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Can the Business Outlook Survey Help Improve Estimates of the Canadian Output Gap?

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Abstract

The output gap is a key variable used to assess inflationary pressures in the economy, but estimates in real time are subject to uncertainty and often revised significantly. This paper assesses whether questions in the Bank of Canada's Business Outlook Survey (BOS) can provide useful signals for broader capacity pressures in the economy. The concept of capacity pressures is captured in the BOS through various questions on firms' ability to meet demand and labour shortages. In particular, we examine whether these BOS questions, as well as a summary measure of the BOS results, produce information that can be used to improve real-time output gap estimates for Canada. We find that survey data help predict the various measures of the output gap used by the Bank of Canada. This supports the Bank's practice of using information contained in the BOS to refine its assessment of the current state of the economic cycle. It further provides a framework for incorporating the survey information into quantitative estimates of the output gap.

Bank topics: Business fluctuations and cycles; Central bank research; Economic models; Monetary policy and uncertainty; Potential output

JEL codes: E3

1. Introduction

For central banks that target inflation, the link between inflation and the output gap is key to the conduct of monetary policy. The output gap—the difference between economic output and its potential level—is commonly used to gauge the state of the business cycle and provide signals for inflationary pressures in the economy. However, the output gap is unobservable and highly uncertain. Therefore, monetary policy decisions are made in a context of economic uncertainty.[1] To deal with economic uncertainty, the Bank of Canada uses various strategies, one of which is to consider a wide range of information. Two elements of this information set are relevant for this paper. First, the Bank uses various statistical models to estimate potential output to produce a range of output gap estimates. Second, the Bank derives signals on capacity pressures in the economy from businesses across the country through the Business Outlook Survey (BOS), which Bank staff in regional offices have conducted every quarter since the autumn of 1997. The BOS consultations are structured around a survey questionnaire, which includes questions aimed at assessing pressures on production capacity and labour shortages.

This paper examines to what extent firms' responses to qualitative questions in the BOS may help refine the Bank's assessment of the Canadian output gap in real time. It is well known that output gap estimates are highly unreliable in real time and subject to substantial revisions over time, as documented, for example, by Orphanides and van Norden (2002), Cayen and van Norden (2005) and Marcellino and Musso (2011). However, Champagne, Poulin-Bellisle and Sekkel (2018a) find that the reliability of the Bank's output gap estimates has improved significantly since the early 2000s. They attribute this improvement to the development and adoption of new statistical tools as well as to new sources of information—such as the BOS—that allow the Bank to better characterize the state of the business cycle in real time. In practice, Bank of Canada staff supplement the various model estimates with informal judgment from soft indicators, including the BOS questions on capacity pressures and labour shortages.[2]

Our paper builds on the findings of Champagne, Poulin-Bellisle and Sekkel (2018a) by formally testing the ability of BOS data to significantly improve upon the Bank's usual model estimates of the output gap in real time, and by assessing which variables have the most useful information content. BOS results have the advantage of not being revised, allowing us to evaluate their signalling power in real time. Several studies find that using survey data can help improve the reliability of output gap estimates or forecasts across several advanced economies (e.g., Graff and Sturm 2012; Kaufmann and Scheufele 2017; Galimberti and Moura 2016), but little has been published using Canadian data. We expand on the work of Pichette and Robitaille (2017), who assess the predictive content of the BOS for growth in real gross domestic product (GDP) and real business investment using real-time data vintages. In particular, we follow their approach of constructing nowcasts using autoregressive equations augmented with BOS variables.

We show that the BOS indicator (a summary measure of business sentiment) and responses to questions on capacity pressures and labour shortages contain useful information that can improve the Bank's

[1] Jenkins and Longworth (2002) discuss different sources of uncertainty that monetary authorities face.

[2] The output gap measures we use in this paper differ from the Bank of Canada staff output gap estimates assessed in Champagne, Poulin-Bellisle and Sekkel (2018a) in the sense that the former are used as inputs into the latter. Bank staff measures are not assessed in this paper because they already incorporate information from the BOS by construction.

assessment of the output gap in real time. In fact, the BOS indicator appears to be the most useful variable for predicting final output gap estimates. These results provide concrete support for the Bank of Canada's current practice of using BOS results to help assess the output gap. Our findings also provide a framework to incorporate BOS data in the output gap estimates derived from the various models used by the Bank.

This paper is organized as follows: The next section describes the data with a brief overview of the various measures of the output gap and the BOS variables pertaining to pressures on capacity. In section 3, we present the methodology used to assess the information content of the BOS using real-time data. We discuss the main results in section 4. Finally, section 5 provides concluding remarks.

2. Output gap estimates and survey data

In this section, we first briefly describe the models used at the Bank of Canada to derive the output gap estimates considered in this paper. Our focus is on three of the models developed to support Canada's monetary policy: a simplified version of the integrated framework (IF), the extended multivariate filter (EMVF) and the multivariate state-space framework (MSSF).[3] We use a database, constructed by Pichette et al. (2019), of real-time output gap estimates based on various models, including models that incorporate a large number of variables as inputs. Second, we describe the BOS data used to refine the Bank's assessment of capacity pressures in the economy.

2.1. Measures of output gap

Three of the models used at the Bank to estimate and project potential output (and the output gap) decompose it into trend labour input and trend labour productivity. The IF, a production-function approach, further decomposes trend labour input into the working-age population, trend employment rate and trend average weekly hours, while trend labour productivity is the sum of capital deepening and trend total factor productivity. This approach estimates the trend employment rate and trend average weekly hours with models that include variables such as interest rates, the job-offer rate, wealth, education level, an employment disincentive index and the share of the services sector in the economy.[4] As in Pichette et al. (2019), we use a simplified version of the IF (SIF) because real-time data do not exist for some of the variables used in the model.

The EMVF, developed by Butler (1996), is a mix of mechanical filtering (Hodrick–Prescott filter), end-of-sample conditions and conditioning information applied to labour productivity and to components of labour input (participation rate, unemployment, average hours worked). Pichette et al. (2015) propose a modified version of the EMVF, which we use in this paper. Output gap estimates based on the IF and EMVF are available on the Bank's website.

The third main approach in the Bank's tool kit, proposed by Pichette, Bernier and Robitaille (2018), is the MSSF. Their approach uses a state-space model developed by Blagrave et al. (2015) (which we refer to as

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[3] For more details, see Pichette et al. (2015) for the EMVF and IF, and Pichette, Bernier and Robitaille (2018) for the MSSF.

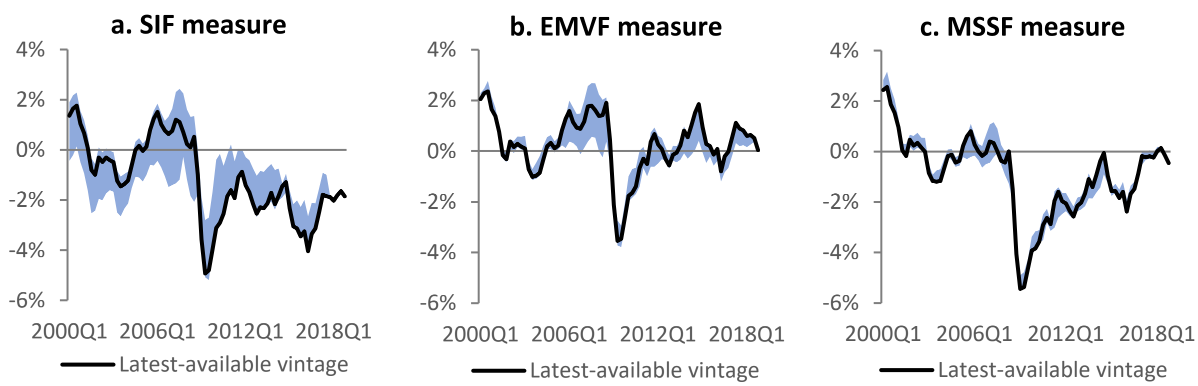
[4] Although not a structural method *sensu stricto*, the IF allows for some interpretation of potential output developments. For instance, it allows for some analysis of how demographic developments and shocks to physical capital investment can affect potential output.

the basic multivariate filter, BMVF). In the MSSF, each component of GDP (trend labour input and productivity) is modelled as a stochastic process similar to that assumed in the Blagrave et al. (2015) model, with three types of shocks: a level shock to the trend variable, a shock to the trend growth and a demand shock to the gap. They add a Phillips curve, Okun's law and consensus forecasts for output growth and inflation to help identify potential output.

In addition to these three approaches, we also include output gap estimates from the BMVF model proposed by Blagrave et al. (2015), as well as from two simple mechanical filters: the HP filter (HP) proposed by Hodrick and Prescott (1997) and the band-pass filter (BP) developed by Christiano and Fitzgerald (2003).

All estimates of the output gap are subject to revisions—sometimes substantial—as documented, for example, by Orphanides and van Norden (2002), Cayen and van Norden (2005) and Marcellino and Musso (2011). Those revisions originate from two main sources: (i) data revisions of the variables used to estimate potential output, and (ii) revisions implied by the statistical approaches. In the first case, revisions may come from multiple sources, ranging from new information gathered by Statistics Canada, to methodological changes. In the second case, it is well known that many techniques used to estimate trends suffer from end-of-sample limitations. Consequently, as we obtain more observations, we can refine those estimates. **Chart 1** illustrates the latest available output gap estimates for the SIF, EMVF and MSSF measures, along with the range of estimates from vintages since 2006Q1 (since 2007Q1 for the SIF).

Chart 1: Output gap estimates from different data vintages*



*The range of estimates from different data vintages is shown by the blue shaded area. Real-time vintages begin in 2007Q1 for the simplified version of the integrated framework (SIF) measure and in 2006Q1 for the extended multivariate filter (EMVF) and multivariate state-space framework (MSSF) measures.

Table 1 summarizes some key statistical properties of cumulative revisions to the various measures of the output gap after eight quarters. Similar to the literature, we assume that data must be close to final after eight revisions (e.g., Jacobs and Sturm 2004).[5] The table shows the mean, absolute mean and standard deviation of the revisions, as well as two measures of the noise-to-signal ratio (NSR, where NSR_1 is the ratio of the standard deviation of the revision to that of the output gap estimate after eight revisions, and NSR_2 is the ratio of the root mean square of the revision to the standard deviation of the gap estimate

[5] For most approaches used, statistics after eight revisions are similar to those that use the latest available vintage.

after eight revisions). It also shows the correlation between the output gap after eight revisions and the first release, and the frequency at which the sign of the output gap changes between the first release and the eighth revision.

Table 1: Properties of output gap revisions after eight quarters (sample: 2006Q4 to 2016Q4)

	Mean	Absolute mean	Standard deviation	NSR_1	NSR_2	Correlation	Freq. of opposite signs
MSSF	0.37	0.45	0.43	0.29	0.38	0.96	12%
BMVF	0.52	0.62	0.68	0.46	0.58	0.91	20%
HP filter	0.35	0.54	0.64	0.53	0.60	0.88	37%
BP filter	0.49	0.57	0.61	0.53	0.68	0.88	44%
EMVF	0.86	0.86	0.55	0.42	0.78	0.92	41%
SIF	0.28	1.13	1.39	0.84	0.85	0.56	24%

Note: NSR_1, a measure of noise-to-signal ratio, is the ratio of the standard deviation of the revision to that of the output gap estimate after eight revisions. NSR_2 is the ratio of the root mean square of the revision to the standard deviation of the gap estimate after eight revisions. The Correlation column shows the correlation between the output gap after eight revisions and the first release. The final column shows the frequency at which the sign of the output gap changes between the first release and the eighth revision. The first column lists the various output gap measures examined: the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP), the band-pass filter (BP), the extended multivariate filter (EMVF) and the simplified version of the integrated framework (SIF).

As documented in Champagne, Poulin-Bellisle and Sekkel (2018a), **Table 1** shows that for all approaches, output gap estimates tend to be revised up on average, implying some downward biases in the first estimates.[6] This is highlighted by the similarity between mean and absolute mean revisions, and it is particularly evident for the EMVF, which is significantly revised, consistently on the upside. This tendency to overestimate the size of excess supply following a recession is consistent with results from previous studies (e.g., Grigoli et al. 2015).

The standard deviation provides a signal about the volatility of the revisions. Revisions to the SIF are the most volatile across all approaches. As explained in Pichette et al. (2019), this partly reflects the large revisions to the data feeding into this method, including data on capital stock and the job offer rate. However, revisions to some of these data may be smaller going forward; for instance, since 2016, Statistics Canada has been publishing new job vacancy data that are used in calculating the job offer rate and should be more reliable.

2.2. BOS data

Because the output gap is defined as the difference between the level of real output and the level of potential output, it is an aggregate measure of excess or spare capacity in the economy. Potential output can thus be related to the microeconomic concept of full capacity, which is commonly interpreted as the maximum quantity of output that can be produced under normal conditions, when capital and labour operate the usual number of hours producing the normal mix of output (Klein and Long 1973). This “maximum practical capacity” is the definition used in measuring Statistics Canada’s rates of capacity

[6] Mean revisions from the first release to the latest available data are somewhat smaller than after eight revisions, and were in fact slightly negative for the SIF measure.

utilization for goods-producing industries. Capacity utilization rates are commonly recognized in the literature as a determinant of inflation (Stock and Watson 1999; Cooley, Hansen and Prescott 1995). Since capital and labour are largely fixed in the short run, working them beyond their optimum levels can bid up the cost for each incremental unit of output. Firms facing capacity constraints may thus respond to demand increases by raising prices.

The BOS questionnaire includes three questions designed to capture capacity pressures in the economy (see Appendix for the wording of these questions).[7] The first question asks firms to rate their current ability to meet an unexpected increase in demand as either "no difficulty," "some difficulty" or "significant difficulty." The variable (which we refer to as capacity pressures, or *CAPP*) is defined as the proportion of firms reporting they would have some or significant difficulty. Those firms are then asked a follow-up question to identify the most important bottlenecks they would face in meeting the demand.[8]

The second question asks whether the firm is facing any shortages of labour that restrict its ability to meet demand. In this case, the variable for labour shortages (referred to as *LS*) is defined as the proportion of firms responding "yes." Finally, the third question, added to the survey in 2001 to better assess the evolution of those labour shortages, asks firms whether labour shortages are generally more intense, less intense or about the same intensity compared with 12 months ago. The resulting measure of labour shortage intensity (referred to as *LSI*) is constructed as a balance of opinion, obtained by subtracting the percentage of firms answering "less intense" from the percentage responding "more intense." Overall, responses from these three BOS questions are well correlated with measures of output gap and indicators of labour market conditions (see Bank of Canada 2015).

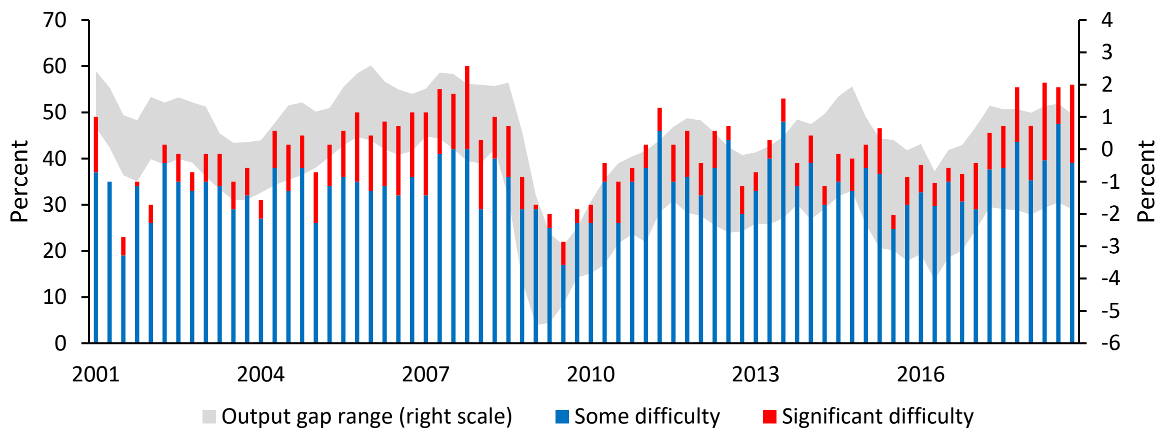
Finally, we also consider a fourth variable, called the BOS indicator (referred to as *BOSi*)—a summary measure of the main survey questions that serves as a gauge of overall business sentiment. This indicator was developed by Pichette and Rennison (2011) using principal-component analysis (PCA) to extract common movements from the different BOS variables.[9] In addition to capturing a common source of variation, the BOS indicator provides an appealing alternative to using all survey questions in a forecasting exercise, since it conserves degrees of freedom and lessens concerns about issues of multicollinearity. The BOS indicator can be useful for measuring the output gap because, in addition to the responses from questions on production capacity, it includes related variables such as output price expectations.[10]

[7] For more details, see Martin and Papile (2004), Bank of Canada (2015) and Amirault, Rai and Martin (forthcoming).
[8] In a general equilibrium system, capacity can be measured as the "bottleneck" point in expansion given a fixed product mix (Malenbaum 1969; Griffin 1971): when a bottleneck constrains production of one input, it may restrict all other dependent inputs to below full utilization, defining the maximum output point for a given product mix. The BOS question on capacity pressures captures this broader concept of capacity, recognizing that scarcity of inputs in the wider macroeconomy may restrict a firm's production even if it is operating below its own full production capacity.
[9] See Box 1 in the *Business Outlook Survey—Spring 2017*.
[10] Although responses to BOS questions are never revised, the BOS indicator is revised every quarter, as coefficients of the PCA are re-estimated when new observations are available. However, as shown in Pichette and Robitaille (2017), revisions to the BOS indicator are very small and tend to decrease as the sample period of the BOS lengthens.

The *CAPP*, *LS*, *LSI* and *BOSi* variables are plotted against the range of the various output gap estimates (latest vintage) in **Chart 2**, **Chart 3**, **Chart 4** and **Chart 5**.

Chart 2: Business Outlook Survey measure of capacity pressures

Percentage of firms that would have difficulty meeting an unanticipated increase in demand

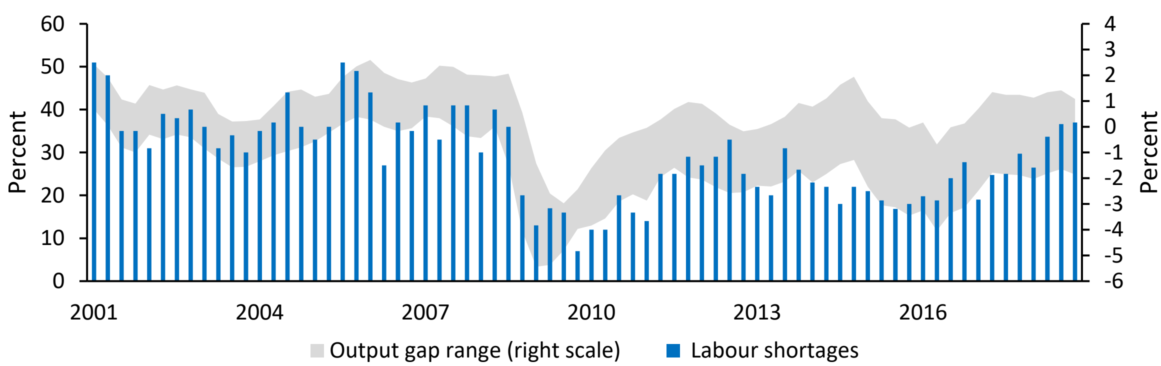


Source: Bank of Canada

Last observation: 2018Q4

Chart 3: Business Outlook Survey measure of labour shortages

Percentage of firms facing shortages of labour that restrict their ability to meet demand

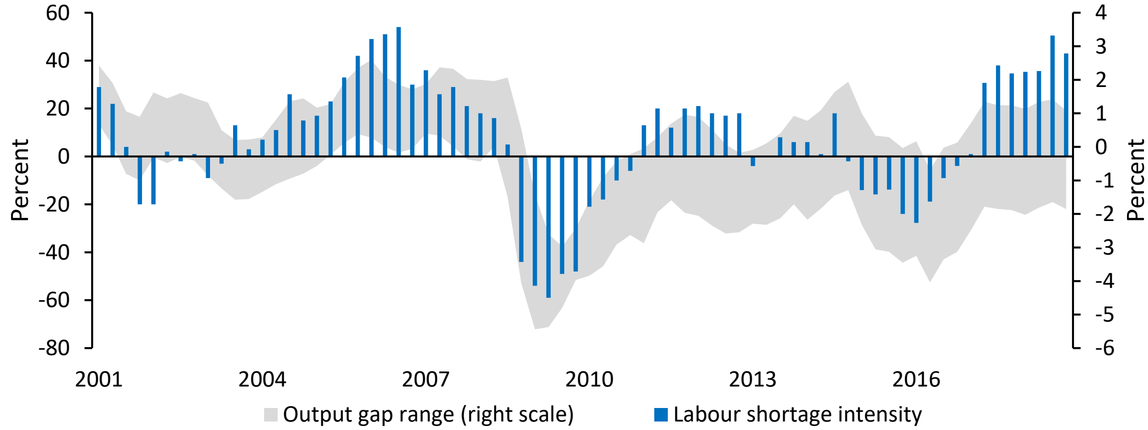


Source: Bank of Canada

Last observation: 2018Q4

Chart 4: Business Outlook Survey indicator of labour shortage intensity

Balance of opinion: Percentage of firms reporting labour shortages are more intense than 12 months ago minus percentage of firms reporting they are less intense

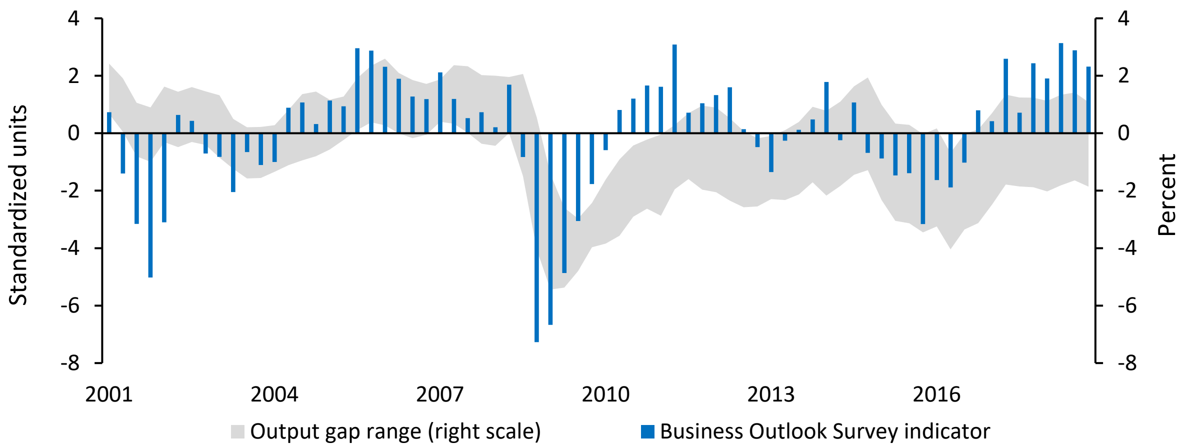


Source: Bank of Canada

Last observation: 2018Q4

Chart 5: Business Outlook Survey indicator

Created from the first principal component of 10 core BOS indicators



Note: BOS is Business Outlook Survey.
Source: Bank of Canada

Last observation: 2018Q4

3. Methodology

To assess the information content of the BOS, we adopt four approaches. In the first, we perform simple regressions using only the latest available vintages for the output gap. This is the conventional method used when the real-time perspective is not taken into account. Second, the same specifications are estimated using the method proposed by Koenig, Dolmas and Piger (2003), which uses the first-release data. Third, following Stark and Croushore (2002), we conduct various real-time forecasting performance exercises using different sets of data vintages. The objectives of these exercises are to examine whether data vintages matter when assessing the predictive content of the BOS and to determine whether the BOS is better at forecasting revised or unrevised output gap estimates. Fourth, we test whether BOS data can be used to predict future revisions to the output gap.

For the first approach, we estimate the following equations:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon_t \tag{1}$$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 BOS_t + \varepsilon_t, \tag{2}$$

where y_t is the output gap estimate for quarter *t* and BOS_t is any of the BOS variables described in the previous section. In this case, the output gap estimates are from the latest available vintage, and we perform a pseudo real-time analysis to see whether the BOS adds any information beyond that contained in the lagged output gap to nowcast the current one.

In the second approach, we follow the methodology of Koenig, Dolmas and Piger (2003), who suggest that for optimal use of the real-time data, equations should be estimated using the first-release data only. This means using only the first-release data at each point in time for each of the variables to estimate the equation parameters.[11] The argument supporting this method assumes that the revisions consist of new information, and therefore that the first-release data are an efficient estimate of subsequent releases and will capture the empirical relationship between variables most relevant for forecasting. Let $y_{t,v}$ represent the realization *of y* in period (or quarter) *t* as reported in vintage *v*. Since the first estimate for the output gap *y* in period *t* is available in period *t+1*, when GDP for quarter *t* is first released, the equations can be rewritten as follows:

$$y_{t,t+1} = \beta_0 + \beta_1 y_{t-1,t} + \varepsilon_t \tag{3}$$

$$y_{t,t+1} = \beta_0 + \beta_1 y_{t-1,t} + \beta_2 BOS_{t,t} + \varepsilon_t. \tag{4}$$

Since this estimation method also uses a single set of historical data, the first release, we test the forecasting performance of these equations using a typical pseudo out-of-sample forecasting exercise.

In the third approach, we conduct a real-time out-of-sample forecasting exercise as proposed by Stark and Croushore (2002), which uses a wider range of vintages and historical data. Specifically, at each quarter *t*, we estimate the equations using the data vintage that was available at that point in time to produce a nowcast for the output gap in quarter *t*. Because the available data vintage at each quarter *t* will contain the first-release estimate for the output gap from quarter *t-1* and the BOS survey data for quarter *t,* we can thus rewrite the equations as follows:

$$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \varepsilon_t \tag{5}$$

$$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} BOS_{t,v} + \varepsilon_t. \tag{6}$$

[11] If there were more than one lag of the dependent variable on the right side of the equation, the inclusion of subsequent releases of data would be required.

Here, we estimate the equations recursively with each vintage of data *v*, starting with the first vintage from 2007Q1 until the latest vintage in 2019Q1. Within each vintage, *t* runs from 2001Q1 to *v* minus one quarter. With those models above, we examine (i) whether the BOS variables are useful to predict the output gap, and (ii) if so, which vintage they are most useful for.

In the fourth approach, we test whether BOS variables contain information that may explain future output gap *revisions*. To the extent that initial estimates of the output gap might be inefficient, we test whether BOS variables could thus be used to improve upon the first estimate. This strategy was adopted by Jacobs and Sturm (2004, 2009) for German industrial production and Swiss current account data respectively, and by Graff and Sturm (2012) for OECD output gap estimates. We consider the below specification based on that of Graff and Sturm (2012):

$$y_{t,t+X} - y_{t,t+1} = \beta_0 + \beta_1 \cdot y_{t,t+1} + \beta_2 BOS_{t,t} + \varepsilon_t. \tag{7}$$

In this case, we aim to test whether BOS variables at time *t* contain information beyond that included in the first estimate of the output gap for time *t* (available in the data vintage at time *t+1*) that can explain subsequent *revisions* incorporated into the final estimate at time *t+X*. Under the hypothesis that first estimates of the output gap are efficient and incorporate all information available up to that point, subsequent revisions would contain only new information and should thus be unpredictable and orthogonal to the first release. This hypothesis is rejected if the parameter estimate for β_1 is statistically different from zero. Furthermore, if β_2 is statistically significant, it means that using the BOS variables available at the time can help produce estimates that are closer to the final output gap. We estimate equation (7) for all output gap estimates up to time *t+8*, using the eighth revision as a proxy for the final estimate.

4. Empirical results

In this section we start by discussing the results from using the first three approaches to assess the information content of the BOS data for the output gap. We then turn to the fourth approach and evaluate whether the BOS can explain subsequent revisions to the output gap. Finally, we test the robustness of these results by controlling for other relevant variables that would normally be available in real time, such as the unemployment rate, monthly GDP at basic prices, the exchange rate and commodity prices.

4.1 Reduced-form equations for the output gap

In **Table 2** we summarize the results from the first approach—where equations (1) and (2) are estimated using the latest available vintage of output gap estimates—for the various measures of the output gap and BOS variables considered. The estimation sample begins in 2001Q1, since this is when all relevant BOS series are available. Although output gap estimates are available from 1981Q1 for most measures (and 1989Q4 for the BMVF and MSSF measures), real-time vintages for the full set of measures are available only from 2007Q1, with the latest vintage of 2019Q1 providing a first estimate for the output gap in 2018Q4. Using the eighth revision as a proxy for the final data, we cut off the sample period at 2016Q4, as this guarantees that each observation has undergone at least eight quarterly revisions. **Table 3** shows the corresponding results for the second approach, where equations (3) and (4) are estimated using the first estimate of the output gap. In this case, the estimation sample begins only in 2006Q4 because vintages prior to this period, and thus first estimates, are not available for all output gap measures.

Table 2: In-sample results using latest vintage of output gap estimates (2001Q1 to 2016Q4)

		SIF	EMVF	MSSF	BMVF	HP	BP
	y_{t-1}	**0.92*** **	**0.86*** **	**0.9*** **	**0.89*** **	**0.85*** **	**0.89*** **
1	*R2-adj*	*0.86*	*0.75*	*0.85*	*0.82*	*0.73*	*0.83*
	y_{t-1}	**0.85*** **	**0.71*** **	**0.88*** **	**0.81*** **	**0.68*** **	**0.75*** **
	$CAPP_t$	**2.77***	**4.08*** **	0.95	**3.13** **	**4.35*** **	**3.67*** **
2a	*R2-adj*	*0.87*	*0.8*	*0.85*	*0.84*	*0.79*	*0.88*
	y_{t-1}	**0.73*** **	**0.69*** **	**0.77*** **	**0.73*** **	**0.67*** **	**0.77*** **
	LSI_t	**1.89*** **	**1.55*** **	**1.2** **	**1.64*** **	**1.57*** **	**1.21*** **
2b	*R2-adj*	*0.9*	*0.83*	*0.87*	*0.88*	*0.81*	*0.89*
	y_{t-1}	**0.73*** **	**0.72*** **	**0.81*** **	**0.73*** **	**0.7*** **	**0.79*** **
	LS_t	**4.4** **	**3.49***	1.7	**3.95** **	**3.78** **	**2.48***
2c	*R2-adj*	*0.88*	*0.79*	*0.82*	*0.84*	*0.78*	*0.82*
	y_{t-1}	**0.86*** **	**0.81*** **	**0.83*** **	**0.86*** **	**0.79*** **	**0.83*** **
	$BOSi_t$	**0.18*** **	**0.18*** **	**0.15*** **	**0.17*** **	**0.18*** **	**0.16*** **
2d	*R2-adj*	*0.91*	*0.85*	*0.89*	*0.89*	*0.84*	*0.93*
	y_{t-1}	**0.93*** **	**0.74*** **	**0.92*** **	**0.87*** **	**0.68*** **	**0.79*** **
	$CAPP_t$	**3.21** **	**3.85*** **	2.27	**3.38** **	**4.00*** **	**3.56*** **
	$CAPP_{t-1}$	0.57	1.71	-2.33	1.05	2.1	0.99
	$CAPP_{t-2}$	**-3.63** **	-2.07	-1.04	**-2.92***	-1.79	-1.45
2e	*R2-adj*	*0.89*	*0.81*	*0.86*	*0.85*	*0.8*	*0.88*
	y_{t-1}	**0.81*** **	**0.69*** **	**0.87*** **	**0.79*** **	**0.66*** **	**0.75*** **
	$CAPSOME_t$	1.77	**3.32***	0.89	2.5	**3.54** **	**3.2*** **
	$CAPSIG_t$	**5.75***	**5.73** **	1.09	**4.58***	**6.08** **	**4.58*** **
2f	*R2-adj*	*0.87*	*0.8*	*0.85*	*0.84*	*0.79*	*0.88*
	y_{t-1}	**0.84*** **	**0.78*** **	**0.88*** **	**0.82*** **	**0.76*** **	**0.90*** **
	LSI_t	**1.78*** **	**1.36** **	**2.38*** **	**1.52*** **	**1.36** **	**1.67*** **
	LSI_{t-1}	0.95	1.13	-1.21	1.01	1.14	0.11
	LSI_{t-2}	**-1.66*** **	**-1.36** **	-0.71	**-1.42** **	**-1.31** **	**-1.06*** **
2g	*R2-adj*	*0.91*	*0.83*	*0.88*	*0.88*	*0.82*	*0.91*
	y_{t-1}	**0.64*** **	**0.68*** **	**0.68*** **	**0.69*** **	**0.64*** **	**0.73*** **
	LS_t	1.24	-0.03	-0.86	0.47	0.31	-0.88
	LSI_t	**1.96*** **	**1.71*** **	**1.85*** **	**1.73*** **	**1.75*** **	**1.71*** **
2h	*R2-adj*	*0.91*	*0.84*	*0.85*	*0.88*	*0.84*	*0.91*
	y_{t-1}	**0.72*** **	**0.65*** **	**0.77*** **	**0.72*** **	**0.63*** **	**0.73*** **
	$CAPP_t$	0.33	1.86	-1.13	0.6	2.13	**2.03***
	LSI_t	**1.83*** **	**1.25*** **	**1.42** **	**1.53*** **	**1.23*** **	**0.87*** **
2i	*R2-adj*	*0.9*	*0.83*	*0.87*	*0.88*	*0.82*	*0.9*

*, * and *** represent statistical significance at the 10%, 5% and 1% levels respectively.

Note: The first row lists the various output gap measures examined: the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), including the share of firms that have some difficulty (CAPSOME) or significant difficulty (CAPSIG) meeting an unexpected increase in demand; labour shortages (LS); and labour shortage intensity (LSI).

Table 3: In-sample results using first estimate of output gap estimates (2006Q4 to 2016Q4)

		SIF	EMVFM	MSSF	BMVF	HP	BP
	$y_{t-1,t}$	**0.75*** **	**0.87*** **	**0.91*** **	**0.86*** **	**0.77*** **	**0.88*** **
3	*R2-adj*	*0.54*	*0.75*	*0.84*	*0.74*	*0.59*	*0.76*
	$y_{t-1,t}$	**0.69*** **	**0.7*** **	**0.86*** **	**0.73*** **	**0.59*** **	**0.7*** **
	$CAPP_t$	1.36	**3.2** **	1.24	**2.92* **	**2.91** **	**2.49** **
4a	*R2-adj*	*0.54*	*0.79*	*0.84*	*0.77*	*0.65*	*0.81*
	$y_{t-1,t}$	**0.57*** **	**0.66*** **	**0.74*** **	**0.73*** **	**0.59*** **	**0.66*** **
	LSI_t	1.21	**1.36*** **	**1.2** **	**1.15*** **	**1.06*** **	**0.92*** **
4b	*R2-adj*	*0.57*	*0.84*	*0.88*	*0.81*	*0.71*	*0.84*
	$y_{t-1,t}$	**0.76*** **	**0.74*** **	**0.84* **	**0.73*** **	**0.66*** **	**0.81*** **
	LS_t	-0.63	**2.31* **	1.46	**2.52* **	**1.86* **	0.96
4c	*R2-adj*	*0.53*	*0.77*	*0.85*	*0.76*	*0.62*	*0.77*
	$y_{t-1,t}$	**0.54*** **	**0.81*** **	**0.82*** **	**0.85*** **	**0.74*** **	**0.78*** **
	$BOSi_t$	**0.18** **	**0.14*** **	**0.15*** **	**0.12*** **	**0.11*** **	**0.1*** **
4d	*R2-adj*	*0.61*	*0.84*	*0.9*	*0.8*	*0.69*	*0.85*
	$y_{t-1,t}$	**0.71*** **	**0.73*** **	**0.94*** **	**0.75*** **	**0.58*** **	**0.8*** **
	$CAPP_t$	2.55	**2.86* **	1.91	**2.49* **	**2.44* **	**2.58*** **
	$CAPP_{t-1}$	0.65	2.02	-1.01	2.19	2.11	0.85
	$CAPP_{t-2}$	-3.28	-2.26	-1.74	-2	-1.56	**-2.12** **
4e	*R2-adj*	*0.55*	*0.8*	*0.85*	*0.78*	*0.67*	*0.84*
	$y_{t-1,t}$	**0.69*** **	**0.69*** **	**0.87*** **	**0.71*** **	**0.59*** **	**0.7*** **
	$CAPSOME_t$	1.75	**2.8* **	1.38	2.36	**2.83* **	**2.83** **
	$CAPSIG_t$	0.65	**4.05* **	0.67	**4.24* **	3.05	1.93
4f	*R2-adj*	*0.53*	*0.79*	*0.84*	*0.77*	*0.64*	*0.81*
	$y_{t-1,t}$	**0.60*** **	**0.77*** **	**0.92*** **	**0.83*** **	**0.65*** **	**0.79*** **
	LSI_t	0.75	**1.13** **	**2.47*** **	0.78	0.36	**0.69** **
	LSI_{t-1}	**3.19** **	1.16	**-1.16**	**1.65** **	**1.84** **	**1.06** **
	LSI_{t-2}	**-3.17*** **	**-1.34** **	**-0.99* **	**-1.67** **	**-1.34*** **	**-1.19*** **
4g	*R2-adj*	*0.67*	*0.86*	*0.91*	*0.83*	*0.74*	*0.87*
	$y_{t-1,t}$	**0.44** **	**0.67*** **	**0.76*** **	**0.73*** **	**0.6*** **	**0.68*** **
	LS_t	-5.63	-0.68	-0.76	-0.26	-0.72	-1.16
	LSI_t	**3.1** **	**1.5*** **	**1.33** **	**1.2** **	**1.22** **	**1.18*** **
4h	*R2-adj*	*0.63*	*0.84*	*0.87*	*0.8*	*0.7*	*0.85*
	$y_{t-1,t}$	**0.58*** **	**0.65*** **	**0.76*** **	**0.72*** **	**0.57*** **	**0.63*** **
	$CAPP_t$	-0.98	0.43	-1.14	0.29	0.73	1.1
	LSI_t	1.45	**1.29*** **	**1.38** **	**1.09** **	**0.93** **	**0.73** **
4i	*R2-adj*	*0.56*	*0.84*	*0.87*	*0.8*	*0.7*	*0.84*

*, * and *** represent statistical significance at the 10%, 5% and 1% levels respectively.

Note: The first row lists the various output gap measures examined: the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), including the share of firms that have some difficulty (CAPSOME) or significant difficulty (CAPSIG) meeting an unexpected increase in demand; labour shortages (LS); and labour shortage intensity (LSI).

Each column represents the results from each equation using a different output gap measure. The first row in **Table 2** and **Table 3** shows the results from the baseline autoregressive equations (1) and (3), which indicate a high degree of persistence in all output gap measures, with the adjusted R^2 ranging from

50 percent to roughly 85 percent. The rows (2a) to (2i) in **Table 2** (and rows 4a to 4i in **Table 3**) display results when the first equation is augmented with various combinations of the BOS variables—*CAPP*, *LS*, *LSI* and *BOSi*. We also test whether including lags of the BOS variables affects the results, shown in rows 2e and 2g of **Table 2** (rows 4e and 4g in **Table 3**). We further test whether the results differ when *CAPP* is split into two components: the share of firms responding that they would face "some" difficulty meeting an unexpected increase in demand (*CAPSOME*), and the share reporting that they would face "significant" difficulty (*CAPSIG*). These results are shown in row 2f of **Table 2** and row 4f of **Table 3**.

The results suggest that the *CAPP*, *LS*, *LSI* and *BOSi* variables all contain information that is statistically significant for most measures of the output gap when included individually in the equation. Because of the high degree of persistence in the autoregressive component, however, the BOS variables explain only about 5 to 10 percent of the historical variation in the output gap, based on gains in the adjusted R^2. All survey variables appear to be most informative for the output gap contemporaneously. Splitting *CAPP* into *CAPSOME* and *CAPSIG* does not generally improve the fit of the equation but reveals a larger coefficient and often higher statistical significance for *CAPSIG*, although this applies mainly to the final output gap estimates. Among the three BOS capacity measures, the *LSI* tends to improve the in-sample fit the most and renders both *CAPP* and *LS* insignificant when included simultaneously. This result suggests that the variables contain similar information, and that the LSI has the highest signalling power for the output gap among the three BOS capacity measures. Of all the variables, however, *BOSi* appears to generate the best fit across most output gap measures.

For the real-time forecasting exercise, out-of-sample nowcasts are produced over the period from 2007Q1 to 2016Q4. Starting with an initial sample window from 2001Q1 to 2006Q4, an output gap nowcast is produced for 2007Q1 from each of the various equations using the data vintage that would have been available in that quarter. The sample window is then expanded by one quarter, and the nowcast shifts forward by one period using the vintage available in 2007Q2 to estimate the equations, and so on. Although the "actual" output gap is unobservable, we take the latest available vintage as the closest approximation to the true value, assuming each revision adds relevant information and hence accuracy improvements. We thus calculate the forecast errors by comparing the nowcasts against the output gap estimates in the latest vintage.[12] Root mean square forecast errors (RMSEs) are constructed from this forecasting exercise for each of the equations (6a) to (6i). Their forecast performance is then compared with that of the baseline equation (5) by examining the ratio of each equation's RMSE relative to that of the baseline in **Chart 6**, with a value below one (depicted by the black line) indicating that the equation outperforms the baseline.

[12] Forecast errors are also calculated against the first estimate and eighth revision of each output gap measure. These results are not shown but are available upon request. For the most part, the results for the eighth revision are very similar to those for the latest vintage, supporting the hypothesis in the literature that the data are close to final after eight revisions; the main exception is for the SIF measure, probably because this measure is subject to larger revisions than other measures (see **Chart 1**).

Chart 6: Out-of-sample real-time forecast performance of equations with Business Outlook Survey variables relative to baseline equation

Equation	Specification
5	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \varepsilon_t$
6a	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} CAPP_t + \varepsilon_t$
6b	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} LSI_t + \varepsilon_t$
6c	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} LS_t + \varepsilon_t$
6d	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} BOSi_{t,v} + \varepsilon_t$
6e	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} CAPP_t + \beta_{3_v} CAPP_{t-1} + \beta_{4_v} CAPP_{t-2} + \varepsilon_t$
6f	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} CAPSOME_t + \beta_{3_v} CAPSIG_t + \varepsilon_t$
6g	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} LSI_t + \beta_{3_v} LSI_{t-1} + \beta_{4_v} LSI_{t-2} + \varepsilon_t$
6h	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} LS_t + \beta_{3_v} LSI_t + \varepsilon_t$
6i	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} CAPP_t + \beta_{3_v} LSI_t + \varepsilon_t$

Note: The output gap measures are the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), including the share of firms that have some difficulty (CAPSOME) or significant difficulty (CAPSIG) meeting an unexpected increase in demand; labour shortages (LS); and labour shortage intensity (LSI).

The results shown in **Chart 6** suggest that, in most cases, equations including the BOS variables *CAPP* (6a), *LSI* (6b) and *BOSi* (6d) produce superior out-of-sample nowcasts for the output gap, with smaller RMSEs relative to the baseline autoregressive equation. This suggests that information contained in the BOS can be exploited in real time to produce estimates that are closer to the final output gap. Using tests developed by Clark and McCracken (2009), we find that, although not all improvements are statistically significant, the addition of the *BOSi* variable provides significant gains in accuracy across most measures of output gaps.

4.2 Forecasting revisions

Results for equation (7), in which we assess the information content of the BOS variables for *revisions* in the output gap after eight quarters, are displayed in **Table 4**. For all output gap measures, the percentage of firms that indicate they would have difficulty meeting an unexpected increase in demand (*CAPP)* helps explain future revisions. This is even more evident with the percentage of firms saying they would have serious difficulties (*CAPSIG*); this variable has an even larger coefficient, as shown in equation (7f), which boasts the highest adjusted R^2. Similarly, the *LS* and *LSI* variables are also significant and provide a relatively good fit. While the *BOSi* is significant, it contributes to a more modest increase in the adjusted R^2. In almost all cases, adding BOS variables in the equation makes the estimated parameter on the first estimate of the output gap become insignificant. These results suggest that the first estimate of the output gap is informationally inefficient, and that considering firms' responses to the BOS capacity questions may help predict the upcoming revisions after eight quarters.

Table 4: Predicting output gap revisions from first estimate to 8th revision (2006Q4 to 2016Q4)

		SIF	EMVFM	MSSF	BMVF	HP	BP
	$y_{t-1,t}$	-0.2	**0.18****	**0.14*****	**0.32*****	**0.41*****	**0.4*****
7	*R2-adj*	*0*	*0.08*	*0.14*	*0.21*	*0.21*	*0.2*
	$y_{t-1,t}$	**-0.6*****	-0.08	0.04	0.06	0.05	-0.02
	$CAPP_t$	**11.44*****	**4.49*****	**2.17****	**5.11*****	**5.08*****	**5.17*****
7a	*R2-adj*	*0.36*	*0.31*	*0.22*	*0.44*	*0.46*	*0.45*
	$y_{t-1,t}$	**-0.73*****	-0.09	-0.03	0.06	-0.04	-0.23
	LSI_t	**3.9*****	**1.47*****	**1.17*****	**1.89*****	**1.99*****	**2.29*****
7b	*R2-adj*	*0.27*	*0.27*	*0.34*	*0.51*	*0.5*	*0.5*
	$y_{t-1,t}$	**-0.39*****	-0.08	0.06	0.05	0.12	0.08
	LS_t	**11.97*****	**4.65*****	1.54	**5.17*****	**4.66*****	**4.7*****
7c	*R2-adj*	*0.53*	*0.38*	*0.17*	*0.46*	*0.48*	*0.49*
	$y_{t-1,t}$	-0.39	0.1	0.04	**0.25*****	**0.26****	0.2
	$BOSi_t$	0.14	**0.09****	**0.11*****	**0.16*****	**0.13*****	**0.12*****
7d	*R2-adj*	*0.01*	*0.18*	*0.36*	*0.45*	*0.37*	*0.32*
	$y_{t-1,t}$	**-0.56*****	**-0.25****	0.04	-0.05	-0.12	**-0.24***
	$CAPP_t$	**5.13****	**3.54*****	**2.14***	**4.16*****	**3.87*****	**3.94*****
	$CAPP_{t-1}$	**5.44****	**2.43***	0.28	1.87	**2.31***	**2.47****
	$CAPP_{t-2}$	**5.22****	1.59	-0.24	1.29	1.45	**1.94***
7e	*R2-adj*	*0.55*	*0.42*	*0.18*	*0.47*	*0.53*	*0.58*
	$y_{t-1,t}$	**-0.5*****	-0.12	0.01	-0.01	0.07	0.05
	$CAPSOME_t$	2.94	1.85	1.36	**2.65****	**2.47***	2.11
	$CAPSIG_t$	**26.58*****	**10.68*****	**4.74****	**11.69*****	**9.98*****	**9.97*****
7f	*R2-adj*	*0.63*	*0.55*	*0.26*	*0.6*	*0.58*	*0.59*
	$y_{t-1,t}$	**-0.58*****	**-0.23***	-0.03	-0.01	-0.18	**-0.44****
	LSI_t	0.35	0.9	**1.08****	**1.63****	**1.46****	**1.68*****
	LSI_{t-1}	1.35	0.68	0.29	-0.08	0.44	0.71
	LSI_{t-2}	2.29	0.48	-0.22	0.62	0.53	0.55
7g	*R2-adj*	*0.41*	*0.29*	*0.31*	*0.51*	*0.52*	*0.55*
	$y_{t-1,t}$	-0.26	-0.16	-0.03	-0.01	-0.06	-0.2
	LS_t	**14.15*****	**3.7*****	-0.02	**2.8****	**2.71****	**2.93****
	LSI_t	-1.19	0.73	**1.18*****	**1.33*****	**1.32*****	**1.47*****
7h	*R2-adj*	*0.52*	*0.4*	*0.33*	*0.55*	*0.55*	*0.57*
	$y_{t-1,t}$	**-0.71*****	-0.17	-0.04	0.01	-0.11	**-0.32****
	$CAPP_t$	**8.62****	**3.23****	**0.56**	**2.39**	**2.82****	**3.18****
	LSI_t	1.59	**0.87***	**1.06****	**1.39*****	**1.39*****	**1.67*****
7i	*R2-adj*	*0.37*	*0.34*	*0.33*	*0.53*	*0.55*	*0.56*

*, * and *** represent statistical significance at the 10%, 5% and 1% levels respectively.

Note: The first row lists the various output gap measures examined: the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), including the share of firms that have some difficulty (CAPSOME) or significant difficulty (CAPSIG) meeting an unexpected increase in demand; labour shortages (LS); and labour shortage intensity (LSI).

4.3 Robustness check: adding control variables

To verify the robustness of the results presented above, we test whether the BOS remains informative for the output gap after we take into account other relevant variables that would be available in real time. In practice, Bank of Canada staff monitor numerous data releases throughout each quarter that may influence their assessment of the output gap. For example, staff normally formulate their baseline projections for the Canadian economy about four weeks before the release of the *Monetary Policy Report*. At that time, two months of unemployment data are typically available for the first quarter being forecasted. We thus test whether the BOS adds any useful information, over and above what is contained in the data available at that time, that would help improve output gap estimates. The real-time dataset is constructed from historical Statistics Canada data releases stored at the Bank of Canada, as well as the Bank of Canada real-time Staff Economic Projection database described in Champagne, Poulin-Bellisle and Sekkel (2018b).

Using historical vintages from four weeks prior to each *Monetary Policy Report* release as the cut-off point, we test whether BOS variables remain informative after we add various real-time variables X to the first, second and third approaches discussed earlier. For the first approach, equations (1) and (2) thus become

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 X_t + \varepsilon_t \tag{8}$$

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 X_t + \beta_3 BOS_t + \varepsilon_t. \tag{9}$$

The unemployment rate is a variable that we expect would provide the most informative signals on the output gap, given that it captures a similar concept of economic slack, with very high rates corresponding to periods of excess capacity and low rates associated with excess demand.[13] Furthermore, because the Labour Force Survey is released on a monthly basis with a short publication lag, two months of data are available for the quarter being nowcasted. We thus average the two months of data to approximate that quarter's unemployment rate.

The in-sample results using the latest available data vintage indicate that the unemployment rate (*UR)* indeed bears a significant negative relationship with most measures of the output gap contemporaneously—as displayed in the first row of **Table 5**—except for the SIF and MSSF gap measures. Rows 9a to 9d in **Table 5** indicate that for the most part, the BOS variables continue to remain highly significant even after accounting for signals provided by the unemployment rate, and in some cases render the unemployment rate insignificant. As before, of all the BOS variables, including the *BOSi* tends to improve the equation fit the most.

[13] Other real-time monthly variables tested include the exchange rate, the Bank of Canada commodity price index GDP at basic prices, and exports. The results with these variables were generally worse than those that include the unemployment rate and are thus not shown. Because of the longer publication lag, GDP at basic prices data are not available for the quarter being nowcasted at the cut-off time, which makes this variable less informative in practice for forecasting in real time.

Table 5: In-sample results using latest vintage of output gap estimates and real-time unemployment rate (2001Q1 to 2016Q4)

		SIF	EMVF	MSSF	BMVF	HP	BP
	y_{t-1}	**0.88*** **	**0.51*** **	**0.93*** **	**0.74*** **	**0.55*** **	**0.76*** **
	UR_t	-0.16	**-0.78*** **	0.09	**-0.44** **	**-0.67*** **	**-0.33*** **
8	*R2-adj*	*0.86*	*0.81*	*0.85*	*0.84*	*0.78*	*0.85*
	y_{t-1}	**0.85*** **	**0.5*** **	**0.92*** **	**0.74*** **	**0.52*** **	**0.73*** **
	UR_t	0.01	**-0.59*** **	0.23	-0.26	**-0.46** **	-0.11
	$CAPP_t$	**2.82** **	**2.64** **	1.79	**2.31* **	**3.18*** **	**3.3*** **
9a	*R2-adj*	*0.87*	*0.82*	*0.85*	*0.84*	*0.81*	*0.88*
	y_{t-1}	**0.74*** **	**0.5*** **	**0.82*** **	**0.68*** **	**0.53*** **	**0.74*** **
	UR_t	0.06	**-0.51*** **	**0.27* **	-0.19	**-0.39** **	-0.08
	LSI_t	**1.94*** **	**1.2*** **	**1.43*** **	**1.5*** **	**1.27*** **	**1.12*** **
9b	*R2-adj*	*0.9*	*0.85*	*0.87*	*0.88*	*0.83*	*0.89*
	y_{t-1}	**0.47*** **	**0.76*** **	**0.54*** **	**0.68*** **	**0.54*** **	**0.81*** **
	UR_t	**-0.73*** **	**-0.31** **	**-0.6*** **	-0.2	**-0.51*** **	0.06
	LS_t	**1.43** **	0.32	1.19	**3.89*** **	**3.56*** **	1.94
9c	*R2-adj*	*0.82*	*0.85*	*0.79*	*0.89*	*0.87*	*0.85*
	y_{t-1}	**0.86*** **	**0.61*** **	**0.89*** **	**0.81*** **	**0.63*** **	**0.79*** **
	UR_t	0.02	**-0.45*** **	**0.23* **	-0.15	**-0.38** **	-0.11
	$BOSi_t$	**0.18*** **	**0.15*** **	**0.16*** **	**0.16*** **	**0.16*** **	**0.15*** **
9d	*R2-adj*	*0.91*	*0.87*	*0.89*	*0.89*	*0.85*	*0.93*

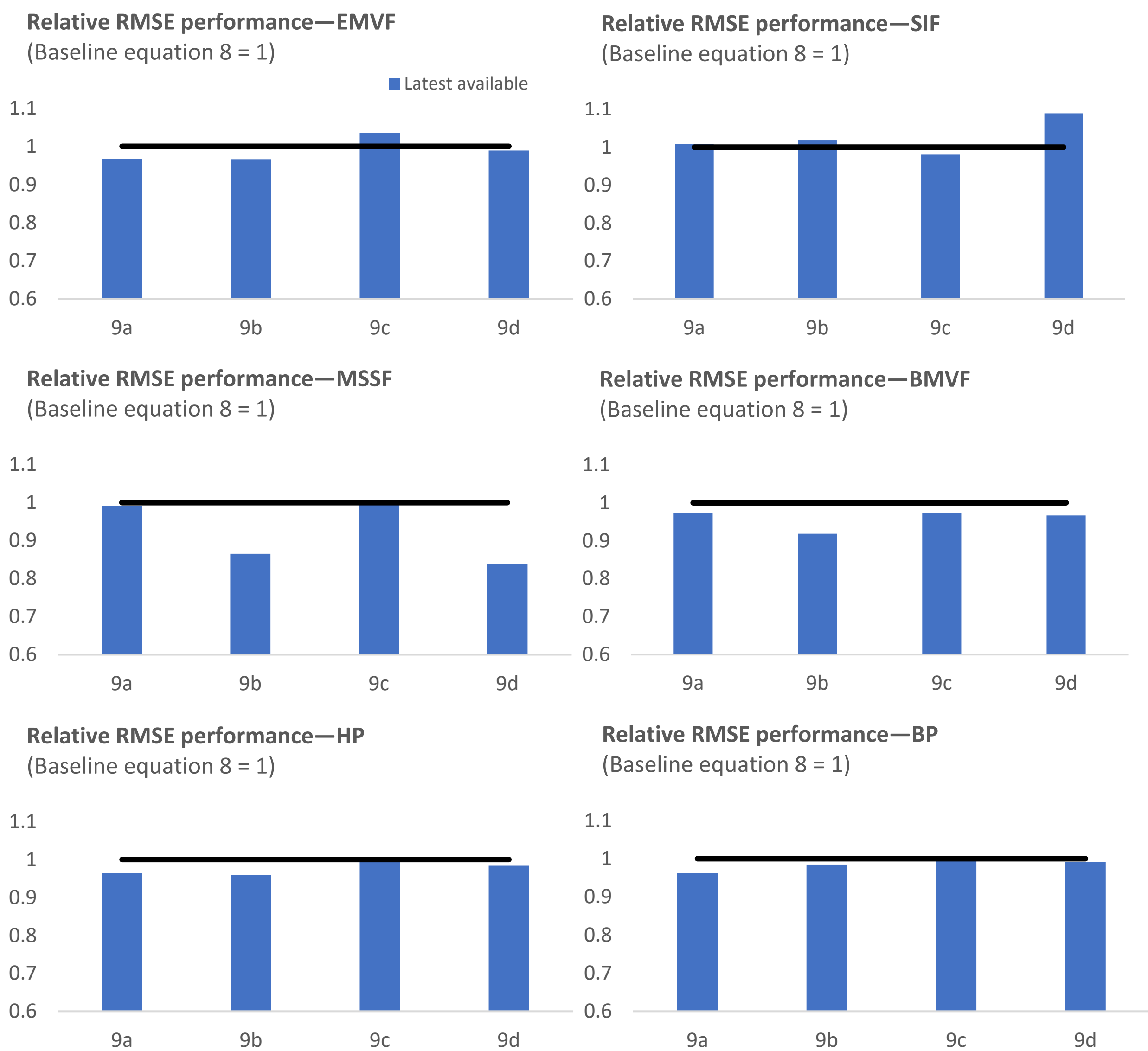
*, * and *** represent statistical significance at the 10%, 5% and 1% levels respectively.

Note: The first row lists the various output gap measures examined: the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), labour shortages (LS) and labour shortage intensity (LSI).

Results from real-time nowcasts exploiting information in the unemployment rate show that performance still improves once the BOS variables are included in the equation, based on lower RMSEs shown in **Chart 7**. Including BOS variables improves the nowcasts most for the MSSF output gap measure, especially when using the *BOSi* variable. However, in most cases these forecast improvements are not statistically significant based on Clark and McCracken tests.

Chart 7: Out-of-sample real-time forecast performance of equations with BOS variables relative to a baseline equation including real-time unemployment rate

Equation	Specification
8	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} UR_{t,v} + \varepsilon_t$
9a	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} UR_{t,v} + \beta_{3_v} CAPP_{t,v} + \varepsilon_t$
9b	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} UR_{t,v} + \beta_{3_v} LSI_{t,v} + \varepsilon_t$
9c	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} UR_{t,v} + \beta_{3_v} LS_{t,v} + \varepsilon_t$
9d	$y_{t,v} = \beta_{0_v} + \beta_{1_v} y_{t-1,v} + \beta_{2_v} UR_{t,v} + \beta_{3_v} BOSi_{t,v} + \varepsilon_t$



Note: The output gap measures are the simplified version of the integrated framework (SIF), the extended multivariate filter (EMVF), the multivariate state-space framework (MSSF), the basic multivariate filter (BMVF), the Hodrick–Prescott filter (HP) and the band-pass filter (BP). The Business Outlook Survey (BOS) variables examined are the BOS indicator (BOSi) as well as responses to questions on capacity pressures (CAPP), labour shortages (LS) and labour shortage intensity (LSI).

5. Conclusion

Real-time estimates of the output gap—an unobservable measure—can be obtained using various methods but remain highly uncertain and subject to large revisions.

We find that BOS data provide useful contemporaneous signals for almost all model-based output gap estimates used by the Bank of Canada, namely (i) responses to the questions on the ability to meet an unexpected increase in demand (*CAPP*) and on labour shortages (*LS, LSI*), and (ii) a summary measure of survey responses (*BOSi*). Using the BOS indicator (*BOSi)* tends to produce nowcasts that are closest to the final output gap estimates. This suggests that information contained in the BOS can be exploited to refine the Bank's assessment of the current state of the economy when monetary policy decisions are being made. This is also supported by results indicating that BOS variables have significant information content for predicting future revisions to output gap estimates.

Our findings support the conclusion of Champagne, Poulin-Belisle and Sekkel (2018a) that using BOS information may have helped improve the revision properties of the Bank's judgment-based staff estimates of the output gap since the early 2000s. Although the true output gap remains unknown, our results provide a framework for incorporating BOS data more systematically to produce output gap estimates that are significantly closer to the final estimates, thus improving their reliability in real time. Including BOS variables continues to produce superior output gap nowcasts even after accounting for other variables that are available to policy-makers in real time, although the gains in forecast accuracy are not statistically significant.

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Appendix: Details on the Business Outlook Survey Questions

The Bank of Canada's quarterly Business Outlook Survey includes the following questions to gauge pressures on capacity:

Ability to meet demand: *How would you rate your firm's ability to meet an unexpected increase in demand or sales? (i) No difficulties (operating below capacity), (ii) Some difficulties (at or near capacity), (iii) Significant difficulties (operating beyond capacity)*

Since the 2004–05 winter survey, firms that respond to the above question with either "some difficulties" or "significant difficulties" are also asked the following supplementary question:

What would be the most important obstacles/bottlenecks to being able to meet demand?

As described in Bank of Canada (2018), the bottlenecks are generally categorized as:

- *a fully utilized labour force*
- *limits on physical capacity (e.g., equipment, space limitations)*
- *an inability to find new labour at the current wage*
- *raw material shortages*
- *regulatory, transportation and logistics bottlenecks*

Labour shortages: *Does your organization face shortages of labour that restrict your ability to meet demand? (i) yes (ii) no*

Labour shortage intensity: *As compared to 12 months ago, are labour shortages generally: (i) more intense, (ii) less intense, (iii) about the same intensity?*