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FRONTIERS OF REAL-TIME DATA ANALYSIS

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FRONTIERS OF REAL-TIME DATA ANALYSIS

ABSTRACT

This paper describes the existing research (as of February 2008) on real-time data analysis, divided into five areas: (1) data revisions; (2) forecasting; (3) monetary policy analysis; (4) macroeconomic research; and (5) current analysis of business and financial conditions. In each area, substantial progress has been made in recent years, with researchers gaining insight into the impact of data revisions. In addition, substantial progress has been made in developing 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

The analysis of real-time data dates back to Gartaganis-Goldberger (1955), who found that the statistical properties of the discrepancy between gross national product (GNP) and gross national income differed after the data were revised in 1954, compared with the 1951 vintage of the data. 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. Researchers have examined the properties of data revisions, how data revisions affect forecasting, the impact of data revisions on monetary policy analysis, how macroeconomic research is affected by data revisions, and the use of real-time data in current analysis.

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 Croushore-Stark (2001). 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. 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, many 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, rivalry between the Federal Reserve Banks of Philadelphia and St. Louis has hastened the development of the data, and both

institutions have allowed unrestricted access to their data as soon as they have been produced. The OECD recently made their data available to everyone, with data for all OECD countries and a few others, with vintages beginning in 1999, based on data that appear in *Main Economic Indicators*. Researchers at the Bank of England produced a real-time data set in 2001 and recently updated it in 2007, with vintages beginning in 1990; see Castle-Ellis (2002). A data set with somewhat restricted access was produced and is updated by the EABCN for the euro area, with vintages beginning in 2001. Individual researchers have developed smaller data sets for many other countries, though as far as I know they do not provide ready access to their data. 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.

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; see Kennedy (1990). Revisions to data often reflect information from censuses that are taken every five or 10 years; it would be too costly to take such censuses more frequently. As a result, every five or 10 years, the government statistical agencies make large changes in the weights applied to different sectors of the economy in measuring GDP and prices, a process that 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.

The typical structure of a real-time data set is demonstrated in Table 1. Each column represents a different vintage of data (a date at which the data are observed), while each row shows a different date for which the economic 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						
Real-Time Data Structure						
Real Output						
Vintage: Date	11/65	2/66	5/66	...	11/07	2/08
47Q1	306.4	306.4	306.4	...	1570.5	1570.5
47Q2	309.0	309.0	309.0	...	1568.7	1568.7
47Q3	309.6	309.6	309.6	...	1568.0	1568.0
.
.
.
65Q3	609.1	613.0	613.0	...	3214.1	3214.1
65Q4	NA	621.7	624.4	...	3291.8	3291.8
66Q1	NA	NA	633.8	...	3372.3	3372.3
.
.
.
07Q1	NA	NA	NA	...	11412.6	11412.6
07Q2	NA	NA	NA	...	11520.1	11520.1
07Q3	NA	NA	NA	...	11630.7	11658.9
07Q4	NA	NA	NA	...	NA	11677.4

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 1966 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 simply represent changes in the (arbitrary) base year. Notice that in data vintage November 2007, the data value for the third quarter of 1947 is below the value for the second quarter, unlike the vintages in the 1960s.

DATA REVISIONS

The most common application of real-time data is in the analysis of data revisions. Researchers have examined (1) what data revisions look like; (2) characterization of the revision process as adding news or reducing noise; (3) whether the government is using information efficiently; (4) if revisions are forecastable; and (5) how the data revision process should be modeled. The underlying theme of all this research is: Are data revisions economically large enough to worry about?

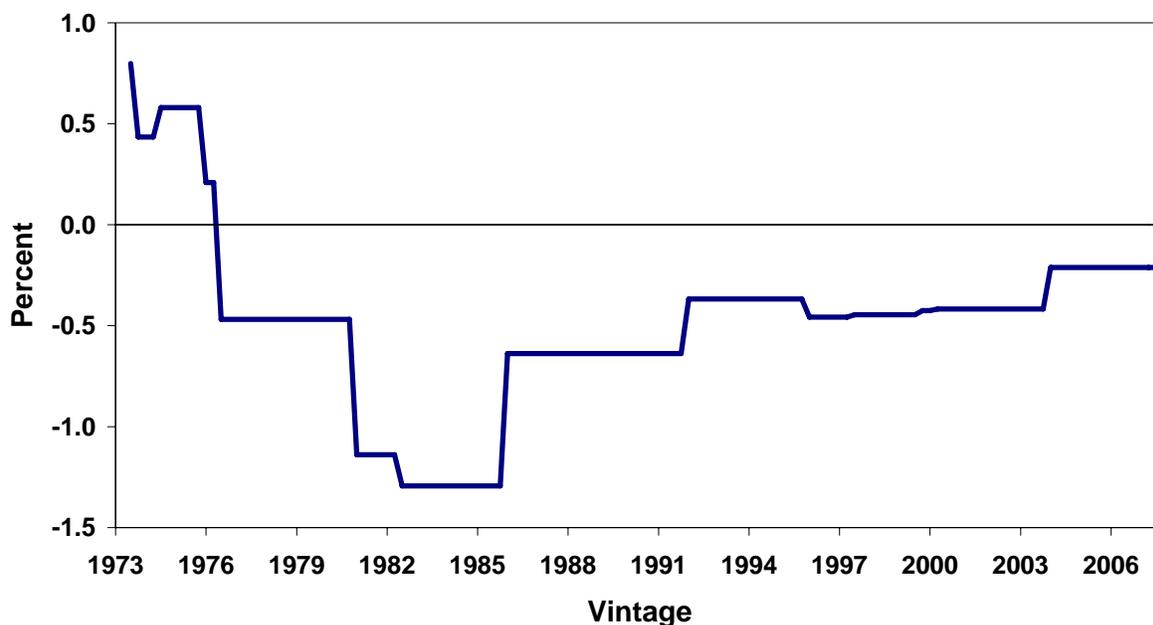
One of the best examples of papers that analyze data revisions is Diebold-Rudebusch (1991), who showed that the U.S. index of leading economic indicators does a fine job at

predicting recessions ex-post, but only 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 from 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 catalog some basic statistics on data revisions, beginning with 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. The data point 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 occur only when there are redefinitions of variables, so perhaps this number will never be changed again (though I wouldn't count on it).

Figure 1
Real Consumption Growth for 1973Q2
(as viewed from the perspective of 138 different vintages)



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 1975 to 1979 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 1990 to 1994 was 2.1% per year, as measured in the August 1999 vintage, but revised up to 2.6% as measured in the August 2007 vintage.

Table 2								
Average Growth Rates of Real Consumption over Five Years								
Benchmark Vintages								
Annualized percentage points								
Vintage Year: Period	'75	'80	'85	'91	'95	'99	'03	'07
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

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,

$$y_t^* = y_t^v + e_t^v, \quad (1)$$

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

$$y_t^v \perp e_t^v, \quad (2)$$

that is, y_t^v is orthogonal to e_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:

$$r_t^{v',v} = y_t^{v'} - y_t^v = e_t^v - e_t^{v'}. \quad (3)$$

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 plus a measurement error:

$$y_t^v = y_t^* - u_t^v, \quad (4)$$

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

$$y_t^* \perp u_t^v. \quad (5)$$

Now, the revision equals:

$$r_t^{v',v} = y_t^{v'} - y_t^v = u_t^v - u_t^{v'}. \quad (6)$$

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

Various authors have examined whether particular variables are characterized as having revisions that reduce noise or add news. Mankiw-Runkle-Shapiro (1984) found that revisions to the money supply data reduced noise, while Mankiw-Shapiro (1986) found that GDP revisions added news. Mork (1987) used 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, Patterson-Heravi (1991) found that revisions to most components of GDP reduce noise.

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, as explored by 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 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. Zarnowitz (1982) evaluated the quality of differing series, with mixed results. McNees (1989) found 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. In the U.K., Garratt-Vahey (2004) found that many data series were biased and inefficient based on ex-post tests, while Aruoba (2008) found 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, as suggested by Kavajecz-Collins (1995) and Swanson-Ghysels-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; for example, see Fixler-Grimm-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.

If initial data are based on incomplete information, or they are forecasts that are smoother than the later data will be, then the state of the business cycle could be related to later data revisions. That is, data revisions could be systematically related to business-cycle conditions. Dynan-Elmendorf (2001) found evidence that GDP was misleading at turning points, while Swanson-van Dijk (2004) found that the volatility of revisions to industrial production and producer prices increases in recessions.

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) Conrad-Corrado (1979), who used a Kalman filter to improve the government's data on retail sales; (2) Guerrero (1993), who combined historical data with preliminary data on Mexican industrial production to get improved estimates of final data; and (3) Faust-Rogers-Wright (2005), who found that among the G-7 countries, revisions to GDP in Japan and the U.K. were forecastable in real time; and (4) Aruoba (2008), who used similar methods to predict revisions for many different variables.

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. For U.S. data, Howrey (1978), Conrad-Corrado (1979), and Harvey-McKenzie-Blake-Desai (1983) describe models of revisions. For

U.K. data, Holden-Peel (1982), Patterson (1995), and Kapetanios-Yates (2004) establish the key properties of data revisions.

There are now an increasing number of papers that describe data revisions in various countries. Perhaps the only fruitful area in this line of research is showing the predictability of revisions (beyond those induced by revisions to seasonal factors) between initial and intermediate releases of the data, which could help data agencies improve their methods, if they desire to release data with revisions that add news.

FORECASTING

Revisions to data may affect forecasts considerably.* The literature on forecasting with real-time data has focused mainly on model development, in which researchers are attempting to build a new and improved forecasting model. They want to compare forecasts made with a new model with forecasts made with other models or forecasts reported in real time. We examine five main areas: (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? (5) How should forecasts be made when we know that the data will be revised?

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

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

itself may change, given the use of some procedure for model specification. Stark-Croushore (2002) perform a variety of experiments that illustrate how each of these mechanisms works in practice.

One issue that arises in all of 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 starting in 2013, it is considering 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 first paper to engage in an exercise of comparing forecasts based on real-time data versus forecasts based on latest-available data was Denton-Kuiper (1965). They found significant differences in the forecasts made for Canadian data depending on whether real-time data or latest-available data were used. Cole (1969) found that data errors reduced forecast efficiency and led to biased forecasts. Trivellato-Rettore (1986) showed that data errors (using Italian data) in a simultaneous-equations model affected everything, including the estimated coefficients and forecasts, but did not affect the forecast errors too much. However, Faust-Rogers-Wright (2003) showed that for exchange-rate forecasting, the forecasts were extremely sensitive to the vintage of the data. Some vintages showed that it was possible to forecast exchange rates in real time; but

other vintages showed that such forecasts performed worse than a naïve model. Molodtsova (2007) found that combining real-time data with a Taylor rule for monetary policy in numerous OECD countries shows that exchange rates can be predicted. Similarly, Molodtsova-Nikolsko-Rzhevskyy-Papell (2007) found that the dollar/mark exchange rate was predictable using only real-time data, not with revised data.

Overall, the literature shows that the impact of using real-time data compared with latest available data in forecasting depends on the specific exercise in question — sometimes such a difference in the data matters, but other times it makes no difference.

Levels versus growth rates. Howrey (1996) found that level forecasts of real output were more sensitive to data revisions than forecasts of growth rates, so he suggested that policy should feed back on growth rates, not levels (a result similar to that found in the monetary-policy literature on policy making with analytical revisions). Kozicki (2002) showed that the choice of forecasting with real-time or latest-available data is important for variables with large revisions to levels.

Model selection and specification. Given that data are revised, how do alternative vintages of the data affect the specifications of forecasting models? Swanson-White (1997) explored model selection with real-time data. The sensitivity of model specification to the vintage of the data may depend on the variable in question, as Robertson-Tallman (1998) found that specification of the model for industrial production was sensitive to the vintage of the data, but the same was not true for GDP. Harrison-Kapetanios-Yates (2005) showed that it may be optimal to estimate a model without using the most recent preliminary data because those data have not been revised as much as earlier data. This is a subject to which I will return later.

The predictive content of variables. In forecasting out-of-sample, does it matter whether a forecaster bases a model on real-time data or latest available data? That is, 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? Croushore (2005) suggested that consumer confidence indicators have no out-of-sample predictive power for consumption spending. The real-time nature of the data matters, since using latest available data or examining in-sample predictive power increases the ability of consumer confidence indexes to predict consumer spending.

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? Howrey (1978) showed 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 et al. (1983) used state-space methods with missing observations to account for irregular data revisions and found a large gain in efficiency from doing so, compared with ignoring data revisions. Patterson (2003) illustrated 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 found little scope for improvement. For example, Howrey (1984) found that using state-space models to improve forecasts of inventory investment yields little improvement.

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 Koenig-Dolmas-Piger (2003) and Kishor-Koenig (2005) argue that forecasters could make better forecasts by focusing on the diagonals of the real-time data matrix, 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.

Overall, there are sometimes gains to accounting for data revisions. But the predictability of revisions may be small relative to the forecast error. To some extent, the predictability of revisions is a function of the procedure that statistical agencies use for seasonal adjustment. They seldom adjust seasonal factors contemporaneously but instead change the seasonal factors only once each year. As a result, such revisions are easily predictable but small and usually not economically significant, as Swanson et al. (1999) showed. A troublesome issue in the state-space modeling approach is specifying an ARIMA process for data revisions because benchmark revisions tend to be idiosyncratic. Also, forecasters need to ask themselves whether the costs of dealing with real-time issues are worth the benefits. Are data revisions small relative to other problems in forecasting?

MONETARY POLICY

Given the real-time nature of policymaking, it is natural that much research with real-time data is geared toward monetary policy. I will distinguish between data revisions and revisions to measures of analytical concepts. The former is what we normally think of when we

consider the government releasing data with larger samples. But the latter may be more important because macroeconomic models depend on analytical concepts, especially the output gap and the level of potential GDP, the natural rate of unemployment, and the equilibrium real interest rate. I begin by looking at research on data revisions, including: (1) How much does it matter that data are revised? (2) How misleading is monetary policy analysis based on final data instead of real-time data? (3) How should monetary policymakers handle data uncertainty?

How much does it matter that data are revised? Data revisions clearly matter for monetary policy. 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 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 Maravall-Pierce (1986) show. Kugler et al. (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.

How misleading is monetary policy analysis based on final data instead of real-time data? If data are revised, but researchers do not take that fact into account, then it is possible that their research results will be misleading. However, Croushore-Evans (2006) find that data revisions do not significantly affect measures of monetary policy shocks. However, in a simultaneous system of equations, identification is a difficult problem when data revisions exist.

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. Coenen-Levin-Wieland (2001) show that policymakers facing uncertainty about output can use data on money supply to help them make better decisions. More recently, many researchers have suggested that monetary policymakers use factor models to summarize the information in large numbers of variables, in the hopes that uncertainty in any particular data series washes out across many variables. Bernanke-Boivin (2003) 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, Giannone-Reichlin-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. Monetary policymakers should respond to shocks to these two factors.

Theoretically, in situations in which there is no certainty equivalence, policymakers facing potential data revisions should be less aggressive with monetary policy, as Aoki (2003) illustrates. Similar results obtain when there is uncertainty about potential output and other analytical concepts, as I discuss in the next section.

Analytical revisions. 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 policymaking of revisions to conceptual variables begins with 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 known the true value of the output gap, which would have required it to catch on more quickly to the

1970s slowdown in productivity, it would not have eased policy nearly as much, and the Great Inflation of the 1970s might have been avoided.

If policymakers do not respond to the possibility of analytical revisions at all, they are likely to be overly aggressive in their policy actions. Research shows that this leads to overly volatile movements in output and inflation. For example, using Taylor rules to explain the central bank's behavior, the consequences of policy making that ignores analytical revisions can be seen in research that plugs alternative data vintages into the Taylor rule to see how different policy would be. Kozicki (2004) does so with U.S. data and Kamada (2005) does the same for Japan.

Rudebusch (2001) does some reverse engineering of the Taylor rule to show that data uncertainty matters significantly in determining why the rule has the coefficients it does. If the data were not uncertain, the optimal Taylor rule would be much more aggressive than it is in the data. Orphanides (2003) shows that if policymakers adopt optimal rules based on revised data, then in real time they will make substantial policy errors. The optimal rules are too aggressive given the difficulty in measuring inflation and the output gap in real time. Cukierman-Lippi (2005) 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) used real-time data to find that the Fed changed policy parameters over this period, and that the poor performance in the 1970s occurred when the Fed temporarily reduced its response to inflation.

Issues concerning the measurement of various natural rates have been explored in several papers. Orphanides-Williams (2002) find that there are large costs to ignoring potential mismeasurement of the natural rate of unemployment and the natural rate of interest. Staiger-

Stock-Watson (1997) show how much uncertainty there is about the natural rate of unemployment, while Clark-Kozicki (2005) demonstrate the tremendous uncertainty about natural rates of interest.

Data from the United States on the output gap has been studied most frequently because of data availability; Orphanides-van Norden (2002) demonstrate how uncertain is the U.S. output gap in real time. But as data become more readily available in other countries, new research on output gaps in other countries has been produced. Nelson-Nikolov (2003) find that errors in the output gap were even greater in the U.K. than they were in the U.S. and may have led policymakers astray. Gerberding-Seitz-Worms (2005) show that the Bundesbank responded to real-time data on the output gap, inflation, and deviations of money growth from target, whereas previous studies using only latest available data found no role for money growth. Gerdesmeier-Roffia (2005) show how different Taylor rule estimations are for the Euro area depending on whether revised data or real-time data are used. Analysis focused on the implications of different vintages of output gaps in various countries includes Bernhardsen et al. (2005) for Norway; Cayen-van Norden (2005) for Canada; and Döpke (2005) for Germany.

Revisions in analytical concepts may lead the models used by monetary policymakers to change significantly. As Tetlow-Ironside (2007) show, changes in the Fed's FRB-U.S. model from the mid-1990s to the early 2000s caused substantial changes in the input that the model provided to policymakers.

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.

MACROECONOMIC RESEARCH

Macroeconomic research can be influenced by data revisions in a number of ways. First, we explore the question of whether research results are robust to alternative vintages of the data. 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 was explored by Croushore and Stark (2003). They reran a number of major macroeconomic studies using different vintages of the data. 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 tested a number of major macroeconomic studies. First, they used the same sample period but more recent vintages of data. Then, they used both a more recent vintage as well as a larger sample. They found that while RBC business-cycle facts were robust to a change in the data set, evidence for the life-cycle–permanent-income hypothesis was not nor were 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 paper to do so was Boschen-Grossman (1982), which used data revisions in an analysis of the neutrality of money under rational expectations; this paper provided key evidence against equilibrium models in the classical tradition. Boschen-Grossman explicitly modeled 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

showed that empirical results that were based on latest-available data led to substantially different results than those based on real-time data.

A paper by Amato-Swanson (2001) found 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. 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. Aruoba finds that business-cycle dynamics are better captured in such a framework than in one that does not incorporate data revisions. Edge-Laubach-Williams (2004) examine 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? Oh-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. Thus, false announcements that the economy is doing well still lead to increased economic activity. Oh-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.

Bomfim (2001) asks whether economic agents are better off if data is 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.

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?

Christoffersen-Ghysels-Swanson (2002) show that researchers should use real-time data to properly evaluate announcement effects in financial markets; prior studies based on latest available data were misleading. The use of real-time data provides a more accurate view of the rewards in financial markets to taking on macroeconomic risks.

A number of papers have examined the issue of identifying turning points in the business cycle in real time. Chauvet-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-Piger (2005) 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-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 (2007) finds that the use of gross domestic income (GDI) in a Markov-switching model produces more accurate recession probabilities than the same model using gross domestic product (GDP).

To date, there has been relatively little research on current analysis in real time, with much scope for additional work.

CONCLUSIONS

The field of real-time data analysis is a fertile one, and there are many unanswered questions. The most promising areas are in macroeconomic research, since there has been relatively little incorporation of data revisions into macroeconomic models and in current analysis of business and financial conditions. Explorations of the nature of data revisions, of forecasting, and of monetary policy have reached a more mature stage, so new papers in these areas will need to be more refined.

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