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COMPARING TIME-SERIES AND SURVEY FORECASTS OF WEEKLY CHANGES IN MONEY: A METHODOLOGICAL NOTE

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Preliminary: Please do not quote without permission.

1. Introduction

Numerous studies have appeared recently examining the effect of unanticipated weekly changes in the money stock (M1) on nominal interest rates [see, for example, Urich and Wachtel (1981); Grossman (1981); Urich (1982); Figlewski and Urich (1983); Roley (1983); and Cornell (1983a, b).] In these papers, unanticipated money is measured as the difference between the actual, announced change and that predicted from the Money Market Services, Inc. survey of government securities dealers prior to the announcement. The survey measure is used for two reasons: First, it is believed to represent the expectations of the financial market.[1/] Second, there is some evidence that the mean survey forecast is "clearly superior to the predictions from an ARIMA model." (Figlewski and Urich, 1983, p. 696).

Our purpose in this paper is <u>not</u> to re-examine the effects of unanticipated money changes on nominal interest rates. Rather, we address a more basic issue concerning the methodology of forecasting weekly money changes. Although not explicitly stated, it is apparent that previous researchers have used the weekly money series without regard to certain "abnormalities" that are well-known to financial market participants. These abnormalities influence the data released during weeks that include benchmark revisions, seasonal revisions and weeks in which there is a "social security effect." Failure to account for these weeks may change one's perception about the relative superiority of the survey forecasts to those derived from an appropriate ARIMA model.

The format of the paper is as follows: Section 2 describes the data. The time series models used to forecast weekly changes in M1 are presented in Section 3. Also in this section, the models' forecasts are compared to those from the survey. The outcome of this comparison indicates that once the abnormal weeks are deleted from the sample, a simple time-series model predicts weekly M1 changes as well as the survey. Concluding remarks are offered in Section 4.

2. DATA

The data used consist of actual and expected weekly changes in the money supply (M1) for the period October 1979 to June 1982. Actual changes in M1 were taken from the Federal Reserve's H.6 statistical release. In each case, the figure used is the change from the previous week's initially announced figure.[2/] The data sample begins in October 1979 to avoid any problems inherent with the change in operating procedures by the Federal Reserve. Because this sample period encompasses a period of changing definitions, the following scheme is used: from October 3, 1979 to January 31, 1980, weekly changes in money are based on the old definition of M1. From February 8, 1980, to November 20, 1981, the money stock used is the M1B measure not adjusted for NOW accounts movements. And, from November 27, 1981 to June 16, 1982, the then current definition of M1 is used.

One aspect of this series not discussed in previous studies is that it contains numerous weeks where some "exogenous" factor may have distorted the announced change in money. Some of these factors are institutional: benchmark revisions which generally occur in January and June; and seasonal factor revisions, which also occur in January.

Changes in the money stock brought about by these factors cannot be forecast with the data used by market participants.[3/]

Another factor that occurs frequently but without a systematic pattern is the advent of so-called social security weeks. Social security weeks occur when the third day of the month--the day many social security checks are deposited directly by mail into transactions accounts--falls on a weekend, or a holiday that also happens to be a Friday or a Monday. The effect of this quirk in the payment mechanism is that because these payments are deposited on Friday, they generally are held on the bank's balance sheet as transaction accounts for an extra amount of time, say, two or three days, relative to weeks in which the deposit takes place on a week-day. The well-known consequence is to artificially enlarge the M1 statistics reported for that week. During the sample period, ten such weeks exist.[4/]

The data used to measure the market's expectation of the weekly change in M1 were obtained from Money Market Services, Inc. This firm conducts a telephone survey of 50 to 60 government securities dealers to get their predictions for the upcoming change in money. Prior to early 1980, the poll was conducted each Tuesday and Thursday. Since then, only the Thursday survey has been conducted, because of the shift in the announcement day from Thursday to Friday afternoon. Consequently, we use only the mean forecast derived from the Thursday survey.

3. Models of Weekly Changes in M1

Two ARIMA models are developed in this section to predict weekly changes in M1. One model is constructed using all the data: this model represents the basis for comparison of survey and ARIMA forecasts in previous studies. The other deletes those weeks (15 weeks in all) in which a benchmark revision, a seasonal adjustment revision and/or a social security effect takes place.

The time-series models were determined by first examining the autocorrelation functions of the two data series. The autocorrelation function for the series that uses <u>all</u> data points is presented in table 1. There we see two spikes at lags 1 and 13 that clearly exceed two standard errors. Autocorrelations at lags 7 and 22 also are about two standard errors from zero. Along with the partial autocorrelations, some experimentation revealed that the "best" specification is an AR model with terms at 1, 7 and 13 lags. The estimated model is (standard errors in parenthesis):

$$(1)\quad (1 + \underset{(0.08)}{0.1966} + \underset{(0.080)}{0.1824}B^{7} - \underset{(0.082)}{0.3587}B^{13})\,\Delta M_t = \underset{(0.227)}{0.5531} + a_t$$

$$Q(12) = 13.68 \qquad SE = 2.630$$

The results in equation 1 indicate that the model has adequately captured the movement in weekly M1 changes. Each of the estimated AR coefficients is statistically significant at the 5 percent level. The reported Q-statistic, distributed as a χ^2 with 12 degrees of freedom, is less than the critical 5 percent value of 21.0. Consequently, we cannot reject the hypothesis of white noise residuals or the empirical model.[5/]

Table 2 presents the autocorrelation function for the weekly money series that <u>excludes</u> the abnormal weeks. The important feature of these autocorrelations is that at no lag is there a statistically

4. Conclusion

The evidence presented in this study suggests that survey forecasts are not "clearly superior" to those based on appropriately specified ARIMA models. Based on a sample of weeks from October 1979 to June 1982, the two approaches yield forecasts that are statistically indistinguishable.[9/]

We also have argued that it may be inappropriate to use weekly money without considering the effect of certain weeks on the results. These weeks include benchmark adjustments, seasonal revisions and social security payments. A comparison of survey and ARIMA forecast errors revealed that deleting these weeks a) improved the forecast performance of each model improves by about 15 percent and b) reduced the difference between the ARIMA model's forecasts and those taken from the survey diminish by a relatively large amount.

Perhaps the most interesting outcome, and one that is relevant for those actively involved with modeling weekly money changes, is the finding that deleting the abnormal weeks reduces the weekly M1 change series to white noise with mean zero. Consequently, the model that forecasts the weekly change in M1 as well as the survey is the model that predicts no change at all.

FOOTNOTES

[1]/It has been argued that using survey responses to approximate the market's expectation is a dubious approach at best. The problem is that many surveys do not poll actual market participants, but only ask individuals for a variety of predictions. In this instance, however, much of the force from this line of criticism would seem to be lessened. On this, see Kane and Malkiel (1976).

[2]/We use the initially announced data because it is known with certainty by the forecasters before the next announcement. Using the one-week revised-to-first-announced change in M1 would impart information not available to the forecaster. That is, it would presume that the forecaster knows the revision. See, also, Cornell (1983 a,b).

We also have examined the time series of the revision itself. Because the revision was found to be a white noise process (Q(12) = 8.20), it also seemed quite reasonable statistically to use the first announced-to-first announced change.

[3]/The benchmark/seasonal weeks deleted include 1/30/80, 6/11/80, 1/7/81, 6/10/81 and 1/6/82.

[4]/The social security weeks omitted from the sample are the weeks ending 11/7/79, 2/6/80, 5/7/80, 8/6/80, 8/10/80, 4/8/81, 5/6/81, 7/8/81, 10/7/81 and 4/7/82. During these weeks, the average change in M1 was $5.5 billion. This is more than two standard errors away from the mean of the series that excludes these weeks.

[5]/Note that the money series using all observations has a significant, positive trend estimated to be $0.55 billion.

[6] It should be noted that the forecast errors are calculated for the period 1/2/80 to 6/16/82. The loss of the weeks early in the sample is due to the ARIMA model's specification.

[7] The forecast errors for the ARIMA model using all weeks are the in-sample errors. Clearly, this violates the assumption that forecasters know only past data. One approach would be to estimate the model up to some period t, predict t + 1, and iterate the estimation sample by one week. In this paper, however, we have chosen the less computationally laborious procedure of using in-sample errors. Note also that this argument cannot be made against the no-change model, due to its randomness characteristic.

[8] No statistical criterion exists to compare RMSEs. To get some idea of the statistical differences between the MAEs, we tested the differences of MAE by using the simple means test. The resulting t-statistic for the full data set is -0.58 and, for the subset, -0.48. These statistics suggest that there is no statistical difference between the two forecast error series.

[9] This finding also suggests that the survey responses may be considered "rational" in the sense that a time series model does not improve upon their forecasts. On this approach to testing for rationality, see Pearce (1979).

Table 1
Sample Autocorrelations for Weekly Change in M1
Full Data Set

Lag	1	2	3	4	5	6	7
Autocorrelation	-0.24	-0.08	-0.12	0.09	0.07	0.03	-0.17
Standard Error	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Lag	8	9	10	11	12	13	14
Autocorrelation	0.05	0.14	-0.18	-0.06	-0.13	-0.10	-0.17
Standard Error	0.10	0.10	0.10	0.10	0.10	0.11	0.11
Lag	15	16	17	18	19	20	21
Autocorrelation	-0.14	-0.14	0.19	0.04	-0.06	-0.14	-0.02
Standard Error	0.11	0.11	0.11	0.11	0.12	0.12	0.12
Lag	22	23	24				
Autocorrelation	-0.24	-0.06	-0.04				
Standard Error	0.12	0.12	0.12				

Table 2
Sample Autocorrelations for Weekly Change in M1
Abnormal Weeks Omitted

Lag	1	2	3	4	5	6	7
Autocorrelation	-0.03	0.01	-0.08	-0.01	-0.09	0.04	-0.05
Standard Error	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Lag	8	9	10	11	12	13	14
Autocorrelation	-0.03	-0.07	-0.012	-0.06	0.08	0.06	-0.12
Standard Error	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Lag	15	16	17	18	19	20	21
Autocorrelation	-0.02	-0.02	-0.16	0.06	0.05	0.08	-0.01
Standard Error	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Lag	22	23	24				
Autocorrelation	-0.01	-0.03	0.08				
Standard Error	0.10	0.10	0.10				