EMPIRICAL TESTS OF THE RATIONALITY OF ECONOMIC FORECASTERS:

A FIXED HORIZONS APPROACH

William D. Nordhaus

and

Steven Durlauf

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Section 1. Introduction

The rationality of economic agents has become one of the most hotly debated issues in macroeconomic analysis. The potential implications of the rational expectations (RE) assumption for such issues as stabilization policy are too well known to require enumeration. Whereas an extraordinarily rich body of theoretical work on RE has been produced, examinations of the validity of the RE assumption have been far less extensive. The stringent implications of RE for policy efficacy demand that the nature of information processing itself be scrutinized. A major task for empirical work is thus to test rationality as an operational assumption. This paper attempts a new examination of the empirical validity of rationality which we hope will provide a number of new insights into the nature of information processing.

Previous attempts to test the rationality of expectations have all relied upon the same general model for testing. These tests are all based upon fairly weak forms of RE. In essence, such tests examine whether forecast errors by economic agents are unpredictable. A time series of expectations is obtained either from surveys of economic agents or from data realizations. Then, the following regression is run:

\begin{equation}
  e(t) = c + bP(t) + v(t)
\end{equation}
where \( e(t) \) equals expectational errors
\( c \) equals a constant
\( p(t) \) equals prediction of the event
\( v(t) \) equals regression residual.

Unbiasedness in expectations requires that \( c = 0 \) and \( b = 0 \), i.e., the expected value of the forecast error is zero.

In slightly more sophisticated versions of rationality testing, one may test models of the form:

\[
(2) \quad e(t) = B' \cdot X(t) + v(t)
\]

where \( e(t) \) = forecast error
\( X(t) \) = column vector of variables observable at time forecast is made
\( B' \) = row vector of coefficients.

Fully efficient information processing requires that expectational errors be independent of all information available at time \( t-1 \), i.e. \( B' \) equals zero. If the information set defined by \( X(t) \) consists of a constant and the forecast itself, this general efficiency test is identical to the unbiasedness test described above. If there exist elements of the information set which are independent of both the constant and the forecast yet which are not independent of the expectational error, then the general efficiency test may fail even when the expected value of a prediction equals the actual event. When the information set is restricted to a constant and the current or lagged set of forecasts, the tests examine what is commonly called the "weak version" of RE. When other, publicly available regressors are included, the tests examine the "semi-strong" form of RE. Thus all rationality tests are reducible to regressions of forecast errors on agents' information sets where these sets are defined as observable time series.\(^2\)
A number of studies over the last few years have employed this framework to analyze expectational data sets. These tests have in general provided mixed results. In analyzing the rationality of the Livingston Surveys, Gramlich (1983), Figlewski and Wachtel (1981) and Pesando (1975) have all rejected RE in finding that unbiasedness of the survey expectations for inflation, output growth and interest rates is inconsistent with the data. The RE hypothesis has found more comfort from such work as Mullineaux (1978) and Mishkin (1981). The Mullineaux results demonstrated the heteroscedasticity in the error structures across agents may bias survey rationality tests towards rejection. Mishkin constructed an artificial expectations series for holding returns on long bonds by assuming that these expected holding returns differed from the known holding returns on short bonds exclusively by a constant risk premium. (Holding returns on a bond are known if the maturity is shorter than the observation period, thereby eliminating the potential for capital gains.) The difference between long and short realized holding returns thus will be equal to the expectational errors plus a constant. Analyzing the expectational error on government bonds, Mishkin found that these expected holding returns did in fact fulfill the unbiasedness and efficiency conditions for rationality.

This paper seeks to improve upon these previous studies in two important respects. First, the objects of our scrutiny will be the forecasts of several major forecasters in the American economy, including Data Resources Incorporated, the UCLA forecasting model, Wharton Economic Forecasting associates, Chase Econometrics and the Eggert Consensus. Utilization of the forecasts of these groups, we think, will allow us to avoid the Scylla and Charybdis of irrelevant and imprecise expectational measures. On the
one hand, the use of massive surveys along the lines of the Livingstone series is likely to bias the tests of rationality improperly towards rejection (in the sense of examining the rationality of macroeconomically irrelevant expectations). If some agents have irrational expectations and others rational ones, arbitrage opportunities will make the rational agents' expectations relevant from a policy perspective. On the other hand, the use of artificial measures of expectations will induce a larger variance in the error of equation (1) thereby reducing the power of rationality tests and incline the hypothesis tests towards acceptance.

The use of major forecasters as the representative agents will ensure that the agents examined are those most likely to have the most accurate expectations. As the success of these services is presumably a function of accuracy, and given the differing nature of risk premia across the customers of these services, these forecasts are the most likely to be impervious to adjustments consistent with the internal interests of the forecaster yet inconsistent with pure statistical rationality. In other words, individual agents might have asymmetric loss functions which generate deviations from statistical rationality. As a forecaster caters to many different customers, it is likely the customers would prefer an unbiased forecast which the buyer can then adjust. With disparate buyers, a forecaster could not perform the adjustment, as disparate buyers are likely to have different loss functions. Hence, one would expect the performance of these forecasters to define an upper bound on the expectational accuracy of agents in the economy as a whole.

Second, we hope in this paper to develop a new methodology for empirically analyzing expectational rationality. This new methodology should act as a complement to the standard rationality tests. In fact, some basis
may exist for believing these new tests possess greater power in testing forecast rationality. Section II below will develop this methodology in detail. Briefly, rather than examine the relationship between a series of one step ahead or n-step ahead forecasts and their realizations, we will examine the behavior of a sequence of forecasts of the same event. Rationality requires that these forecast adjustments be unpredictable over time. Analysis of these forecast adjustments will provide insights into the structure of information processing as new information is made available over time.

The organization of this paper is as follows: Section II will develop the methodology concerning the relationship between forecast adjustments and rationality. Section III will present a number of tests of the rationality of the macroeconomic forecasters based upon the results just derived. These tests will pay special attention to the problems of stationarity and heteroscedasticity which are likely to plague the statistical validity of both parametric and nonparametric hypothesis testing. Section IV will analyze the potential sources of irrationality in the forecasts. Optimal forecasts will be derived based upon the implicit time series properties of the actual forecasts. Comparison of the accuracy of these corrected forecasts to the accuracy of the actual forecasts will permit discrimination between partial adjustment and excessive volatility types of irrationality. Section V will provide summary conclusions.

Section II: The Martingale Property of Forecasts

The analysis in this paper will focus on the critical property of optimal forecasts: a sequence of rational forecasts of a given model made over subsequent time periods must follow a martingale. Formally,

\[(4) \quad E_{t-1}(P_t) = P_{t-1}\]
where $E_{t-1}$ represents the mathematical expectation at $t-1$. A time series with this property is of course a martingale. Correspondingly, the adjustments in forecasts of a given event must be unpredictable at $t-1$. First, we shall prove this property formally, and then provide some intuition as to why this result holds.

**Martingale Property of Forecasts**

Define a sequence of information sets $\phi_i$ such that $\phi_{i-1} \subset \phi_i$. Thus information increases with $i$. For notational purposes, define the realization of the event we wish to forecast as $E(Y|\phi_T)$ where $T$ is the time at which the event is actually realized.

Let $E(Y|\phi_T) - E(Y|\phi_{T-1}) = \eta_1$.

If the forecast error is unpredictable, then

$$E(\eta_1|f(\phi_{T-1})) = 0$$

for any function $f(\cdot)$.

Now, consider

$$E(Y|\phi_T) - E(Y|\phi_{T-2}) = \eta_2.$$

Again, rationality requires

$$E(\eta_2|f(\phi_{T-2})) = 0$$

for any function $f(\cdot)$.

Given these definitions, we can consider the forecast adjustment

$$E(Y|\phi_{T-1}) - E(Y|\phi_{T-2}).$$

Add and subtract $E(Y|\phi_T)$ from forecast adjustment, yielding

$$-E(Y|\phi_T) + E(Y|\phi_{T-1}) - E(Y|\phi_{T-2}) + E(Y|\phi_T) = -\eta_1 + \eta_2.$$
But \( E(-\eta_1 + \eta_2 | f(\phi_{T-2})) = 0 \) by assumption of rationality.

... Forecast adjustments are unforecastable as well, since we could have replaced \( T-1 \) and \( T-2 \) with \( T-i \) and \( t-j \) for any \( i \) and \( j \). Therefore the conditional expectation at \( T-1 \) of \( P_t \) is \( P_{t-1} \) --i.e., the definition of a martingale.

The intuition is quite straightforward for this result. The forecast at \( t \) of a particular event is superior (in a minimum variance sense) to that at \( t-1 \) as more information is available at \( t \). If one could predict the movements between \( t-1 \) and \( t \), one would immediately incorporate this information into the \( t-1 \) forecast in order to move the forecast toward the superior one.

Again, we emphasize that the nature of the data set which we shall employ differs from the data employed in the standard test. Rather than looking at a time sequence of terminal and near terminal forecasts (which we define as rolling horizon tests), we shall be examining the relationship of the sequence of forecasts for a small number of independent events (which we define as fixed horizon tests). Therefore, our results will not so much test the unbiasedness of expectations over time but rather the ways that informational shocks affect forecasts. Thus, our results are complementary to the standard time series analysis.

The full stochastic model of forecasts provides some insights into the sources of statistical bias which may plague the fixed horizon and rolling horizon analyses. Specifically, the critical issues from a regression perspective concern the stationarity and normality of the forecast adjustments under the null hypothesis that the forecasts are in fact rational. If the underlying model of the economy is changing over time, the forecast adjustments are likely not to be stationary. This problem
of heteroscedasticity can adversely affect the behavior of hypothesis tests, as noted above. The fixed horizon test will be more susceptible to heteroscedasticity if the flow of information shocks is lumpy in the sense that different time intervals (defined by proximity to the event realization) will contain different amounts of information. One would expect the month immediately preceding the realization of the annual rate of inflation to possess less potential information than an earlier month, if monthly inflation movements are autoregressive.

On the other hand, if the structure of the economy is shifting over time, treatment of forecast errors as emanating from the same stochastic process is likely to be incorrect, especially if the informational shocks enter the structure nonlinearly. Some years, like those surrounding oil shocks have much larger intrinsic volatility than others. The resolution of which approach will be plagued more by heteroscedasticity is ultimately irresolvable due to data limitations, but should nevertheless be kept in mind.

This "fixed horizon" approach to rationality testing, we believe, is particularly interesting for a number of reasons. First, by analyzing rationality on a year-by-year basis, we shall be able to identify those periods when information processing is particularly inefficient. The relationship between these periods and the stability of economic structures during these periods (such as government policy) may potentially shed light on the adaptability of agents' expectations to new stochastic environments --an ability which lies at the core of both the Lucas critique of standard econometric inference and the Sargent/Wallace policy ineffectiveness theorems. Second, the fixed horizon approach to expectations formation may prove to be a more powerful test of rationality than the standard time series tests. If the statistical inefficiency in the expectation formation of agents lies in lags in the processing of information, for example, then
it is likely that agents' expectations will appear to be rational as the
time gap between forecasts and actual events becomes narrow. However,
the inefficiency of policy in many models requires rationality of expecta-
tions over quite long horizons. In general, it seems much more plausible
that information processing be inefficient yet unbiased in predicting an
uncertain event than that a sequence of forecasts fulfill a set of intern-
ally consistent statistical conditions yet be biased even as the forecast
times coverage with the event in question.

Thus, we find that the standard rolling horizon analyses of ration-
ality are actually a subset of the general properties of optimal forecasts.
Our tests of rationality thus augment the current battery of rationality
tests most frequently seen in the literature.

Section III. Parametric and Nonparametric Tests of Martingales

A. Description of Data

As mentioned in the introduction, the object of our concern will
be the predictions of a number of leading macroeconomic forecasters: DRI,
Wharton, Chase, UCLA, and the Eggert Consensus. These forecasters span
the range of academic and business concerns. The specific forecasts which
we shall be concentrating on are the predictions of annual growth of GNP
and the GNP deflator for the US in the years 1980, 1981 and 1982. Some
attention will be paid later on to a number of other macroeconomic aggre-
gates and other forecasters.

The construction of the sequence of forecasts was done by Eggert
Economic Enterprises, Inc. For each month of the sample period, Eggert
receives at the beginning of the month the forecast for the annual vari-
able in question. Eggert then constructs a consensus forecast by taking
an unweighted average of all forecasts which have been received for the month. The time lag between the actual construction of a forecast and the month for which the forecast is reported appears to be uniform both across forecasters and across time periods. Thus we may take the underlying forecasts to be roughly contemporaneous—which will prove essential in the subsequent estimations.

B. First Passes through the Data

In analyzing the martingale property of these forecasts, it is useful to view the adjustment of forecasts graphically. In Figures 1, 2, 3 and 4 we find graphs of the adjustments in forecasts for the year 1982. Under the assumption of rationality, these adjustments must have zero mean and be independent over time. As is visually clear, these properties are not borne out by the data.

A number of features of these graphs deserve particular mention. First, the 1982 forecast adjustments appear to be overwhelmingly negative. The adjustments clearly do not have a zero mean. All the forecasts suffered severe downturns in late 1981. This particularly poor performance coincided with the rapid collapse of belief in the efficacy of the Reagan fiscal policies. The adverse impact of Reagonomics on interest rates and the deep recession were dramatically brought to the public's attention by the Industrial Production index (a precipitous decline in October 1981). Barring a rather extraordinary nonstationarity in the structure of shocks to the economy at that time, one can only conclude that the major forecasters decisively misunderstood the relationship between the Reagonomics policy change and the economy. In fact, here we have an example where the economy's expectation of the efficacy of government policy was severely overoptimistic, yet this extreme optimism seems not to have translated into a substantive real boom.
The presence of non stationarity is unlikely to have generated the 1982 results for a number of reasons. First, if a single information shock is the source of the huge 1982 downturn, this shock should not have caused the subsequent observations to have also been negative. Second, the date at which the forecasts' downturns occurred differs across forecasters. If all forecasters were victimized by a large information shock, their adjustments to the shock, under rationality, would necessarily have been contemporaneous.

A second important observation is that for 1982, the consensus forecast generally appears less rational than the individual forecasters, in terms of deviations from the martingale hypothesis. The inferiority of the consensus is consistent with the possibility that the majority of forecasters are guilty of ignoring potentially useful elements of their information sets. This fact, of course, does not tell us anything about the relative accuracy of the consensus versus the major forecasters, especially if each individual forecaster has access to some idiosyncratic piece of information concerning the economy. We shall return to the role of the consensus as an aggregator of information later below.

C. General Independence Tests

Our most preliminary tests of the data will center on non-parametric tests—tests which do not require the assumption of normality. These tests will provide us with some guidance in determining what sorts of regression tests will be appropriate when we append the normality assumption. In general, non-parametric tests have extremely low power. Thus, we should not be disturbed if tests of the null hypothesis fail to exceed asymptotic confidence bounds. Non-parametric tests really fall in the category of exploratory data analysis.
Our first test of the white noise nature of forecasts adjustments will center on the most basic property of the series: the value of its mean. If the expected value of an adjustment is non-zero, then rationality proposition is rejected. The most basic test of whether the sample means are in fact zero may be constructed by use of the Chebychev Inequality, which states:

$$\text{Prob}(|x| > k) < \frac{E(x^2)}{k^2}.$$ 

Now, under the null hypothesis that the sequence of adjustments has zero mean, where we define $x$ to be the sample mean random variable and $k$ as the sample mean realization, we can calculate the probability that the sample mean should be at least as big as its realization assuming its true mean is zero. To construct a statistical test of this null hypothesis, we need merely note that when the true mean is zero, the expected value of $x^2$ is equal to the variance of $x$. The true variance of the mean is unknown, but we can reasonably approximate the value by the realized sample variance. The magnitude of the ratio of the sample variance to the sample mean will therefore provide the statistic of interest.

Note that if the distribution of the adjustments is near normal, then the test will have extremely low power. The low power of the Chebychev test under the assumption of normality can be directly seen when we note that the calculation of the ratio

$$\frac{\sigma^2}{\bar{x}^2}$$

is exactly equal to the calculation of

$$(1/t)^2$$

where $t = n\bar{x}/\sigma$, i.e., the standard test of whether a normal series has
a non-zero mean. Notice that a t-statistic of 2 which is the 95% confidence bound under normality, will generate a Chebychev bound of only .25.

The Chebychev bounds are reported in Table 1. As is apparent, the non-zero means of the 1982 forecast adjustments are statistically confirmed. In fact, the consensus output statistic is so overwhelmingly significant that the Chebychev test will reject the hypothesis of a zero mean at 5%.

Equally noteworthy is the poor performance of the 1978 adjustments of both inflation and GNP growth forecasts.

Thus, the Chebychev tests give general confirmation that for at least 2 of the 5 years we are scrutinizing, forecasts adjustments are inconsistent with the martingale hypothesis.

In analyzing the statistical properties of the forecasts, we shall next analyze the temporal independence within the data. This approach is reasonable given the graphics we have displayed. One approach, which provides a method of analysis which will avoid reliance upon the assumption of normality and to a certain extent the assumption of stationarity, is the Chi-Squared contingency test. For this test, we examine the signs of the forecasts adjustments. Under the assumption of temporal independence the probability that an observation has a certain sign in a given period should be independent of the sign observation of the previous period. This test merely requires that under the null hypothesis the probability that an observation has a particular sign does not change over time. Thus the behavior of the underlying distribution in the tails may be changing if the distribution retains symmetry about zero. Formally, the following quantity is calculated:

\[
(6) \quad \left( \frac{\sigma(i,j) - e(i,j)}{e(i,j)} \right)^2
\]
where \( o(i,j) \) = number of observations in cell \( i, j \)
\( e(i,j) \) = expected number of observations in cell \( i, j \)

where expectation is defined as sample probability that observation lies in \( i^{th} \) row of contingency table times probability that observation lies in \( j^{th} \) column times number of observations.

The contingency table is constructed as 3 by 3 where each row entry is determined by the sign of current forecast change and each column entry is determined by lagged forecast change.

This statistic is asymptotically distributed Chi-Squared and thus we may use the Chi-Squared table as a guide to interpreting the magnitude of our calculations. In constructing the various cells, we need to generate cells for zero value observations as a number of forecasts adjustments equal zero.

Table 2 presents the results of the calculations when we pool the entire 1977 to 1982 data collection together as well as for the individual years 1979 to 1982. The pooling will be legitimate if the underlying cell probabilities are constant across years. If so, the pooling will bring the finite sample distribution of the statistics closer to the asymptotic distribution, as we have more observations.

The pooled results indicate little basis for rejecting rationality across the models. Given a 95% confidence level of 9.5 for the Chi-Square (4) distribution, we see that only one of the ten possible tests rejects rationality. In the case of GNP growth the Consensus alone rejects the hypothesis of rationality. The other four cases do not even remotely reject rationality. For the case of inflation, the rationality tests reflect even better on the forecasters. Both Wharton and Chase have generated forecasts which are overwhelmingly consistent with intertemporal independence in forecast adjustments. Acceptance for the other models is slightly weaker although the Chi-Squared values for the other "rational" forecasts are still quite small.
One can provide some interpretation to the poor consensus inflation forecasts. The large Chi-Square value suggests that the less prominent forecasters which dominate the consensus forecast are far less likely to fulfill statistical rationality criteria than the prominent forecasters we have singled out for individual scrutiny. Averages of white noise series will still be white noise. Thus, one may conclude that the pooled forecasts indicate that statistical independence should be accepted for the major forecasters and rejected for the minor forecasters.

In order to minimize the problem of nonstationarity in the error structures for some years and to isolate the sources of the pooled rationality, one can examine the Chi-Squared statistics over the various years. The statistics are reported in the final four columns of Table 2. It is important to remember that the low degrees of freedom implied by the relatively small numbers of observations reduce the power of any inferences we can make. Year-by-year, there now exist no cases of irrationality!

To verify that the Chi-Squared tests were relatively robust in accepting rationality, the tests were modified to increase their statistical power. Under a number of potential adjustment mechanisms, it may be the case that observations around zero are in approximate "equilibrium." For example, the willingness of a forecaster to adjust upwards one period and downward the next is small due to credibility effects. Thus, the irrationality would reflect a small number of sign changes than predicted by the row and column probabilities. To test this subset of the general independence hypothesis, we drop all cells which contain zeroes and recalculate the Chi-Square statistics. The power of the test is enhanced to the extent that the zero cells possess sample probabilities consistent with independence whereas the non-zero cells do not. These statistics were calculated
for the pooled data and comprise the last part of Table 3.

The results of this modification do not radically alter the initial conclusions. The new Chi-Squared statistics are generally supportive of rationality once again. In a few cases, the magnitudes of the statistics begin to hint at the rejection of rationality. Most notable is the 1982 DRI inflation forecast.

Perhaps most interesting is the behavior of the Consensus statistics. The Chi-Squared values are virtually unchanged from the 3 by 3 contingency analysis. Given the reduction in degrees of freedom, the statistics are now gigantic. These results demonstrate the large degree of smoothing implicit in the Consensus behavior. Again, we emphasize that under the null hypothesis of rationality, weighted averages of individual adjustments must display the same rationality required of the individuals. Thus the extremely poor behavior of the Consensus reflects large informational asymmetries across agents.

A final question concerns the implications of these tests for the structural form of the forecast adjustment mechanism. Specifically, we need to determine whether the adjustment process follows

\[ \Delta P_t = c + \epsilon_t \]

or

\[ \Delta P_t = \beta \Delta P_{t-1} + \epsilon_t. \]

Our non-parametric results do in fact allow us to discriminate between these two cases.

The acceptance of rationality in these cases is generated by the non-zero means associated with the different forecast adjustment series. An autoregressive model, with adjustments of the form

\[ \Delta P_t = \beta \Delta P_{t-1} + \epsilon_t \]
has an unconditional mean of 0 and a conditional mean of $\beta \Delta P_{t-1}$ for each $\Delta P_t$. Such a model is identified for a finite data sample only if the initial values of the sequence are close to zero (and $\beta$ is not too high). Otherwise, the entire sequence will be above or below zero and will be close to a model of the form

$$\Delta P_t = c' + \beta' \Delta P_{t-1} + \epsilon'$$

where $c' = \beta \Delta P_{-1}$, where $\Delta P_{-1}$ represents the first observation prior to the sequence over which the regression is run.

In the data of forecast adjustments, the early values are in fact close to zero. Thus, the tendency of any sequence to stay above or below zero cannot be attributed to a high initializing value for the autoregressive process. Thus, it is likely that the source of the rationality implicit in the Chi-Squared tests is the presence of a non-zero mean to the adjustments.

In conclusion, our preliminary data analysis indicates strong evidence that forecast adjustments have a non-zero mean and a little evidence of an autoregressive process in absence of a non-zero mean. In the next section we shall formalize these intuitions in a formal set of regression tests.

D. Linear Orthogonality Tests

The stark contrast between the Chi-Squared and Chebychev tests provides a strong basis for moving into direct regression tests of rationality. These tests represent the fixed horizon equivalents to the standard rolling horizon rationality tests which have been discussed earlier. By assuming normality and a linear relationship between forecast adjustments across time as the alternative hypothesis, we can uncover more powerfully the
basic deviations of forecast adjustments we have observed in the data from white noise.

For the various monthly forecasts we have been examining, we shall make the standard assumptions of stationary, normal errors. Under these assumptions, regressions of the form:

\[ e(t) = R'X(t) + v(t) \]  

where \( e(t) \) = forecast adjustment

\( X(t) = \) set of variables observable at time \( t-1 \) forecast is made should result in all coefficients being equal to zero. The candidates for the \( X(t) \) vector will be determined by our understanding of expectation formation. Our prior beliefs on what sort of deviations from rationality we are likely to expect will dictate our choice of \( X(t) \). Specifically, we shall test two possibilities: \( X(t) \) consists of a constant adjustment value and \( X(t) \) consists of the lagged level of the forecast adjustment. We choose this set of variables to test for deviations from the rationality principle per se. If agents experience costs in adjusting forecasts due to lost credibility or some other reason, then the orthogonality principle for changes in a martingale series will be violated even by variables in the agent's information sets. Alternatively, missing elements in agents' information sets will result in nonorthogonality.

The interpretation of the significance of these variables is related to the structure of the underlying adjustment process. For example, if the forecast is generated by the minimization of a quadratic loss function, then only the lagged forecast adjustment will be significant. Specifically, suppose that the forecaster is somehow penalized for the magnitude of his
forecast changes over time, i.e. minimizes $L$. Then the optimal forecast each period would minimize under the quadratic assumption:

$$L = a(p(t) - p(t-1))^2 + (1-a)(p(t) - E_t(P(t)))^2$$

where $p(t) = \text{actual forecast at } t$

$E_tP(t) = \text{mathematical expectation at } t$

$a = \text{weight.}$

First order conditions imply that the current forecast will equal

$$p(t) = ap(t-1) + (1-a)E_t(P(t)).$$

Differencing this equation will yield

$$p(t) - p(t-1) = e(t) = ae(t-1) + (1-a)\Delta E_t[p(t)]$$

e(t) of course corresponds exactly to the notation for forecast changes used earlier. However, $\Delta E_t[p(t)]$ is not observable. However, by rationality it is orthogonal to the information set available at $t-1$, of which $e(t-1)$ is an element. Therefore, equation (10) represents a consistent regression which will reveal the coefficient of adjustment $(1-a)$.

The interpretations of a constant is difficult as it is unrelated to a quadratic adjustment framework. One alternative possibility is that the loss function itself is of some unusual form. Suppose, for example, that the loss function is quadratic in deviations from the mathematical mean and linear in absolute magnitude of adjustment. Further, suppose that the adjustments each period do not impose any cost if they are below a certain magnitude. This might arise if a forecaster's clientele were accustomed to small changes, but became alarmed at large changes. The loss function,
$L'$ would then resemble:

$$
L' = \begin{cases} 
    a(p(t) - E_t[p(t)])^2 + b|p(t) - p(t-1)|, & \text{if } \text{abs}(p(t) - p(t-1)) < k \\
    a(p(t) - E_t[p(t)])^2, & \text{otherwise}
\end{cases}
$$

where $a$, $b$ are weights.

The behavior of this system will be highly nonlinear. However, we can get some clues as to its likely behavior. For a $E_t[p(t)]$ series which is stationary and normal, the $p(t)$ series will be similarly normal for small movements over time. Once a large shock hits, the $p(t)$ forecast will adjust to the point where

$$2a|p(t) - E_t[p(t)]| = b.$$

After the initial large adjustment, the subsequent adjustments will be equal in magnitude to $k$ at most.

Thus in periods where there is a single large information lump, such as the failure of supply side economics to live up to its promises, one would find a large adjustment, followed by a sequence of smaller shocks in the same direction (which is precisely what happened). A forecast path of this kind would imply an adjustment path which is dominated by adjustments with an absolute valued mean equal to $k$. This loss function is purely ad hoc, but is nevertheless suggestive as to the sorts of ways in which modified quadratic loss functions can approximate the usual behavior of the adjustment series such as the ones we have observed.

The results of our linear orthogonality tests are presented in Tables 4 through 7. Table 4 indicates those regressions for which the constant
is significant at the 5% level. In the case of output, the coefficient of
significant for nearly every forecaster during the years 1978 and 1982.
These years are significant in that they represent the years in our sample
when the entire sequence of observations follows a shift in presidential
administration. Apparently, the ability of forecasters to rationally
predict conditions during a shift in regime--a major assumption in the
policy neutrality literature--comes into clear question. It is striking
that in both cases, the new administration generated excessively optimis-
tic forecasts of GNP growth, as can be gleaned from the output constant
coefficient estimates which are reported in the upper half of Table 5.
Evidently, forecasters are willing to follow the tide of public opinion
--at least in times of the optimism which a new administration ushers in.

Another striking result concerning the output coefficient estimates
is the within year similarity across forecasters. The 1982 adjustment
rates all are near -.25 whereas the 1978 estimates seem to center around
.1. The -.25 level would seem to be plausible in terms of a fixed cost
to forecast changes, as discussed above. However, the small magnitude
of the 1978 coefficients makes it unlikely that a fixed barrier to the
magnitude of forecast adjustments generated this result. After all, the
1979-1982 forecast adjustments very frequently are of a magnitude greater
than .1. The smoothing implicit in the 1978 regressions most probably is
generated by some sort of asymmetric loss function which is dissimilar in
form from those discussed above.

The adjustments in inflation forecasts provide even more dramatic
verification of the absence of rationality in forecast adjustments. Irra-
tionality appears frequently in the 1979 and 1980 forecast adjustments in
addition to the past regime change years. With the exception of 1982, when
the coefficients were negative, the forecasters have tended to systematically underestimate the magnitude of inflation growth.

One interesting result is the general consistency of the magnitude of the inflation constant across the different years as well as the different forecasters. The magnitude of .1 is relatively consistent with the hypothesis of a fixed adjustment cost: we do not see years where every adjustment is of a substantially greater magnitude.

The poor performance of the rationality of the inflation forecasts corresponds, of course, to the generally poor forecasting performance of inflation. A possible explanation of the poor inflation regression results may be that in the absence of a well accepted and useful theory of inflation behavior, forecasters have relied upon intuition rather than statistical procedures in constructing inflation forecasts. If this is so, the presence of statistical irrationality may be one of the inadvertent results.

Table 6 reports those cases where a pure partial adjustment model is used in place of the constant term. As is apparent, with the exception of the Chase output forecasts and the consensus inflation forecasts, the partial adjustment model appears to be inconsistent with the data. The implicit rate of adjustment for the Chase regressions is approximately .35 and the approximate rate of adjustment for the consensus regression coefficients appears to be around .5—as Table 7 indicates.

In results not reported, regressions were also run to test whether the constant and lagged adjustment terms were jointly zero. In virtually all regressions, the previously significant lagged adjustment terms dropped out in the presence of the constant terms. The most notable exceptions are the 1982 Consensus output regressions and the 1978, 1979, 1980 and 1982 Consensus inflation regressions. Thus, we are forced to conclude that the
partial adjustment model fails to adequately model the deviations from white noise which are implicit in the data.

A couple of additional points should be made in terms of the significance of the constants in our regressions. To check on the problem of nonstationarity in the adjustment structure, the regressions were rerun dropping firstly the largest observation in absolute magnitude and secondly the largest three observations in absolute magnitude. In neither case did the significance of the coefficients waver. If a nonstationarity were induced due to information shocks with a far larger magnitude in some periods than others --we failed to detect it. Actually, the relative robustness of the sample mean hypothesis tests follows directly from the form of the t-statistic. Nonstationarity really means that the sample variance improperly estimates the true variance of the sample mean. Increasing the variance of a single observation by a factor of say 10 will not appreciably underestimate this value when we have 25 or so observations as is apparent from the definition of the sample variance.

Second, the observations in Table 4 may be considered independent across years, although not across forecasters. If we alter the regression samples such that there is no longer any overlap across forecasts of different years, no significance levels are affected. Thus, if we are interested in the probability that a particular forecaster is rational for a particular variable, we must merely calculate the binomial probability:

\[
\binom{5}{5-K}(.5)^K(.95)^{5-K}
\]

where \( K \) = number of times constant is significant.

Thus, we find that for any forecaster with at least 2 significant constants,
rejection is overwhelming, since it would engender twice observing an event with a probability of one in twenty.

Clearly, the rationality estimates for a given year are independent neither across forecasters nor across inflation and output growth. However, estimation of dependent regressions jointly using Zellner's SUR techniques failed to appreciably affect the coefficient results, and thus is not reported.

Finally, the pooling of the data on forecasts of a single event failed to provide any new information. The 1982 forecast adjustments completely dominated the pooled regressions. Partial adjustment significance was completely lost. This should not have been unexpected due to the fact that the magnitude of the 1982 forecast adjustment was much larger and much more irrational (in the sense of coefficient magnitude) than other years.

Our single event tests, then reveal strong evidence of irrationality for the 1982 and 1978 output growth forecasts and overwhelming evidence of irrationality for the inflation forecasts across all years.

D. Individual Forecasters and the Consensus

Given the fact that forecasts do differ in their predictions, a logical question concerns the added value in possessing more than one of the forecasts. If all the forecasts were unbiased and if we had knowledge of the covariance matrix (V) of forecast errors across agents, then the problem would be: Construct an a'F_t where F_t = vectors of forecasters such that we

\[ \min a'Va \text{ such that } Ea_i = 1 \]

or

\[ a^* = \frac{V^{-1}e}{e'V^{-1}e} \]

where V = covariance of forecast errors
i.e., we would construct a portfolio of forecasts. The extent to which any \( P_t \) deviates from \( \alpha^*F_t \) would be a measure of the extent to which the information set of forecasters as a whole is superior to that of an individual forecaster. Further the importance of \( \alpha^*F_{t-1} \) in predicting \( F_t \) is a measure of the extent to which agents augment their forecast adjustments by relying on the information of others.

We do not possess a set of optimal forecasts, of course, nor do we know \( V \). We do, however, possess the consensus forecast, which represents a second best solution to the problem of constructing an optimal forecast. The diversification implicit in the averaging of the forecasts might very well render the consensus superior to the other forecasts, in the minimum variance sense. Further, independent of the optimality of the weighting scheme, there exists an optimal weighting scheme between any of the individual forecasts and the consensus so long as the weight between the individual forecast and a modified consensus which drops the individual forecast is not exactly equal to the weight the individual forecast receives in the exact consensus.

A final point relates to the exact relationship between the consensus and the sufficient statistic for processing information. The conditional probability density function for an outcome \( y \) may be written

\[
f_t(y|\phi_{t-1})
\]

where \( \phi_{t-1} \) represents the realization of all relevant variables at \( t-1 \).

If the complete set of information \( \phi_t \) can be reduced down to a specific piece of information or sufficient statistic which forecasters at time \( t \) employ, then

\[
f_t(y|\phi_{t-1}) = f_t(y|T(\phi_{t-1}))
\]
and our interest in the consensus lies in determining a relationship between the consensus and the $T(\phi_{t-1})$ variable. Ideally, the consensus may function as an approximation of the sufficient statistic and therefore be of use to a forecaster. The presence of idiosyncratic information on the part of any forecaster will find its way into the consensus and thus make the consensus useful to a given forecaster.

We make these general observations in order to provide a background for the next set of experiments which we shall examine. Specifically, we shall accept for the moment that each forecaster is conditionally rational. Thus, we would like to find out something about the sources of their forecast discrepancies. An appealing alternative hypothesis is that the consensus forecast functions as an indirect, yet powerful aggregator of information across agents. One way of verifying this proposition is to test whether the martingale property of forecasts continues to function in the presence of the consensus series.

The tests we shall use follow directly and intuitively when we consider the interaction of a forecast at time $t$ with the consensus assuming the consensus weight were optimal. Suppose that at time $t-1$, the consensus were the sufficient statistic for the probability distribution conditioned on all information at time $t-1$. Further, suppose that the consensus is public knowledge with a 1 period lag. Then the optimal predictor of a forecast at time $t$ would be the lagged consensus rather than the lagged own forecast. This follows, because from the perspective of $t-1$, there does not exist any old information beyond the consensus which could provide potential benefit to the forecast. Even if the consensus is not a perfect aggregator, if the consensus provides useful information, then the only value of the own lagged forecast to predicting the current forecast
is in adjusting the weight of the own forecasts in the consensus weighting scheme. Therefore a natural regression to examine is:

\[ P(t) = c + b_1^*P(t-1) + b_2^*\text{CONS}(t-1) \]

where \( P(t) \) equals own forecast, \( \text{CONS}(t-1) \) equals consensus forecast.

The significance of the lagged consensus will give us some insight into the extent to which the forecasts function as bootstraps for one another. Estimations for the pooled and individual years are reported in Tables 8 and 9.

Table 8 reports the number of times where a regression including both a constant and the lagged consensus generates failure of the martingale hypothesis. Notice that we are now using levels rather than changes as our variables. As is clear, the inflation forecasts provide strong evidence of the failure of the martingale hypothesis for most years. The output regressions with the exception of 1982 are in general consistent with the martingale hypothesis.

Table 9, providing the actual regression results, is essential in determining whether the martingale hypothesis fails due to inclusion of the consensus, or rather, due to the inclusion of the constant. (Running the level regression runs the risk of the lagged consensus proxying for the omitted constant term.)

In only 7 of the 32 cases is the lagged consensus variable statistically significant by itself. In 16 of the 32 cases the lagged own forecast is statistically significant. In only 2 cases—the 1982 Wharton output growth rate and the 1979 Wharton inflation prediction—are the two variables both significant. In the remaining 11 cases the multicollinearity between the two variables is too great to allow determination of which lagged
forecast is driving the regression results. Thus, there is some evidence
to support the hypothesis of the consensus functioning as a sufficient
statistic.

Two final points should be made. First the 1982 consensus regressions
have overwhelmingly rejected the consensus variable as a significant
explanatory variable. In the other years, the presence of the consensus
appears to be responsible for the failure of the martingale hypothesis.
This would appear to make sense in that the 1982 consensus predictions
were overwhelmingly the most inaccurate of the years we scrutinized. In
1982 the consensus (based upon a RMSE criterion) was outdistanced by vir-
tually all the forecasters for both inflation and output growth. The other
years, however, the consensus was usually more accurate than our major
forecasters. Evidently, the presence of erroneous information in the 1982
consensus invalidated its usefulness as an information source.

Second, the implicit smoothing in the consensus, reflected in its
variance being much lower over time than the individual forecasters,
renders its multicollinearity with the constant term relatively high.
Hence the regression results were inclined towards insignificance.
Therefore, our results should be considered a lower bound on the signifi-
cance of the consensus in affecting forecasts.

The significance of the lagged consensus in the forecast regres-
sions, it must be emphasized, does not prove irrationality on the part of
individual forecasters per se. Rather, it reflects the presence of idio-
syncratic information on the part of agents. Our results indicate that in
a significant number of cases, the consensus does function as an aggregate
of information across forecasters.
Section IV. Optimal Forecasts and Irrationality Criteria

In this section, we shall consider the issue of optimal forecasts based upon the actual sequence of forecasts which we have observed. We shall consider two cases: First, we shall examine the issue of how one would construct an optimal forecast given knowledge of the stochastic process generating the forecasts a priori. Second, we shall examine the construction of optimal forecasts when this knowledge is not available a priori.

Knowledge of the stochastic process governing a sequence of forecasts of a particular event is equivalent to knowing the true expected values of a regression such as:

\[ p_t = \alpha + \beta p_{t-1} + e_t. \]

If we presume, as is borne out by the data, that the terminal forecast is in fact the most accurate forecast, then we may define the optimal forecast (for a given forecaster) in a straightforward fashion. All we need know is the value of \( p_t \), \( \alpha \), and \( \beta \). \( \alpha \) and \( \beta \) may be estimated through OLS over the entire sample. Using these estimates, the Weiner-Kolmogorov optimal forecast of the terminal forecast in our sequence will be:

\[ p_{t_{optimal}} = \sum_{i=1}^{T-t} \alpha^i + \sum_{i=1}^{T-t} \beta^i p_t. \]

All we do is project our given forecast along the stochastic structure of the forecast sequence to eliminate all temporal dependence within the forecast sequence. Information about future forecasts is exactly equivalent to knowledge about the terminal event---i.e. the realization.

In order to measure the increases in forecast accuracy generated
by this set of optimal forecasts, we have elected to calculate the average squared deviation of sequence of forecasts from the truth. This procedure tends to place greater weight upon earlier forecasts so these have the greater potential for error (Dec. 1982 forecasts of March 1982 GNP growth have little room for error). We feel this implicit weighting is appropriate, as accuracy in earlier forecasts would seem to be more desirable than accuracy in later forecasts, given the need to plan relatively far ahead in the future. The comparison of the average squared errors is given in the first 2 columns of Table 10 for the 1982 forecast sequence.

As is apparent, our optimal forecasts provide an overwhelming improvement in the accuracy of forecasts. Average squared deviations drop by an extraordinary factor of 16. These numbers should be taken as an additional metric for the extent of irrationality in the macroeconomic forecasts.

These improvements, however, must be taken with a grain of salt. Even if we were to examine a sequence of optimal forecasts, there would be some improvement in the quality of forecasts if we projected forecasts by employing the full sample regression coefficients. Consider the following simple example. Suppose that we are looking at a random walk starting at zero. We observe $X_1$, $X_2$ and wish to predict $X_3$. Let $X_1 = \epsilon_1$, $X_2 = \epsilon_1 + \epsilon_2$ and $X_3 = \epsilon_1 + \epsilon_2 + \epsilon_3$. Our optimal forecast sequence would equal 0, $X_1$, $X_2$, $X_3$. However, suppose that we were to take the forecast adjustment sample mean $\frac{1}{3}(\epsilon_1 + \epsilon_2 + \epsilon_3)$ and erroneously assume that $\Delta X_1 = \frac{1}{3}(\epsilon_1 + \epsilon_2 + \epsilon_3)$. Our optimal forecasts would use knowledge of $X_1$, $X_2$ and $X_3$ prior to their realization. We would then take the post-realization mean of adjustments and use that to forecast $X_3$. In this case our optimal forecasts would be $\epsilon_1 + \frac{2}{3}(\epsilon_1 + \epsilon_2 + \epsilon_3)$, $\epsilon_1 + \epsilon_2 + \frac{1}{3}(\epsilon_1 + \epsilon_2 + \epsilon_3)$ and $\epsilon_1 + \epsilon_2 + \epsilon_3$ (at time = 3, we see realization of event, so forecast is completely accurate).
Now what would the average forecasts deviations be \((X_t^{\text{expected}} - X_t^{\text{actual}})^2\)?

For the actual sequence they would be

\[
\begin{align*}
\epsilon_1 + \epsilon_2 + \epsilon_3 & \quad \text{expected squared error} = \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_2}^2 + \sigma_{\epsilon_3}^2 \\
\epsilon_2 + \epsilon_3 & \quad \text{expected squared error} = \sigma_{\epsilon_2}^2 + \sigma_{\epsilon_3}^2 \\
\epsilon_3 & \quad \text{expected squared error} = \sigma_{\epsilon_3}^2
\end{align*}
\]

whereas for our constructed optimal sequence, where we have failed to restrict our information to that available at the time of a forecast, we would have

\[
\begin{align*}
0 & \quad \text{expected squared error} \quad 0 \\
\frac{2}{3} \epsilon_1 - \frac{1}{3} \epsilon_2 - \frac{1}{3} \epsilon_3 & \quad \text{expected squared error} \quad \frac{4}{9} \sigma_{\epsilon_1}^2 + \frac{1}{9} \sigma_{\epsilon_2}^2 + \frac{1}{9} \sigma_{\epsilon_3}^2 \\
\frac{1}{3} \epsilon_1 + \frac{1}{3} \epsilon_2 - \frac{2}{3} \epsilon_3 & \quad \text{expected squared error} \quad \frac{1}{9} \sigma_{\epsilon_1}^2 + \frac{1}{9} \sigma_{\epsilon_2}^2 + \frac{4}{9} \sigma_{\epsilon_3}^2
\end{align*}
\]

Thus if the variance of \(\epsilon_1\) is not appreciably larger than \(\epsilon_2\) and \(\epsilon_3\), we shall be erroneously reducing the average squared deviation, as we are taking weighted averages of the errors which reduce the variance just as a convex combination of 2 i.i.d. random variables will have a lower variance than either of the variables individually. Hence—in absence of knowledge of the extent to which forecast errors reduce in variance over time—we cannot accurately judge the extent of improvement in average squared error.

To correct for this problem, we shall consider a set of optimal forecasts which adjust actual forecasts only by employing information which was available at the time a forecast was made. This naturally leads us to the area of optimal filtering rules. These are potentially ad hoc, but again,
we emphasize that they are consistent with controlling for information set properties. We shall reexamine the 1982 consensus forecast to see whether optimal forecasts can be improved with a couple of intuitive filters.

Two candidates easily come to mind. First, we shall consider a rolling regression where we assume that

\[ P_t = P_{t-1} + c \]

represent the underlying structure. At each point in time, \( c \) will represent the sample mean of the forecast adjustments up to \( t \). Thus:

\[ P^*_t = P_t + \hat{\mu}(t-T) \quad \text{where} \quad \hat{\mu} = \frac{\sum_{i=1}^{t} \Delta P_i}{t}. \]

For the 1982 consensus, this sequence would generate an average squared error as reported in column 3 of Table 10.

The average squared error is reduced by this filter, although not by the dramatic levels of the earlier set of optimal forecasts. The GNP growth equation is improved by about 30% whereas the inflation errors are improved by approximately 10%.

A second filter tries to correct for possible misspecification in the estimated forecast adjustment equation. In the forecast sequence, it is apparent that observations fluctuate randomly about some mean until a sequence of information shocks hit around 10/81. If these observations were equilibrium observations, then the rolling regression procedure would erroneously adjust these observations. In order to isolate periods of "irrational" adjustments we postulate the following form:
\[ p^* = p_t + \delta_{ij} \hat{u}(t-T) \], \( \delta_{ij} = 1 \) if 3 consecutive adjustments have the same sign \[ 0 \] otherwise \[ \hat{u} = \text{sample mean of last three adjustments.} \]

Thus we only extrapolate sample means generated in periods where the adjustments are unidirectional. Column 4 of Table 10 reports the average mean squared errors of this approach.

Again, this filter provides significant, although unspectacular improvements in the average squared errors. The improvement is slightly inferior to the earlier filters.

To understand the relationships between the three filters we have prepared (the first being the full sample optimal) we have reproduced the forecast sequences along with the actual forecast sequences in Tables 11 and 12. As is clear from the tables, the full sample forecast filters immediately render stationary the entire forecast sequence. The other 2 filters increase the rate at which information shocks are assimilated into the forecasts, albeit much more slowly. The third filter possesses a tendency to overshoot the realization as is evidenced by observations near the end of 1981. Evidently the degree of information assimilation which occurs after 3 consecutive periods of unidirectional adjustment is sufficiently high to render full extrapolation an overestimate of the degree of irrationality.

Our optimal forecast research clearly needs to be extended to other forecasters and other periods. However, preliminary research indicates that within sample adjustment of actual forecasts can definitely improve the accuracy of forecasts—which is the bottom line of the forecasting game.
Section V. Conclusions

Our examination of the behavior of 5 major forecasters has provided clear evidence that forecasts do not obey the requirements of statistical rationality. Informational shocks tend to be processed slowly, which implies deviations of forecast adjustments from the white noise properties which optimal conditional expectations must possess. This irrationality appears to be centered upon the forecasting of inflation and in forecasts which follow presidential elections. Preliminary research indicates that accounting for the deviations of forecasts from rationality improves the accuracy of forecasts under reasonable information restrictions.

The clear direction for future research lies in determining the reasons for the evident deviations from rationality. If the source of the irrationality lies in the failure of forecasters to account for these elementary statistical properties, then the hypothesis of rational expectations on the part of any agents must be reexamined. If forecasters are adjusting their forecasts irrationally due to the preferences of their customers, then the sources of these preferences must be scrutinized. Asymmetric loss functions, a desire to have priors reinforced or any host of explanations suggested by our research have profound implications in determining the nature of information processing throughout the economy.
FOOTNOTES

We are grateful to Anne Jenkins and Ellen McGratten for superb research assistance. We thank Sam Ouliaris for helpful comments.

By construction of expectations, we refer to techniques such as equating expectations to least square forecasts generated by the researcher.

The use of the terms unbiasedness and efficiency differs slightly from the definitions usually employed, such as in Mincer and Zarnowitz (1969). The standard definitions are that $c = 0$ constitutes unbiasedness and $b = 1$ constitutes efficiency. Our use of the terms unbiasedness and efficiency are designed to distinguish between misuse of available information and optimal and suboptimal sufficient statistics. If the information sets consists solely of the prediction and a constant, the unbiasedness test is examining whether given information constraints of the forecaster, the information is correctly used. On the other hand, a more natural definition of efficiency revolves around whether the expectational errors can be reduced in variance by use of other publicly available information not used by the forecaster. As we do not know what information is actually employed by forecasters outside of their actual forecasts and a constant, the unbiasedness/efficiency dichotomy we employ is appropriate.

This point is discussed in more detail by Mishkin (1981). The main intuition is that the prevailing market equilibrium is determined by the most rational agents just as the level of risk premia on assets is determined by the presence of some risk neutral agents.

One can posit a number of reasons for this phenomenon. First, the expectations which are reported are ex ante ones and not necessarily the ones which agents actually employ when engaging in market transactions. This would be especially likely if prices in actual markets function as sufficient statistics for the aggregation of information. Alternatively, if each agents' behavior is observable by all members of the market, then information will be transmitted across agents and disparate expectations
disappear. Second, in the presence of futures markets and risk neutral rational agents, the market equilibrium would necessarily be determined by those agents. This explanation particularly applies to the area of interest rates.

See Berger and Krane (1982) for a full discussion of this problem in the context of expectational models of the term structure of interest rates. This problem is exactly equivalent to the increased coefficient variance associated with the use of instruments rather than actual variables in regression.

By this argument, we mean to deal with the problem that announced expectations on the parts of agents may not reflect their true mathematical expectations but rather the mathematical expectations adjusted by some sort of risk premia. For example, firms may adjust profit forecasts downwards in order to avoid unfulfilled dividend predictions. The aim of a forecasting service, on the other hand, is presumably to provide information to disparate agents whose internal adjustment decisions are likely to vary. In addition, some customers may desire unbiased expectations. Thus the forecaster will not be in a position to perform the desired adjustment for its customers, and thus will release unbiased forecasts.

By partial adjustment models, we refer to models of expectation formation whereby agents process information subject to some lag structure. For example, permanent changes in government policy are temporarily perceived as transitory adjustments. By excessive volatility irrationality, we refer to models where agents improperly add elements to the true information set. An example would occur if bond traders assumed that each positive change in the money stock were an automatic signal of an impending credit crunch. Thus the former type of irrationality is related to the omission of elements of the true information set from expectation formation, whereas the latter refers to misperception of the true model which results in expectations formed over incorrect information.
An exception to this use of time series tests of rationality is the work of Berger and Krane (1983). They independently derive a set of tests which are equivalent to the cross-sectional tests which we derive below. Their paper should be read as a complement to the work which we present.

This proof is merely a restatement of the well known property of double conditional expectations. See Chung (1974) for the most general proof. The technique we employ is different from the method of proof employed by Samuelson (1965) in proving the martingale nature of futures prices. We feel our use of expectation operators unlocks the intuition of the result.

The importance of long range foresight in macroeconomic models can be easily seen in such areas as rational expectations models of hyperinflation.

The definition of cross-sectional forecast accuracy which we employ is the RMSE of the sequence of forecasts from the eventual result. This calculation has implicit effect of attaching greater weight to the earlier forecasts, as the expected forecast error is declining over time. (As one approaches the event, the potential variance in prediction will become quite small.) We feel that this weighting is justified as the value of forecast accuracy will be higher when this accuracy can be attained early. Investment decisions which require knowledge of GNP growth will be best augmented by early accuracy. Also, the informational value of the macro forecasts will diminish as the event draws near as information concerning the event moves more and more into the realm of free publicly available information such as government estimates.
FIGURE 1

FORECAST ADJUSTMENTS
DRI 1982

Legend
- REAL GNP
- GNP DEFlator
FIGURE 2

FORECAST ADJUSTMENTS
UCLA 1982

Legend

○ REAL GNP
○ GNP DEFLATOR
FIGURE 3

FORECAST ADJUSTMENTS
Wharton 1982

Legend
- REAL GNP
- GNP DEFlator
FIGURE 4

FORECAST ADJUSTMENTS
Chase 1982

Legend
- REAL GNP
- GNP DEFLATOR
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**Inflation**

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TABLE 2. Chi-Squared Contingency Statistics (3×3) $\chi^2(9)$

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**Inflation**

<p>| Consensus  | 31.68        | 2.1  | 3.3  | 4.6  | 9.1  |
| DRI        | 6.84         | 2.11 | 3.21 | 3.3  | 2.2  |
| UCLA       | 3.91         | 4.88 | 8.13 | .9   | .22  |
| Wharton    | 2.35         | 3.7  | 5.7  | 4.7  | 4.3  |
| Chase      | 2.4          | 3.0  | 1.6  | 4.2  | 3.1  |</p>
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TABLE 4. Constant Significance Tests

\[ \Delta \text{Forecast}_t = C + \epsilon_t \]

* denotes regression significant at 5%

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24 out of 50 cells significant.
TABLE 5. Linear Orthogonality Tests—Estimates of Means $\Delta P_t = C + \epsilon_t$

Where $C = 0$ under Rationality Estimated Coefficients and Standard Errors Reported

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TABLE 6. Lagged Adjustment Significance Tests

\[ \Delta \text{Forecast}_t = \beta \Delta \text{Forecast}_{t-1} + \epsilon_t \]

* denotes \( \hat{\beta} \) significant at 5%

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TABLE 7. Linear Orthogonality Tests--Estimates of Autoregression  
\[ \Delta P_t = \beta \Delta P_{t-1} + \epsilon_t, \beta = 0 \]  
under Rationality Estimated  
Coefficients and Standard Errors Reported

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### TABLE 8. Lagged Consensus Tests--Hypothesis Tests

\[ P_t = c + \beta_1 P_{t-1} + \beta_2 \text{Consensus}_{t-1} + \varepsilon_t \]

Rationality implies that \( c = 0; \ \beta_1 = 1; \ \beta_2 = 0 \)

* denotes rejection at 5%

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22/38 cells.
TABLE 9. Lagged Consensus Tests--Regression Results
\[ P_t = c + \beta_1 P_{t-1} + \beta_2 \text{Consensus}_{t-1} + \epsilon_t \]

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| Inflation | | | | |
| 1982 | .8 | .13 | .51 | .44 | .57 | .46 | .47 | .61 |
| | (.2) | (.24) | (.24) | (.27) | (.28) | (.34) | (.25) | (.28) |
| 1981 | .48 | .22 | .85 | -.31 | -.27 | .63 | .25 | .51 |
| | (.22) | (.36) | (.19) | (.24) | (.29) | (.32) | (.27) | (.37) |
| 1980 | .2 | .6 | -.17 | .67 | .29 | .21 | .7 | .29 |
| | (.3) | (.35) | (.24) | (.29) | (.25) | (.25) | (.2) | (.29) |
| 1979 | .46 | .53 | .36 | .59 | .45 | .48 | -.04 | .9 |
| | (.3) | (.3) | (.35) | (.37) | (.21) | (.21) | (.24) | (.23) |
| 1978 | -.16 | .77 | .45 | 1.00 | .65 | .46 | 1.01 | -.06 |
| | (.20) | (.20) | (6.1) | (.97) | (.26) | (.29) | (.16) | (.24) |
TABLE 10. 1982 Forecast Accuracy: Averaged Squared Error

Average squared error = \( \frac{1}{n} \sum_{t=1}^{n} (\text{prediction}(t) - \text{truth})^2 \)

\( P_t = \alpha + \beta P_{t-1} \) = underlying forecast structure

Sample: 1981:2 1982:12

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TABLE 12. Optimal Forecasts--1982 Consensus Inflation

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BIBLIOGRAPHY


