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Research article

Further Evidence on the Usefulness of Real-Time Datasets for Economic Forecasting

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Abstract: In this paper, we assess the relevance of real-time datasets for forecasting. We construct a variety of real-time prediction models and evaluate their performance in a series of ex-ante prediction experiments that are designed to mimic forecasting approaches used when constructing forecasts in real-time for output, prices and money. We assess the models within univariate and multivariate frameworks by including revision errors as regressors, allowing us to examine the marginal predictive content of the revision process. In another multivariate application for output we add money, thus examining the real-time predictive content of money for income. The most important result we obtain is that the choice of which release of data to predict seems not to have an impact on which releases of data should be used in estimation and prediction construction but that differences in how to utilize real-time datasets do arise when the variable being modelled and predicted changes. Overall our findings point to the importance of making real-time datasets available to forecasters, as the revision process has marginal predictive content, and because predictive accuracy increases when multiple releases of data are used when specifying and estimating prediction models. This underscores the importance of collecting and maintaining such real-time datasets.

Keywords: out-of-sample forecasting; rationality; preliminary, final, and real-time data

1. Introduction

Recent empirical research has presented strong evidence in favor of the usefulness of making real-time datasets available to economists. Aruoba (2008) finds that for most U.S. macroeconomic time series, revision errors have a positive bias and are highly predictable. These finding are based on the use of information available at the time of the first release. In Aruoba, Diebold, and Scotti (2008), the findings of Aruoba (2008) are used as one of the main motivating factors for the construction of a real-time business conditions measurement index. In summary, both of these papers suggest that there is much to be gained by using multiple vintages of data in the construction of predictions and prediction models. For example, one might fruitfully choose to estimate prediction models that employ all vintages (releases) of available variables, say using the Kalman filter or some other filtering procedure (see, e.g., Mariano and Tanizaki (1995)). However, the literature has said little about which release of data to predict, and whether it is preferable to use mixed releases of data when forming predictions and prediction models (as is done when "latest available release" data are used). In this paper, we attempt to shed new light on the above issues. Key precedents to our research on the informational content of real-time datasets include: Diebold and Rudebusch (1991), Hamilton and Perez-Quiros (1996), Bernanke and Boivin (2003), and the papers cited therein.

Our approach is to construct a variety of different real-time prediction models and to evaluate their performance in a series of ex-ante prediction experiments that are designed to mimic forecasting approaches used when constructing forecasts in real-time, for the purpose of policy setting and generic real-time decision making. For this purpose we use real-time datasets on output, prices, and money. Our prediction models include, among others, one that uses only first release data and one that utilizes only the latest available data (i.e., uses a mixture of most recent first release data and more distant later release data). Some of our models include revision errors as regressors, hence allowing us to examine the marginal predictive content of the revision process. In addition, our experiments are designed to find out whether it matters which release of data one chooses to forecast, which release(s) of data should be used when estimating prediction models, and how definitional change in real-time variables affects our findings regarding which release of data to predict. In another implementation of our experimental setup within a multivariate framework, we carry out an empirical analysis in which we examine the real-time predictive content of money for income, building on the work of Stock and Watson (1989), Amato and Swanson (2001), and others. Finally, our experiments are used to form simple rationality tests that are based solely on the examination of ex-ante predictions, rather than being based on in-sample regression analysis, as are many tests in the extant literature (see Corradi, Fernandez, and Swanson (2009) for further discussion).

The results of our prediction experiments point clearly to the need for making real-time datasets available to empirical researchers. In almost all cases that we consider, multiple releases of a variable are useful for constructing MSFE-best predictions. More important, we present evidence concerning whether or not one should aim to predict the "first release" or "final" release of a variable, and which data are most useful for model estimation and prediction construction. We find that regardless of which release of prices one specifies as the "target" variable to be predicted, using only "first release" data in model estimation and prediction construction yields MSFE-best predictions. On the other hand, models estimated and implemented using "latest available release" data are MSFE-best for predicting all releases of money. Thus, perhaps surprisingly, in our empirical analysis we find that the choice of which release of data to predict seems not to have an impact on which releases of data should be used in estimation and prediction construction. However, differences in how to utilize real-time datasets do arise when the variable being modelled and predicted changes. As for our multivariate forecasting experiment involving the real-time predictive content of money for income, while we find little marginal predictive content in money, we note that vector autoregressions with money do not perform significantly worse than autoregressions, when predicting output in the past 20 years. This is somewhat surprising because models with irrelevant variables should be less efficiently estimated, leading in many cases to worsened predictive performance. Finally, we also find new evidence that early releases of money are rational, whereas prices and output are irrational.

The rest of the paper is organized as follows. In Section 2, we outline our notation, discuss the empirical methodology used by presenting the variety of real-time prediction models that we analyze, and we discuss the real-time datasets used. Section 3 contains our empirical findings. Concluding remarks are given in Section 4. Tables and figures are collected at the end of the paper.

2. Methodology and Data

2.1. Setup

Let ${}_{t+k}X_t$ denote a variable (reported as an annualized growth rate) for which real-time data are available, where the subscript t denotes the time period to which the datum pertains, and the subscript $t+k$ denotes the time period during which the datum becomes available. In this setup, if we assume a one-month reporting lag, then first release or "preliminary" data are denoted by ${}_{t+1}X_t$. In addition, we denote fully revised or "final" data, which is obtained as $k \to \infty$, by ${}_fX_t$. Data are grouped into releases and vintages. The first release is preliminary data, the second release is 2^{nd} available data, and so on. In regard to vintages, the 2000:1 vintage is the time series of latest release data available in 2000:1, and the 2000:2 vintage is the time series of latest release data available in 2000:2, and so on. Regression models parameterized using the latest available release of data at each point in time use the most recently available vintage. Such models correspond to those usually used in practice. Regression models parameterized using only a single release of data use time series constructed by taking a single observation from each vintage of data. To further set notation, let ${}_{t+2}u_t^{t+1} = {}_{t+2}X_t - {}_{t+1}X_t$, thus, ${}_{t+2}u_t^{t+1}$ and ${}_{t+1}u_{t-1}^{t}$ denote the errors between the second and the first releases at time $t+2$ and at time $t+1$, respectively.

2.2. Prediction

In this subsection, we discuss the prediction models that will be used for addressing the questions outlined above. In particular, we consider the issue of prediction using various variable/vintage combinations as defined in the following set of models.

Model A (First Available Data): ${}_{t+k}X_{t+1} = \alpha^A_{t+1,t} + \sum_{i=1}^{p^A} \beta^A_{i,t+1,t}\ {}_{t+2-i}X_{t+1-i} +_{t+k} \epsilon^A_{t+1}$;

Model B (k^{th}Available Data): ${}_{t+k}X_{t+1} = \alpha^B_{t+1,t} + \sum_{i=1}^{p^B} \beta^B_{i,t+1,t}\ {}_{t+2-i}X_{t+3-k-i} +_{t+k} \epsilon^B_{t+1}$;

Model C (Latest Available Data): ${}_{t+k}X_{t+1} = \alpha^C_{t+1,t} + \sum_{i=1}^{p^C} \beta^C_{i,t+1,t}\ {}_{t+1}X_{t+1-i} +_{t+k} \epsilon^C_{t+1}$.

In the above models, the time subscripts on the model coefficients are meant to indicate that the parameters are estimated using particular calendar and release dated observations from our real-time datasets and correspond to the final calendar date and release combination in the dataset used to estimate the models. Our analysis is carried out by recursively estimating the above models and constructing sequences of ex-ante 1-step ahead predictions, for various values of k. Notice that when $k = 2$, we are assuming that the "target variable" to be forecast is the first release.

Model A has explanatory variables that are formed using only first available data. Thus, the first model corresponds to the approach of simply using first available data and ignoring all later releases, regardless of which release of data is being forecasted. This model should be expected to perform well if data revisions are "news" and/or if type of definitional changes do not contaminate the data.

Model B is specified using explanatory variables that are available $k-1$ months ahead, corresponding to $(k-1)^{st}$ available data. Thus, this model uses data that have been revised $k-1$ times in order to predict data that likewise have been revised $k-1$ times. In this sense, Model B is included only as a "reality check", as the model uses stale information in all instances other than the case in which $k=2$ (in which case Models A and B are equivalent). However, when $k>2$, the calendar date of information used to predict one-step ahead is at least two periods prior to the prediction period. Therefore, the "cost" of using Model B is the inclusion of "stale" data, and hence the model should be expected to perform poorly.

In Model C, the latest release of each observation is used in prediction, so that the dataset is fully updated prior to each new prediction being made. We refer to this model as our "latest available data" model because policy makers and others who construct new predictions each period, after updating their datasets and re-estimating their models, generally use this type of model. If useful information accrues via the revision process, then one might expect that using latest available data (Model C) would yield a better predictor of ${}_{t+k}X_t$ than when only "stale" first release data are used (Model A), for example. Of course, the last statement has a caveat. Namely, it is possible that first release data are best predicted using only first release regressors, second release using second release regressors, etc. This might arise if the use of real-time data as in Model C results in an "informational mix-up" due to the fact that every observation used to estimate the model is a different release, and only one of these releases corresponds to the release being predicted, at any point in time. For further discussion of real-time forecasting using models such as Model C, the reader is referred to Swanson and van Dijk (2006) and Faust and Wright (2009).

Given the above considerations, one natural approach is to compare the following prediction equations using least squares estimators. For example, the cases with only the intercept and first order slope parameter in each model are:

Model A Prediction Equation: ${}_{t+k}\widehat{X}^f_{t+1} = \widehat{\alpha}^A_{t+1,t} + \sum_{i=1}^{p^A} \widehat{\beta}^A_{i,t+1,t}\ {}_{t+2-i}X_{t+1-i}$, for $t = R, ..., T-k$, where

$$\begin{bmatrix} \widehat{\alpha}^A_{t+1,t} \\ \widehat{\beta}^A_{1,t+1,t} \end{bmatrix} = \begin{bmatrix} t-1 & \sum_{j=2}^{t}\ {}_jX_{j-1} \\ \sum_{j=2}^{t}\ {}_jX_{j-1} & \sum_{j=2}^{t}\ {}_jX^2_{j-1} \end{bmatrix}^{-1} \begin{bmatrix} \sum_{j=2}^{t}\ {}_{j+1}X_j \\ \sum_{j=2}^{t}\ {}_{j+1}X_j\ {}_jX_{j-1} \end{bmatrix}$$

Model B Prediction Equation: ${}_{t+k}\widehat{X}^f_{t+1} = \widehat{\alpha}^B_{t+1,t} + \sum_{i=1}^{p^B} \widehat{\beta}^B_{i,t}\ {}_{t+k-i}X_{t+1-i}$, for $t = R, ..., T-k$, where

$$\begin{bmatrix} \widehat{\alpha}^B_{t+1,t} \\ \widehat{\beta}^B_{1,t+1,t} \end{bmatrix} = \begin{bmatrix} t-1 & \sum_{j=2}^{t}\ {}_jX_{j+1-k} \\ \sum_{j=2}^{t}\ {}_jX_{j+1-k} & \sum_{j=2}^{t}\ {}_jX^2_{j+1-k} \end{bmatrix}^{-1} \begin{bmatrix} \sum_{j=2}^{t}\ {}_{j+1}X_{j+2-k} \\ \sum_{j=2}^{t}\ {}_{j+1}X_{j+2-k}\ {}_jX_{j+1-k} \end{bmatrix}$$

Model C Prediction Equation: ${}_{t+k}\widehat{X}^f_{t+1} = \widehat{\alpha}^C_{t+1,t} + \sum_{i=1}^{p^C} \widehat{\beta}^C_{i,t}\ {}_{t+1}X_{t+1-i}$, for $t = R, ..., T-k$, where

$$\begin{bmatrix} \widehat{\alpha}^C_{t+1,t} \\ \widehat{\beta}^C_{1,t+1,t} \end{bmatrix} = \begin{bmatrix} t-1 & \sum_{j=2}^{t}\ {}_{t+1}X_{j-1} \\ \sum_{j=2}^{t}\ {}_{t+1}X_{j-1} & \sum_{j=2}^{t}\ {}_{t+1}X^2_{j-1} \end{bmatrix}^{-1} \begin{bmatrix} \sum_{j=2}^{t}\ {}_{t+1}X_j \\ \sum_{j=2}^{t}\ {}_{t+1}X_j\ {}_{t+1}X_{j-1} \end{bmatrix}$$

In our prediction experiments, we set: (i) $p=1$; (ii) $p=SIC$; (iii) $p=AIC$; (iv) $p=0$ (random walk with drift model).* Additionally, we set $k=\{2, 3, 4, 6, 12, 24\}$.

*Models with lags selected using the Schwarz Information Criterion (SIC) yielded more accurate predictions, on average; therefore

Notice that the estimators used in the three prediction models are indeed quite different. Moreover, analogous least squares estimators for all other parameters in the prediction equations follow immediately (by simply setting $k = 2$ in the original models). Given the above formulation, it is also clear that the straw-man random walk with drift prediction model that we also consider in our experiments has intercept parameter that differs across the three models. Importantly, note that, in order to carry out true real-time prediction, we must assume that we have observations for calendar dates only up until period t, using only vintages $t + 1$ and earlier.

All experiments are based on the examination of the MSFEs associated with 1-step ahead predictions constructed using recursively estimated models, where R observations are used in our first estimation, $R + 1$ observations are used in our second estimation, etc. We thus construct sequences of $P - k$ ex-ante predictions and prediction errors, where $T = R + P$ is the sample size. We set R to be 1969:4, so that our first prediction is calendar date 1970:1. The start calendar date of our dataset is 1959:4, and we have vintages of data from 1965:4. Another set of predictions are constructed using recursively estimated models with ex-ante prediction periods beginning in 1983:1 or 1990:1.

In the multivariate version of the forecasting experiment that we undertake we include: (i) money, income, prices, and interest rates; and (ii) income, prices, and interest rates. In these models, it is assumed that the target variable of interest is output growth. Thus, we are examining, in real-time, the marginal predictive content of money for output, using various data vintages, various revision errors, and for a target variable that corresponds to various releases of output growth. Other recent papers examining the usefulness of real-time data for prediction include Robertson and Tallman (1998), Gallo and Marcellino (1999), and the papers cited therein.

MSFEs are examined via the use of Diebold and Mariano (DM: 1995) and Clark and McCracken (2001) predictive accuracy test (see also Clark and McCracken (2005), Clark and McCracken (2009)).[†] The test has a null hypothesis of equal predictive accuracy and is defined as follows:

$$DM = \sqrt{P-k}\frac{\frac{1}{P}\sum_{t=R}^{T-k}\widehat{d}_{t,k}}{\frac{1}{P-k}\sum_{j=-\overline{j}}^{\overline{j}}\sum_{t=R+j}^{T-k}K\left(\frac{j}{M}\right)\left(\widehat{d}_t-\overline{d}\right)\left(\widehat{d}_{t-j}-\overline{d}\right)},$$

where $\widehat{d}_{t,k} = l(\widehat{\varepsilon}_{1,t,k}) - l(\widehat{\varepsilon}_{2,t,k})$ is a random variable defined to be the difference between the prediction errors of two models that are being compared, when transformed according to a given loss function, l, $\overline{d} = \frac{1}{P-k}\sum_{t=R}^{T-k}\widehat{d}_{t,k}$, and the denominator is a heteroskedasticity and autocorrelation consistent covariance estimator, such as the Newey-West estimator. The limiting distribution of the DM statistic is given in Theorems 3.1 and 3.2 in Clark and McCracken (2005) under quadratic loss, so that $\widehat{d}_{t,k} = \widehat{\varepsilon}^2_{1,t,k} - \widehat{\varepsilon}^2_{2,t,k}$, and is $N(0, 1)$ in cases in which the prediction models are nonnested and parameter estimation error vanishes (or the in-sample and out-of-sample loss functions are the same - see also Corradi and Swanson (2006)). In the sequel, we consider only quadratic loss and hence report mean square forecast errors (MSFEs) as well as DM test statistics based on quadratic loss.

we do not report findings for cases (i) and (iii). Complete results have been tabulated, though, and are available on request from the authors.

[†]Clark and McCracken (2009) reconsider tests for comparing nonnested as well as nested forecasting models, when forecasts are produced using real-time data. They show that, under the news hypothesis, data revisions do not affect the limiting distributions of tests for predictive evaluation. On the other hand, the use of real-time data plays a crucial role whenever revisions are noisy and effects are different, depending on whether we are comparing nonnested or nested models.

In addition to examining MSFE performance using DM statistics, we also formally examine the rationality of early releases. Following the literature[‡], we test for the rationality of ${}_{t+k}X_t$, by finding out whether the conditioning information in a vector ${}_{t+1}W_t$, available to the data issuing agency at the time of first release, has been efficiently used. Our implementation involves including ${}_{t+1}W_t'$ in the regression of each of the three models suggested above with various different revision errors. Formally, we consider the following alternatives: ${}_{t+1}W_t' = {}_{t+1}\ u_{t-1}^t$, ${}_{t+1}W_t' = ({}_{t+1}u_{t-1}^t, {}_t u_{t-2}^{t-1})$, ${}_{t+1}W_t' = {}_{t+1}\ u_{t-2}^{t-1}$, and ${}_{t+1}W_t' = ({}_{t+1}u_{t-1}^t, {}_{t+1}u_{t-2}^t)$, where the notation used in these regressors is defined at the end of the previous subsection. Thus, we directly use the regression models to construct sequences of ex-ante predictions. Then, the accuracy of these predictions is assessed using the DM test. This is therefore a truly out-of-sample rationality test and is in the spirit of those suggested in Ashley, Granger, and Schmalensee (1980), Chao, Corradi, and Swanson (2001), and Corradi and Swanson (2002).

2.3. Data

Our real-time dataset includes real GDP (seasonally adjusted), the GDP chain-weighted price index (seasonally adjusted), the money stock (measured as M1, seasonally adjusted) and the interest rate (measured as the rate on the three-month Treasury bill). All series have a quarterly frequency and our real-time dataset for each of the four variables was obtained from the Federal Reserve Bank of Philadelphia's real-time dataset for Macroeconomists (RTDSM). The RTDSM can be accessed online at *http://www.phil.frb.org/econ/forecast/readow.html*. The series were obtained from the "*by-variable*" files of the "*core variables/quarterly observations/quarterly vintages*" dataset, and are discussed in detail in Croushore and Stark (2001, 2003) and Croushore (2006). Note also that interest rates are not revised, and hence our interest rate dataset is a vector rather than a matrix (see Swanson, Ghysels and Callan (1999) and Ghysels, Swanson, and Callan (2002) for a detailed discussion of the calendar date/vintage structure of real-time datasets).

The first vintage in our sample is 1965:4, for which the first calendar observation is 1959:3. This means that the first observation in our dataset is the observation that was available to researchers in the fourth quarter of 1965, corresponding to calendar-dated data for the third quarter of 1953. The datasets range up to the 2006:4 vintage and the corresponding 2006:3 calendar date, allowing us to keep track of the exact data that were available at each vintage for every possible calendar-dated observation up to one quarter before the vintage date. This makes it possible to trace the entire series of revisions for each observation across vintages.

Various summary information about the datasets is depicted in the first six plots in Figures 1-3. We use log-differences throughout our analysis (except for interest rates); and various releases of the log-differences of all variables, except the interest rate, are depicted in the plots. Also included are plots of the first and second revision errors measured as the difference between the first vintage (e.g. first available) of a calendar observation and the second and third vintages, respectively, and cumulative revision errors for various releases. As can readily be seen on inspection of the distributions of the revision errors as well as via examination of the summary statistics reported in Table 1, the first revision (i.e., the difference between the first and second vintages) is fairly close to normally distributed. On the other hand, the distribution of the second revision errors is mostly concentrated near zero, implying

[‡]See Mankiw, Runkle, and Shapiro (1984), Mankiw and Shapiro (1986), Kavajecz and Collins (1995), Mork (1987), Keane and Runkle (1990) , and Rathjens and Robins (1995) for further details. A summary of this sort of test is given in Swanson and van Dijk (2006).

that much of the revision process has already taken place in the first revision.

Table 1. Growth rate and revision error summary statistics – output, prices, and money.[(*)]

Vrbl	*Vint*	*R-Err*	*smpl*	$\bar{y}$	$\widehat{\sigma}_y$	$\widehat{\sigma}_{\bar{y}}$	*skew*	*kurt*	*LB*	*JB*	*ADF*
Output	1	–	65:4	0.00657	0.00790	0.00061	-1.259	6.734	111.5	134.5	-6.035
	2	–	65:4	0.00705	0.00851	0.00066	-1.148	6.678	107.1	123.8	-6.350
	–	1	65:4	0.00046	0.00189	0.00015	0.118	2.950	23.58	0.424	-6.050
	–	2	65:4	-0.00002	0.00106	0.00008	0.324	8.982	32.01	237.0	-5.471
	1	–	70:1	0.00626	0.00817	0.00068	-1.190	6.395	96.90	101.0	-5.729
	2	–	70:1	0.00675	0.00877	0.00073	-1.111	6.446	92.42	98.05	-4.911
	–	1	70:1	0.00048	0.00193	0.00016	0.041	2.873	28.17	0.208	-5.620
	–	2	70:1	-0.00001	0.00108	0.00009	0.300	9.087	27.70	216.9	-5.128
	1	–	83:1	0.00734	0.00486	0.00050	0.230	3.940	44.55	3.728	-6.299
	2	–	83:1	0.00766	0.00538	0.00056	0.379	3.958	53.06	5.179	-6.178
	–	1	83:1	0.00029	0.00171	0.00018	-0.301	2.677	25.53	1.944	-9.994
	–	2	83:1	0.00012	0.00098	0.00010	1.753	9.658	14.73	207.4	-9.753
	1	–	90:1	0.00682	0.00463	0.00057	-0.376	3.470	30.12	1.892	-5.513
	2	–	90:1	0.00724	0.00510	0.00063	-0.195	3.277	38.83	0.490	-5.508
	–	1	90:1	0.00037	0.00161	0.00020	-0.091	2.077	17.02	2.755	-3.667
	–	2	90:1	0.00008	0.00093	0.00012	2.090	12.60	13.24	275.2	-8.226
Prices	1	–	65:4	0.00958	0.00608	0.00047	1.163	4.093	1040	44.05	-1.613
	2	–	65:4	0.00988	0.00636	0.00049	1.245	4.272	925.4	51.79	-1.463
	–	1	65:4	0.00026	0.00114	0.00009	1.235	7.277	35.13	160.8	-5.384
	–	2	65:4	-0.00001	0.00054	0.00004	-1.335	13.30	10.61	745.4	-12.93
	1	–	70:1	0.00968	0.00638	0.00052	1.093	3.716	955.5	31.43	-1.411
	2	–	70:1	0.01001	0.00666	0.00055	1.173	3.884	852.6	37.00	-1.274
	–	1	70:1	0.00029	0.00118	0.00010	1.175	6.844	33.78	118.5	-4.891
	–	2	70:1	-0.00003	0.00055	0.00005	-1.484	13.28	12.24	669.0	-9.487
	1	–	83:1	0.00624	0.00297	0.00030	0.471	2.992	191.9	3.429	-1.998
	2	–	83:1	0.00646	0.00296	0.00030	0.424	2.693	192.4	3.256	-1.699
	–	1	83:1	0.00020	0.00096	0.00010	1.423	10.95	16.40	264.2	-8.831
	–	2	83:1	-0.00001	0.00053	0.00006	-1.506	17.27	14.99	783.4	-7.982
	1	–	90:1	0.00528	0.00261	0.00032	0.872	4.549	50.94	13.71	-1.914
	2	–	90:1	0.00553	0.00252	0.00031	0.661	3.499	60.61	5.018	-1.285
	–	1	90:1	0.00023	0.00083	0.00010	2.748	17.87	13.34	644.4	-7.535
	–	2	90:1	-0.00004	0.00056	0.00007	-2.321	18.07	13.61	627.0	-8.304
Money	1	–	65:4	0.01207	0.01200	0.00093	0.077	3.119	169.2	0.209	-3.364
	2	–	65:4	0.01240	0.01191	0.00093	0.097	3.169	173.2	0.374	-4.922
	–	1	65:4	0.00018	0.00135	0.00011	1.800	12.30	15.50	660.0	-13.33
	–	2	65:4	0.00009	0.00113	0.00009	1.316	14.54	11.80	923.2	-12.13
	1	–	70:1	0.01221	0.01244	0.00103	0.068	2.983	166.7	0.131	-4.488
	2	–	70:1	0.01256	0.01235	0.00103	0.088	3.029	170.3	0.187	-4.464
	–	1	70:1	0.00018	0.00140	0.00012	1.785	11.72	16.31	521.8	-12.67
	–	2	70:1	0.00005	0.00117	0.00010	1.344	14.26	10.67	782.4	-11.62
	1	–	83:1	0.01085	0.01403	0.00145	0.283	2.682	159.2	1.783	-3.108
	2	–	83:1	0.01120	0.01391	0.00144	0.301	2.728	163.1	1.805	-3.131
	–	1	83:1	0.00010	0.00138	0.00014	2.155	12.96	11.76	438.3	-10.04
	–	2	83:1	0.00009	0.00090	0.00009	-0.056	7.032	19.05	58.43	-9.292
	1	–	90:1	0.00788	0.01302	0.00160	0.360	2.955	162.5	1.437	-2.218
	2	–	90:1	0.00827	0.01302	0.00161	0.454	3.170	159.7	2.188	-2.273
	–	1	90:1	0.00009	0.00139	0.00017	1.383	9.642	16.40	131.0	-8.506
	–	2	90:1	0.00001	0.00095	0.00012	-0.488	6.006	18.34	24.04	-7.682

[(*)] Notes: Summary statistics are reported for a generic variable denoted by y, where y = output, price, and money growth rates (see table rows where *vint* = 1,2, corresponding to first and second available data), as well where y = the *revision error* associated with these variables (see table rows where *R-Err* = 1,2, corresponding to revision errors associated with second and third available data - i.e., ${}_{t+2}u_t^{t+1}$ and ${}_{t+3}u_t^{t+2}$). Statistics are reported for samples beginning in 1970:1, 1983:1, and 1990:1. All samples end in 2006:4. Additionally, $\bar{y}$ is the mean of the series, $\widehat{\sigma}_y$ is the standard error of the series, $\widehat{\sigma}_{\bar{y}}$ is the standard error of $\bar{y}$, *skew* is skewness, *kurt* is kurtosis, *LB* is the Ljung-Box statistic, *JB* is the Jarques-Bera statistic, and *ADF* is the augmented Dickey-Fuller statistic, where lag augmentations are selected via use of the Schwarz information criterion. See Section 2 for further details.

Indeed, the distributional shape of revision errors beyond the first revision is very much the same as that reported for the second revision in these plots, with the exception of revision errors associated with definitional and/or other structural issues associated with the variables. This is one of the reasons why much of our analysis focuses only on the impact of first and second revision errors - later revision errors appear to offer little useful information other than signalling the presence of definitional and related structural issues associated with the variables. This feature of the data is illustrated in plots with title “Calendar data across vintages” in Figures 1-3, where we have plotted early calendar dates (e.g., 1959:1; 1962:1; and 1965:3) across all available vintages in our sample. Data for a particular calendar date sometimes vary significantly across vintages. For instance, looking at the 1959:Q4 calendar observation for output across all vintages, one can observe several discrete movements driving the value of that particular observation from a monthly growth of 1% for the earlier vintages to 0.5% for the later vintages. It seems reasonable to argue that most (if not all) of the discrete variations in that particular calendar observation are not due to “pure revisions”, but are solely a consequence of definitional breaks in the measurement of output. Similar breaks are observed for prices and money in Figures 2 and 3.

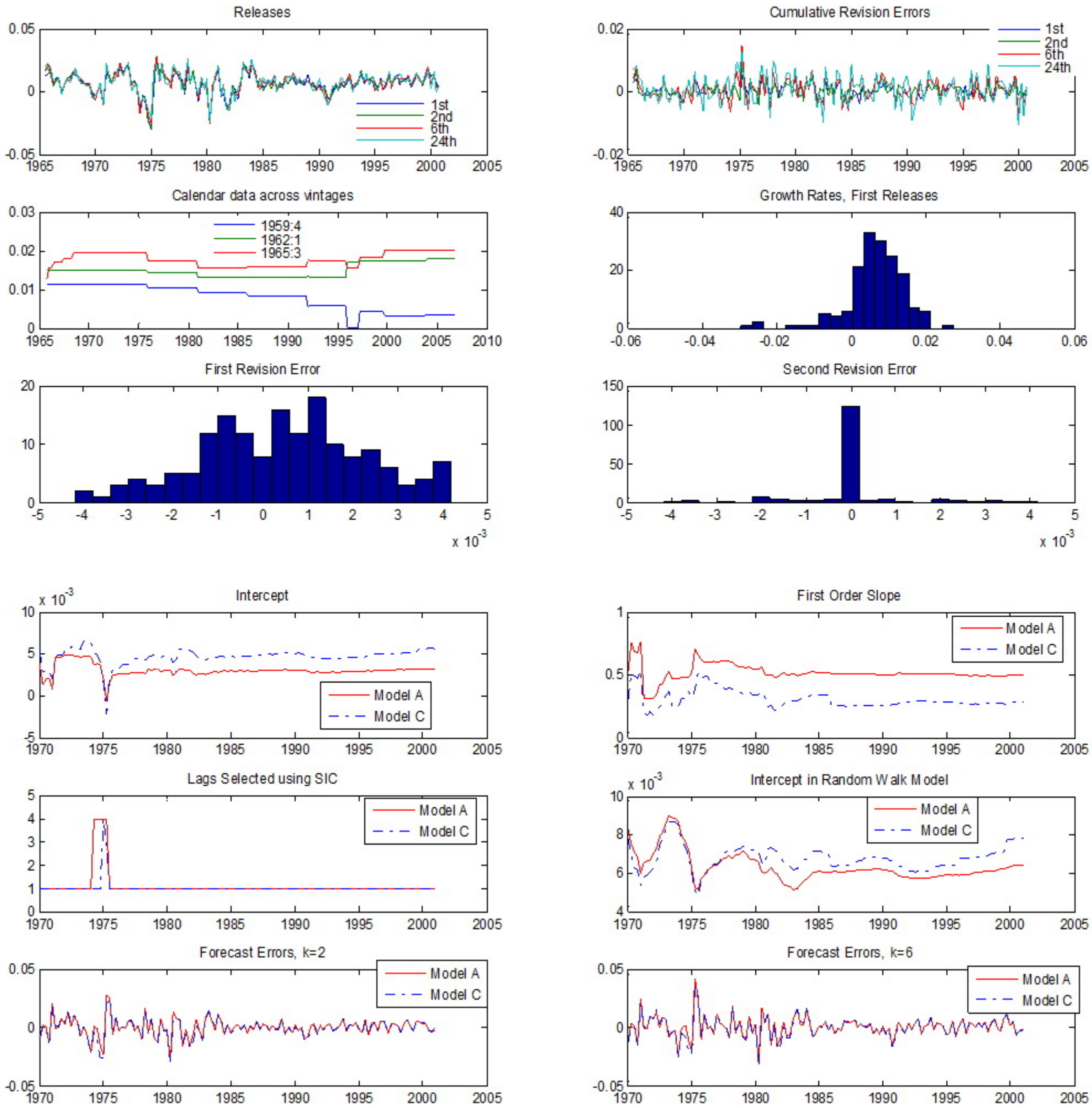

Figure 1. Output - historical data and prediction results.

(*)Notes: See notes to Figure 2.

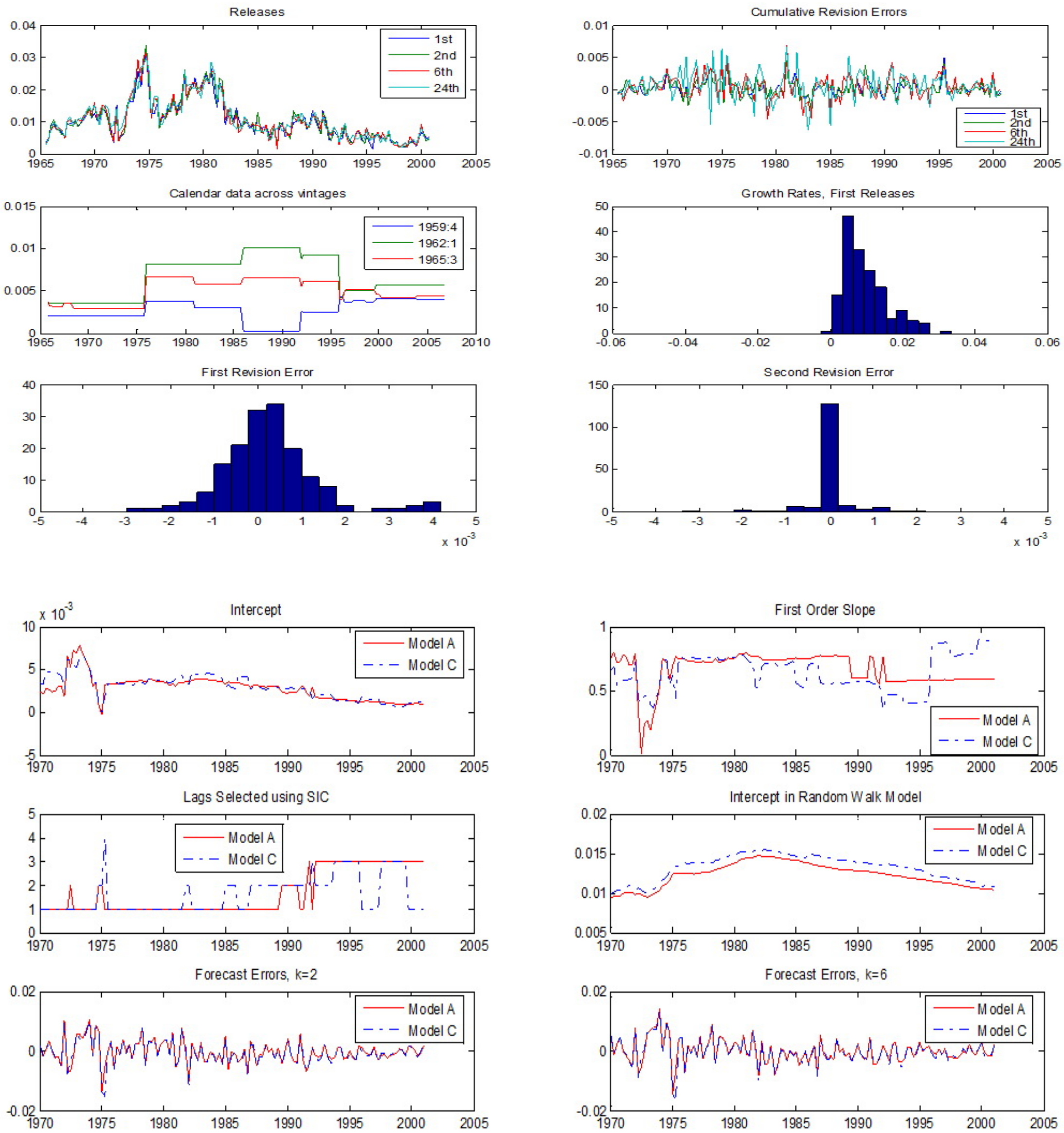

Figure 2. Prices - historical data and prediction results.

(*)Notes: The upper six panels describe the main properties of the real-time dataset for the growth rate of output (X) as follows: (i) ”Releases” plots the time series for ${}_{t+k}X_t$, $k = 1, 2, 6, 24$; ”Cumulative Revision Errors” plots the time series for ${}_{t+k}X_t - {}_{t+1}X_t$, $k = 1, 2, 6, 24$; (iii) ”Calendar data across vintages” plots the time series for three calendar dates across all available vintages, where the calendar dates are ${}_{1959:4+k}X_{1959:4}, {}_{1962:1+k}X_{1962:1}, {}_{1965:3+k}X_{1965:3}$, for all k; (iv) ”Growth Rates, First Releases” plots the distribution of ${}_{t+1}X_t$ across the entire sample; and (v) ”First” and ”Second Revision Error” plots the distribution of ${}_{t+2}X_t - {}_{t+1}X_t$ and ${}_{t+3}X_t - {}_{t+2}X_t$, respectively. The lower six panels describe the main results from the recursive estimation of Models A and C as follows: (i) ”Intercept”, ”First order Slope”, and ”Intercept in Random Walk Model” plot the recursive estimates of, respectively, $a^M_{t+1,t}, \beta^M_{1,t+1,t}, a^{RWM}_{t+1,t}$, for $M = A, C$, where $a^{RWM}_{t+1,t}$ is the slope of the random walk model associated to model M (see notes to Table 2); (iii) ”Lags Selected using SIC” reports the number of lags selected using the SIC across all recursively estimated models; and (iv) ”Forecast Errors, k=2” and ”k=6” report, respectively, ${}_{t+k}X_t - {}_{t+k}X^M_t$ $k = 2, 6$; $M = A, C$.

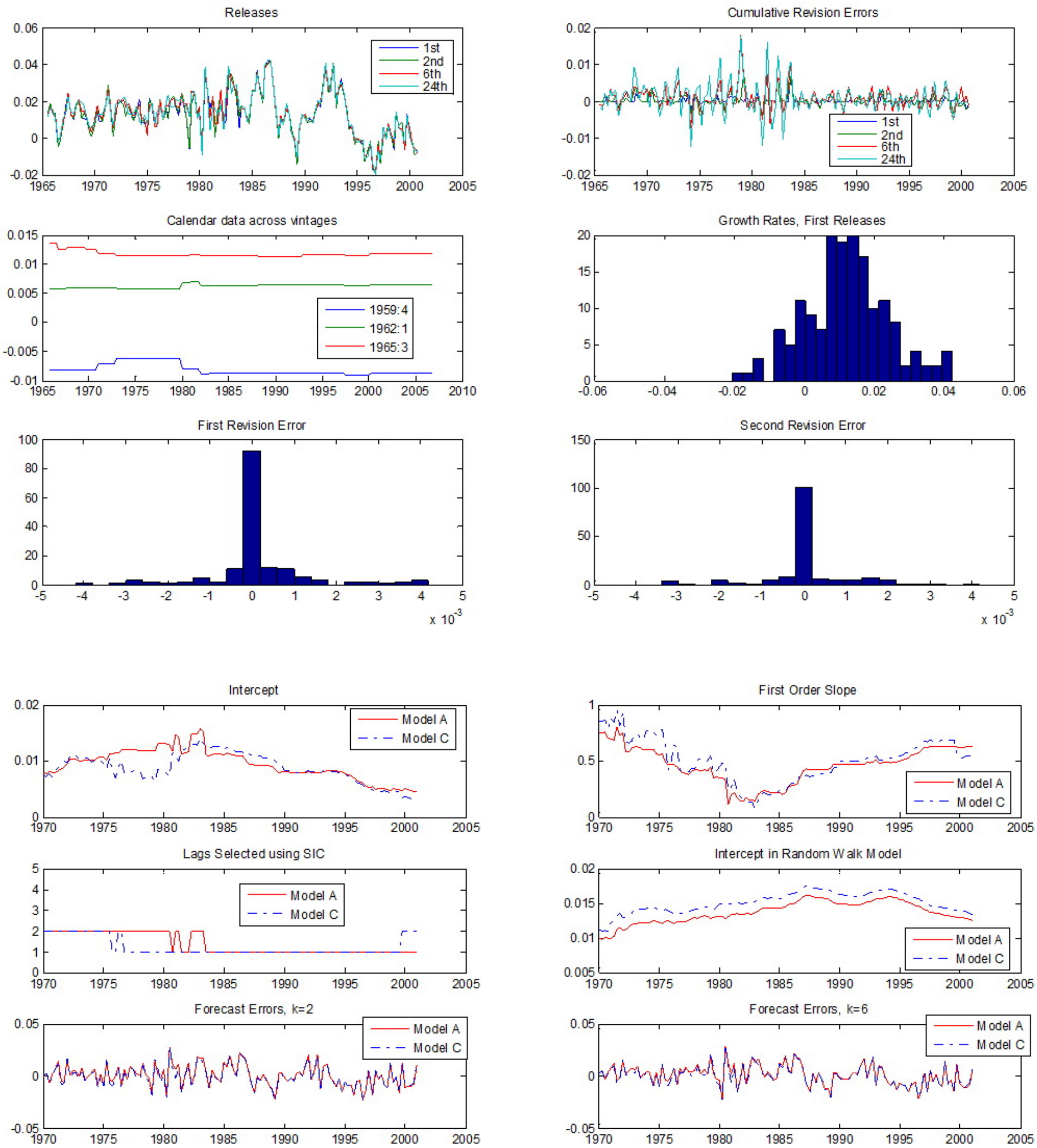

Figure 3. Money - historical data and prediction results.

(*)Notes: See notes to Figure 2.

3. Results

3.1. Prediction Experiments

As discussed in Section 3, we carried out three types of autoregressive prediction experiments, in which the objective was to forecast output, prices, and money. The methods involved fitting regression Models A, B, and C. Recall that Model B is our "strawman" model, and should be expected to perform increasingly poorly as k increases. Moreover, Model A involves constructing predictions using only first release data and hence might be expected to perform poorly for predicting k^{th} releases, when k is large, assuming that either our data are irrational, or definitional changes result in "contamination" of the earliest first release calendar-dated observations used in the construction of our prediction models. On the other hand, Model C uses a mixture of releases both in parameter estimation and in prediction construction. Thus, even if there are efficiency problems associated with using first release data in Model A, these may be outweighed by the cost of using mixed releases of data in Model C, and hence Model A might still be MSFE-best.

Tables 2-4 report our results on the predictive accuracy of Models A-C using simple autoregressive models. Entries in the tables are MSFEs and DM test statistics that are calculated with Model A as the benchmark. In Tables 2-4, entries in bold denote lowest MSFEs for a particular value of k, across all three models. Each Table is subdivided into different panels according to the date of the first prediction (either 1970:1, 1983:1, or 1990:1). All predictions are constructed using recursively estimated models.

A number of clear-cut conclusions emerge when the results reported in these tables are examined. In Table 2, the MSFE-best output predictions result when using Model A for low values of k, and using Model C for high values of k. However, for price predictions (see Table 3), Model A is always MSFE-best, while for money, Model C is always MSFE-best, regardless of release being predicted and data subsample (see Table 4). As expected, Model B performs poorly and is particularly ineffective for larger values of k for all three variables. Additionally, the real-time random walk with drift models that we estimate never yields predictions as accurate as those based on our autoregressive type models.

We have clear evidence that whether or not one should use the latest or earlier releases of data in model parameter estimation and prediction construction is not just dependent on the release of data to be predicted, but is also dependent on what the target variable of interest is. When the target variable is money, Model C is preferred (i.e., use the latest available data). However, when the target variable is prices, Model A is preferred. Most importantly, precisely which model is preferred is *independent of the release, k, being predicted,* for both prices and money. This suggests that the "target release" to be predicted is actually not very important for these variables, which is quite surprising as one might expect the cumulative effect that the combination of inefficiency, measurement error, and definitional change has on model choice will result in different models being chosen when the target release to be predicted increases from preliminary to final data, as is the case with output.

Table 2. MSFEs calculated based on simple real-time autoregressions without revision errors for output.(*)

Model	*RevErr*	$k = 2$	$k = 3$	$k = 4$	$k = 6$	$k = 12$	$k = 24$
Panel A: Mean Square Forecast Errors							
Begin Date of Forecast Period =1970:1							
A	None	**0.642**	**0.783**	**0.825**	0.841	0.839	0.836
B	None	0.642	0.983	1.028	1.232	1.090	1.134
C	None	0.661	0.792	**0.825**	**0.828**	**0.817**	**0.815**
RWD-A	None	0.768	0.879	0.890	0.861	0.833	0.843
RWD-B	None	0.768	0.896	0.916	0.905	0.846	0.925
RWD-C	None	0.766	0.874	0.884	0.856	0.829	0.838
Begin Date of Forecast Period =1983:1							
A	None	0.212	**0.259**	0.270	0.303	0.322	0.354
B	None	0.212	0.303	0.322	0.490	0.466	0.573
C	None	**0.206**	**0.259**	**0.267**	**0.299**	**0.316**	**0.346**
RWD-A	None	0.275	0.337	0.345	0.374	0.382	0.419
RWD-B	None	0.275	0.326	0.337	0.359	0.345	0.363
RWD-C	None	0.248	0.309	0.314	0.343	0.356	0.387
Begin Date of Forecast Period =1990:1							
A	None	**0.175**	**0.204**	**0.216**	0.278	**0.286**	0.332
B	None	0.175	0.247	0.236	0.343	0.432	0.491
C	None	0.176	0.214	**0.216**	**0.275**	0.289	**0.329**
RWD-A	None	0.224	0.275	0.270	0.322	0.327	0.371
RWD-B	None	0.224	0.271	0.266	0.324	0.344	0.379
RWD-C	None	0.208	0.258	0.250	0.304	0.319	0.356
Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A							
Begin Date of Forecast Period =1970:1							
A	None	—	—	—	—	—	—
B	None	—	-1.415	-1.423	-2.216	-1.148	-1.586
C	None	-0.349	-0.159	-0.008	0.213	0.348	0.368
RWD-A	None	-1.077	-0.718	-0.446	-0.125	0.035	-0.047
RWD-B	None	-1.077	-0.811	-0.589	-0.359	-0.041	-0.470
RWD-C	None	-1.070	-0.689	-0.411	-0.097	0.057	-0.012
Begin Date of Forecast Period =1983:1							
A	None	—	—	—	—	—	—
B	None	—	-1.096	-1.056	-2.558	-2.467	-2.542
C	None	0.480	-0.053	0.255	0.344	0.378	0.562
RWD-A	None	-1.525	-1.826	-1.718	-1.688	-1.568	-1.582
RWD-B	None	-1.525	-1.638	-1.576	-1.421	-0.568	-0.200
RWD-C	None	-0.989	-1.366	-1.242	-1.181	-1.001	-0.936
Begin Date of Forecast Period =1990:1							
A	None	—	—	—	—	—	—
B	None	—	-1.419	-0.683	-1.943	-1.743	-2.365
C	None	-0.060	-0.570	-0.039	0.166	-0.149	0.157
RWD-A	None	-1.316	-1.771	-1.499	-1.182	-1.188	-1.157
RWD-B	None	-1.316	-1.557	-1.336	-1.075	-1.027	-0.764
RWD-C	None	-0.852	-1.281	-0.976	-0.711	-0.845	-0.647

(*)Notes: In Panel A, forecast mean square errors (MSFEs) are reported based on predictions constructed using recursively estimated models with estimation period beginning in 1965:4 and ex-ante prediction periods beginning in 1970:1, 1983:1, or 1990:1. Corresponding Diebold-Mariano predictive accuracy test statistics are reported in Panel B. In all cases, Model A is set as the "benchmark" model, so that a negative statistic means that Model A is "MSFE-better" than the particular model against which it is being compared. All estimated models are either pure autoregressions or autoregressions with revision error(s) included as additional explanatory variables. Lags are selected using the Schwarz Information Criterion. The pure autoregression models are: Model A (*First Available Data)*, Model B *(k^{th}Available Data)* , and Model C *(Latest Available Data)* . In the models, X denotes the growth rate of either output, prices, or money. Also, RWD is the random walk with drift model in log levels, $u_{C1} = {}_{t+1}u^{t}_{t-k}$, $k = 1$; $u_{C2} = {}_{t+1}u^{t}_{t-k}$, $k = 1, 2$; and $u_{C3} = {}_{t+1}u^{t+2-k}_{t+1-k}$, $k = 3$. Further details are contained in Section 2.

Finally, note that MSFEs associated with the "best" models for money (i.e., Model C) largely decrease as k increases. This is consistent with the view that using "latest available" data that have been revised as much as possible, when forming model coefficient estimates, leads to estimates that are more accurate when the objective is the prediction of later release or even "final" data. This in turn suggests that later releases of data should be predicted more accurately using Model C (as is indeed the case for money, where Model C is actually the MSFE-best model), but not necessarily when using other models. Indeed, notice that for prices, where Model A wins, the MSFEs actually increase as one increases k from 2 to 3 to 4, before beginning to decrease. The same sort of mixed pattern of increasing and decreasing MSFEs characterizes output.

Table 3. MSFEs calculated based on simple real-time autoregressions without revision errors for prices.(*)

Model	*RevErr*	$k=2$	$k=3$	$k=4$	$k=6$	$k=12$	$k=24$
		Panel A: Mean Square Forecast Errors					
		Begin Date of Forecast Period =1970:1					
A	None	**0.149**	**0.166**	**0.167**	**0.163**	**0.139**	**0.125**
B	None	0.149	0.214	0.211	0.339	0.516	0.608
C	None	0.160	0.179	0.182	0.178	0.151	0.137
RWD-A	None	0.430	0.463	0.457	0.442	0.444	0.437
RWD-B	None	0.430	0.486	0.489	0.495	0.557	0.739
RWD-C	None	0.472	0.500	0.496	0.480	0.478	0.469
		Begin Date of Forecast Period =1983:1					
A	None	**0.072**	**0.076**	**0.075**	**0.069**	**0.063**	**0.063**
B	None	0.072	0.077	0.076	0.088	0.257	0.556
C	None	0.075	0.079	0.079	0.073	0.066	0.065
RWD-A	None	0.395	0.376	0.374	0.362	0.349	0.360
RWD-B	None	0.395	0.414	0.416	0.394	0.380	0.303
RWD-C	None	0.512	0.488	0.486	0.474	0.458	0.469
		Begin Date of Forecast Period =1990:1					
A	None	**0.057**	**0.047**	**0.050**	**0.049**	**0.040**	**0.043**
B	None	0.057	0.059	0.054	0.073	0.108	0.191
C	None	0.061	0.051	0.053	0.053	0.042	**0.043**
RWD-A	None	0.440	0.406	0.409	0.387	0.368	0.378
RWD-B	None	0.440	0.447	0.455	0.426	0.419	0.388
RWD-C	None	0.561	0.522	0.526	0.500	0.478	0.489
		Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A					
		Begin Date of Forecast Period =1970:1					
A	None	—	—	—	—	—	—
B	None	—	-1.419	-1.222	-3.003	-4.030	-5.085
C	None	-0.704	-0.758	-0.788	-0.826	-0.807	-0.741
RWD-A	None	-5.584	-5.526	-5.408	-5.565	-5.575	-5.926
RWD-B	None	-5.584	-5.802	-5.647	-5.648	-5.614	-5.647
RWD-C	None	-6.462	-6.544	-6.417	-6.587	-6.677	-6.936
		Begin Date of Forecast Period =1983:1					
A	None	—	—	—	—	—	—
B	None	—	-0.061	-0.074	-1.589	-2.627	-3.793
C	None	-0.747	-0.782	-0.715	-0.971	-0.735	-0.452
RWD-A	None	-8.740	-8.298	-8.206	-8.827	-8.798	-8.741
RWD-B	None	-8.740	-8.787	-8.724	-9.020	-8.444	-6.042
RWD-C	None	-9.928	-9.616	-9.594	-10.408	-10.37	-10.06
		Begin Date of Forecast Period =1990:1					
A	None	—	—	—	—	—	—
B	None	—	-1.669	-0.280	-1.763	-3.278	-3.967
C	None	-0.703	-0.983	-0.429	-0.628	-0.341	-0.171
RWD-A	None	-7.913	-7.974	-7.956	-7.497	-7.640	-7.676
RWD-B	None	-7.913	-8.341	-8.378	-7.720	-7.768	-7.149
RWD-C	None	-8.813	-9.031	-9.185	-8.671	-8.850	-8.730

(*) Notes: See notes to Table 2 .

Table 4. MSFEs calculated based on simple real-time autoregressions without revision errors for money.[*]

Model	*RevErr*	$k = 2$	$k = 3$	$k = 4$	$k = 6$	$k = 12$	$k = 24$
			Panel A: Mean Square Forecast Errors				
			Begin Date of Forecast Period =1970:1				
A	None	1.030	1.024	1.008	0.937	0.984	0.998
B	None	1.030	1.253	1.284	1.253	2.000	1.692
C	None	**1.025**	**1.016**	**0.999**	**0.918**	**0.948**	**0.971**
RWD-A	None	1.633	1.630	1.612	1.556	1.565	1.567
RWD-B	None	1.633	1.650	1.646	1.611	1.666	1.752
RWD-C	None	1.650	1.643	1.623	1.560	1.562	1.561
			Begin Date of Forecast Period =1983:1				
A	None	1.168	1.140	1.099	1.007	1.022	1.040
B	None	1.168	1.366	1.475	1.682	2.824	2.308
C	None	**1.117**	**1.088**	**1.042**	**0.949**	**0.955**	**0.979**
RWD-A	None	2.257	2.235	2.199	2.140	2.142	2.148
RWD-B	None	2.257	2.277	2.281	2.285	2.344	2.314
RWD-C	None	2.323	2.300	2.260	2.201	2.198	2.208
			Begin Date of Forecast Period =1990:1				
A	None	1.058	1.058	1.035	0.916	0.907	0.955
B	None	1.058	1.155	1.219	1.591	3.001	2.480
C	None	**1.023**	**1.023**	**0.995**	**0.877**	**0.861**	**0.915**
RWD-A	None	2.383	2.395	2.387	2.319	2.279	2.312
RWD-B	None	2.383	2.452	2.499	2.541	2.589	2.487
RWD-C	None	2.539	2.551	2.542	2.475	2.431	2.464
			Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A				
			Begin Date of Forecast Period =1970:1				
A	None	—	—	—	—	—	—
B	None	—	-2.499	-2.621	-2.391	-3.486	-3.087
C	None	0.155	0.252	0.301	0.666	1.251	0.914
RWD-A	None	-3.635	-3.643	-3.624	-3.671	-3.379	-3.268
RWD-B	None	-3.635	-3.630	-3.583	-3.520	-3.395	-4.090
RWD-C	None	-3.419	-3.390	-3.370	-3.364	-3.078	-2.958
			Begin Date of Forecast Period =1983:1				
A	None	—	—	—	—	—	—
B	None	—	-2.099	-2.444	-3.821	-4.059	-3.758
C	None	1.423	1.474	1.622	1.805	1.917	1.802
RWD-A	None	-4.404	-4.439	-4.466	-4.577	-4.482	-4.380
RWD-B	None	-4.404	-4.455	-4.504	-4.562	-4.507	-4.695
RWD-C	None	-4.266	-4.279	-4.294	-4.392	-4.317	-4.232
			Begin Date of Forecast Period =1990:1				
A	None	—	—	—	—	—	—
B	None	—	-0.710	-1.014	-2.736	-3.411	-3.222
C	None	1.264	1.264	1.366	1.777	1.788	1.553
RWD-A	None	-3.770	-3.803	-3.840	-3.969	-3.850	-3.717
RWD-B	None	-3.770	-3.825	-3.892	-4.042	-4.001	-4.080
RWD-C	None	-3.796	-3.825	-3.858	-3.974	-3.874	-3.753

[*] Notes: See notes to Table 2.

Table 5. MSFEs calculated based on simple real-time autoregressions with revision errors for output.[(*)]

Model	*RevErr*	$k=2$	$k=3$	$k=4$	$k=6$	$k=12$	$k=24$
		Panel A: Mean Square Forecast Errors					
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	0.636	0.778	0.822	0.848	0.848	0.848
A	u_{C2}	0.729	0.883	0.932	0.962	0.967	0.961
A	u_{C3}	0.681	0.830	0.873	0.889	0.887	0.883
A	u_{C4}	0.645	0.783	0.827	0.862	0.868	0.873
C	u_{C1}	0.656	0.798	0.828	0.845	0.841	0.852
C	u_{C2}	0.781	0.945	0.986	1.023	1.031	1.028
C	u_{C3}	**0.618***	**0.749***	**0.781***	**0.827***	**0.804***	0.818
C	u_{C4}	0.659	0.811	0.846	0.886	0.892	0.902
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	0.220	0.268	0.278	0.310	0.332	0.364
A	u_{C2}	0.226	0.274	0.284	0.312	0.335	0.365
A	u_{C3}	0.216	0.263	0.274	0.304	0.322	0.354
A	u_{C4}	0.224	0.272	0.282	0.313	0.336	0.371
C	u_{C1}	0.247	0.301	0.307	0.335	0.366	0.393
C	u_{C2}	0.245	0.300	0.306	0.333	0.365	0.392
C	u_{C3}	0.230	0.285	0.290	0.321	0.337	0.370
C	u_{C4}	0.260	0.316	0.324	0.350	0.389	0.415
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	0.184	0.211	0.222	0.286	0.295	0.342
A	u_{C2}	0.186	0.212	0.224	0.288	0.297	0.343
A	u_{C3}	0.176	0.205	0.217	0.279	0.288	0.332
A	u_{C4}	0.185	0.213	0.224	0.288	0.300	0.351
C	u_{C1}	0.206	0.238	0.241	0.306	0.324	0.366
C	u_{C2}	0.201	0.233	0.237	0.303	0.321	0.365
C	u_{C3}	0.193	0.227	0.231	0.293	0.302	0.348
C	u_{C4}	0.215	0.246	0.250	0.321	0.340	0.383
Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A							
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	0.277	0.209	0.111	-0.260	-0.335	-0.445
A	u_{C2}	-0.889	-0.881	-0.872	-0.863	-0.889	-0.915
A	u_{C3}	-1.748	-1.744	-1.646	-1.485	-1.418	-1.448
A	u_{C4}	-0.099	-0.001	-0.070	-0.445	-0.651	-0.814
C	u_{C1}	-0.217	-0.207	-0.044	-0.058	-0.034	-0.232
C	u_{C2}	-1.410	-1.438	-1.315	-1.294	-1.320	-1.381
C	u_{C3}	0.353	0.453	0.567	0.208	0.488	0.276
C	u_{C4}	-0.373	-0.543	-0.404	-0.815	-0.983	-1.224
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	-1.084	-0.958	-0.884	-0.742	-1.118	-0.978
A	u_{C2}	-1.539	-1.404	-1.308	-0.853	-1.154	-1.022
A	u_{C3}	-1.309	-1.304	-1.277	-0.302	-0.104	-0.111
A	u_{C4}	-1.180	-1.045	-0.974	-0.851	-1.151	-1.253
C	u_{C1}	-1.284	-1.369	-1.200	-1.058	-1.362	-1.154
C	u_{C2}	-1.248	-1.342	-1.167	-1.018	-1.369	-1.174
C	u_{C3}	-0.954	-1.267	-0.996	-0.891	-0.704	-0.688
C	u_{C4}	-1.448	-1.544	-1.469	-1.214	-1.594	-1.430
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	-1.720	-1.358	-1.277	-1.276	-1.299	-1.295
A	u_{C2}	-1.583	-1.263	-1.210	-1.149	-1.213	-1.162
A	u_{C3}	-0.466	-0.455	-0.382	-0.168	-0.426	-0.167
A	u_{C4}	-1.412	-1.042	-0.904	-1.031	-1.141	-1.360
C	u_{C1}	-1.084	-1.252	-0.965	-0.867	-1.041	-0.935
C	u_{C2}	-1.022	-1.195	-0.890	-0.833	-1.024	-0.978
C	u_{C3}	-0.791	-1.025	-0.685	-0.598	-0.569	-0.551
C	u_{C4}	-1.051	-1.178	-0.976	-0.918	-1.072	-1.003

[(*)] Notes: See notes to Table 2. Revision errors included as additional regressors in the prediction equations reported on in Table 2 are: $u_{C1} = {}_{t+1}u^{t}_{t-1}$, $u_{C2} = ({}_{t+1}u^{t}_{t-1}, {}_{t}u^{t-1}_{t-2})$, $u_{C3} = {}_{t+1}u^{t-1}_{t-2}$, and $u_{C4} = ({}_{t+1}u^{t}_{t-1}, {}_{t+1}u^{t}_{t-2})$. Bold numbers highlight cases in which the inclusion of revision errors lowers the MSFE compared to models without revision errors. A star denotes cases in which a different model than the one found in Tables 2-4 reaches a lower MSFE. Further details are contained in Section 2.

Table 6. MSFEs calculated based on simple real-time autoregressions with revision errors for prices.(*)

Model	*RevErr*	$k = 2$	$k = 3$	$k = 4$	$k = 6$	$k = 12$	$k = 24$
		Panel A: Mean Square Forecast Errors					
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	0.145	0.163	0.164	0.161	0.136	0.124
A	u_{C2}	**0.143**	**0.161**	**0.162**	**0.160**	**0.136**	**0.121**
A	u_{C3}	0.153	0.170	0.170	0.167	0.141	0.124
A	u_{C4}	0.150	0.166	0.167	0.166	0.139	0.122
C	u_{C1}	0.155	0.174	0.177	0.173	0.146	0.132
C	u_{C2}	0.164	0.183	0.187	0.185	0.155	0.137
C	u_{C3}	0.159	0.178	0.181	0.178	0.150	0.136
C	u_{C4}	0.156	0.174	0.177	0.175	0.148	0.133
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	0.072	0.076	0.075	0.069	0.063	0.063
A	u_{C2}	**0.070**	**0.073**	**0.073**	0.069	0.064	0.061
A	u_{C3}	0.072	0.076	0.076	0.070	0.064	0.064
A	u_{C4}	0.073	0.076	0.076	0.071	**0.062**	**0.060**
C	u_{C1}	0.076	0.081	0.081	0.076	0.069	0.068
C	u_{C2}	0.077	0.081	0.082	0.080	0.074	0.069
C	u_{C3}	0.080	0.084	0.083	0.079	0.071	0.069
C	u_{C4}	0.078	0.082	0.081	0.077	0.070	0.067
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	0.057	0.046	0.050	0.049	0.041	**0.042**
A	u_{C2}	**0.053**	**0.043**	**0.048**	**0.048**	0.042	0.043
A	u_{C3}	0.058	0.047	0.051	0.050	0.041	0.043
A	u_{C4}	0.057	0.045	0.050	0.049	0.041	0.044
C	u_{C1}	0.063	0.053	0.055	0.055	0.045	0.045
C	u_{C2}	0.060	0.050	0.056	0.056	0.048	0.048
C	u_{C3}	0.066	0.055	0.057	0.057	0.046	0.046
C	u_{C4}	0.065	0.054	0.056	0.057	0.046	0.047
Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A							
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	0.397	0.284	0.247	0.185	0.347	0.110
A	u_{C2}	0.592	0.567	0.478	0.279	0.378	0.486
A	u_{C3}	-1.086	-0.862	-0.846	-0.902	-0.472	0.132
A	u_{C4}	-0.127	0.033	-0.033	-0.241	0.087	0.292
C	u_{C1}	-0.480	-0.619	-0.702	-0.765	-0.618	-0.621
C	u_{C2}	-1.074	-1.141	-1.234	-1.387	-1.260	-0.904
C	u_{C3}	-0.792	-0.930	-0.961	-1.076	-1.007	-0.908
C	u_{C4}	-0.563	-0.670	-0.756	-0.857	-0.732	-0.676
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	0.070	0.455	0.317	0.219	0.064	0.653
A	u_{C2}	0.665	0.957	0.741	0.213	-0.427	0.822
A	u_{C3}	-0.440	-1.109	-1.249	-1.680	-1.528	-1.568
A	u_{C4}	-0.217	0.131	-0.020	-0.325	0.292	0.599
C	u_{C1}	-1.151	-1.301	-1.242	-1.610	-1.337	-0.976
C	u_{C2}	-1.062	-0.878	-1.454	-2.333	-2.420	-1.502
C	u_{C3}	-1.914	-1.866	-1.730	-2.235	-1.705	-1.158
C	u_{C4}	-1.474	-1.400	-1.355	-1.677	-1.529	-0.936
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	0.614	0.445	0.569	0.370	-0.176	1.601
A	u_{C2}	0.836	0.861	0.723	0.241	-0.414	-0.007
A	u_{C3}	-0.613	-0.991	-1.176	-1.751	-1.665	-1.380
A	u_{C4}	0.156	0.367	0.221	-0.109	-0.206	-0.339
C	u_{C1}	-1.316	-1.496	-0.902	-1.107	-0.794	-0.561
C	u_{C2}	-0.600	-0.640	-1.257	-1.503	-2.111	-1.646
C	u_{C3}	-1.856	-1.951	-1.279	-1.341	-0.962	-0.672
C	u_{C4}	-1.656	-1.768	-1.186	-1.409	-1.091	-0.870

(*) Notes: See notes to Table 2 and Table 5.

Table 7. MSFEs calculated based on simple real-time autoregressions with revision errors for money.(*)

Model	*RevErr*	$k = 2$	$k = 3$	$k = 4$	$k = 6$	$k = 12$	$k = 24$
		Panel A: Mean Square Forecast Errors					
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	1.035	1.030	1.013	0.937	0.982	0.992
A	u_{C2}	1.030	1.026	1.012	0.934	0.979	0.992
A	u_{C3}	1.030	1.024	1.008	0.935	0.983	1.001
A	u_{C4}	1.043	1.038	1.020	0.944	0.988	1.001
C	u_{C1}	1.037	1.029	1.014	0.935	0.961	0.979
C	u_{C2}	1.044	1.036	1.023	0.942	0.969	0.991
C	u_{C3}	1.040	1.030	1.012	0.933	0.963	0.983
C	u_{C4}	1.075	1.067	1.050	0.968	0.992	1.001
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	1.161	1.135	1.093	0.992	1.010	1.033
A	u_{C2}	1.147	1.121	1.080	0.984	1.002	1.031
A	u_{C3}	1.157	1.130	1.089	0.998	1.011	1.036
A	u_{C4}	1.163	1.137	1.095	0.994	1.012	1.035
C	u_{C1}	1.117	1.089	1.043	0.948	0.958	0.984
C	u_{C2}	**1.112**	**1.084**	**1.039**	**0.947**	0.956	0.987
C	u_{C3}	1.119	1.089	1.042	0.950	0.960	0.985
C	u_{C4}	1.121	1.093	1.046	0.951	0.960	0.987
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	1.064	1.065	1.042	0.905	0.897	0.950
A	u_{C2}	1.051	1.051	1.028	0.892	0.884	0.937
A	u_{C3}	1.050	1.049	1.025	0.907	0.896	0.948
A	u_{C4}	1.068	1.069	1.046	0.907	0.900	0.953
C	u_{C1}	1.028	1.028	1.002	0.875	0.861	0.916
C	u_{C2}	**1.021**	**1.020**	0.996	**0.870**	**0.857**	**0.911**
C	u_{C3}	1.028	1.025	0.997	0.877	0.864	0.918
C	u_{C4}	1.031	1.031	1.005	0.877	0.862	0.918
Panel B: Diebold-Mariano Test Statistics Corresponding to Entries in Panel A							
		Begin Date of Forecast Period =1970:1					
A	u_{C1}	-0.282	-0.344	-0.287	0.033	0.165	0.413
A	u_{C2}	-0.028	-0.075	-0.121	0.122	0.192	0.254
A	u_{C3}	-0.031	-0.003	0.030	0.227	0.100	-0.272
A	u_{C4}	-0.613	-0.615	-0.533	-0.318	-0.242	-0.162
C	u_{C1}	-0.221	-0.171	-0.183	0.085	0.728	0.597
C	u_{C2}	-0.334	-0.300	-0.370	-0.119	0.387	0.174
C	u_{C3}	-0.325	-0.207	-0.133	0.140	0.689	0.461
C	u_{C4}	-1.051	-1.016	-0.972	-0.785	-0.194	-0.075
		Begin Date of Forecast Period =1983:1					
A	u_{C1}	0.245	0.197	0.224	0.685	0.553	0.339
A	u_{C2}	0.441	0.410	0.408	0.562	0.471	0.231
A	u_{C3}	0.506	0.510	0.510	0.441	0.500	0.211
A	u_{C4}	0.169	0.123	0.145	0.610	0.462	0.256
C	u_{C1}	1.199	1.214	1.350	1.636	1.695	1.527
C	u_{C2}	1.035	1.046	1.137	1.284	1.308	1.154
C	u_{C3}	1.303	1.384	1.552	1.656	1.728	1.603
C	u_{C4}	1.106	1.121	1.258	1.548	1.627	1.441
		Begin Date of Forecast Period =1990:1					
A	u_{C1}	-0.162	-0.188	-0.183	0.357	0.325	0.150
A	u_{C2}	0.185	0.175	0.162	0.758	0.703	0.523
A	u_{C3}	0.649	0.699	0.714	0.786	0.821	0.556
A	u_{C4}	-0.255	-0.280	-0.279	0.262	0.219	0.060
C	u_{C1}	0.767	0.743	0.801	1.353	1.429	1.111
C	u_{C2}	0.987	0.982	1.001	1.574	1.577	1.292
C	u_{C3}	0.946	1.032	1.158	1.328	1.424	1.199
C	u_{C4}	0.674	0.649	0.714	1.245	1.337	1.020

(*) Notes: See notes to Table 2 and Table 5.

Tables 5-7 repeat the above experiments adding revision errors into the mix, hence allowing us to assess rationality from a different perspective. If revision errors are useful in ex-ante predictions of the sort that we report on in our tables, then we have direct evidence of inefficiency. To aid in the presentation of our results, in Tables 5-7 bold numbers highlight experiments in which the inclusion of revision errors lowers the MSFE compared their counterparts in Tables 2-4. Starred entries in the tables denote cases in which a different model than the one found in Tables 2-4 obtains a lower MSFE. Consider the case of prices first (Table 6). Point MSFEs reported for Model A in this case are often lower than the comparable MSFEs reported in Table 3. This interesting result suggests that early price releases are actually irrational and that the reason Model A "wins" in Table 3 is that the use of mixed release data associated with the estimation and implementation of Model C is simply "too costly" relative to the predictive accuracy losses associated with using mildly irrational first release data. This finding is consistent with the finding that prices are irrational when extant tests in the literature are carried out (see, e.g., Corradi, Fernandez, and Swanson (2009)). It should be noticed that, however, although point MSFEs are lower in virtually every case (when considering Model A) when u_{C_1} and u_{C_2} are included, the absolute magnitude of the difference in MSFEs is rather small, suggesting that the difference is likely insignificant. Moreover, examination of Tables 5 and 7 suggests that there is little information in the revision processes for the other two variables. In particular, for the case of output, notice that in Table 5, MSFEs are lower than those reported in Table 2 for only a small number of cases that correspond to the longest forecasting period starting in 1970:1, and where Model C is now preferred to Model A. Likewise, for the case of money, there is no clear evidence to indicate that the revision process is useful when predicting money, particularly when the two longest forecasting periods are used. This is consistent with our earlier findings and those reported in Corradi, Fernandez, and Swanson (2009) that money is rational.

Taken together, these results constitute strong evidence that real-time datasets are indeed useful as failure to use them will result in sub-optimal predictions, when the objective is to minimize MSFEs. There are many noteworthy empirical analyses in the literature that present evidence concerning the empirical usefulness of real-time datasets. A key early paper that underscores the importance of revisions for predicting industrial production is Diebold and Rudebusch (1991). Hamilton and Perez-Quiros expand on results in the Diebold and Rudebusch paper by asking the question: "What do the leading indicators lead?" These authors find that simple linear models that include leading indicators are useful for predicting GDP. Further empirical evidence on the usefulness of real-time data is discussed in Bernanke and Boivin (2003), Gilbert (2011), Franses (2013), Franses and Segers (2010), and the references cited therein. Our results clearly complement the findings in this literature.

3.2. Real-Time Marginal Predictive Content of Money for Output

In this section we implement our experimental setup within a multivariate framework that examines the real-time predictive content of money for income, building on the work of Stock and Watson (1989), Amato and Swanson (2001), Garratt, Koop, Mise, and Vahey (2009), and others. To this end we implement vector versions of Models A and C to examine whether money and revision errors from money and other variables have marginal predictive content for output. Results are gathered in Table 8 and correspond to those reported in Table 2, except that vector autoregressions are estimated rather than autoregressions and the target variable to be predicted is output. Note that models with and without money (and revision errors of money) are estimated. The number of lags in the regression models for output, money, prices, and interest rates is selected using the SIC.

Following the notation used in the previous Section, the models that we examine are:

Model A (output equation from associated vector autoregression):

$$
{}_{t+k}Y_{t+1} = \alpha + \sum_{i=1}^{p} \beta^{A,Y}_{i,t+2-i,t} Y_{t+1-i} + \theta \left[{}_{t+1}Y_{t-1} - {}_{t}Y_{t-1}\right] + \sum_{i=1}^{p} \beta^{A,P}_{i,t+2-i,t} P_{t+1-i} + \sum_{i=1}^{p} \beta^{A,M}_{i,t+2-i,t} M_{t+1-i} + \sum_{i=1}^{p} \beta^{A,R}_{i,t+2-i,t} R_{t+1-i} + \theta'_{t+1} W_t + \varepsilon_{t+k}
$$

Model C:(output equation from associated vector autoregression):

$$
{}_{t+k}Y_{t+1} = \alpha + \sum_{i=1}^{p} \beta^{C,Y}_{i\,t+1} Y_{t+1-i} + \theta \left[{}_{t+1}Y_{t-1} - {}_{t}Y_{t-1}\right] + \sum_{i=1}^{p} \beta^{C,P}_{i\,t+1} P_{t+1-i} + \sum_{i=1}^{p} \beta^{C,M}_{i\,t+1} M_{t+1-i} + \sum_{i=1}^{p} \beta^{C,R}_{i\,t+1} R_{t+1-i} + \theta'_{t+1} W_t + \varepsilon_{t+k},
$$

where $W_t = {}_{t+1}\, u^{t}_{t-1}$ or $W_t = ({}_{t+1}u^{t}_{t-1}, {}_{t}u^{t-1}_{t-2})'$, corresponding to the two cases considered (the two cases are denoted u_{C_1} and u_{C_2} in Table 8, respectively), ${}_{t+1}u^{t}_{t-1} = {}_{t+1}\, Y_{t-k} - {}_{t}\, Y_{t-k}$, for $k = 1, 2$.

Entries in Table 8 are MSFEs, and starred entries denote rejection of the Diebold-Mariano null hypothesis of equal predictive accuracy at a 10% level, using standard normal critical values, and assuming that the benchmark model is the simple autoregression given as Model A in Table 2. Entries in bold denote the lowest MSFEs across all models reported on in the table, for a given value of k. Finally, entries in italics are MSFE-best across all models that include money, for a given value of k.

On inspection of Table 8, it is clear that it is always the case that (regardless of sample period, model, and vintage) the models with money yield higher MSFEs than the models without money (entries that are in bold denote MSFE-best models). This result holds for Models A and C, regardless of whether or not revision errors are included. Thus, at least based on the comparison of point MSFEs, there is evidence that money does not contain any marginal predictive content for output. This result should be viewed with caution, however, unless the sole purpose of the modeler is to predict output as accurately as possible. In particular, when carrying out policy analysis, for example, one often aims to include control variables that the government can manipulate. Simply specifying an autoregressive model has little use in such cases. For this reason, a better measure of the usefulness of money might be whether these money can be added to the prediction model *without worsening predictive performance*. If such is the case, then one has evidence that increased parameter and model uncertainty associated with including extra explanatory variables does not worsen predictive performance, hence suggesting that the "bigger" model is "adequately" specified. In light of this argument, note that the lack of starred entries associated with the MSFE-best models in Table 8 (i.e., see entries in bold in the table) for values of k greater than 3 suggests the "adequacy" of vector autoregression models for predicting later release data. This is because the failure of the DM test to reject the null of equal predictive accuracy implies that nothing is lost by moving from a simple autoregression to a vector autoregression. However, this result still tells us nothing about the "adequacy" of models with money. For this reason, we examine the "adequacy" of our models with money by italicizing the MSFE-best models that include money for each release. Interestingly, for our longer prediction periods beginning in 1971 and 1983, models with money do not appear to be "adequate", as the autoregression models yield significantly more accurate predictions, as indicated by the fact that all italicized entries are starred (indicating that the simpler autoregressive model is preferred). However, for the shortest forecast period from 1990, the MSFE-best models with money are "adequate" for all releases except first release data, since in these cases the DM test does not find evidence that simple autoregressive models without models yield more accurate predictions (see the second row of entries in the third panel of the table).

Table 8. MSFEs calculated based on real-time vector autoregressions with and without money and revision errors.$^{(*)}$

Model	*RevErr*	$k=2$	$k=3$	$k=4$	$k=6$	$k=12$	$k=24$
		Panel A: Mean Square Forecast Errors					
		Begin Date of Forecast Period =1971:2					
VAR - NoM Mod A	None	0.866	1.004	1.031	1.049	1.088	1.083
VAR - M Mod A	None	*1.069**	*1.196**	*1.190**	*1.200**	*1.226**	*1.235**
VAR - NoM Mod C	None	0.889	1.027	1.054	1.049	1.074	1.042
VAR - M Mod C	None	1.499	1.629	1.639	1.628	1.662	1.602
VAR - NoM Mod A	u_{C1}	**0.719**	**0.856**	**0.876**	**0.891**	**0.929**	**0.916**
VAR - M Mod A	u_{C1}	1.172	1.296	1.285	1.296	1.330	1.355
VAR - NoM Mod A	u_{C2}	1.036	1.168	1.219	1.235	1.281	1.271
VAR - M Mod A	u_{C2}	1.562	1.691	1.706	1.708	1.731	1.716
VAR - NoM Mod C	u_{C1}	0.840	0.982	1.006	1.009	1.037	1.014
VAR - M Mod C	u_{C1}	2.213	2.322	2.362	2.356	2.406	2.303
VAR - NoM Mod C	u_{C2}	1.107	1.267	1.317	1.327	1.372	1.341
VAR - M Mod C	u_{C2}	1.334	1.499	1.489	1.463	1.482	1.466
		Begin Date of Forecast Period =1983:1					
VAR - NoM Mod A	None	0.270	**0.315***	0.322	0.342	**0.338**	0.366
VAR - M Mod A	None	*0.324**	*0.378**	*0.377**	*0.396*	*0.389*	*0.409*
VAR - NoM Mod C	None	0.274	0.323	0.326	0.334	0.345	**0.364***
VAR - M Mod C	None	0.466	0.524	0.509	0.511	0.500	0.519
VAR - NoM Mod A	u_{C1}	**0.269***	**0.315***	0.322	0.340	0.339	0.366
VAR - M Mod A	u_{C1}	*0.324**	*0.378**	0.378	*0.396*	0.391	0.410
VAR - NoM Mod A	u_{C2}	0.293	0.341	0.348	0.361	0.358	0.382
VAR - M Mod A	u_{C2}	0.390	0.451	0.454	0.447	0.438	0.447
VAR - NoM Mod C	u_{C1}	**0.269***	0.319	**0.320**	**0.328**	0.346	**0.364**
VAR - M Mod C	u_{C1}	0.454	0.512	0.496	0.505	0.504	0.518
VAR - NoM Mod C	u_{C2}	0.278	0.325	0.328	0.336	0.354	0.371
VAR - M Mod C	u_{C2}	0.516	0.585	0.567	0.562	0.546	0.561
		Begin Date of Forecast Period =1990:1					
VAR - NoM Mod A	None	**0.227***	**0.243**	**0.253**	0.313	**0.316**	**0.343**
VAR - M Mod A	None	*0.241**	*0.252*	*0.260*	*0.316*	*0.319*	*0.344*
VAR - NoM Mod C	None	0.242	0.266	0.265	0.313	0.333	0.344
VAR - M Mod C	None	0.319	0.334	0.329	0.366	0.386	0.392
VAR - NoM Mod A	u_{C1}	0.230	0.245	0.255	0.315	0.318	0.347
VAR - M Mod A	u_{C1}	*0.241**	0.253	0.261	0.317	*0.319*	0.346
VAR - NoM Mod A	u_{C2}	0.239	0.254	0.265	0.323	0.326	0.351
VAR - M Mod A	u_{C2}	0.253	0.264	0.273	0.327	0.329	0.351
VAR - NoM Mod C	u_{C1}	0.235	0.258	0.258	**0.308**	0.329	**0.343**
VAR - M Mod C	u_{C1}	0.326	0.338	0.333	0.378	0.404	0.413
VAR - NoM Mod C	u_{C2}	0.246	0.270	0.270	0.316	0.336	0.343
VAR - M Mod C	u_{C2}	0.332	0.349	0.344	0.387	0.412	0.417

$^{(*)}$ Notes: See notes to Table 2. Vector autoregressions with and without money are used to predict real-time output. Entries are MSFEs, and starred entries denote rejection of the Diebold-Mariano null hypothesis of equal predictive accuracy at a 10% level, using standard normal critical values, and assuming that the benchmark model is Model A from Table 2. Entries in bold are the lowest MSFEs across all models reported on in the table, for a given value of k. Finally, entries in italics are MSFE-best across all models that include money, for a given value of k. See Section 2 of the paper for complete details.

Also interesting is the fact that when considering VAR models, output is always best predicted using varieties of Model A, *regardless of release being predicted*, placing this variable together with prices as being variables for which use of preliminary data yields the most accurate predictions. Needless to say, the findings of this illustration suggest that there is much to be learned via analysis of real-time datasets, again underscoring the importance of building and maintaining such datasets.

4. Concluding Remarks

While recent empirical research has presented strong evidence in favor of the usefulness of making real-time datasets available to economists, the literature has not yet carefully assessed the relevance of these datasets for macroeconomic forecasting. In this paper, we attempt to shed new light on these issues by constructing a variety of different real-time prediction models and evaluating their performance in a series of ex-ante prediction experiments that are designed to mimic forecasting approaches used when constructing forecasts in real-time for three macroeconomic variable: Output, prices and money. The prediction models we use include, among others, autoregressive processes that uses only first release data and others that utilize only the latest available data. We also assess the models in a multivariate framework by including revision errors as regressors, hence allowing us to examine the marginal predictive content of the revision process and forming simple rationality tests that are based solely on the examination of ex-ante predictions. In another multivariate application we examine the real-time predictive content of money for income.

Perhaps the most important result we obtain is that the choice of which release of data to predict seems not to have an impact on which releases of data should be used in estimation and prediction construction but that differences in how to utilize real-time datasets do arise when the variable being modelled and predicted changes. For example, we find that regardless of which release of prices one specifies as the "target" variable to be predicted, using only "first release" data in model estimation and prediction construction yields MSFE-best predictions, and that models estimated and implemented using "latest available release" data are MSFE-best for predicting all releases of money. Our experiments that include revision errors as regressors point that early releases of money are rational, whereas prices and output are irrational. As for our multivariate forecasting experiment involving the real-time predictive content of money for income, while we find little marginal predictive content in money, we note that vector autoregressions with money do not perform significantly worse than autoregressions, when predicting output in the past 20 years. Taking together we view our results as providing strong evidence that real-time datasets are indeed useful as failure to use them will result in sub-optimal predictions, when the objective is to minimize MSFEs. Clearly, many of our conclusions would not have been possible without the availability of real-time datasets, underscoring the importance of collecting and maintaining such datasets.

Many issues in this literature remain unresolved. For example, from an empirical perspective it remains to extend the analysis that we carry out to more releases of data and to other variables in order to further examine the relevance of real-time datasets for forecasting. Another topic that we briefly mention is the importance of definitional change, particularly when considering forecasting final releases. From a theoretical perspective, it remains to examine the properties of various predictive accuracy tests in the recursive and real-time framework employed in this paper.

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Conflict of Interest

All authors declare no conflict of interest in this paper.

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