FRONTIERS OF REAL-TIME DATA ANALYSIS

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FRONTIERS OF REAL-TIME DATA ANALYSIS

ABSTRACT

This paper describes the existing research on real-time data analysis, divided into six areas: (1) data revisions; (2) structural macroeconomic modeling; (3) forecasting; (4) monetary policy; (5) current analysis; and (6) revisions to conceptual variables. Substantial progress has been made in recent years, with researchers gaining insight into the structure of data revisions and their impact. In addition, researchers and institutions have developed better real-time data sets around the world. Still, additional research is needed in key areas and research to date has uncovered even more fruitful areas worth exploring.

FRONTIERS OF REAL-TIME DATA ANALYSIS

Real-time data analysis refers to research for which data revisions matter or for which the timing of the data releases is important in some way.[1] For example, consider the Federal Reserve's policy decision made in October 1992. The transcript of the policy meeting shows that policymakers were concerned that the economy was slipping back into recession, after only 1½ years of expansion. When you look at the data, though, you are surprised to find that GDP grew 3.3 percent in 1992, far from indicating a recession. So, you wonder why policymakers were so worried. But a look at the real-time data—the data that policymakers had available to them when they made their policy decision, was much weaker. If you analyze the policy decision using the data available to you today, you will make an incorrect inference about policymaking. If you look at the data that was available to the policymakers at the time they made their decision, you are engaging in real-time data analysis.

As another example, suppose you are an econometrician with a brilliant new idea on how to forecast inflation better using a modified version of the Phillips curve. You find that you are able to predict inflation fairly well over time. You decide to compare your simulated out-of-sample forecasts to those of the Survey of Professional Forecasters (SPF), and you find that your root-mean-squared-forecast errors are significantly less than those of the SPF. You rush to write up your results and send your paper off to a top-rated journal. But your paper is rejected because you have made a fundamental error. You used a recent data set to generate your forecasts, but the

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[1] The term "real-time analysis" was coined by Francis X. Diebold and Glenn D. Rudebusch (1991). Rudebusch (2002) defines real-time analysis as "the use of sequential information sets that were actually available as history unfolded." My definition is somewhat broader.

SPF participants had very different data than you did. When you repeat your exercise using data that were available to the SPF forecasters at the time they made their forecasts, you are engaging in real-time data analysis.

In January 2009, in the middle of the financial crisis that began in September 2008, the initial release of the national income accounts showed a decline in real GDP of 3.8% (at an annual rate) for the fourth quarter, a bad number for sure, but not as bad as might be expected considering the damage caused by the financial meltdown. But one month later, the GDP growth rate was revised down by 2.4 percentage points, showing a decline in real GDP of 6.2%, and confirming that the U.S. economy was in the middle of the worst recession in over 25 years. The 2.4 percentage point downward revision from the initial release to the first revised number was the largest revision ever recorded for quarterly real GDP.[2] Real-time data analysis of the history of revisions of real GDP shows us that the largest revision came at a very inopportune moment. Although there is a tendency for revisions in recessions to be negative, the average revision in recessions is to reduce the quarterly real GDP growth rate (annualized) by just 0.08 percentage points; on average real GDP growth is revised up by 0.18 percentage points in expansions.

Until recently, macroeconomists assumed that data revisions were small and random and thus had no effect on structural modeling, policy analysis, or forecasting. But real-time research has shown that this assumption is false and that data revisions matter in many unexpected ways.

In the past ten years, researchers have explored the impact of data revisions in many different contexts. Researchers have examined the properties of data revisions, how structural modeling is affected by data revisions, how data revisions affect forecasting, the impact of data

[2] Quarterly real GDP began to be reported on a regular basis in the mid-1960s.

revisions on monetary policy analysis, and the use of real-time data in current analysis. This paper summarizes many of the questions for which real-time data analysis has provided answers.

Data sets. The ability of researchers to perform real-time data analysis has been enhanced by the production of real-time data sets that provide researchers with the data that was available at dates in the past. Tom Stark and I began developing a large data set containing U.S. real-time data in the mid-1990s and made it widely available online in 1999, as discussed in Dean Croushore and Stark (2001), called the Real-Time Data Set for Macroeconomists. Development of this real-time data set is ongoing, with cooperation between the Federal Reserve Bank of Philadelphia and the University of Richmond, and is available on the Philadelphia Fed's website at *www.philadelphiafed.org/econ/forecast/real-time-data/index.cfm*. Similar data sets have subsequently been developed all over the world, though the need remains for institutional support for such efforts.[3] Such data sets are a club good, being nonrival but excludable. If institutions, such as the Federal Reserve in the United States, provide support for data development, the data can be made available to all interested researchers. Unfortunately, some producers of such data have chosen to restrict use to members of the club, and some government agencies have chosen to restrict access as well. In the United States, the Federal Reserve Bank of St. Louis developed ALFRED, which contains an extensive set of real-time data organized in a different manner than the Philadelphia Fed's data set. Rivalry between the Federal Reserve Banks of Philadelphia (data set: RTDSM) and St. Louis (data set: ALFRED) has hastened the development of the data, and both institutions have allowed unrestricted access to their data as soon as it has been produced. In addition, the St. Louis Fed has created an array of useful data

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[3] For links to all publicly available data sets containing real-time data, see my web site at: http://facultystaff.richmond.edu/~dcrousho/data.htm.

and publication archives, such as FRASER, which provides pdf files of major statistical publications. Clearly, institutional support helps to promote good data. Without it, many data sets die and are never updated after a researcher finishes work on the topic.

Benefits of real-time data analysis for government statistical agencies. Analysis of data revisions should not be taken as criticism of the government statistical agencies, merely as a fact of life when the government does not have unlimited resources for collecting data. The development of real-time data sets may help government statistical agencies understand the revisions better and may lead to modifications of the process for producing data. For example, predictable revisions of U.S. industrial production led the Federal Reserve to modify its procedures for compiling the data, and the predictability disappeared (James E. Kennedy 1990). Revisions to data often reflect information from censuses that are taken every 5 or 10 years. It would be too costly to take such censuses more frequently. As a result, the government statistical agencies make large changes every 5 or 10 years in the weights applied to different sectors of the economy in measuring GDP and prices, which leads to large revisions. Generally, revisions improve the quality of the data. For example, the U.S. consumer price index, which is not revised (in its seasonally unadjusted form), is inferior to the personal consumption expenditures price index, which is revised; the revisions to the PCE price index incorporate improved methods, more-current weights, and more-recent data.[4]

The typical structure of a real-time data set, as introduced by Diebold and Rudebusch (1991), is demonstrated in Table 1. Each column represents a different vintage of data (a date at which the data are reported), while each row shows a different date for which the economic

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[4] There exist some alternative versions of the CPI that are revised, including the chained CPI index, but these were not available until relatively recently.

activity is measured. The last data value shown in each column is the initial release of the data point for the date shown in the first column. As time passes, we move to the right in terms of vintages. So, we can trace out the data value for any particular date by moving from left to right across a row, which shows us the value for that date in successive vintages of the data. Moving down the main diagonal (the diagonal connecting the last data values in each column) shows the initial data release for each date.

[Table 1 here]

For example, someone in November 1965 who looked up the values of real GDP would observe the values shown in the column headed 11/65; that is, real GDP would have been seen as increasing from 306.4 (all numbers in billions of constant dollars) in the first quarter of 1947, to 309.0 in the second quarter, to 309.6 in the third quarter, and so on, while the value for the third quarter of 1965 of 609.1 was the most recently released data point. Three months later, in February 1966, that value for the third quarter of 1965 was revised up to 613.0, and the first release of the data for the fourth quarter of 1965 came out at 621.7.

The large jump in the numbers as you move across the first row of Table 1 shows the effects of benchmark revisions. Such changes are not meaningful for real GDP, as they mainly represent changes in the (arbitrary) base year.

Table 1 illustrates several important notions about the structure of macroeconomic data and revisions to that data. First, data for a given period (the activity date) are not released until some time has passed after the end of that period. For example, the first estimate of GDP for a particular quarter is reported at the end of the month following the end of a quarter (but other variables have longer reporting lags). Second, data are revised numerous times. For GDP, the data are revised one and two months after the initial release, then at the end of July of each of the following three years, and again every five years after that.

Economists are interested not only in data released by the government, but also in conceptual variables that are thought to drive the macroeconomy, such as potential output, the natural rate of unemployment, and the equilibrium real federal funds rate. Calculations of such variables for a particular activity date may improve as time passes, because related data (such as real GDP) are revised, and also because as time passes, data for several years after the activity date help improve the estimates of such conceptual variables.

Table 1 can also be used to illustrate what we mean by the term "real-time data analysis." In August 2009, a researcher, or policy analyst, or forecaster who works with only the last column in Table 1, which represents the data that one would pull down from a macroeconomic database, is using latest-available data. This is the standard procedure in most of the macroeconomic literature. But if the researcher, policy analyst, or forecaster uses some or all of the other vintages of data (the other columns of Table 1) she is engaging in real-time data analysis.

Sometimes such analysis uses different vintages of the data, which corresponds to different columns of Table 1. But sometimes it is useful to examine data for which a given amount of time has passed since the initial release of the data, which can be calculated by pulling data from a diagonal in Table 1. For other purposes, a research might want to examine the data released during the annual revision each year, which means pulling the data from the August vintage each year, leading to a stair-step data structure.

Much macroeconomic research has made heroic assumptions about the data in the information set available to a decision-maker or forecaster at each point in time. The standard assumptions are that data are immediately available (when in fact they are available only with a lag) and that data revisions either do not exist or are inconsequentially small (when in fact they are often large and significantly affect empirical results). This is especially true of conceptual variables, such as the output gap, where researchers and policy analysts often proceed as if the variable is known with certainty when decisions are made (when in fact, the variability of the conceptual variable across vintages often swamps the volatility of the variable over time).

Real-time data analysis is thus potentially important for both theory and empirical work. At this point, however, much of the real-time literature has focused on showing that data revisions matter for theory and empirical work rather than making data revisions a major ingredient in theoretical models or empirical models. Consequently, the first area of the literature that we will discuss, and largest, is analysis of data revisions. Once a researcher has a handle on the structure of such revisions, she may apply the analysis to tackle a problem for which data revisions are relevant. One such area, and the subject of the second section, is structural macroeconomic modeling, which examines how data revisions have influenced macroeconomic models and empirical research. Next, in a discussion of forecasting, we examine both descriptive forecasting (examining the implications of data revisions for standard forecasting models), and prescriptive forecasting (which accounts for the existence of data revisions). Clearly, building a new forecasting model, or evaluating such a model and comparing the results of such a model to forecasts that were made in the past, requires the use of real-time data. The other area that has been the subject of a considerable amount of real-time research is the analysis of monetary policy, which I cover in the fourth section. Analyzing monetary policy using today's data set is certain to be misleading, as it gives the analyst no sense of the data that policymakers had available to them when they made decisions. Instead, the use of real-time data is essential for understanding such decisions. A section on current analysis shows how the examination of the data production process can help policymakers and analysts interpret newly released data. Finally, revisions to conceptual variables, such as the rate of potential GDP growth and the natural rate of unemployment, are examined to show how they influence structural modeling, forecasting, and policy analysis.

DATA REVISIONS

The most common application of real-time data is in the analysis of data revisions. Researchers have focused on examining what data revisions look like; documenting the size of revisions to different variables and across the business cycle; characterizing the revision process as adding news or reducing noise; determining whether the government is using information efficiently; investigating if revisions are forecastable; and showing how the data revision process should be modeled. The underlying theme of all this research is: Are data revisions large enough economically to worry about?

One of the best examples of papers that analyze data revisions is Diebold and Rudebusch (1991), who show that the U.S. index of leading economic indicators does a fine job at predicting recessions ex-post, but only does so because it was constructed to explain the past. Its track record in real time is very poor because initial releases of the data may look very different than later releases and because the index methodology changed over time after the real-time index failed to predict recessions.

What do data revisions look like? Much research has simply tried to catalogue some basic statistics on data revisions, beginning with Arnold Zellner (1958). In the short term, data revisions can be substantial. For example, Figure 1 shows the history over vintage time of the growth rate of real personal consumption expenditures (PCE) for 1973Q2. Data for that date was first released in late July 1973, and at that time the government announced that real PCE grew 0.8% in the second quarter. But one month later, that was revised down to 0.4%. In the annual revision released in late July 1974, the growth rate for real PCE for 1973Q2 was up to 0.6%. The benchmark revision of January 1976 brought the growth rate down to 0.2%, but then the annual revision of July 1976 dropped it to negative territory for the first time, at -0.5%. After that, it was mainly revised in benchmark revisions, but as the chart shows, those revisions still changed it substantially, to -1.1% in December 1980, to -1.3% in July 1982 (correcting an error in the benchmark release), to -0.6% when the base year changed in the benchmark revision of December 1985, to -0.4% in the benchmark revision of November 1991, back to -0.5% (where it had been 20 years earlier) in the switch to chain weighting in February 1996, to -0.4% in the correction to that benchmark revision in April 1997, and finally to -0.2% in the benchmark revision of December 2003. Note that this data point was most recently revised over 30 years after its initial release. Data in the National Income and Product Accounts are never final, though under chain weighting, the changes should only occur when there are redefinitions of variables, so perhaps this number will never be changed again (though redefinitions seem to be never-ending).

[Figure 1 here]

All these wiggles in the growth rate of this variable suggest that data revisions can considerably affect any analysis in the short run. For example, if the quarterly growth rate of consumption was the jumping off point for a forecasting model, forecasts are likely to be very sensitive to the vintage of the data that is used. If monetary policy depends on short-term growth rates, then clearly policy mistakes could be made if the central bank does not account for data uncertainty.

We might not worry too much about data revisions if short-run revisions offset each other in subsequent periods. That is, if consumption spending gets revised up 0.5% one quarter, but revised down 0.5% the next quarter, then all that has happened is a change in timing, but we end up in about the same place at the end of the two quarters. If subsequent errors offset each other, then relevant economic aggregates, such as the average inflation rate over a year or the average annual growth rate of GDP over five years, would not be affected much. But we find instead that data revisions can be substantial, even for five-year averages of the data. Table 2 gives an example, for real consumption spending, of growth rates over five-year periods and how much they can change across vintages. Looking across vintages of the data just before benchmark revisions shows substantial changes in the growth rate of real consumption spending. For example, the average annual growth rate of real consumption spending from 1974Q4 to 1979Q4 was 4.4% per year, as measured in the November 1980 or November 1985 vintages, but only 3.9% as measured in November 1991 or November 1995. To some extent, large revisions in five-year growth rates arose because of the nature of fixed-weight indexes used in the United States before 1996. But even in the chain-weighted era, some large revisions have occurred. For example, the average annual growth rate of real consumption spending from 1989Q4 to 1994Q4 was 2.1% per year, as measured in the August 1999 vintage, but revised up to 2.6% as measured in the August 2009 vintage.

[Table 2 here]

The size of data revisions differs across variables and over the business cycle. The revision pattern for variables in the U.S. national income and product accounts is that the data for a particular activity date are released at the end of the month following the quarter for which the activity is measured, and then revised in each of the following two months. The data are revised again in July of each of the following three years (annual revisions). Then the data are revised about every five years during benchmark revisions. Other variables that are not part of the national income accounting system (for example, employment and industrial production) follow somewhat different patterns, but for most variables there are both annual revisions (which incorporate new source data and adjust seasonal factors) and benchmark revisions (which make base-year changes and improvements in methods used to construct the data).

Analysis of revisions suggests that much valuable information is added to the data during the annual revisions. For data in the national income and product accounts, the annual revisions, usually made in July each year, cause data for the previous three years to be revised. To give you some idea of how significant these revisions are, Table 3 shows statistics for several different sets of revisions for five different variables: the growth rates of output, consumption, employment, and industrial production, and the inflation rate (defined as the growth rate of the GDP deflator), all quarterly values expressed at seasonally adjusted annual rates.

[Table 3 here]

The first three columns of data in Table 3 show, for each variable, the mean and standard deviation of the revisions and the mean absolute revision, for each of three revisions to each variable: the revision from the initial release of the data to the annual revision, the revision from the annual revision to the latest-available value (which is based on the data as recorded in the Real-Time Data Set for Macroeconomists in August 2009), and the overall revision from initial release to latest-available vintage. The mean revision for most variables and revision concepts is fairly small, though there is some tendency for mean revisions to be positive (S. Borağan Aruoba 2008). Whether that tendency is large enough to allow us to predict an upward revision is a subject that we will discuss shortly. More importantly, note that the standard deviation of the revisions varies substantially across variables, with employment having a much lower standard deviation than the other variables, while industrial production is revised more than the others. The size of the standard deviation of the revisions is not a measure of data quality, however, but may instead reflect the method used to obtain the data (for example, employment data are based on monthly surveys of employers, while output is measured using a wide variety of methods including industry reports, with more accurate source data becoming available once each year in various census reports) and the scope and nature of the variable. For example, consumption spending, especially on services and non-durable goods tends to be more stable over time than output is, because output includes volatile components such as business fixed investment spending, whose growth rate fluctuates more dramatically and is thus more difficult to estimate using incomplete source data. The mean absolute revision follows roughly the same pattern as the standard deviation; but provides some information on the size of revisions that may be expected. Note that between the initial release and the annual release of the data, the average quarterly revision to output is about one percentage point in magnitude (regardless of sign), so that the initial release may often be quite different for a quarterly vale than the value recorded in the vintage of the data one year later.

The last two columns of Table 3 suggest that there is some difference in the sizes of data revisions depending on whether the state of the business cycle. When the economy is in a recession, the revisions from initial release to annual release tend to be smaller than the revisions during an expansion, except for the inflation rate. This may not be surprising, as we know that a forecast is generally smoother than a data series being forecast, and with missing source data, government statistical agencies are implicitly making forecasts of missing data. Thus, when better data become available later, they would tend to show downward revisions in recessions (for variables measuring economic activity) and upward revisions in expansions. However, this tendency may be swamped when we look at the revisions from the annual release to the latest-available data by changes in methods, which may systematically change the nature of revisions across the business cycle, as is clearly the case for revisions to output, consumption, and industrial production. Formal tests of the relationship between revisions and the business cycle have been carried out by Karen E. Dynan and Douglas Elmendorf (2001), who find evidence that GDP was misleading at turning points, while Norman R. Swanson and Dick van Dijk (2006) find that the volatility of revisions to industrial production and producer prices increases in recessions.

Does the revision process add news or reduce noise? Researchers have suggested that government data agencies could behave in one of two ways: adding news or reducing noise. If data revisions contain news, that means that when the data are initially released, they are optimal forecasts of the later data, so revisions are orthogonal to each data release. That is,

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

where y_t^* is the true value of the variable, y_t^v is the data released by the government statistical agency for period *t* in the data release at vintage time *v*, where *v* > *t*. The variable e_t^v is the error term for that data release, showing the difference between the true value of the variable and the government's data release for that variable, and is independent of the government's data release, so that

$$y_t^v \perp e_t^v, \qquad e_t^v \perp X_t^v, X_t^v \in \Omega^v \tag{2}$$

that is, y_t^v is orthogonal to e_t^v and e_t^v is orthogonal to X_t^v. In this case, revisions to the data will not be predictable because the revision between vintages *v* and *v'* (where *v'* > *v*) equals:

$$r_t^{v',v} = y_t^{v'} - y_t^v = e_t^v - e_t^{v'}. \tag{3}$$

By construction, both terms on the right-hand side of (3) are orthogonal to anything in the information set for vintage *v*, so the projection of the revision on anything in the information set is zero. Thus the revision is not predictable.

Alternatively, if data revisions reduce noise, then each vintage release equals the truth minus a measurement error:

$$y_t^v = y_t^* - u_t^v, \tag{4}$$

where variable u_t^v is the measurement error, which is independent of the truth, so that

$$y_t^* \perp u_t^v. \tag{5}$$

Now, the revision equals:

$$r_t^{v',v} = y_t^{v'} - y_t^{v} = u_t^{v} - u_t^{v'}. \tag{6}$$

But the right-hand side of (6) is predictable because it is correlated with data known at v, namely y_t^v.

If you know that the government produces data such that data revisions reduce noise, then you can form an optimal linear projection of a later value of the data with just the data at hand. The optimal linear projection in this case is $P[\, y_t^* \mid 1,\; y_t^v \,] = a\, y_t^v$, where[5]

$$a = \frac{E y_t^v y_t^*}{E y_t^{v^2}} = \frac{E(y_t^* - u_t^v) y_t^*}{E(y_t^* - u_t^v)^2} = \frac{E y_t^{*^2}}{E y_t^{*^2} + E u_t^{v^2}} < 1.$$

To minimize the expected squared forecast error between the projection and the later value (or the final value), it is optimal to down-weight the government's initial data release. However, if the government data revisions were produced such that they added news, the optimal projection would have a coefficient of 1:

$$a = \frac{E y_t^v y_t^*}{E y_t^{v^2}} = \frac{E y_t^v (y_t^v + e_t^v)}{E y_t^{v^2}} = \frac{E y_t^{v^2}}{E y_t^{v^2}} = 1,$$

where the orthogonality between the error term and the measured value is critical. This distinction will clearly have implications for forecasting models and policy analysis because the relevant model to use will depend on whether the data revisions add news or reduce noise.

Various authors have examined whether particular variables are characterized as having revisions that reduce noise or add news. N. Gregory Mankiw, David E. Runkle, and Matthew D. Shapiro (1984) find that revisions to the money supply data reduce noise, while Mankiw and

[5] See Thomas Sargent (1979), p. 229, for a simple example. To keep things simple, we assume that the expected value of the true value equals zero, as does the expected value of the error term.

Shapiro (1986) find that GDP revisions add news. Knut A. Mork (1987) uses GMM methods to show that "final" NIPA data contain news, while other vintages are inefficient and neither add news nor reduce noise. Using U.K. data, K.D. Patterson and S.M. Heravi (1991) find that revisions to most components of GDP reduce noise. Of course, revisions need not be either pure news nor pure noise, but a mixture (Mork 1987 and Jan P.A.M. Jacobs and Simon van Norden 2006).

Is the government using information efficiently? The results of the news-noise research raise the question of what the government should report to the public (Sargent 1989). Consider, for example, the government agency reporting GDP. One option is for the agency to simply report its sample information alone. An alternative would be to look at other data to help it guess what will happen to GDP as its sample becomes more complete. For example, suppose the sample information on the components of GDP suggests that it will grow 1.2% for the quarter (at an annual rate). However, suppose the agency observes that employment, which is highly correlated with GDP, grew at a 1.5% rate, and recently productivity has been growing at a 1.0% rate. Also, the agency observes that gross domestic income has increased at a 0.8% rate. The government could make its release of GDP equal to its sample information alone, which would be a 1.2% growth rate. Then, as time passes and the sample of data improves, the noise in the data is reduced; but the initial data release is not an optimal forecast of the later releases. Or, based on the relationship in the past between GDP, employment, and income, the agency could release a measure that is an optimal forecast of later revised data. For example, an optimal forecast of later releases of GDP might show that the agency should equally weight its sample information, the growth rate of employment plus recent productivity growth, and the growth of income. So, it releases GDP growth as: 1/3[1.2% + (1.5% + 1.0%) + 0.8%] = 1.5%. This makes the initial GDP release an optimal forecast of later vintages of GDP. Revisions add news, and because a forecast is smoother than the object being forecast, the standard deviation of later vintages of the data is higher than that of earlier vintages.

A more formal model of this process is helpful in relating these issues to the news and noise discussion above. Consider a variable, such as GDP, in which various data sources and surveys are compiled, with some becoming available at different dates. If all the data sources were immediately available and measured precisely, the true level of output could be calculated as

$$y_t^* = \sum_{s=1}^{S} \lambda_t^{s*}\, x_t^{s*}, \qquad (7)$$

where the asterisk (*) indicates the true value of the variable, y is the variable that the agency cares about providing data for, x^s represents a sector, where S sectors comprise variable y, λ^s is the share of sector s in variable y, and t is the date at which the activity occurs.[6] However, the government data agency never observes the true values of anything but instead has imperfect measures of each sector ($x_t^{s,t+i}$) and imperfect weights applied to each sector ($\lambda_t^{s,t+i}$), where $t+i$ is the date at which the sectoral data are available to the data agency.

Now suppose that the government wants to release a measure of variable y at date $t+i$, but has only some of the sectors of data. Suppose it has data from sectors 1, 2, . . ., N^i, at time $t+i$,

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[6] For example, suppose the government had data on consumption (C), investment (I), net exports (NX), and government purchases (G); then to calculate GDP using equation (7), the λ terms would be 1 and $S = 4$. In reality, each of those components of GDP is composed of many subcomponents, samples for the subcomponents are obtained, and the samples are blown up to the population using different weights.

and has no data on sectors N^i+1, N^i+2, . . ., S. One way to release data for y is to fill in the missing sectoral data with forecasts for those sectors ($x_t^{sf,t+i}$). Then a data release could be formed by using the weights from equation (7) and applying them to the appropriate sectors, to get a forecast formed on the basis of the following equation:

$$y_t^{t+i} = \sum_{s=1}^{N^i} \lambda_t^{s,t+i} x_t^{s,t+i} + \sum_{s=N^i+1}^{S} \lambda_t^{s,t+i} x_t^{sf,t+i} , \qquad (8)$$

where the first summation term contains data that are observed and the second contains forecasts.

The problem with equation (8) is that while the sectoral forecasts might represent optimal forecasts of the components, they may lead to biased forecasts of the aggregate. Suppose, for example, other data (Z_t^{t+i}) are available that could be useful for forecasting y_t^{t+i} and there could be correlations between the observed sectors and unobserved sectors. In this case, the best estimate of y_t^{t+i} might not be given by equation (8), but by a different equation:

$$y_t^{t+i} = \alpha_0 + \sum_{s=1}^{N^i} \alpha^{s,t+i} x_t^{s,t+i} + \sum_{s=N^i+1}^{S} \alpha^{s,t+i} x_t^{sf,t+i} + \sum_{m=1}^{M} Z_t^{m,t+i} , \qquad (9)$$

where $\alpha^{s,t+i} \neq \lambda_t^{s,t+i}$ because of correlations across variables, so the optimal forecasting weights do not equal the sector weights.

For example, suppose the y variable is real GDP and the Z variable is payroll employment. For the first release of GDP, the government may put a fair amount of weight on payroll employment, even though it is not a measure of sector within GDP, but it is clearly correlated with GDP. In fact, forecasters trying to predict the first release of GDP often use payroll employment as a major explanatory variable (Terry J. Fitzgerald and Preston J. Miller 1989).

What happens as time passes and the government receives additional sample information? Over time, the sample becomes more complete, so

$$N^1 \leq N^2 \leq \cdots \leq S.$$

Also, as time passes, seasonal factors for seasonally adjusted variables get adjusted (usually once each year), so each of the sectoral measures ($x_t^{s,t+i}$) may change. In addition, periodic censuses show the government data agency that the weights they have assigned to different sectors need to be revised, so that $\lambda_t^{s,t+i} \neq \lambda_t^{s,t+j}$, for some $j > i$.

The preceding paragraphs describe certain variables, such as GDP or industrial production, reasonably well. Other variables have a simpler structure. For example, the unemployment rate is based on a survey of households. The survey, once taken, does not change and the weights do not change over time. The only change each year is that the seasonal factors are adjusted. Thus revisions to the unemployment rate are small and inconsequential.

A complicating factor in the government's decision about how to develop data is the tradeoff between timeliness and accuracy. The government could produce better data if it waited until its sample was more complete. But policymakers, especially those at the central bank, need data quickly if they are to engage in activist stabilization policy, and the public needs the data without a long delay to make consumption and investment decisions. Victor Zarnowitz (1982) evaluates the quality of differing series, with mixed results. Stephen K. McNees (1989) finds that the within-quarter (flash) estimate of GDP that the U.S. government produced for a few years was as accurate as the estimate released in the month following the quarter. Despite that result, the government discontinued the series. For U.K. data, Anthony Garratt and Shaun P. Vahey (2006) find that many data series are biased and inefficient based on ex-post tests, while Aruoba (2008) finds the same result for U.S. data.

To some extent, the findings that initial data releases are biased and inefficient relative to later releases could be simply an artifact of the way that seasonal adjustment is performed (Kenneth Kavajecz and Sean Collins 1995, and Swanson, Eric Ghysels, and Myles Callan 1999). Of course, it may be convenient for the government data agencies to revise their seasonal factors only once each year, as opposed to continuously revising them, which would lead to some small predictability of revisions. In some cases, the revisions to seasonal factors are larger (in terms of mean absolute revisions) than revisions to the non-seasonally adjusted estimates (Dennis J. Fixler, Bruce T. Grimm, and Anne E. Lee 2003). But the size of the predictable revisions is likely too small to be economically important, especially since such revisions must, by definition, wash out over the year.

Government statistical offices often provide documentation on their data production methods. But given the size and scope of the data production process, it is often difficult to determine whether the methods they follow lead to overall statistics that add news or reduce noise. When data are missing at a low level of aggregation, and no other indicators are available, forecasts of the missing source data are formed using ARIMA models or judgmentally adjusted trends.[7] But if other available indicators are correlated with the missing data, then models of the relationship between the indicator and the variable of interest can be used to forecast the missing source data. Later, when the source data become available, the forecasts are replaced with the newly available data.

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[7] For example, see Bureau of Economic Analysis (2008a, 2008b) for U.S. methods and Hugh Skipper (2005) for U.K. methods.

At a higher level of aggregation, however, government statistical agencies generally add up the components and do not attempt to ensure that their estimates are necessarily optimal forecasts of later revised data. For example, GDP could, in theory, be measured in three different ways: measuring production, measuring spending, and measuring income. With appropriate methods of dealing with inventories, all three methods should lead to the same measure of GDP. Although the U.S. Bureau of Economic Analysis has discussed the possibility of reconciling their separate measures of expenditures and income, rather than reconciling them they simply report both separate measures with the difference listed as a statistical discrepancy. Yet because both measure the same concept, it might be possible to use the information in both to estimate GDP more precisely (Christian Eheman and Brent Moulton 2001 and Fixler and Jeremy J. Nalewaik 2006). In the United Kingdom, expenditure, production, and income estimates are balanced to create one measure of GDP (Heather Robinson 2005). Despite that, one study with a consistent methodology across countries suggests predictability of GDP revisions in the United Kingdom but little predictability for the United States (Jon Faust, John H. Rogers, and Jonathan H. Wright 2005).

Are revisions forecastable? If data revisions reduce noise, then data revisions are predictable. Given the finding that many variables are characterized as having noise revisions, it should be possible to use real-time data to predict revisions. But there have been relatively few papers that were actually able to do so. In part, that may be because bias that is observed after the fact could arise because of redefinitions during benchmark revisions that were not predictable in real time. The papers that have been able to document explicitly that revisions were forecastable in real time are: (1) William Conrad and Carol Corrado (1979), who use a Kalman filter to improve the government's data on retail sales; (2) Victor M. Guerrero (1993), who combines historical data with preliminary data on Mexican industrial production to get improved estimates of final data; and (3) Faust, Rogers, and Wright (2005), who find that GDP revisions are forecastable in real time for most G-7 countries, especially in Japan and the United Kingdom; (4) Aruoba (2008), who uses similar methods to predict revisions for many different variables; and (5) Valentina Corradi, Andres Fernandez, and Norman R. Swanson (2009), who show that revision errors may depend in a non-linear manner on information available at the time of a data release.

How should data revisions be modeled? In part, research into data revisions is designed to help us discover how to model such revisions for use in macroeconomic models, for forecasting models, or for use in monetary policy.

E. Philip Howrey (1978) established the simplest baseline model of revisions, modeling them according to the structure:

$$y_t = \theta x_t + \upsilon_t, \tag{10}$$

where y_t is the measured value of the data at time t, and x_t is the true value of one or several variables, which are not observed, at time t. The measurement error υ_t is modeled as an AR(1) process because of the observation that revisions are often serially correlated, so

$$\nu_t = \psi \nu_{t-1} + w_t, \tag{11}$$

where w_t is not serially correlated.

Patterson (1995) extended this concept to allow the measurement errors for several variables to be related and generalized to a longer lag structure, so that

$$\nu_t^1 = A_1^1(L)\nu_{t-1}^1 + A_1^2(L)\nu_{t-1}^2 + w_t^1, \tag{12}$$

$$v_t^2 = A_2^1(L)v_{t-1}^1 + A_2^2(L)v_{t-1}^2 + w_t^2,$$

where the *A(L)* terms are polynomials in the lag operator.

For U.S. data, Howrey (1978), Conrad-Corrado (1979), and A.C. Harvey, C.R. McKenzie, D.P.C. Blake, and M.J. Desai (1983) describe such models of revisions. For U.K. data, K. Holden and D.A. Peel (1982a and 1982b), and Patterson (1995) establish the key properties of data revisions. They all find that either the Howrey model or the Patterson model fit the data revision process reasonably well.

Most of these models assume that data revisions are not predictable in advance. But in some countries, such as the United Kingdom, data revisions may be predictable. In such a case, exploiting the predictability (Alastair Cunningham, Jana Eklund, Christopher Jeffery, George Kapetanios, and Vincent Labhard, forthcoming) is worthwhile, by essentially adding a constant term to the measurement error equation and estimating it based on past data.

A further generalization of the structure of measurement errors by Jacobs and van Norden (2006) allows for revisions to be modeled as news or noise or both (see the section above "Does the revision process add news or reduce noise?"). They modify Equation (10) above to become:

$$y_t = \theta x_t + v_t + \varepsilon_t, \tag{13}$$

where one component of the measurement error (υ_t) is the news component and is orthogonal to the observed data (y_t), while the other component of the measurement error (ε_t) is the noise component and is orthogonal to the true values of the variables in the system (x_t). The separation of the measurement equation in this way allows for richer specifications of the revision process, and seems to fit the data well.

How do people respond to imperfect data? Knowing that data are certain to be revised, how might people respond? There is little evidence on this question, except for the response of policymakers, which we discuss in the later section on policymaking with real-time data. Until the last decade, when real-time research has become more prevalent, most economists thought that data revisions were likely to be small and inconsequential. Only recently has the research described in this paper made a convincing case that data revisions may be large and have important implications. Further, the fact that there is limited predictability of U.S. data revisions means that even though data revisions have consequences (which might lead agents to hedge against the uncertainty that data revisions generate), people cannot easily predict the direction of the revisions. In other countries, such as the United Kingdom and Japan, revisions are larger and more predictable, and there is more scope for people to adjust and anticipate the revisions.[8]

STRUCTURAL MACROECONOMIC MODELING

Structural macroeconomic modeling can be influenced by data revisions in a number of ways. If you are modeling the decision-making process of an economic agent, proper structural modeling requires that you consider the information set of the agent and that the agent knows that the data are subject to revision. This means that agents may consider the nature of data revisions (news or noise, as discussed above) in making decisions or in deciding to filter the data.

In this section, we first explore the question of whether research results are robust to alternative vintages of the data; relationships can look different depending on which vintage of

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[8] See Faust, Rogers, and Wright (2005) for evidence on predictability of GDP revisions in the United Kingdom and Japan.

data is used to estimate structural models. Second, we ask if data revisions are important enough to the economy that they should become an explicit part of large macroeconomic models. Third, we look at whether data revisions affect economic activity.

The robustness of research results. One particularly beneficial use of real-time data is that it gives us a chance to perform some simple replication experiments. Empirical macroeconomic research has established a number of important results, but there has been relatively little research replicating those results. We would like to know how robust those results are to the use of alternative data sets, and thus how general the results are.

One way to test robustness is explored by Croushore and Stark (2003). They rerun a number of major macroeconomic studies using different vintages of the data, which is one version of the replication studies that were originally suggested by William G. Dewald, Jerry G. Thursby, and Richard G. Anderson (1986). The idea is that the original research was based on a particular data set. But over time, the data used in the study become revised. What if the research was done again using a more recent data set? If the results are robust, the change of data set should not cause a problem; but if the results are sensitive to the particular data set, then the major results of the research should change. Croushore and Stark test a number of major macroeconomic studies. First, they use the same sample period but more recent vintages of data. Then, they use both a more recent vintage as well as a larger sample. They find that while RBC business-cycle facts are robust to a change in the data set, evidence for the life-cycle–permanent-income hypothesis is not, nor are impulse responses of output and unemployment to demand shocks.

There have been few other tests of the robustness of research results to data revisions. The first researchers to do so were John F. Boschen and Herschel I. Grossman (1982), who use data revisions in an analysis of the neutrality of money under rational expectations; this paper provides key evidence against equilibrium models in the classical tradition. Boschen and Grossman explicitly model the data revision process to develop a model that shows how the economy would react to preliminary data subject to later revisions. One hypothesis of rational-expectations equilibrium macroeconomics is that the contemporaneously observed money supply should not affect output or employment. Tests based on final, revised data support the hypothesis; but Boschen-Grossman's tests using real-time data reject the hypothesis. A second hypothesis is that revisions to money-supply data should be positively correlated with output and employment; but again real-time data are not consistent with the hypothesis. Thus, the Boschen-Grossman analysis shows that empirical results that were based on latest-available data lead to substantially different results than those based on real-time data.

Could randomly choosing a vintage of data to use in a macroeconomic study influence the outcome? Dewald, Thursby, and Anderson (1986) investigate this question by replicating a study on the growth of foreign banks in the U.S. market. They find that randomly choosing which data vintage (over a ten-year period) to use in the empirical estimation could lead to substantially different results, casting doubt on the study's robustness. In a similar vein, Jeffery D. Amato and Swanson (2001) find that tests confirming the predictive content of money for output, which used latest-available data, do not hold up when real-time data are used (with recursive estimation, moving sequentially across vintages, that is, across the columns in Table 1).

In real-time, and in out-of-sample forecasting exercises, money is not useful for predicting future output.

Should macroeconomic models incorporate data revisions? If data revisions are large and not white noise, then incorporating them into macroeconomic models may be a desirable step to take. One approach, developed by Aruoba (2004), is to incorporate data revisions into a DSGE model. Agents know that data will be revised and filter the data they receive to account for the predictability of data revisions. Aruoba calibrates the model based on the past history of data revisions. He finds that business-cycle dynamics are better captured in such a framework than in one that does not incorporate data revisions. A similar approach by Rochelle M. Edge, Thomas Laubach, and John C. Williams (2007) examines uncertainty about transitory and permanent shocks to productivity growth. The transitory-permanent confusion affects agents, especially because data on productivity are revised substantially, and helps to explain cycles in employment, investment, and long-term interest rates in a DSGE model.

Do data revisions affect economic activity? Are economic outcomes more strongly influenced by true, underlying economic activity, or by announcements about economic activity, which could be false? Seonghwan Oh and Michael Waldman (1990) hypothesize that, based on a model of strategic complementarity, an announcement of a forecast of strong future economic activity will lead people to produce more, simply because they believe the announcement and they desire to produce a lot when the economy is stronger. This is true even if the data are subsequently revised down (relative to a situation where the true, lower value was released initially and not changed). Thus, false announcements that the economy is doing well still lead to increased economic activity. Oh and Waldman test this using data on the index of leading indicators and industrial production. They find that output is higher when the leading indicators are initially released and then later revised down, than if the initial release of the leading indicator was correct. So, output tends to respond positively to the leading indicator announcement. The implication of their research is that initial data releases are more important for structural modeling than the true data.

If data announcements that differ from the truth affect people's behavior, then the quality of data may affect the volatility of the economy. This hypothesis is explored by Antulio Bomfim (2001) asks whether economic volatility changes if data are of higher quality. In his real-business-cycle-framework, agents must make factor allocation decisions before they know what productivity is. Later, they can observe productivity but cannot distinguish between permanent and transitory shocks to productivity. As a result, they must engage in signal extraction, based on the data they observe. Interestingly, if data quality improves, and if agents use optimal signal-extraction methods, then economic aggregates become more volatile. The increased volatility occurs because the data are more reliable, so agents do not discount new releases of the data but respond more strongly to them. On the other hand, if agents naively believe that the initial releases of the data are accurate and do not perform any signal extraction, then improvements in data quality would lead to a reduction of economic volatility.

In all three areas (testing robustness of research results, incorporating data revisions into macroeconomic models, and examining how or whether data revisions affect economic activity) the literature is in its infancy and there is great need for additional exploration. Little has been written on what methodologies are most useful for uncovering structural relationships, given that data will be revised continuously. We also do not know whether the best methodology to use depends on the revision process, the information set of agents and how it evolves over time, or how agents perceive data revisions. What we would truly like to capture are the true structural relationships between variables when data are subject to revision and we would like to know if we should use all available data, or just the subset of data that have been revised enough to be trustworthy, in estimating structural models.

FORECASTING

Revisions to data may affect forecasts considerably.[9] Consider two alternative exercises: descriptive and prescriptive. In descriptive exercises, we examine standard forecasting techniques to see how such methods perform when data are revised (and the revisions are not accounted for in the forecasting model). These exercises are designed to show how forecasters who ignore data revisions will perform in real time. For example, researchers who are attempting to build a new and improved forecasting model want to compare forecasts made with a new model with forecasts made with other models, but their results may depend on data revisions. In examining descriptive forecasting, we examine: (1) How do forecasts differ between real-time and latest-available data? (2) Does it matter whether the forecasts are in levels or growth rates? (3) How is model selection affected by data revisions? (4) Does the predictive ability of variables depend on revisions?

Given that the results of descriptive forecast analysis suggest that data revisions may substantially affect forecast performance, we then turn to prescriptive forecast analysis: how

[9] This section summarizes the more detailed discussion in Croushore (2006) and discusses some additional recent research.

forecasts should be made when we know that the data will be revised. The optimal forecasting method may require the use of the entire real-time data matrix shown in Table 1, not just one column or one diagonal, as is commonly used.

Descriptive forecast analysis. Forecasts are affected by data revisions because the revisions change the data that are input into the model, the change in the data affects the estimated coefficients, and the model itself may change, given the use of some procedure for model specification. Stark and Croushore (2002) perform a variety of experiments that illustrate how each of these mechanisms works in practice.

One issue that occurs in all the forecasting literature with real-time data is: What version of the data should be used as "actuals"? After all, data may continue to get revised forever, so we may never know the true value of a variable. The best overall measure of the "truth" may be the latest-available data, as such data presumably reflect the best economic methodology to arrive at a measure that matches the theoretical concept for that variable. But that may not have been a good idea in the era of fixed-weighting of real aggregates, which is known to distort growth rates in years distant from the base year. Under chain-weighting, this is not a problem. However, even though we might think that the latest-available data are as close as possible to the truth, that does not mean they are useful for evaluating forecasts. Forecasters generally produce forecasts of variables based on currently existing methodologies and cannot be expected to predict future changes in methodology. We should not expect forecasters to anticipate redefinitions of variables that will not occur for many years in the future. For example, in 2008, the U.S. Bureau of Economic Analysis announced that, it is considering, starting in 2013, capitalizing expenditures on research and development, a move that would likely cause real GDP to be revised up, on average, over time. No forecaster today is going to modify her forecasts to account for the possibility five years hence; nor should anyone do so. Thus, evaluations of forecasts should usually focus on early releases of the data, or the last vintage of the data after a forecast is made but prior to a benchmark revision that changes base years or redefines variables. Still, most evaluations of forecast exercises are based on latest-available data for convenience, even though they may provide a distorted view of forecast ability. With real-time data sets becoming more readily available, there is less need to do this, so we should see more papers in the forecasting literature based on using some real-time concept as actuals for evaluating the forecasts.

How do forecasts differ between real-time and latest-available data? The idea that triggered the creation of the Real-Time Data Set for Macroeconomists was a forecasting paper that claimed that a new forecasting model could beat the U.S. Survey of Professional Forecasters (SPF) that I had created by taking over the defunct ASA-NBER survey in 1990. A researcher "built a better mousetrap" and showed that it provided better forecasts than the SPF. But, of course, the new model used only the latest-available data and was not tested on real-time data, because no such data set existed in the United States. But clearly the right way to test the new model against the SPF would be to run the real-time data through the new model to simulate how the model would forecast in real time.

The question is: does using real-time data lead to very different forecasts than using latest-available data? The first paper to examine this question, by Frank T. Denton and John Kuiper (1965), finds significant differences in the forecasts made for Canadian data depending on whether real-time data or latest-available data were used. Rosanne Cole (1969) finds that data errors reduced forecast efficiency and led to biased forecasts, so there are significant differences between forecasts made with different data sets. Ugo Trivellato and Enrice Rettore (1986) show that data errors (using Italian data) in a simultaneous-equations model have large effects.

Forecasts of exchange rates seem to be even more sensitive to real-time data issues. Faust, Rogers, and Wright (2003) show that it is possible to forecast exchange rates in real time with some data vintages but not others. Tanya Molodtsova (2008) and Molodtsova, Alex Nikolsko-Rzhevskyy, and David H. Papell (2008) find that exchange rates are predictable only using real-time data, not with revised data.

Model selection and specification. Given that data are revised, how do alternative vintages of the data affect the specifications of forecasting models? Swanson and Halbert White (1997) explore model selection with real-time data, finding that the in-sample SIC criterion leads to very different model choices than an out-of-sample measure. The sensitivity of model specification to the vintage of the data may depend on the variable in question, as John C. Robertson and Ellis W. Tallman (1998) find.

Overall, it appears that in many situations, the use of real-time data matters for forecasting. Given that result, the key question is: How should forecasters adjust their forecasts to account for the uncertainty about the data?

Prescriptive Forecast Analysis. How should forecasts be made when we know data are going to be revised? Can forecasting models be modified in a sensible way when we know that data will be revised, to account for the greater uncertainty about more recent data? Two main approaches deserve consideration: (1) factor models and (2) state-space models.

(1) Factor Models. Factor models are simple forecasting models that assume that one or several factors are the driving force(s) behind the movements of all relevant variables. This

assumption suggests extracting a principal component from a large number of data series (the factor), in the hope that measurement error averages out to zero across many variables.

To illustrate how a factor model works, consider the following situation. Suppose that two variables, x^1 and x^2 are both measures of economic activity that depend on the overall state of the economy, S. An example might be non-farm payroll employment and industrial production. The variables are related, though they may have very different revision patterns:

$$x_t^1 = \gamma_1 S_t + \varepsilon_t^1,$$

$$x_t^2 = \gamma_2 S_t + \varepsilon_t^2,$$

where the error terms incorporate potentially complex dynamics, reflecting potential data revisions, as well as other variable-specific features that are uncorrelated with the factor (James H. Stock and Mark W. Watson, 1999 and 2002). The state of the economy is unobserved but is a common factor in both equations. So, it is possible to estimate the value of the factor (the state of the economy) from the first two equations and use it to forecast y. As long as the revisions to the two measures of economic activity are not correlated, then in principle a factor model can reduce forecast errors caused by data revisions.

Ben S. Bernanke and Jean Boivin (2003) suggest that factor models based on large numbers of data series may provide much better forecasts than models based on smaller numbers of data series or forecasts based on structural models, such as the Fed's Greenbook. They find that such a factor model is useful and that whether the data used in the model are real-time or latest-available does not have much impact on the results. In a similar vein, Domenico Giannone, Lucrezia Reichlin, and Luca Sala (2005) show how a dynamic factor model can be used to extract real-time information, finding that two factors are present in U.S. data—one nominal and one real.

Faust and Wright (2009) are the first to study this question using real-time data on a large number of data series, finding that for inflation forecasting the factor models perform better in real time than univariate time-series methods but perform worse than the Greenbook. But they also note that factor models, for which averaging across large numbers of variables helps to wash out data revisions, fare worse in forecasting than averaging across a number of small (bivariate) models. This result implies that forecasters should not necessarily look at a large number of variables with factor models, as the gains from averaging the results from small models dominate the gain from washing out data revisions.

(2) State-Space Models. If a forecaster models a data generating process along with a data revision process, the increased structure imposed on the model (relative to a factor model) could in principle provide improved forecasts. Howrey (1978) shows how data can be adjusted for differing degrees of revisions using the Kalman filter. This suggests that rather than ignoring recent data, the forecasting model should use it, but filter it first. Harvey, McKenzie, Blake, and Desai (1983) use state-space methods with missing observations to account for irregular data revisions and find a large gain in efficiency from doing so, compared with ignoring data revisions. Patterson (2003) illustrates how to combine the measurement process with the data generation process to improve upon forecasts for income and consumption. However, some attempts at using these methods in practice find little scope for improvement. For example, Howrey (1984) found that using state-space models to improve forecasts of inventory investment yields little improvement.

The conflicting results suggest that state-space modeling cannot be applied blindly without an eye towards knowledge of the revision process and the data generating process. Overall, there are sometimes gains to accounting for data revisions. But the predictability of revisions may be small relative to the forecast error. A troublesome issue in the state-space modeling approach is specifying an ARIMA process for data revisions because benchmark revisions tend to be idiosyncratic and poorly described by ARIMA models.

One issue in the literature that has only been addressed sparingly is how much of the information set to use in trying to improve forecasts. Typically, forecasters use latest-available data in constructing and estimating their forecasting models. But Evan Koenig, Sheila Dolmas, and Jeremy Piger (2003) and N. Kundan Kishor and Koenig (2005) argue that forecasters could make better forecasts by focusing on the diagonals of the real-time data matrix (see Table 1), so that they are modeling data in a consistent way depending on how much each piece of data has been revised. Thus, forecasters need to treat data that have not been revised differently from data that have gone through one annual revision, which should in turn be treated differently from data that have gone through a benchmark revision.

Changes in the data production process may also strongly affect forecasts. A state-space model incorporating data revisions may be blown off course if the government changes its data production methods. For example, in 1996, the U.S. Bureau of Economic Analysis moved from fixed-weight indexes to chain-weight indexes for the national income and product accounts, substantially modifying the revision process.

One possible method for adjusting forecasting models to account for data revisions is to forecast an object that is less sensitive to data revisions. Howrey (1996) finds that level forecasts of real output are more sensitive to data revisions than forecasts of growth rates. In related work, Sharon Kozicki (2002) shows that the choice of forecasting with real-time or latest-available data is important for variables with large revisions to levels.

The predictive content of variables. Would we draw the same conclusions about whether one variable is helpful in forecasting another variable when we use real-time data compared with latest-available data? Diebold and Rudebusch (1991) provide a clear answer in discussing the index of leading economic indicators, finding that their predictive ability in real time is much less than with latest-available data. Koenig (2003) finds that the markup only helps predict inflation with latest-available data, but not in real time. Croushore (2005) suggests that consumer confidence indicators have no out-of-sample predictive power for consumption spending. The real-time nature of the data matters, as using latest-available data or examining in-sample predictive power increases the ability of consumer-confidence indexes to predict consumer spending. Thus, failure to use real-time data can lead to misleading conclusions about the ability to forecast a variable. Garratt, Gary Koop, Emi Mise, and Vahey (2009) find the same general result for the predictive content of money in the United Kingdom—inference about predictive content is quite different using real-time data than using revised data.

Hypothesis testing in real time. Making inferences about predictive content is problematic in real time, however, as key assumptions of standard tests are violated. Atsushi Inoue and Barbara Rossi (2005) consider how forecasters can avoid overfitting, which is a common problem in real-time forecasting. Todd E. Clark and Michael W. McCracken (2009) illustrate how the problem of making inference with real-time data can be overcome under some conditions, though noting that the power of the tests is lower than the case for non-revised data.

MONETARY POLICY

Given the real-time nature of policy making, it is natural that much research with real-time data is geared toward monetary policy. I will distinguish between data revisions (discussed here) and revisions to measures of analytical concepts, discussed in a later section.

How much does it matter that data are revised? Data revisions clearly matter for monetary policy. Overreaction to current data can lead a central bank to make mistakes. Peter Kugler, Thomas J. Jordan, Carlos Lenz, and Marcel R. Savioz (2005) show how the Swiss central bank's reaction function should change in the presence of GDP revisions, showing that the economy would be more volatile if the central bank reacted too strongly to initial data. On the other hand, if monetary policymakers know that data will be revised, they may optimally extract the signal from the data, so data revisions may not significantly affect monetary policy, as Augustin Maravall and David A. Pierce (1986) show. The Federal Reserve's main indicators of inflation are the PCE inflation rate and the core PCE inflation rate (excluding food and energy prices). But revisions to these variables are substantial and could mislead the Fed, as Croushore (2008) shows.

If data are revised and policymakers know they will be revised, but researchers trying to model policy decisions do not take that fact into account, then it is possible that their research results will be misleading. Rudebusch (1998) suggests that estimates of monetary policy shocks and reaction functions may depend importantly on use of real-time data. However, Croushore and Charles L. Evans (2006) find that data revisions do not significantly affect measures of monetary policy shocks. However, in a simultaneous system of equations, identification is problematic when data revisions exist. In their model, policy decisions depend on real-time data, but the economy evolves according to the true but unobserved state of the economy.

How should monetary policymakers handle data uncertainty? Given that the data are likely to be revised, what can policymakers do? One possibility is to use information on additional variables. Gunter Coenen, Andrew Levin, and Volker Wieland (2005) show that policymakers facing uncertainty about output can use data on money supply to help them make better decisions.

Another possibility, which can be used in situations in which there is no certainty equivalence, is that policymakers facing potential data revisions that reduce noise should be less aggressive with monetary policy, as Kosuke Aoki (2003) illustrates, in line with William C. Brainard's (1967) early suggestion. Similar results obtain when there is uncertainty about potential output and other analytical concepts, as discussed in the later section on "Revisions to Conceptual Variables."

CURRENT ANALYSIS

As economists in real time sift through the macroeconomic data to discover turning points, does the real-time nature of the data lead us to pay attention to variables in a manner different than if we were looking at revised data?

In the finance literature, event studies are common, but they often fail to use real-time data. Peter Christoffersen, Ghysels, and Swanson (2002) show that researchers should use real-time data to properly evaluate announcement effects in financial markets; studies based on latest available data are misleading. The use of real-time data provides a more accurate view of the rewards in financial markets to taking on macroeconomic risks.

How do we know the state of the economy in real time? Policy analysts can use factor models to evaluate the current state of the economy (Martin D.D. Evans 2005 and Aruoba, Diebold, and Chiara Scotti 2009). The model of Aruoba, Diebold, and Scotti is being used by the Federal Reserve Bank of Philadelphia to produce a real-time business conditions index for use by policymakers, and is updated at least once each week.[10]

A number of papers have examined the issue of identifying turning points in the business cycle in real time. Marcelle Chauvet and Piger (2003) use a Markov-switching model applied to real-time data on output growth and payroll employment to see if they can identify NBER turning points in real time. They are able to match the NBER business-cycle dates fairly accurately and identify business-cycle troughs (but not peaks) on a more timely basis. Chauvet and Piger (2008) extend this approach with additional data (on the main four variables used by the NBER itself) and a nonparametric model as well as the Markov-switching model used in their 2003 paper; they confirm the results of their earlier paper. Chauvet and James D. Hamilton (2006) then use the Markov-switching model and the four main NBER variables to develop a monthly model that produces a recession-probability index. The index calls business cycle turning points very similarly to the NBER's chronology but declares turning points on a more timely basis. In a related paper, Nalewaik (2006) finds that the use of real-time gross domestic

[10] The index can be found on-line at http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/.

income (GDI) in a Markov-switching model produces more accurate recession probabilities than the same model using gross domestic product (GDP).

REVISIONS TO CONCEPTUAL VARIABLES

Models of the economy often rely on analytical concepts, such as the output gap, the natural rate of unemployment, and the equilibrium real federal funds rate. Such concepts are never observed, but policymakers and their staffs may estimate such concepts in real time. If their estimates are far from the mark, policy decisions may be poor.

The literature on the consequences for monetary policy making of revisions to conceptual variables begins with Athanasios Orphanides (2001), who finds that the Fed overreacted to bad measures of the output gap in the 1970s, causing monetary policy to be much too easy. Had the Fed quickly perceived the slowdown in productivity in the 1970s, it would not have eased policy nearly as much, and the Great Inflation of the 1970s might have been avoided. When monetary policy is set using the level of the output gap, as suggested by the Taylor rule, real-time measurement difficulties cause policy errors (Orphanides, Richard D. Porter, David Reifschneider, Robert Tetlow, and Frederico Finan 2000, Frank Smets 2002, and Rudebusch 2001).

Numerous research papers have examined the reaction of policy to conceptual variables and the problems caused if policymakers do not respond to the possibility of analytical revisions at all, they are likely to be overly aggressive in their policy actions. The implications for Taylor rules are explored by Kozicki (2004) with U.S. data and Koichiro Kamada (2005) for Japan. Rudebusch (2001, 2002) shows that uncertainty about data significantly alters the coefficients of optimal monetary-policy rules. For example, if the data were not uncertain, the optimal Taylor rule would be much more aggressive than the estimated rule appears to be, a result confirmed by Orphanides (2003). The same result is found by Alex Cukierman and Francesco Lippi (2005), who suggest that the Fed was too aggressive given the nature of the data in the 1970s, but was appropriately conservative in response to the initial data in the 1990s, which explains the better macroeconomic performance of the later period. Boivin (2006) finds that the poor performance on inflation in the 1970s occurred when the Fed temporarily reduced its response to inflation.

One vein of research explores the uncertainty about the natural rate of unemployment, which may guide policymakers (Douglas Staiger, Stock, and Watson 1997, and Orphanides and Williams 2002). Other research shows the uncertainty there is about the natural rate of interest (Orphanides and Williams 2002, and Clark and Kozicki 2005). Work on uncertainty about output gaps is pervasive, with key contributions by Orphanides and van Norden (2002) for U.S. data, Edward Nelson and Kalin Nikolov (2003) for U.K. data, Christina Gerberding, Franz Seitz, and Andreas Worms (2005) for German data, Dieter Gerdesmeieir and Barbara Roffia (2005) for the Euro area, Tom Bernhardsen, Øyvind Eitrheim, Anne Sofie Jore, and Øistein Roisland (2005) for Norway, Jean-Philippe Cayen and van Norden (2005) for Canada, and Jörg Döpke (2005) for Germany.

A key issue in this literature is how policymakers and their advisers can optimally use real-time data to make some inference about the output gap or some other forward-looking concept given the uncertainty in real time. The output gap or natural rate of unemployment or natural rate of interest is much easier to calculate for the past, but nearly impossible to pin down very well in real time. Much of the research described above uses some method to try to calculate the analytical concept at the end of the sample, but the accuracy of a gap or trend measure improves dramatically as time passes. As Watson (2007) notes: "one-sided estimates necessary for real-time policy analysis are substantially less accurate than the two-sided estimates used for historical analysis." This may not be an area that will be fruitful for future research, as there may be no better solution than those that have already been tried. What hasn't been examined, however, is a more theoretical approach to creating a model of the evolution of analytical concepts; instead, much of the work is purely statistical.

CONCLUSIONS

With real-time data sets having become available only recently, the field of real-time data analysis is fertile and there are many unanswered questions. Little work has been done to date on the correlations of revisions across variables, the relationship of revisions to the business cycle, or theoretical or empirical work on how people respond to imperfect data revisions. Researchers need to work to develop methodologies to uncover structural relationships, given the existence of data revisions. Though much work with state-space models seems promising, no one has solved the problem of how to model benchmark revisions that are idiosyncratic and cannot be easily captured by ARIMA models.

If you want to analyze policy or forecasts, you *must* use real-time data, or your results are irrelevant; given the existence of real-time data sets for many countries, there is no excuse for not using real-time data. If you want to develop a structural model of the economy, you may find it useful to see how robust it is to alternative data vintages. No doubt researchers will find many more uses for real-time data in decades to come.

Table 1

Real-Time Data Structure

Real Output

Vintage Date:	11/65	2/66	5/66	. . .	5/09	8/09
Activity						
Date						
47Q1	306.4	306.4	306.4	. . .	1570.5	1772.2
47Q2	309.0	309.0	309.0	. . .	1568.7	1769.5
47Q3	309.6	309.6	309.6	. . .	1568.0	1768.0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
65Q3	609.1	613.0	613.0	. . .	3214.1	3636.3
65Q4	NA	621.7	624.4	. . .	3291.8	3724.0
66Q1	NA	NA	633.8	. . .	3372.3	3815.4
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
08Q3	NA	NA	NA	. . .	11,712.4	13,324.6
08Q4	NA	NA	NA	. . .	11,522.1	13,141.9
09Q1	NA	NA	NA	. . .	11,340.9	12,925.4
09Q2	NA	NA	NA	. . .	NA	12,892.4

Source: ***Real-Time Data Set for Macroeconomists***

Table 2

Average Growth Rates of Real Consumption over Five Years
Pre-Benchmark Vintages
Annualized percentage points

Vintage Year: Period	‘75	‘80	‘85	‘91	‘95	’99	’03	‘09
49Q4 to 54Q4	3.6	3.3	3.3	3.7	3.9	3.8	3.8	3.8
54Q4 to 59Q4	3.4	3.3	3.3	3.3	3.4	3.5	3.5	3.5
59Q4 to 64Q4	4.1	3.8	3.8	3.7	3.8	4.0	4.1	4.1
64Q4 to 69Q4	4.5	4.3	4.4	4.4	4.5	4.8	4.8	4.8
69Q4 to 74Q4	2.3	2.6	2.6	2.5	2.6	2.8	2.8	2.9
74Q4 to 79Q4	NA	4.4	4.4	3.9	3.9	4.1	4.2	4.1
79Q4 to 84Q4	NA	NA	2.8	2.5	2.5	2.6	2.8	2.9
84Q4 to 89Q4	NA	NA	NA	3.2	3.1	3.4	3.7	3.7
89Q4 to 94Q4	NA	NA	NA	NA	2.3	2.1	2.4	2.6
94Q4 to 99Q4	NA	NA	NA	NA	NA	NA	4.0	4.1

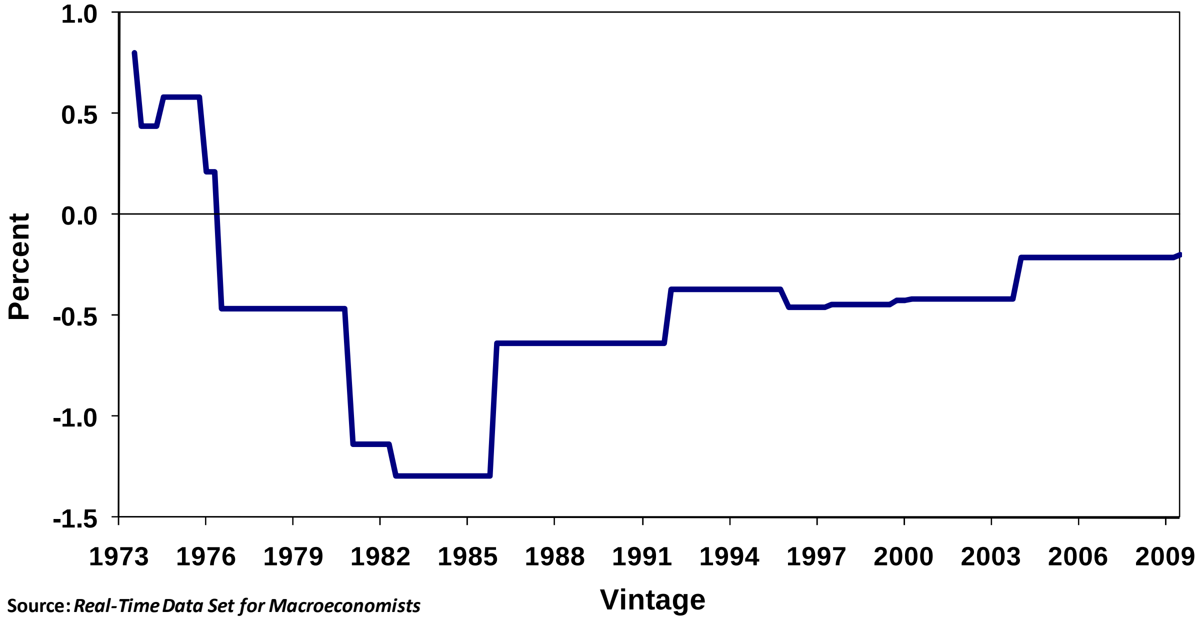
Table 3: Revision Statistics

(1965:Q3 to 2006:Q4, Quarterly Data at Annual Rates)

Revisions from Initial Release to Annual Release					
	Mean	Standard Deviation	Mean Absolute Revision	Mean in Recessions	Mean in Expansions
Output	0.18%	1.34%	1.01%	-0.14%	0.23%
Consumption	-0.01	1.16	0.89	-0.49	0.07
Employment	0.10	0.42	0.32	0.07	0.11
Industrial Production	0.41	2.20	1.57	0.27	0.43
Inflation (GDP deflator)	0.16	0.71	0.52	0.29	0.14
Revisions from Annual Release to Latest-Available Data					
	Mean	Standard Deviation	Mean Absolute Revision	Mean in Recessions	Mean in Expansions
Output	0.34%	1.92%	1.46%	1.24%	0.19%
Consumption	0.34	1.47	1.11	0.50	0.31
Employment	0.07	0.57	0.43	-0.06	0.09
Industrial Production	0.00	2.73	1.94	0.99	-0.16
Inflation (GDP deflator)	0.02	0.86	0.68	-0.31	0.07
Revisions from Initial Release to Latest Available Data					
	Mean	Standard Deviation	Mean Absolute Revision	Mean in Recessions	Mean in Expansions
Real Output	0.52%	2.18%	1.67%	1.10%	0.42%
Consumption	0.33	1.66	1.28	0.01	0.38
Employment	0.17	0.74	0.56	0.01	0.19
Industrial Production	0.41	2.81	2.18	1.26	0.27
Inflation (GDP deflator)	0.18	0.90	0.68	-0.02	0.21

Source: ***Real-Time Data Set for Macroeconomists***

Figure 1
Real Consumption Growth for 1973Q2
(as viewed from the perspective of 145 different vintages)



Source: ***Real-Time Data Set for Macroeconomists***

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