

Tests of Efficiency and Unbiasedness
of the Livingston Price Expectations

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Staff Papers Series #152

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The authors wish to thank an anonymous referee for several helpful comments
on an earlier draft of this paper.

A Reexamination of the
Rationality of the Livingston
Price Expectations

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Abstract

The Livingston survey data have been subjected to numerous tests of the rationality of expectations. The empirical strategies of each of these previous efforts is, however, flawed in one way or another. Here we remedy these shortcomings by recognizing and correcting for the problems of overlapping forecast intervals and heteroscedasticity in the forecast errors. The principal empirical findings are that the hypotheses of unbiasedness and efficiency can be rejected for the CPI forecasts but not for the PPI forecasts. There seems also to be some tendency for survey panel members to underestimate the inflationary effects of recent M_1 expansion in forecasting the CPI and PPI.

I. Introduction

The Livingston survey data have been used often, although not always appropriately, to test the rationality of price expectations. Carlson [1977] was the first to point out that the Livingston survey data were subject to misinterpretation. The semiannually published survey results were presented as six and twelve month forecasts although the forecasters based their predictions primarily on data available no less than eight and fourteen months prior to the dates for which forecasts were made. Livingston was aware of this and therefore amended the survey results to try to account for the information which became available during the approximately two month period between the time forecasts were made and his publication of the survey results.¹ Since it would have been impossible for Livingston to duplicate those changes respondents would have made in their forecasts if the extra two months information had actually been available to them, Carlson considered Livingston's amendments to be largely arbitrary. This view prompted Carlson to readjust the Livingston data to reflect only actual survey responses. The "Carlson adjusted data" are thus properly viewed as eight and fourteen month forecasts sampled at six month intervals. One problem with using the Carlson adjusted data is that the forecast intervals overlap which necessarily introduces autocorrelation into the forecast error series. This problem was addressed by Brown and Maital [1981] using a technique developed by Hansen [1979]. Brown and Maital used Livingston's published data though, and not the more appropriate Carlson adjusted version, for their empirical analysis.

There is one other characteristic of these data which demands proper treatment in estimation. Both the number of respondents to Livingston's survey and the within panel variance of survey responses differ substantially

from year to year. Both of these factors introduce heteroscedasticity into the series of errors in panel mean forecasts. Figlewski and Wachtel [1981] alone have attempted to correct for heteroscedasticity in an empirical analysis of the Carlson adjusted data. However, they used individual survey responses as data whereas all other previous work has been done with aggregated data, or mean responses for each sample period.

While each characteristic of the Livingston survey data has been addressed in the literature at one time or another, all previous tests of rationality are deficient in that they do not properly account for all of these characteristics at once. Here we remedy this deficiency by using Carlson adjusted data and invoking the Brown and Maital procedure to deal with overlapping forecast intervals in another analysis of the rationality of the Livingston survey data. Also we develop and apply a procedure to correct for the heteroscedasticity present in the errors in panel mean forecasts.

II. Basic Concepts

In this section, we present a framework for testing for expectational rationality. The discussion closely follows Brown and Maital's [1981] treatment except that we take care to portray panel mean forecasts as aggregates of individual forecasts.

At time t , each individual in a panel of N_t individuals forecasts the value that a variable will assume at time $t+f$. Let A_{t+f} denote the realized value at $t+f$ and let $P_{i,t}^f$ denote individual i 's forecast, formed at time t , of A_{t+f} . Individuals' forecasts may differ for either of two reasons: 1.) Individuals have access to different information, and 2.) Individuals possess different forecast rules; that is, in forming predictions, individuals process

available information in different ways. Let I_t be the set of all information available at time t . Suppose that the panel's forecasts of A_{t+f} are distributed about a mean, P_t^f , which depends on I_t . We write: $P_t^f = P^f(I_t)$.

Differences in individual forecasts, arising through either of the sources identified above, are modelled as:

$$P_{i,t}^f = P^f(I_t) + \varepsilon_{i,t}^f \quad \text{for } i = 1, 2, \dots, N_t, \text{ all } t \quad (1)$$

where, for any given t , the N_t $\varepsilon_{i,t}^f$'s are assumed to be independently, identically distributed with ²

$$E[\varepsilon_{i,t}^f] = 0$$

$$\text{and Var} [\varepsilon_{i,t}^f | I_t] = \sigma_{\varepsilon,t}^2 \quad \text{for } i = 1, 2, \dots, N_t, \text{ all } t.$$

The panel's forecasts are said to possess full informational efficiency if

$$P^f(I_t) = E[A_{t+f} | I_t] \quad \text{for all } I_t. \quad (2)$$

Following Brown and Maital, we also consider a weaker rationality characteristic. Forecasts will be termed unbiased if

$$P^f(I_t) = E[A_{t+f} | P^f(I_t)] \quad \text{for all } I_t. \quad (3)$$

Since (3) follows from (2) by an iterated expectation argument, it is clear that efficiency implies unbiasedness. Intuitively, efficiency requires that the panel's mean forecast utilize all available information in an optimal way. Unbiasedness guarantees that no independent forecaster, equipped only with the panel's mean forecast as a summary of available information, could produce a better prediction.

Consider the projection of A_{t+f} on I_t :

$$A_{t+f} = E[A_{t+f} | I_t] + u_t^f$$

where $E[u_t^f | I_t] = 0$. Since P_t^f depends only on elements of the information set I_t , one can write:

$$A_{t+f} = P_t^f + R^f(I_t) + u_t^f$$

where the above equation implicitly defines $R^f(\cdot)$. Using (1):

$$A_{t+f} = P_{i,t}^f - \varepsilon_{i,t}^f + R^f(I_t) + u_t^f \quad \text{for all } i = 1, 2, \dots, N_t. \quad (4)$$

Summing versions of equation (4) for $i = 1, 2, \dots, N_t$, and dividing the result by N_t one obtains, upon rearrangement:³

$$A_{t+f} - \bar{P}_t^f = R^f(I_t) + \eta_t^f \quad (5)$$

where

$$\bar{P}_t^f \equiv \frac{1}{N_t} \sum_{i=1}^{N_t} P_{i,t}^f$$

$$\text{and } \eta_t^f = u_t^f - \frac{1}{N_t} \sum_{i=1}^{N_t} \varepsilon_{i,t}^f. \quad (6)$$

We will assume that $E[\eta_t^f | I_t] = 0$, so that (5) is a regression equation⁴.

With the additional assumptions that u_t^f and $\varepsilon_{i,t}^f$ are independent for $i = 1, 2, \dots, N_t$ and

$$\text{Var}[u_t^f | I_t] = \sigma_u^2 \quad \text{for all } t,$$

one can write

$$\text{Var}[\eta_t^f | I_t] = \sigma_u^2 + \frac{1}{N_t} \sigma_{\varepsilon,t}^2. \quad (7)$$

From (2) and the definition of $R^f(\cdot)$, it follows that efficiency implies $R^f(I_t) = 0$ for all I_t . Equation (5) can then be used as a basis for testing efficiency. If the error in the panel's average forecast can be shown to be a statistically significant function of information available at time t , this will constitute evidence against full informational efficiency.

To establish a framework for testing unbiasedness, consider the projection of A_{t+f} on P_t^f .

$$A_{t+f} = E[A_{t+f} | P_t^f] + v_t^f \quad (8)$$

where $E[v_t^f | P_t^f] = 0$. Assuming that the conditional expectation in (8) can be written as a linear function of the conditioning random variable, one obtains

$$A_{t+f} = a + bP_t^f + v_t^f. \quad (9)$$

Using (1), summing over i , and dividing by N_t , one obtains

$$A_{t+f} = a + b\bar{P}_t^f + \xi_t^f \quad (10)$$

where

$$\xi_t^f = v_t^f - \frac{b}{N_t} \sum_{i=1}^{N_t} \epsilon_{i,t}^f. \quad (11)$$

As before, assume that $E[\xi_t^f | \bar{P}_t^f] = 0$. With the additional assumptions that v_t^f has constant conditional variance, σ_v^2 , and that v_t^f and $\epsilon_{i,t}^f$ are independent for $i = 1, 2, \dots, N_t$, it follows that

$$\text{Var}[\xi_t^f | \bar{P}_t^f] = \sigma_v^2 + \frac{b^2}{N_t} \sigma_{\epsilon,t}^2. \quad (12)$$

From (8) and (9) and the definition of unbiasedness, it is clear that this property corresponds to parameter values of 0 for a and 1 for b . Equation (10) can serve as a basis for testing this hypothesis.

III. Estimation Strategies

The properties of the error terms, η_t^f and ξ_t^f , will dictate strategies for estimating equations (5) and (10). Both error terms are heteroscedastic and autocorrelated. Means of coping with these features will be dealt with in turn.

A. Heteroscedasticity

The procedure for dealing with heteroscedasticity will be weighted least squares in which the weights, themselves, must be estimated. The Livingston data include the number of panel members and the sample variance of panelist's forecasts in each period; that is, values for N_t and estimates $\sigma_{\epsilon,t}^2$, of $\sigma_{\epsilon,t}^2$, for all t .⁵ These values enable estimation of the second terms in the conditional variances of the η_t^f 's, as specified by equation (7). An estimate of the first term, σ_u^2 , must also be obtained in order to determine the appropriate weights. Equation (5) will be estimated by OLS. In view of the form of equation (7), it is natural to express the absolute value of the residuals from equation (5) as the following function of σ_u^2 :

$$|\eta_t^f| = \left(\sigma_u^2 + \frac{1}{N_t} \sigma_{\epsilon,t}^2 \right)^{1/2} + e_t \quad (13)$$

where e_t is an error term. σ_u^2 in (13) will be estimated by nonlinear least squares. The dependent and independent variables of equation (5) will then be weighted by the factors $\left(\sigma_u^2 + \frac{1}{N_t} \sigma_{\epsilon,t}^2 \right)^{-1/2}$ prior to a second OLS run.

This will produce a second series of residuals which can be used in equation (13) to generate a second estimate of σ_u^2 . These steps will be repeated until estimates of σ_u^2 and the parameters of equation (5) change by no more than .1% from one iteration to the next.⁶ The heteroscedasticity correction in equation (10) will proceed in an entirely analogous fashion.

B. Autocorrelation

An additional econometric problem arises because the unavoidable forecast errors, the u_t^f 's or v_t^f 's, are likely to be serially correlated if the

forecast interval is longer than the observation interval. Suppose, for example, that the forecast interval spans all or part of s observation intervals. In this event, the realized values of A_{t-1+f} , A_{t-2+f} , ..., A_{t-s+f} and, consequently, the realized values of u_{t-1}^f , u_{t-2}^f , ..., u_{t-s}^f would not be observable when A_{t+f} is forecast at time t . Since these lagged, unavoidable forecast errors are not in I_t they need not be uncorrelated with u_t^f . OLS estimates remain consistent in this case, but a correction to the usual estimated covariance matrix becomes necessary. A derivation of the corrected covariance matrix along with additional assumptions required for its asymptotic validity are supplied by Hansen [1979]. Expositions of applications of the technique are available in Hansen and Hodrick [1980] and Brown and Maital [1981]. The reader is referred to those references for details. Here we simply note that the corrected covariance matrix of parameter estimates is given by:

$$Q = (X'X)^{-1} X'\Omega X(X'X)^{-1} \quad (14)$$

where X is the $T \times k$ matrix of k right hand side variables and Ω is an estimate of Ω , the covariance matrix of the disturbance process. The specific nature of the overlap problem will dictate which elements of Ω are zero and which are unrestricted. Ω will be formed by replacing potentially nonzero elements of Ω with sample covariances of OLS residuals.

IV. The Data

Livingston's questionnaires, mailed to panelists in early November and early May of each year in the sample period, solicited forecasts of economic

variables, including the consumer and wholesale price indexes, for June and December of the following year, in the case of the November surveys, or December of the same year and June of the following year in the case of the May surveys.⁷ The consensus among users of the Livingston survey data seems to be that the panelist's forecasts are thus appropriately viewed as 8 and 14 month forecasts formed at 6 month intervals.⁸ The 8 and 14 month forecast intervals will then overlap all or part of 2 and 3 sampling intervals respectively. In analyzing the 8 month forecast data, we thus allow the covariance matrix of the disturbance process, Ω , to have nonzero first order covariances. In the case of the 14 month forecast data, Ω is permitted to have nonzero first and second order covariances.⁹

The forecast data used in this study are based on Carlson's revision of the Livingston series, and are expressed as percentage expected changes at an annual rate. Both the numbers of respondents and the panel variances of responses for each survey are also available. These will be used in the estimation procedure in the manner described in Section III.

Tests of efficiency will be carried out through estimation of equation (5) with linear functions of lagged policy and state variables replacing $R^f(I_t)$. The variables chosen are as follows: actual inflation in the price index being forecast, and rates of change in M_1 , the index of industrial production, and the federal deficit as a percentage of GNP. All regressors were expressed as percentage changes over six-month intervals adjusted to annual rates.¹⁰ Actual inflation and the index of industrial production were included as convenient characterizations of the current state of the economy; M_1 and the deficit as a percentage of GNP were chosen as crude summaries of

monetary and fiscal policy. Unrevised data, defined here as only those estimates of the variables which were available to respondents at the time their forecasts were made, were used for all tests of efficiency.¹¹ The rates of change over the most recent six month intervals prior to the date of formation of the forecasts were used along with one lag of these variables. Thus, one year's worth of information was included for each of the regressors.

V. Empirical Results

Table 1 reports the results of estimation of equation (10) for the 8 and 14 month forecasts of the consumer price index and the producer price index. The sample consists of all June and December forecasts from June 1948 through December 1981, for a total of 68 observations. Parameter estimates are those from the last (convergent) iteration of the heteroscedasticity correction procedure described in the previous section. Reported standard errors are corrected for the presence of autocorrelation in the disturbance series.

On the null hypothesis, $H_0: (a, b) = (0, 1)$, the test statistic

$$(a, b-1) Q^{-1}(a, b-1)',$$

where Q is defined in (14), is asymptotically chi-squared with two degrees of freedom. The tabulated values for this statistic reveal that H_0 , the hypothesis of unbiasedness, cannot be rejected at the 5% level for either series of forecasts of the PPI. Unbiasedness can, however, be rejected at the 1% level in the cases of the CPI forecast series. Moreover these rejections are due primarily to the significantly positive estimates of a .

Table 2 reports the results of estimation of equation (5) using 8 and 14 month forecast errors of CPI and PPI, and the menu of regressors detailed in the previous section. As before, reported parameter estimates are those of the last iteration of the heteroscedasticity correction procedure and the

standard errors are corrected for autocorrelation. Again the sample extends from June 1948 to December 1981 for a total of 68 observations.

If the parameter vector is denoted $(\alpha_1, \alpha_2, \dots, \alpha_9)$ then, on the null hypothesis, $H_0: (\alpha_1, \alpha_2, \dots, \alpha_9) = (0, 0, \dots, 0)$, the test statistic

$$(\alpha_1, \alpha_2, \dots, \alpha_9) Q^{-1} (\alpha_1, \alpha_2, \dots, \alpha_9)',$$

where Q is as defined in (14), is asymptotically chi-squared with nine degrees of freedom. As the table shows, the hypothesis of efficiency can be rejected at the 1% significance level in the cases of the two CPI forecast series, but cannot be rejected at the 5% level in the cases of the two PPI series.

Hafer and Resler [1980] have observed that the results of tests of rationality of the Livingston data are sensitive to, among other things, the choice of a sample period used for analysis. It is interesting, therefore, to apply our procedures to the samples used in previously published investigations. Pesando [1975], Carlson [1977], Mullineaux [1978], and Pearce [1979], citing Turnovsky and Gibson's [1970 and 1972] finding of a structural break in the accuracy of the Livingston data, began their samples in 1959 and continued through 1969. Brown and Maital [1981] used roughly the period from December 1961 to December 1977. Pearce [1979] also presented evidence of a deterioration in the quality of the Livingston forecasts during the early seventies, a period of increased price variability. Thus we also examined a sample period extending from 1971 to 1981.

Our results for the Pesando sample period are presented in Tables 3 and 4. Test results for this sample of 22 observations are identical to those reported in Tables 1 and 2 for the full sample.¹² Specifically, both unbiasedness and efficiency can be rejected at the 1% level for the CPI forecasts

and cannot be rejected at the 5% level for the PPI forecasts. This pattern generally applied to results for the Brown and Maital sample also, the one noteworthy difference being the finding of inefficiency in the PPI, 8 month forecasts.¹³ Results of analysis of the seventies sample were markedly different, however. Here unbiasedness could not be rejected at conventional significance levels in any case, while efficiency could be rejected in all cases at the 2.5% level or better.

It is interesting also to inquire about the efficiency of utilization of specific types of information. Table 5 displays chi-squared statistics relevant to tests of hypotheses that both lags of a variable have zero coefficients. These pertain to results achieved using the June 1948 to December 1981 sample. In the case of M_1 , the hypothesis can be rejected at the 1% level for one and at the 5% level for two of the four forecast series. None of the statistics for the other explanatory variables have marginal significance levels approaching those of the statistics for M_1 . There is strong evidence, then, that information conveyed by relatively recent rates of growth of M_1 is not efficiently utilized in forming price index forecasts. Moreover, since all estimated coefficients for this variable are positive, the implication is that forecasters tend to underestimate the inflationary effect of monetary growth.¹⁴

Table 1

Results of Estimation of Equation (10)
and Unbiasedness Tests^a
Sample = June 1948 - December 1981

Dependent Variable	a	b	χ^2 statistic for test of $H_0: (a,b) = (0,1)$
CPI, 8 month	1.3017 (.4215)	1.0441 (.1011)	20.00**
CPI, 14 month	1.5992 (.5579)	.9496 (.1311)	11.95**
PPI, 8 month	1.0669 (.8778)	1.0180 (.1833)	2.35
PPI, 14 month	1.7586 (1.0469)	.8263 (.2266)	2.86

Note

^aAsymptotic standard errors in parentheses.

**Significant at the 1% level.

Table 2

Results of Estimation of Equation (5) and Efficiency Tests^a
 Sample = June 1948 - December 1981

Dependent Variable	Constant	Actual Inflation		M ₁		Leading Indicator Index		Deficit as Proportion of GNP		χ^2 statistic for test of H_0 : all parameters=0
		1 lag	2 lags	1 lag	2 lags	1 lag	2 lags	1 lag	2 lags	
CPI, 8 month	.9249 (.5646)	.0145 (.0551)	-.0227 (.0635)	.0349 (.0618)	.0775 (.0588)	.0100 (.0263)	.0247 (.0241)	-.69 E-5 (.14 E-4)	.45 E-5 (.14 E-4)	26.86**
CPI, 14 month	1.2446 (.7098)	-.0201 (.0656)	-.0998 (.0727)	.0605 (.0709)	.1396 (.0663)	-.0004 (.0259)	-.0023 (.0237)	-.30 E-5 (.15 E-4)	.26 E-5 (.15 E-4)	22.29**
PPI, 8 month	-.0891 (1.0781)	.0019 (.1075)	-.0429 (.0571)	.2238 (.1389)	.1592 (.1396)	.0083 (.0600)	-.0104 (.0556)	-.13 E-4 (.32 E-4)	.15 E-4 (.33 E-4)	6.48
PPI, 14 month	.3779 (1.2351)	-.0248 (.1138)	-.0800 (.0554)	.2387 (.1457)	.2022 (.1420)	-.0232 (.0580)	-.0548 (.0527)	-.45 E-6 (.31 E-4)	.14 E-4 (.32 E-4)	7.97

a: Asymptotic standard errors in parentheses.
 **: Significant at the 1% level.

Table 3

Results of Estimation of Equation (10)
and Unbiasedness Tests^a

Sample = June 1959 - December 1969

Dependent Variable	a	b	χ^2 statistic for test of $H_0: (a,b) = (0,1)$
CPI, 8 month	.0538 (.2694)	1.5479 (.1418)	62.84**
CPI, 14 month	-.2597 (.2277)	1.6632 (.1110)	119.34**
PPI, 8 month	-.8167 (.5910)	1.7611 (.3812)	4.12
PPI, 14 month	-.5955 (.7185)	1.5431 (.4576)	1.52

Note

^aAsymptotic standard errors in parentheses.

**Significant at the 1% level.

Table 4

Results of Estimation of Equation (5) and Efficiency Tests^a
 Sample = June 1959 - December 1969

Dependent Variable	Constant	Actual Inflation		M ₁		Leading Indicator Index		Deficit as Proportion of GNP		χ^2 statistic for test of H ₀ : all parameters=0
		1 lag	2 lags	1 lag	2 lags	1 lag	2 lags	1 lag	2 lags	
CPI, 8 month	-.3333 (.3683)	.1199 (.0581)	.1685 (.0792)	.0827 (.0533)	.0190 (.0682)	.0398 (.0226)	-.0022 (.0168)	-.22 E-3 (.20 E-3)	.46 E-3 (.18 E-3)	102.15**
CPI, 14 month	-.6084 (.2931)	.1560 (.0598)	.2372 (.0842)	.1302 (.0481)	-.0029 (.0773)	.0195 (.0239)	.0134 (.0177)	.28 E-4 (.18 E-3)	.18 E-3 (.21 E-3)	286.13**
PPI, 8 month	-.2894 (.8825)	.2358 (.2456)	.0322 (.0257)	.2082 (.1155)	-.0490 (.1949)	-.0644 (.0483)	-.0100 (.0412)	.61 E-4 (.39 E-3)	.23 E-3 (.39 E-3)	12.52
PPI, 14 month	-1.3366 (.7273)	-.1523 (.2215)	-.0098 (.0225)	.2681 (.0963)	.2634 (.1753)	-.0439 (.0368)	-.0158 (.0362)	.24 E-3 (.34 E-3)	.21 E-3 (.34 E-3)	14.44

a: Asymptotic standard errors in parentheses.
 **: Significant at the 1% level.

Table 5

Chi-squared Statistics for Tests of Joint Significance
 Sample = June 1948 - December 1981

Dependent Variable	Actual Inflation	M_1	Index of Industrial Production	Deficit of Proportion of GNP
CPI, 8 month	.209	4.065	1.301	.710
CPI, 14 month	3.631	11.005**	.012	.253
PPI, 8 month	.667	6.726*	.077	.687
PPI, 14 month	2.559	6.408*	1.354	.421

** : Significant at 1% level.

* : Significant at 5% level.

Notes

¹Livingston's rationale for the modifications is discussed in footnote 2 of Brown and Maital [1981].

²Additional assumptions about the conditional means of the $\epsilon_{i,t}^f$'s will be introduced later.

³According to equations (5) and (6), if forecasts are efficient, the panel's average forecast error can be expressed as the sum of two terms. The first, u_t^f , might be called the "unavoidable forecast error". It captures the effect, on A_{t+f} , of occurrences between t and $t+f$ which were unforeseeable given time t information. The second term involves the $\epsilon_{i,t}^f$'s which might be described as "avoidable forecast errors". They are present because particular individuals may have access to limited information sets or may use inappropriate forecast rules.

⁴Since $\epsilon_{i,t}^f$ represents the departure between individual i 's forecast and the panel mean forecast, and since individual i can base his or her forecast only on information available at time t , one would expect $E[\epsilon_{i,t}^f | I_t] \neq 0$. This suggests the presence of correlation between the error term and the regressors in equation (5) which, of course, would render OLS estimates inconsistent. This problem was first identified by Dietrich and Joines [3] in a slightly different context. Figlewski and Wachtel [5] offer one way out. Suppose that, at time t , there is a subset of I_t that is available to everyone, $S(I_t)$ say. Individuals possess personalized information sets, $S_i(I_t)$, which are typically larger than $S(I_t)$. That is: $S(I_t) \subset S_i(I_t)$ for all i .

Let our P_t^f be an efficient forecast of A_{t+f} based on $S(I_t)$'s and let the $P_{i,t}^f$'s be efficient forecasts based on the corresponding $S_i(I_t)$'s. Then

$$\varepsilon_{i,t}^f = E[A_{t+f} | S_i(I_t)] - E[A_{t+f} | S(I_t)].$$

Taking expectations conditioned on $S(I_t)$ one finds

$$E[\varepsilon_{i,t}^f | S(I_t)] = 0.$$

Given these assumptions, $\varepsilon_{i,t}^f$ would at least be uncorrelated with the information available to all panel members. We make the stronger assumption that

$$E\left[\sum_{i=1}^N \varepsilon_{i,t}^f \middle| I_t\right] = 0; \text{ that is, differences in individual information sets}$$

"average out" in the sense made precise by this condition. Clearly this assumption is less than perfectly satisfactory but it is implicit in all previous tests of expectation rationality using panel mean forecasts.

$\sigma_{\varepsilon,t}^2$ is given by $\frac{1}{N_t-1} \sum_{i=1}^N (P_{i,t}^f - \bar{P}_t^f)^2$ where \bar{P}_t^f is defined in equation

(6). If the $\varepsilon_{i,t}^f$'s were contemporaneously correlated and $\text{Cov}(\varepsilon_{i,t}^f, \varepsilon_{j,t}^f) = s_{\varepsilon,t}^2 > 0$ for all $i \neq j = 1, \dots, N_t$, the expectation of $\sigma_{\varepsilon,t}^2$ would be $\sigma_{\varepsilon,t}^2 - s_{\varepsilon,t}^2$. Thus, the contemporaneous differences between individual's forecasts and the mean forecast must be uncorrelated if $\sigma_{\varepsilon,t}^2$ is to provide an unbiased estimate of $\sigma_{\varepsilon,t}^2$. This is an assumption which we maintain.

⁶This convergence criterion was generally achieved in about four iterations.

⁷Carlson [1977] provides a good summary of the survey methodology.

⁸Carlson [1977] provides evidence of the fact that respondents to the May (November) surveys typically were aware of the most recent April (October) estimates of each index or variable.

⁹As Brown and Maital [1981] point out, this is equivalent to modelling the disturbance processes as first and second order moving average processes in the case of 8 and 14 month forecasts respectively.

¹⁰Percentage changes for six-month intervals were determined from April and October estimates of each series (for a November survey), except for the deficit as a percentage of GNP variable in which case first and third quarter observations were used.

¹¹Revised estimates of these variables would not have been available to respondents when forming their forecasts and thus would not be appropriate for use as known information in tests of efficiency. Unrevised data for all regressors were obtained from the Survey of Current Business, various issues 1947-1982. We were unable, however, to obtain a consistent unrevised series for the federal deficit. The differences between the revised and the corresponding unrevised estimates we did obtain were only a small percentage of the average variation in the deficit over a six-month interval, so the revised deficit series we used is a reasonable proxy for its unrevised version. As one would expect, tests performed using revised data yielded lower marginal significance levels for the rejection of full informational efficiency.

¹²It is the case, however, that rejections of null hypotheses generally occurred for different reasons in the two samples. The findings of bias in the full sample were due mainly to significantly positive estimates of a whereas, in the Pesando sample, such findings resulted from estimates of b that were significantly different from one. In the test of efficiency in the 14 month forecasts of CPI using the full sample, the rejection of the null hypothesis appears to be due mainly to the significance of rates of change of

M_1 as explainers of forecast errors. In the CPI forecast efficiency tests using the Pesando period, actual inflation rates seem to contain the overlooked information. Notice also that marginal significance levels are much lower in the Pesando sample than in the full sample. We offer no explanation for these differences here but merely reiterate a point made in the text: Other investigators have also found Livingston data results to be sensitive to the choice of a sample period.

¹³ These results stand in contrast, however, with Brown and Maital's findings of unbiasedness in both the CPI and PPI forecasts, and strong evidence of the inefficiency in all series including the PPI, 14 month forecasts. These differences appear to be mainly attributable to our use of the Carlson adjusted data since the effects of our heteroscedasticity correction typically were relatively minor.

¹⁴ Suppose, for example, that the lagged rate of growth in M_1 is above average. The significantly positive coefficient on this variable suggests that the forecast error would then also be likely to be above average; that is, positive. Since the forecast error is defined as actual minus expected inflation, panel members tend to underestimate the actual inflation.

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