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In Plato's Cave:

Sharpening the Shadows of Monetary Announcements

GIAMPIERO M. GALLO and MASSIMILIANO MARCELLINO

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In Plato's Cave: *

Sharpening the Shadows of Monetary Announcements

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Abstract

In this paper we provide a framework for assessing the degree of reliability of provisional estimates of final data. Various desirable properties for provisional data are suggested, as well as procedures for testing them, taking into account the possible nonstationarity of economic variables. We then reexamine the question of the most appropriate way information should be extracted from available data in the presence of a data revision process. The methodology is applied to study the quality of US M1 data production process.

^{*}In the seventh book of *The Republic*, Plato (427-348 B.C.) suggests a metaphore about the perception and the description of reality, likening them to the observation of shadows projected by objects from the entrance of a cave onto its bottom. We would like to thank Neil Ericsson for kindly providing the data on M1 used in this paper. We benefitted from discussions with Glenn Rudebusch. Financial support from the Italian MURST and CNR is kindly acknowledged by the first author.

1 Introduction

Information about macroeconomic variables is collected and processed by agencies which release preliminary figures and later revise them until they are considered "final", i.e. not in need of further revisions¹. The process of convergence to finalized data may take a long time, although later ordinary revisions are less and less important. The impact that such provisional data have on the economic activity is quite relevant: consider, for example, the effects that announcements on money supply, inflation or GNP have on the expectation climate and therefore on investment decisions and financial markets.

As the rational expectation literature emphasized, the impact of an announcement is relevant only if it was unexpected, i.e. if it constitutes a surprise. Thus, from an empirical point of view, the correct evaluation of what a surprise is and of its impact hinges on a correct specification of the expectation formation process, conditional on the information *currently* available. In fact, it is unrealistic to assume that final data are available without any delay, or that agents wait for their release before deciding their own behavior.

Actually, in defining the surprises, a distinction has been made in the literature between unanticipated and unperceived movements in a macroeconomic variable. In reference to money supply, for example, unanticipated money growth is usually taken to be the difference between an extrapolation of past behavior of money growth and actual current money growth (final data), whereas unperceived money supply is the difference between preliminary and final values. Barro and Hercowitz (1980) find that if unperceived money growth is used in the model instead of unanticipated money growth, it loses all significant explanatory power for unemployment and output (cf. also Boschen and Grossman, 1982, for similar conclusions).

The fact that timely published data contain errors (which will be

¹We will refer to the former as *provisional* figures, using the term *preliminary* for the first published data. Occasionally, even final figures are further revised, say, to harmonize them with changes in definitions.

corrected at a later stage) should also be taken into account. For example, provisional data might signal a deviation in monetary policy even when such a deviation is not present and, as noted by Maravall and Pierce (1986), attempts at correcting such a deviation can insert noise into the system.

A further reason for studying the information contained in provisional data relative to final data is to evaluate the "rationality" of the data production process, i.e. whether the additional cost to get more accurate observations outweighs the benefits. In particular, it should not be possible to increase the accuracy of provisional data by using already available information. If this were not so, it would be convenient for the agents to revise provisional data themselves, instead of referring to officially published data.

The consequences of the presence of provisional data have long been analyzed in the literature: previous studies focus on descriptive assessments of the quality of provisional data and their effects on estimation and forecasting with large-scale and time series models (see, for example, Harvey et al., 1982, Mankiw et al., 1984, Mankiw and Shapiro, 1986). Another stream of literature this paper is in line with is concerned with real-time forecasting (Diebold and Rudebusch, 1991), which takes into explicit account the fact that at the time of performing a forecast them most recent data available are provisional.

In this paper we set the problem in more general terms, suggesting a procedure which addresses the two fundamental issues in this area:

- 1. What are the statistical properties of a given data production process?
- 2. Can we improve on published provisional data if we want to forecast final data?

The main novelty of our procedure is that it considers explicitly the long-run restrictions implied by cointegration to assess the properties of provisional data. Most of the previous contributions in this area have overlooked the fact that many economic variables are integrated. By

neglecting this aspect, one may misspecify the model used to assess the properties of provisional data and therefore get unreliable results.

The procedure is indeed more general, because it is easily adapted to study the relationship between all anticipating variables such as forward rates of exchange rates, futures rates, leading indicators, and so on) and their realized counterparts. The idea of using cointegration analysis in this context is not new; see, for example, Hakkio and Rush (1989) and Hamilton and Perez-Quiros (1995). The original methodological aspects of this paper lie in having cast properties and procedures into a more formal framework.

From an empirical point of view, we contribute to the study of US money supply (M1) applying the methodology to monthly data from 1973 to 1995. We show that there exist two structural breaks in the data production process, and isolate three subperiods characterized by an increasing degree of accuracy of provisional data.

We show also that in the past a suitable model might have been of help in sharpening the shadows of preliminary announcements, while in more recent times this is less so, due to a greatly improved degree of accuracy in provisional information relative to final data.

The structure of the paper is as follows: in Section 2 we develop the econometric framework based on cointegration which will be used throughout the paper. In Section 3 we apply the methodology to monthly data for US M1. Some extensions are considered in Section 4 together with the ensuing empirical analysis for the data of interest. The procedure to forecast final data from currently available provisional values is introduced in Section 5, and is then applied to the series at hand. Concluding remarks follow.

2 The Basic Econometric Methodology

In what follows, we will simplify somewhat the complex reality of the various data production processes. Extensions of the analysis to actual cases can be notationally burdensome, but can easily be adapted from our framework. We will assume that preliminary figures, revisions and final data are published at regular intervals². This is in agreement with recent common practice by data production agencies. We will assume also that final data are the outcome of a process of successive data revisions.

Given a finite number of revisions, n, the sequence of data available through time for the value of a variable y_t at time t can be represented as:

$$t+1p_t, t+2r_t^1, t+3r_t^2, \ldots, t+nr_t^{n-1}, t+n+1f_t,$$

where we have indicated by $_{t+1}p_t$ the preliminary value for period t which becomes available in period t+1, $_{t+1+i}r_t^i$ are the i^{th} revisions for y_t which become available in period t+1+i, and $_{t+1+n}f_t$ are the final data available n+1 periods after t.

At each period, then, a number of preliminary, revised, and final data are announced for the series of interest. For example, taking time t+1 as a reference, the values

$$t+1p_t$$
, $t+1r_{t-1}^1$, $t+1r_{t-2}^2$, ..., $t+1r_{t-n}^{n-1}$, $t+1f_{t-n-1}$,

are published at time t + 1.

As the number of revisions increases, it is unlikely that informative changes occur, so that considering successive revisions is less relevant than concentrating just on first published data and first revisions. For this reason, and also to simplify the notation (but without loss of generality), we will assume throughout that n = 2.

In order to characterize the nature of the relationship between provisional and final data from an *ex post* point of view, the relevant variables to be considered are

$$p_t = t+1$$
 p_t , $r_t = t+2$ r_t^1 , $f_t = t+3$ f_t , $t = 1, \dots, T-2$.

When these variables are integrated of order 1, I(1), cointegration between provisional and final data is a necessary condition for the data

²We will avoid, by so doing, the so-called *ragged-edge* problem studied by Wallis (1986).

production process to be of interest. Actually, large and systematic discrepancies between provisional and final data could suggest either unreliability of data collection and processing, or an attempt at "fooling" the public. Either one would not be sustainable in the long run and would require some adjustment.

A second property to be examined relates to efficient information processing: can provisional data be considered Minimum Mean Squared Error Predictors of final data, or does there exist some combination of current provisional and past provisional and final data having this property ³?

A third related issue is the one of unbiasedness of provisional data as forecasts of the final data.

All these issues can be conveniently dealt with in the by now familiar statistical framework of cointegration, where testing procedures for their validity can also be set up. We will start by examining the properties of data revisions in a bivariate system (provisional versus final data) to gain some insights, and extend the results to the trivariate system in Section 4. The inclusion of further revisions is straightforward, although notationally cumbersome, and will not be explicitly taken into account here.

2.1 Preliminary and Final Data

In a bivariate context, we could consider any relationship between preliminary p_t , revised r_t and final f_t data. For the sake of simplicity, let us consider just one case, and let us assume that a suitable statistical representation for $\{f_t, p_t\}_{t=0}^{\infty}$, is given by a VAR(q)

$$\mathbf{A}(L)\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{e}_t \tag{1}$$

³When we consider the various provisional measures, we could also consider the somewhat weaker requirement that successive revisions should include all the information that was contained in the previous revisions and have a smaller prediction variance.

1, 2, positive definite and $\mathbf{A}(L) = \{a_{ij}(L)\} = (\mathbf{I} - \mathbf{A}_1 L - \mathbf{A}_2 L^2 - \dots - \mathbf{A}_n L^q)$ is a matrix polynomial in the lag operator L. We will keep the relevant initial values fixed.

A common reparameterization of (1) yields the basis for cointegration testing.

$$\mathbf{B}(L)\Delta\mathbf{v}_{t} = -\mathbf{A}(1)\mathbf{v}_{t-1} + \boldsymbol{\mu} + \mathbf{e}_{t} \tag{2}$$

where $\Delta = (1 - L)$ is the first-difference operator, $\mathbf{B}(L) = (\mathbf{I} - \mathbf{B}_1 L - \mathbf{B}_2 L)$ $\mathbf{B}_2 L^2 - \ldots - \mathbf{B}_{q-1} L^{q-1}$) is a matrix polynomial of order q-1, with $\mathbf{B}_i =$ $-\sum_{i=i+1}^{q} \mathbf{A}_{i}$

If f_t and p_t are cointegrated (Engle and Granger, 1987; Johansen, and 1995), that is if $\mathbf{A}(1) = \alpha \boldsymbol{\beta}' = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (\beta_1 \ \beta_2),$ then we can write (2) as the restricted Vector Error Correction Model

$$\mathbf{A}(1) = \alpha \beta' = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} (\beta_1 \ \beta_2),$$

(VECM)

$$\mathbf{B}(L)\Delta\mathbf{y}_{t} = -\alpha s_{t-1} + \boldsymbol{\mu} + \mathbf{e}_{t} \tag{3}$$

where $s_t = \beta' \mathbf{y}_t$ expresses the distance from the long-run equilibrium between f_t and p_t and is stationary. In this simple bivariate case, we \mathfrak{D} can have just one cointegrating relationship which we will normalize by considering $s_t^* = f_t + \beta_2 p_t$.

Exploiting Johansen's (1995) equality

$$\mathbf{I} = \boldsymbol{\beta}_{\perp} (\boldsymbol{\alpha}_{\perp}' \boldsymbol{\beta}_{\perp})^{-1} \boldsymbol{\alpha}_{\perp}' + \boldsymbol{\alpha} (\boldsymbol{\beta}' \boldsymbol{\alpha})^{-1} \boldsymbol{\beta}', \tag{4}$$

we see that the constant term μ in (3) can be decomposed into two parts

$$\boldsymbol{\beta}_{\perp}(\boldsymbol{\alpha}'\boldsymbol{\beta}_{\perp})^{-1}\boldsymbol{\alpha}_{\perp}\boldsymbol{\mu} \equiv \mathbf{d}$$

and

$$\alpha(\beta'\alpha)^{-1}\beta'\mu \equiv \alpha\beta_0$$

⁴The assumption of normally distributed errors can be relaxed without changing the substance of the following results, since we can reinterpret the procedure in terms of linear projections.

Existing testing procedures (e.g. Johansen, 1992) focus either on $\mu = 0$ or $\mathbf{d} = \mathbf{0}$. What we are interested in, as will be clearer in the sequel, is to test whether $\beta_0 = 0$. With this in mind, the error correction term can then be redefined to be

$$z_t = \beta_0 + f_t + \beta_2 p_t \tag{5}$$

and hence the restricted VECM can be rewritten as

$$\mathbf{B}(L)\Delta\mathbf{y}_t = -\alpha z_{t-1} + \mathbf{d} + \mathbf{e}_t. \tag{6}$$

Such a representation will be tested for and cointegration used as a minimal requirement to be satisfied for the revision process of I(1) variables to be meaningful.

We can now consider a second set of properties which we will call efficiency, as they relate to the possibility that the current preliminary data also contain all information available in past values of final and of preliminary data. We will distinguish between two different concepts of efficiency, according to whether the property holds on levels or on first-differences.

Level efficiency (LE) is a necessary and sufficient condition for p_t to yield an efficient forecast of f_t in the MSPE sense

$$LE_{fp} \Leftrightarrow E\left(f_t|p_t, F_{t-1}, P_{t-1}\right) = E\left(f_t|p_t\right),\tag{7}$$

where
$$F_{t-1} = \{f_{t-j}, j = 1, 2, \ldots\}$$
 and $P_{t-1} = \{p_{t-j}, j = 1, 2, \ldots\}$.

Defining now $\omega_{fp} = \sigma_{12}/\sigma_{22}$, i.e. the ratio of conditional covariance between Δf_t and Δp_t to the conditional variance of Δp_t , we can exploit the properties of the conditional expectations for a bivariate normal random variable (see e.g. Spanos, 1986) to manipulate the VAR in levels representation (1) to yield the model for f_t conditional on p_t :

$$(a_{11}(L) - \omega_{fp}a_{21}(L)) f_t = (\omega_{fp}a_{22}(L) - a_{12}(L)) p_t + (\mu_1 - \omega_{fp}\mu_2) + u_t.$$
(8)

 LE_{fp} holds if and only if no lags of f_t nor of p_t are relevant in the conditional model. Recalling the definition of $a_{ij}(L)$, we can say that LE_{fp} is equivalent to

$$f_t = \omega_{fp} p_t + (\mu_1 - \omega_{fp} \mu_2) + u_t. \tag{9}$$

Hence, LE_{fp} corresponds to cointegration, and to having uncorrelated error correction terms $z_t = f_t - \mu_1 - \omega_{fp}(p_t - \mu_2)$, t = 1, 2, ..., T, which are easier conditions to be tested for.

By the same token, we can define first-difference efficiency (DE) as the property

$$DE_{fp} \Leftrightarrow E\left(\Delta f_t | \Delta p_t, z_{t-1}, \Delta F_{t-1}, \Delta P_{t-1}\right) = E\left(\Delta f_t | \Delta p_t, z_{t-1}\right). \tag{10}$$

Using the same algebra as in the LE case we get

$$(b_{11}(L) - \omega_{fp}b_{21}(L)) \Delta f_t = (\omega_{fp}b_{22}(L) - b_{12}(L)) \Delta p_t$$

$$+ (\omega_{fp}\alpha_2 - \alpha_1) z_{t-1} + (d_1 - \omega_{fp}d_2) + u_t,$$
(11)

and, as before, DE_{fp} holds if and only if no lags of Δf_t nor of Δp_t are relevant in the conditional model. We can thus say that DE_{fp} is equivalent to

$$\Delta f_t = \omega_{fp} \Delta p_t + (\omega_{fp} \alpha_2 - \alpha_1) z_{t-1} + (d_1 - \omega_{fp} d_2) + u_t.$$
 (12)

Note that LE_{fp} implies DE_{fp} (recall that $\mathbf{B}_i = -\sum_{j=i+1}^q \mathbf{A}_j$), but the reverse in general does not hold, as simple examples would show.

A third set of conditions can be derived relative to *unbiasedness*, that is, to the property that preliminary data are unbiased forecasts of the corresponding final data. Formally, a necessary and sufficient condition for preliminary data to be *level unbiased* (LU) is

$$LU_{fp} \Leftrightarrow E(f_t|p_t, F_{t-1}, P_{t-1}) = p_t.$$
 (13)

Rewriting the long-run equilibrium relationship (5) as

$$f_t = -\beta_0 - \beta_2 p_t + z_t, \tag{14}$$

we have zero-mean revision errors (ZMRE) when

$$ZMRE_{fp} \Leftrightarrow (\beta_0, \ \beta_1, \ \beta_2) = (0, \ 1, \ -1). \tag{15}$$

Thus,

$$LU_{fp} \Leftrightarrow LE_{fp} \cup ZMRE_{fp}.$$
 (16)

As remarked before, we are allowing for the presence of a constant both in the VECM, \mathbf{d} , and in the cointegration relationship, β_0 , and this requires special attention in the testing procedure. In order to test for ZMRE, we suggest a two-step procedure, whereby we first test whether upon normalization of $\beta_1 = 1$, we have $\beta_2 = -1$, and then we test for $\mu_1 = \mu_2$ given that, conditional on $(\beta_1, \beta_2) = (1, -1)$,

$$\beta_0 = 0 \Leftrightarrow \mu_1 = \mu_2.$$

Turning our attention to first-differences, one may be tempted to require a similar property to hold, namely:

$$DU_{fp} \Leftrightarrow E\left(\Delta f_t \middle| \Delta p_t, z_{t-1}, \Delta F_{t-1}, \Delta P_{t-1}\right) = \Delta p_t. \tag{17}$$

or

$$\Delta f_t = \Delta p_t + \epsilon_t$$

with $E\left(\epsilon_{t}|\Delta p_{t},z_{t-1}\Delta F_{t-1},\Delta P_{t-1}\right)=0$. This implies that the revision errors $(f_{t}-p_{t})$ follow a random walk: therefore, the cointegrating vector $(\beta_{0},\ \beta_{1},\ \beta_{2})$ is different from $(0,\ 1,\ -1)$ and LU_{fp} does not hold. Conversely, LU_{fp} holds if and only if $f_{t}=p_{t}+z_{t}$, i.e. if and only if

$$\Delta f_t = \delta_0 + \delta_1 \Delta p_t + \delta_2 z_{t-1} + v_t$$

holds with $(\delta_0, \ \delta_1, \ \delta_2) = (0, \ 1, \ -1)$.

Moreover, property (17) requires DE_{fp} as a necessary condition, i.e. that the conditional model

$$\Delta f_t = \omega_{fp} \Delta p_t + (\omega_{fp} \alpha_2 - \alpha_1) z_{t-1} + (d_1 - \omega_{fp} d_2) + u_t.$$
 (18)

holds. In addition, DU_{fp} holds if and only if $\omega_{fp} = 1$, together with $(\omega_{fp}\alpha_2 - \alpha_1) = 0$ and $(d_1 - \omega_{fp}d_2) = 0$.

All properties and testing procedures are summarized in Table 1.

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Table 1
Bivariate Analysis: Summary of Properties and Testing Procedures

Bivariate	Analysis: 51	Bivariate Analysis: Summary of Properties and Testing Procedures	nd Testing Procedures	
Property	VECM	Hypothesis	Test Used	
Cointegration	Unrestr. (2)	$rank(\mathbf{A}(1) = 1)$	Johansen	
Level Efficiency	Restr. (6)	z_t uncorrelated	LM for uncorrelation	
Zero-Mean Rev. Errors	Restr. (6)	$(\beta_0, \beta_1, \beta_2) = (0, 1, -1)$	LR for $(\beta_1,\beta_2)=(1,-1)$ and Wald for $(\mu_1=\mu_2 [(\beta_1,\beta_2)=(1,-1)])$	
Level Unbiasedness		LE + ZMRE		
Diff. Efficiency	Cond. (11)	No lagged differences	Wald	
Diff. Unbiasedness	Cond. (12)	$DE + \omega_{fp} = 1, \alpha_1 = \alpha_2,$	Wald	
		$d_1 = d_2$		

2.2 Forecast or Measurement Errors: A Relevant Issue?

So far we have considered preliminary data as forecasts of final data, and stated conditions for them to be unbiased and efficient forecasts. Yet, preliminary data could also be thought of as final data subject to a measurement error.

The suggestion by Mankiw *et al.* to discriminate between the two characterizations was to test whether in

$$\underline{\Delta f_t = \gamma_0 + \gamma_1 \Delta p_t + \xi_t}, \quad \underline{\Delta p_t = \delta_0 + \delta_1 \Delta f_t + \eta_t}, \quad \underline{\Delta p_t = \delta_0 + \delta_1 \Delta f_t + \eta_t}, \quad (19)$$

 $(\gamma_0, \gamma_1) = (0, 1)$ or $(\delta_0, \delta_1) = (0, 1)$. If the forecast relationship is the correct one, $var(\Delta p) < var(\Delta f)$, and the OLS estimator $\hat{\delta}_1$ converges in probability to a value which is smaller than one.

However, the testing procedure followed in (19), which corresponds to testing for the DU_{fp} or DU_{pf} properties, is valid only after having assessed that the relevant conditioning sets can be restricted by dropping past values of final and preliminary data. Moreover, the evidence of, say, $(\gamma_0, \gamma_1) = (0, 1)$ has the strong consequence that $f_t - p_t$ would be a random walk so that the cointegrating vector could not be (0, 1, -1), which is in contrast with the desired feature for revision errors to be stationary. ⁵

In order to examine the difficulties in discriminating between the two cases also for the levels of I(1) cointegrated variables, let us consider

$$\underbrace{f_t = \gamma_0 + \gamma_1 p_t + \xi_t}_{\text{forecast}}, \quad \underbrace{p_t = \delta_0 + \delta_1 f_t + \eta_t}_{\text{measurement}}, \tag{20}$$

From cointegration theory, when $(\gamma_0, \gamma_1) = (0, 1)$, it follows that $(\delta_0, \delta_1) = (0, 1)$ and viceversa. In other words, deciding which variable coefficient

⁵Of course, ξ_t could be an MA process with a unit root, in which case, $f_t - p_t$ would be stationary under the hypothesis $(\gamma_0, \gamma_1) = (0, 1)$. But in this case the error correction term would be a relevant omitted variable from 19.

in the cointegrating relationship should be normalized to 1 (and hence the other to -1) is just a matter of taste in this context.

For these reasons, we will rather concentrate on the most appropriate way of modelling provisional and final data jointly, and avoid the issue of measurement versus forecast errors altogether.

3 Preliminary and Final Data on US M1

The importance of the properties now described can be assessed in reference with the relationship between preliminary and final data on M1 for the US.⁶. We study the period from January 1973 to August 1995, using monthly seasonally adjusted data⁷. For the sake of brevity, we will devote greater attention on the bivariate relationship between preliminary and final data (i.e. the first published and the latest available data), while the results on the other relationships (preliminary–first revision and first revision–final) are similar (cf. Figures 2 and 3 below); the full details will be summarized below (Table 8) and are available upon request.

A graphical analysis of the data shows that the behavior of preliminary and final data is fairly similar (cf. Fig 1a or the cross-plot in Fig. 1b), although the difference between final and preliminary data, $f_t - p_t$, oscillates around a value quite different from zero (Fig. 1c). Moreover (Fig. 1d), it seems possible to identify three distinct subperiods where $f_t - p_t$ behaves differently: up to the end of 1979 there appears to be an upward trend with wide fluctuations, even if $f_t - p_t$ remains negative for most of the sample period. After that, and until the end of 1987 the slope of the trend seems to become slightly negative, the variability decreases,

⁶For an exhaustive description of the data production for this aggregate, see Anderson and Kavajecz, 1994

⁷The analysis could be repeated on non seasonally adjusted data (not available to us at the time of the present study), in view of the results by Kavajecz and Collins (1995). These authors detect the relevance of seasonal adjustment in assessing the properties of provisional data. However, their methodology neglects cointegration and the search for a correct dynamic specification, which could bias the outcome. We performed most of the econometric computations using PCGIVE and PCFIML Version 8.0 (Doornik and Hendry, 1994a and b).

and p_t tends to be always larger than f_t . Finally, in the last period there is no apparent trend in the data, and the mean value seems to be around zero.

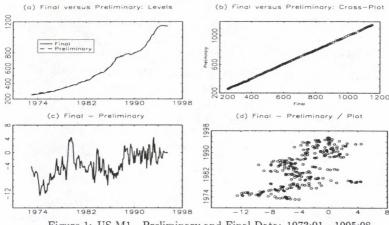


Figure 1: US M1 - Preliminary and Final Data: 1973:01 - 1995:08

The relevance of the division into three subperiods also for the levels of the variables can be deduced from Fig. 1b, where the observations tend to cluster in three discontinuous zones around the diagonal.

This evidence of structural breaks occurring throughout the sample is confirmed by the diagnostics on a VAR model estimation with 13 lags for the whole period, which highlight many problems (Table 2), particularly for heteroskedasticity and lack of normality of the residuals. The same problems exist for specifications with a different number of lags.

The question becomes one of detecting the points of structural change more accurately, to be interpreted as periods after which either the series itself or the data collection process exhibit a different behavior. Hence, we will refer here to changes in the environment around money supply, and in particular to policy changes, such as the change in operating procedures by the Fed between October 1979 and September 1982 documented by various authors (e.g. Hamilton, 1988) whereby the interest rate targeting was abandoned in favor of money supply. This marks a focus on the announcements of monetary aggregates.

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A third event to be investigated as a possible break point is the Stock Exchange crash: after October 1987 the Fed has put in place an increasingly transparent announcement procedure, and possibly paid more attention to the quality of preliminary data.

Table 2
Relationship between Preliminary and Final Data
Diagnostics on VAR Estimation – 1973:06-1995:08

	M1 final	M1 prelim	Vector
Autocorr.	0.54 [0.79]	0.47 [0.85]	0.50 [0.98]
Heterosk.	2.02 [0.00]	2.35 [0.00]	1.36 [0.00]
Normality	19.2 [0.00]	11.63 [0.00]	8.43 [0.07]
ARCH	2.77 [0.00]	2.30 [0.02]	

13 lags used, p-values in brackets. Autocorrelation Test is Godfrey's (1988); Heteroskedasticity Test is White's (1980); Normality Test is Doornik and Hansen's (1994); ARCH Test is Engle's (1982).

In order to investigate these possibilities we have run Chow forecast stability tests, adopting the most conservative ones derived by Clements and Hendry (1994) which take into consideration potential heteroskedasticity and parameter uncertainty. The results are presented in Table 3 and show that only the September 1979 and the October 1987 are detected as presenting a structural break, whereas October 1982 does not. Evidently, the change in operating procedures by the Fed had already put in place a different data production process which was not changed when the interest rate targeting was partially resumed.

Table 3

Relationship between Preliminary and Final Data

Chow Structural Stability Tests

Sample	1-Period Ahead	3-Periods Ahead
1973:01 - 1979:09	2.80 [0.06]	3.50 [0.00]
1979:10 - 1982:10	1.06 [0.36]	0.76 [0.60]
1979:10 - 1987:10	4.60 [0.01]	2.09 [0.06]

We will then conduct our analysis on the three sub-samples separately, namely, January 1973 to September 1979, October 1979 to October 1987, and November 1987 to August 1995 and highlight the differences across periods. The starting dates will vary accordingly under the constraint that the first used sample point belongs to the proper regime. Among the many results obtained we will present here the diagnostics which confirm the adequacy of the VAR representation, the results on tests for cointegration and for level and first-difference unbiasedness and efficiency. The full details on parameter estimation are omitted and are available upon request.

Table 4

Relationship between Preliminary and Final Data

Diagnostics on VECM Estimation on the Various Sub-samples

Sample	1973	3:01-197	9:09	1979	:10-198	7:10	1987	7:11-199	5:08
Test	M1f	M1p	Vec	M1f	M1p	Vec	M1f	M1p	Vec
Autocorr.	1.97	0.82	1.51	0.60	0.69	0.65	1.40	1.00	0.71
	[0.09]	[0.53]	[0.08]	[0.72]	[0.65]	[0.88]	[0.22]	[0.43]	[0.82]
Heterosk.	1.53	0.53	0.81	1.20	1.27	1.15	1.33	2.02	1.35
	[0.12]	[0.91]	[0.78]	[0.28]	[0.23]	[0.22]	[0.19]	[0.02]	[0.06]
Normality	0.97	4.43	6.72	3.56	0.20	5.45	0.47	0.22	0.35
	[0.61]	[0.10]	[0.15]	[0.16]	[0.90]	[0.24]	[0.78]	[0.89]	[0.98]
ARCH	0.74	0.69		1.31	0.21		0.49	1.24	
	[0.59]	[0.62]		[0.26]	[0.97]		[0.80]	[0.29]	
Struct. Stab.	1.71	2.06		2.67	2.61		2.50	2.33	
Lags		4			5			5	

p-values in brackets. Structural stability test is Hansen's (1992). 5% critical values: 1973:01-1979:09 = 2.54; 1979:10-1987:10 and 1987:11-1995:08 = 2.96.

The evidence from unrestricted VECM estimated on each sub-sample is fairly reassuring in that all diagnostics point to the congruence of the estimated models⁹, including tests for structural stability. We collect the results on such diagnostics in Table 4; the last row indicates the

⁸By comparing these dates with the timeline provided by Kavajecz (1994), we notice that no definitional changes occurred at the break points isoleated here.

⁹Congruence basically means that 'the model is coherent with the available information' (Mizon, 1995, p.9), and therefore requires that estimated residuals are well behaved.

number of lags in each model which were retained in a general-to-specific modelling strategy based on their significance from a Wald test and the non-correlation of the residuals.

Using these congruent models for cointegration testing, we see from the results proposed in Table 5 that the hypothesis of the existence of one cointegrating vector is accepted in all periods¹⁰. Hence the basic requirement for the data revision process is satisfied.

Table 5

Relationship between Preliminary and Final Data

Tests on the Data Revision Properties – Cointegration

TCDOD OIL OIL	c Dava recv.	DIOIL I	Operates	COLLEG	Brancion
Sample	H ₀ : rank=p	λ-max	95% C.V.	Trace	95% C.V.
1973:01-1979:09	p = 0	19.09	16.9	19.09	18.2
	$p \leq 1$	0.001	3.7	0.001	3.7
1979:10-1982:10	p = 0	24.3	14.1	26.56	15.4
	$p \leq 1$	2.26	3.8	2.26	3.8
1979:10-1987:10	p = 0	36.56	14.1	36.96	15.4
	$p \leq 1$	0.399	3.8	0.399	3.8

Critical values from Osterwald-Lenum (1992). Trend included in the first subsample.

As for the properties for levels, we test whether the hypothesis of ZMRE is supported empirically. In fact, we see that there is a different behavior across periods. In particular, looking at the first row of Table 6, we see that, in the first period even the hypothesis (β_1, β_2) equal to (1, -1) is rejected, and hence there is no interest in testing the second requirement for level unbiasedness, i.e. whether $\beta_0 = 0$. Thus, the revision error seen as the difference between preliminary and final data is not stationary. Recall from our previous discussion that this is a period characterized by interest rate targeting and hence the need for accuracy in the data

 $^{^{10}}$ As Johansen (1991) points out, we would not need to run tests for unit roots before passing onto cointegration analysis, because the existence of one cointegrating vector in our case would be enough to justify the treatment of the variables as I(1). However, following standard practice, we have run Augmented Dickey Fuller tests, which always accept the null hypothesis of I(1)-ness for the two variables in the three subperiods.

production process for money supply was less stringent.

Table 6
Relationship between Preliminary and Final Data
Tests on the Data Revision Properties – Levels

Sample	$(\beta_1, \beta_2) = (1, -1)$	$(\mu_1 = \mu_2 (\beta_1, \beta_2) = (1, -1)$	Level Efficiency
1973:01-1979:09	6.53 [0.01]		743.43 [0.00]
1979:10-1987:10	0.06 [0.80]	10.33 [0.00]	117.76 [0.00]
1987:11-1995:08	0.01 [0.93]	3.41 [0.06]	90.26 [0.00]

Test for $\beta_1, \beta_2 = (1, -1)$ is a LR $\sim \chi^2(1)$;

Test for $\mu_1 = \mu_2 | \beta_1 = 1, \beta_2 = -1$ is a Wald $\sim \chi^2(1)$;

Test for level efficiency is an LM test for uncorrelation of the error correction term.

As for the second sub-sample, the tests point to the stationarity of the revision errors. However, the hypothesis of no constant term in the error correction term is rejected. The estimated β_0 is equal to 2.95 which is consistent with the value of the negative average of $(f_t - p_t)$ in this subsample from Figure 1c. This corresponds to a period where targeting was changed and the systematic overevaluation of preliminary data relative to final data might signal an imperfect learning process or an attempt at hiding the extent of the monetary tightness.

The third and last subsample is instead characterized by zero mean stationary revision errors. In this respect, the data production process becomes more accurate, in agreement with the higher transparency of announcements desired by the Fed.

Note that level efficiency is rejected for all periods since all test statistics are highly significant, which means that the contemporaneous preliminary data do not summarize all the informational value contained in previous preliminary and final data. This also implies that level unbiasedness does not hold and justifies the need for modelling the relationship between preliminary and final data keeping into account the lagged values as well.

Moving to first-differenced variables, the results are obtained from a congruent conditional error correction model such as (11). In Table 7 we report the tests for difference efficiency from which we see that a test on lags would tend to accept the null hypothesis of joint irrelevance of lagged Δf_t and Δp_t . Yet, the resulting model is quite unsatisfactory from the residual diagnostics point of view (not reported). This is due to the fact that the maintained model should include the significant lagged variables reported in the last column of Table 7, besides the appropriate error correction term derived from the analysis on levels.

As noted in section 2, difference efficiency is a necessary condition for difference unbiasedness, and hence in the light of these results, we can conclude that the latter property does not hold in any of the sub-samples.

Table 7 Relationship between Preliminary and Final Data Tests on the Data Revision Properties – First Differences

Sample	Joint Test on Lags	Signif. Lags
1973:01-1979:09	1.86[0.07]	Δf_5
1979:10-1987:10	1.90[0.07]	$\Delta f_5, \Delta p_3$
1987:10-1995:08	4.97[0.00]	First 4 on Δf and Δp

We are now in a position to summarize the results for the other bivariate relationships in Table 8. We have first verified that the same structural changes are valid for all couples of variables, and that congruence of a VAR representation is attainable for all relationships.

Cointegration is present in all cases; note that the existence of cointegration in any two bivariate systems implies that the third couple of variables are also cointegrated. This transitivity characteristic carries over also to the case of ZMRE, since $(\beta_0, \beta_1, \beta_2) = (0, 1, -1)$ in any two cointegrating vectors implies the same in the third one as well, and to the case of level unbiasedness.

Level efficiency holds instead just for the relationship between preliminary and revised data. The uncorrelation of the error correction term, though, is accompanied by the rejection of the hypothesis of normality. This seems to be due to the presence of many outlying observations corresponding to major revisions without a clear pattern in the first revision process (cf. Figure 2c and 2d). We can consider this as an intrinsic characteristic of the first revision errors, and the removal or smoothing of

outliers would not be appropriate in this context.

Table 8 - Bivariate Analysis: Summary of the Results

Sample	197	3:01-	1979:09	197	79:10-	1987:10	198	37:11-	1995:08
Property	fp	rp	fr	fp	rp	fr	fp	rp	fr
VAR Representation	\checkmark	\checkmark	\checkmark	\vee	\checkmark	\checkmark	V	\checkmark	\checkmark
Cointegration	V	\checkmark	\checkmark	V	\checkmark	\checkmark	✓	\checkmark	\checkmark
Zero Mean Rev. Err. $(\beta_1, \beta_2) = (1, -1)$		\checkmark		✓	\checkmark	\checkmark	✓	\checkmark	\checkmark
$\beta_0 = 0$		\checkmark			\checkmark		√	\checkmark	\checkmark
Level Efficiency		\checkmark			\checkmark			\checkmark	
Level Unbiasedness Diff. Efficiency		\checkmark			\checkmark			\checkmark	
Diff. Unbiasedness									

For the same two series, level unbiasedness holds as well, that is, the contemporaneous preliminary data are efficient and unbiased forecasts of the first revisions. As a consequence, the results for the relationship between revised and final data (Figure 3) are very similar to what we have presented for preliminary and final. For neither one does level efficiency hold, and hence the lagged values are to be considered. As for the cointegrating vector, in the first period the revision errors are nonstationary, in the second they are so, but around a nonzero mean. In the third period, as already noticed, although the revision errors are zero mean and stationary level unbiasedness does not hold for f_t , p_t and f_t , r_t since level efficiency is rejected.

Difference efficiency does not hold but for preliminary and revised data. Difference unbiasedness is never satisfied for any of the series involved.

Overall, our results cast serious doubts on the possibility of studying the bivariate relationship between provisional and final data on the basis of a static model on first differences. Moreover, the contemporaneous presence of cointegration among all three variables suggests the extension of the analysis to a trivariate framework. This is the object of next section.

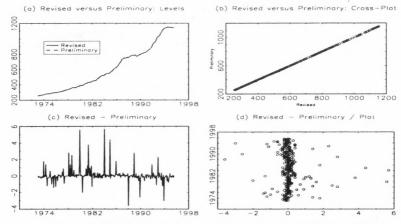


Figure 2: US M1 - Preliminary and Revised Data: 1973:01 - 1995:08

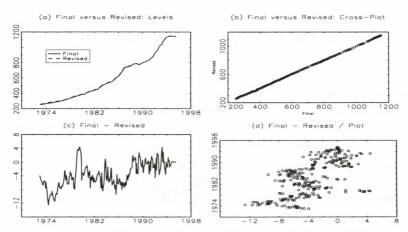


Figure 3: US M1 - Revised and Final Data: 1973:01 - 1995:08

4 The Trivariate Case

In order to analyse (f_t, r_t, p_t) jointly, we still assume that their generating process is a VAR(q)

$$\mathbf{A}(L)\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{e}_t \tag{21}$$

where, this time, $\mathbf{y}_t = (f_t, r_t, p_t)'$, $\boldsymbol{\mu} = (\mu_1, \mu_2, \mu_3)'$, $\mathbf{e}_t \sim i.i.d.N(\mathbf{0}, \boldsymbol{\Sigma})$, $\boldsymbol{\Sigma} = \{\sigma_{ij}\}, i, j = 1, 2, 3$, positive definite and $\mathbf{A}(L) = \{a_{ij}(L)\} = (\mathbf{I} - \mathbf{A}_1 L - \mathbf{A}_2 L^2 - \ldots - \mathbf{A}_q L^q)$, as before, is a matrix polynomial in the lag operator L.

Extending the definitions for the bivariate analysis, the following properties can be of interest here:

Cointegration: this corresponds to the existence of two stationary variables, z_{1t} and z_{2t} , such that $z_{1t} = \beta_0 + \beta_1 f_t + \beta_2 r_t + \beta_3 p_t$, and $z_{2t} = \beta_4 + \beta_5 f_t + \beta_6 r_t + \beta_7 p_t$, and requires rank(A(1)) = 2. Note that this is the desirable property since it corresponds to just one common trend driving all three variables; as before, we will think of it as a minimal requirement for the data production process to be meaningful.

Level Efficiency: this corresponds to finding uncorrelated error correction terms z_{1t} and z_{2t} .

First Difference Efficiency: this corresponds to the non significance of the lagged values of Δf_t , Δr_t , Δp_t , in a conditional error correction model for Δf_t .

Level Unbiasedness: this corresponds to the hypotheses of joint zero mean revision errors:

$$(\beta_0, \beta_1, \beta_2, \beta_3) = (0, 1, -1, 0)$$

 $(\beta_4, \beta_5, \beta_6, \beta_7) = (0, 0, 1, -1),$

together with level efficiency.

First Difference Unbiasedness: this corresponds to $(\delta_0, \delta_1, \delta_2) = (0, 1, 0)$ in the static relationship $\Delta f_t = \delta_0 + \delta_1 \Delta r_t + \delta_2 \Delta p_t + v_t$.

The results on the trivariate system for money supply data are summarized in Table 9. On the basis of the estimated bivariate systems, we will maintain the distinction in three subperiods. A VAR representation works well for all subsamples although the diagnostics point out to the presence of nonnormality in a few instances, seemingly due to relationship between r_t and p_t . This is hardly a problem for the subsequent cointegration analysis since simulation results by Eithreim (1992) and Gonzalo

(1994) show that Johansen's tests are quite robust with respect to deviations from normality. In fact, cointegration is present in all subsamples and the presence of two cointegrating vectors is always accepted with coefficients consistent with those derived in the bivariate cases.

Table 9 - Trivariate Analysis: Summary of the Results

Level Efficiency Level Unbiasedness Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	Sample	1973:01-1979:09	1979:10-1987:10	1987:11-1995:08
Cointegration Zero Mean Rev. Err. Level Efficiency Level Unbiasedness Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	Property	frp	frp	frp
Zero Mean Rev. Err. Level Efficiency Level Unbiasedness Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	VAR Representation	✓	✓	\checkmark
Level Efficiency Level Unbiasedness Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	Cointegration	✓	✓	✓
Level Unbiasedness Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	Zero Mean Rev. Err.			✓
Diff. Efficiency Diff. Unbiasedness As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stational	Level Efficiency			
As for the remaining properties, the results for levels are still constant with those previously obtained, namely that zero mean stational	Level Unbiasedness			
As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stations	Diff. Efficiency		✓	✓
istent with those previously obtained, namely that zero mean stationa	Diff. Unbiasedness			
istent with those previously obtained, namely that zero mean stationa				
	istent with those p	reviously obtained	, namely that zero	mean stationary
evision errors are present in the most recent subsample only, while le	evision errors are p	resent in the most	t recent subsample	e only, while level

As for the remaining properties, the results for levels are still consistent with those previously obtained, namely that zero mean stationary revision errors are present in the most recent subsample only, while level efficiency and unbiasedness never hold. This confirms the results on the bivariate systems, and is due to the nature of the long-run relationship between final and revised data.

The lack of difference unbiasedness is verified even on three variables, whereas the property of difference efficiency cannot be rejected this time. Hence, the structure of the data is such that once contemporaneous first differences of preliminary and revised data are inserted in a conditional ECM for Δf_t , lagged values are not significant anymore.

Overall, these results confirm that the accuracy of the data production process for money supply has increased through time. 11 The extent to which provisional data are of help in forming forecasts of future values of the variables of interest ex ante, i.e. based on currently available

¹¹The series of final data used for this paper corresponds to what was available as of October 1995. This includes definitional changes operated in the past as well which might bias our results in favor of the most recent period.

information, is the question which will be analyzed next.

5 Ex ante analysis

The analysis proposed in Section 2 aims at assessing certain properties of the data production process *ex post*, that is once all sorts of data are available. When considering expectations formation, forecasting is involved and the actual content of the currently available information set becomes a binding constraint.

We will assume the mean square forecast error as a loss function, and, to simplify matters but without loss of generality, that the final data are available with a three period lag, so that the final value relative to period t-2 is published at time t+1. Hence, if we indicate with $f_{t|t+1}$ the optimal forecast of final data for period t made at t+1 (after data for p_t and r_{t-1} have been published), it is

$$f_{t|t+1} \equiv E(f_t|I_{t+1}) = E(\Delta f_t + \Delta f_{t-1} + f_{t-2}|I_{t+1}) = E(\Delta f_t|I_{t+1}) + E(\Delta f_{t-1}|I_{t+1}) + f_{t-2},$$
(22)

where we have assumed

$$I_{t+1} = \{p_j, r_{j-1}, f_{j-2}, \quad j = 3, ..., t\}.$$
 (23)

Notice that we can focus on forecasting Δf ,¹² since optimal forecasts of the levels can be derived from them, and that in period t+1 we lack values of Δf_t and of Δf_{t-1} .

To start with, it is useful to rewrite the model in (21) in the following error correction formulation:

$$\Delta \mathbf{y}_{t} = \mathbf{d} - \alpha \mathbf{z}_{t-2} - \mathbf{G} \Delta \mathbf{y}_{t-1} + \mathbf{H}(L) \Delta \mathbf{y}_{t-3} + \mathbf{e}_{t}. \tag{24}$$

where $\mathbf{G} = \{g_{ij}\} = (\mathbf{I} - \mathbf{A}_1)$ and $\mathbf{H}(L) = (\mathbf{H}_0 + \mathbf{H}_1 L + \ldots + \mathbf{H}_{q-3} L^{q-3}),$ $\mathbf{H}_i = -\sum_{j=i+3}^a \mathbf{A}_j$. (24) differs from the usual EC representation because lagged twice variables in levels appear as regressors.

 $^{^{12}\}mathrm{A}$ straightforward extension of the analysis would apply also to Δr and Δp as well.

From (24) we need to derive a conditional EC model for Δf_t to be used for forecasting purposes. We have:

$$\Delta f_{t} = a_{1} \Delta f_{t-1} + u_{t}
+ \omega_{13} \Delta p_{t} + c + \gamma_{1} z_{1t-2} + \gamma_{2} z_{2t-2}
+ a_{2} \Delta r_{t-1} + a_{3} \Delta p_{t-1} + \mathbf{h}(L)' \Delta \mathbf{y}_{t-3}
\equiv a_{1} \Delta f_{t-1} + u_{t} + K_{t-1}$$
(25)

where $\omega_{13} = \sigma_{13}/\sigma_{33}$, and, in an obvious notation, $\gamma_1 = \alpha_{11} - \omega_{13}\alpha_{31}$, $\gamma_2 = \alpha_{12} - \omega_{13}\alpha_{32}$, $c = d_1 - \omega_{13}d_3$, $a_1 = g_{11} - \omega_{13}g_{31}$, $a_2 = g_{12} - \omega_{13}g_{32}$, $a_3 = g_{13} - \omega_{13}g_{33}$, $u_t = e_{1t} - \omega_{13}e_{t3}$, while $\mathbf{h}(L)$ is a 3×1 vector whose elements are $\mathbf{h}_i(L) = h_{1i}(L) - \omega_{13}h_{3i}(L)$, i = 1, 2, 3.

Care is to be exerted in this case, since such a model contains Δf_{t-1} , itself unknown¹³ at time t+1. Therefore, we need to substitute this unknown value with its expression in terms of known variables and the lagged error term. The outcome is a model which is notationally cumbersome and involves an MA(1) error term, as it is usual with more than one-step ahead forecasts. Thus, by backward substitution of Δf_{t-1} in (25), we find the model which will be used to forecast in practice:

$$\Delta f_t = a_1^2 \Delta f_{t-2} + e_t + K_{t-1} + a_1 e_{t-1} + a_1 K_{t-2}. \tag{26}$$

Notice that if $a_1 = 0$ (a condition to be verified in practice), the model reduces to $\Delta f_t = K_{t-1} + e_t$ and hence it implies an uncorrelated error term and a simpler forecasting structure.

One period later, at t+2 we still do not know the value of Δf_t , but we have additional information in the form of Δp_{t+1} , Δr_t , z_{1t-1} , and z_{2t-1} . From an empirical perspective, then, we will add these variables to the regressors in the forecasting conditional model (25). Recall that we do not need to substitute for Δf_{t-1} , since its value is known at t+2. By lagging this model one period, we can derive $\Delta f_{t-1|t+1}$.

We will perform here an *ex ante* forecasting exercise on the three subperiods detected at the estimation stage (Section 3). We construct three congruent conditional error correction models for 1973:01-1978:09,

 $^{^{13}}$ Also Δr_t is unknown at time t+1 and we cannot condition on its value.

1979:10-1986:10, 1987:11-1994:09, leaving an horizon of 12 periods each to evaluate their performance in (one-step ahead) forecasting.

Starting from the trivariate restricted VECM, we have derived the implied conditional models for Δf_t and Δf_{t-1} , by deleting irrelevant regressors. The resulting models retained have a very different specification across subsamples, indicating that the suitable structure to be considered in forecasting varies a lot. In particular, for Δf_t we have the following list of regressors¹⁴:

73:01 - 78:09 : Constant, Δp_t , $r_{t-1} - p_{t-1}$

79:10 - 86:10 : Constant, Δp_t , $r_{t-1} - p_{t-1}$, Δr_{t-1} ,

 $f_{t-2} - r_{t-2}, \, \Delta f_{t-i}, i = 3, 4, 5$

87:11 - 94:09 : Constant, Δp_t , Δr_{t-1} , $f_{t-2} - r_{t-2}$

while for Δf_{t-1} we have

73: **01** – **78**: **09** : Constant, Δr_{t-1} , $r_{t-1} - p_{t-1}$

79: 10 - 86: 10 : Constant, $r_{t-1} - p_{t-1}$, Δr_{t-1} , $f_{t-2} - r_{t-2}$, Δp_{t-4}

87: 11 - 94: 09 : Constant, Δp_{t-i} , $i = 0, 1, \Delta r_{t-i}$, $i = 1, \dots, 5$

 $\Delta f_{t-i}, i = 2, \dots, 5, f_{t-2} - r_{t-2}$

As we can see, the list of retained regressors in the model for Δf_t is a subset of K_{t-1} in expression (25), from which we can infer $a_1 = 0$ and hence we do not need to consider MA(1) disturbances. This is also confirmed by the autocorrelation tests which are reported together with other diagnostics on the estimated models in Table 10. No detected problems in the residuals are apparent.

As a benchmark for comparison, the forecasting performance of these conditional models is contrasted against simple alternative forecasts constructed from available data at time t+1, namely, p_t-r_{t-1} for Δf_t and $r_{t-1}-f_{t-2}$ for Δf_{t-1} . The results are summarized in terms of average forecast error, standard deviation and root mean square forecast error (Table 11).

¹⁴The existence of a cointegrating relationship which involves preliminary and revised data only allows us to consider $p_{t-1} - r_{t-1}$ as a regressor.

Table 10 Forecast of Δf_t and Δf_{t-1} Diagnostics on Conditional Model Estimation

Sample	73:01	-78:09	79:10	-86:10	87:11	-94:08
Test	Δf_t	$\Delta \mathbf{f}_{t+1}$	$\Delta \mathbf{f}_t$	$\Delta \mathbf{f}_{t+1}$	$\Delta \mathbf{f}_t$	Δf_{t+1}
Autocorr.	1.70	1.53	0.84	1.30	0.26	1.68
	[0.14]	[0.19]	[0.52]	[0.27]	[0.93]	[0.15]
Heterosk.	0.58	0.18	0.92	0.61	0.67	0.95
	[0.67]	[0.94]	[0.54]	[0.76]	[0.67]	[0.54]
Normality	2.55	1.99	1.65	2.29	0.33	0.99
	[0.27]	[0.36]	[0.43]	[0.31]	[0.84]	[0.60]
ARCH	1.49	1.38	0.53	0.46	0.99	1.32
	[0.20]	[0.24]	[0.74]	[0.80]	[0.42]	[0.26]

p-values in brackets.

Jniversity Institute. As one can see, the results are mixed and show a better performance of our estimated models for the early periods, and more so for the model which predicts Δf_{t-1} . In comparing RMSFEs, in fact, our models show sizable gains for the first period both for $\Delta f_{t|t+1}$ and $\Delta f_{t-1|t+1}$ (RMSFE ratio 0.80, respectively, 0.30), performing somewhat worse for Δf_t in the second subsample (RMSFE ratio 1.34), but much better for Δf_{t-1} (RMSFE ratio 0.18), mainly due to large average revision errors. For the most recent subsample, we can say that the degree of accuracy obtained with the data production process following October 1987 is such that the contemporaneously available data provide a very accurate forecast of what the true value will be (RMSFE ratio 2.21, respectively, 1.66).

Finally, a word of caution must be spent in commenting these results, since we have assumed that final data are available with a two-period delay. The proper conditional models would change when this hypothesis is relaxed to allow for a higher period delay, since the relevant final values in the information set would have to be substituted with intermediate revisions. The stylized facts about the lesser degree of importance in successive revisions suggests that the empirical evidence should not vary by much.

Table 11 Forecast of $\Delta \mathbf{f}_t$ and $\Delta \mathbf{f}_{t-1}$ Forecasting Diagnostics

Diagnostic	$\Delta \mathbf{f}_{t t+1}$	$\mathbf{p}_t - \mathbf{r}_{t-1}$	$\Delta \mathbf{f}_{t-1 t+1}$	$\mathbf{r}_{t-1} - \mathbf{f}_{t-2}$
Mean				
78:10-79:09	0.87	0.98	1.00	-0.07
86:11-87:10	-0.21	0.24	0.14	-5.78
94:09-95:08	-0.33	-0.05	0.12	-0.10
St.Dev.			=	
78:10-79:09	1.02	1.38	0.94	4.75
86:11-87:10	1.78	1.31	1.10	1.25
94:09-95:08	0.94	0.39	0.88	0.39
RMSE				
78:10-79:09	1.31	1.65	1.34	4.55
86:11-87:10	1.71	1.28	1.06	5.90
94:09-95:08	0.96	0.43	0.74	0.44

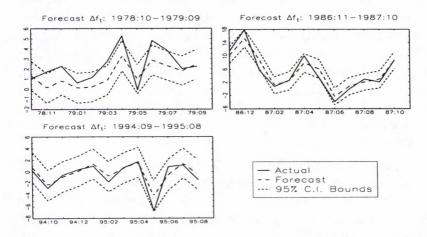


Figure 4: US M1 - One-step Ahead Forecasts for Δf_t .

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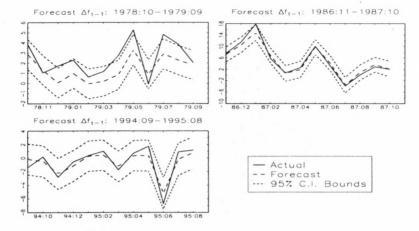


Figure 5: US M1 - One-step Ahead Forecasts for Δf_{t-1} .

6 Conclusions

The unavailability of error-free data in a timely fashion can have serious consequences in empirical work and in the process of expectations formation. In this paper we have suggested a general econometric framework to treat the relationship between provisional and final data which takes into account the nonstationarity and cointegration properties of the variables involved. On the basis of our model, we are able also to suggest the proper conditional model which should be used to forecast unavailable final data on the basis of currently available information. The conditioning set which we operate on is admittedly the smallest possible. Other improvements and richer models could be investigated by including other variables of interest.

The empirical application of this procedure was performed on US money supply data (M1). Using monthly data, our results show that the period from 1973:01 to 1995:08 was characterized by two structural breaks, one in correspondence to the adoption of the "new operating procedures" by the Fed (Oct. 1979) and the other following the Stock Exchange crash of October 1987 in coincidence with an increased preference

by the Fed towards transparency of the announcements.

The in-sample study of the characteristics of the data indicates that cointegration between provisional and final data is always present which has strong consequences for the specification of the most suitable model describing such a relationship. As one would expect, the relationship between preliminary and revised data is the strongest and exhibits most of the desirable properties. With the notable exception of the first subsample, the cointegration analysis shows that the difference between provisional and final data is stationary, but only in the last period around a mean of zero.

One of the interesting empirical results of the paper is that the quality of provisional data has improved across the subsamples. From situations where there was a tendency to overstating the final values, the period starting in November 1987 is marked by a higher stability of revision errors.

This is confirmed also by the ex ante forecasting analysis where we estimated congruent models taking into account just the contemporaneously available information and performing a one-step ahead forecasting exercise for Δf_t and Δf_{t-1} on the basis of the information available at t+1. The results show an improvement obtainable with a suitable econometric model relative to provisional estimates of Δf_t and Δf_{t-1} , mainly for the first two periods.

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