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Abstract

Uncertainties in reported money supply data stem from several sources, including seasonal adjustment, transitory variation, sampling error, reporting error, and definitional error. Some of the error is in preliminary data only and is removed when the series are revised; other errors persist in the final data. This paper analyzes the relative and joint impacts of these various sources of uncertainty. The current Board procedures for data collection, survey sampling, publication and seasonal adjustment are examined, and ways in which changes in these procedures might reduce error in the monetary aggregates are assessed.

The paper also evaluates the possible effects of these errors on monetary policy. The danger that the monetary authority will misjudge an incoming money supply figure or string of figures and thereby take inappropriate action, or fail to take appropriate action, is analyzed. Additionally, it is shown how errors and uncertainty in the monetary aggregates obscure their relationship to other series of importance such as inflation, output or unemployment, thus making the formation as well as the implementation of monetary policy more difficult.

1. INTRODUCTION

For a variety of reasons observed data on the monetary aggregates are subject to uncertainty or error. In some instances first published data are revised at a later date due to errors in preliminary data which can be observed and corrected; in others the error persists in the final data. Cutting across this classification are the numerous sources of error, including definitional error, transitory error, seasonal adjustment error, sampling, clerical or reporting error, etc.

This paper deals with the sources and, where possible, magnitudes of uncertainties in monetary series. The next three sections discuss conceptual and definitional issues and the current procedures for collecting and publishing the money supply data. Sections 5 through 7 then consider, respectively, uncertainty due to sampling and reporting, transitory variation, and seasonal adjustment. Some implications of these, including possible consequences for monetary policy and the effects on relationships to other series, are assessed in Sections 8 and 9, and the concluding section presents some suggestions for dealing with errors in the aggregates.

2. CONCEPTUAL ISSUES

The variation in an observed series generally has several sources. The contributions of each may be formalized as components of an overall model. Each component is, in a sense, an unobservable construct. When the model for a component is identified, the component will have a unique estimate for a given data set. When the model is not identified, some additional conditions must be imposed to obtain an estimate (or even a definition) of the construct. When agreement on a model is lacking, as in seasonal adjustment, there are further possible definitions available. In these situations a range of answers is possible in addition to statistical variation in each answer. Since component estimates are interrelated, a change in the specification of one component may affect estimates of another. In the case of seasonal adjustment, the component specifications are interrelated.

This paper will discuss both statistical variation in a component estimate due to the presence of other components, and alternative component specifications. The deviation of a component estimate from its true value is error. Other components are error only in contributing to the variance of the component estimate of interest. Each may be the signal in another situation.

3. DEFINITIONAL ERROR

There are several measured versions of the money supply, M-1a, M-1b, M-2, and so forth. There are also several points from which money is viewed -- as a store of value, medium of exchange, index of liquidity, among others. Some analysts attempt to use the money supply to forecast values of such variables as prices and national income, while others use the money supply to guess what will be the reaction of the Federal Reserve to it (i.e., forecast interest rates). It seems clear that no single series can serve as all these measures or satisfy everyone's purposes. Moreover, it is doubtful that any of the available measures represents exactly what any individual user has in mind.

The difference between the measured money supply and a user's notion of what is means is what we call definitional error. The size of the definitional error is particular to the user. There would not seem to be much the Federal Reserve can do to affect this type of error except to spell out just what it is counting -- certain selected liabilities of the

Federal Reserve Banks and deposit-taking financial institutions. Or, alternatively, the money stock could be constructed in ways designed to measure what the user is interested in; for example, Barnett, et. al. (1980) proposes such a measure.

4. ESTIMATION OF THE MONEY SUPPLY

Before discussing other types of error, it may be useful to briefly describe how estimates of the money supply are produced.

Generally speaking, the published money supply consists of the net liabilities to the public of the Federal Reserve and certain financial institutions -- commercial banks, mutual savings banks, savings and loan associations, and credit unions. Each week the 5,500 banks that are members of the Federal Reserve System report their daily closing balances. Samples of nonmember banks and the other institutions also report each week giving essentially the same information as do member banks. 1/ Using these data, weekly estimates of the money stock are calculated and published nine days after the end of the statement week. One week later, the "second published" estimates are made and released along with the first published estimates for the following week. Third published estimates are released after another week has passed, although newspapers generally don't bother to report these estimates. The revisions are the result of incorporating data from late reporting banks and corrections of various reporting and processing errors. The average absolute difference between the first and third published estimates over the last couple of years has been around $200 million.

At the end of each quarter, balance sheets ("call reports") are obtained from all 8,700 nonmember banks. The sample-based estimates are then revised to incorporate this new information. (These are called "benchmark revisions.") Because the assembly of call report data is a lengthy process, these revisions are typically made about six months after the call report date. Similar benchmark revisions are made for the other financial institutions.

A third type of revision occurs at the beginning of each year when a revised seasonally adjusted series is published. The seasonal factors to be used during the coming year are also published at this time.

The effects of these revisions on month-to-month growth rates of M-2 were studied by Bach et. al. (1976). They found that the standard deviation of the difference between the first published annualized growth rate (made about 10 days after the end of the month) and the first revised estimate (made about 20 days later) was 1.25 percentage points; the standard deviation of the difference between the final (benchmarked and re-estimated seasonals) estimates and the first published growth rates was about 3.2 percentage points; and that about 2.1 percentage points of the latter standard deviation was due to revisions in the seasonal factors.

5. SAMPLING, REPORTING, AND PROCESSING ERROR

For illustrative purposes, we concentrate on one component of the money supply -- demand deposits at commercial banks. As noted in the preceding section, the 5,500 banks that are members of the Federal Reserve System report each week their daily closing balances. Thus we know the total deposits of these banks, aside from reporting and processing errors, which constitute about three-quarters of all commercial bank demand deposits. The other 8,700 banks ("nonmember banks") report only once each quarter (on the "call report") and provide daily deposit data for the week that contains the last day of the quarter. However, a sample of 600 nonmember banks reports each week giving essentially the same information as do member banks.

While daily estimates of the money supply can be constructed, the more common approach has been to prepare only weekly (daily average) estimates for Board and public consumption. The current week's commercial bank demand deposit component can be written 2/

$$\hat{Y}_D = \hat{Y}_M + \hat{Y}_{NM}$$
$$= \hat{Y}_M + (\hat{y}_{NM}/x_{NM})X_{NM}$$

where

$\hat{Y}_M$ is the total demand deposit balances reported by member banks

$\hat{y}_{NM}$ is the total demand deposits reported by the 600 nonmember sample banks

x_{NM} is the total demand deposits reported by the sample banks on a previous call report

X_{NM} is the total demand deposits reported by all nonmember banks on the previous call report

Now $\hat{Y}_M$ differs from actual demand deposits at member banks, Y_M, because of reporting and processing errors. Similarly, $\hat{y}_{NM}$ differs from actual demand deposits at the sample nonmember banks.

The estimate for nonmember banks also suffers by being based only on a sample of currently reporting banks. The conventional measure of the sampling variance (which is used at the Board) is

$$\text{Var}_s(\hat{Y}_{NM}) = (1 - n/N)(N^2/n)S^2_{\hat{y}}$$

where

$$S^2_{\hat{y}} = \frac{1}{N-1} \sum_{i=1}^{N} (\hat{y}_i - Rx_i)^2$$

$$R = \sum_{i=1}^{N} \hat{y}_i / \sum_{i=1}^{N} x_i$$

$\hat{y}_i$ = the ith bank's current reported demand deposits

x_i = the ith bank's demand deposits as reported on the call report

n = number of banks in the sample

N = number of banks in the population

Reporting and processing errors cause this formula to overstate the true sampling variance but to understate the sampling-plus-reporting variance, which can be written (assuming, for the moment, that reporting variance is constant across bank) approximately as

$$\mathrm{Var}_{sr}(\hat{Y}_{NM}) = \mathrm{Var}_s(\hat{Y}_{NM}) + NS_r^2$$

where $S_r^2 = E(\hat{y}_i - y_i)^2$ and the "sr" subscript denotes that the variance is over sampling and reporting errors. The overall sampling plus reporting variance of the demand component can then be written

$$\mathrm{Var}(\hat{Y}_D) = (N_M + N_{NM})S_r^2 + \mathrm{Var}_s(\hat{Y}_{NM}),$$

where N_M and N_{NM} are the numbers of member and nonmember banks, respectively.

The reporting variance S_r^2 is a measure of the variation of reporting and processing errors that remain after the data have been edited at the Board. The more intensive the editing, the smaller, presumably, will be S_r^2. Alternatively, given finite resources at the Board, there may be a tradeoff between sampling and reporting error; that is, if a smaller sample can be more intensively edited, the reduction in reporting variance may offset the increase in sampling variance. The estimation of S_r^2 and is relationship to sample size are matters for further research.

The preceding development is in terms of the monetary aggregates estimated weekly. Sampling error is reduced substantially by moving from weekly to monthly estimates even though each weekly estimate is based on the same sample of banks and, hence, the errors are highly correlated. The nonmember bank sample estimates of weekly-average demand deposits, for example, have an estimated standard error of about $520 million. The standard error of a monthly average is estimated to be about $325 million, a 37 percent reduction. (As noted elsewhere, these estimated standard errors incorporate some of the reporting error effects.)

The reduction in the (unknown) standard deviation of reporting error depends upon the covariance (over time) structure of these errors. There are at least two reasons to believe that these covariances are likely to be positive: (1) if a bank misunderstands a definition on the reporting form, its error in reporting is likely to be fairly consistent over time; (2) one of the editing procedures is to question large day-to-day changes -- so if, for example, deposits are underreported one day and overreported the next day, those data are likely to be questioned and corrected. Thus, the standard deviation of reporting error for a monthly average is likely to be somewhat more than the figure (approximately one-half the standard deviation for a weekly average) which would be appropriate in the absence of serial correlation.

6. TRANSITORY ERROR

Over time the money stock is subject to very short run -- transitory -- variations that bear little, if any, relation to the economy in general. For example, if a government check on its way to a bank is delayed at the post office for a day, the measured money stock will be lower on that day than it would otherwise have been. But no one feels poorer as a result and economic activity is totally unaffected. These kinds of variations are called transitory because they are fleeting in nature and provide no information about the underlying economic process.

A single precise definition of transitory error does not exist. Most operational definitions have centered around a statistical (or economic) model for the "systematic" part of the series, the transitory error being the model's residual. Given the evanescent nature of this source of variation, it is reasonable to require the transitory component to be serially uncorrelated, except possibly in a model for monetary aggregates measured daily. In general, the effect of temporal aggregation in terms of reducing transitory error depends upon the definition of transitory error. If one thinks of transitory variations as those that have lives of one week or less, aggregation from a week to a month would reduce the transitory standard deviation by about one-half.

An extreme view on transitory variation would be to label as transitory whatever part of a signal-plus-noise decomposition of a series that is serially uncorrelated. That is, monetary aggregate x_t is represented as

$$x_t = n_t + \xi_t$$

in such a way that ξ_t is serially uncorrelated (white noise) with maximum variance σ_ξ^2. Such a component is transitory in the sense of being unrelated to past or future values of the aggregate. It is of interest that the irregular component produced by the X-11 seasonal adjustment procedure (see Section 5) has this maximum variance property (Tiao and Hillmer, 1978).

It is important to note that the fact that ξ_t is serially independent and independent of x_t does not mean that there is not some other time series of interest with which ξ_t is cross correlated, and for this reason σ_ξ^2 could overstate the transitory variance relative to a larger information set. Yet in some instances it is possible to specify n_t so as to "explain" a great deal of the series. For example, if x_t is a temporal aggregate (say measured monthly) of a basic (weekly or daily) series then a model for the disaggregated series, which can include deterministic as well as stochastic effects, will generally leave a residual which, when re-aggregated, possesses smaller variance than when the series x_t is modelled directly. (This is closely related to a result of Geweke (1978).)

The uncertainties in model specification and the resulting ranges of estimates of transitory error variances for the monetary aggregates are illustrated by a series of studies in Porter et. al. (1978). Both daily and weekly data on M-1 were employed; for daily data the basic model used was

$$x_t = p_t + s_{1t} + \xi_t$$

where s_{1t} represents only fixed day-of-week effects and the trend term p_t represents all inter-week and longer-term effects. Three ways of estimating the trend p_t were employed, with different results; the method with the median transitory variance consisted of taking

$$p_t = \frac{1}{5}\sum_{j=-2}^{2} x_{t+j}$$

the moving average of the 5-day week centered about x_t. The standard deviation of ξ_t in this approach was $\sigma_\xi = 0.41\%$, translating into about 0.1% for monthly data. (Using a moving "quadratic" formula for p_t yielded $\sigma_\xi = 0.31\%$, using (2.3) except summing only over the statement week yielded $\sigma_\xi = 0.56\%$.) Note that this value is approximately the same as the standard deviation of δ_t, the final seasonal adjustment error (Section 7), with which ξ_t is negatively correlated (Pierce, 1980b).

Using weekly data, however, the corresponding estimates of σ_ξ varied about 0.55% (depending in this case on how the weekend was treated), yielding transitory standard errors of about one-fourth percent for monthly data, contrasted with one-tenth when constructed from variances of the daily model (2.2).

Note that these figures are for individual monthly money supply series. For annualized monthly M-1 growth rates, the transitory standard deviation correspnding to the figure σ_ξ = .41% is about 1.8 percent; thus if a reported M-1 monthly growth rate was, say, 6%, then a 90% confidence interval for nontransitory M-1 would be approximately 3% to 9%.

Finally, it should be noted that transitory error in the historical series is partially eliminated by the seasonal adjustment procedure; a positive transitory component one month, for example, tends to increase the estimate of the seasonal factor for that month and thereby decrease the seasonally adjusted value. (On the other hand, such an error would increase the error in the seasonally adjusted series for the same month in nearby years.) In addition, the preceding procedures used to estimate transitory error were applied to data containing sampling and reporting error, part of which is probably also included in the transitory estimate. Thus, while "nontransitory" M-1 is still subject to these other error sources, to an extent an offsetting effect would be anticipated.

7. SEASONAL ADJUSTMENT ERROR

Seasonal factors suffer from three problems. They have no precise definition, their estimates can be adversely affected by inadequate treatment of other components, and their optimal final estimates require future data under most specifications.

Science is coming to seasonal adjustment, but seasonal adjustment remains largely an art at the moment. The most frequent definition of a seasonal factor is what the X-11 program using default options produces after three to five years of future data are in. This is allowing a computer program to make the artistic decisions. When the results of various options are examined and a procedure selected, the statistician makes decisions according to his artistic criteria. This may include special treatment of certain data values. Model based approaches bring some science to bear on the problem, but an identification problem remains which requires some choice on the part of the statistician, see e.g., Pierce (1978) or Box, Hillmer and Tiao (1978).

A model for a current observation x_t is

$$x_t = p_t + s_t + e_t(t) \quad . \tag{7.1}$$

In this model p_t includes trends and business cycles, and s_t is the seasonal behavior. The term $e_t(t)$ denotes sampling error, transitory error, and reporting errors at time t. At some later time t+k this observation might be represented as

$$x_t = p_t + s_t + e_t(t+k) \tag{7.2}$$

where $e_t(t+k)$ differs from $e_t(t)$ due to later edits and more complete data. In monetary series the variance of $[e_t(t+\infty) - e_t(t)]$ is usually small compared with the variance of $e_t(t)$, so the symbol e_t will be used for $e_t(\infty)$. The e_t may be correlated if the sampling errors are correlated.

We shall assume that the components s_t, p_t, and e_t of x_t in (7.1) are mutually independent (except when otherwise noted) and each generated by stationary or homogeneously nonstationary stochastic processes as described in Box and Jenkins (1970). Thus, s_t and p_t are representable in the form

$$\Delta_p(B)p_t = \psi_p(B)\alpha_t \tag{7.3}$$

$$\Delta_s(B)s_t = \psi_s(B)\beta_t \tag{7.4}$$

where α_t and β_t are white noise sequences with variances σ_α^2 and σ_β^2 ; the one-sided polynomials

$$\psi_p(z) = \sum_{j=0}^{\infty} \psi_{pj}z^j \quad , \quad \psi_s(z) = \sum_{j=0}^{\infty} \psi_{sj}z^j$$

are absolutely convergent and nonzero for $|z| \leq 1$; and $\Delta_p(B)$ and $\Delta_s(B)$ are "differencing operators" such that the zeroes of $\Delta_p(z)$ and $\Delta_s(z)$ are on the unit circle. Examples of such operators are the ordinary and "seasonal" differencing operators, $1 - B$ and $1 - B^{12}$ respectively. It is also assumed that suitable initial conditions (see, e.g., Box and Jenkins (1970), pages 114-119) are given for p_t and s_t. The e_t component is assumed to be stationary and have mean zero.

The models (7.3) and (7.4) for p_t and s_t together with e_t are known to imply a model for the observable series x_t of the same form,

$$\Delta(B)x_t = \psi(B)a_t \ , \tag{7.5}$$

so that $\Delta(B)x_t$ is a linear, stationary, nondeterministic time series. If all differencing and summing operators are identically unity, the series x_t and its components are stationary; if $\Delta(z) \not\equiv 1$ then x_t, and at least one of p_t, s_t and e_t, are nonstationary.

The components of the observed series x_t can be estimated using the component models given their parameters. It has been shown that given all x_t the minimum mean square error estimate $\hat{s}_t$ of s_t is

$$\hat{s}_t = \nu_s(B)x_t = \sum_{j=-\infty}^{\infty} \nu_j x_{t-j} \tag{7.6}$$

where

$$\nu_s(z) = \frac{\sigma_\beta^2 |\psi_s(z)|^2}{\sigma_a^2 |\psi\ (z)|^2} = \frac{f_s(z)}{f_x(z)} \tag{7.7}$$

where, e.g.,

$$f_s(z) = \sigma_\beta^2 |\psi_s(z)|^2$$

and where the convention

$$|h(z)|^2 = h(z)h(z^{-1})$$

is employed. Thus the filter is symmetric, $\nu_j = \nu_{-j}$, as expected from the reversibility of the x-process. The numerator and denominator of (7.7) are the autocovariance generating functions (acfg's), or spectra at $z = e^{i\omega}$, of the component and over-all processes $\{s_t\}$ and $\{x_t\}$.

The nature of the seasonal adjustment error $\delta_t = \hat{s}_t - s_t$ given past and future data was examined by Pierce (1979) who found that δ_t is stationary (the MSE finite) if and only if the roots of the component process differencing operators $\Delta_s(z)$ and $\Delta_p(z)$ are distinct. Assuming this restriction is always imposed, then the seasonal adjustment error follows a stationary linear process. The variance of this process is the variance of δ_t. Strictly speaking, this means for determining the variance of the seasonal adjustment error is valid only for "optimal" seasonal adjustment procedures of the form (7.7). But it is important to note that a linear approximation to the Census X-11 seasonal adjustment procedure (Shiskin, Young and Musgrave, 1967), which is essentially of the form (7.6). Moreover, in Cleveland (1972) a model of the form (7.4), (7.5) is presented such that the particular filter weights $\{\nu_j\}$ in (7.7) match very closely those of the X-11 program with standard options. This model has been found to be close to those fitted to a large number of economic time series, and therefore for such series it should be possible to use this model to obtain a good approximation (perhaps a lower bound) to the variance of δ_t.

In particular, ARIMA models for the log of the money supply (M-1), measured monthly, have often been of this form, when fitted with recent year's data, and in Pierce (1979) it was found that the standard deviation of the SA error was about .09 of one percent.

7.1 Revisions Due to Seasonal Adjustment

The seasonal adjustment procedures described above make use of data both prior and subsequent to the datum being adjusted, as both future and past observations ordinarily contain information pertinent to seasonality at a given point in the series. However, for the seasonal adjustment of current or recent data and for forecasting seasonal factors, which are more important problems than historical seasonal adjustment for interpreting or reacting to movements in the series, the relevant future of the series is not yet available. Thus, based on the observations that are available, preliminary estimates of the seasonal component are made, which are subsequently revised as more series values are observed, perhaps repeatedly, until the unobserved future no longer contains significant relevant information. These are revisions in unobservable component estimates, as opposed to revisions in the observed data discussed elsewhere.

The nature and extent of these seasonal revisions is examined in (Pierce, 1980) under the assumption that the series x_t can be adequately represented by a homogeneously nonstationary stochastic model of the form (7.5). The revisions themselves follow a stochastic process which in general can be characterized. An important case occurs when the seasonal estimate $s_t^{(m)}$ can be represented as

$$s_t^{(m)} = \nu(B)x_t^{(t-m)} \qquad (7.8)$$

where t-m is the date of the last available data,

$$x_t^{(\tau)} = \begin{cases} x_t, & t \leq \tau \\ E(x_t | x_\tau, x_{\tau-1}, \ldots), & t > \tau \end{cases}$$

is the extended series obtained by adjoining to-the available series $\{x_\tau, \tau \leq t-m\}$ a set of forecasts of $x_{t-m+1}, x_{t-m+2}, \ldots$, and where $\nu(B)$ is independent of m. The successive revisions are independent of each other and of the error δ_t in the final estimate s_t. Given a symmetric filtering procedure such as X-11, application of that procedure on the extended series minimizes the revision mean square of preliminary seasonally adjusted data. Thus, X11-ARIMA would for this reason be expected to produce better initial data (smaller revisions) than the ordinary X-11 procedure.

In practice, the seasonal component is forecasted a year in advance so that the first published seasonally adjusted data is of the form

$$\tilde{x}_t^{(m)} = x_t - s_t^{(m)} \quad , \quad m = 1, \ldots, 12. \qquad (7.9)$$

The above result then implies that the mean square of the total error in $\tilde{x}_t^{(m)}$ due to seasonal adjustment, say $\delta_t^{(m)}$, may be expressed as the sum

$$E(\delta_t^{(m)})^2 = E(r_t^{(m)})^2 + E(\delta_\tau^2) \qquad (7.10)$$

of the revision mean square and the variance of the error in the final estimate.

When the U.S. money supply (old M-1) was investigated it was found that the mean square revision in first published data over 1974-77 was 0.18%, with little variation between months of the year (representing different values of "m"). If this is combined with the final-data error variance, the standard deviation of the total error in M-1 due to seasonal adjustment is

$$[(.18)^2 + (.09)^2]^{1/2} = .20\% \tag{7.11}$$

For example, if a preliminary seasonal factor was .955, then the true value would be less than .953 or over .957 almost one-third of the time, simply due to uncertainty in seasonal adjustment.

7.2 Alternative Specification

Different seasonal adjustment procedures may lead to different estimates of seasonal factors. Even a given model for an observed series does not provide a unique determination of the seasonal. At issue primarily is how much noise will be allowed to get into the seasonal factors in order to permit a varying seasonal pattern. Two model based adjustments were performed on a demand deposit series. The root mean square difference between the minimum variance estimate and the other was 2% of $\hat{n}_t$. The root mean square difference from the X-11 result was .5%. These numbers compare with a revision error of .18% for X-11 itself, and illustrate the magnitude of the identification problem for seasonal components.

7.3 Policy Seasonal

Until about a year ago, the Fed attempted to determine what interest rate would be consistent with a desired rate of growth of the money stock. Since there has been virtually no seasonal pattern in interest rates, seasonal patterns in the demand for money presumably translated into seasonal patterns in the quantity of money. Assuming seasonal patterns change over time, the current seasonal factors published and used by the Fed are usually slightly out of date, since they are based on past seasonal patterns in the demand for money. However, assuming that those patterns don't change too rapidly, the estimated factors will not differ by much from the "actual" seasonal factors.

In October, 1979 the Fed changed its method of operation so that it now attempts to control the supply of money by holding reserves at a level consistent with the desired level of money. The target is the seasonally adjusted money stock so that in the near future seasonal patterns can probably be interpreted in the same way as they have been in the past. But eventually the seasonal patterns of the demand for money will likely change, and under the new procedures these changes will not be reflected in the seasonal pattern of the money stock. Assuming that the Fed is successful in making the "seasonally adjusted" money stock grow at a stable rate, the apparent seasonal patterns will simply be replications of those patterns that existed previously.

As time progresses, the differences between the seasonally adjusted money stock and the (unobserved) seasonal adjusted demand for money will show themselves by producing a seasonal pattern in market interest rates. Should the Fed decide that this result is undesirable, it will have to estimate the seasonal factors in the demand for money by some other method (probably using interest rates) and use those factors in calculating the seasonally adjusted money stock. In other words, the Fed would be making a policy decision in setting the seasonal factors.

Thus the connection between the seasonal patterns of the demand for money and those of the money stock itself can be expected to become somewhat looser in the future. The observed seasonal patterns will be to a greater degree the result of Fed policy (or supply) and less exclusively a result of the public's demand. [3/]

8. EFFECTS OF ERROR ON POSSIBLE MONETARY POLICY ACTIONS

In the preceding sections, we have described the major sources of uncertainty in the monetary aggregates, measured the extent of their separate and joint effects, and provided some indication of ways by which this uncertainty might be reduced. We now consider effects of uncertainty on the formulation and implementation of monetary policy. This section, taken from [Maravall and Pierce (1980)], examines the danger that, because of error or uncertainty, the monetary authority will misjudge an incoming money supply figure and thereby take inappropriate action, or fail to take appropriate action. Attention is largely confined to the effects of observable error or revisions, which can be measured both theoretically (from models) and empirically. The added presence of unobservable error would increase still further the effects on policy of the uncertainty which we do measure.

8.1 Revisions in M-1 growth rates

As seen earlier, the major revisions in the money supply data are those due to seasonal factors and those due to benchmarking for non-member banks. If other revisions (including those made in the first week or two following initial publication and more minor ones such as from uncovering reporting errors) are included in the latter category, we may speak of seasonal and nonseasonal revisions.

Let m_t denote a two-month rate of growth in M-1 at time t, that is,

$$m_t = (M1_t - M1_{t-2})/M1_{t-2} \ .$$

We use a two-month period in this section since this is the interval for which FOMC tolerance bounds are set (Section 8.2). Further, denote preliminary aggregates and growth rates by $M1_t^{(o,a)}$ and $m_t^{(o,a)}$, and final data by $M1_t^{(f,A)}$ and $m_t^{(f,A)}$. Thus the use of o or f signifies preliminary or final data with respect to benchmarking and other nonseasonal effects, and the use of a or A signifies seasonal adjustment using preliminary (forecasted, first published) or final seasonal factors. Finally, let $m_t^{(o,A)}$ and $m_t^{(f,a)}$ be growth rates calculated from M-1 which are preliminary in one of these respects and final in the other; for example, $M1_t^{(f,a)}$ is the result of applying the preliminary seasonal factors to the final NSA data.

Figure 8.1 is a schematic representation of the various two-month growth rates, separated into these seasonal and nonseasonal components. Also shown are the seasonal, nonseasonal and total revisions, for example

$$\begin{aligned} d_t &= m_t^{(f,A)} - m_t^{(o,a)} \\ &= d_t^S + d_t^N . \end{aligned}$$

(The series $d_t^{S'}$ and $d_t^{N'}$ are virtually identical to d_t^S and d_t^N.)

These series are analyzed in further detail in [Maravall and Pierce (1980)], using M-1 data over the period 1974-1977 inclusive. Some of the main findings are that d^S and d^N appear to be independent and to have zero mean (null hypotheses asserting same are not rejected at even the 25% significance level) and that the sample standard deviations of d^S, d^N and d are 2.7%, 2.1% and 3.4%, respectively (all annualized). These results are in line with the figures mentioned at the end of Section 4.

8.2 Tolerance regions for M-1

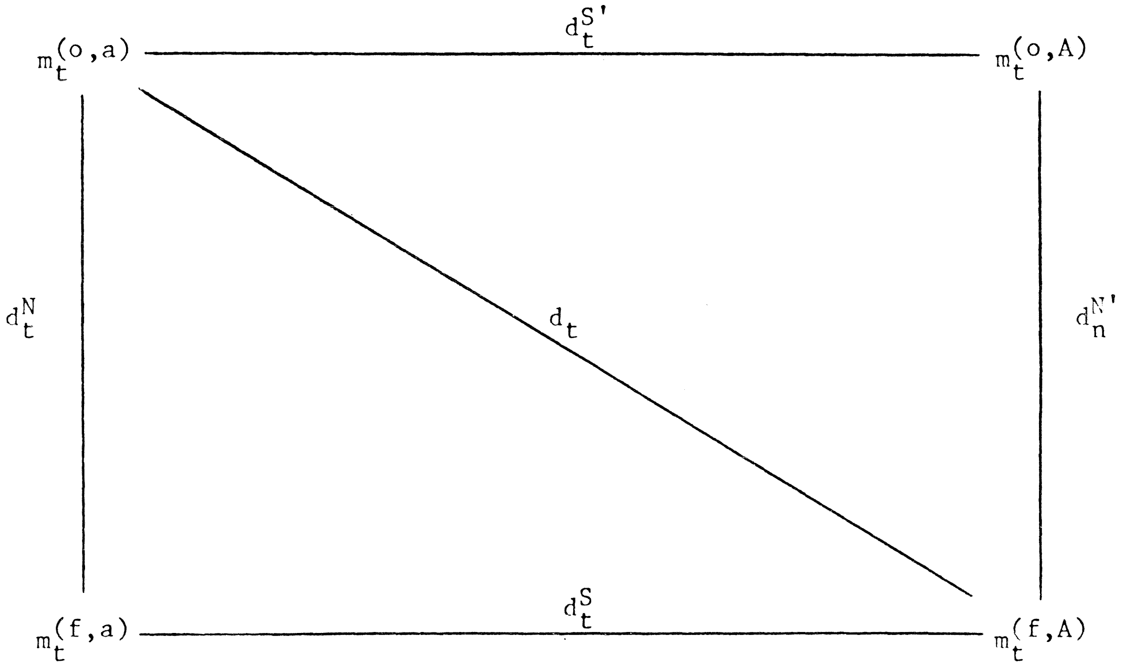
At each monthly meeting the Federal Open Market Committee sets a target range for the rate of growth of the monetary aggregates over a two-month period. Policy action depends (among other things 4/) on whether or not the growth of the aggregates falls within this range (see e.g. Wallich and and Kier, 1978, for further discussion).

Of necessity, however, policy is made on an ongoing basis, continually in the current time period for which only preliminary data are available. Therefore, the policymaker is confined to observing whether the growth rate $m_t^{(o,a)}$ [and like measures for other aggregates], calculated from data containing errors not yet observed, lies within the range of tolerance. The question we address is thus the extent to which the monetary authority may take different action by relying on the preliminary growth rate $m_t^{(o,a)}$ than would be appropriate if the final growth rate $m_t^{(f,A)}$ were known. That is, we examine the frequency with which preliminary and revised growth rates $m_t^{(o,a)}$ and $m_t^{(f,A)}$, give conflicting signals as a result of one figure lying inside and the other outside (or one above and the other below) the range of tolerance. Insofar as this range is intended to be for "true" M-1 growth rates, or at least the reported final rates, policy actions taken on the basis of such signals may be regarded as mistakes, caused by errors in the money supply data.

Figure 8.2 shows, again for the 1974-77 period, the FOMC range of tolerance for the M1 growth rate, and the preliminary and final versions of that rate, $m_t^{(o,a)}$ and $m_t^{(f,A)}$. Note first that the midpont of the tolerance range does not vary greatly over this period, though the width appears to increase over time, perhaps reflecting a growing awareness of the problem of uncertainty in the data. Moreover, the means (over 1974-77) of the midpoint of the tolerance interval and of the two m_t series are all about 6 percent, so that in the long run the targeted or forecasted growth-rate path and the actual M1 path appear to coincide.

In the short run, however, the situation is very different. Over this period, the proportion of times a "mistake" would be made (by relying on $m_t^{(o,a)}$ rather than $m_t^{(f,A)}$ is 21/48 or 44%. It is not possible to decompose

Figure 8.1. Preliminary and Revised M-1 Growth Rates (m_t), and Revisions (d_t)



o: Preliminary data with respect to nonseasonal effects

f: Final data with respect to nonseasonal effects

a: Seasonally adjusted using preliminary seasonal factors

A: Seasonally adjusted using final seasonal factors this figure (44%) into amounts due to seasonal and nonseasonal revisions separately. However, we can compare $m_t^{(o,A)}$ and $m_t^{(f,A)}$ with the tolerance bands to see how often conflicting policy signals would be given if seasonal revisions were not a problem; and using $m_t^{(f,a)}$ and $m_t^{(f,A)}$ would address the role of seasonal revisions in this regard if revision errors due to benchmarking and other nonseasonal sources were not needed. Thus, it is found that using $m_t^{(o,A)}$ rather than $m_t^{(f,A)}$ results in a mistake 9/48 or 19 percent of the time over this period; and comparing $m_t^{(f,A)}$ and $m_t^{(f,a)}$ the proportion is 20/48 or 42%. From this it appears that error in preliminary seasonal factors has dominated other types of preliminary-data error in causing uncertainty in monetary aggregate targeting.

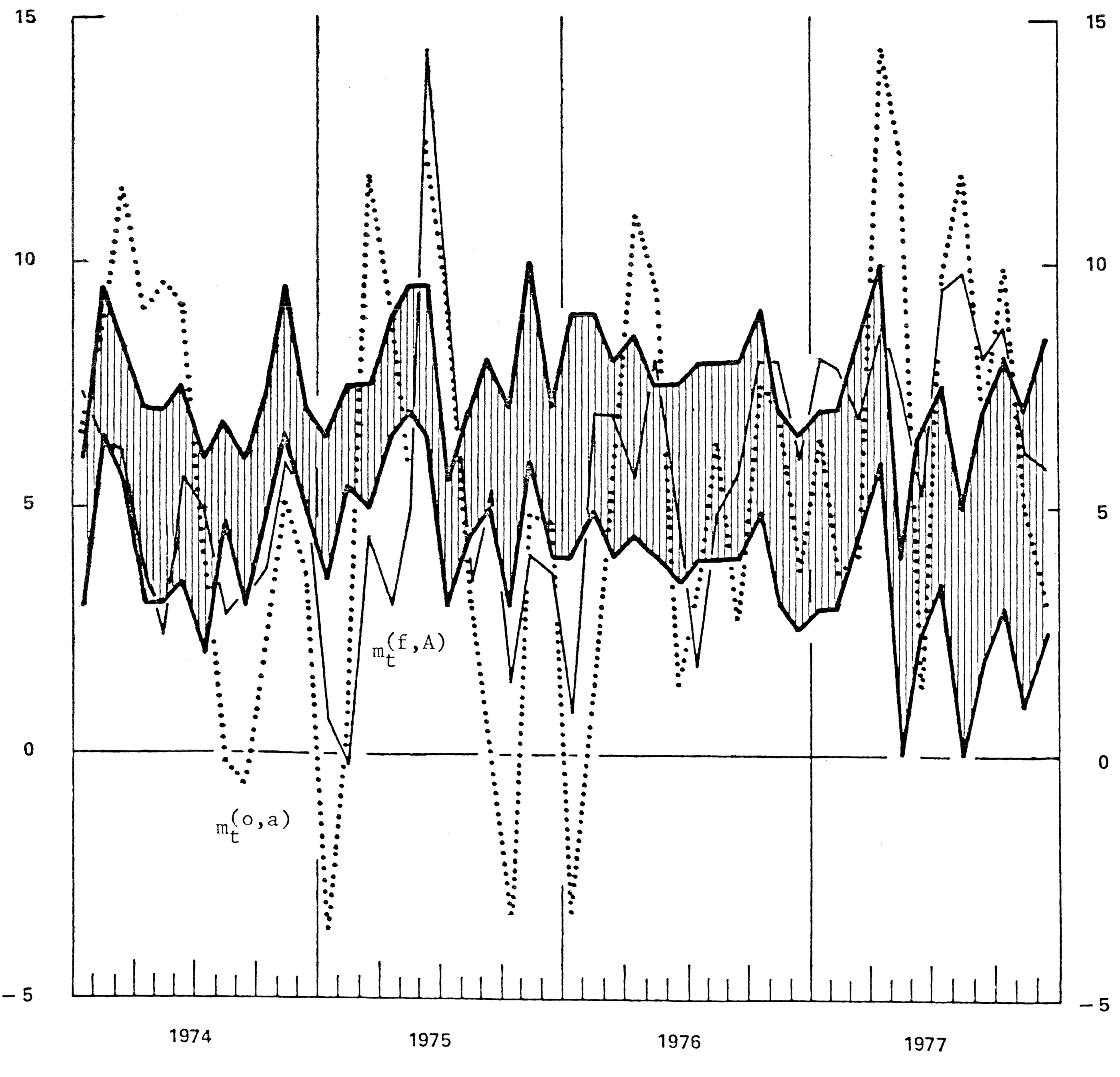
Overall the percentages of misleading initial data may appear quite high; however, given the standard deviations of d^S and d^N (2.7% and 2.1%) in relation to the average width of the interval (5-3/4%), these results are less surprising. In [ ] an analytical calculation gives similar values for the probability of erroneous signals.

Finally, we note that $m_t^{(f,A)}$ is itself inside the tolerance interval more often than is $m_t^{(o,a)}$. This event could simply reflect the higher degree of noise in preliminary data, and the monetary authority's awareness of this noise in conducting policy. For example, smoothing current data by seasonally adjustting on a <u>concurrent</u> basis each month results in preliminary growth rates which may more accurately predict the final figures (e.g., Dagum, 1978; Geweke, 1978).

9. UNCERTAINTY IN RELATIONS BETWEEN MONETARY AGGREGATES AND OTHER VARIABLES

Thus far we have examined sources of error and uncertainty in the aggregates themselves and the resultant effects on the implementation

Figure 8.2. M-1 Tolerance Region (shaded) in Relation to Preliminary and Final M-1 Growth Rates



does error in that series either render it difficult to maintain that path, or inadvertently alter the actual path. But this path is itself chosen to of monetary policy: *given* a targeted path for an aggregate series, how achieve a desired performance in other variables of importance, such as inflation, output or employment. Thus an equally important concern is the uncertainty or error in the relationships between the monetary aggregates and these variables. Lack of information (or misinformation) concerning such relationships complicates the formation, as well as the implementation, of monetary policy. Additionally, errors of measurement, sampling, seasonal adjustment, etc., in both the monetary aggregates and other series, are a prime cause of error in estimated relationships between those series.

Knowledge of relationships between the aggregates and the ultimate target variables is necessary in order to choose an appropriate path for the aggregates. In the face of widespread theoretical disagreement on the nature of the required relationships (the monetarist-Keynesian debate being but one example), it is natural to turn attention to observation of the data themselves so as to elucidate the required relationships, either judgmentally or through the use of models, by observing and taking account of what has in fact happened in the recent past.

But such empirical enquiry is fraught with uncertainty and error. Several recent investigations have demonstrated the lack of "firm" empirical relationships between important economic time series, in the sense that alternative and incompatible model specifications, including often the purely autoregressive specification in which the dependent variable is related only to its own past, can each use valid statistical methods to produce fitted equations with comparable estimation and/or forecast accuracy; (for example, Naylor, Seaks and Wichern, 1972; Nelson, 1972). A related finding (Pierce,

1977) is that predictions of many economic time series, once effective use of their own pasts has been made, can be little improved by using other series in addition in forming the predictions. Even when there is a highly statistically significant relationship it is often "weak" in the sense that the prediction error variance is reduced only a few percentage points relative to the autoregressive extrapolation.

As one of many possible illustrations, consider the "effect" of money on prices, specifically of M-2 (new definition) on the consumer price index, using monthly data (NSA) over the period December 1969-December 1979. Letting p_t and m_t denote the changes in the logarithms (essentially the monthly growth rates) of the CPI and of M-2 respectively, the regression

$$p_t = \sum_{i=1}^{d_t+12} \alpha_i p_{t-i} + e_{1t} \tag{9.1}$$

was fitted, where d_t is a set of seasonal dummies and length-of-month calendar effects (Cleveland and Pollner, 1980). The standard error of estimate was

$$\sigma_{e1} = .00195 ,$$

which is the one-month standard error in forecasting the inflation rate based only on its past history (and known seasonal/calendar information). Secondly the regression

$$p_t = d_t + \sum_{i=1}^{12} \alpha_i p_{t-i} + \sum_{i=1}^{12} \beta_i m_{t-i} + e_{zt} \tag{9.2}$$

gave

$$\sigma_{e2} = .00191 .$$

The second equation differs from the first by adding past values of M-2; but note that this knowledge results in a relative reduction in the regression standard error (or one-month forecast standard error) only two percent, and the hypothesis that all m-coefficients are zero is not rejected at the 10 percent significance level. Equally weak results were obtained for M-1 and prices. Thus, as important as money is felt to be, and surely is, in influencing inflation, observed monetary aggregate data "explain" very little of observed price data, beyond that explained merely by past history effects.

Some reasons for the occurrence of this "independence phenomenon" are given in Pierce (1977). First, of greatest relevance to the earlier part of this paper is the fact that measurement error in an independent-variable series (sampling error, seasonal adjustment error, etc.) biases regression coefficients toward zero. This would be the situation when a regression (such as (9.2)) was constructed with the aim of assessing the impact on an ultimate target variable of movements in a monetary aggregate.

A second problem concerns the "design" of the data. In order to measure relationships it is necessary that a sufficiently wide range of combinations of values of the relevant variables appear. The design of a statistical investigation is just as important as its analysis, a point long emphasized by several authors, e.g., Fisher (1935), Box (1959); yet time series are "happenstance data" as far as experimental design is concerned, so that for this reason relationships may remain unidentifiable or at best poorly measurable. In a sense, in these instances, there is a multicollinearity, in explaining one variable, between past values of that variable on one hand and (perhaps alternative groups of) other economic variables on the other.

The data may be even worse than "happenstance," insofar as closed-loop control has probably been operative over the sample period for many macroeconomic series, including such instruments as the monetary aggregates and such targets as inflation, unemployment and income. In the context of a distributed lag model, suppose an instrument x has been adjusted to keep a target y on a desired path according to a specific feedback control strategy. Then it can be shown [e.g., see Box and McGregor, 1974; Lucas, 1976] that the lag distribution connecting x and y is unidentifiable, and that identical residuals and model forecasts can result from (i) a model chosen so that the disturbances will be white noise; (ii) at the other extreme, a "model" such that y is formally related only to its past, and (iii) an infinite number of "intermediate" models. Perhaps this is not surprising; if x is determined from present and past y then, knowing y, knowing x in addition tells us nothing new. Control strategies over the past 30 years have been imprecise in the short run and shifting in the long run, but certainly they have existed.

These and other problems can and do render economic relationships connecting monetary aggregates to other variables of interest difficult to determine with more than very small precision and confidence; thus, in the conduct of monetary policy there is uncertainty about what the appropriate paths are for the "true" monetary aggregates, in addition to uncertainty stemming from both observable and unobservable errors in the first published versions of these series.

Similar comments can be made concerning the relationships of monetary aggregates, regarded as intermediate targets, to instruments of policy such as reserves and interest rates.

10. DISCUSSION AND CONCLUSIONS

That the published monetary aggregates are highly uncertain measures of the "true" U.S. money supply, for numerous reasons, is documented and discussed in this paper. We conclude this survey by mentioning some potential implications of this for the construction and use of the monetary statistics.

The major sources of uncertainty were seen to be errors due to sampling and reporting, seasonal adjustment, and transitory effects. Reporting error can be kept to a minimum by continued efforts aimed at timely and accurate data collection and at monitoring the deposit data submitted to the Board and the Federal Reserve Banks. While sampling will soon cease to be a source of error in estimating nonmember-bank components of monetary aggregates, survey sampling will continue to be needed for estimating credit union drafts and other deposits at institutions not required to report these data by the 1980 Monetary Control Act.

A recent research area in sample survey estimation is the use of historical information to improve the current survey estimate. Various types of econometric/statistical models could presumably be employed to capture this information, but the models employed in the literature have usually been univariate autoregressions, or ARIMA's (Box and Jenkins, 1970). The general idea is this: suppose the survey estimate y_t of the aggregate M_t at time t can be written

$$y_t = M_t + e_t$$

where e_t, the sampling/reporting error, has mean zero, variance σ_1^2, and for expositional purposes, we assume that the e_t are serially uncorrelated. Now consider a forecast $\hat{y}_t$ of y_t given the past observations $y_{t-1}, y_{t-2}, \cdots$, with forecast-error variance σ^2. The lack of correlation among the e_t enables us to regard $\hat{y}_t$ as an unbiased estimate of M_t as well as of y_t, and it can be shown (Scott and Smith, 1974) that the best linear unbiased estimate of M_t is of the form

$$\hat{M}_t = (1 - p)y_t + p\hat{y}_t$$

where $p = \sigma_1^2/\sigma^2$. Thus $\hat{M}_t$ is in general a more accurate estimate of M_t than is the usual sample survey estimate; a result which also holds when e_t is serially correlated. We are investigating the use of this method in estimating the money stock series.

This procedure could be extended to reduce the effects of transitory as well as sampling/reporting error, by writing the model as

$$y_t = M_t + e_{1t} + e_{2t}$$

where e_{1t} is the sampling/reporting error as above, e_{2t} is the transitory error (with variance σ_2^2), and M_t is now the quantity of interest. In this case, the best linear unbiased estimate of M_t is

$$\hat{M}_t = (1 - q)y_t + q\hat{y}_t$$

with $q = (\sigma_1^2 + \sigma_2^2)/\sigma^2$. This presupposes, of course, knowledge of the value of σ_2^2.

The possibilities for reducing seasonal adjustment error have been extensively researched in recent years, and Section 7 highlights some of the concerns. The Federal Reserve Board has engaged an outside Committee to examine problems in seasonally adjusting the monetary aggregates, which is expected to report its recommendations shortly. As noted earlier in the paper, greater flexibility (than X-11 enjoys) in tailoring the procedure to the statistical and economic characteristics of each series could reduce unobservable seasonal adjustment error. Observable error (revisions) could also be reduced in this way, and additionally by basing preliminary factors on both (i) all available information including the current value and (ii) well-constructed forecasts of future values.

These and other ways to reduce error and uncertainty in the reported monetary aggregates are continually under study. But some error will always remain, reflecting both the present state of the art and of practice and the perhaps intrinsic limits on what can be achieved. Thus it is of greatest importance that error in these data be recognized and quantified to the extent possible. (The potential for achieving this is, as seen in the past above, a major advantage of constructing models for these series.) Determination and dissemination of error estimates would warn users of the monetary aggregates against placing unwarranted emphasis on them.

If there were to be a single measure of error or uncertainty in the monetary aggregates published, probably the most useful number would be the (estimated) standard deviations of the total revision (difference between first-published and final data), due to seasonal, benchmark and all other effects. There is already widespread awareness of errors in <u>preliminary</u> data, and release of estimated standard deviations of revisions would be an important step in acknowledging and quantifying this fact.

Unobservable error is, of course, equally important but, partly because it is not even defined except with respect to a not always unambiguous concept or model of the series, there would need to be an education of the public on the nature and source of such error. If this were gone ahead with, publication of a measure of error in final data, or alternatively, of total preliminary/final error (transitory, seasonal, sampling/reporting,...) would then be very useful.