Monitoring Short-Term Economic Developments in Foreign Economies

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- Assessing the economic prospects of key foreign economies—the United States, the euro area, Japan and China—is necessary because of their important direct and indirect links to the Canadian economy.
- The forecasting models constructed for each of these economies take into account the level of detail required for each region and key features of the data, such as timeliness and volatility.
- Forecasts from different models are typically combined to mitigate model uncertainty, and judgment is applied to the model forecasts to incorporate information that is not directly reflected in the most recent indicators.

Current and future developments in foreign economies can have important consequences for the conduct of domestic monetary policy in Canada because of the extensive linkages between the Canadian economy and the rest of the world through trade, commodity price, confidence and financial channels.[1] The International Economic Analysis Department at the Bank of Canada therefore carefully assesses the economic prospects of key foreign economies, specifically, the United States, the euro area, Japan and China.[2]

The Bank faces a number of challenges when building short-term forecasting models for these economies (i.e., for the current quarter and the next),[3] including the timeliness of data releases, reliance on data that may be volatile and subject to historical revisions, and the short sample periods for some variables. The level of detail required in the forecasts is another important consideration. Since the characteristics of the available data and the Bank's forecasting requirements differ across economies, a tailored

1 The importance of foreign shocks is illustrated by noting that roughly one-third of the variables used in Canada's Short-Term Indicator (CSI) model are related to foreign economic indicators, commodity prices or Canada's terms of trade (see Binette and Chang in this issue).

2 The Bank also monitors a number of other economies/regions and is currently expanding its coverage to include other major emerging markets.

3 Coletti and Kozicki (this issue) discuss the role of short-term forecasts in the Bank's economic projections. Macklem (2002) describes how economic projections, in conjunction with other Bank analysis and information, influence monetary policy decisions in Canada.

approach generates more-accurate forecasts. To this end, the Bank's choice of short-term forecasting models is aimed at meeting the challenges and needs for each country or region.

This article discusses the Bank's approach to assessing the short-term economic prospects of each of the four key foreign economies that it monitors closely. The influence of specific challenges on the choice of modelling approach for each economy is also highlighted. The concluding remarks suggest avenues for future work.

Monitoring the Global Economy

United States

The United States is Canada's largest trading partner, accounting for roughly 75 per cent of Canadian exports. It also plays an important role in the determination of commodity prices and financial conditions in the global economy, which can have a significant impact on the Canadian economy. Analyzing and forecasting U.S. economic conditions in detail is therefore essential, and this requirement is a key consideration in producing short-term forecasts of the U.S. economy. Unlike the other economies discussed in this article, where the primary focus is on aggregate real GDP growth and inflation, the Bank analyzes the U.S. economy on a disaggregated basis by producing individual forecasts for the major components of GDP (i.e., consumption, residential investment, business investment, inventory investment, government spending, exports and imports). This level of granularity is important, since forecasting Canadian exports is significantly improved by focusing on the components of U.S. GDP (Morel 2012). For example, the Bank's foreign activity measure, which captures the composition of foreign demand for Canadian exports, attaches a much larger weight to U.S. business and residential investment than that implied by their respective nominal shares of U.S. GDP (**Table 1**).[4]

The Bank of Canada analyzes the U.S. economy on a disaggregated basis by producing individual forecasts for the major components of GDP

Although this greater level of detail is necessary, it creates an additional challenge for Bank staff, since forecasts for individual components of GDP must also be consistent with a coherent view of overall economic conditions in the United States. To meet this challenge, the Bank uses a combination of error-correction (EC) and indicator models, as well as staff judgment,[5] to produce short-term forecasts for most components of U.S. GDP (see **Box 1** for a description of the models). The EC model, which incorporates a long-run behavioural relationship between variables, allows economic theory to help guide the short-term forecast, in particular, during the early part of any given quarter when few, if any, published monthly economic indicators are available.

Table 1: The composition of the foreign activity measure and U.S. GDP

	Weight in the foreign activity measure	Nominal share of GDP (2012)
U.S. consumption	0.207	0.686
U.S. residential investment	0.175	0.027
U.S. business investment	0.486	0.121

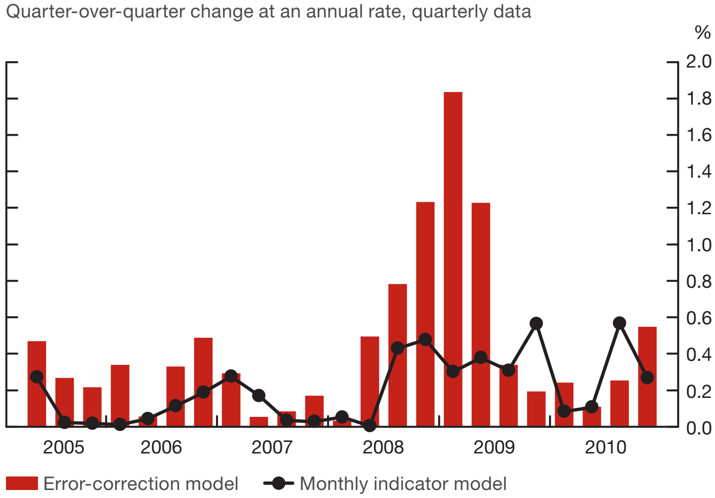
Sources: U.S. Bureau of Economic Analysis and Bank of Canada calculations

4 The foreign activity measure also assigns a weight of 13.2 per cent to foreign GDP outside the United States.

5 The relevance of judgment for macroeconomic forecasting is illustrated in Wright (2013), who finds that incorporating macroeconomic predictions from a survey of experts (i.e., judgment-based forecasts) in standard macroeconomic forecasting models yields substantial forecasting gains.

Chart 1: Absolute forecast errors in models of U.S. personal consumption expenditures at the end of each quarter, 2005Q2–2010Q4

Quarter-over-quarter change at an annual rate, quarterly data



Sources: U.S. Bureau of Economic Analysis and Bank of Canada calculations — Last observation: 2010Q4

At the same time, the indicator models allow staff to incorporate the most recent high-frequency data that are released throughout the quarter. The short-term forecast is typically generated using a weighted average of forecasts from different models (plus judgment), with the weights updated as new information becomes available during the quarter. Recently published data are also subject to revision, which often leads staff to reassess current economic conditions to reflect this additional information (see **Box 2** on page 29 for a discussion of data revisions to selected indicators).

To illustrate, consider how the short-term forecast for U.S. personal consumption expenditures (PCE) is produced. Bank staff have found that, early in the quarter, the indicator models add little additional information relative to the EC model. Therefore, at the beginning of a quarter, the short-term PCE forecast is heavily weighted toward an EC model that captures the behavioural response of consumption to movements in income, wealth and interest rates (Gosselin and Lalonde 2005). As the quarter proceeds, however, a number of important high-frequency indicators for consumption—such as motor vehicle sales, retail trade, consumer confidence and electricity output—become available. Each of these data series feeds into at least one of the indicator models used to generate forecasts of monthly and quarterly real PCE. The forecasts from these indicator models are then assigned a weight relative to the forecast from the EC model. This weight is continually updated throughout the quarter as more monthly data become available. Eventually, to minimize forecast errors, most of the weight will be given to the monthly data and indicator models, leaving the EC model with only a small weight. **Chart 1** shows how, over the 2005Q2–2010Q4 period, the forecast errors in one of the Bank's monthly indicator models of PCE were substantially lower than those of the EC model at the end of most quarters, once all the monthly indicators were available.[6]

Each of the components of U.S. real GDP is analyzed using a similar framework, although the weights assigned to the EC and the indicator models differ across components. Once the short-term forecasts of each

6 The 2005Q2–2010Q4 period was chosen to approximate the evaluation samples in the studies cited in Table 1-A of Box 1. The root-mean-square prediction error (RMSPE) of the indicator model was a little less than half that of the EC model over the sample period.

Box 1

Short-Term Forecasting Models for Monitoring Foreign Economies

The Bank currently uses three main types of model to monitor foreign economies:

(i) Error-correction (EC) models: In an EC model, economic variables are tied together by a long-term behavioural relationship, which is based on economic theory. This long-term relationship is complemented by other indicator variables to capture shorter-term dynamics. EC models can be particularly beneficial when few monthly indicators for the current quarter are available, and over medium-term horizons when economic theory can serve as an accurate anchor for forecasting.

For example, the EC model of U.S. personal consumption expenditures includes an estimated long-term relationship between consumption (C) and human wealth (HW), real housing wealth ($HOUSING$), real financial wealth (FIN) and the real interest rate (R), where the variables are included in this relationship based on economic theory[1]:

$$lC_t^* = -2.47 + 0.74 * lHW_t + 0.09 * lHOUSING_t + 0.17 * lFIN_t - 0.40 * R_t .$$

This long-term relationship is complemented with lags in consumption growth (C_{t-i}), expected growth in the desired level of consumption (C^*), movements in oil prices (OIL) and growth in real disposable income ($YPDI$) to capture some of the remaining short-run variation[2]:

$$dlC_t = \underbrace{0.34 * dlC_{t-1} + 0.11 * dlC_{t-2} + 0.55 * dlC_t^* + 0.19 * dlYPDI_t + 0.01 * dlOIL_t}_{\boxed{\text{Short-term dynamics}}}$$
$$\underbrace{- 0.09 * (lC_{t-1} - lC^*_{t-1})}_{\boxed{\text{Error correction}}}$$

The long-term relationship affects the dynamic short-term forecast through the error-correction term in the above equation. The error-correction term causes current consumption to adjust to the value suggested by the long-term relationship based on economic fundamentals.

(ii) Factor models: These models are based on the idea that the information in a large number of data series and indicators can be summarized in a few factors that describe the underlying trend in the data (see **Box 1** in Binette and Chang on page 5 of this issue).

(iii) Indicator models: These models are more parsimonious in terms of information content, since they use just a few indicators to forecast the variable of interest. For example, models based on industrial production or survey indicators such as the purchasing managers' index (PMI) are typically used to predict GDP growth. Often, the results of several indicator models are combined to form a single forecast.

(continued...)

1 For more details, see Gosselin and Lalonde (2005).

2 The EC model is estimated in log-level (l) and difference-of-log (dl) format.

Box 1 (*continued*)

Table 1-A shows the performance of factor and indicator models for predicting GDP growth in the euro area, Japan and China. Forecasts are evaluated using the root-mean-square prediction error (RMSPE) criterion relative to the RMSPE obtained from a univariate autoregressive (AR) model. As the forecasting horizon shortens, the forecasting performance of both the factor model and the indicator model frequently improves relative to the AR model. For Japan and China, the factor model exhibits a substantially lower RMSPE than the indicator model, while, for the euro area, the forecasting performance of the indicator model is similar to that of the factor model.

Table 1-A: Forecasting GDP growth—root-mean-square prediction error relative to the autoregressive model

Forecast horizon (months)	0	1	2	3	4	5
Factor model						
Euro area	0.58	0.74	0.80	0.79	0.94	0.98
Japan	0.37	0.57	0.81	1.28	1.47	1.12
China	0.47	0.55	0.82	0.42	0.52	0.86
Indicator model						
Euro area	0.64	0.68	0.87	0.88	0.94	0.96
Japan	0.75	0.92	1.30	1.18	1.20	1.24
China	0.81	0.82	0.87	0.90	0.90	0.95

Note: This table shows the RMSPE of a factor model and an indicator model relative to an AR model (results are from Lombardi and Maier (2010) for the euro area, Godbout and Lombardi (2012) for Japan, and Maier (2011) for China). The evaluation samples are from 2005Q2 to 2010Q1 for the euro area, 2006Q2 to 2010Q2 for Japan and 2008Q2 to 2010Q4 for China. Forecasts with horizon $h = \{0, 1, 2\}$ refer to forecasts for the current quarter, and forecasts with horizon $h = \{3, 4, 5\}$ refer to forecasts for the next quarter. The indicator is the headline composite PMI for the euro area, PMI manufacturing for Japan and the Hong Kong Monetary Authority indicator for China. Additional details on the models are provided in the respective studies.

component are produced, they are compiled to produce an aggregate GDP forecast as well as a forecast of the Canadian foreign activity measure. Although a similar approach is used for each component, it is important to note that judgment is sometimes added to complement the model's forecast. Many unexpected events occur that the models cannot capture in real time, for example, Hurricane Sandy in October 2012, the 2012 drought, and the Los Angeles and Long Beach port strikes late last year. When such events take place, analysts need to combine their judgment with the results of monitoring models to produce a more reliable short-term forecast.

Euro area

The monitoring tools developed for the euro area focus on the challenges related to the substantial lag in the publication of important "hard" indicators. Variables such as industrial production and GDP are released about 45 days following the end of the reference period (**Table 2**).[7] In comparison, the first estimates of GDP in China and the United States are released only 15 days and 30 days, respectively, after the end of the reference period. The survey data (or "soft" indicators) that are readily available at the end of the month (e.g., the purchasing managers' index (PMI)) deliver timely updates on the current business-cycle conditions and therefore receive greater weight in the monitoring of the euro area.[8]

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7 The reference period is one quarter for GDP and one month for industrial production.

8 Angelini et al. (2011) also underline the importance of survey data for predicting euro-area GDP growth, owing to the timeliness of the data.

Table 2: Publication lags for key indicators in the United States, the euro area, Japan and China

	GDP growth				Industrial production			
	United States	Euro area	Japan	China	United States	Euro area	Japan	China
Publication lag (days)	30	45	45	15	15	45	30	10–15

Sources: U.S. Bureau of Economic Analysis; Eurostat; Cabinet Office, Government of Japan; and National Bureau of Statistics of China

The Bank's monitoring models for the euro area build on the work of Lombardi and Maier (2010), which compares the forecasting performance of dynamic factor models[9] that exploit the informational content of a wide range of variables with that of indicator models that are based solely on the composite PMI (**Box 1**). Lombardi and Maier find that the PMI indicator model provides better forecasting results for the growth in euro-area GDP during the Great Recession of 2008–09 than the factor model, although the latter provides better forecasts during the preceding period, from 2000 to 2007. While this comparison highlights the general value of using information from many sources, it also suggests that models based exclusively on survey data may adjust more quickly to rapidly changing economic conditions. Factor models, which summarize information across a large number of indicators (including hard indicators released with a substantial delay), may be more sluggish to react to rapidly evolving economic conditions. This observation suggests that the weights allocated to different models often require adjustment based on judgment in the face of quickly changing economic conditions.

Japan

Forecasting growth in Japanese GDP is more challenging than for the other economies under consideration, owing to the volatility of Japanese macroeconomic aggregates, large data revisions (**Box 2**) and the substantial shocks to the Japanese economy observed over the past few decades (see, for example, Stock and Watson (2005)). In such an environment, factor models are often considered to be useful forecasting tools, since they summarize information from a large set of indicators, thereby potentially mitigating problems related to data volatility and revisions to individual series. Godbout and Lombardi (2012) compare the forecasting performance of two factor models for Japan with that of an indicator model based on the PMI and a simple model where GDP growth depends only on its own previous values (i.e., an autoregressive (AR) model). They find that factor models provide a greater number of accurate forecasts than both the AR benchmark model and the PMI model (**Box 1**). **Chart 2** shows that the most important explanatory factor extracted from principal-component analysis is related primarily to industrial production, real exports, survey data indicators (PMI manufacturing and its new orders subindexes), industrial activity and the Chinese PMI indicator for manufacturing output.[10] These empirical findings highlight the importance of foreign trade to the Japanese real economy and the relevance of survey data for monitoring its evolution.

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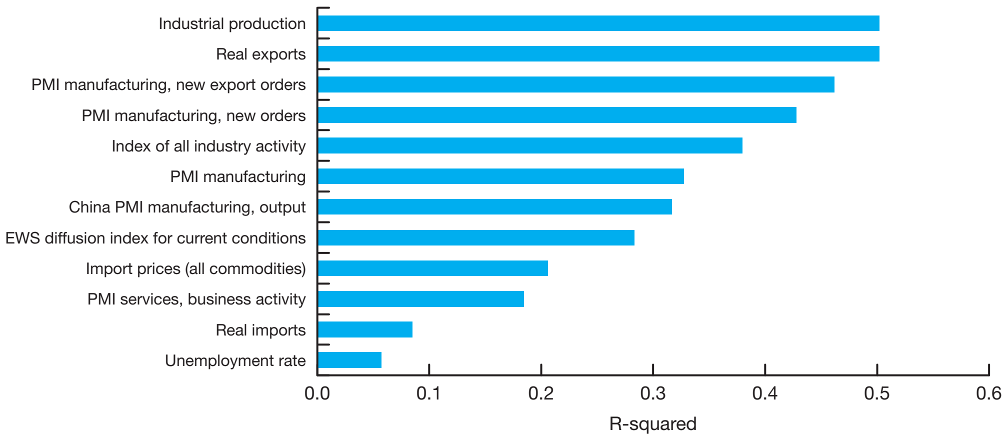
9 Dynamic factor models are described in Binette and Chang (this issue).

10 The R-squared in Chart 2 indicates the relative importance of selected individual time series in explaining the variations in the factor.

Chart 2: Relative importance of variables in forecasting growth in Japanese real GDP

R-squared between factor and selected individual time series



Note: The estimation sample is from October 2001 to December 2010.
PMI = purchasing managers' index; EWS = Economy Watchers Survey
Source: Bank of Canada calculations

China

The swift emergence of China as a major player in the global economy and, in particular, its significant influence on commodity prices (IMF 2011)[11] have triggered the need to develop monitoring tools that address a number of challenges specific to the Chinese economy. These challenges include such things as the shortness of available time-series data and inconsistencies in statistics (e.g., the quarterly GDP growth series does not necessarily add up to the annual GDP growth series). In addition, the rapid changes to the Chinese economy are likely to give rise to structural breaks in the data, which complicate attempts to design robust forecasting models. Maier (2011) evaluates the forecasting performance of a factor model and a set of indicator models comprising 33 indicators. He finds that both the factor model and a weighted average of the forecasts from the indicator models strongly outperform a standard AR benchmark model in forecasting Chinese GDP growth (**Box 1**). Indeed, the factor model closely tracks Chinese GDP growth in the current quarter (**Chart 3**). Indicators such as electricity and industrial production, as well as the PMI manufacturing component and Chinese equity prices, prove to be the most relevant for the indicator models. Forecasting performance is further improved when the forecasts from the factor model are combined with the forecasts from the indicator models. Overall, Maier's results suggest that there are significant gains in forecasting accuracy when forecasting methods are combined, likely because of the significant structural changes to the Chinese economy over the past few decades. Other studies of forecasting performance also find that model combinations or model averaging can improve forecasting performance (see Granziera, Luu and St-Amant in this issue).[12]

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11 According to estimates by the International Monetary Fund (IMF) of the purchasing-power-parity valuation of Chinese GDP, China accounted for 14.3 per cent of global GDP in 2011, compared with 7.5 per cent in 2001 and 4.1 per cent in 1991. Likewise, based on U.S. Energy Information Administration estimates, China's share of global primary energy consumption was 20.1 per cent in 2011, compared with 10.6 per cent in 2001 and 7.9 per cent in 1991.

12 Using data for six industrialized countries, Kuzin, Marcellino and Schumacher (2013) find that pooling nowcasts provides more-stable forecasts than selecting a single forecasting model sequentially, based on statistical information criteria.

Box 2

Volatility and Revisions

Data volatility and revisions present challenges for assessing the state of an economy. The volatility of macroeconomic indicators may lead to a greater reliance on a specific class of models, since it is more difficult to extract the underlying trend in economic conditions when data are highly volatile. Thus, factor models are often seen as useful devices to mitigate the volatility of indicators. Data revisions complicate monitoring because the historic data used in the analysis are not known with certainty.

Table 2-A provides statistics on the mean growth and volatility (standard deviation) of quarterly GDP and of monthly industrial production in the United States, the euro area and Japan from late 2001 to the end of 2010. Revisions to growth estimates are also included. Data revisions compared with the estimates available 4 months, 8 months and 16 months after the reference period are reported.[1] Following Giannone et al. (2012), we use the estimates available 24 months after the end of the reference period as a "true value" to calculate revision statistics.

A few key observations are worth noting. First, the volatility of GDP and industrial production varies across regions, with the Japanese data exhibiting the largest standard deviation for both series. Second, on average, over the sample examined, GDP growth tends to be revised down in the United States and Japan, and revised up in the euro area. Third, the standard deviation of the revisions to Japanese GDP estimates available four months after the end of the quarter (2.56 per cent) is about four times larger than the standard deviation of the revisions to euro-area GDP (0.57 per cent), and about twice as large as that for U.S. GDP (1.09 per cent). Similarly, industrial production, a monthly series, is also subject to substantial revisions.[2] Survey data, such as the purchasing managers' index, have an advantage over hard indicators, such as industrial production, since they are available on a more timely basis and are typically not subject to revisions.[3]

Table 2-A: Revision statistics for key indicators in the United States, the euro area and Japan

	GDP growth (per cent, quarter over quarter, seasonally adjusted annual rate)			Industrial production (per cent, year over year)		
	United States	Euro area	Japan	United States	Euro area	Japan
Mean	2.05	1.01	0.72	-0.01	0.16	0.53
Mean of revisions						
$Y_{t\|t+24} - Y_{t\|t+4}$	-0.30	0.09	-0.57	-0.44	0.13	0.13
$Y_{t\|t+24} - Y_{t\|t+8}$	-0.23	0.04	-0.32	-0.45	0.10	0.09
$Y_{t\|t+24} - Y_{t\|t+16}$	-0.23	0.09	-0.38	-0.34	0.02	0.02
Standard deviation (volatility)	2.74	2.61	5.18	5.15	6.32	10.96
Standard deviation of revisions						
$Y_{t\|t+24} - Y_{t\|t+4}$	1.09	0.57	2.56	0.78	0.50	0.83
$Y_{t\|t+24} - Y_{t\|t+8}$	1.11	0.44	2.36	0.72	0.37	0.67
$Y_{t\|t+24} - Y_{t\|t+16}$	0.73	0.21	1.70	0.77	0.26	0.21

Note: We calculate revision statistics as in Giannone et al. (2012). We report the mean and the standard deviation of the revisions defined as $(Y_{t|t+24} - Y_{t|t+i})$, where t indicates the reference period, while $t+i$ for i = {4, 8, 16} is the time in which the value of the series is observed. We consider the observation available two years later $(Y_{t|t+24})$ as the "true" value. We report the mean and standard deviation of this series to provide a benchmark for assessing the mean and standard deviation of the revisions. For quarterly GDP growth, all statistics refer to the 2001Q3–2010Q4 period. For industrial production, all statistics refer to the September 2001–December 2010 period.

Sources: Organisation for Economic Co-operation and Development real-time database, except euro-area industrial production, from the European Central Bank real-time database

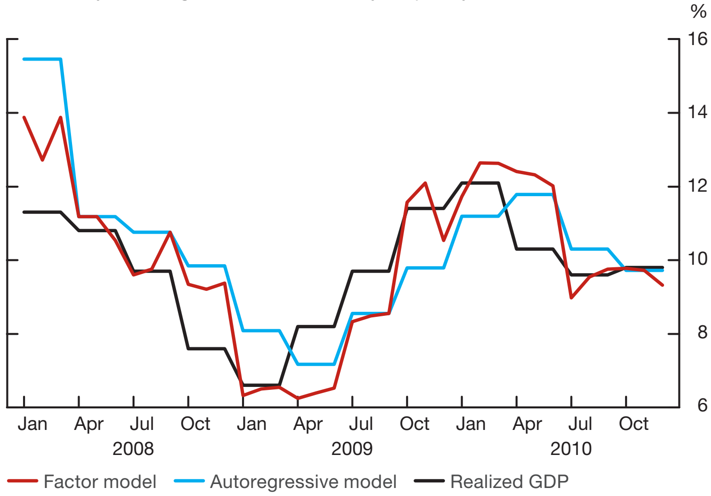
1 Revision statistics are not relative to the initial estimates, since these data are not fully available for the euro area and Japan over the full estimation sample. However, calculating revision statistics using the vintages available 4 months, 8 months and 16 months after the end of the reference period illustrates the trends of data revisions.

2 However, unlike revisions to GDP growth, the standard deviation of the revisions to the estimates of Japanese industrial production is similar to, or lower than, those for the United States or the euro area.

3 In most cases, all relevant information is available at the time of the publication of survey data. In contrast, revisions to hard indicators typically reflect the fact that additional (more accurate) information has become available.

Chart 3: Chinese GDP growth compared with factor-model and autoregressive-model forecasts

Year-over-year change in real GDP, monthly frequency



Sources: National Bureau of Statistics of China and Bank of Canada calculations

Last observation: December 2010

Conclusion

To better understand the evolution of foreign economies in the short term, Bank of Canada staff analyze an extensive set of indicators using a wide range of models that are selected based on the circumstances of the specific country and the level of detail required. Staff also use judgment in constructing forecasts to incorporate information that may not be directly reflected in the most timely high-frequency indicators. The Bank of Canada strives to improve the forecast accuracy of its short-term forecasting models. Avenues for future work include, but are not limited to, incorporating time variations in the parameters of the monitoring models to better account for the substantial volatility in some macroeconomic data, and incorporating density forecasts (i.e., a measure of uncertainty around mean forecasts).

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