# FORECASTING WITH REAL-TIME DATA VINTAGES

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When researchers develop forecasting models, they usually pull down data on a variety of economic variables from a current database, as has been described elsewhere in this volume. But there is a potential drawback to this strategy—the researcher is using data that are not the same as the data that will face a forecaster in real time. Data are revised, sometimes significantly, over time.

Data revisions might not affect forecasts or forecasting models much if the revisions are small and random. But the evidence, which I will discuss in the section "Data Revisions and Their Impact on Forecasts," suggests that revisions are often large and have systematic tendencies. As such, they may have a major impact on forecasts. I discuss the empirical literature showing how much forecasts are affected by data revisions in that section as well.

If data revisions affect forecasts, how can forecasters modify their models to account for such revisions? Many methods have been proposed, as we discuss in the section "Optimal Forecasting When Data Revisions Exist." However, no method appears to solve all the forecasting problems caused by the existence of data revisions.

## Data Revisions and Their Impact on Forecasts

When government statistical agencies release data, they generally do so long before their samples are complete. Over time, they gather more complete samples and develop better weights and methodologies and can make improved estimates of the economic activity they are attempting to measure. As this process occurs over time, they release newer and improved data to the public. The implication for forecasters is that their forecasts will be a function of the particular data they observe at the time they make their forecasts.

Typically, government statistical agencies make an initial release of the data in the first or second month after the economic activity has occurred. For example, in the United Kingdom, the Office of National Statistics (ONS) reports GDP for a quarter for the first time in the month after the end of a quarter, then revises it in the following month and the month after that.[1] These reports are each based on incomplete samples, which become more complete over time. However, much more accurate measures of GDP come after annual reports from business firms are reported and incorporated into the GDP calculations. Variables other than GDP often follow a similar process, with initial releases that are revised once or twice, and then an annual revision each year in which the values for the previous several years are modified. In addition, many variables are also subject to benchmark revisions, which occur every five to ten years and might incorporate changes in the base year (for real variables) or changes in methodology.

The evolving nature of the data is typically represented in a scheme such as Table 1, which shows each data release date and how the data for each period evolve over time. Table 1 shows U.K. GDP (E), real expenditures, showing activity dates from 1970Q1 to 2009Q1, as measured at vintage dates every 3 months from February 1990 to April 2009. Each column in Table 1 shows the data that one would observe if one used a database at the date shown in the column header; we call this the vintage date. Each row represents the dates for which the economic activity is measured. Thus the value of 65128 for expenditures in 1970Q1, as measured in February 1990, shows the value for expenditures that someone in February 1990

[1] U.S. GDP data follow the same pattern.

would observe in the government statistical release at that time. If you start with this number and move from left to right along the same row, you can see how the measure of economic activity for 1970Q1 is revised over time as the government statistical agency makes its revisions, ending in April 2009 with a value of 127192. Of course, the increase from 65128 in vintage February 1990 to 127192 in April 2009 does not mean that the early estimate was only about half of the estimate today, but reflects both additional source data and most importantly a change in the base year used in calculating real values of variables.

{Table 1 about here}

Revisions to quarterly data occur for the reasons described above. Figure 1 gives an example of the revisions that occur for a particular quarter, in this case the quarterly growth rate of real expenditures for the third quarter of 1990. The initial release of the data showed a substantial decline in expenditures of 1.3% (not at an annual rate). A few months after the initial release, the growth rate was revised down, but later and more complete data showed a less severe decline, as you can see in the figure.

{Figure 1 about here}

How might such a change in the short-run growth rate have affected forecasts? If a forecasting model follows a short autoregressive process in the growth rate with a large coefficient on the first autoregressive term, then clearly the jumping-off point for the forecast is crucial. So, if you were forecasting the growth rate for 1990Q4, and you thought the growth rate for 1990Q3 was -1.6%, your forecast for 1990Q4 is likely to be quite different than if you thought the growth rate for 1990Q3 was -1.0%.

Of course, it may be the case that you are forecasting with a model for which short-run variations in the jumping-off point are not relevant, but instead your forecasts depend on long-run average growth. But even here, data revisions may have a large impact on your forecasts. For example, if you were making a forecast of U.K. expenditure growth in early 1995, you would observe that the growth rate in the first half of the 1990s was 0.9% per annum, and you might make a forecast for the second half of the 1990s in line with that fact. But if you knew that by September 1998 the growth rate for the first half of the 1990s would be revised up to 1.4%, your forecast for the second half of the decade might be considerably higher.

**Data.** In the discussion above, I have taken advantage of a data set created by researchers at the Bank of England, who have painstakingly put together data vintages from the past from official government publications (see Castle and Ellis, 2002). Similar exercises have been undertaken in other countries as well; see Croushore and Stark (2001) for the first large real-time database, and see a list of other such datasets from all over the world on-line at http://facultystaff.richmond.edu/~dcrousho/data.htm. Without such data being available, it is unlikely that forecasters will consider accounting for data revisions in their models. But now that such data sets are becoming widespread, forecasters and researchers need to consider whether data revisions are important for their projects.

**A model of data revisions.** Consider the following model:

$$y_t^v = y_t^* + \varepsilon_t^v, \tag{1}$$

where $y_t^*$ is the true value of the variable at time $t$, $y_t^v$ is the value of the data as reported by the government statistical agency at date $v$, and $\varepsilon_t^v$ is an error term, whose properties can vary, depending on how the government reports its measures. However, because we never observe the true value of a variable, but only successive reported values of the data in different vintages, the following model may prove more useful:

$$y_t^v = y_t^{v-1} + r_t^{v,v-1}, \tag{2}$$

where $r_t^{v,v-1}$ is the revision to the data from vintage $v - 1$ to vintage $v$. Collecting the various revisions of the data and examining their properties has been a major effort in the real-time literature as Croushore (forthcoming) demonstrates.

Early explorations of the nature of these revisions in U.K. data were undertaken by Holden and Peel (1982a and 1982b). They note that the time-series properties of data change as the data are revised, suggesting that revised data following a different data generating process than first-release data. They also suggest that first-release data are biased estimates of later, revised data, but find it difficult to use that bias to forecast the later, revised data. Patterson (1995) goes even further, setting up a state-space model to incorporate both a data generating process and a data measurement process, then using the model to forecast revisions successfully. Similar exercises have been undertaken for U.S. data by Howrey (1978), who finds that one can use estimated bias and serial correlation in first-release data to predict revisions to consumption data, and Conrad and Corrado (1979), who perform a similar exercise with data on retail sales. In recent years, as real-time data for other countries have become available, such studies have begun to proliferate. The real-time bibliography posted on my web site at https://facultystaff.richmond.edu/~dcrousho/docs/realtime_lit.pdf provides many examples.

Although the papers mentioned in the previous paragraph attempted to exploit apparent bias in first-release data for certain variables, Croushore (forthcoming) suggests that such opportunities are not common. Some ability to forecast revisions may be apparent only long after the fact and could not be exploited in real time. Some forecastability of data revisions arises only as a consequence of the government statistical agency choosing to revise its seasonal factors once a year, so that seasonal revisions can be predicted but they are likely to be relatively small. However, in their study of revisions in the G-7 countries, Faust, Rogers, and Wright (2005) found that data revisions were forecastable in real time in every country in the G-7 except the United States. For U.K. data, Cunningham, Eklund, Jeffery, Kapetanios, and Labhard (forthcoming) provide convincing evidence that revisions to GDP can be predicted.

**What data should we use to evaluate forecasts?** Because data are revised, one question that a researcher or forecaster must answer is: which vintage of the data should be used to evaluate a set of forecasts? Should we assume that a forecaster is attempting to forecast the government's first release of the data, or do we think instead that the forecaster is after some measure of "truth," which might be taken to mean the value of the data after many years and many revisions? In other words, because most forecast evaluations require comparing the forecast with the "actual," what vintage of the data should be used as "actual"? With a real-time data set at hand, nearly any definition of "actual" is possible, and indeed the forecast evaluation literature has used many different concepts. Unsophisticated research analysis simply uses the values in the data base at the time the research was undertaken—essentially the last column in Table 1. But this is problematic if there have been redefinitions and significant changes in methodology that a forecaster would not have known in real time. Instead, other actuals are more sensible, including first-release data, data that have been subject to at least one annual revision (so that more accurate survey data have been used to generate the data), and data that appeared just before a benchmark release (to get the best value of the underlying economic activity possible while avoiding methodological changes).

**The impact of data revisions on forecasts.** If data revisions are minor and are random, then the revisions probably do not matter much for forecasting. But the evidence makes clear that data revisions are large and systematic. As such, they may have a large impact on forecasting models. A large branch of the literature shows that if one uses revised data (for example, the last column in Table 1) in a forecasting model and then one compares the results to what happens if one were using the model in real time, the differences in forecasts can be substantial.

The most comprehensive study comparing the impact of data revisions on forecasts is that of Stark and Croushore (2002). They examine three key ways in which data revisions affect forecasts, or, more precisely, in which forecasts generated in real-time (i.e., marching across the columns in Table 1, using the appropriate vintage at each date) differ from forecasts using latest-available data (using as an information set the last column in Table 1 and thus ignoring the process of data revisions). The three ways in which data revisions affect forecasts are: (1) changes in the data that affect the jumping-off point for forecasts (discussed briefly above), (2) effects on the estimated coefficients of a model; and (3) changes in the lag structure of the model, or other model specification changes.

Stark and Croushore developed a novel method of showing how changes in the data that affect the jumping-off point for forecasts can be visualized—a method known as repeated observation forecasting. The concept is to use different vintages of data in the same forecasting model. Essentially, this tells one how one's forecasts vary depending on the exact vintage of the data being used for forecasting. What is remarkable in these repeated observation forecasting exercises is how wide the range of forecasts is, far exceeding standard measures of forecast uncertainty. The range of outcomes suggests that accounting for data revisions is not just another consideration in forecasting, but may be the major source of forecast uncertainty, yet it is ignored in nearly all calculations of forecast uncertainty.

Stark and Croushore find that inflation forecasts tend to be more sensitive to data revisions than were forecasts of output growth. They speculate that this outcome is the result of the fact that the inflation process is more persistent than the process for output growth.

To analyze the impact of changes in the data on forecasts, consider the following model. Suppose the data generating process for variable $y_t$ is given by:

$$y_t = \mu + \phi_1 y_{t-1} + \varepsilon_t , \tag{3}$$

where we are assuming an AR(1) process for simplicity. In equation (3), $y_t$ is the true value of the economic activity that is the focus of the model. But this value is never actually observed. Suppose that all we observe is an estimate of $y_t$ provided by a government statistical agency. That agency produces a set of estimates of the data over time, with the data release at date $v$ being $y_t^v$, as we described earlier, and in each successive vintage we can calculate the revision $r_t^{v,v-1}$.

If we use the process given by equation (3) to generate forecasts, $y_{t|t-1,v}$, at each date *t*, when we are using vintage *v* and an information set containing data through activity date *t* – 1 to form our forecasts. The one-step-ahead forecast is

$$y_{t|t-1,v} = \hat{\mu}_v + \hat{\phi}_v y_{t-1,v}, \tag{4}$$

where the hats (^) denote our estimated coefficients, each of which has a vintage subscript to underscore the fact that the estimate depends on the vintage of the data. But consider a later vintage of the data, *w*, and the forecast emanating from the use of *w*-vintage data:

$$y_{t|t-1,w} = \hat{\mu}_w + \hat{\phi}_w y_{t-1,w}. \tag{5}$$

Then the differences between the forecasts can be expressed as:

$$y_{t|t-1,w} - y_{t|t-1,v} = (\hat{\mu}_w - \hat{\mu}_v) + (\hat{\phi}_w y_{t-1,w} - \hat{\phi}_v y_{t-1,v}). \tag{6}$$

From equation (6), the sources of the impact of data revisions on forecasts should be clear: changes in the data matter, as they make $y_{t|t-1,v}$ differ from $y_{t|t-1,w}$, and changes in the coefficient estimates matter. Now, if data revisions are small and random, then the differences in equation (6) will be near zero; but if data revisions have a significant impact on the coefficient estimates or the variables included in equation (6), then forecasts may change substantially.

In addition to these effects, forecasts might also be affected because different vintages of data might lead a forecaster to choose a different lag length in the model (whereas in the immediately preceding discussion, we assumed a fixed lag length, forcing the model to remain an AR(1)). Many forecasters and researchers use information criteria to determine the lag length, which might change across vintages, adding another source of forecast error.

Having established the potential for significant changes in forecasts because of data revisions, we now turn to the empirical literature on how much, in practice, data revisions affect forecasts of different types.

Diebold and Rudebusch (1991a and 1991b) highlighted the impact of the use of real-time data compared with revised data in their study of the index of leading indicators in the United States. They showed that despite all the claims made about the index ex-post, in fact ex-ante it did a poor job of forecasting recessions and output. Not only were data revised, thus making the index perform very differently in real time than it did ex-post, the indicators used in the index were also changed over time to make the apparent fit in the past appear much better than it really did. Their argument was convincing and was the first major paper to show researchers that real-time data could matter.

The Diebold and Rudebusch research had a number of precursors, however. Back in 1965, Denton and Kuiper examined forecasting models using Canadian data, finding significant differences depending on whether they used real-time data or revised data. A careful analysis by Cole (1969) showed a similar result, arguing that data measurement errors caused forecasts to be biased and inefficient. In an example with consumption data, the use of preliminary data led to a doubling of the forecast errors. She argued that improving the accuracy of preliminary data would help reduce forecast errors. The first paper to examine the impact of data revisions in a simultaneous-equations model was that of Trivellato and Rettore (1986), who used Italian data and found a very significant impact on the forecasts in using real-time data compared with using revised data.

In the past 15 years, researchers have demonstrated why real-time data matters in a variety of contexts.

*Levels vs. Growth Rates.* Howrey (1996) shows that forecasts of levels are very sensitive to data revisions, whereas forecasts of growth rates are much less sensitive.

*Forecasting Output Growth.* Robertson and Tallman (1998) present a convincing application to using the leading indexes to forecast real GDP and industrial production. Their results contradict those of Diebold and Rudebusch, finding that even in real time, the leading indicators have value.

*Predicting Recessions.* Given that macroeconomists had been developing a number of models to attempt to predict recessions, Filardo (1999) shows how unreliable such models are in real time, an apparent consequence of the fact that model developers have put the models together using only revised data.

*Forecasting Inflation.* Koenig (2003) shows that macroeconomists who had begun using the markup between costs and prices to help predict inflation were unlikely to be successful, as the markup is a useful predictor of inflation with revised data, but fails to predict inflation in real time. Orphanides and van Norden (2005) show that in real time, the estimation of output gaps is plagued by so much uncertainty that they cannot be reliably used for forecast inflation.

*Forecasting Stock Returns, Income, and Consumption.* Guo (2003) debunks the idea that the consumption-wealth ratio can be used to predict stock-market returns, as was claimed in the literature; there is no predictive power of that ratio in real time. In a related context, Croushore (2005) shows that consumer-confidence indexes have no value for forecasting consumption spending, and sometimes make forecasts significantly worse than if such indexes were not used in a forecasting model. Nakamura and Stark (2007) show that the saving rate in real time is worse for forecasting income than with revised data; and it has no ability to forecast consumption spending, despite many claims about its forecasting ability in the macroeconomics literature.

*Forecasting Concepts Useful for Monetary Policymaking.* Garratt, Koop, and Vahey (2008) show that there are large differences in output gap density forecasts in real time compared with revised data.

*Forecasting Exchange Rates.* Forecasting exchange rates has always been difficult. In the early 2000s, some researchers thought that exchange rates might be forecastable, but Faust, Rogers, and Wright (2003) show that those results were sensitive to the data sample used—other vintages of data showed no predictive ability. On the other hand, research by Molodtsova (2007) and Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) suggests that exchange rates might be more predictable with the right type of real-time data and *not* with revised data.

In summary, most of the studies that have been published in the past 15 years on this question show that our forecasting ability in real time is much worse than our forecasting ability when using revised data. Forecasters and researchers need to account in their models for the data measurement process, which is the subject of the next section.

## Optimal Forecasting When Data Revisions Exist

Table 1 above illustrates the data that a forecaster has available in real time. A forecaster who makes no account of data revisions will simply use the latest column of data available in Table 1 to construct forecasts. But many researchers have thought about ways to use some or all of the matrix in Table 1 to attempt to account for data revisions in a way that improves the forecasts. To do so properly requires writing down a model of the data revision process. This, in turn, requires taking a stand on the nature of the data revisions, which is itself a difficult decision.

**Does the revision process add news or reduce noise?** When we wrote down equation (1) earlier, we said little about the error term in that equation. That was intentional, because the assumption about the error term is crucial, and depends on how government statistical agencies construct their estimates of the data, as discussed initially by Sargent (1989).

We described above the methods by which government statistical agencies receive their data—first from incomplete samples, with the samples becoming more and more complete over time. The crucial question is whether the agency simply reports its sample information, or if it combines that information with other useful information to produce an optimal estimate of the true value of the data. In the first case, the government's release of the data will have the property that the error term represents measurement error that is uncorrelated with the true value of the variable in question, a situation in which subsequent data revisions reduce the noise in the estimate. In the latter case, the government's release of the data is such that each data release is an optimal forecast of any later data release, a situation in which subsequent data revisions add news to the previously released estimate. We model these polar cases in the following manner:

*News revisions:* If the data released in any vintage are optimal forecasts of later releases, then equation 1 can be written as in Croushore (forthcoming):

$$y_t^* = y_t^v + e_t^v, \tag{7}$$

where the error term is such that it is orthogonal to the data release:

$$y_t^v \perp e_t^v. \tag{8}$$

In this situation, revisions are not predictable as there is no correlation between the error term and the data release, by construction.

*Noise revisions.* The alternative is that each data release is correlated with the error term, which we model as:

$$y_t^v = y_t^* - u_t^v, \tag{9}$$

where

$$y_t^* \perp u_t^v. \tag{10}$$

In this case, revisions will be correlated with earlier data because the error terms of successive vintages are orthogonal to the true value of the variable, not with each other. This means that revisions are predictable and each data release is not an optimal forecast of later data releases.

You might ask why a government statistical agency would release noisy estimates as opposed to estimates that add news. The reason is that to construct estimates that add news requires a forecasting model, thus entailing judgment on the part of the government statistical agency. Producing noisy estimates is less subjective, as the agency can follow a standard protocol, reporting its sample information and using naïve projections to fill in missing data. Thus, by its nature, a procedure that adds news entails much more subjective procedures than one that simply reduces noise. And those in the employ of the government know that any subjective procedure is potentially subject to political influence.

To be able to model data revisions in the context of a forecasting model, one must determine whether data revisions add news or reduce noise. The empirical evidence on this question is mixed and varies by country (not surprisingly), across variables (even those produced by the same government statistical agency, in some cases), and over time (as government statistical agencies change their methods). For example, for U.K. data, Patterson and Heravi (1991) show that GDP estimates are noisy, as are estimates of the components of GDP. For U.S. data, GDP revisions add news according to Mankiw and Shapiro (1986), but reduce noise according to Aruoba (2008). Mork (1987) found that the second revision of U.S. GDP was a news estimate but the initial release and first release were a mix of news and noise. The possibility of such a mixture is explored further by Jacobs and van Norden (2006), who find that when there is neither pure news nor noise, modeling efforts are greatly complicated.

If one has both a model of the data generating process for one's variable and a model of the data measurement process, how might one proceed, and does adding the data measurement process to the model actually improve the forecasts? This has been the subject of much of the research of the past few years, with some early work suggesting directions and more recent work providing rich examples.

**Factor models.** One possibility for handling data revisions in a forecasting context is simply to use a factor model with a large number of variables, with the idea that data revisions across many variables wash out, so that the factor model provides a reasonable forecast. As developed by Stock and Watson (1999, 2002), these models are based on the idea that one or a small number of unobserved variables (factors) generates movements in many different variables, each of which also moves idiosyncratically; see the chapter in this volume by Stock for a description of research using such models. Estimation of the model using principal components methods can estimate the values over time of the factors. The advantage of such models is that they can easily accommodate dozens or even hundreds of variables in a parsimonious way. If data revisions are not correlated across variables, then such models may be an ideal way to avoid data revisions from affecting forecasts.

One key paper that was among the first to use a factor model for forecasting is that of Bernanke and Boivin (2003). They used such a model to form forecasts using a large number of data series and argued that the resulting forecasts had numerous desirable properties. Though they did not have real-time data for all the variables used in their complete model, when they ran their model on a subset of variables, they found that the forecasts were quite similar whether they used revised data or real-time data, suggesting that the factor model was indeed successful in wiping out the impact of data revisions. Such factor models may also be useful in forecasting quarterly series from monthly data, as Giannone, Reichlin, and Small (2008) find.

The Bernanke and Boivin results have been challenged by Faust and Wright (2009), who show that other forecasting methods work better than factor models. In particular, a variety of bivariate models outperform the factor model that they use, suggesting that the noise added from using many variables may do more damage than the good that comes from wiping out data revisions as a source of error.

**State-space models.** In a state-space model (see the chapter by Koopman), structure is imposed on the data measurement process (in contrast with factor models that assume the measurement errors wash out across variables) and that process becomes an integral part of the estimation. The question is, empirically, whether adding such a measurement equation adds so much noise and additional parameters that it might make forecasts worse, or if the enhanced structure allows for more accurate forecasts.

One way to deal with data revisions is simply to use a model based on revised data, then estimate the model using only revised data, ignoring recently released data that have not gone through enough revisions. But over 30 years ago, Howrey (1978) discussed how to adjust data that have been revised a different number of times using the Kalman filter, showing that this gives improved forecasts compared with ignoring recent data completely. Another paper using such methods by Harvey, McKenzie, Blake, and Desai (1983) accounts for data revisions using state-space methods and also finds that this greatly helps the forecasts. However, sometimes the model is not successful, as Howrey (1984) shows when he forecasts investment in inventories with a state-space model and makes no significant improvement compared with a model that doesn't account for data revisions at all. As Croushore (2006) notes, based on the plots in Croushore and Stark (2001), benchmark revisions are so irregular that they follow a data measurement process that cannot be modeled simply, and thus state-space models may fail to improve the forecasts. If such benchmark revisions do not follow the ARIMA model specified in the data measurement equation, then adding such an equation to the overall forecasting model may make forecasts less accurate. This may be the reason why Ghosh and Lien (2001) find that incorporating the data-measurement process in a state-space model produced less accurate forecasts than if data revisions were ignored, and why Fukuda (2007) finds only marginal gains from this method, despite substantial use of ex-post knowledge in constructing the forecasting model.

**Other methods.** A variety of other models have been used to account for data revisions in a forecasting model. Here is a sampling.

*Incorporating expectations.* Lee, Olekalns, and Shields (2008) suggest that in addition to modeling the data generating process and the data measurement process, a forecaster should model the expectations process. The combination of all three processes provides an overall model that dominates models that use only one or two of the three processes.

*Cointegration and Common Trends.* Patterson (2003) illustrates how to incorporate the data measurement process when there is cointegration. Garratt, Lee, Mise, and Shields (2008) incorporate cointegrating VARs in forecasting the trend in output to use in estimating the output gap.

*Forecast Combination.* Altavilla and Ciccarelli (2007) recommend forecast combination methods across both models and data vintages to make forecasts more accurate.

*Single-Equation Modeling.* Without specifying separate equations for the data generating process and data measurement process, Koenig, Dolmas, and Piger (2003) show that using preliminary data in a forecasting equation leads to more accurate forecasts than using revised data, even when trying to forecast the revised data.

**Methods for evaluating forecasts in real time.** One difficulty in evaluating forecasts made with real-time data is that standard methods of forecast comparison may not apply. Inoue and Rossi (2005) show that using standard predictability tests while rolling through time and across vintages leads to overfitting of models and reduced forecast accuracy. They develop a procedure to prevent such problems. Clark and McCracken (2009) tackle the difficult problem of generating forecast evaluation tests to accurately handle real-time data, showing how standard tests must be modified.

## CONCLUSIONS

When data revisions exist, forecasting becomes more complicated. Data revisions may have a significant impact on forecasts, as the evidence presented here suggests. To adjust for the existence of data revisions requires a forecaster to explicitly model the data measurement process. Doing so often, but not always, leads to more accurate forecasts.

Research on forecasting when data revisions exist is still in its relative infancy because large real-time databases have only recently become widely available. But now, given the existence against such databases, research on forecasting to account for data revisions is likely to accelerate.

**Table 1**

**Real-Time Data Structure**

**Real Expenditure**

| **Vintage Date:** | **Feb90** | **May90** | **Aug90** | **. . .** | **Jan09** | **Apr09** |
|---|---|---|---|---|---|---|
| **Activity Date** | | | | | | |
| **70Q1** | **65128** | **65128** | **65128** | **. . .** | **127192** | **127192** |
| **70Q2** | **66625** | **66625** | **66625** | **. . .** | **130028** | **130028** |
| **70Q3** | **66939** | **66939** | **66939** | **. . .** | **131063** | **131063** |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| **89Q4** | **103500** | **103319** | **104000** | **. . .** | **205279** | **205279** |
| **90Q1** | **NA** | **103797** | **104595** | **. . .** | **206986** | **206986** |
| **90Q2** | **NA** | **NA** | **105631** | **. . .** | **208078** | **208078** |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| . | . | . | . | . | . | . |
| **08Q2** | **NA** | **NA** | **NA** | **. . .** | **321160** | **321188** |
| **08Q3** | **NA** | **NA** | **NA** | **. . .** | **319078** | **318888** |
| **08Q4** | **NA** | **NA** | **NA** | **. . .** | **314292** | **313939** |
| **09Q1** | **NA** | **NA** | **NA** | **. . .** | **NA** | **307974** |

**Source:** ***Bank of England, Gross Domestic Product Real-Time Database***

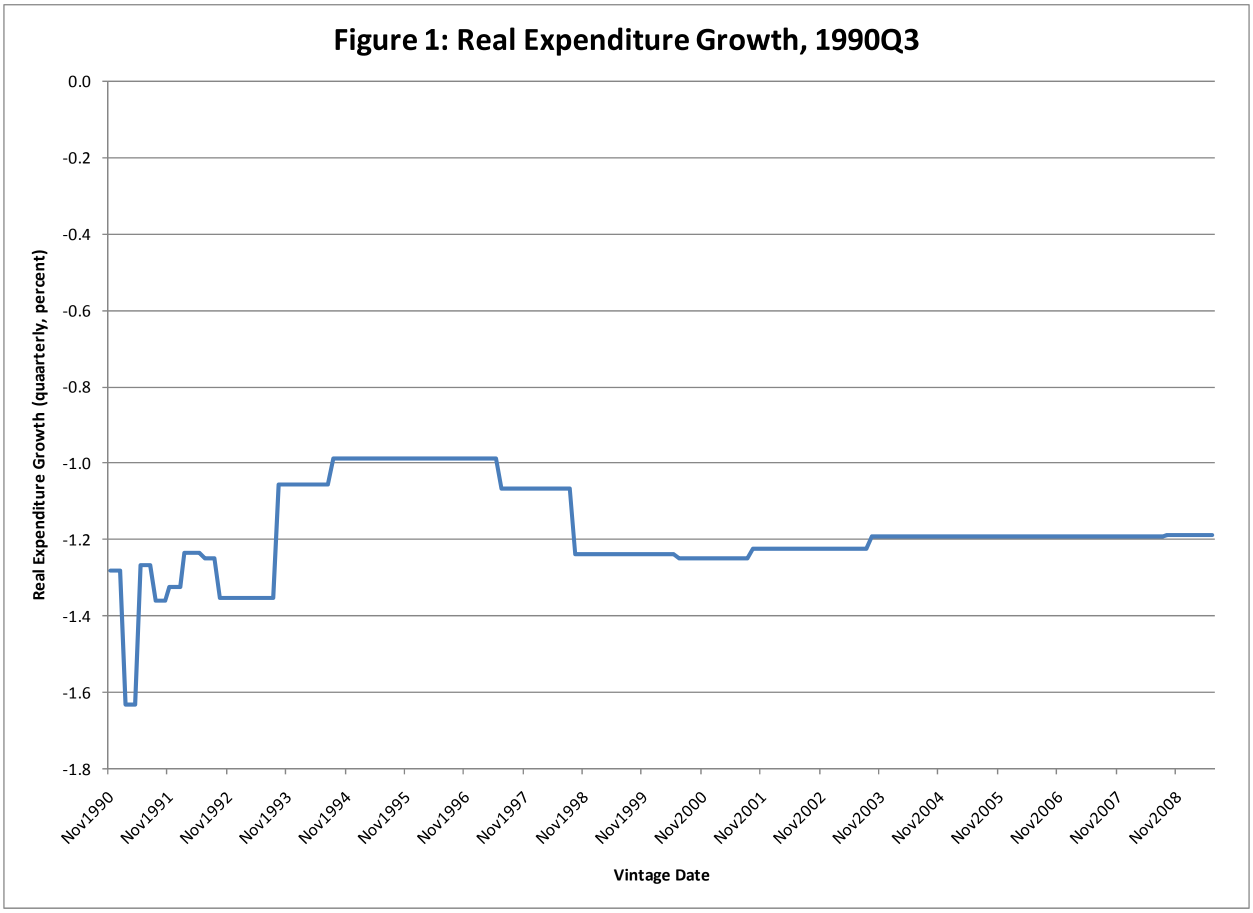

Figure 1: Real Expenditure Growth, 1990Q3
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
-1.4
-1.6
-1.8
Real Expenditure Growth (quaarterly, percent)
Nov1990
Nov1991
Nov1992
Nov1993
Nov1994
Nov1995
Nov1996
Nov1997
Nov1998
Nov1999
Nov2000
Nov2001
Nov2002
Nov2003
Nov2004
Nov2005
Nov2006
Nov2007
Nov2008
Vintage Date

## REFERENCES


Altavilla, Carlo, and Matteo Ciccarelli. "Information Combination and Forecast (St)ability: Evidence from Vintages of Time-Series Data." European Central Bank working paper 846, December 2007.

Aruoba, S. Borağan. "Data Revisions Are Not Well Behaved." *Journal of Money, Credit, and Banking* 40 (March-April 2008), pp. 319–340.

Bernanke, Ben S., and Jean Boivin. "Monetary Policy in a Data-Rich Environment." *Journal of Monetary Economics* 50 (2003), pp. 525–546.

Castle, Jennifer, and Colin Ellis. "Building a Real-Time Database for GDP(E)." Bank of England *Quarterly Bulletin* (Spring 2002), pp. 42–49.

Clark, Todd E., and Michael W. McCracken. "Tests of Equal Predictive Ability with Real-Time Data." *Journal of Business and Economic Statistics* 27 (October 2009), pp. 441–454.

Cole, Rosanne, "Data Errors and Forecasting Accuracy," in Jacob Mincer, ed., *Economic Forecasts and Expectations: Analyses of Forecasting Behavior and Performance*. New York: National Bureau of Economic Research, 1969, pp. 47-82.

Conrad, William, and Carol Corrado. "Application of the Kalman Filter to Revisions in Monthly Retail Sales Estimates," *Journal of Economic Dynamics and Control* 1 (1979), pp. 177-98.

Croushore, Dean. "Do Consumer Confidence Indexes Help Forecast Consumer Spending in Real Time?" *North American Journal of Economics and Finance* 16 (December 2005), pp. 435–450.

Croushore, Dean. "Forecasting with Real-Time Macroeconomic Data." In: Graham Elliott, Clive W.J. Granger, and Allan Timmermann, eds., *Handbook of Economic Forecasting* (Amsterdam: North-Holland, 2006).

Croushore, Dean. "Frontiers of Real-Time Data Analysis." *Journal of Economic Literature* (forthcoming).

Croushore, Dean, and Tom Stark. "A Real-Time Data Set for Macroeconomists," *Journal of Econometrics* 105 (November 2001), pp. 111–130.

Cunningham, Alastair, Jana Eklund, Christopher Jeffery, George Kapetanios, and Vincent Labhard. "A State Space Approach to Extracting the Signal from Uncertain Data." *Journal of Business and Economic Statistics* (forthcoming).

Denton, Frank T., and John Kuiper. "The Effect of Measurement Errors on Parameter Estimates and Forecasts: A Case Study Based on the Canadian Preliminary National Accounts," *Review of Economics and Statistics* 47 (May 1965), pp. 198-206.

Diebold, Francis X., and Glenn D. Rudebusch. "Forecasting Output With the Composite Leading Index: A Real-Time Analysis," *Journal of the American Statistical Association* 86 (September 1991a), pp. 603-10.

Diebold, Francis X., and Glenn D. Rudebusch. "Turning Point Prediction with the Composite Leading Index: An Ex Ante Analysis." 1991. In: K. Lahiri and G.H. Moore, eds., *Leading Economic Indicators: New Approaches and Forecasting Records* (Cambridge: Cambridge University Press, 1991b), pp. 231-256.

Faust, Jon, and Jonathan H. Wright. "Comparing Greenbook and Reduced Form Forecasts using a Large Realtime Dataset." *Journal of Business and Economic Statistics* 27 (October 2009), pp. 468–479.

Faust, Jon, John H. Rogers, and Jonathan H. Wright. "Exchange Rate Forecasting: the Errors We've Really Made." *Journal of International Economics* 60 (2003), pp. 35-59.

Faust, Jon, John H. Rogers, and Jonathan H. Wright. "News and Noise in G-7 GDP Announcements." *Journal of Money, Credit, and Banking* 37 (June 2005), pp. 403–419.

Filardo, Andrew J. "How Reliable are Recession Prediction Models?" Federal Reserve Bank of Kansas City *Economic Review* (Second Quarter 1999), pp. 35-55.

Fukuda, Kosei. "Forecasting Real-Time Data Allowing for Data Revisions." *Journal of Forecasting* 26 (September 2007), pp. 429-444.

Garratt, Anthony, Gary Koop, and Shaun P. Vahey. "Forecasting Substantial Data Revisions in the Presence of Model Uncertainty." *Economic Journal* 118 (July 2008), pp. 1128-1144.

Garratt, Anthony, Kevin Lee, Emi Mise, and Kalvinder Shields. "Real Time Representations of the Output Gap." *Review of Economics and Statistics* 90 (November 2008), pp. 792-804.

Ghosh, Sucharita, and Donald Lien. "Forecasting with Preliminary Data: A Comparison of Two Methods." *Applied Economics* 33 (2001) pp. 721-26.

Giannone, Domenico, Lucrezia Reichlin, and David Small. "Nowcasting: The Real-Time Informational Content of Macroeconomic Data." *Journal of Monetary Economics* 55 (May 2008), pp. 665-676.

Guo, Hui. "On the Real-Time Forecasting Ability of the Consumption-Wealth Ratio." Working paper 2003-007B, Federal Reserve Bank of St. Louis.

Harvey, A.C., C.R. McKenzie, D.P.C. Blake, and M.J. Desai. "Irregular Data Revisions," in Arnold Zellner, ed., *Applied Time Series Analysis of Economic Data.* Washington, D.C.: U.S. Department of Commerce, Economic Research Report ER-5, 1983, pp. 329–347.

Holden, K., and D.A. Peel. "The Relationships Between Preliminary and Revised Estimates of GDP and Consumers' Expenditure in the UK," *The Statistician* 31 (June 1982a), pp. 259–266.

Holden, K., and D.A. Peel. "Data Revisions and Time Series Models of GDP and Its Components," *Applied Economics* 14 (1982b), pp. 101–110.

Howrey, E. Philip. "The Use of Preliminary Data in Econometric Forecasting," *Review of Economics and Statistics* 60 (May 1978), pp. 193-200.

Howrey, E. Philip. "Data Revision, Reconstruction, and Prediction: An Application to Inventory Investment." *Review of Economics and Statistics* 66 (August 1984), pp. 386–93.

Howrey, E. Philip. "Forecasting GNP With Noisy Data: A Case Study." *Journal of Economic and Social Measurement* 22 (1996), pp. 181-200.

Inoue, Atsushi, and Barbara Rossi. "Recursive Predictability Tests for Real-Time Data." *Journal of Business and Economic Statistics* 23 (July 2005), pp. 336–345.

Jacobs, Jan P.A.M., and Simon van Norden. 2006. "Modeling Data Revisions: Measurement Error and Dynamics of 'True' Values." University of Groningen, CCSO Centre for Economic Research Working Paper 2006/07.

Koenig, Evan. "Is the Markup a Useful Real-Time Predictor of Inflation?" *Economics Letters* 80 (2003), pp. 261–267.

Koenig, Evan, Sheila Dolmas, and Jeremy Piger. "The Use and Abuse of 'Real-Time' Data in Economic Forecasting," *Review of Economics and Statistics* 85 (2003), pp. 618-628.

Lee, Kevin, Nilss Olekalns, and Kalvinder Shields. "Nowcasting, Business Cycle Dating and the Interpretation of New Information when Real Time Data are Available." Working paper, University of Melbourne, April 2008.

Mankiw, N. Gregory, and Matthew D. Shapiro. "News or Noise: An Analysis of GNP Revisions." *Survey of Current Business* (May 1986), pp. 20-5.

Molodtsova, Tanya. "Real-Time Exchange Rate Predictability with Taylor Rule Fundamentals." Working paper, University of Houston, November 2007.

Molodtsova, Tanya, Alex Nikolsko-Rzhevskyy, and David H. Papell. "Taylor Rules with Real-Time Data: A Tale of Two Countries and One Exchange Rate."*Journal of Monetary Economics* 55 (Supplement1, October 2008), pp. S63-S79.

Mork, Knut A. "Ain't Behavin': Forecast Errors and Measurement Errors in Early GNP Estimates," *Journal of Business and Economic Statistics* 5 (April 1987), pp. 165-75.

Nakamura, Leonard I., and Tom Stark. "Mismeasured Personal Saving and the Permanent Income Hypothesis." Federal Reserve Bank of Philadelphia working paper 07-8, February 2007.

Orphanides, Athanasios, and Simon van Norden. "The Reliability of Inflation Forecasts Based on Output Gaps in Real Time." *Journal of Money, Credit, and Banking* 37 (June 2005), pp. 583–601.

Patterson, K.D. "Forecasting the Final Vintage of Real Personal Disposable Income: A State Space Approach." *International Journal of Forecasting* 11 (1995), pp. 395–405.

Patterson, K.D. "Exploiting Information in Vintages of Time-Series Data," *International Journal of Forecasting* 19 (2003), pp. 177-197.

Patterson, K.D., and S.M. Heravi. "Data Revisions and the Expenditure Components of GDP," *Economic Journal* 101 (July 1991), pp. 887-901.

Robertson, John C., and Ellis W. Tallman. "Data Vintages and Measuring Forecast Model Performance." Federal Reserve Bank of Atlanta *Economic Review* (Fourth Quarter 1998), pp. 4-20.

Sargent, Thomas. "Two Models of Measurements and the Investment Accelerator," *Journal of Political Economy* 97 (1989), pp. 251-287.

Stark, Tom, and Dean Croushore. "Forecasting with a Real-Time Data Set for Macroeconomists." *Journal of Macroeconomics* 24 (December 2002), pp. 507–31 and reply to comments, pp. 563–567.

Stock, James H., and Mark W. Watson. "Forecasting Inflation." *Journal of Monetary Economics* 44(2, 1999), pp. 293-335.

Stock, James H., and Mark W. Watson. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business and Economic Statistics* 20 (2002), pp. 147–162.

Trivellato, Ugo, and Enrice Rettore. "Preliminary Data Errors and Their Impact on the Forecast Error of Simultaneous-Equations Models," *Journal of Business and Economic Statistics* 4 (October 1986), pp. 445-53.