Data Revisions are not Well-Behaved*

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Abstract

We document the empirical properties of revisions to major macroeconomic variables in the United States. Our findings suggest that they do not satisfy simple desirable statistical properties. In particular, we find that these revisions do not have a zero mean, which indicates that the initial announcements by statistical agencies are biased. We also find that the revisions are quite large compared to the original variables and they are predictable using the information set at the time of the initial announcement, which means that the initial announcements of statistical agencies are not rational forecasts.

Key Words : Forecasting, news and noise, real-time data, NIPA variables

JEL Codes : C22, C53, C82

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1 Introduction

Most macroeconomic variables are substantially revised by statistical agencies in the months after their initial announcements. These revisions generally reflect the arrival of new information which wasn't available at the time of the initial announcement. Users of data understand the uncertainty surrounding the initial announcement and make their decisions accordingly. If revisions are "well-behaved", by which we loosely mean that they are rational forecast errors, then the arrival of a new revision is not relevant for them. In this paper, however, we will argue that revisions are not, in fact, "well-behaved".

To facilitate the discussion, we will use the following notation. Let y_t^{t+1} denote a statistical agency's initial announcement of a variable that was realized at time t and y_t^f denote the *final* or *true* value of the same variable. The two objects will be related by the following identity

$$y_t^f \equiv y_t^{t+1} + r_t^f$$

where r_t^f is the final revision which is potentially never observed.

From a statistical point of view, we expect the final revision to satisfy three properties in order to consider it well-behaved. First, we expect its mean to be zero. This would imply that the initial announcement of the statistical agency is an unbiased estimate of the final value. Second, we expect the variance of the final revision to be small, compared to the variance of the final value. Finally, we expect the final revision to be unpredictable given the information set at the time of the initial announcement. When the final revision is predictable, the initial announcement of the statistical agency is not an optimal forecast of the final value and a better forecast, one with a lower forecast error variance, can be obtained. We summarize these three properties as follows:

$$
\begin{aligned}
(P1): &\qquad E\left(r_t^f\right) = 0 \\
(P2): &\qquad var\left(r_t^f\right) \text{ is small} \\
(P3): &\qquad E\left(r_t^f | I_{t+1}\right) = 0
\end{aligned}
$$

where I_{t+1} is the information set at the time of the initial announcement. Our goal in this paper is to investigate the validity of these properties for revisions to some major macroeconomic variables in the United States.

We are certainly not the first to analyze the statistical properties of data revisions. Indeed, that macroeconomic data are revised is well understood by economists and various aspects of data revisions have been studied for decades. An important part of the literature considers the question we devote most of this paper to, the predictability of data revisions. Mankiw et al. (1984) assess whether the preliminary announcements of money stock are rational forecasts of the final announcements (news hypothesis) or are observations of the revised series, measured with error (noise hypothesis). A similar analysis was applied to GNP data by Mankiw and Shapiro (1986) [henceforth MS]. The conclusion from these two studies is that while the revisions to GNP are news, those of money stock data are better characterized as noise. In other words, they find evidence of predictability for the revisions to the money stock data while revisions to GNP data seems to be unpredictable. Mork (1987) and Mork (1990) consider the same question and find predictability in both GNP and money stock revisions using a slightly different methodology.

In a recent paper Faust et al. (2005) look at the revisions to the GDP growth rates for the G-7 countries and find that while for the United States, revisions are only slightly predictable, for Italy, Japan and United Kingdom, about half the variability of subsequent revisions can be accounted for by information available at the time of the preliminary announcement by using methods similar to Mankiw et al. (1984) and MS.

A recent paper by economists at the BEA (Fixler and Grimm, 2002) analyzes the reliability of NIPA data for the period 1983-2000. It reports mean revisions that are close to those we find in this paper and concludes that they are not significant. As for forecastability, they only consider forecasting a vintage of the data using an earlier vintage, and they conclude that revisions are not predictable. Our methodology as well as our conclusions will be different.

After analyzing some of the basic statistical properties of revisions to a variety of important macroeconomic variables, we find strong evidence against the three properties outlined above. In particular, we find that the unconditional mean of revisions are positive for all variables – significantly so for a majority of them. Moreover, we find that variance of the revisions are quite large compared to the variance of the original data series. We also show that the zero forecast implied by $(P3)$ can be improved significantly in both an ex-post forecasting exercise and in a real-time forecasting exercise. We find that these results are robust in subsamples, if not stronger since the mid-1980s. Interestingly, we find a larger variability in revisions and a larger degree of predictability in periods which coincide with the decline in volatility that is well-documented for the U.S. economy. We also show that the findings are robust if we group revisions by the quarter of the initial announcement and analyze intermediate revisions.

The rest of this paper is organized as follows. In Section 2 we describe the data used in the paper. In Section 3 we report the unconditional properties of revisions, investigating the validity of (P1) and (P2). In Section 4 we turn to predictability of revisions and consider the validity of (P3). In Section 5 we explore the robustness of our results. We conclude in Section 6. An appendix provides some details of the analysis.

2 Data

2.1 Data Sources

Most of our data come from the "Real-Time Data Set" (RTDS) produced by the Federal Reserve Bank of Philadelphia.[1] The RTDS records the information set that would be available to someone on the 15^{th} day of a month of the middle month of a quarter starting from the last quarter of 1965 through the last quarter of 2005. It has quarterly observations and quarterly vintages for major National Income and Product Account (NIPA) variables such as real and nominal output, consumption, investment and their sub-categories, monetary measures, banking system data, price level and unemployment rate. It also includes monthly observations and monthly vintages on capacity utilization, industrial production

[1] The data set is publicly available on the internet at http://www.phil.frb.org/econ/forecast/reaindex.html. See Croushore and Stark (2001) for the details of the data set. Croushore and Stark (2003), provides some examples of empirical applications using this data set.

and employment.

Our analysis will focus on eight variables derived from two original NIPA variables (nominal and real output)[2] – growth of real output, real final sales,[3] nominal output and inflation based on output deflator, annual and quarterly, – unemployment rate and levels and growth rates of employment, capacity utilization and industrial production. In Section 5.2 we also summarize our results for revisions to the growth rates of the components of real output in order to understand which components are responsible for the results we report in the paper regarding revisions to real output.

We also put together a small-scale real-time data set for this paper using nonfarm business labor productivity (measured as output per hour) as announced by the Bureau of Labor Statistics (BLS) in the Monthly Labor Review (MLR) covering 1971-2005. [4]

Overall we have a mixture of 19 monthly and quarterly variables. All of our variables are in percentage terms either by transformation (e.g. growth rates) or by definition (e.g. unemployment rate). All growth rates are expressed in annual terms. More details about the data set and list of variables, their respective samples, observation frequencies and sources are provided in the appendix and in Table A.1.

[2]The RTDS uses GNP before 1992 and GDP afterwards, following the "headline variable" announced by the Bureau of Economic Analysis. As such, we will use the term "output" instead of GNP or GDP.

[3]Real final sales is defined as the difference between real output and real change in inventories.

[4]Unlike the RTDS, we only recorded the first announcement regarding each quarter and did not attempt to record intermediate revisions.

2.2 Initial Announcements

Our first task is to derive the initial announcements for each variable, y_t^{t+1}. To that end, we use the first available announcement in the RTDS for date t. In most instances, this corresponds to using the number that appears in the vintage of next quarter, which is the most recent announcement as of the 15^{th} of the middle month of the quarter, 45 days after the end of the quarter.[5] For variables with monthly vintages, we use the first available announcement after the end of the month, which is typically 15 or 45 days later. For the set of variables we use, it is unlikely that two announcements are made within 45 days following the end of the month, which would cause us to miss the initial announcement.[6]

2.3 Defining the Revisions

We define revisions as follows:

$$r_t^h = y_t^{(t+1)+h} - y_t^{t+1}$$

which measures the cumulative revision up to time $t + 1 + h$, which is h periods after the initial announcement.[7]

[5] A concern one might have is whether the first number that appears in the RTDS is indeed the first number announced by the statistical agency. For quarterly variables, all of which are announced by the Bureau of Economic Analysis (BEA), except for labor productivity, the $t+1$ vintage captures the "advance" announcement which is indeed the first number announced by the BEA. To be specific, for 2005Q1, for example, the "advance" estimate of the BEA was published on April 28, 2005, the "preliminary" estimate was published on May 26, 2005 and the 2005Q2 vintage of the RTDS would record the information on May 15, 2005, capturing the "advance" estimate and not the "preliminary" estimate. The "flash" estimate which was announced 15 days before the end of the quarter until 1985 is not used in this study.

[6] One exception to the otherwise fairly regular announcement schedule of the BEA was during the government shutdown at the end of 1995 where the release of data was delayed. For 1995Q4 initial release we look at the March 1996 issue of Survey of Current Business.

[7] For variables which are growth rates, the revision is defined on the growth rates, rather than computing the growth rate of the revision of the level of the variable.

2.4 Benchmark Revisions

Most of the revisions we observe are due to arrival of new information. However, occasionally (e.g. about every five years for NIPA variables) statistical agencies make changes to their methodologies or make statistical changes such as change of base years or seasonal weights. Such revisions are called benchmark revisions. For some variables, such as real output, benchmark revisions are problematic for the users of the data because they would not be able to extract information from these revisions that they can compare with their old information set. To avoid contaminating our analysis with these benchmark revisions, we only focus on growth rates of variables whose levels jump up or down following a benchmark revision.

2.5 Defining the Final Revision

In the literature, the final revision is usually defined as the difference between the latest available observation for the variable and its initial announcement.[8] This may not necessarily be the best choice due the benchmark revisions. It is true that benchmark revisions often use new information (such as Census data which arrive every 10 years) and enhance the existing estimates in addition to all the other methodological changes. However, it is not reasonable to expect a benchmark revision in the 1990s to have some new information about 1970s. Moreover, because statistical agencies make changes to the historical data in order to have a consistent variable over time, the benchmark revisions may distort how the economy looks in

[8]The final revision concept we use in this paper is not related to the "final" announcement of NIPA variables which is announced by the BEA about 3 months after the end of the quarter, following the "advance" and the "preliminary" announcements in the previous months.

the past.[9] This would suggest, therefore, instead of using the latest available revision as the final revision, we should include as many revisions as possible in our final revision in order to include all relevant revisions, but we want to avoid including more than one benchmark revision.

To define the final revision we determine the numbers of periods after which there are no more revisions for each variable, except for benchmark revisions. For some variables such as the NIPA variables, the statistical agencies follow a very specific schedule for revisions which makes it very easy for us to define the final revisions. For other variables, we look at the incremental revisions at different horizons and find a pattern in revisions. Essentially, for each variable we find a finite number K, and define the K^{th} revision of the variable as the final revision. For most of the variables we analyze, K roughly corresponds to three years. The details are provided in the appendix.

Figures 1 and 2 shows the final revision series we derive for two of the variables we use, annual growth of real output and annual growth of labor productivity. The rest of the paper is devoted to analyzing the statistical properties of these final revisions.

3 Unconditional Properties of Final Revisions

In this section we first consider whether revisions to macroeconomic data in the United States satisfy the first two of the three properties we listed in Section 1. The results are

[9]For example, the weight on goods related to information technology in the 1970s is certainly not the same as that in 1990s. If a benchmark revision applies the same weights to both periods, the picture for the 1970s will be distorted.

reported in Table 1.

The first column of Table 1 reports the number of observations for each variable. For quarterly variables we have about 37 years of data while for the monthly variables we have between 20 and 40 years of data. The next column reports the mean of the final revision for each variable. We use Newey West (1987) heteroskedasticity and autocorrelation consistent standard errors in computing the test of significance for these means due to the apparent autocorrelated structure of revisions.[10] The results indicate that the means of final revisions for all 19 variables are positive and except for six variables (annual growth of real output and real final sales, quarterly growth of labor productivity, unemployment rate and two different measures of capacity utilization) they are statistically different from zero. The interpretation of this result is that the initial announcements of the statistical agencies are biased estimates of the final values. In addition to being statistically significant, the means of final revisions are quite large : the numbers range from 0.1% to 1.2%, excluding the unemployment rate. It is worth noting that the average revision for real output growth is between 17 and 26 basis points, depending on the measure, which is economically significant, considering that the average growth rate of real output in this period is about 2.8%. We can conclude that there is strong evidence against $(P1)$, i.e. the revisions do not have a zero mean.

The next two columns report the minimum and maximum final revision for each variable. We see that the range of final revisions for all variables are quite large. For example, the final revision of annual real output growth fluctuates between -1.6% and 2.9% while the

[10] All statistical tests in this paper uses 10% significance. In some tables we also report the p-values for reference and, where relevant, mark the coefficients with p-values less than 10% with boldface.

final revision of annual labor productivity growth fluctuates between -2.9% and 3.3%. The only possible exception is the final revision to unemployment rate which only fluctuates between -0.2% and 0.2%, which is consistent with the observation that the revisions to the unemployment rate are small and confined to changes in seasonal factors.

Next, we report the standard deviation of final revisions. because the standard deviation of final revisions by itself may not be very informative of the size of final revisions, we also report the noise-to-signal ratio for final revisions, which is defined as the standard deviation of final revisions divided by the standard deviation of the final value of the variable.[11] This statistic, along with the minimum and maximum final revisions, will give us an idea about the size of final revisions relative to the size of the original variables. The numbers we find range from 0.05 to 0.94 with an average of 0.39. Such large numbers suggest that the final revisions are sizable compared to the original variables, and we conclude that ($P2$) is not supported by the data.[12]

The next column reports the simple correlation of the final revision with the initial announcement. While it is not possible to talk about a general pattern in terms of sign of the correlations, all but one of the significant correlations are negative. They are as large as -0.46 and the average absolute correlation is 0.19. This is our first evidence that ($P3$) may not be consistent with the data because the final revisions are correlated with the initial announcements. We take up this issue more rigorously in the next section.

The last column report the first order autocorrelation coefficients for final revisions. The

[11] Note that this number is bounded below by zero but not necessarily bounded above by unity due to the possible (negative) correlation between r_t^f and y_t^{t+1}.

[12] It is interesting to note that the signal-to-noise ratios for annual growth variables are about half of their counterparts for monthly or quarterly growth variables.

final revisions to all annual growth variables and both measures of capacity utilization show strong signs of persistence, with positive autocorrelation coefficients between 0.60 and 0.92. On the other hand, the persistence of the revisions to the quarterly and monthly growth variables is quite weak, and some variables display negative autocorrelation.[13] We must stress that while the persistence in final revisions suggests the possibility of their predictability, this cannot be used as direct evidence to that effect. The autocorrelated structure documented here cannot be exploited to provide a forecast of r_t^f, because r_{t-1}^f is not realized until $t+K$ and thus is not in the information set of $t+1$.

To summarize our results from Table 1, we find that the mean final revision is positive for all variables that we consider and statistically significant for most of the variables. We also find that the final revisions are large relative to the original variables. We have some evidence that suggests predictability of revisions. In Section 5, we explore the sources of these results by looking at intermediate revisions, subsamples, revisions to the components of output and analyzing the final revision corresponding to each quarter separately.

4 Forecastability of Final Revisions

Having analyzed the unconditional properties of data revisions in the previous section, we now turn to investigating the validity of $(P3)$, which states that the revisions must be unpredictable given the information set at the time of the initial announcement. We start

[13] One explanation of the persistence in revisions is the particular schedule that revisions follow. As in the case of annual BEA revisions, we often see revisions effecting a number of consecutive periods announced on the same date. If a common information shock such as tax return data or census data causes the revisions to the variable in these periods, the final revisions will appear correlated.

our analysis by revisiting a classic methodology which labels data revisions as "news" or "noise". Next we conduct two forecasting exercises, an ex-post exercise which looks at the predictability of final revisions using the full sample and a real-time exercise which attempts to mimic the forecasting problem of a user of statistical data who is trying to forecast final revisions in real time.

4.1 News vs. Noise Revisited

Two of the most important papers in the literature that analyze the nature of the revisions to macroeconomic variables is MS and Mankiw et al. (1984) where the authors analyze whether the preliminary announcements of GNP and money stock are rational forecasts of the true, or "final" announcements. In this section we replicate some of their analysis with our new (and longer) data set in order to provide a comparison between results from our new data set and the old and well-known results.[14]

In the framework of the aforementioned papers, final revisions can be classified into two categories:

- **Noise**: The initial announcement is an observation of the final series, measured with error. This means that the revision is uncorrelated with the final value but correlated with the data available when the estimate is made.

- **News**: The initial announcement is an efficient forecast that reflects all available information and subsequent estimates reduce the forecast error, incorporating new

[14] The methodology of these two papers have been further improved in Mork (1987) and Mork (1990) and Kavajecz and Collins (1995). We use the original methodology to be able to compare our results with MS.

information. The revision is correlated with the final value but uncorrelated with the data available when the estimate is made, i.e. unpredictable with using the information set at the time of the initial announcement.

To classify revisions as noise or news, they consider the regressions

$$y_t^{t+1} = \alpha_1 + \beta_1 y_t^f + \nu_t^1 \quad (1)$$

$$y_t^f = \alpha_2 + \beta_2 y_t^{t+1} + \nu_t^2 \quad (2)$$

where the joint hypothesis $\alpha_1 = 0$, $\beta_1 = 1$ would test the noise hypothesis, and the joint hypothesis $\alpha_2 = 0$, $\beta_2 = 1$ would test the news hypothesis. As can be easily shown (see the appendix), these hypotheses are mutually exclusive but, they are not collectively exhaustive, that is, we can reject both hypotheses, especially when the unconditional mean of revisions is not equal to zero.[15] In this case, we can reject both hypotheses and there is no guidance in the original MS methodology when this happens. Using this framework, they conclude that the revisions to GNP (both as level in constant dollars and growth in current dollars) are news and those of money stock data are better characterized as noise, because they reject one and fail to reject the other hypothesis in each case.

Using the exact subsample that MS have used (1975Q4–1982Q4) we are able to replicate their results, that is we reject the noise hypothesis and fail to reject the news hypothesis for real output growth. However, this conclusion is not robust, even within the same subsample.

[15] All these statements are made in the population. Due to sampling errors, we can reject or fail to reject both hypotheses in small samples.

If the news hypothesis was true, that is if revisions were errors from a rational forecast, then any other explanatory variable that was observed at the time of the initial announcement included in (2) should have a coefficient of zero. When we estimate the following equation

$$y_t^f = \alpha_2 + \beta_2 y_t^{t+1} + \gamma r_{t-1}^1 + \nu_t^2 \tag{3}$$

where r_{t-1}^1 is the first revision to output of $t-1$ that is announced at time $t+1$, we find that γ is statistically significant and, more importantly, the F-test with null hypothesis $\alpha_2 = 0$, $\beta_2 = 1$, $\gamma = 0$ is now rejected.[16]

Next, we repeat the same analysis for all variables. We find that for all variables except annual growth of real output and real final sales, unemployment and the two measures of capacity utilization, we reject both the news and the noise hypotheses and we are unable to classify revisions as optimal forecast errors or measurement errors for these variables. On the other hand, we reach an equally ambiguous conclusion for annual growth of real output and real final sales and the unemployment rate where we fail to reject both hypothesis. The only two variables for which we have a definite conclusion are the two measures of capacity utilization whose revisions can be classified as noise. When we look at the source of the rejection of both hypotheses, we see that in most of the regressions, the slope coefficient is statistically different from unity and the constant is significantly different from zero in more than half of the regressions. This means that the positive unconditional mean of revisions contribute to this result but it is not the sole source.

[16] Although the inclusion of r_{t-1}^1 in the regression seems arbitrary, it must be clear that this is perfectly consistent with the news hypothesis.

To sum up, we find that the original MS results are special because introducing a small variation in the methodology or looking at a longer sample reverses the results.[17] All of these results are presented in the appendix.

4.2 An Ex-Post Forecastability Exercise

In this section we turn to testing if $(P3)$ is supported by the data, that is, if the conditional mean of final revisions with respect to the information set at the time of the initial announcement is zero.[18]

To that end, we estimate the following equation.

$$\text{Model 1} : r_t^f = \alpha + \gamma y_t^{t+1} + \sum_{i=1}^{s} \beta_i r_{t-i}^i + \sum_{i=1}^{4} \lambda_i Q_t^i + \delta t + \phi \Delta N_t + \varepsilon_t \tag{4}$$

where the dependent variable is the final revision and the explanatory variables are a constant, the initial announcement, revisions to past months or quarters announced at time $t+1$, quarterly dummy variables, Q_t^i, a linear trend and the first difference of the initial announcement of the unemployment rate only for quarterly variables.[19] We use quarterly dummy variables for both quarterly and monthly variables in an effort to limit the number of coefficients estimated. Except for the presence of past revisions as explanatory variables, these equations are very similar to forecasting equations considered in similar studies that

[17] One factor behind our results may be our increased power in the tests arising from our sample size. Our regressions have at least 150 observations whereas the regressions in MS have 29 quarterly observations.

[18] This is essentially the same as testing the news hypothesis since both are a restatement of efficiency (rationality) of preliminary announcements as rational forecast errors must be orthogonal to the information set at the time of the forecast.

[19] Since we do not have intermediate revisions for labor productivity we do not use any revisions as explanatory variables when we estimate the equation for labor productivity.

analyze the predictability of revisions. We include these revisions to analyze the predictive power of past revisions in explaining future revisions. We also include seasonal dummies in our estimations because there might be some seasonality in the final revisions due to the specific revision schedules of statistical agencies, even though the original series might be de-seasonalized. Finally, we include the quarterly change in the unemployment rate to capture any systematic patterns in revisions due to business cycles. It is important to note that all explanatory variables, including past revisions, are chosen such that they are all known at time $t+1$ and as such it is a valid forecasting exercise.[20]

By estimating this equation we are not trying to find the best model for revisions. If that were the case, one would imagine many other variables potentially being relevant, or a multivariate analysis would be warranted.[21] Our aim by estimating these equations is to show that we can find *a* forecasting model that can perform better than the model implied by (P3), one that has a zero conditional mean.

We conduct the exercise using the following algorithm. For each variable, we estimate (4) by considering all possible combinations of explanatory variables.[22] Using both Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC) as a guide we choose the best model for each variable and label this model as Model 1. Using the parameter estimates of this model we get the fitted value of r_t^f which we denote as $\hat{r}_t^1$.

To understand the marginal contribution of the past revisions to forecasting the final

[20] Since a variable that was realized in time $t-k$ is announced for the first time in $t-k+1$, its k^{th} revision will be in period $t+1$.

[21] For example, one can imagine using information from monthly industrial production to forecast revisions to quarterly output.

[22] For most variables, we have 18 explanatory variables with $2^{18} = 262,144$ possible combinations.

revision, we eliminate them from the model and re-estimate the simple linear regression with the initial announcement, the trend term and seasonal dummy variables. We label this model Model 2 and denote the fitted value as $\hat{r}_t^2$. In Section 3, we showed that for almost all of the variables we consider, the mean final revision is positive and statistically significant. To assess the contribution of all other variables, over and above the gain due to getting the mean right, we define $\hat{r}_t^3$ as the unconditional mean of the final revision. Finally, we consider the forecast of r_t^f based on (P3) and define this case as Model 4 with the forecast given by $\hat{r}_t^4 = 0$ for all t. To summarize we estimate

$$\begin{aligned} \text{Model 2}: \quad & r_t^f = \alpha + \gamma y_t^{t+1} + \sum_{i=1}^{4} \lambda_i Q_t^i + \delta t + \varepsilon_t \\ \text{Model 3}: \quad & r_t^f = \alpha + \varepsilon_t \\ \text{Model 4}: \quad & r_t^f = \varepsilon_t \end{aligned} \tag{5}$$

Given the forecasts from these four models, we conduct two tests. First, along the lines of our test of rational data revisions, we test for the joint significance of all coefficients in (4). This test will essentially have Model 4 or $(P3)$ as its null hypothesis. We also compare the predictive powers of $\hat{r}_t^1$, $\hat{r}_t^2$, $\hat{r}_t^3$ versus $\hat{r}_t^4$. In order to do so, we compute the root mean squared errors (RMSE) of forecasts from Model 1,2 and 3, relative to the RMSE of the forecast from Model 4.[23]

The results from this exercise are summarized in Table 2. The first panel shows the results

[23] The relative RMSEs, $RMSE_i/RMSE_4$ are in fact identical to Theil's U-statistic and it is equal to $\sqrt{1-R^2}$ if the mean of r_t^f is zero and decreases as the latter increases.

when the best model is chosen using AIC and the second panel shows the results when the best model chosen using SIC. While the quantitative results differ slightly as SIC is more conservative in model choice, the qualitative results are the same across the two columns. The second column lists the explanatory variables that are chosen for Model 1 for each variable. Almost all models picked by AIC include at least one past revision which demonstrates the importance of including these variables in predictive regressions. Interestingly the linear trend is important for 10 of the 19 variables we consider. This suggests a potentially time-varying pattern in revisions and we take up this issue in Section 5.1. It is also interesting to note that for the measures of real output growth, the change in unemployment rate is picked as an explanatory variable with coefficients as large as -0.95 (not reported). This means a one percent change in the unemployment rate from $t-1$ to t would cause bias in the initial announcement of output growth in t as large as one percent, with a downward revision on average during recessions.

The next column reports the p-value of the Wald statistic testing the significance of all coefficients in the regressions. All p-values are less than 5% and in fact most of them are zero, indicating that we can reject the null hypothesis of $(P3)$. In the terminology of the previous section, this means a rejection of the news hypothesis for all of the variables we consider. The next two columns report the R^2 and $\bar{R}^2$ for each regression. In the models chosen by AIC, the R^2's range from zero (none of the explanatory variables except the constant are relevant) to 0.24 with an average of 0.12 while the average $\bar{R}^2$ is 0.11. For important variables such as annual growth of real output, inflation and labor productivity growth, the R^2's are

0.19, 0.05 and 0.21, respectively. These numbers may not seem too large in other contexts but we think they are economically important in this context.

The last three columns report the RMSEs of Model 1, Model 2 and Model 3 relative to Model 4.[24] The average relative RMSE is 0.91, 0.93 and 0.97 for Model 1, Model 2 and Model 3, respectively while we find numbers as low as 0.84. We also compute that on average our forecasting model provide a 9% improvement over the zero forecast, a 7% improvement over the unconditional mean and using past revisions as explanatory variables provide an improvement of 3%.

In Figures 1 and 2 we plot the final revision, r_t^K, and the fitted values from the ex-post forecasting exercise in this section (thick dotted line) and the forecasted values from the real-time exercise from the next section (dotted line) for the annual growth of real output and annual growth of labor productivity. In each figure we also show the zero line and the unconditional mean of the final revisions as solid vertical lines as reference. Although much smoother, the ex-post forecast picks up the broad pattern of final revisions.

To sum up our findings from this ex-post forecastability exercise, we find that using a very limited information set that is known at time $t+1$, we are able to predict the final revision that will be realized at $t+K+1$. Using three different statistics, goodness-of-fit, a Wald test and relative RMSE, we find that the forecasting model we estimate performs significantly better than a zero forecast that $(P3)$ would imply. We conclude that $(P3)$ is not supported by the data and that the initial announcements of statistical agencies are not

[24] All relative RMSE's are less than unity indicating that our forecasting models perform better than a zero forecast for all variables, which is not at all surprising because these are in-sample RMSEs.

rational forecasts of the true value of variables.

4.3 A Real-Time Forecastability Exercise

It is of great interest for practitioners and policy makers to find ways of exploiting the potential forecastability in real time we identified in the previous section.[25] In this section, we conduct a real-time forecasting exercise using some of the insights from the previous sections and demonstrate that one can produce a better forecast than a zero forecast in real time.[26] The first insight we use is the apparent first-order autocorrelation of final revisions. As we argued above, we cannot use r_{t-1}^K to forecast r_t^K in real-time in the context of a simple linear regression because the former is not realized until K periods later. However, one can exploit this autocorrelation in a state-space framework where the final revision is treated as an latent state. The Kalman filter can produce the optimal forecast in a linear environment.[27] The second insight we are going to use is the significant negative correlation between the final revision and the initial announcement. Because we want to limit the number of coefficients estimated, we only include a constant, r_{t-1}^K, y_t^{t+1} and the first difference of the unemployment rate as explanatory variables.

[25] The most obvious way of doing so would be estimating (4) recursively, using only the available information at each point in time. This would mean dropping the observations in the 3-year period prior to the time of estimation. While in principle there is no problem with doing this, in practice this scheme does not perform well due to parameter instability and sensitivity to the choice of explanatory variables.

[26] We must stress that the aim in this section is to simply show that we can find a scheme which works fairly well for the variables we consider. Developing a more general scheme (e.g. using cross-variable relationships) is beyond the scope of this paper.

[27] This general idea has been previously pursued in the literature. Howrey (1978) is one of the first papers to show how one can use the preliminary announcements to get an optimal prediction of the true variable. Conrad and Corrado (1978) apply the Kalman filter for getting better estimates for monthly retail sales. Finally, Tanizaki and Mariano (1995) derive a non-linear and non-gaussian filter using importance sampling and Monte Carlo integration methods with Kalman Filter and apply this filter to the per capita consumption of the US.

We proceed as follows. Starting from 1984, in every period $t+1$, we estimate the following state space system via maximum likelihood

$$x_t = \mu + \rho(x_{t-1} - \mu) + \sigma\nu_t \tag{6}$$

$$r_t^K = x_t + \gamma y_t^{t+1} + \phi\Delta N_t \tag{7}$$

where x_t is a latent state variable, ν_t is an iid standard normal disturbance and r_t^K includes only the observed final revisions, typically up to three years prior to $t+1$ with missing observations for the remaining periods. Once the system is estimated, the forecast for the final revision at time t is obtained by forecasting x_t by the Kalman filter which is initialized using the one-step ahead states from the estimation and using (7) to forecast r_t^K. The resulting forecast is denoted by $\hat{r}_t^5$. In order to produce on observation point in $\hat{r}_t^5$ the state space is estimated once. We proceed recursively carefully adjusting the information set as we go forward in time to include only the information available at the time of estimation. For investigating the value-added of this relatively complicated forecasting scheme, we also compute the mean of all realized final revisions at time $t+1$ and denote the forecast using this mean $\hat{r}_t^6$.

In order to assess the forecast accuracy of our real-time model, we use the test developed in Clark and West (2006) which is for nested models. In our context, this test amounts to testing if the time series

$$f_t = \left(r_t^K\right)^2 - \left[\left(r_t^K - \hat{r}_t^5\right)^2 - \left(\hat{r}_t^5\right)^2\right] \tag{8}$$

has a mean of zero, which can simply be tested by a regression of f_t on a constant.[28] The null hypothesis of this test (CW for short) is equal forecast accuracy between the zero forecast and the forecast from our real-time model and the test uses a one-sided alternative.[29]

The results from this exercise are reported in Table 3. Columns two through four report the main results where we compare the real-time forecast with the zero forecast. We report the RMSE of the zero forecast $\hat{r}_t^4$ relative to the RMSE from the real-time forecast $\hat{r}_t^5$ and the CW statistic with its p-value. For 10 out of 19 variables, the real-time forecast has a lower RMSE. More importantly, for all but two variables the CW statistic is positive, indicating superior forecast accuracy of the real-time model, with 13 of them statistically significant.[30] For important variables such as annual growth of nominal output, inflation and labor productivity, we conclude that using the real-time scheme outlined above would give significant gains in forecasting the final revision over a naive forecast of zero. Looking at the last three columns, we find that for 14 variables the real-time model has additional power over the forecast that only uses the mean, with 11 statistically significant CW statistics.

In Figures 1 and 2, we plot the forecast from this exercise for revisions to annual growth of real output and labor productivity. We see that the real-time forecast not only gets the mean right, it also uses the variation in the explanatory variables. Interestingly, the correlation between the real-time and ex-post forecasts are very high for annual growth of real output and labor productivity.

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[28] We use Newey West (1987) standard errors with appropriate lags for this test.

[29] This test statistic adjusts the more common statistic that involves only the first two terms for the additional number of estimated coefficients in the more complicated model that nests the simpler model.

[30] As explained in detail in Clark and West (2006), the CW statistic can be positive even though the RMSE of the more complicated model is higher than the simple model.

5 Sensitivity Analysis and Further Results

In this section, we repeat most of the analysis carried out in the previous sections with a number of variations to investigate the source of the findings so far and to see if they are sensitive to these variations.

5.1 Subsamples

As a first sensitivity analysis, we divide the sample into two: before and after 1984 which roughly corresponds to the midpoint of our sample for NIPA variables. It is interesting to do this analysis because we may find that our results are highly dominated by revisions in one of the two subperiods. This may be the case, for example, as a result of improvements in data collection due to technological progress. However, another equally plausible argument is that technological progress makes data collection harder due to increased variety of goods. This would suggest that as the statistical agencies are struggling to make the necessary corrections, they might create revisions which do not satisfy these three properties. This date is also important because the post-1984 period roughly corresponds to the period where real economic activity in the U.S. is much less volatile. (See, for example, Stock and Watson, 2003). Therefore, it is an independently interesting exercise to analyze the link between this observation and a possible change in the data revision processes.

The results for the unconditional properties of data revisions for the two subsamples are reported in panel (a) of Table 4, along with the full sample results for comparison. We find that, out of the 18 variables considered, 11 of them has a higher and statistically significant mean revision in the earlier subsample. Important variables such as real output growth have a much smaller and insignificant mean in the later subsample. However, the mean revision for growth of nominal output or inflation continue to be positive and significant. On the other hand, we find that all variables have higher noise-signal ratio in the later subsample, indicating that statistical agencies make bigger revisions.[31]

The results for the ex post forecasting exercise for the two subsamples using AIC are reported in panel (b) of Table 4. The first important observation is that for 9 out of 18 variables, the R^2 for both subsamples is greater than the R^2 for the full sample. In general, different sets of explanatory variables are chosen in the two subsamples and in the full sample. Moreover, for all variables the R^2 for at least one subsample is greater than the R^2 for the full sample. We also find that for 11 variables the degree of predictability is bigger in the post-1984 period compared to the pre-1984 period.

To sum up, we find a clear evidence of a regime change before and after 1984 as evidenced by the larger noise-signal ratios and the fact that the degree of predictability is higher in subsamples than the full sample.[32] The mean revisions are in general lower in the post-1984 period but they continue to be statistically significant for some key variables. We can also safely conclude that the failure of the three properties (P1), (P2) and (P3) we documented in the full sample is not necessarily due to a certain part of the sample. However, we find increased evidence against these properties in the second half of the sample which lends

[31] When one looks at the standard deviations of revisions, we see an increase for 6 out of the 18 variables, as much as 18% and an average decline of 13% for all 18 variables. This number is clearly significantly lower than the reduction in volatility of macroeconomic variables documented in the literature. One would expect the magnitude of revisions to fall one-to-one with the magnitude of the true variable. Our results indicate that this is not the case.

[32] We do not claim that the break is necessarily in the first quarter of 1984.

support for the second view about the effect of technological progress on the quality of data described above. The observation that the regime change in data revisions seems to coincide with the "great moderation" is also very interesting.

5.2 Summary of Other Results[33]

In order to understand which revisions, among the many revisions our variables go through, are responsible for the rejection of (P1), (P2) and (P3), we analyze the intermediate revisions, r_t^h for $h < K$, for some key variables.[34] We find that the mean revision for most of the variables increase with each incremental revision and they are statistically significant. Moreover about half of the volatility of the final revision comes from the revision after one quarter and about 72% of it comes from the one-year revision. Finally, we reject the news hypothesis for almost all variables. We conclude that most of the intermediate revisions contribute to the rejection of (P1), (P2) and (P3). We can also infer from our results that simply ignoring the initial announcement and using the second or third announcement would not eliminate the problems with revisions.

Next, we analyze the revisions to NIPA variables realized in a certain quarter. We find that for the most part revisions for variables realized in a particular quarter share the same characteristics with the final revision. Moreover, revisions for Q3 variables are more "well-behaved" than others and revisions for Q1 variables are the least "well-behaved".

Finally, we repeat our analysis for components of real output in order to identify the

[33] Here we summarize our findings regarding a number of sensitivity analyses. Details of the analyses including tables are available on the author's webpage.

[34] We exclude labor productivity and final sales from this analysis.

source of the results we find for revisions to real output. We find that the mean revisions for the annual and quarterly growth of all components are positive, except for three of them. Of these, only three of them are statistically significant but the magnitudes are in general bigger than the mean revision for output. Durables consumption[35] and exports stand out as two components with significant (both statistical and economic) mean revisions. We also find that all components have larger noise-signal ratios as output itself with only two exceptions. Similarly, almost all $R^{2\prime}s$ are higher and most of the relative RMSEs are lower for the components than for output itself. It is interesting to note that the real-time forecastability of the components of output is significantly stronger than output itself, especially consumption and its subcomponents.

6 Conclusion

As users of data, there is nothing we can do about macroeconomic data revisions if they are well-behaved. In this paper, we postulate three properties that we expect these revisions to satisfy and we find that none of them are satisfied. In particular, we find that the means of final revisions are not zero, indicating that the initial announcements of statistical agencies are biased. We also find that the magnitudes of revisions are quite large compared to the original variables. We further show that the forecast from a forecasting equation is significantly better than a naive zero-forecast, which would be optimal if initial announcements

[35] This result is quite significant given the debate concerning measurement of consumer electronics and similar goods whose quality changes quite remarkably in short amounts of time. Our results are at least suggestive that the revisions to components of output which are arguably harder to measure contribute to the results we find in this paper regarding revisions to output.

of statistical agencies are optimal forecasts of the final values. This is true for both in an ex-post exercise and a real-time exercise.

We repeat our analysis for two subsamples and find that while all the findings go through in both samples, the evidence against the three properties seems to be stronger in the second half of the sample. This finding is consistent with the view that technological progress makes collecting data harder due to the difficulty in adjusting the quality of goods in the economy. Another piece of evidence that supports this view is that revisions to durables consumption seem to be an important source of the problem for the results we get regarding the revisions to real output. We also repeat our analysis grouping revisions by the quarter they are first announced and looking at intermediate revisions and find that our results are not driven by one or two sources.

We do not wish to interpret the findings in this paper as failures of the statistical agencies. We believe that these institutions have certain loss functions and use their resources for producing the best possible data and they may be avoiding some other problems at the expense of the problems we outline in this paper. However, whatever the cause of these findings, we think they create problems for the users of the data.

An interesting topic for future research is extending the forecastability analysis to a multivariate framework. There are some interesting and unexpected cross-correlations between revisions to unrelated variables and it would be interesting to explore whether these correlations can be exploited to add to the predictability and forecastability results we obtain in this paper. Moreover, there might be some more expected links between revisions to related variables such as monthly industrial production and quarterly GDP.

Finally, one of the interesting observations from our analysis is the apparent concurrent reduction in the variance of major macroeconomic variables and the increase in the noise-to-signal ratios and predictability. The former is an important observation that has big implications for policy and economic research. Any potential links between these two observations will be of interest to many and is the subject of our ongoing research.

A Appendix

A.1 Data

RTDS includes two sets of variables: core and non-core variables. Core variables refer to the original set of variables that was initially released in 1999 and they are available in two versions: monthly observations or quarterly observations, both of which contain quarterly vintages. The monthly observations version include only the core variables that are available monthly. In this analysis we use the version of the data set that has quarterly observations for the core variables.

The variables we use, along with their respective samples, observation frequencies and sources are listed on Table A.1. The variables listed as Main Variables are the set of variables that we use throughout the paper. We also list the Components of Real Output that we use in Section 5.2. In the last two columns we list the original source that produces the data and source of the real-time data that we use for our analysis.

A few comments as to why we chose not to use the variables available in the RTDS in our analysis are in order. We do not use monetary measures in our analysis due to the numerous fundamental definition changes they underwent, especially in the 1980s. Even though the dates and the natures of these changes are known today,[36] the severity of these definitional changes makes it impossible to track them through time. For example the definition of M1 was changed three times in the two year period between February 1980 to February 1982. There was also another definitional change in 1988. The same problem is also true for banking system data. The Consumer Price Index in the data set, on the other hand, starts from 1987, leaving very few observations for the analysis.[37]

A.1.1 Defining the Final Revision

NIPA Variables

From BEA documents, we are able to find the specific schedule for informative revisions of the NIPA variables which we summarize below:

[36] See Kavajecz (1994).

[37] There is a more fundamental reason for not including CPI in our analysis. By its nature CPI is based on measurement of prices at given dates and any further revisions would simply change the weights of these prices or be due to seasonal adjustment. As we explain in Section 2.3 we would not want to include such revisions in our analysis.

Time	Announced	Revised	Revised	Revised	Revised
t Q1	t Q2	t Q3	t+1 Q3	t+2 Q3	t+3 Q3
t Q2	t Q3	t Q4	t+1 Q3	t+2 Q3	t+3 Q3
t Q3	t Q4	t+1 Q1	t+1 Q3	t+2 Q3	t+3 Q3
t Q4	t+1 Q1	t+1 Q2	t+1 Q3	t+2 Q3	t+3 Q3

As can be seen from the table, the variables are not revised after three years from their announcement. When we look at the actual revisions in our data set, most incremental revisions except those shown on the table are zero, confirming the validity of the information in the table.

Using these results, for the NIPA variables, we replace r_t^f with r_t^K where

$$K = \begin{cases} 13 & \text{if } t \text{ is Q1} \\ 12 & \text{if } t \text{ is Q2} \\ 11 & \text{if } t \text{ is Q3} \\ 10 & \text{if } t \text{ is Q4} \end{cases}$$

Labor Productivity

As we collected the labor productivity data from published issues of MLR, we have a very limited deep history information. In particular, we are able to track the data corresponding to a certain quarter for approximately 10 quarters. This might suggest using the last observed revision as the final revision. However, we do not have any information about the revision schedule for labor productivity data and doing this may mean omitting some important revisions. The data for a certain quarter will be no longer reported in the MLR due to, most probably, lack of space rather than lack of revisions. Therefore, we choose to use the vintage at the time of our analysis (March 2006) as the final observation and define the final revision to be difference between this vintage and the initial observation. In order to allow sufficient revisions, we omit the data for the last three years.

Other Variables

For the remaining variables we look at the incremental revisions and identify the number of periods that is necessary for the them to converge to zero. We find that for all monthly variables three years and for the unemployment rate five years is sufficient. Because we have no information about the revision schedule for these variables, the numbers we report above are a compromise between allowing enough informative revisions and avoiding uninformative revisions.

A.2 News vs. Noise Revisited

As we will demonstrate below, the news and noise hypotheses are mutually exclusive. The analysis of MS proceed as if they are in fact collectively exhaustive. In fact, in both of the papers, the authors are able to reject one of the hypotheses and fail to reject the other. It turns out, however, in general these two hypotheses are not collectively exhaustive, that is, we can reject both hypotheses. The key is the mean of final revisions. To see why this is the case, suppose the final revision have a zero mean and the noise hypothesis is true.

Then in (1), since the independent variable and the residual are orthogonal, least squares will give $\alpha_1 = 0$ and $\beta_1 = 1$. On the other hand, it is straightforward to show that in (2), $\alpha_2 = 0$ and $\beta_2 = 1 + \frac{cov\left(r_t^f, y_t^{t+1}\right)}{var\left(y_t^{t+1}\right)} \neq 1$, which shows that when noise hypothesis is true, we will reject the news hypothesis. The reverse result can also be easily shown. Now suppose that $E\left(r_t^f\right) = \mu > 0$. If the noise hypothesis is true we get $\alpha_1 = -\mu$ and $\beta_1 = 1$, which violates the joint hypothesis $\alpha_1 = 0, \beta_1 = 1$. Similarly we get $\alpha_2 = \mu$ and $\beta_2 = 1$ when news hypothesis is true. Therefore, when the revisions have a non-zero mean (as is the case in the data), we can reject both hypotheses and there is no guidance in the original MS methodology when this happens.

Using the original MS framework, we run two experiments. First, we replicate the results obtained in MS for real output growth using our data set and their original sample. We then extend this analysis to all relevant variables in our data set and to the full samples of each variable.

The results for the first exercise is reported in Table A.2. On the left side of the table, we report results regarding the noise hypothesis and on the right we report results regarding the news hypothesis. In the first and the second column we replicate the MS results by estimating (1) and (2) using our data set and the MS sample (1975Q4-1982Q4). We obtain the same result, that is, we reject the noise hypothesis and fail to reject the news hypothesis, which leads to the conclusion that initial announcements of real output growth are best characterized as rational forecasts of the final value. In the last column we estimate (2) with the addition of r_{t-1}^1. The estimated coefficient of r_{t-1}^1 is statistically significant and, more importantly, the F-test with null hypothesis setting all coefficients to zero is now rejected. Therefore, with this small change, which simply follows from the statement of the news hypothesis, we now reject both hypotheses. As explained above, there is no guidance in MS about this case.

Next, we apply the MS methodology for all variables except for the level of nominal output and employment using the longest available sample for each variable and report the results in Table A.3. The upper panel of the table contains the results for the noise hypothesis and the lower panel contains the results for the news hypothesis. For each variable and hypothesis, we report the estimated coefficients along with the R^2 from the regressions and the results of the F-test with the null that the intercept is zero and the slope is one in each regression. We denote coefficients that are statistically different from the appropriate values (zero for the intercept and one for the slope) at the 10% level and F-statistics whose p-values are less than 10% by boldface. The results are discussed in the paper in detail.

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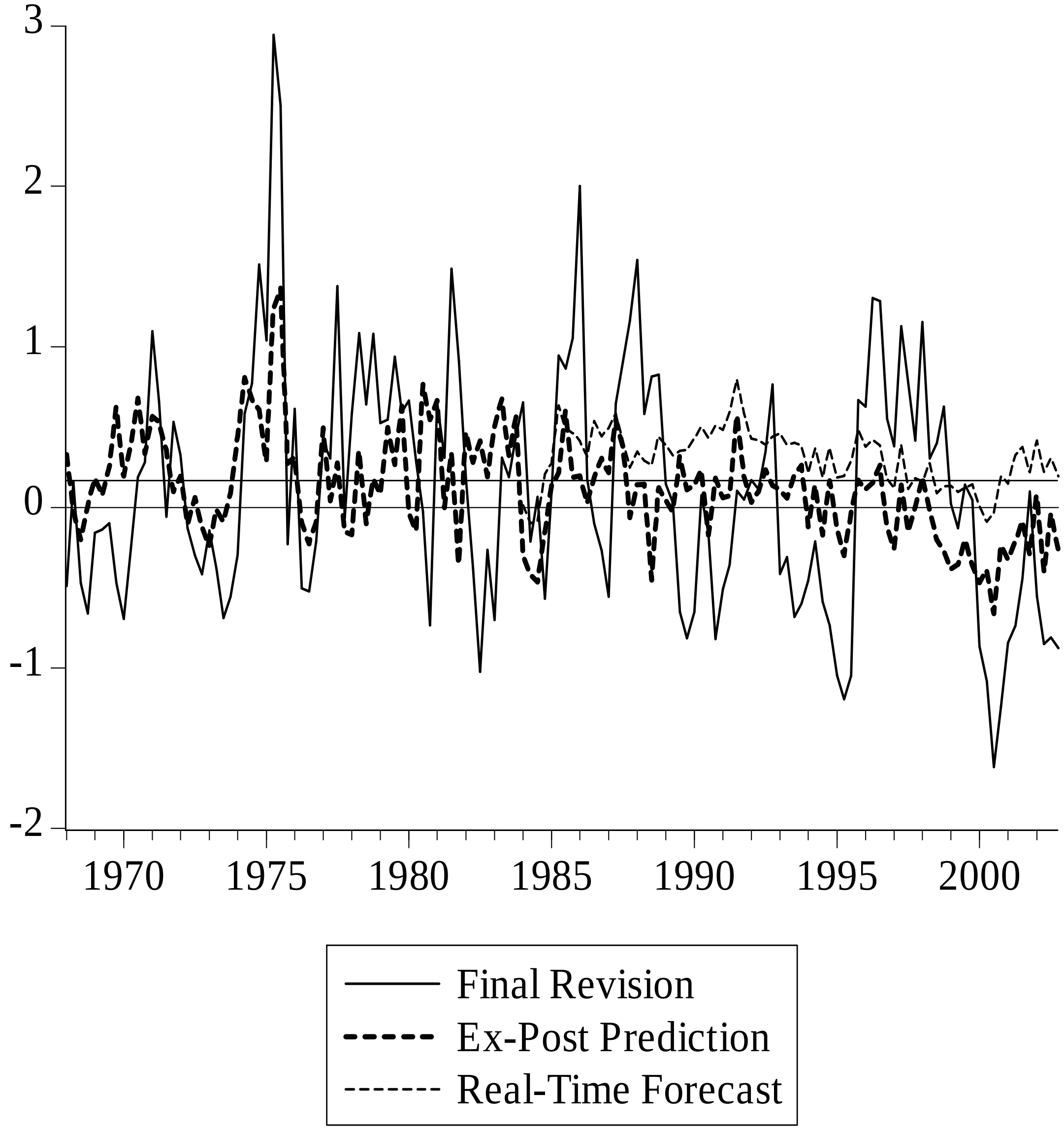
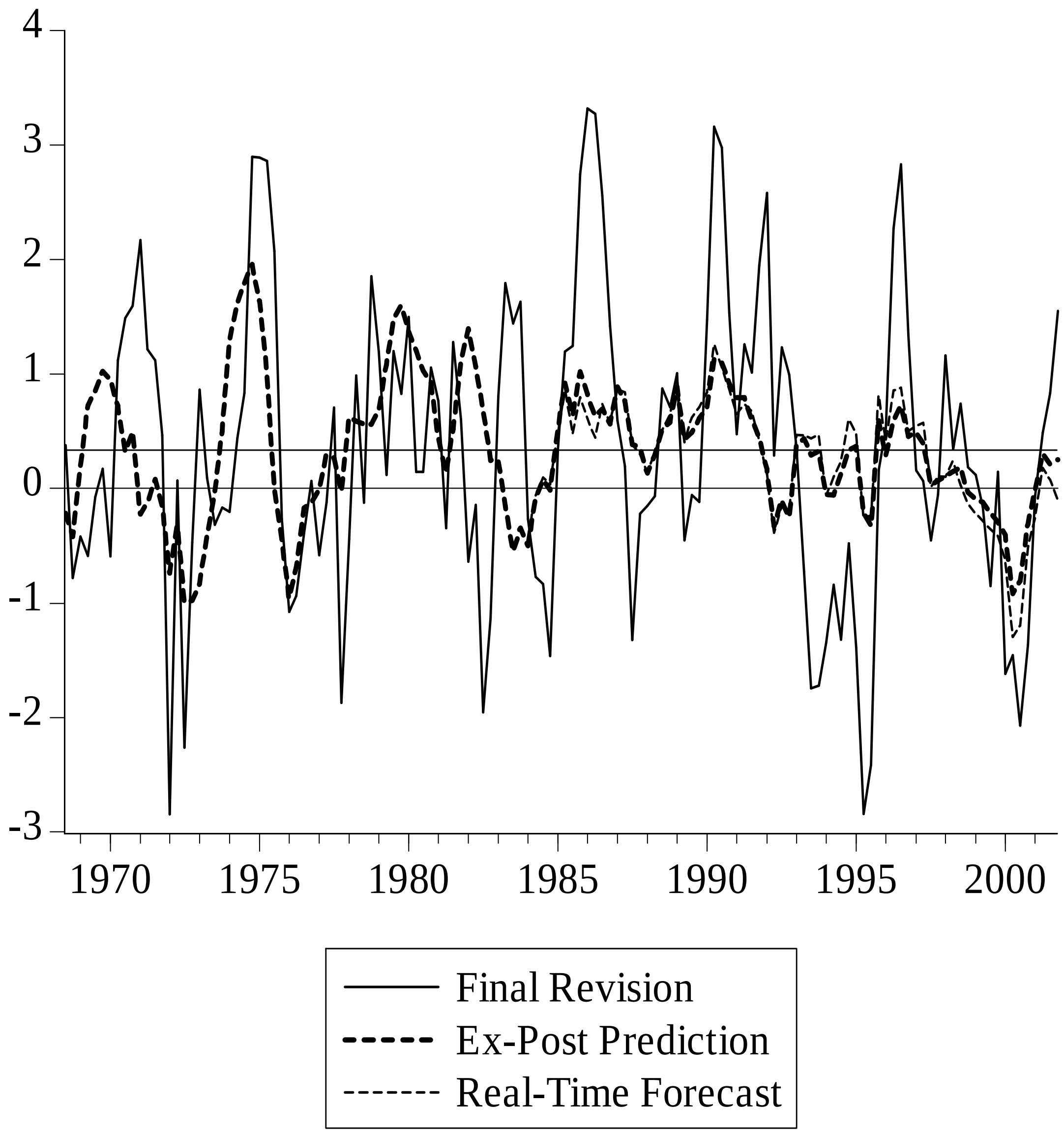
Figure 1 - Final Revision and Forecasts
Annual Growth of Real Output



Notes: The lowest horizontal line is the zero-line and the other one shows the unconditional mean of the final revision.

Figure 2 - Final Revision and Forecasts
Annual Growth of Labor Productivity



Notes: The lowest horizontal line is the zero-line and the other one shows the unconditional mean of the final revision.

Table 1 - Summary Statistics of Final Revisions

	N	Mean	Minimum	Maximum	Std. Dev.	Noise / Signal	Corr. with Initial	A/C (1)
Annual Growth Variables								
Nominal Output	150	**0.31**	-1.74	3.61	0.79	0.28	0.09	**0.66**
Real Output	150	0.17	-1.62	2.94	0.78	0.31	**-0.16**	**0.67**
Inflation (Output Deflator)	150	**0.12**	-0.81	1.12	0.37	0.15	-0.07	**0.60**
Labor Productivity	134	**0.34**	-2.85	3.32	1.31	0.79	**-0.46**	**0.65**
Real Final Sales	108	0.17	-1.21	1.78	0.70	0.32	**-0.23**	**0.67**
Non-Farm Payroll Employment	458	**0.13**	-0.83	1.22	0.39	0.21	**0.36**	**0.92**
Industrial Production (Total Industry)	483	**0.41**	-2.66	5.40	1.04	0.21	0.05	**0.81**
Industrial Production (Manufacturing)	336	**0.52**	-2.70	6.20	1.29	0.23	0.05	**0.83**
Quarterly Growth Variables								
Nominal Output	150	**0.47**	-3.60	7.33	1.71	0.46	-0.02	0.02
Real Output	150	**0.26**	-3.42	6.56	1.72	0.49	-0.12	-0.04
Inflation (Output Deflator)	150	**0.20**	-2.56	2.93	0.85	0.33	-0.13	0.02
Labor Productivity	134	0.31	-8.67	6.98	2.99	0.94	**-0.40**	**-0.18**
Real Final Sales	108	**0.29**	-4.09	5.96	1.69	0.52	**-0.32**	**-0.20**
Monthly Growth Variables								
Non-Farm Payroll Employment	458	**0.35**	-4.85	5.19	1.40	0.52	**-0.29**	**0.12**
Industrial Production (Total Industry)	483	**1.00**	-20.28	24.12	5.17	0.54	**-0.13**	0.03
Industrial Production (Manufacturing)	336	**1.19**	-12.81	25.58	5.44	0.55	**-0.19**	0.06
Variables in Percentage								
Civilian Unemployment Rate	150	0.00	-0.20	0.20	0.07	0.05	-0.02	**-0.18**
Capacity Utilization (Total Industry)	235	0.14	-1.50	2.30	0.81	0.32	**-0.23**	**0.85**
Capacity Utilization (Manufacturing)	282	0.11	-2.10	2.40	0.91	0.25	**-0.32**	**0.86**

Notes: All monthly and quarterly growth variables are annualized. Boldface denote significance at 10% level. A/C(1) column reports the first order autocorrelation coefficient.

Table 2 - Results of the Ex Post Forecasting Exercise

	Explanatory Variables	Wald	R^2	$\bar{R}^2$	RMSE1/ RMSE4	RMSE2/ RMSE4	RMSE3/ RMSE4
AIC							
Annual Growth Variables							
Nominal Output	C, Trend	**0.02**	0.03	0.03	0.93	0.93	0.94
Real Output	C, Init, Rev9, Rev10, Trend, Unemp	**0.01**	0.19	0.16	0.89	0.94	0.99
Inflation (Output Deflator)	C, Rev3, Rev6	**0.04**	0.05	0.04	0.92	0.94	0.95
Labor Productivity	C, Init	**0.00**	0.21	0.21	0.86	0.86	0.97
Real Final Sales	C, Init, Rev2, Rev6, Trend	**0.00**	0.24	0.20	0.84	0.89	0.97
Non-Farm Payroll Employment	Init, Trend	**0.00**	0.12	0.12	0.89	0.89	0.95
Industrial Production (Total Industry)	C	**0.00**	0.00	0.00	0.93	0.93	0.93
Industrial Production (Manufacturing)	Rev7, Rev10, Trend	**0.00**	0.06	0.05	0.90	0.93	0.93
Quarterly Growth Variables							
Nominal Output	C, Rev1, Rev2, Rev5, Trend	**0.00**	0.09	0.07	0.92	0.95	0.97
Real Output	C, Init, Rev1, Rev3, Rev5, Rev9, Q1, Trend, Unemp	**0.00**	0.18	0.13	0.90	0.95	0.99
Inflation (Output Deflator)	C, Init, Rev1, Trend	**0.00**	0.06	0.04	0.94	0.95	0.97
Labor Productivity	C, Init, Q3	**0.00**	0.18	0.17	0.90	0.91	0.99
Real Final Sales	Init, Rev3, Q3	**0.00**	0.22	0.21	0.87	0.88	0.98
Monthly Growth Variables							
Non-Farm Payroll Employment	C, Init, Rev5, Rev6, Q2, Q3, Trend	**0.00**	0.16	0.15	0.88	0.90	0.97
Industrial Production (Total Industry)	C, Init, Rev1, Rev2, Rev4, Rev7, Rev9, Trend	**0.00**	0.06	0.04	0.95	0.97	0.98
Industrial Production (Manufacturing)	C, Init, Rev2, Rev4, Rev7, Rev9	**0.00**	0.11	0.09	0.93	0.96	0.98
Variables in Percentage							
Civilian Unemployment Rate	Rev5, Rev8, Rev9	**0.00**	0.14	0.12	0.93	0.99	1.00
Capacity Utilization (Total Industry)	C, Init, Rev7	**0.01**	0.11	0.10	0.91	0.95	0.99
Capacity Utilization (Manufacturing)	C, Init, Rev7, Rev10	**0.00**	0.16	0.15	0.91	0.94	0.99
SIC							
Annual Growth Variables							
Nominal Output	Init	**0.00**	0.00	0.00	0.94	0.93	0.94
Real Output	C, Init, Trend, Unemp	**0.02**	0.16	0.15	0.90	0.94	0.99
Inflation (Output Deflator)	C	**0.01**	0.00	0.00	0.95	0.94	0.95
Labor Productivity	C, Init	**0.00**	0.21	0.21	0.86	0.86	0.97
Real Final Sales	C, Init, Trend	**0.00**	0.17	0.15	0.88	0.89	0.97
Non-Farm Payroll Employment	Init	**0.00**	0.12	0.12	0.89	0.89	0.95
Industrial Production (Total Industry)	C	**0.00**	0.00	0.00	0.93	0.93	0.93
Industrial Production (Manufacturing)	Rev7, Trend	**0.00**	0.05	0.04	0.91	0.93	0.93
Quarterly Growth Variables							
Nominal Output	C, Rev5	**0.00**	0.04	0.03	0.95	0.95	0.97
Real Output	Rev1, Q1	**0.01**	0.06	0.06	0.96	0.95	0.99
Inflation (Output Deflator)	C	**0.01**	0.00	0.00	0.97	0.95	0.97
Labor Productivity	C, Init	**0.00**	0.16	0.15	0.91	0.91	0.99
Real Final Sales	Init, Q3	**0.00**	0.20	0.19	0.88	0.88	0.98
Monthly Growth Variables							
Non-Farm Payroll Employment	C, Init, Rev6, Q2, Trend	**0.00**	0.15	0.14	0.88	0.90	0.97
Industrial Production (Total Industry)	C, Init	**0.00**	0.02	0.01	0.97	0.97	0.98
Industrial Production (Manufacturing)	C, Init, Rev4, Rev9	**0.00**	0.08	0.07	0.94	0.96	0.98
Variables in Percentage							
Civilian Unemployment Rate	Rev5	**0.00**	0.08	0.08	0.96	0.99	1.00
Capacity Utilization (Total Industry)	C, Init	**0.02**	0.09	0.09	0.91	0.95	0.99
Capacity Utilization (Manufacturing)	C, Init, Rev7	**0.00**	0.15	0.14	0.92	0.94	0.99

Notes : "C" refers to a constant, "Init" refers to the initial announcement, "RevX" revers to the xth revision, "QX" refers to the dummy variable for the xth quarter and "Unemp" refers to the first difference of quarterly unemployment.

Table 3 - Results of the Real Time Forecasting Exercise

	N	RMSE4/ RMSE5	CW Statistic	CW P-value	RMSE6/ RMSE5	CW Statistic	CW P-value
Annual Growth Variables							
Nominal Output	76	0.91	**0.19**	**0.07**	0.95	-0.04	**0.05**
Real Output	76	0.95	**0.07**	0.23	**1.01**	**0.04**	0.17
Inflation (Output Deflator)	76	**1.04**	**0.04**	**0.04**	**1.01**	**0.01**	0.19
Labor Productivity	72	**1.20**	**0.96**	**0.00**	**1.19**	**0.86**	**0.00**
Real Final Sales	47	0.94	**0.04**	0.33	0.99	0.00	0.45
Non-Farm Payroll Employment	228	0.80	-0.02	0.24	0.86	-0.03	**0.09**
Industrial Production (Total Industry)	228	**1.06**	**0.33**	**0.00**	**1.00**	**0.01**	0.23
Industrial Production (Manufacturing)	228	**1.06**	**0.40**	**0.00**	0.99	-0.01	0.36
Quarterly Growth Variables							
Nominal Output	76	0.99	**0.33**	**0.05**	**1.00**	**0.02**	0.21
Real Output	76	0.98	**0.16**	0.18	**1.01**	**0.11**	0.10
Inflation (Output Deflator)	76	**1.04**	**0.14**	**0.01**	**1.02**	**0.03**	**0.07**
Labor Productivity	72	**1.13**	**2.00**	**0.00**	**1.12**	**1.93**	**0.00**
Real Final Sales	72	**1.08**	**0.72**	**0.00**	**1.08**	**0.54**	**0.01**
Monthly Growth Variables							
Non-Farm Payroll Employment	228	**1.03**	**0.41**	**0.00**	**1.07**	**0.30**	**0.00**
Industrial Production (Total Industry)	228	**1.04**	**2.91**	**0.00**	**1.02**	**1.04**	**0.00**
Industrial Production (Manufacturing)	228	**1.04**	**4.42**	**0.00**	**1.03**	**1.85**	**0.00**
Variables in Percentage							
Civilian Unemployment Rate	76	0.99	0.00	0.13	1.00	0.00	0.11
Capacity Utilization (Total Industry)	156	0.65	**0.96**	**0.00**	0.65	**1.00**	**0.00**
Capacity Utilization (Manufacturing)	228	0.73	**0.15**	0.16	0.78	**0.26**	**0.03**

Notes: *N* denotes the number of periods used for out-of-sample forecasting. RMSE5 refers to the real-time forecast and RMSE4 refers to the zero forecast. Boldface in the RMSE5/RMSE4 column shows entries greater than unity. Boldface in the CW column shows positive statistics while boldface in the p-value column shows entries less than 0.10.

Table 4 - Summary of Results for Subsamples

(a) Unconditional Properties

	Full Sample			Pre-1984			Post-1984		
	N	Mean	Noise / Signal	N	Mean	Noise / Signal	N	Mean	Noise / Signal
Annual Growth Variables									
Nominal Output	150	**0.31**	0.28	74	**0.47**	0.33	76	**0.16**	0.36
Real Output	150	0.17	0.31	74	**0.33**	0.25	76	0.02	0.43
Inflation (Output Deflator)	150	**0.12**	0.15	74	**0.11**	0.16	76	**0.12**	0.36
Labor Productivity	134	**0.34**	0.79	62	0.36	0.56	72	0.32	1.24
Real Final Sales	108	0.17	0.32	61	**0.25**	0.26	47	0.06	0.48
Non-Farm Payroll Employment	458	**0.13**	0.21	230	**0.21**	0.17	228	0.05	0.26
Industrial Production (Total Industry)	483	**0.41**	0.21	255	**0.39**	0.16	228	**0.43**	0.32
Industrial Production (Manufacturing)	336	**0.52**	0.23	108	**0.49**	0.16	228	**0.53**	0.34
Quarterly Growth Variables									
Nominal Output	150	**0.47**	0.46	74	**0.68**	0.48	76	0.26	0.61
Real Output	150	**0.26**	0.49	74	**0.49**	0.42	76	0.03	0.67
Inflation (Output Deflator)	150	**0.20**	0.33	74	0.19	0.37	76	**0.21**	0.66
Labor Productivity	134	0.31	0.94	62	0.22	0.88	72	0.39	1.07
Real Final Sales	108	**0.29**	0.52	61	**0.35**	0.42	47	0.20	0.81
Monthly Growth Variables									
Non-Farm Payroll Employment	458	**0.35**	0.52	230	**0.54**	0.49	228	**0.15**	0.59
Industrial Production (Total Industry)	483	**1.00**	0.54	255	**1.14**	0.49	228	**0.86**	0.72
Industrial Production (Manufacturing)	336	**1.19**	0.55	108	**1.71**	0.45	228	**0.94**	0.73
Variables in Percentage									
Civilian Unemployment Rate	150	0.00	0.05	74	-0.01	0.05	76	0.01	0.05
Capacity Utilization (Manufacturing)	282	0.11	0.25	54	**0.42**	0.20	228	0.03	0.32

(b) Ex-Post Forecasting (AIC)

	Full Sample		Pre-1984		Post-1984	
	R^2	RMSE1/ RMSE4	R^2	RMSE1/ RMSE4	R^2	RMSE1/ RMSE4
Annual Growth Variables						
Nominal Output	0.03	0.93	0.11	0.79	0.17	0.89
Real Output	0.19	0.89	0.15	0.88	0.20	0.89
Inflation (Output Deflator)	0.05	0.92	0.18	0.85	0.25	0.81
Labor Productivity	0.21	0.86	0.13	0.88	0.42	0.75
Real Final Sales	0.24	0.84	0.23	0.79	0.29	0.84
Non-Farm Payroll Employment	0.12	0.89	0.31	0.73	0.09	0.96
Industrial Production (Total Industry)	0.00	0.93	0.05	0.90	0.06	0.91
Industrial Production (Manufacturing)	0.06	0.90	0.47	0.68	0.05	0.91
Quarterly Growth Variables						
Nominal Output	0.09	0.92	0.16	0.83	0.11	0.93
Real Output	0.18	0.90	0.21	0.87	0.12	0.94
Inflation (Output Deflator)	0.06	0.94	0.09	0.93	0.23	0.84
Labor Productivity	0.18	0.90	0.20	0.87	0.24	0.89
Real Final Sales	0.22	0.87	0.08	0.94	0.36	0.79
Monthly Growth Variables						
Non-Farm Payroll Employment	0.16	0.88	0.15	0.88	0.20	0.89
Industrial Production (Total Industry)	0.06	0.95	0.06	0.95	0.15	0.89
Industrial Production (Manufacturing)	0.11	0.93	0.28	0.83	0.18	0.89
Variables in Percentage						
Civilian Unemployment Rate	0.14	0.93	0.30	0.84	0.20	0.89
Capacity Utilization (Manufacturing)	0.16	0.91	0.78	0.42	0.08	0.96

Notes: All monthly and quarterly growth variables are annualized. Boldface denote significance at 10% level. There are too few observations for Capacity Utilization (Total Industry) before 1984 to conduct the analysis.

Table A.1 -Variables Used in the Analysis

Name	Frequency	Number of Obs	Full Sample	Source	Original Source
Main Variables					
Annual Growth of Real Output	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Annual Growth of Nominal Output	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Annual Inflation (Output Deflator)	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Annual Growth Real Final Sales	Quarterly	108	(1965Q3 - 1995Q3)	RTDS - Core (*)	BEA (*)
Annual Growth of Labor Productivity	Quarterly	134	(1968Q3 - 2001Q4)	MLR	BLS
Annual Growth of Non-Farm Payroll Employment	Monthly	458	(1964:11 - 2002:12)	RTDS - Non-Core	BLS
Annual Growth of Industrial Production (Total Industry)	Monthly	483	(1962:10 - 2002:12)	RTDS - Non-Core	BOG
Annual Growth of Industrial Production (Manufacturing)	Monthly	336	(1975:01 - 2002:12)	RTDS - Non-Core	BOG
Quarterly Growth of Real Output	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Quarterly Growth of Nominal Output	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Quarterly Inflation (Output Deflator)	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BEA
Quarterly Growth of Real Final Sales	Quarterly	108	(1965Q3 - 1995Q3)	RTDS - Core (*)	BEA (*)
Quarterly Growth of Labor Productivity	Quarterly	134	(1968Q3 - 2001Q4)	MLR	BLS
Monthly Growth of Non-Farm Payroll Employment	Monthly	458	(1964:11 - 2002:12)	RTDS - Non-Core	BLS
Monthly Growth of Industrial Production (Total Industry)	Monthly	483	(1962:10 - 2002:12)	RTDS - Non-Core	BOG
Monthly Growth of Industrial Production (Manufacturing)	Monthly	336	(1975:01 - 2002:12)	RTDS - Non-Core	BOG
Civilian Unemployment Rate	Quarterly	150	(1965Q3 - 2002Q4)	RTDS - Core	BLS
Capacity Utilization (Total Industry)	Monthly	235	(1983:06 - 2002:12)	RTDS - Non-Core	BOG
Capacity Utilization (Manufacturing)	Monthly	282	(1979:07 - 2002:12)	RTDS - Non-Core	BOG
Annual and Quarterly Growth Components of Real Output (**)					
Real Personal Consumption Expenditures	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Personal Consumption Expenditures, Durables	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Personal Consumption Expenditures, Nondurables	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Personal Consumption Expenditures, Services	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Business Fixed Investment Expenditures	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Residential Investment Expenditures	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Government Purchases of Goods and Services	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Exports of Goods and Services	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA
Real Imports of Goods and Services	Quarterly	137	(1965Q4 - 2000Q4)	RTDS - Core	BEA

Notes: RTDS : Real-Time Data Set of Federal Reserve Bank of Philadelphia. MLR : Monthly Labor Review published by Bureau of Labor Statistics. BEA : Bureau of Economic Analysis. BLS : Bureau of Labor Statistics. BOG : Board of Governors of the Federal Reserve.

(*) Author's own calculations using output and change in inventories.

(**) For these variables, we have observations for only Q4 for years 1965-1969.

Table A.2 - Tests for News and Noise Hypotheses - 1975Q4-1982Q4

	Regression of Initial Announcement of Quarterly Output Growth on the Final Value (Noise Hypothesis)	Regression of Final Value of Quarterly Output Growth on the Initial Announcement (News Hypothesis)	
Intercept	-0.13	0.61	0.00
Slope	**0.82**	0.97	0.91
Revision1 (-1)	-	-	**1.55**
F -test	**13.56**	1.76	**15.39**
p -value	0.00	0.19	0.00
R^2	0.79	0.79	0.90
N	29	29	29

Notes : Revision1(-1) is the first revision to the variable at t-1, announced at the time of the current announcement. *F* -tests in the first two columns test the joint hypothesis that the intercept is zero and the slope is one and in the third column the hypothesis includes the restriction that coefficient of Revision1(-1) is equal to zero. All tests conducted using Newey-West standard errors. Boldface denotes rejection of the relevant null hypothesis at the 10% significance level. N denotes the number of observations in each regression.

Table A.3 - Tests for News and Noise Hypotheses - Full Sample

	Intercept	Slope	F-test	R^2	N
Regression of Initial Announcement on the Final Value (Noise Hypothesis)					
Annual Growth Variables					
Nominal Output	**0.44**	**0.90**	**0.00**	0.92	150
Real Output	-0.03	0.95	0.15	0.90	150
Inflation (Output Deflator)	-0.07	0.99	**0.04**	0.98	150
Labor Productivity	0.08	**0.77**	**0.01**	0.51	134
Real Final Sales	-0.09	0.97	0.24	0.90	108
Non-Farm Payroll Employment	**0.10**	**0.89**	**0.00**	0.96	458
Industrial Production (Total Industry)	**-0.23**	**0.94**	**0.00**	0.96	483
Industrial Production (Manufacturing)	**-0.32**	**0.94**	**0.00**	0.95	336
Quarterly Growth Variables					
Nominal Output	**0.97**	**0.80**	**0.00**	0.79	150
Real Output	0.27	**0.82**	**0.00**	0.76	150
Inflation (Output Deflator)	0.09	**0.93**	**0.00**	0.89	150
Labor Productivity	**0.68**	**0.44**	**0.00**	0.25	134
Real Final Sales	-0.03	**0.90**	**0.00**	0.76	108
Monthly Growth Variables					
Non-Farm Payroll Employment	-0.11	**0.88**	**0.00**	0.75	458
Industrial Production (Total Industry)	-0.32	**0.77**	**0.00**	0.71	483
Industrial Production (Manufacturing)	-0.54	**0.80**	**0.00**	0.71	336
Variables in Percentage					
Civilian Unemployment Rate	0.01	1.00	0.87	1.00	150
Capacity Utilization (Total Industry)	2.12	0.97	0.36	0.90	235
Capacity Utilization (Manufacturing)	-1.81	1.02	0.44	0.94	282
Regression of Final Value on the Initial Announcement (News Hypothesis)					
Annual Growth Variables					
Nominal Output	0.12	1.03	**0.00**	0.92	150
Real Output	0.31	0.95	0.21	0.90	150
Inflation (Output Deflator)	**0.16**	0.99	**0.03**	0.98	150
Labor Productivity	**0.82**	**0.66**	**0.00**	0.51	134
Real Final Sales	**0.35**	**0.93**	0.13	0.90	108
Non-Farm Payroll Employment	-0.03	**1.08**	**0.00**	0.96	458
Industrial Production (Total Industry)	**0.38**	1.01	**0.00**	0.96	483
Industrial Production (Manufacturing)	**0.48**	1.01	**0.00**	0.95	336
Quarterly Growth Variables					
Nominal Output	0.53	0.99	**0.01**	0.79	150
Real Output	**0.42**	0.94	**0.09**	0.76	150
Inflation (Output Deflator)	**0.37**	0.96	**0.00**	0.89	150
Labor Productivity	**0.93**	**0.57**	**0.00**	0.25	134
Real Final Sales	**0.65**	**0.84**	**0.00**	0.76	108
Monthly Growth Variables					
Non-Farm Payroll Employment	**0.61**	**0.85**	**0.00**	0.75	458
Industrial Production (Total Industry)	**1.16**	**0.92**	**0.00**	0.71	483
Industrial Production (Manufacturing)	**1.41**	**0.89**	**0.00**	0.71	336
Variables in Percentage					
Civilian Unemployment Rate	0.00	1.00	0.95	1.00	150
Capacity Utilization (Total Industry)	**6.11**	**0.93**	**0.08**	0.90	235
Capacity Utilization (Manufacturing)	**6.21**	**0.92**	**0.00**	0.94	282

Notes: Boldface denotes rejection of the appropriate null at 10%. N denotes the number of observations in each regression.