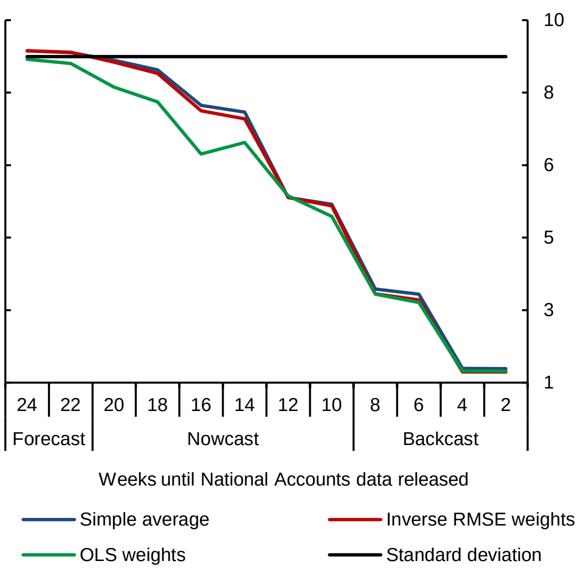
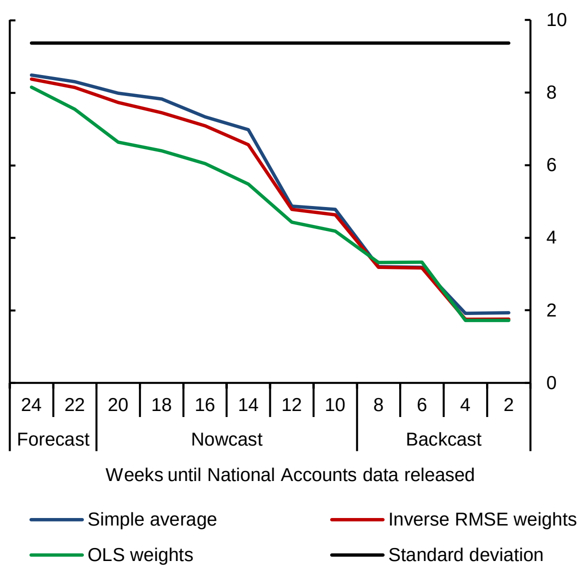


Figure 11: **RMSE: Imports**

Different combination methods, 2000Q2 to 2016Q4



Note: p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

On the models front, the DFM model class performs the best across almost all forecast horizons (**Figure 12** and **Figure 13**). However, once the monthly goods exports data arrive the relative performance narrows, and the performance of all models increases rapidly. At the last nowcasting period the MIDAS model starts to forecast slightly worse than the others, while the AR and leading indicators have similar performance to the DFM. In the last backcast period the AR model performs the best. At this point there is a complete quarter of merchandise trade data[17] available (with a publication lag of slightly less than five

[17] The National Accounts trade statistics include trade of services, which accounts for a sizeable amount of trade. For example, exports of services accounted for around 16 per cent of 2015 nominal exports. Merchandise data exclude services.

weeks), and simply using that information appears to be enough to forecast well. However, as noted by Tkacz (2010), the growth rate of exports and imports tends to be subject to the largest revisions, suggesting that this result should be taken with caution. Again, the relatively strong performance of the DFM is driven by the great recession. Excluding the great recession period shows the models perform much more similarly. See appendix for details.

Figure 12: RMSE: Exports

Different combination methods, 2000Q2 to 2016Q4

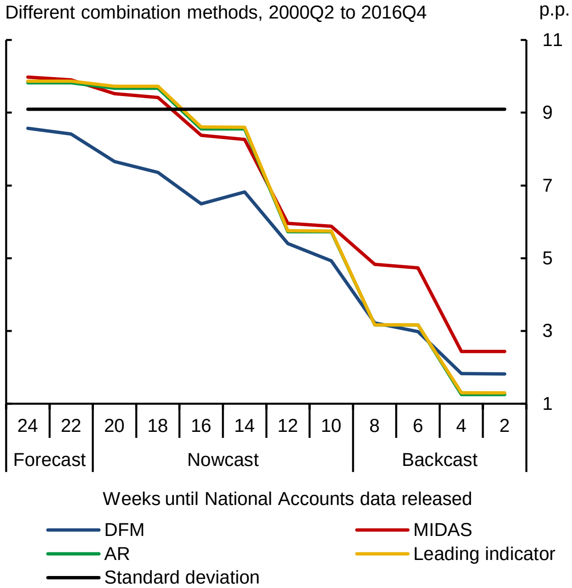
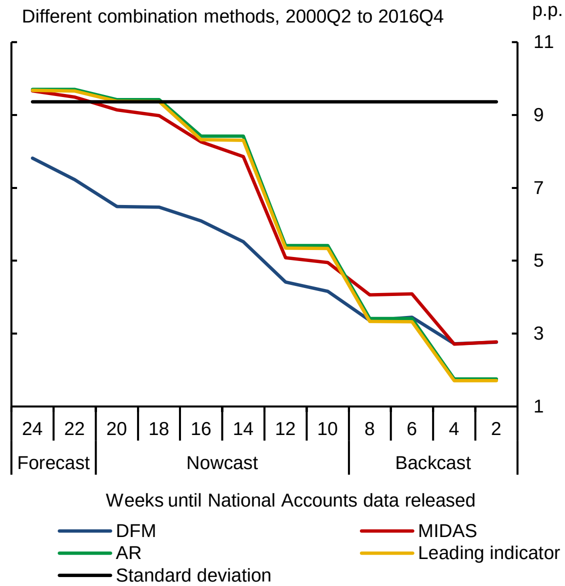


Figure 13: RMSE: Imports

Different combination methods, 2000Q2 to 2016Q4



Note: p.p. is percentage points, DFM is dynamic factor model, AR is autoregression and MIDAS is mixed data sampling.

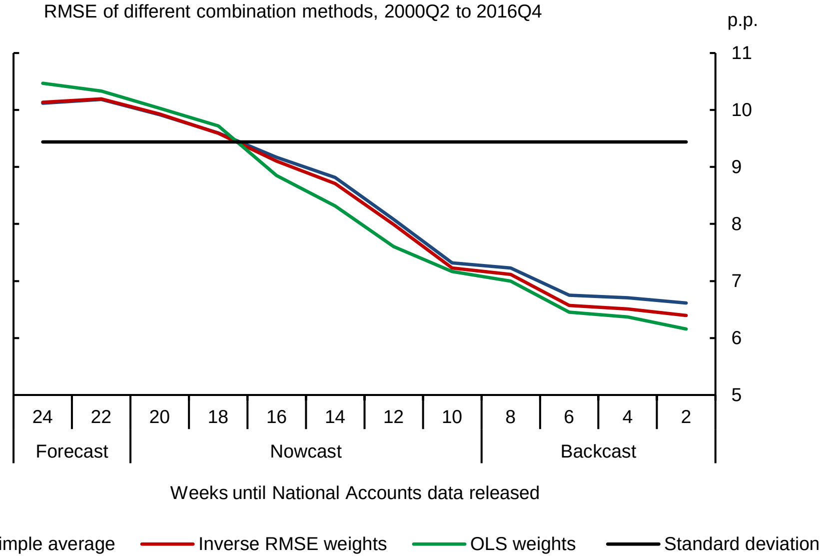
Housing

Residential investment is also a challenging series to forecast. While there is a wealth of indicator data available (such as housing starts, residential construction production, and permits) none of these series have the same predictive power as the monthly indicators available for trade or GDP. This is evidenced in the combination results in **Figure 14**, where it is difficult to beat the unconditional mean model until the second month of nowcasts.

The results of the combined forecasts do not clearly show a best method. Over most horizons the combination methods are very competitive with each other, and it is only at the 16- to 12-week nowcasting horizons that the OLS combination weights seem to perform better. Contrary to the other results discussed in this paper, the relative performance of the OLS weights is not heavily influenced by the financial crisis. **Figure C-3** and **Figure C-4** in Appendix C show the evolution of the combination weights.

Figure 14: RMSE: Housing

RMSE of different combination methods, 2000Q2 to 2016Q4

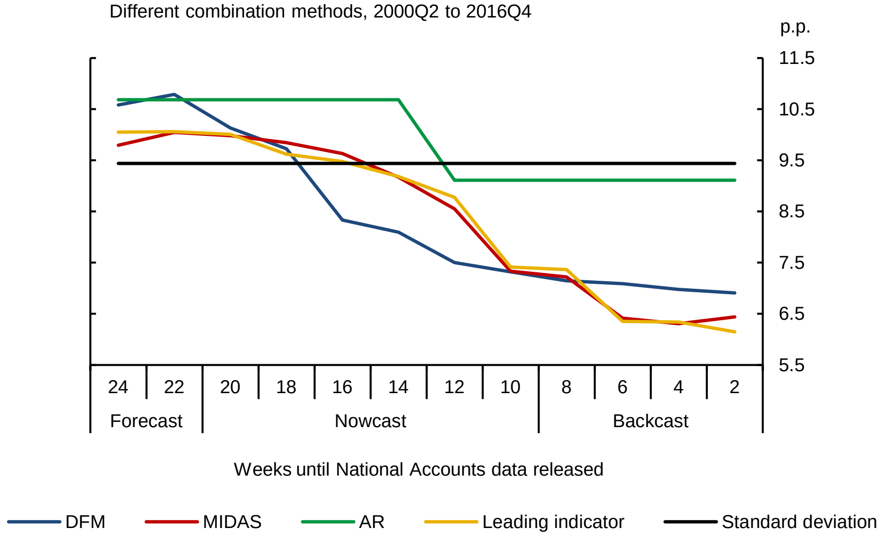


Note: p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

The performance of the model classes for residential investment is heterogeneous. Between the forecast and early nowcast horizons, the MIDAS and leading indicator models perform the best (**Figure 15**). By contrast, through the nowcast periods of 16 weeks and onwards the DFM performs the best. However, when backcasting, the relative performance reverses and the MIDAS and leading indicator models perform slightly better than the DFM. The results for housing exemplify the observation that different models perform better over different forecasting horizons and different time periods. **Table B-5** in Appendix B shows the result, while the changing distribution of forecast weights in **Figure C-3** and **Figure C-4** in Appendix C furthers this point.

Figure 15: RMSE: Housing

Different combination methods, 2000Q2 to 2016Q4



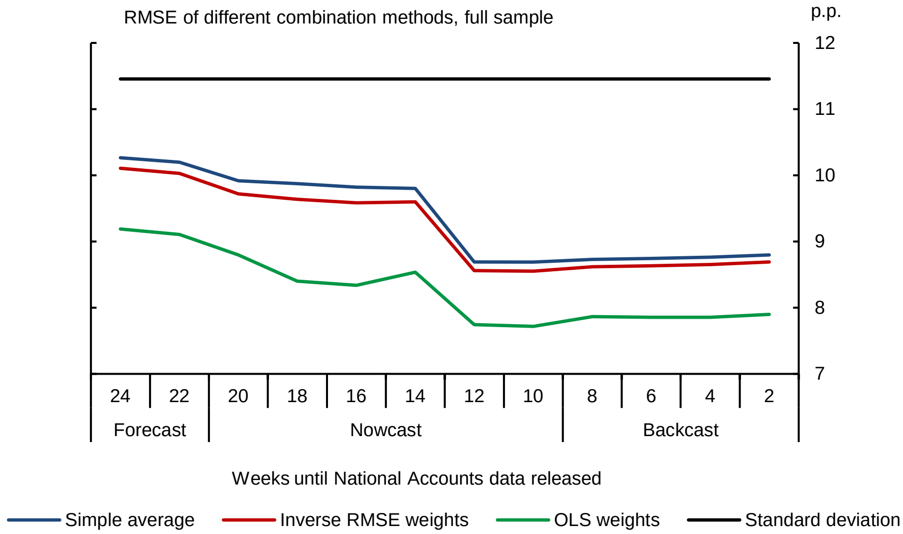
Note: p.p. is percentage points, DFM is dynamic factor model, MIDAS is mixed data sampling and AR is autoregression.

Investment

The combination forecast results for investment are shown in **Figure 16**. While in absolute terms the RMSE is large, all combination methods perform better than the unconditional mean model. Across forecast horizons the RMSE of the combination methods falls slightly, with the largest reduction during the nowcasting period when the National Accounts data for the previous quarter are released. The OLS combination method performs meaningfully better across all horizons. This result is largely due to its tendency to put a large amount of weight on the DFM.

Figure 16: RMSE: Investment

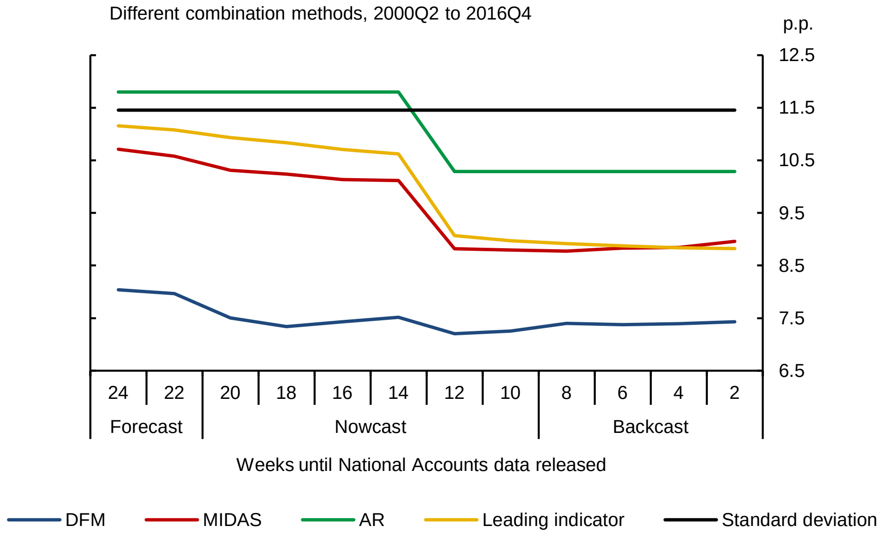
RMSE of different combination methods, full sample



Note: p.p. is percentage points, RMSE is root mean squared error and OLS is ordinary least squares.

The discussion on the weights is a preview for the model level results in **Figure 17**. The DFM performs much better than any of the other models. Starting in the forecast horizons, the DFM performs the best, beating the other models by more than 2 percentage points on the RMSE. As more data come in, the DFM retains its superior performance, but does not improve as much as the other methods. Contrary to the results for total GDP and the other components, new data releases do little to improve the predictions of the DFM. Regardless, the DFM performs the best across all forecast horizons. **Table B-6** in Appendix B shows that this result holds across different time periods, but the difference in performance is smaller outside the recession.

Figure 17: RMSE: Investment



Note: p.p. is percentage points, DFM is dynamic factor model, MIDAS is mixed data sampling and AR is autoregression.

Conclusion

This paper examines methods of combining forecasts from many different models to nowcast GDP and several of its important components. Overall, we find that the combination methods perform well and effectively combine predictions from many models. To varying degrees, the combination weights evolve across time and forecast horizon to reflect different models' forecasting performance over different time periods and forecast horizons.

We find that dynamic factor models perform consistently better than the other model classes. The strong performance of DFMs is not only because of their strong performance during the financial crisis; they also perform well during different time periods. However, the existence of a preeminent model class does not undermine the theme of different models performing better at different time horizons and over different periods. We found many occasions where other models were the best choice. It is these observations that make looking at many models through a forecast-combinations method a consistently good approach.

Appendix A: RMSE Summary Table[18]

Table A-1: Component

Component	Forecast			Nowcast			Backcast		
	OLS weights	SA weights	INV weights	OLS weights	SA weights	INV weights	OLS weights	SA weights	INV weights
GDP	2.09	2.17	2.16	1.76	1.86	1.84	1.19	1.15	1.15
Consumption	1.95	1.88	1.88	1.70	1.68	1.68	1.45	1.46	1.46
Exports	9.03	9.24	9.24	6.67	7.89	7.75	3.20	3.32	3.20
Imports	8.15	8.48	8.37	6.05	7.33	7.08	3.32	3.20	3.18
Housing	10.47	10.12	10.14	8.85	9.17	9.10	7.00	7.23	7.12
Investment	9.19	10.27	10.11	8.34	9.82	9.59	7.87	8.73	8.62

Appendix B: RMSE by Subsample[19]

Table B-1: GDP

GDP	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	2.17	1.86	1.15	**1.71**	**1.56**	1.18	3.39	2.54	1.35	1.94	1.83	0.99
INV weights	2.16	1.84	1.15	1.72	1.56	1.17	3.34	2.46	1.35	1.95	1.83	0.98
OLS weights	2.09	1.76	1.19	1.76	1.63	1.18	2.99	1.99	1.53	1.98	1.82	0.98
DFM	**1.98**	**1.68**	**1.13**	1.83	1.59	1.23	**2.31**	**1.72**	**1.08**	2.01	1.77	0.97
MIDAS	2.42	2.12	1.26	1.76	1.66	1.21	3.97	3.09	1.67	2.18	2.10	1.06
Leading indicators	2.50	2.28	1.21	1.84	1.78	**1.17**	4.49	3.90	1.70	**1.79**	**1.74**	**0.93**
BVAR	2.26	1.97	1.18	1.76	1.64	1.24	3.68	2.70	1.28	1.92	1.96	1.04

Table B-2: Consumption

Consumption	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	1.88	1.68	1.46	1.91	1.84	1.72	**2.78**	2.15	1.77	1.06	1.06	0.73
INV weights	1.88	1.68	1.46	1.91	1.84	1.73	2.79	2.17	1.72	1.06	1.07	0.73
OLS weights	1.95	1.70	1.45	1.94	1.86	1.83	3.00	2.18	1.28	1.07	1.09	0.79
DFM	2.02	**1.64**	**1.40**	1.92	1.85	1.76	3.23	**1.72**	**1.08**	1.17	1.18	0.81
MIDAS	1.98	1.78	1.51	1.90	**1.74**	**1.58**	3.14	2.67	2.21	1.12	1.14	0.74
AR	1.91	1.91	1.83	1.87	1.87	1.85	3.01	3.01	2.75	**1.03**	**1.03**	1.04
Leading indicators	**1.85**	1.78	1.52	**1.84**	1.80	1.66	2.83	2.60	2.12	1.07	1.08	**0.69**

[18] Forecast, nowcast and backcast all refer to the first two weeks of predictions at the specified horizon.
[19] For each prediction horizon, bold figures indicate the model with the lowest RMSE.

Table B-3: Exports

Exports	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	9.24	7.89	3.32	8.65	7.11	3.83	12.03	10.10	2.82	8.24	7.52	2.78
INV weights	9.24	7.75	3.20	8.68	7.07	3.71	11.97	9.62	2.71	8.27	**7.49**	2.65
OLS weights	9.03	6.67	3.20	8.99	6.55	3.75	9.96	5.03	2.48	8.56	7.54	2.68
DFM	**8.57**	**6.49**	3.22	**8.27**	**6.18**	3.69	**9.16**	**5.03**	**2.07**	8.69	7.54	2.96
MIDAS	9.98	8.38	4.83	8.51	7.00	5.23	15.21	12.02	4.96	8.43	7.92	4.09
AR	9.82	8.56	**3.16**	8.44	7.43	**3.54**	15.11	12.39	3.17	**8.06**	7.62	2.51
Leading indicators	9.87	8.61	3.17	8.48	7.47	3.57	15.20	12.51	3.13	8.06	7.62	**2.49**

Table B-4: Imports

Imports	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	8.48	7.33	3.20	7.33	6.72	3.29	14.70	12.17	4.55	**4.52**	3.94	**2.03**
INV weights	8.37	7.08	**3.18**	7.33	6.65	3.23	14.35	11.48	4.57	4.52	**3.91**	2.04
OLS weights	8.15	**6.05**	3.32	7.43	**6.24**	3.24	13.35	8.12	5.03	4.75	4.26	2.05
DFM	**7.82**	6.09	3.37	**6.84**	6.27	3.69	**12.91**	**8.10**	**4.28**	5.20	4.33	2.08
MIDAS	9.66	8.26	4.07	7.87	7.08	4.40	17.85	14.78	5.35	4.72	4.09	2.46
AR	9.70	8.42	3.42	7.89	7.12	3.25	17.97	15.17	5.16	4.68	4.21	2.35
Leading indicators	9.68	8.32	3.33	7.88	7.11	**3.20**	17.95	14.90	4.97	4.59	4.14	2.30

Table B-5: Housing

Housing	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	10.12	9.17	7.23	9.91	8.92	7.40	15.63	14.12	10.31	5.83	5.47	4.54
INV weights	10.14	9.10	7.12	9.92	8.89	7.27	15.66	13.92	10.18	5.83	**5.46**	4.46
OLS weights	10.47	8.85	**7.00**	10.32	8.82	7.14	16.14	12.94	10.10	5.90	5.69	**4.32**
DFM	**10.58**	**8.33**	7.15	9.90	**7.86**	7.85	17.07	**12.61**	**8.49**	6.26	5.83	4.95
MIDAS	**9.79**	9.64	7.22	**9.38**	9.03	6.96	**15.35**	15.50	11.00	5.88	5.71	4.66
AR	10.69	10.69	9.11	10.13	10.13	8.85	16.96	16.96	13.67	6.40	6.40	5.97
Leading indicators	10.05	9.48	7.36	9.54	9.14	**6.72**	16.14	14.90	11.61	**5.72**	5.49	5.06

Table B-6: Investment

Investment	Full Sample			Until 2008			2008–10			2010 onwards		
	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast	Forecast	Nowcast	Backcast
SA weights	10.27	9.82	8.73	7.83	7.62	7.05	17.33	16.66	14.34	7.82	7.23	6.68
INV weights	10.11	9.59	8.62	7.84	7.61	7.04	16.85	16.04	14.04	**7.78**	7.06	6.59
OLS weights	9.19	8.34	7.87	7.99	7.59	7.17	13.44	12.21	11.31	7.81	6.61	6.45
DFM	**8.04**	**7.43**	**7.40**	**7.22**	**6.87**	**6.46**	**10.33**	**10.01**	**10.81**	7.81	**6.61**	6.45
MIDAS	10.71	10.13	8.77	7.63	7.42	6.91	19.25	18.10	15.14	8.05	7.47	**6.38**
AR	11.80	11.80	10.29	7.95	7.95	7.45	22.30	22.30	18.22	8.05	8.05	7.89
Leading indicators	11.16	10.70	8.92	7.75	7.58	6.98	20.41	19.60	15.42	8.19	7.64	6.52

Appendix C: Combination Weights

Figure C-1: Consumption: Estimated inverse RMSE weights

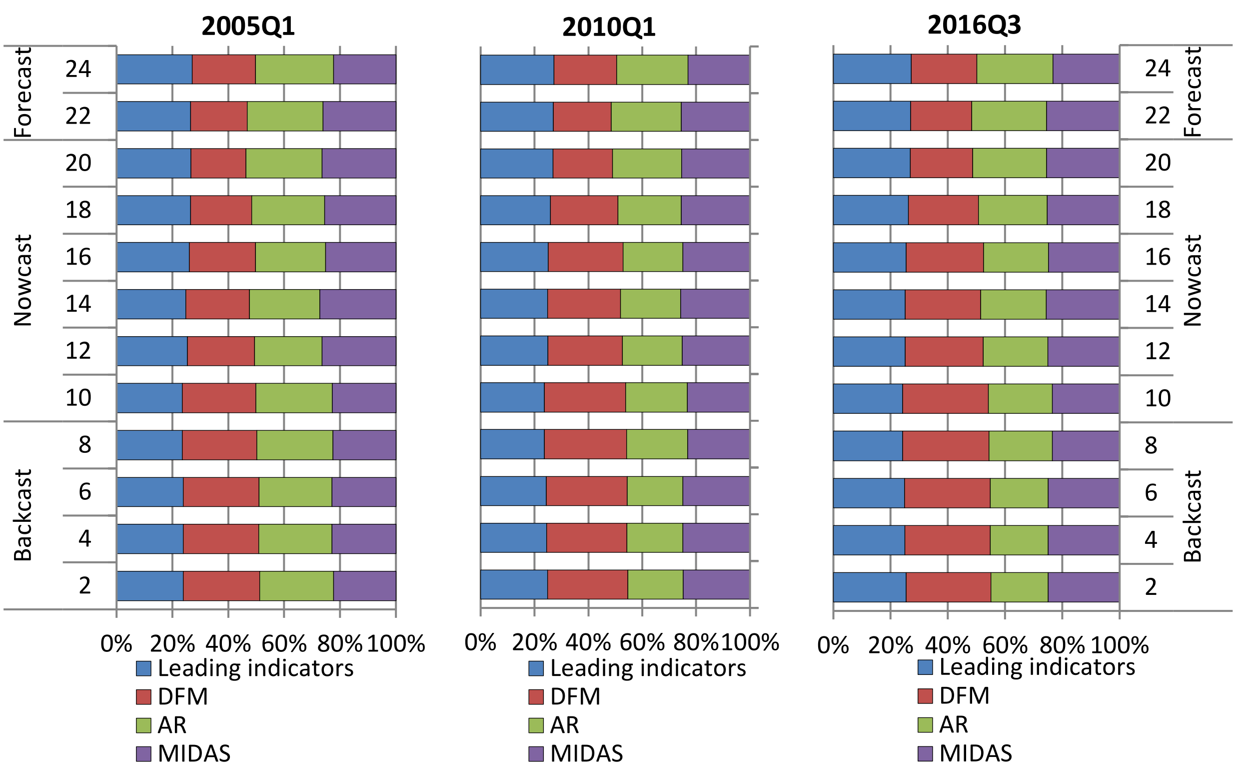


Figure C-2: **Consumption: Estimated OLS weights**

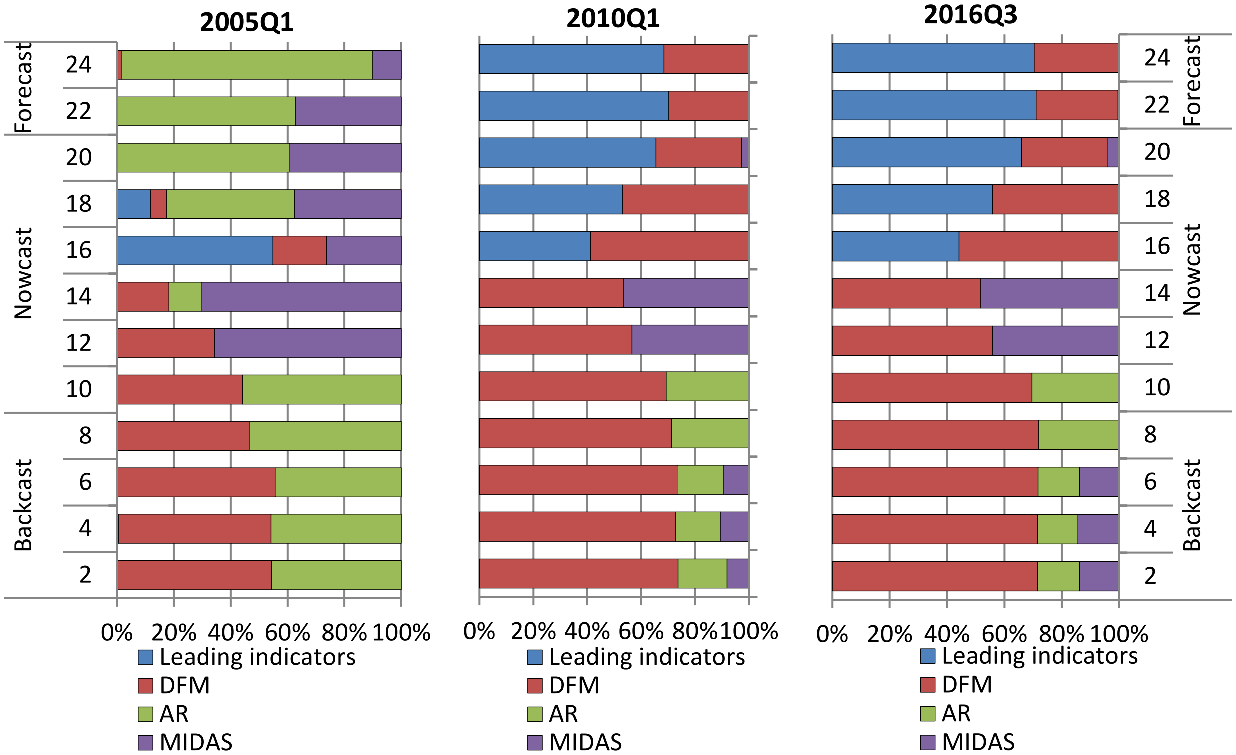


Figure C-3: **Housing: Estimated inverse RMSE weights**

Figure C-4: Housing: Estimated OLS weights

Figure C-5: Exports: Estimated inverse RMSE weights

Figure C-6: Exports: Estimated OLS weights

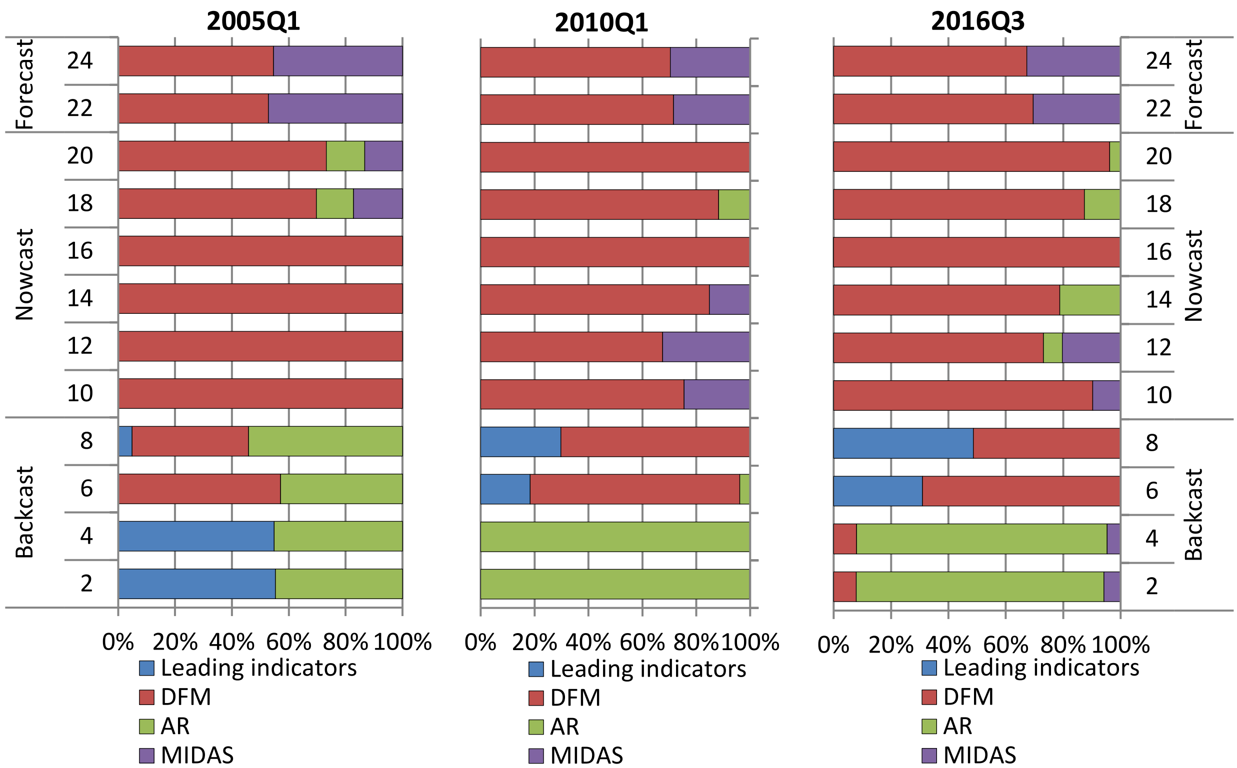


Figure C-7: Imports: Estimated inverse RMSE weights

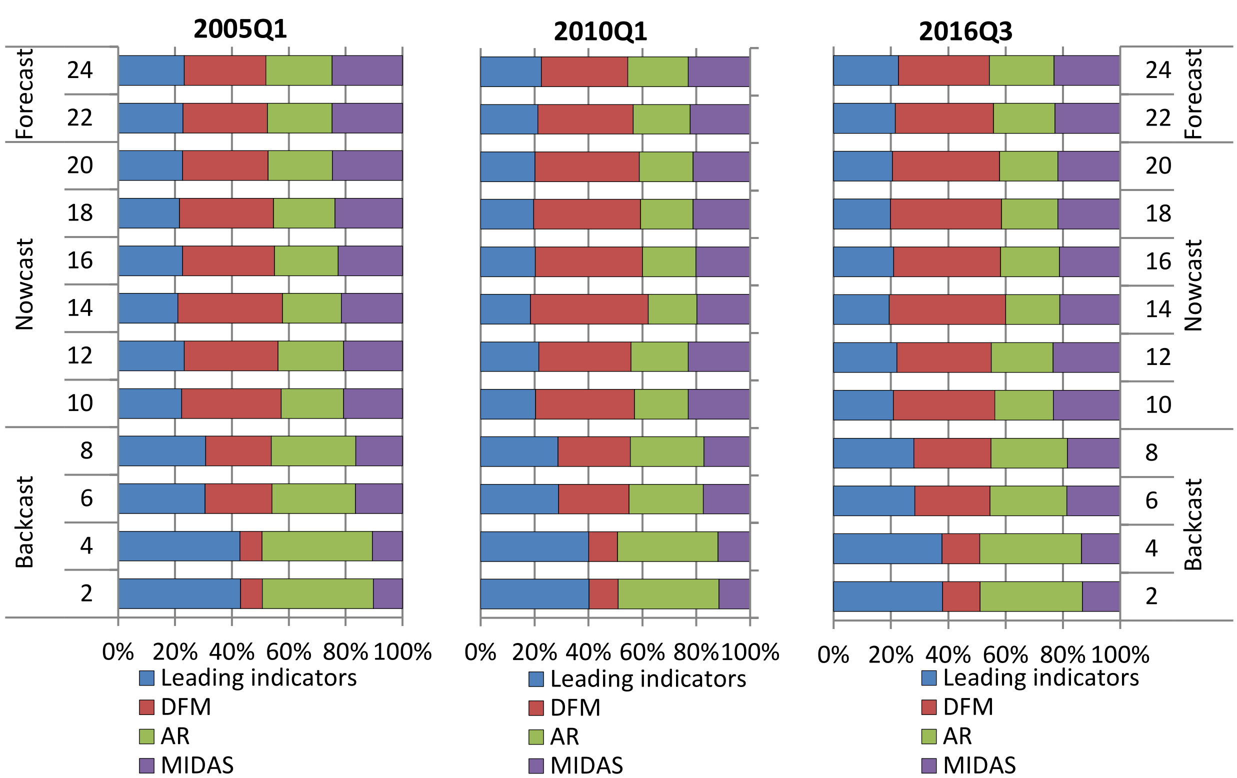


Figure C-8: **Imports: Estimated OLS weights**

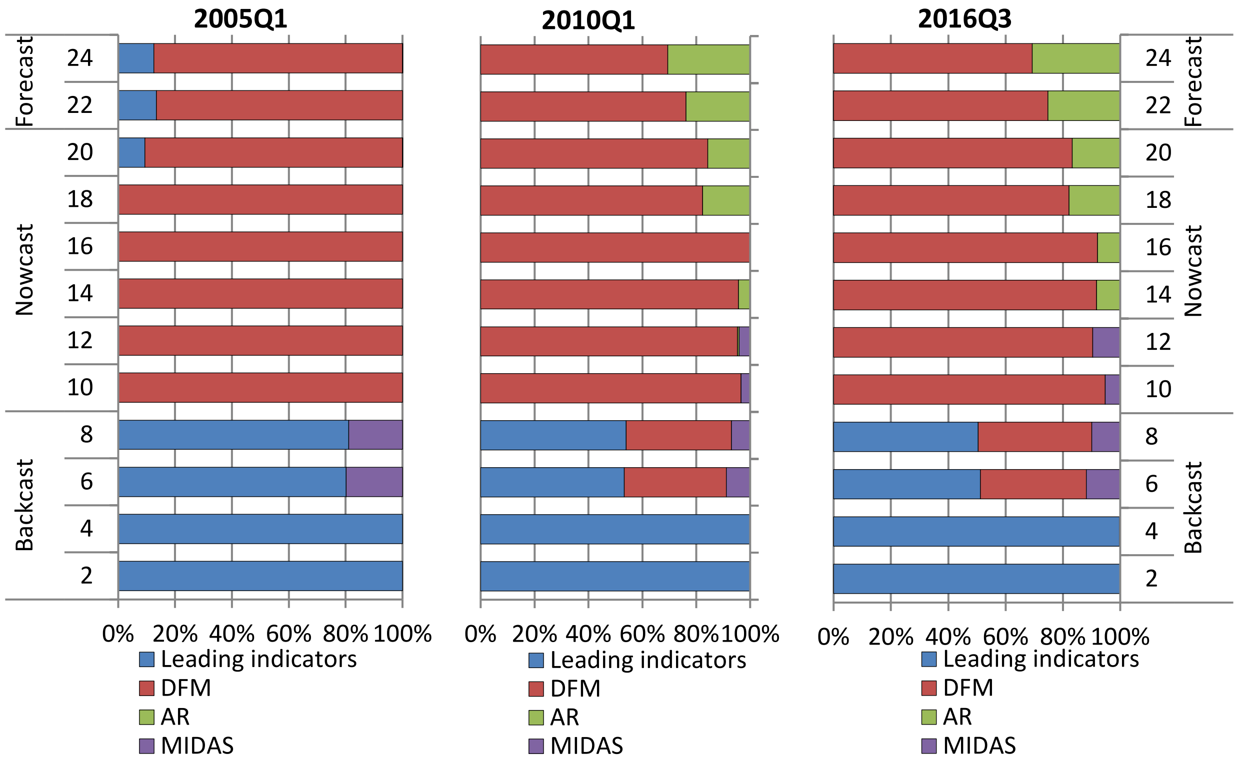


Figure C-9: **Investment: Estimated inverse RMSE weights**

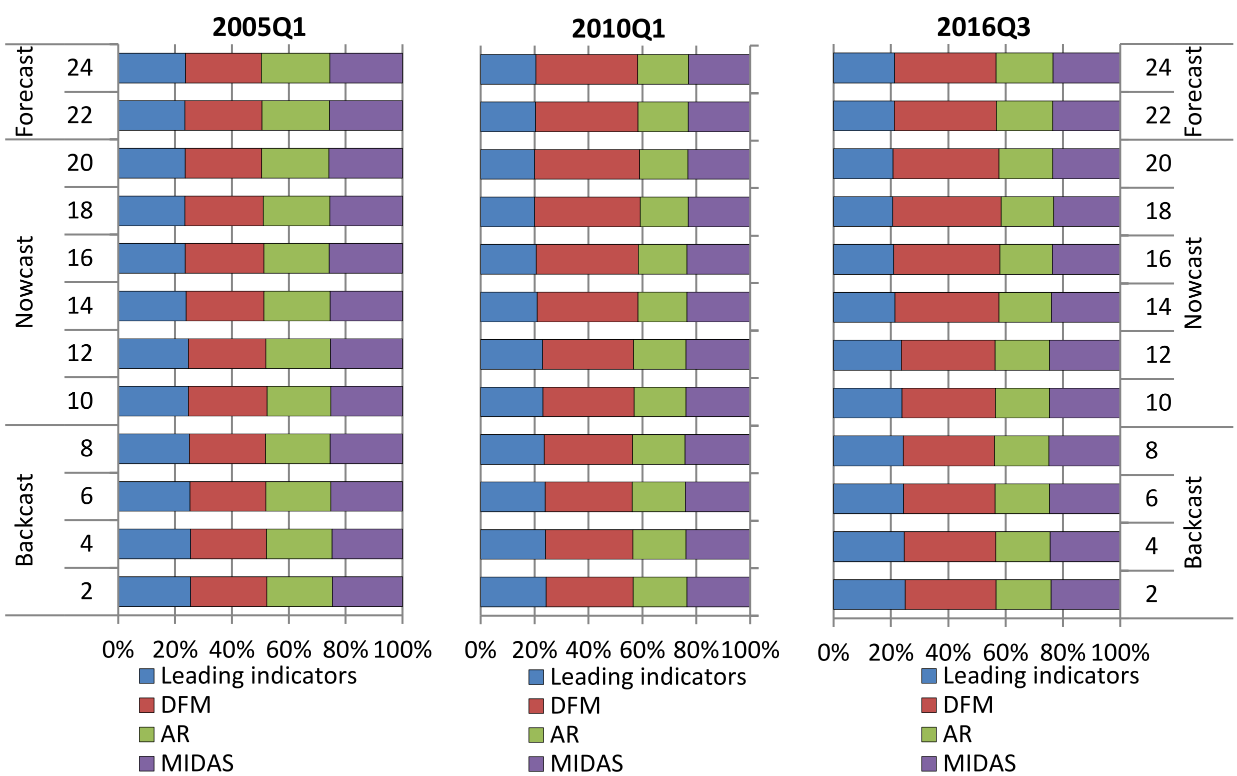
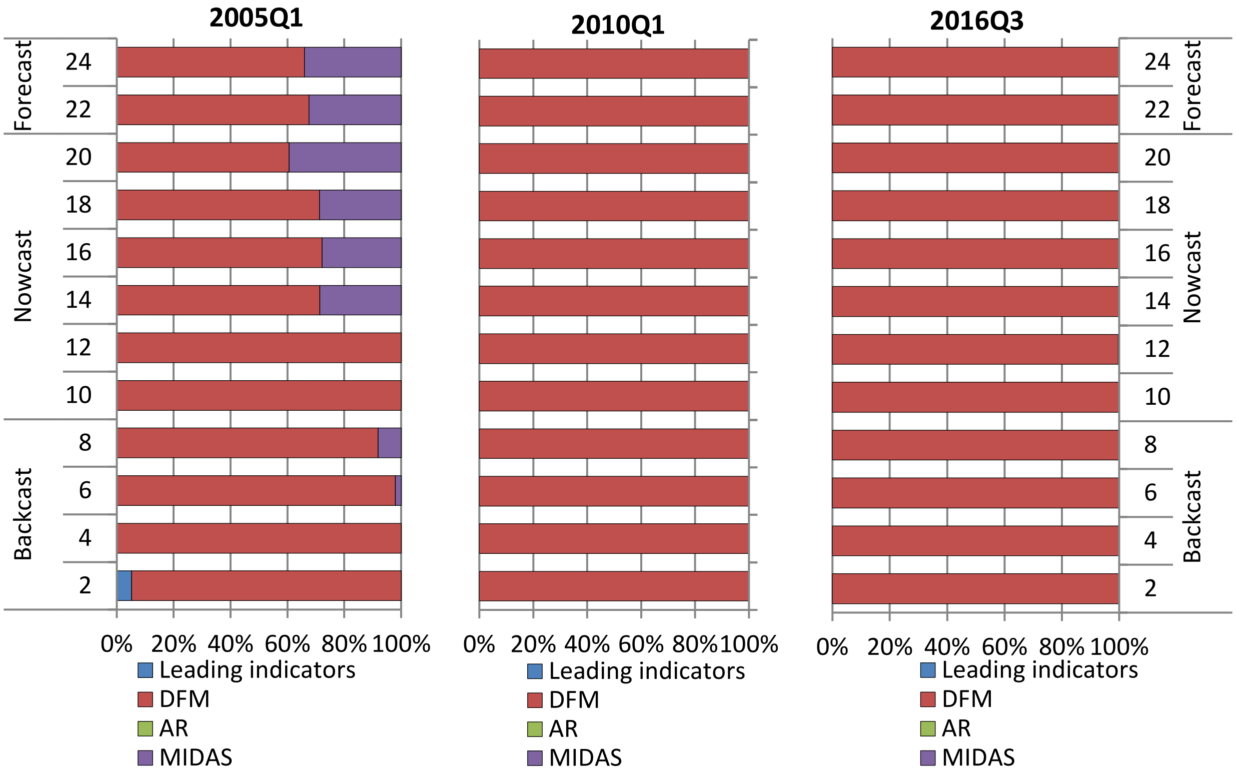


Figure C-10: Investment: Estimated OLS weights



Appendix D: List of Variables

Variable	Release Schedule	Components	Start Date	Transformation
GDP at Market Prices (Quarterly)	End	Y	Q2-61	4
GDP at Basic Prices (Monthly)	End	Y, I	Jan-81	3
Consumption (Quarterly)	End	C	Q2-61	4
Canadian Motor Vehicle Production	Middle	Y, X, M, C, H, I	Jan-93	5
Finished Goods Price Index	Beginning	Y, X, M, C, H, I	Jan-72	3
Canadian Terms of Trade	Beginning	Y, X, M, C, H, I	Jan-81	3
Manufacturing New Orders	Middle	Y, X, M, C, H, I	Jan-81	5
Railway Carloadings	End	Y, X, M, C, H, I	Jan-70	5
US Industrial Production	Middle	Y, X, M, C, H, I	Jan-21	3
US Retail Sales	Middle	Y, X, M, C, H, I	Jan-67	3
Wholesale Trade	Middle	Y, X, M, C, H, I	Jan-81	3
Total Actual Hours Worked	Beginning	Y, X, M, C, H, I	Jan-76	3
Retail Trade	End	Y, X, M, C, H, I	Jan-81	3
Canadian Car Sales	Beginning	Y, X, M, C, H, I	Jan-46	3
Housing Starts	Middle	Y, X, M, C, H, I	Jan-56	3
US Housing Starts	Middle	Y, X, M, C, H, I	Jan-59	3
Building Permits	Beginning	Y, X, M, C, H, I	Jan-48	5
Cement Production	Middle	Y, X, M, C, H, I	Jan-79	5
Merchandise Exports	Beginning	Y, X, M, C, H, I	Jan-68	3
Merchandise Imports	Beginning	Y, X, M, C, H, I	Jan-68	3
Toronto Stock Exchange	Beginning	Y, X, M, C, H, I	Jan-56	3
Consumer Confidence Index	End	Y, X, M, C, H, I	Mar-61	3
Global Purchasing Managers Indicator	Beginning	Y, X, M, C, H, I	Jan-98	3
US Car Sales	Beginning	Y, X, M, C, H, I	Jan-76	5
Food Services and Drinking Places Prices	End	Y, X, M, C, H, I	Jan-81	5
Employment Rate - Labour Force Survey	Beginning	Y, X, M, C, H, I	Jan-76	2
Chicago Fed National Activity Index	Beginning	Y, X, M, C, H, I	Mar-67	0
West Texas Intermediate Crude Oil Prices	End	Y, X, M, C, H, I	Jan-72	3
Baker Hughes Rig Count	Middle	Y, I	Jan-68	5
Composite Leading Index	End	Y, X, M, C, H, I	Jan-52	3
Baltic Dry Index	Beginning	Y, X	Jan-85	3
Manufacturing Sales Indicator	Middle	Y, X, M, C, H, I	Jan-97	5
BOS Future Sales Growth Indicator	End	Y, X, C, H	Q3-97	0
BOS Credit Conditions Indicator	End	Y, C, H	Q3-00	4
US GDP (Quarterly)	End	Y, X	Q3-65	4
US Purchasing Managers' Index	Beginning	I	Jan-48	3
Monthly Residential Unit Sales – MLS	Middle	C, H	Jan-80	3
Government of Canada Bond Yields	End	X, M, C, H, I	Nov-80	6

Stock Dividend Yield – Toronto Stock Exchange	Middle	X, M, C, H, I	Jan-56	1
Total Household and Business Credit	Beginning	X, M, C, H, I	Jan-69	1, 7
5-Year Government of Canada Bonds	End	X, M, C, H, I	Nov-80	1
6-Month Treasury Bill	End	X, M, C, H, I	May-59	1
US Corporate Bond Risk Spread	Beginning	X, M, C, H, I	Apr-53	0
Real Canadian Dollar Effective Exchange Rate Index	Middle	X, M, C, H, I	Jun-81	3
Real CAD/USD Exchange Rate	Middle	X, M, C, H, I	Jan-92	3
Short-Term Effective Household Credit Rate	Beginning	X, M, C, H, I	Mar-99	1
Household Credit Spread	Beginning	X, M, C, H, I	Jan-99	0
Canadian Bond Risk Spread	End	X, M, C, H, I	Dec-96	0
Service-producing Industries – GDP at Basic Prices	End	C	Jan-97	3
Retail Trade Excluding Autos – GDP at Basic Prices	End	C	Jan-91	3
Car and Truck Production	End	C	Jan-93	3
Car Production	Beginning	C	Jan-46	3
Truck Production	Beginning	C	Jan-46	3
Automobile Imports	Beginning	C	Jan-97	3
Financial Consumer Confidence Indicator	End	C	Mar-61	0
Future Financial Consumer Confidence Indicator	End	C	Mar-61	0
Employment Consumer Confidence Indicator	End	C	Mar-61	0
Major Purchase Consumer Confidence Indicator	End	C	Mar-61	0
Average Weekly Earnings – SEPH	End	C	Jan-91	3
Average Hourly Wage – LFS	Beginning	C	Jan-97	5
US Residents Travelling by Automobile, Same Day Entering Canada	Middle	C	Jan-72	3
Canadian Residents Travelling by Automobile, Same Day Returning to Canada	Middle	C	Jan-72	3
Non-Resident International Travellers Entering Canada	Middle	C	Jan-72	3
Canadian Residents from Abroad Entering or Returning to Canada	Middle	C	Jan-72	3
National Average of Cooling Degree Days	Beginning	C, H	Jan-80	2
National Average of Heating Degree Days	Beginning	C, H	Jan-80	2
Gasoline Prices	End	C	Jan-49	3
S&P 500 Index	Beginning	C, I	Oct-81	3
Consumer Credit	Beginning	C	Jan-71	3
Sporting Goods, Hobby, Book and Music Stores – Retail Trade	End	C	Jan-91	3
Imports of Consumer Goods	Beginning	C	Jan-97	3
Accommodation and Food Services – GDP at Basic Prices	End	C	Jan-81	3
Residential Structures – Quarterly GDP	End	H	Q1-81	4
Residential Building Construction – GDP at Basic Prices	End	H	Mar-81	3
Housing Absorptions Indicator	Middle	H	Jul-88	5
Construction Employment – LFS	Beginning	H	Jan-76	3
Construction Employment – SEPH	End	H	Jan-01	3
Repair Construction Indicator	End	H	Jan-97	3
Construction – GDP at Basic Prices	End	H	Jan-81	3
National Residential New Listings	Middle	H	Jan-80	3
Canadian Building Permits	Beginning	H	Jan-57	3

Apartment Housing Starts	Middle	H	Jul-88	5
Row House Housing Starts	Middle	H	Jul-88	5
Semi-Detached Housing Starts	Middle	H	Jan-90	3
Singles Housing Starts	Middle	H	Jan-90	3
Average MLS House Prices	Middle	H	Jan-80	5
Building Material, Garden Equipment and Supplies Dealers – Retail Trade	End	H	Jan-91	3
Real Estate and Leasing, Finance, Insurance LFS Employment	Beginning	H	Jan-76	3
Real Estate and Leasing, Finance, Insurance SEPH Employment	End	H	Jan-02	3
Teranet House Price Index	Middle	H	Apr-99	5
Housing Under Construction	Middle	H	Jul-88	5
Lumber Millwork Hardware and Other Building Supplies Sales	Middle	H	Jan-04	3
Real Estate and Leasing, Finance, Insurance SEPH Total Hours Worked	Beginning	H	Jan-87	3
LFS Construction Total Hours Worked	Beginning	H	Jan-87	3
SEPH Construction Total Hours Worked	End	H	Jan-01	3
Real Estate and Leasing, Finance, Insurance LFS Total Hours Worked	End	H	Jan-02	3
Newly Completed Units	Middle	H	Jan-67	3
Housing Inventories	Middle	H	Jan-92	3
Under Construction	Middle	H	Jan-72	3
Work Put In Place	End	H	Jan-94	5
Conversion Permits	Beginning	H	Jan-65	3
Renovation Permits (Singles)	Beginning	H	Jan-95	5
Renovation Permits (Multiples)	Beginning	H	Jan-95	5
Imports – Quarterly GDP	End	M	Q1-81	4
Euro Area 19: Industrial Production Index	Middle	X, M	Jan-91	3
Japan: Industrial Production Index	Middle	X, M	Jan-53	3
Euro Area Purchasing Managers' Index	Beginning	X, M	Jan-11	3
Japan Purchasing Managers' Index	Beginning	X, M	Jan-11	3
BOS Investment in Machinery and Equipment Indicator	End	I, M	Q3-97	0
Exports – Quarterly GDP	End	X	Q1-81	4
Retail Trade – GDP at Basic Prices	End	X	Jan-81	3
Manufacturing – GDP at Basic Prices	End	X	Jan-81	3
Transportation and Warehousing – GDP at Basic Prices	End	X	Jan-81	3
Canadian Industrial Production	End	X	Jan-97	3
Japan Industrial Production	Middle	X	Jan-98	5
US Employment	Beginning	X	Jan-48	3
Japan Retail Sales	Middle	X	Aug-78	3
UK Retail Sales	Middle	X	Jan-96	3
US Leading Indicators	Middle	X	Jan-60	0
Japan Leading Indicators	Middle	X	Jan-60	0
UK Leading Indicators	Middle	X	Jan-60	0
Non-Energy Exports	Beginning	X	Jan-88	3
Japan Housing Starts	End	X	Jan-65	3
Japan Employment	End	X	Jan-78	3

Japan Consumer Confidence	Beginning	X	Mar-73	0
UK Consumer Confidence	End	X	Jan-85	0
US Consumer Confidence	End	X	Jan-67	0
US Manufacturing Total Hours Worked	Middle	X	Jan-60	3
Japan Manufacturing Total Hours Worked	Beginning	X	Jan-90	3
Canadian Manufacturing Total Hours Worked	Beginning	X	Jan-87	3
Bank of Canada Commodity Price Index – Energy Products (USD)	Middle	I	Jan-72	3
Bank of Canada Commodity Price Index – Forest Products (USD)	Beginning	I	Jan-72	3
Brent Crude Oil ($/Barrel)	Beginning	I	Jan-72	3
Canada-US Exchange Rate	End	I	Nov-50	3
Engineering and Other Construction Activities – GDP at Basic Prices	End	I	Jan-07	3
Business Fixed Investment – Quarterly GDP	End	I	Q1-81	4
Industrial Machinery, Equipment and Parts Imports	Beginning	I	Jan-97	3
M&E Imports – Electronics	Beginning	I	Jan-97	3
Machinery Manufacturing – GDP at Basic Prices	End	I	Jan-97	3
Machinery and Equipment Manufacturing Sales	Middle	I	Jan-92	3
Natural Gas Prices	End	I	Jan-49	3
Non-Residential Construction	End	I	Jan-97	3
Non-Residential Building Permits	Beginning	I	Jan-48	3
Non-Residential Building Construction Indicator	Beginning	I	Q1-97	4
Support Activities for Mining, Oil and Gas Extraction – GDP at Basic Prices	End	I	Jan-97	3

Note: The transformation applied to each of the series: 0 = No Change, 1 = Log Level, 2 = M/M Difference, 3 = M/M Log Difference, 4 = Q/Q Log Difference, 5 = Seasonally Adjusted (X12) M/M Log Difference, 6 = Term Spread, 7 = Two-Month Moving Average

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