Federal Reserve Bank of Dallas
Globalization and Monetary Policy Institute
Working Paper No. 96
http://www.dallasfed.org/assets/documents/institute/wpapers/2011/0096.pdf

A Real-Time Historical Database for the OECD *

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December 2011

Abstract

Ongoing economic globalization makes real-time international data increasingly relevant, though little work has been done on collecting and analyzing real-time data for economies other than the U.S. In this paper, we introduce and examine a new international real-time dataset assembled from original quarterly releases of 13 quarterly variables presented in the OECD Main Economic Indicators from 1962 to 1998 for 26 OECD countries. By merging this data with the current OECD real-time dataset, which starts in 1999, researchers get access to a standard, up-to-date resource. To illustrate the importance of using real-time data in macroeconomic analysis, we consider five economic applications analyzed from a real-time perspective.

JEL codes: C82, F0, C53

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1 Introduction

Although it is common in empirical macroeconomics to work with revised data, a growing body of literature suggests that analysis using real-time data, or data known to agents at the time they were making decisions, often yields substantially different conclusions than work ignoring data revisions (Croushore and Stark, 2001, Orphanides, 2001, Koenig, 2003, Molodtsova et al., 2008). Mounting evidence indicates the importance of using real-time data in designing and comparing forecasting models, and performing monetary policy analysis. Data revisions are important because first, they may affect current policy decisions and second, they may also influence a wide array of economic indicators such as people's expectations of future economic conditions, estimates of monetary policy rules and measures of monetary policy shocks.

Current research on real-time data owes much to the work of Croushore and Stark (2001), who compiled and analyzed a large real-time dataset for macroeconomists (RTDSM), containing snapshots of the U.S. economy starting in 1965. Their work became the standard dataset for forecasters and others engaged in research affected by data revisions. Although ongoing economic globalization makes real-time international data increasingly relevant, very little work has been done on collecting and analyzing real-time data for economies other than the U.S. International real-time data is scarce because compiling a reliable dataset is difficult. In practice, authors need to undertake the arduous task of putting together their own datasets from different sources.

We are aware of very few examples of real-time datasets for individual countries other than the U.S., and even fewer in a multicountry setting. Egginton et al. (2002) compile and describe a real-time macro dataset with many important indicators for the U.K. Clausen and Meier (2005) and Sauer and Sturm (2003) estimate the Bundesbank policy reaction function using real-time data on Germany's GDP and industrial production, which they assembled on their own, and Gerberding et al. (2005) analyze whether the Bundesbank really followed strict monetary targeting, compiling a well-documented real-time dataset on production, inflation and money growth measures. Similar work on Canada was done by Nikolsko-Rzhevskyy (2011). Additionally, Bernhadsen et al. (2005) analyze Norwegian monetary policy in detail with a meticulously compiled dataset.

We know of only two multicountry real-time datasets. Faust et al. (2003) collect and post on the website quarterly extracts from OECD diskettes and CDs released between April 1988 and January 1996 for Japan, Germany, Switzerland, Canada and the U.S., including variables such as nominal and real GDP, the CPI index, money supply, and the unemployment rate. The second project, which also uses OECD data and is especially relevant for our work in this article, is the official OECD Main Economic Indicators "Original Release Data and Revisions Database (ORDRD)." This Web-based resource covers all OECD and some non-OECD member countries and contains vintages of monthly and quarterly data, updated on a monthly basis beginning in January 1999. A well-documented dataset used by many researchers interested in international real-time issues, its only drawback is that it only covers the last decade. That is why we determined that the dataset is worth extending back as far as possible.

The OECD has been collecting and publishing data on its member countries since its inception in 1961. We have taken published OECD data from 1962-1998 and put it into an electronic form that can easily merged with the OECD's own real-time data set (ORDRD). Our goal is to provide a standard resource helpful to international macroeconomists exploring issues for which real-time data are important. The new data set is available for download at www.rthd-oecd.org.

The rest of the paper is organized as follows: Section 2 explains the steps taken constructing the dataset and provides a general description along with an analysis of the basic properties of revisions. Section 3 illustrates the potential usefulness of our work by analyzing five important economic problems from a real-time perspective. First, we investigate which of the most common univariate detrending techniques best replicates official real-time OECD output gap estimates. Second, we study the usefulness of various measures of the output gap in predicting inflation. Third, we investigate the ways in which the efficiency of output growth rate forecasting can be increased using real-time data structure. Fourth, we uncover the hidden cost of inflation by analyzing the effect of inflation on revisions. And finally, we illustrate the importance of using real-time, rather than revised, data for exchange-rate forecasting. Section 4 concludes.

2 Dataset properties

2.1 General description

The lack of work in real-time international economic issues can largely be attributed to difficulties associated with compiling an international real-time dataset. Aiming to provide a basic foundation for real-time international economic research, we have assembled a comprehensive quarterly international real-time dataset from hard copies of the "OECD Main Economic Indicators." The vintage dates cover the period from 1962:Q1 to 1998:Q4, with data in the earliest vintages typically going back to the first quarter of 1956. The dataset is available for download at http://www.rthd-oecd.org. The dates and coverage of the data allow an interested researcher to easily splice the dataset together with the official OECD Main Economic Indicators "Original Release Data and Revisions Database, (ORDRD)" which contains continuously updated monthly vintages starting in January 1999. This data is available on the web at http://stats.oecd.org/mei.

Our dataset covers the 26 OECD countries: Canada, Mexico, U.S., Japan, Australia, New Zealand, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxemburg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK and Korea. For each country, we have recorded 13 variables: real and nominal GNP/GDP, price level (GNP/GDP deflator index), industrial production, manufacturing production, capacity utilization rate, unemployment rate, consumer price index, money supply, capital holdings, imports, exports, and net capital movements.

As is usual in real-time datasets, we store each variable in matrix form. Each successive column vector of the matrix represents the "vintage" of quarterly data, containing the information available at that date. The data are presented in separate single-sheet Excel files (one file per country per variable). With the passage of time, two important modifications affect each data series. First, as more data become available, the series get longer, and the data matrix becomes wider. Second, old values are revised and updated to correct past errors, reflect changes in methodology or simply to incorporate newly released information.

The reported figures, taken from the hard copy publications of the OECD Main Economic Indicators, were from the public domain in the corresponding vintage. We did not attempt to synchronize the vintage dates with the data, as Croushore and Stark did in the U.S. real-time dataset for macroeconomists (RTDSM). We simply named each vintage with the date the Main Economic Indicators' publication was released to the public, regardless of the exact date the data were collected or the time the publication spent in print. For example, if a country's data were collected during the first days of January 1991, then coalesced in one issue of Main Economic Indicators later that month, and finally printed in February 1991, we names this vintage "February 1991." For each quarterly vintage, we recorded data as it was published in the middle month of each quarter (February, May, August, and November), consistent with the

RTDSM convention.

The coverage of our historical database is not homogeneous; it varies by country depending on the year each country joined the OECD and on data availability (Table 1). The longest time spans of recorded vintages correspond to the 19 core countries (the founding members of OECD in 1961) plus Italy, which joined shortly thereafter (in 1962).[1] For these countries, most of the available variables are recorded beginning in February 1962 with the publication of the first issue of the OECD General Statistics Bulletin, replaced after 1964 by the OECD Main Economic Indicators. Certain variables such as the price level, capacity utilization rate and net capital movements appear in the statistics only years later. As other countries joined the OECD, their published statistics were added to the dataset.[2]

There are some countries for which certain variables are not available in the Main Economic Indicators. There is no historical OECD data on real and nominal GDP/GNP and price level for Greece, Iceland, Ireland, and Luxembourg. Luxembourg, the least-covered country in our dataset, also lacks data on the unemployment rate, money supply, capital holdings and net capital movements. Similarly, there are no data reported for the price level and nominal GNP/GDP for Belgium, industrial and manufacturing production for Iceland, capacity utilization rate for Greece, Ireland and Iceland, and net capital movement for Switzerland.

Over the years, the OECD General Statistics Bulletin, and later the OECD Main Economic Indicators, has discontinued some variables and added others. When the definition of a variable changed, we substituted the closest available alternative. For example, in France, the "manufacturing production" variable is first recorded as "index of production in manufacturing industries," then as "industrial production: total, excluding construction," and finally as "index of production: manufacturing."[3] When the denomination of a variable changed but the technical definition remained the same, we replaced it. For example, "Consumer prices: all goods and services" replaced "Consumer prices: total," which later became "Consumer prices: all items." Given the extensive coverage of our dataset, the change in the definition of some variables was particularly challenging.[4]

[1]The founding members are: Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States

[2]Japan in 1964, Finland in 1969, Australia in 1971, New Zealand in 1973, Mexico in 1994, and South Korea in 1996.

[3]We have kept records of all definition changes in the header of each variable.

The dataset was subject to quality controls and checks. Occasionally, we found instances when the original OECD publications contained obvious typographical errors. As our goal was to replicate the data as they were available to the general public, all values we found suspicious were left "as is" and documented as an attachment in our database.[5] To further ensure the quality of the data, the preliminary release of our dataset is open to comment in the hope any remaining errors may be spotted.

2.2 Analysis of revisions

2.2.1 Definitions

Sound policymaking requires pondering the weight one should place on advance estimates that are likely to be revised in the future (Castle and Ellis, 2002). Understanding the nature of revisions may give policymakers opportunities to minimize the effects associated with the weight imputed to advance estimates and to ultimately avoid policy mistakes.

"Revisions" are typically defined as the difference of the value of a variable in the later vintage (which comprises the cumulative revisions after the initial announcement) minus its value in the earlier vintage. When revisions are released at regular intervals, as is the case in most existing real-time datasets, "releases" are formed out of values that undergo the same number of revisions. This practice presented a problem for our work because we deal with variables whose revised values are released with uneven delays, ranging from 1 to 5 quarters or more. In addition, the lag structures are different not only across countries but within variables themselves, as illustrated in Table 2 for real GDP and money supply, and in Figures 1(a-d) for real GDP, industrial production, price level, and money supply. In fact, throughout the entire sample, no country maintains a constant lag for any single variable.

In view of that, rather than define different releases based on the number of revisions their values undergo, we label them based on the lag length (in quarters) with which revisions are released, avoiding the possibility of mixing values with different statistical properties.[6]

Accordingly, if the value of a variable x at time t as it is thought of at time (vintage) v is

[4]As with any real-time dataset, due to reasons mentioned above, a researcher should be cautious when working with variables in levels. However, the use of growth rates should mitigate the problem.

[5]However, we correct the typos when considering the five empirical applications in Section 3.

[6]For most existing real-time datasets these two methods would be identical. For example, all U.S. real GDP data from RTDSM (with the exception of one vintage) is released with a consistent lag of 1 quarter. This is clearly not the case in our dataset.

x_t^v, "the release i" (or the values released with i number of lags) of a series X would be a set of $\{x_1^{1+i}, x_2^{2+i}, ..., x_{T-i}^{T-i+i}\}$. The "revision i" series, then, is defined as the difference between the release $i+1$ and the release i:

$$r^i(x) = \{x_1^{2+i} - x_1^{1+i}, x_2^{3+i} - x_2^{2+i}, ..., x_{T-i}^{T-i+i} - x_{T-i}^{T-i+i-1}\} \tag{1}$$

To avoid dealing with the jumps associated with benchmark revisions (i.e. changes in the base year and methodologies), in the following analysis, we look only at the growth rates for all the variables included in the dataset. Specifically, for each variable X, we construct an annualized quarter-over-quarter growth rate as $400(\ln x_t - \ln x_{t-1})$.

2.2.2 Efficiency

When preparing data for release, government agencies can either make efficient or non-efficient use of all available information. Revisions exclusively adding new information ("news") are said to be efficient; non-efficient revisions reduce "noise" instead (Mankiw and Shapiro, 1986). Efficient revisions are orthogonal to each data release and are not predictable between vintages. Conversely, later values of non-efficient releases can be predicted provided the optimal projection is obtained. Our dataset allows this type of analysis.

We assess the efficiency of four consecutive revisions ($i = 1..4$) in the growth rates of four important variables – real GDP, price level, industrial production, and money supply – by looking at whether their mean values are significantly different from zero. The results, presented in Table 3, show that for 18 out of 26 countries, revisions appear predictable for at least one of the four variables considered at one of the horizons, i. In these cases, and using the terminology of Mankiw and Shapiro (1986), revisions have a "noise" component.

Within the statistically significant values – those where revisions are predictable – virtually all 1- and 2-quarter lag revisions for real GNP/GDP, prices, and industrial production are positive, implying that releases may be downward biased, on average, meaning that statistical agencies tend to underestimate both real growth and inflation. We also see that early revisions often appear to be considerably larger than later revisions, pointing to a possible trade-off between accuracy and the timing of a release. This conclusion is supported by the analysis of absolute mean revisions that looks at the actual magnitude of revisions. In Figures 2(a-d), we see that longer delayed releases generally have lower absolute mean values for real GNP/GDP, prices, industrial production, and money supply. We also observe that first revisions are typically followed by revisions of smaller magnitude.

Looking at individual countries, the largest mean absolute real GNP/GDP revision values correspond to 2-quarter lag releases in Turkey, New Zealand, Denmark and Sweden, with values of 13.38, 5.63, 3.15, and 3.01, respectively. For industrial production, the largest individual values correspond to Belgium's 3- and 2-quarter lag releases, with 3.83 and 3.12, respectively. Turkey presents the largest first and second revisions in prices and money supply, with an average absolute revision reaching 14.58 for the latter variable.

Overall, our results indicate that revisions have some degree of predictability and seem to be large enough to matter in research. By revealing the basic properties of revisions, our analysis opens the possibility for statistical agencies to improve the data release process.

3 Empirical applications

Our international real-time database meets a growing need for a standard resource for researchers investigating international macroeconomic issues for which real-time data are important. We demonstrate the usefulness of our work in this section, analyzing five economic applications in which data revisions are relevant. First, we determine which measures of the output gap provide the best approximation to the "true" output gap series, as proxied by official OECD estimates. Second, we investigate the marginal predictive ability of various output gap measures in forecasting inflation. Third, we study the ways in which the efficiency of output growth rate forecasting can be increased by utilizing the real-time dataset structure. Fourth, we uncover the hidden cost of inflation by illustrating the association between higher inflation and bigger revisions of important economic indicators, which may potentially result in policy mistakes. Finally, we show that using real-time data could lead to different conclusions when forecasting nominal exchange rates that when using revised data. In all applications, we focus our analysis on the G7 economies only and merge our historical database with the ORDRD, allowing us to extend the sample to May 2010.

3.1 Choosing the best detrending technique to replicate the "true" output gaps

3.1.1 Motivation

Measuring the output gap is crucial in conducting and understanding both monetary and fiscal policies. Using improper output gap estimates could lead to serious policy mistakes (Orphanides, 2001). At each point in time, organizations such as the International Monetary Fund, Congressional Budget Office, and central banks, among others, use a large array of available information, data, and expert opinions to come up with their real-time measures of the output gap, resulting in a reasonably accurate description of the real state of an economy. Unfortunately, "official" estimates are not always available, so researchers often must resort to employing simple univariate methods when working with ex-post real-time historical data, with the estimates from different methods often providing contradicting results (e.g., Nikolsko-Rzhevskyy and Papell, 2011).

The goal of this section is to utilize existing official OECD real-time estimates of the output gaps, published for a number of countries since 1995, to help choose a simple univariate method that closely replicates them. Finding the most successful detrending technique that matches well the official series for a variety of countries would allow calculating sound estimates of the gap for the OECD countries before 1995, when they are not available, as well as obtaining meaningful output gap values for non-OECD countries for which this data does not exist at all.

3.1.2 Setup

By looking at the G7 economies, we search for a univariate measure of potential output that best approximates the "true" real-time estimate for each country, hence, providing the most accurate signals to policymakers. The "true" potential output is approximated by the official real-time OECD estimates, obtained by deep, all-around, multi-variable, real-time evaluation of the countries' economies by the OECD experts, which generally cannot be replicated in typical ex-post settings, which contain only a few available real-time variables.[7] Univariate methods are commonly used because they are relatively easy to handle and only require real GNP/GDP

[7]The OECD potential GDP is estimated using a production function approach that takes into account capital stock, changes in labor supply, factor productivity and underlying non-accelerating wage rates of unemployment or the NAWRU for each member country, except Portugal. Potential output for Portugal is calculated using a Hodrick-Prescott filter of actual output. These data are released on a semi-annual basis; we transform them into quarterly data by using quadratic interpolation. Consistent data on official OECD output gap estimates start in 1995Q1, which determines the starting date of our estimation sample.

or unemployment data. Among the existing methods to calculate the slack in the economy, we consider eight univariate characterizations frequently found in the literature. Each model is recursively applied to each complete real-time vintage of a corresponding variable, and the last residual defines the real-time output gap. Filters 1 through 6 are output-based, while techniques 7 and 8 are unemployment-based.

1. Quadratic (Q) and linear (L). The (log of) real GNP/GDP y_t is regressed on a constant term and a quadratic or linear time trend τ. These detrending mechanisms are used in Taylor (1993) and Clarida et al. (1998). For the case of quadratic detrending, we use an expanding window, as in Molodtsova et al. (2008), while for linear detrending, we follow Nikolsko-Rzhevskyy (2011) and use the rolling window scheme with a window size of 20 years. The output gap c_t is defined as the difference between actual output y_t and the trend τ_t toward which it tends to revert.

2. Hodrick-Prescott (HP). To apply the filter, we use $\lambda = 1600$ and cope with the end-of-sample problem by fore- and back-casting the GDP series by 12 datapoints, following Clausen and Meier (2005).

3. Band-pass (BP). This filter, proposed by Baxter and King (1999), isolates data fluctuations that persist for 1.5 to 8 years. The symmetric nature of the filter creates an end-of-sample problem, which we solve similarly to the HP case by extending each vintage of (log) GDP series by 100 data points in both directions before applying the filter, as suggested by Watson (2007).[8]

4. Unobserved component (UC). The method is based on Clark (1987). It assumes that output can be decomposed into an unobserved non-stationary trend τ_t and a stationary cycle c_t, where τ_t is presumed to follow a random walk and c_t is an AR(2) process. This model assumes no correlation between the trend and cycle innovations.

5. Beveridge-Nelson decomposition (BN). Output y_t is assumed to follow an ARIMA(2,1,2) process, which is identical in setup to the UC model, except it relaxes the assumption of zero correlation between trend and cycle innovations and estimates it from the data,

[8] To extend the series, we estimate an AR(8) model in GDP growth rates. Watson (2007) uses an AR(6) and 300 points forecast in application to monthly data.

making the BN decomposition more theoretically appealing than the UC model. See Morley et al. (2003) for details.

6. Difference filter (DF). The filter assumes that the the stochastic trend τ_t is an observation p periods ago. Accordingly, the cycle component is defined as $c_t = y_t - y_{t-p}$. We apply the filter as in Scott (2000) and assume $p = 4$. The advantage of this filter is its one-sided nature; it does not require a correction for the end-of-sample problem. A notable disadvantage, though, is a zero gain at the annual frequency.

7. Constant NAIRU (CN). This unemployment-based measure defines slack as the difference between the current unemployment rate and its average over the entire sample. The value of potential output τ_t is calculated using Okun's law by multiplying the unemployment gap by -2 to make it comparable to other measures.[9]

8. Moving average NAIRU (MAN). Following Fernandez et al. (2010), we define the MAN output gap as negative 2 times the difference between current unemployment rate and its 20-quarter moving average.

The G7 countries' "true" output gaps ($\tilde{c}$) are taken from the official OECD estimates released in the OECD Economic Outlook, issued semiannually and containing yearly estimates and future projections of the OECD countries' output gaps. Inside each vintage, annual data are converted into quarterly frequencies using quadratic interpolation. Semiannual vintages are converted into quarterly vintages under the assumption that during a quarter for which a vintage is missing, the only available data corresponds to that of the previous quarter.[10] The real-time official OECD gap at time t corresponds to the estimate from vintage t corresponding to calendar date t.

To compare the in-sample performance of the eight methods, we apply the following three metrics for each country:

1. First, we look at the root mean squared prediction error (RMSPE) between the estimated and country's official output gaps as follows: $RMSPE = \sqrt{\frac{1}{T}\sum_1^T(\tilde{c}_t - c_t)^2}$, where c is the estimated output gap, $\tilde{c}$ is the "true" output gap, and T is the sample size.

[9]While the original Okun's coefficient is close to -3.0, we use Weidner and Williams (2011) (-1.7) and Nikolsko-Rzhevskyy and Papell (2011) (-2.0) estimates that appear to better fit recent data. Additionally, we make an assumption that the value of the coefficient is similar for all G7 countries.

[10]The same procedure is used in Molodtsova et al. (2011) and Nikolsko-Rzhevskyy (2011).

2. Then, we assess the degree of co-movement of real-time estimates of the output gap and their official real-time OECD counterparts. Specifically, we look at the correlation between the two series.

3. Finally, we calculate the concordance $C_i = \frac{1}{T}\{\sum_{t=1}^{T}[\delta(c_{i,t} > 0)\delta(\tilde{c}_t > 0)] + [1 - \delta(c_{i,t} > 0)][1-\delta(\tilde{c}_t > 0)]\}$, a non-parametric measure, introduced by Harding and Pagan (1999) and then subsequently used in McDermott and Alasdair (1999) and Scott (2000). We apply this measure to estimate the proportion of time the two output gap series are simultaneously above or below potential, a relevant question in policymaking.[11]

3.1.3 Results and discussion

The results are presented in Table 4. In Panel A, which shows the RMSPE estimates, the lower the values, the closer the in-sample performance of our estimated model trails that of the "true" model. For the correlation and concordance results in Panels B and C, the higher statistic values for a given model correspond to closer estimates of the "true" output gap.

When judged by the number of cases the statistic is significant, our results indicate that the model best replicating the OECD official estimates is rolling window linear detrending, which also shows the highest correlation statistic of 82 percent. This accords well with the results of Nikolsko-Rzhevskyy (2011) who finds this model to closely match the official U.S. "Greenbook" and German Bundesbank's output gap values.

If we look at the individual criteria instead, the unobserved component model is the model with the closest in-sample fit to the "true" OECD output gap, with a weighted average RMSPE of 1.61. However, this method is only sixth in correlation (58 percent) and fourth in concordance (69 percent) rankings. The moving average NAIRU approach results in the highest concordance statistics and has the second best correlation.

Overall, the worst performing model is the difference filter, with an RMSPE of 4.60, a negative correlation of 21 percent and a 46 percent concordance. Among other commonly used models, the Beveridge-Nelson decomposition has the second-lowest overall performance with an average RMSPE of 5.08, the second-lowest correlation (negative 17 percent) and concordance statistics (47 percent) among all the models. This result would be expected given the main

[11]This technique allows us to elude cases in which correlations are dominated by particularly large swings in the data. $\delta(x) = 1$ if $x = true$ and 0 otherwise.

message of the decomposition – there is no cycle.

Looking at individual countries, we see that for Canada, Germany and the UK, the band pass model yields the lowest RMSPE values. The rolling window linear detrending seems to fit better for France and Italy, while for Japan, the best representation seems to be the moving average NAIRU and for the U.S., the unobserved component model.

3.2 Are output gaps useful for forecasting inflation?

3.2.1 Motivation

An inverse relationship between expected inflation and the output gap, usually referred to as a Phillips curve, is an essential component of many theoretical macroeconomic models that form the backdrop of countercyclical stabilization policy. Given the empirical consistency of this inverse relationship, an accurate depiction of the output gap is generally desired when forecasting inflation in a monetary policy context.

Orphanides and van Norden (2005) provide an empirical evaluation of the usefulness of alternative univariate estimates of the output gap for predicting U.S. inflation. The authors conclude that ex-post output gap measures are good at predicting inflation but that their forecasting abilities drop significantly when using real-time data. These results cast doubt on the forecasting power generally attributed to the output gap, and underscore the importance of using real-time – not revised – data in monetary policy analysis, as output revisions may indeed lead to policy mistakes. In this section, we test this conclusion by extending Orphanides and van Norden's analysis on the U.S. to include all the G7 countries.

3.2.2 Setup

We define inflation as $\pi_t = 400(\ln P_t - \ln P_{t-1})$ with the price level p measured by the GDP/GNP deflator and investigate whether any univariate measure of real-time output gap can improve on a naïve univariate inflation forecast.

We assess the contribution of a real-time estimated output gap to inflation forecasting by comparing two models:

1. A naïve direct AR(p) benchmark model that exclusively uses lags of inflation. Following

Orphanides and van Norden (2005), we specify this model as:

$$\hat{\pi}_{t+h} = \rho_0 + \sum_{j=0}^{p} \rho_j \pi_{t-j} \tag{2}$$

where $\hat{\pi}_{t+h}$ is the h-step ahead inflation forecast. The lag length p is chosen to minimize the BIC criterion. For completeness, we also estimate and compare the results of a simple random walk specification.

2. The competing ADL(p, q) model enhances the above equation with up to q lags of the output gap c_t:

$$\hat{\pi}_{t+h} = \rho_0 + \sum_{j=0}^{p} \rho_j \pi_{t-j} + \sum_{i=0}^{q} \gamma_i c_{t-i} \tag{3}$$

where the optimal lag lengths are chosen over all applicable combinations of p and q to minimize the BIC criterion. The maximum lag value for both p and q is set at 8. For this specification, we calculate the output gap c_t using the eight output gap construction methods described in Section 3.1.[12]

Forecasts of both models are compared to "actual" realizations of inflation for different forecast horizons. Following Romer and Romer (2000), we define actual inflation as the one available two quarters after the initial estimate was released, since it makes sense to forecast variables as they are defined at the time the forecast is made. We claim that the output gap has some marginal predictive power if the root mean square prediction error (RMSPE) of the benchmark AR(p) is bigger than that of the output-gap-enhanced ADL(p, q).[13]

For Canada, the U.S., Japan, Germany, and the U.K., the forecasting sample starts in 1985:Q1 and for France, in 1990:Q1.[14] These dates are chosen so as to make the vintages sufficiently "long" for applying the forecasting models. Forecasting is recursive and uses all available historical data in a vintage.

[12]We are not using the official OECD gaps as one of the competing measures due to a fact that those data start only in 1995.

[13]To our best knowledge, there is no MSPE-based test available to formally test the difference in RMSPEs when the left hand side variable is being revised from one period to another.

[14]France's price index data started being recorded in the dataset in November 1987 (1987:Q3), versus May 1974 (1974:Q2) for the rest of the countries in the sample.

3.2.3 Results and discussion

The forecasting results for two different forecast horizons, $h = 1$ (the "nowcast" of inflation) and $h = 5$ (the "one year ahead" forecast of inflation) are presented in Table 5.[15] All values in the table are RMSPEs, normalized by the RMSPE of the AR(p) benchmark model.

The nowcast results ($h = 1$) show that the AR(p) model for all the countries and the ADL(p,q) for some countries beat the random walk (RW) counterpart. This is particularly true for Germany, for whom the AR(p) model performs 26 percent better. We also see that for every country, at least one estimated model forecasts at least as well as both the benchmark and the RW models, though the gain is typically minimal. Looking at individual model performance, we see that on average, the UC, CN and MAN representations do better than the rest. The largest improvement of 8 percent is seen in Germany with the CN model and Italy with the UC model.

The one-year-ahead forecasts ($h = 5$) depict a similar picture, although the RW seems to have a comparatively stronger performance. In 4 out of 7 countries, the RW forecast performs equal to or better than the benchmark, and for the case of the UK, it even results in a significant 17 percent gain. Among individual models, the UC model works well for the U.S. and Italy, and the CN model remains the best performing model for Germany. The Q, L, and HP gaps actually appear to be harmful for forecasting: Their RMSPE are higher than those of the benchmark model for all 7 countries.

In sum, we achieve conclusions very similar to those of Orphanides and van Norden: with rare exceptions, the operational usefulness of output gaps to forecast inflation in a multicountry framework is very limited.[16] In fact, better performance is often achieved by using simple univariate alternatives.

3.3 Using real-time data structure for GDP/GNP growth forecasting

3.3.1 Motivation

Economic forecasting – whether it based on time-series or structural methods – is important because it helps shape the expectations of future economic conditions, which are critical consid-

[15] Note that because of reporting lags, data for quarter t first became available at quarter $t+1$ or later. Therefore, a year-ahead forecast (four-quarter ahead) is a forecast five quarters ahead of the last quarter for which actual data are available.

[16] The term "operational" is used in Orphanides and van Norden to differentiate the real-time out-of-sample analysis from the "suggested usefulness" obtained from revised-data ex-post analysis.

erations in policy, consumption, and investment decisions. Although it is generally known that the predictive abilities of real-time economic forecasting models are considerably affected by revisions (Croushore, 2006, Croushore and Stark, 2011) most models are still developed under standard revised-data techniques.

A step forward was taken by Koenig et al. (2003) who highlighted additional ways to define a real-time series than using data vintages. When applied to U.S. GDP growth rates, these modifications produce superior forecasts.

In this section, we employ the same format characterizations and extend the work of Koenig et al. (2003) to include other developed countries. More specifically, we define and estimate a growth rate forecasting model for the G7 countries and compare the results to the actual growth rate.

3.3.2 Setup

A real-time data series and its lags can be defined in three ways. If we define a variable X_t at time k as it is thought of in vintage v as x_k^v, then the series x_t (for $i = 0$) and its i^{th} lag (for $i > 0$) is defined as the following sequence of values:

1. Vintages, $x_{t-i} = \{x_{1-i}^t, ...x_{t-1-i}^t, x_{t-i}^t\}$, incorporate the latest available information (available at time t) on each variable, so that the dataset is fully updated before a new forecast is made. As stated in Corradi et al. (2009), this is arguably the most commonly used data set-up in general forecasting.

2. Diagonals, $x_{t-i} = \{x_{1-i}^1, ...x_{t-1-i}^{t-1}, x_{t-i}^t\}$, use data from as many different vintages as there are dates in the sample, making both current and previous releases necessary for forecasting. Koenig et al. (2003) find this method to be the most efficient in forecasting current-quarter GDP growth for the U.S., and Nikolsko-Rzhevskyy (2011) shows that this type of data results in the lowest RMSPE for a variety of inflation forecasting models.

3. First releases, $x_{t-i} = \{x_{1-i}^{1-i}, ...x_{t-1-i}^{t-1-i}, x_{t-i}^{t-1}\}$, use only the initial estimates of each variable, eliminating the need to keep track of revisions.

Following Orphanides and van Norden (2005) and Koenig et al. (2003), our forecasting model is defined as the direct AR(p):

$$\hat{g}^i_{t+h} = \rho^i_0 + \sum_{j=1}^{p} \rho^i_j g^i_{t-j} \tag{4}$$

where g_t is the annualized quarter-over-quarter real GNP/GDP growth rate, h is the forecast horizon, and $p = \{1..8\}$ is the lag length. We do not follow any particular rule to choose the number of lags. Instead, we estimate $m = 8$ models, one for each lag length, and then average forecasts using the Bayesian model averaging approach (BMA) in light of the evidence indicating that aggregating forecasts over a set of models produces RMSPE smaller than that for any single model in the set.[17] If we let $\widehat{g}^i_{t+h}$ be the i_{th} model forecast for g_{t+h}, the aggregate forecast is represented as:

$$\hat{g}_{t+h} = \sum_{i=1}^{m=8} \omega_i \hat{g}^i_{t+h} \tag{5}$$

with ω_i being the Bayesian posterior probabilities which, under standard non-informative priors, are proportional to the exponent of the Schwartz criterion.[18] To compare performance under the different data formats, we obtain RMSPE values between our BMA-AR (p) estimated forecasts, $\widehat{g}_{t+h}$, and the "actual" realizations, g_{t+h}, which are defined as before as data available two quarters after the initial estimate was released.

We run recursive forecasting over the entire available span of data up to May of 2010, leaving the earliest 40 vintages (10 years) as an initial window for "first releases" and "diagonals" estimations. We calculate the RMSPE relative to a naïve RW benchmark and compare the results.

3.3.3 Results and discussion

Table 6 shows the results for the G7 countries minus Italy, which was excluded due to poorer data quality.[19] It presents the RMSPE values relative to a RW no-change forecast for horizons

[17]See Bates and Granger (1969), Aiolfi and Timmermann (2006), Faust and Wright (2007), and Nikolsko-Rzhevskyy (2011), among others.

[18]See Garrat et al. (2007) for details.

[19]Sound results could not be obtained for Italy because the real GNP/GDP and price series have irregular data release lag structure. For instance, 73 percent of the price level sample was released with a 2 quarter lag; 10 percent with a 3 quarter lag, and the rest varied between 4 and 6 quarters. For the remaining countries, there were also occasional differences in lag structure. In these instances, we filled in missing values using an AR(8)

$h = \{1..6\}$ quarters, with values below one indicating a superior performance of the BMA-AR(p) model.

The results show that the BMA-AR(p) forecasting model performs better than the RW at all horizons for all countries with the maximum gain of 28 percent (Germany, $h = 6$, vintages data).

As in Koenig et al. (2003) and Nikolsko-Rzhevskyy (2011), our results add to the evidence suggesting that vintages might not be the best forecasting data format when working with real-time data. For the three non-European countries, Canada, U.S., and Japan, vintages perform worse than do both diagonals and first releases, with the loss reaching a significant 10 percent (Japan, $h = 4$, first releases). Moreover, with the exception of France, both diagonals and first releases outperform vintages in one step ahead forecasting for the rest of the countries, with the gain reaching 8 percent (UK, $h = 1$, diagonals). For European countries at longer horizons, however, performance of vintages improves and in some cases even exceeds that of diagonals and first releases.

3.4 The effect of inflation on the revisions

3.4.1 Motivation

In most theoretical models, inflation is thought to have a significant but temporary effect on the economy. We propose a channel which, to our knowledge, is overlooked in the literature and could result in costly permanent impact of inflation on an economy: the effect of inflation on data revisions, which could potentially lead to policy mistakes.

In an inflationary environment, obtaining precise economic estimates becomes increasingly difficult as shifts in relative prices complicate aggregation and indexing. This makes accounting problematic and as a consequence amplifies the magnitude of data revisions. In this section, we estimate the effect of inflation on revisions to both nominal (price level and money supply) and real (real GNP/GDP and industrial production) variables.

3.4.2 Setup

As in previous sections, we define inflation as an annualized quarterly growth rate of the GNP/GDP price level. The impact of inflation, π, on revisions, r, is estimated for the G7

forecast over the "vintage" specification, mimicking the process a forecaster would follow to form her expectations.

countries in a panel-data setting as:

$$r^i_{j,t}(x) = \alpha^i_j + \beta^i_x \pi_{j,t} + \epsilon_{j,t} \tag{6}$$

with α_j being a country-j fixed effect, and i representing the release lag. The coefficient of interest, β, accounts for the effects of inflation on revisions to the growth rate of x .

The sample size for r_i is different for each i, as Figure 1 shows. In Table 3, it is clear that revisions between the first and second quarters are rare in the growth rates of real GNP/GDP, industrial production, and prices, where the vast majority of data releases lag 2-quarters. While most data releases in money supply lag 2 quarters as well, this is the only variable in which 1-lag releases cover a significantly larger percentage of the data. Estimation is done over the entire available sample period for each variable and country.

3.4.3 Results and discussion

Our results are shown in Table 7. Overall, we see that revisions to inflation affect growth in real GNP/GDP ($i = 4$) and prices ($i = 1$): Both coefficients are positive and significant. If instead of examining a single i to $i + 1$ revision, we define cumulative revisions, R, between the ith and the 4th releases, $R^i_{j,t} = x^{t+4+1}_{j,t} - x^{t+i}_{j,t}$ (which for $i = 4$ simplify to simple revisions), we are obtaining one additional significant coefficient, real GNP/GDP for $i = 1$. For this case, we see that a 10 percent increase in a country's inflation rate in a given year would increase the size of growth rate revisions by a full 1 percent over the following year. Revisions in industrial production and money supply, as well as revisions in GNP/GDP and prices for other releases, do not seem to significantly depend on inflation. However, this result is expected: For nearly unbiased revisions, one would expect to find a low or insignificant β, because positive and negative corrections virtually cancel each other out.

The effects of inflation, if they exist, should be more evident if instead we look separately at positive and negative revisions, which is shown in Table 7. The results show that for all variables but the money supply, there exists some i for which the inflation coefficient is significant; moreover, for positive and negative revisions, the signs are opposite. This relationship is expected since inflation amplifies both positive and negative revisions, making positive revisions more positive and negative revisions more negative. To increase efficiency, we have also pooled negative and positive revisions together and run the model with absolute values of revisions, and our results are consistent: Higher inflation increases the magnitude of data revisions.

3.5 Forecasting exchange rates with real-time and revised data

3.5.1 Motivation

Using real-time data is crucial for short-horizon nominal exchange-rate forecasting where information is short-lived. Accordingly, revisions are potentially important because they shape public estimates of current conditions and expectations of future economic circumstances. Nevertheless, since the seminal paper of Meese and Rogoff (1983), most forecasting models are being developed and tested using revised data (e.g. Mark, 1995, Cheung et al., 2005, Molodtsova and Papell, 2008, among others).

Those few studies that do employ real-time data (Faust et al., 2003, Molodtsova et al., 2008, 2011, for example), are first, based on relatively short samples and, second, do not provide a comparison of the results between revised data and different types of real-time data that could shed additional light on the forecasting problem. We are filling this gap.

Using the non-European G7 currencies (Canadian dollar, U.S. dollar, Japanese yen and British pound), we examine how the performance of purchasing power parity (PPP), monetary, and Taylor rule-fundamentals based models, tested against a driftless RW, changes depending on whether revised or real-time data is used and evaluate, which type of real-time data (vintages or first-releases) is most beneficial for forecasting.[20] To measure various models' performance, we use the recently-developed Clark and West (2006) inference procedure for testing equal predictive ability of nested models.[21]

3.5.2 Setup

Suppose the variable s_t is the date-t logarithm of the U.S. dollar nominal exchange rate, determined as the domestic price of one unit of foreign currency, such that a decrease in s is an appreciation of the dollar. We test the following forecasting models:

[20] We do not test the uncovered interest rate parity (UIRP) model, because interest rates are released in real-time and thus are not subject to revisions. Also, we do not test the models using the "diagonals" setup since for all the forecasting models we consider, the "diagonal" setup is identical to "first-releases."

[21] The Clark and West test tests population-level predictive ability. It does not provide inference on predictive abilities in finite samples.

1. Purchasing power parity (PPP) fundamentals. There has been extensive research done on forecasting exchange rates under the assumption of PPP (as an example, see Papell, 2006). The nominal rate s_{t+1} is assumed to respond to deviations z_t of its current rate s_t from the fundamental value f_t:

$$\triangle \hat{s}_{t+h} = \alpha + \beta z_t \tag{7}$$

where

$$z_t = f_t - s_t \tag{8}$$

$$f_t = p_t^* - p_t \tag{9}$$

with p being the log of the price level, P, and * denoting non-U.S. variables. $\triangle s_{t+h}$ is the change in the nominal rate from t to time $t+h$. To measure the price level, we use the GNP/GDP deflator.[22] To our best knowledge, all existing research on PPP uses only revised data; the general consensus is that the PPP model forecasts well in the long run but not in the short run.

2. Monetary fundamentals. Following Mark (1995), we assume PPP and UIRP, and set the income elasticity to zero for simplicity, resulting in a fundamental value, f_t, being:

$$f_t = m_t^* - m_t \tag{10}$$

where m is the log of money supply, M.[23] Faust et al. (2003) estimate this model for Canada, Germany, Japan, and Switzerland using both revised and real-time "vintages" data, and find in many cases that real-time data performs significantly better.

3. Taylor rule fundamentals. This model, proposed by Molodtsova and Papell (2009), assumes that an exchange rate responds to the interest rate differential, $z_t = i_t - i_t^*$, where domestic and foreign interest rates are determined by the corresponding Taylor rules that we assume

[22] Another popular price level measure is CPI, which presents a trivial case for real-time versus revised data comparison exercise because CPI is almost never revised.

[23] Contrary to Mark (1995), we do not average M over 4 consecutive quarters.

to be symmetric and homogenous:[24] For the U.S., then:

$$i_t = \gamma_0 + \gamma_1 \pi_t + \gamma_2 \hat{y}_t + \gamma_2 i_t \tag{11}$$

A similar expression is used for a foreign country. $\hat{y}$ measures the real-time output gaps, which, following Nikolsko-Rzhevskyy (2011), we calculate as deviations from the 20-year rolling window linear GNP/GDP time trends.[25] After substituting z_t back into Equation 7, the forecasting equation becomes:

$$\triangle \hat{s}_{t+h} = \alpha + \tilde{\gamma}_1(\pi_t - \pi_t^*) + \tilde{\gamma}_2(\hat{y}_t - \hat{y}_t^*) + \tilde{\gamma}_3(i_t - i_t^*) \tag{12}$$

where $\tilde{\gamma}_i = \beta\gamma_i$. Molodtsova et al. (2008) apply this model to pre-1999 Germany and Molodtsova et al. (2011) use this model for post-1999 EU; both studies find that the Taylor rule fundamentals model significantly outperforms the RW model. However, while the 2008 study uses real-time first-release data and finds that it performs better than the revised data, the latter study employs real-time vintages data and does not find any difference in performance between revised and real-time setups.

We estimate the PPP, monetary and Taylor rule fundamentals models using revised (May 2010 vintage) and real-time vintages data. The Taylor rule fundamentals model is also estimated using real-time first-release data.[26] Forecasting is performed using the rolling window scheme with window size of 10 years, similar to Molodtsova et al. (2008), and we test the models against a RW using the Clark and West (2006) procedure. We start the sample in 1973:Q4 such that forecasts would begin in 1984:Q1 after accounting for the 10-year moving window. The forecasting sample ends in 2008:Q4 before interest rates hit the zero lower bound and the Taylor rule becomes inapplicable.

3.5.3 Results and discussion

The one-step and four-step-ahead forecasting results are presented in Table 8. As expected, the PPP results (Panel A) reveal no difference between real-time and revised data, probably

[24]This means that the choice of independent variables as well as their response coefficients are assumed to be the same for both countries. Molodtsova et al. (2008, 2011) also consider asymmetric heterogenous Taylor rules.

[25]Using recursive quadratic detrending does not affect the results.

[26]This setup is not defined for the monetary and PPP models due to base year changes.

because prices are seldom revised significantly. Additionally, we find the PPP models performing somewhat better in the long run than in the short run: for $h = 4$, the UK results are significant, though only at the 10 percent level.

Panel B shows results for the monetary model. Similar to Faust et al. (2003), we find some support that real-time data performs better than revised data (the case of Japan). In the long run, however, the model is not able to outperform the random walk.

Panel C presents results for the Taylor-rule-fundamentals model. We can make several observations. First, compared to the PPP and monetary models, the Taylor rule fundamentals model performs exceptionally well: in most instances, the model significantly outperforms the RW model at both short and long horizons. This result is similar to Molodtsova and Papell (2009) who use revised data and also find the Clark and West statistic to be significant at the short horizon for all three exchange rates we study here (CAD, GBP, JPY).

Second, we do not observe much difference between the two types of real-time data – vintages and first-releases: both are either significant or insignificant in tandem. Finally, while CAD and JPY rates can be forecasted out of sample using real-time data, GDP rates cannot. In fact, while the results using revised data show that the GBP rate is predictable at a short horizon, real-time data does not support that conclusion: neither vintages nor first-releases result in a significant statistic. This important result reveals the need to be cautious when using revised data in applications that require relying on real-time data only, since some of the results obtained using revised data could mislead.

4 Conclusions

This paper was motivated by a recurrent need for international real-time data. In an increasingly globalized world and given the proven advantages in using real-time data, there is a fundamental need to rethink international researchers' practice of using revised data, which may yield misleading conclusions. As a solution, we have collected and made publicly available a comprehensive real-time dataset for a number of important variables for OECD countries.

In this paper we present the real-time historical database for the OECD (RTHD-OECD), explaining how the data was compiled and presenting five important economic problems analyzed from a real-time perspective. We hope that this dataset will serve as a standard for forecasters and others engaged in international research who are faced with the economic and methodological problems of data revisions.

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Table 1: Starting dates by variable and country

	Country	nGDP	rGDP	P	IP	MP	CUR	UR	CPI	M	CH	Im	Ex	NCM
1	Canada	May-62	May-62	Feb-68	May-62	May-62	Nov-79	May-62	May-62	May-62	May-62	May-62	May-62	May-74
2	Mexico	Nov-94	Nov-94	Nov-94	Nov-94	Nov-94	Nov-95	Nov-94	Nov-94	Nov-94	Nov-94	Nov-94	Nov-94	Aug-96
3	USA	May-62	May-65	May-65	May-62	May-62*	Nov-79	May-62	May-62	May-62	May-62	May-62	May-62	Nov-76
4	Japan	May-65	Nov-70	Nov-70	May-64	May-64*	Feb-90	May-74	May-64	May-64	May-64	May-64	May-64	May-74
5	Australia	May-74	Nov-79	May-74	Aug-73	Nov-79	Nov-79	May-74	Nov-72	Nov-72	Nov-72	Nov-72	Nov-72	May-74
6	New Zealand	May-95	May-95	May-95	May-94	May-94	May-82	Nov-92	Aug-74	Aug-74	Aug-74	Aug-74	Aug-74	Aug-74
7	Austria	Nov-62*	Nov-62*	Feb-94	May-62	May-62*	May-80	May-62*	May-62	May-62	May-62	May-62	May-62	May-74
8	Belgium	–	May-97	–	May-62	May-62*	Nov-79	May-62*	May-62	May-62	May-62	May-62	May-62	May-74
9	Denmark	Feb-94	Feb-94	Feb-94	May-62*	May-62*	May-83	May-62*	May-62	May-62	May-62	May-62	May-62	Nov-96
10	Finland	May-94	May-94	May-94	Feb-70	Nov-79	Nov-79	Feb-70	Feb-70	Feb-70	Feb-70	Feb-70	Feb-70	Feb-94
11	France	Nov-87	May-74*	Nov-87	May-62	May-62*	Nov-79	Nov-85	May-62	May-62	May-62	May-62	May-62	May-74
12	Germany	May-65	Nov-79	May-74	May-62	May-62*	Nov-79	May-62*	May-62	May-62	May-62	May-62	May-62	May-62
13	Greece	–	–	–	Feb-68	May-62*	–	Feb-83	May-62	May-62	May-62	May-62	May-62	Aug-74
14	Iceland	–	–	–	–	–	–	Feb-95	May-62	May-62	May-62	May-62	May-62	May-94
15	Ireland	–	–	–	Aug-68	May-62	–	May-62*	May-62	May-62	May-62	May-62	May-62	May-92
16	Italy	May-75	Nov-79	May-75	May-62	May-62*	Nov-79	May-74	May-62	May-62	May-62	May-62	May-62	May-65
17	Luxembourg	–	–	–	May-62	May-62*	Feb-85	–	May-62	–	–	May-62*	May-62*	–
18	Netherlands	Feb-94	Feb-94	Feb-94	May-62	May-62*	Nov-79	Aug-81	May-62	May-62	May-62	May-62	May-62	May-74
19	Norway	Feb-94	Nov-65	Feb-94	May-62	May-62*	Nov-79	May-62*	May-62	May-62	May-62	May-62	May-62	Nov-86
20	Portugal	May-93	May-94	May-93	May-62	May-62*	Feb-82	Nov-92	May-62	May-62	May-62	May-62	May-62	Aug-74
21	Spain	Aug-93	May-94	Aug-93	Aug-67	Feb-80	Nov-79	Feb-75	May-62	May-62	May-62	May-62	May-62	May-65
22	Sweden	May-90	Feb-76	May-90	May-62	Nov-66	Nov-79	May-62*	May-62	May-62*	May-62	May-62	May-62	May-74
23	Switzerland	Nov-67	Feb-90	Nov-87	May-66	Nov-79	Nov-82	Feb-83	May-62	May-62	May-62	May-62	May-62	–
24	Turkey	Aug-93	May-94	Aug-93	May-95	Feb-85	Nov-93	Feb-83	May-62	May-62	May-62	May-62	May-62	Aug-74
25	UK	May-65	May-62	Feb-68	May-62	May-62*	Nov-79	May-62*	May-62	May-62	May-62	May-62	May-62	May-74
26	Korea	May-97	–	May-97	–	May-97	Aug-97	May-97	May-97	May-97	May-97	May-97	May-97	May-97

Notes: nGDP–nominal GDP, rGDP–real GDP, P–price level, IP–industrial production, MP–manufacturing production, CUR–capacity utilization rate, UR–unemployment rate, CPI–consumer price index, M–money supply, CH–capital holdings, Im–imports, Ex–exports, NCM–net capital movements. * denotes variables that contain spans of missing vintages after the starting date.

Table 2: Data release lag structure

		Real GNP/GDP			Money Supply		
	Data release lag, quarters	1	2	3 and up	1	2	3 and up
1	Canada		Entire sample		Nov-79...	...Aug-79	
2	Mexico		Entire sample		Aug-95...	...May-95	
3	US	Feb-82...	Aug-70...Nov-81		Feb-81...	...Nov-80	
		Feb-68...May-70	Nov-67...		Feb-81...	...Nov-80	
4	Japan		May-71...	...Feb-71	Aug-90...	...May-90	
5	Australia		Entire sample			Entire sample	
6	New Zealand		Entire sample		May-82...Aug-83	Nov-83...	...Nov-77
						Feb-78...Feb-82	
7	Austria		...Feb-96	Irregular		Entire sample	
8	Belgium		Irregular			Aug-96...	Aug-93...May-96
						...May-93	
9	Denmark		Entire sample			Entire sample	
10	Finland		Entire sample		Nov-92...Nov-95	Feb-96...	
						Feb-70...Aug-92	
11	France		Nov-87...Nov-98	Irregular		Entire sample	
12	Germany		Entire sample		Nov-80...	...Aug-80	
13	Greece		–		Aug-96...	...May-96	
14	Iceland		–		Aug-91...	...May-91	
15	Ireland		–			Entire sample	
16	Italy		Irregular	Irregular		Entire sample	
17	Luxembourg		–			–	
18	Netherlands		Entire sample			Entire sample	
19	Norway		Entire sample			Entire sample	
20	Portugal		Irregular			Irregular	Irregular
21	Spain		Entire sample			Entire sample	
22	Sweden		Entire sample		Nov-79...	...Aug-79	
23	Switzerland		Entire sample			Entire sample	
24	Turkey		Entire sample		May-93...	May-81...Feb-93	...Feb-81
25	UK		Entire sample		Nov-94...	...Aug-94	
26	Korea		–		Feb-98...	...Nov-97	

Notes: An open interval from the left (right) means that the lag is constant starting at the beginning (through the end) of the sample. For example, "Feb-82..." for the U.S. means that real GNP/GDP data are released with a 1-quarter lag from Feb-82 through Nov-98, which corresponds to the end of the sample. Each interval might include occasional instances of irregular data release lag. For example, even though real GNP/GDP data for Australia are regularly released with a 2-quarter lag, in Nov-93, they were released with a 1-quarter lag.

Table 3: Mean revisions by country

		Real GNP/GDP				Price level				Industrial production				Money supply			
	Revision	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	Canada	–	0.28*	-0.01	-0.07	–	0.19	-0.07	0.22**	–	0.04	0.38	0.01	-0.89	0.33	0.14	–
2	Mexico	–	1.57	-1.40*	2.21**	–	-0.06	0.21	-0.71	–	-1.08	-0.25	1.62**	5.63**	0.49	0.00	–
3	US	0.10	0.05	-0.06	0.03	0.12**	0.01	0.00	0.02	0.28**	0.17	-0.19*	0.02	0.32	0.00	0.05	–
4	Japan	–	0.87	-0.47	0.23**	–	0.08	0.19	-0.14	0.32*	-0.27	0.38	-0.24	-0.12	-0.07	-0.05	–
5	Australia	–	0.47**	-0.07	-0.30**	–	0.29	0.28*	-0.29**	–	-0.85*	0.12	0.03	2.09	-0.27*	0.11	–
6	New Zealand	–	5.36	2.15	-2.48	–	0.10	0.10	-0.10	–	-0.20	0.36	0.40	0.24	-0.01	0.06	–
7	Austria	–	-0.15	0.08	-0.02	–	-0.17	0.58	0.44	–	-0.34**	-0.01	0.10	-0.01	0.04	0.01	–
8	Belgium	–	–	-2.16	-0.03	–	–	–	–	–	0.38	-0.48	-0.31	–	0.22	0.09	–
9	Denmark	–	0.00	-1.30	1.36	–	0.79	-0.10	-0.41*	–	–	–	–	–	-0.07	0.05	0.33*
10	Finland	–	-0.26	-0.54	1.81	–	-0.11	-0.19	0.33	–	0.17	-1.17*	0.35	-1.14	-0.16	0.20	–
11	France	–	0.00	0.67	-1.20	–	0.00	0.01	-0.10	0.00	0.33	0.18	0.13	–	0.13	-0.08	–
12	Germany	–	0.17	-0.10	-0.09	–	0.06	-0.17	-0.08	1.06	0.30**	-0.31*	0.21	-0.12	0.19*	0.09	–
13	Greece	–	–	–	–	–	–	–	–	–	0.86*	0.10	-0.68	3.10	-0.04	-0.16*	–
14	Iceland	–	–	–	–	–	–	–	–	–	–	–	–	0.20	0.23	-0.20	–
15	Ireland	–	–	–	–	–	–	–	–	–	0.35	-0.06	-0.01	0.00	-0.33	0.10	–
16	Italy	–	0.15	0.20	-0.17	–	0.50*	-0.08	0.29	–	0.35	0.17	0.10	–	0.24*	-0.44	–
17	Luxembourg	–	–	–	–	–	–	–	–	-0.63	-0.24	0.20	-0.58	–	–	–	–
18	Netherlands	–	-0.09	0.01	0.42**	–	0.09	0.20	-0.12	–	0.31	-0.02	-0.02	-0.27	0.02	0.03	–
19	Norway	–	0.85	-0.45	-0.12	–	-0.76	0.57	0.52*	-0.51	-0.28	0.75	-0.35	-0.37	1.38	-1.79	–
20	Portugal	–	–	–	-0.80	–	–	-0.01	-0.04	–	0.93	-0.22	0.29	-2.66	-0.48*	6.37	–
21	Spain	–	-0.05	0.02	-0.08	–	-0.05	0.30*	0.08	–	0.47	-0.56	-0.10	–	0.19	-0.04	–
22	Sweden	-0.72	0.57	0.32	-0.42	–	0.22	-0.23	-0.12	–	0.29	0.04	-0.15	1.77	-1.30	0.30	–
23	Switzerland	–	0.10	-0.12	0.04	–	1.18**	-0.45	0.50	–	-0.33	0.07	0.13	-0.54	0.05	0.29**	–
24	Turkey	–	-13.37	-3.01	5.23	–	2.86**	-1.73	2.83	–	1.97**	2.23**	-0.89	-6.04	-0.10	0.75	–
25	UK	–	-0.57	1.03	-0.22	–	0.03	0.14	0.13	-0.05	0.24	-0.06	0.15	1.03	-0.29	-0.18	–
26	Korea	–	–	–	–	–	–	0.09	0.20	–	–	–	–	–	0.00	0.00	–

Notes: All variables are expressed in terms of annualized quarter-over-quarter growth rates. Robust Newey-West standard errors are used. * and ** indicate significance at 5 and 10 percent, respectively. "–" indicates that there is not enough data available to calculate the mean revision.

Table 4: Comparison of output gap detrending methods in replicating the official OECD output gaps

		Detrending methods								
		Q	L	HP	BP	UC	BN	DF	CN	MAN
	Panel A: RMSPE									
1	Canada	6.52	2.00	1.42	1.24	1.57	2.20	3.06	1.76	2.46
2	US	2.26	1.43	1.42	1.32	0.95	2.09	4.50	1.61	1.40
3	Japan	2.48	4.43	2.62	2.55	3.02	16.40	6.94	2.76	1.96
4	France	2.23	1.31	1.88	1.84	1.73	13.60	3.61	2.28	2.33
5	Germany	2.40	1.87	1.79	1.64	1.94	1.92	4.51	4.94	2.97
6	Italy	2.87	1.35	2.57	2.41	2.40	2.58	3.29	3.28	3.72
7	UK	4.40	2.04	1.71	1.67	1.93	1.93	3.76	3.53	3.01
	Weighted Average	2.69	1.98	1.77	1.67	1.61	5.08	4.60	2.42	2.03
	Panel B: Correlation									
1	Canada	0.96	0.95	0.46	0.58	0.12	-0.78	0.11	0.57	0.59
2	US	0.85***	0.88***	0.66***	0.84***	0.92***	-0.21	-0.37	0.91***	0.89***
3	Japan	0.79***	0.83***	0.51***	0.44***	0.41***	-0.26	-0.03	0.22*	0.90***
4	France	0.24*	0.83***	0.33**	0.33***	0.15	-0.57	-0.20	0.65***	0.91***
5	Germany	0.78***	0.83***	0.75***	0.82***	0.45***	0.45***	-0.05	0.25**	0.26**
6	Italy	0.44***	0.34***	0.38***	0.28**	0.08	-0.03	0.24*	0.26**	0.60***
7	UK	0.59***	0.73***	0.46***	0.50***	0.04	0.03	-0.35	0.79***	0.51***
	Weighted Average	0.75	0.82	0.58	0.67	0.58	-0.17	-0.21	0.66	0.77
	Panel C: Concordance									
1	Canada	0.28	0.53	0.58	0.78	0.75	0.28	0.58	0.68	0.38
2	US	0.70***	0.67**	0.73***	0.60	0.70***	0.50	0.43	0.82***	0.93***
3	Japan	0.83***	0.97***	0.60	0.63**	0.77***	0.28	0.42	0.78***	0.88***
4	France	0.63**	0.68***	0.52	0.45	0.80***	0.43	0.47	0.57	0.57
5	Germany	0.43	0.62*	0.50	0.70***	0.57	0.55	0.43	0.88***	0.65**
6	Italy	0.47	1.00***	0.50	0.73***	0.73***	0.72***	0.62*	0.68***	0.30
7	UK	0.43	0.50	0.52	0.50	0.45	0.53	0.48	0.48	0.55
	Weighted Average	0.63	0.71	0.63	0.61	0.69	0.47	0.46	0.76	0.77

Notes: Q–recursive quadratic, L–rolling window linear, HP–Hodrick-Prescott, BP–band pass, UC–unobserved component, BN–Beveridge-Nelson, DF–difference, CN–constant NAIRU, MAN–moving average NAIRU. *, **, and *** stay for significant at 10, 5, and 1 percent. For correlation and concordance, no significance level is indicated for values below 0.00 and 0.50, respectively. The weighted average uses individual country weights that are proportional to their GDP. Those data come from the "OECD Factbook 2010" and correspond to 2008. The values, expressed in billions of current USD, constitute 1300.2 for Canada, 14369.4 for the U.S., 4358.3 for Japan, 2121.7 for France, 2909.7 for Germany, 1871.7 for Italy, and 2186.0 for the U.K.

Table 5: Marginal contribution of output gap measures to inflation forecasting

		Absolute RMSPE	Relative to AR(p) RMSPE									
		AR(p)	RW	Q	L	HP	BP	UC	BN	DF	CN	MAN
		Panel A: The "nowcast" (h=1)										
1	Canada	3.38 = 1.00	1.06	1.08	1.00	1.04	1.00	1.00	1.01	1.00	1.00	1.01
2	US	1.09 = 1.00	1.17	1.07	1.01	0.99	0.98	0.98	1.00	1.01	1.01	1.00
3	Japan	2.61 = 1.00	1.19	1.20	1.08	1.00	1.02	1.05	1.15	1.06	1.13	0.96
4	France	0.92 = 1.00	1.05	1.11	1.09	1.13	1.13	1.18	1.07	1.12	1.00	1.03
5	Germany	2.13 = 1.00	1.26	1.04	1.03	1.03	1.01	1.03	1.02	0.99	0.92	1.04
6	Italy	2.92 = 1.00	1.07	0.96	1.07	0.99	1.08	0.92	0.96	1.09	1.03	0.99
7	UK	2.74 = 1.00	1.11	1.39	1.31	1.23	1.00	1.10	1.10	1.09	1.08	1.13
		Panel B: One-year-ahead forecast (h=5)										
1	Canada	3.56 = 1.00	1.03	1.37	1.02	1.09	1.05	1.02	1.00	1.01	1.01	1.07
2	US	1.51 = 1.00	0.90	1.35	1.18	1.12	0.97	0.89	0.90	1.00	1.03	1.04
3	Japan	3.03 = 1.00	1.00	1.55	1.45	1.49	0.94	1.20	1.32	1.01	1.36	0.97
4	France	1.06 = 1.00	1.04	1.02	1.01	1.03	0.98	0.98	0.94	0.93	1.04	1.01
5	Germany	2.14 = 1.00	1.39	1.07	1.03	1.02	1.02	1.03	1.00	1.02	0.88	1.04
6	Italy	2.80 = 1.00	1.00	1.89	1.43	1.63	1.41	0.91	0.97	0.99	1.14	1.19
7	UK	3.75 = 1.00	0.83	1.69	1.54	1.16	1.14	1.12	1.12	1.14	1.37	1.54

Notes: RW (random walk) and AR(p) are benchmark specifications that do not use any output gap measures for forecasting. Q–recursive quadratic, L–rolling window linear, HP–Hodrick-Prescott, BP–band pass, UC–unobserved component, BN–Beveridge-Nelson, DF–difference, CN–constant NAIRU, MAN–moving average NAIRU. *, **, and *** stay for significant at 10, 5, and 1 percent.

Table 6: Growth rate forecasting with different types of real-time data

		Forecast horizon, h					
		1	2	3	4	5	6
		Panel A: Vintages					
1	Canada	1.00	0.93	0.94	0.92	0.92	0.90
2	US	0.88	0.80	0.84	0.88	0.82	0.78
3	Japan	0.82	0.79	0.85	0.94	0.82	0.94
4	France	0.89	0.86	0.92	0.83	0.90	0.88
5	Germany	0.84	0.82	0.76	0.76	0.73	0.72
6	UK	0.96	0.80	0.78	0.77	0.78	0.76
		Panel B: Diagonals					
1	Canada	0.94	0.89	0.89	0.87	0.87	0.89
2	US	0.86	0.80	0.84	0.87	0.81	0.78
3	Japan	0.80	0.73	0.77	0.88	0.77	0.91
4	France	0.95	0.89	0.93	0.83	0.88	0.88
5	Germany	0.82	0.81	0.78	0.81	0.76	0.77
6	UK	0.88	0.83	0.80	0.80	0.80	0.81
		Panel C: First releases					
1	Canada	0.94	0.89	0.88	0.86	0.86	0.88
2	US	0.86	0.80	0.83	0.87	0.81	0.78
3	Japan	0.82	0.76	0.81	0.84	0.76	0.89
4	France	0.94	0.87	0.93	0.83	0.89	0.88
5	Germany	0.83	0.82	0.79	0.82	0.75	0.76
6	UK	0.90	0.84	0.81	0.81	0.81	0.81

Notes: The values are RMSPEs relative to RMSPE of the RW. Values below one mean that a model outperforms the RW. For definitions of vintages, diagonals, and first releases, refer to Section 3.3.

Table 7: The effect of inflation on various types of revisions

Dependent variable	i	Sample size	Type of revisions: i to $i+1$ revisions	i to 4 cumulative revisions	i to $i+1$ positive only revisions	i to $i+1$ negative only revisions	i to $i+1$ absolute revisions
Real GNP/GDP	1	91	0.01	0.10**	0.04***	-0.01***	0.02***
			(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
	2	624	-0.00	0.01	0.01	0.01	0.01
			(0.03)	(0.01)	(0.06)	(0.02)	(0.03)
	3	656	-0.02	0.01	-0.01	0.01	-0.02*
			(0.04)	(0.04)	(0.02)	(0.03)	(0.01)
	4	662	0.02**	0.02**	0.02*	-0.01	0.01
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Price level	1	92	0.05***	-0.03***	–	-0.02***	0.06***
			(0.00)	(0.00)		(0.00)	(0.00)
	2	633	0.00	0.03	0.02***	-0.02	0.02
			(0.03)	(0.05)	(0.01)	(0.03)	(0.01)
	3	683	0.03	0.02	0.06*	-0.03**	0.06***
			(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
	4	689	-0.00	-0.00	0.02	-0.02	0.03*
			(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Industrial production	1	117	0.04	-0.07	0.06	-0.02	0.05
			(0.04)	(0.09)	(0.05)	(0.02)	(0.05)
	2	667	0.03	0.01	0.03	0.01	0.01
			(0.04)	(0.04)	(0.03)	(0.01)	(0.02)
	3	699	-0.01	-0.03	0.00	-0.02***	0.02
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	4	700	-0.01	-0.01	-0.01	-0.01	0.01
			(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Money supply	1	246	-0.14	-0.02	-0.01	-0.19	0.15
			(0.14)	(0.05)	(0.03)	(0.17)	(0.13)
	2	673	0.01	0.02	0.01	0.01	0.01
			(0.02)	(0.03)	(0.02)	(0.01)	(0.02)
	3	685	0.03	0.00	0.01	0.02	-0.00
			(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
	4	688	-0.03	-0.03	-0.03	-0.01	-0.01
			(0.02)	(0.02)	(0.02)	(0.01)	(0.03)

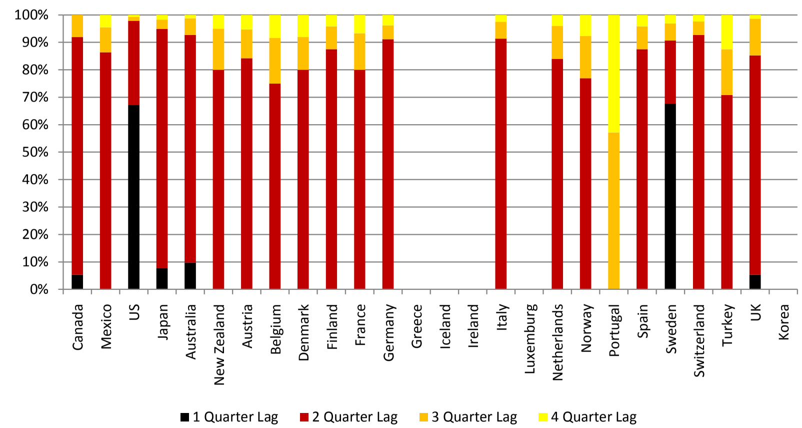
Notes: For definitions of various types of revisions, refer to Section 3.4. All variables are expressed in terms of annualized quarter-over-quarter growth rates. Each regression includes fixed effects. The standard errors are clustered by country. *, **, and *** denote significant at 10, 5, and 1 percent. "–" means there is not enough data to compute the statistics. Sample size is smaller for regressions with positive only and negative only revisions.

Table 8: Exchange rate forecasting results with revised and two types of real-time data

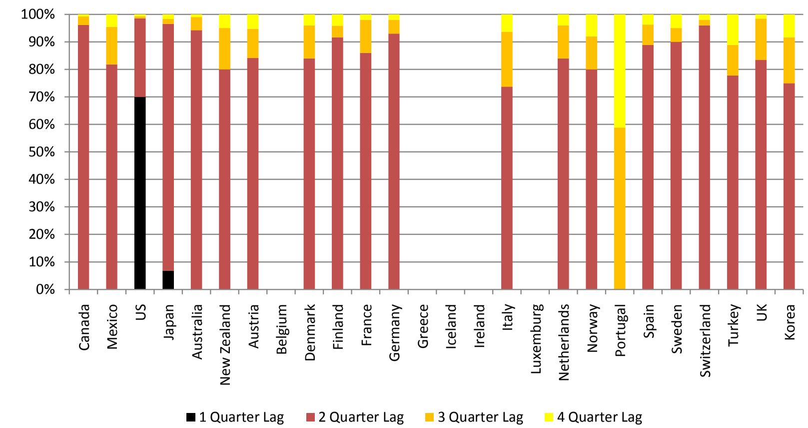
		Clark and West (2006) statistic					
		One-quarter-ahead ($h = 1$)			One-year-ahead ($h = 4$)		
	Exchange rate	Revised	Vintages	First releases	Revised	Vintages	First releases
	Panel A: PPP model						
1	Canada	0.68	0.53	–	-2.39	-2.28	–
2	Japan	1.01	1.15	–	0.70	0.92	–
3	UK	-0.04	0.18	–	1.39*	1.36*	–
	Panel B: Monetary model						
1	Canada	0.14	-0.84	–	-1.69	-2.63	–
2	Japan	-0.48	1.34*	–	-1.52	0.81	–
3	UK	-1.10	-0.11	–	-0.42	-1.38	–
	Panel C: Taylor rule fundamentals						
1	Canada	3.09***	2.80***	2.98***	1.53*	1.69**	1.44*
2	Japan	2.53***	2.37***	3.05***	2.33***	1.95**	3.01***
3	UK	2.16**	1.03	0.67	-0.10	0.73	-0.02

Notes: *, **, and *** denote significant at 10, 5, and 1 percent (one-sided test). "–" means the model is not defined with that type of data. "Revised" means revised data, and "vintages" and "first releases" refer to types of real-time data; for definitions of vintages and first releases, refer to Section 3.3. All exchanges rates are US dollar nominal rates, expressed as the domestic price of one unit of foreign currency. For multistep forecasting ($h = 4$), Newey-West standard errors are used.

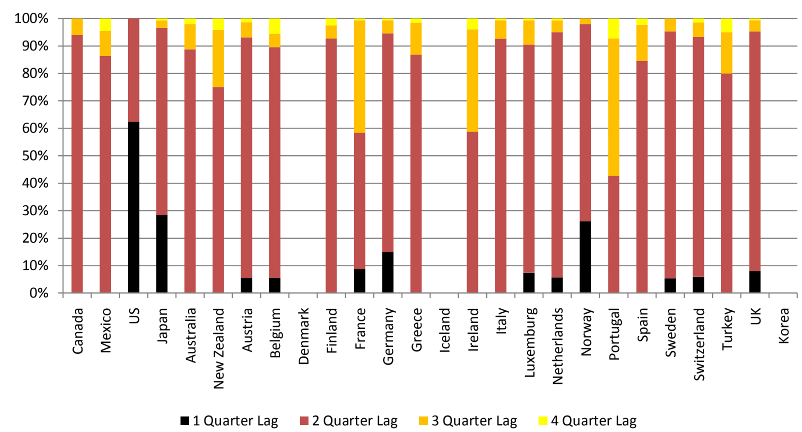
Figure 1: Percentage of data reported with a certain lag



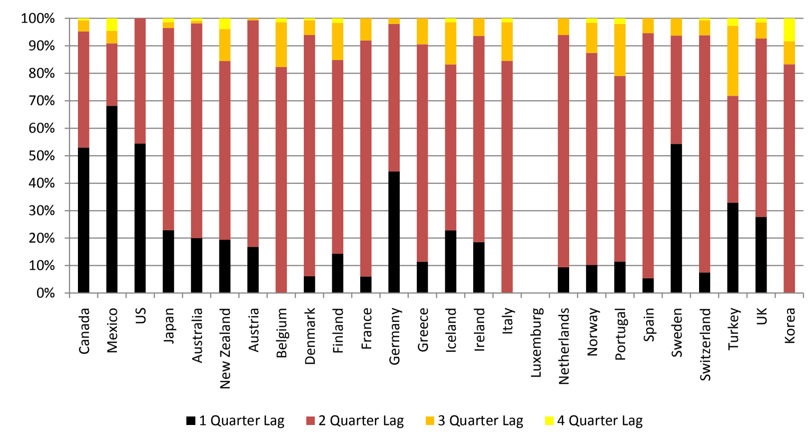
a. Real GNP/GDP



b. Price level



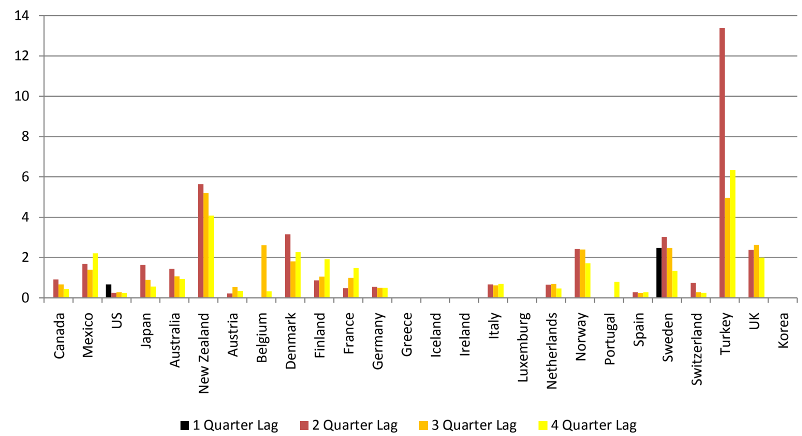
c. Industrial production



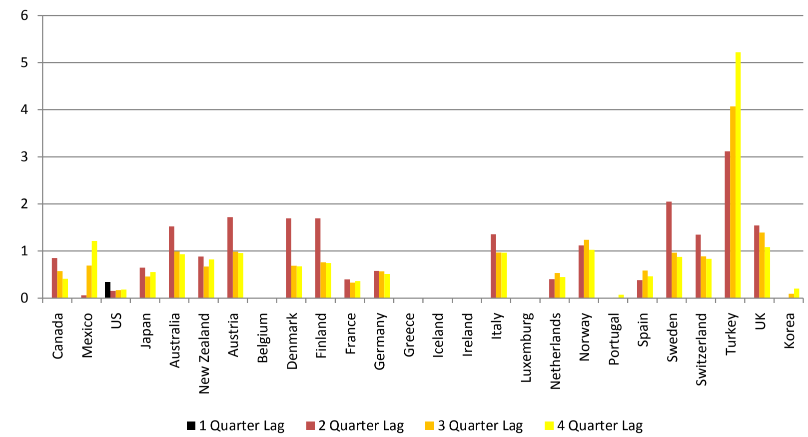
d. Money supply

Notes: Real GNP/GDP data for Greece, Iceland, Ireland, Luxembourg, price level for Belgium, Greece, Iceland, Ireland, Luxembourg, industrial production data for Iceland and Korea, money supply data for Luxembourg are not available.

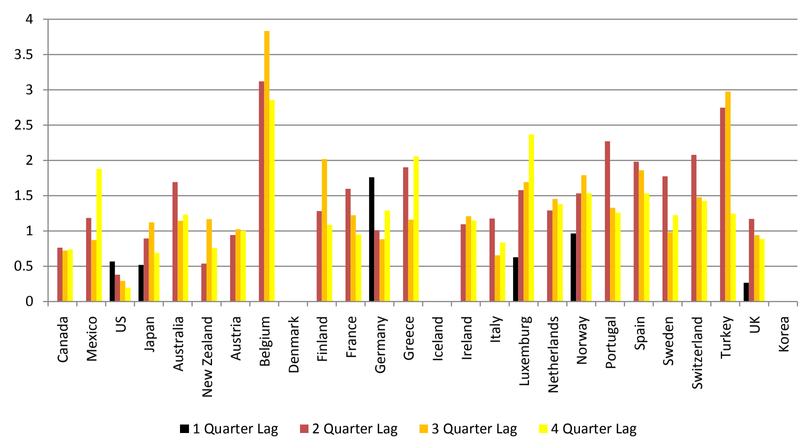
Figure 2: Mean absolute revisions



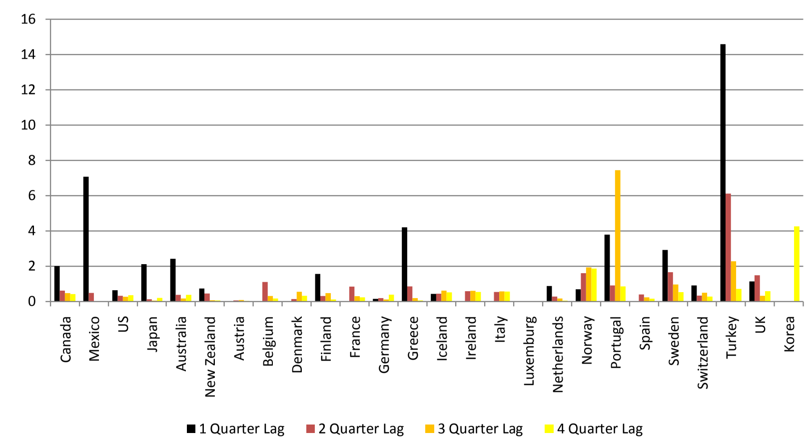
a. Real GNP/GDP



b. Price level



c. Industrial production



d. Money supply

Notes: Real GNP/GDP data for Greece, Iceland, Ireland, Luxembourg, price level for Belgium, Greece, Iceland, Ireland, Luxembourg, industrial production data for Iceland and Korea, money supply data for Luxembourg are not available.