# RATIONAL BIAS IN MACROECONOMIC FORECASTS

by
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**Comments Invited**

### Abstract

This paper develops a model of macroeconomic forecasting in which a forecaster's wage is a function of his accuracy as well as the publicity he generates for his firm by being correct. In the resulting Nash equilibrium, forecasters with identical models, information, and incentives nevertheless produce a variety of predictions, consciously biasing them in order to maximize expected wages. In the case of heterogeneous incentives, the forecasters whose wages are most closely tied to publicity, as opposed to accuracy, produce the forecasts that deviate most from the consensus.

We find empirical support for our model using a twenty-year panel of real GNP/GDP forecast data from *Blue Chip Economic Indicators*. Although the consensus outperforms virtually every forecaster, many forecasters choose to deviate from it substantially and regularly. Moreover, the extent of this deviation varies by industry in a manner consistent with our model.

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Empirical tests of the rational expectations hypothesis as it applies to professional macroeconomic forecasts generally examine whether predictions of a macroeconomic variable are unbiased and efficient.[1] These analyses presume that, because forecasters have strong economic incentives to be accurate, the numbers they produce represent their best estimates. Herein lies an interesting question. A forecast that best allows a forecaster to achieve his economic goals may not be "best" in a statistical sense. Indeed, as Zarnowitz and Braun (1992) have documented, group mean ("consensus") forecasts are more accurate than virtually all individual forecasts. Since consensus forecasts are available publicly on a timely basis, this suggests a conundrum: Why do firms continue to produce forecasts that are unlikely to be more accurate than the consensus? A related puzzle, noted by Lamont (1995), is that some experienced forecasters consistently produce projections that are outliers relative to other professional forecasts. These observations suggest the possibility that forecasters, when making their projections, may have goals in mind unrelated to the pure pursuit of accuracy.

In this paper we develop a model in which forecasters' wages are based on two criteria: their accuracy and their ability to generate publicity for their firms. Accuracy is defined in the usual sense of minimizing expected forecast error. Publicity comes from having the most accurate forecast in a given period. The model demonstrates that, even in the case where all forecasters have identical information and identical incentives, forecasters' efforts to maximize their expected wage will lead many of them to consciously bias their projections in order to differentiate their views from the consensus. Thus, in contrast to the standard rational expectations approach, our model is one of "rational bias." The model has an additional implication for the case where the

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[1]This is the approach followed by numerous researchers in the empirical rational expectations literature, such as Figlewski and Wachtel (1981) and Keane and Runkle (1990). For a current discussion of the issues, see Croushore (1996).

incentives forecasters face vary by industry. Forecasters working in industries that value publicity most will make predictions that deviate most from the consensus.

After examining the model, we test some of its implications using a twenty-year panel of forecasts of annual real GDP and GNP growth from *Blue Chip Economic Indicators*, a widely used survey of professional forecasters. Sorting the forecasters into six industry categories, we find that those who work for banks and industrial corporations -- the types of firms that might be expected to value forecast accuracy -- tend to produce forecasts that are closest to the consensus. Independent forecasters, who stand to benefit most from favorable publicity, tend to associate themselves with outlying forecasts.

The plan of this paper is as follows. The first section briefly reviews prior research and describes the forecasting industry. The next section develops a model of rational bias in forecasting and examines several of its implications. Empirical support for the model is provided in the third section. The final section offers a summary and discussion.

## I. Background

*Previous work*

Research examining whether macroeconomic forecasts are consistent with models of rational expectation has produced mixed results. McNees (1978) finds only limited support for the hypothesis that the forecasts of unemployment, inflation, and real GNP growth by three major econometric forecasting firms are efficient and unbiased. Figlewski and Wachtel (1981) conclude that individual inflation forecasts from the Livingston survey are biased and have serially correlated errors, inconsistent with rational expectations. Critiquing previous empirical studies of the rational expectations hypothesis, Keane and Runkle (1990) perform more carefully controlled tests. These provide evidence that macroeconomic forecasts from the ASA-NBER survey of professional forecasters incorporate full information and are unbiased, "...salvaging the possibility that the rational expectations hypothesis is empirically valid" (p. 730). Bohnam and Cohen (1995), however, question these results on technical grounds. Jeong and Maddala (1996) reject the rational expectations hypothesis for a set of interest rate forecasts from the ASA-NBER survey. In short, a preponderance of statistical evidence calls into question the notion that professional forecasts are rational in the sense of being efficient and unbiased.

Casting further doubt on how closely forecaster behavior conforms to rational expectations models are recent studies that suggest that macroeconomic forecasts are colored by the incentives forecasters face. Ito (1990) finds that exchange rate forecasts are systematically biased toward scenarios that would benefit the forecaster's employer. He terms this bias "wishful expectations," but leaves unresolved whether it reflects irrational wish-fulfilment or whether it is the product of rational behavior by individuals responding to corporate incentive structures. Lamont (1995) hypothesizes that a forecaster's willingness to make predictions that deviate from the consensus may vary systematically with his level of experience or seniority. Analyzing forecasts of GNP and GDP from an annual *Business Week* survey, he finds that forecasters who have been in the industry longer exhibit a greater willingness to deviate from the consensus. Ehrbeck and Waldman (1996) develop several models in which forecasters, wishing to signal their competence, resist changing their forecasts in response to new information. Using data on U.S. Treasury bill rates, they are unable to find evidence consistent with their model of rational bias.

This paper makes two contributions to the literature on forecaster behavior. First, it develops an original model in which identical forecasters consciously differentiate their predictions, creating the impression that there is a divergence of views when in fact there is none. Second, it uses a new panel of data to demonstrate that the extent to which forecasters deviate from the consensus varies by their industry of employment. Before presenting our model of forecaster behavior, we briefly discuss the job of the professional forecaster.

*The roles of the professional forecaster*[1]

Professional macroeconomic forecasters work for a variety of employers such as banks, securities firms, nonfinancial corporations, and consulting firms that specialize in econometric modeling or other types of economic analysis. A key part -- and in some cases the entirety -- of the forecaster's job is to provide analysis internally: to track economic variables, make forecasts, and share insights with the organization's decision makers. Providing macroeconomic forecasts is thus one way the economist supports his firm's efforts for which the *accuracy* of the economic analysis and forecasting is crucial.

The other fundamental role of economic forecasters is to provide marketing for their employers. Through his public speaking engagements, magazine articles, television interviews, and quotes appearing in the press, the economist keeps his employer's name visible before important audiences. This external role requires presenting an image of expertise and originality to the public. In this arena, where the audience is of a broad range of backgrounds, the manner in which an economist presents his analysis may count as much as its content. The forecaster operating successfully in this environment provides *publicity* for his firm.

[1]For a more extensive discussion, see Henry (1989).

*Surveys of professional forecasters*

One way for a forecaster to gain publicity for his firm is by participating in surveys of professional forecasters. These surveys, which appear in the business press as well as in specialized publications, call attention to the firm whose forecasts for the most recent prior period came closest to the actual outcome. *Business Week*, for example, has for a number of years featured a collection of macroeconomic forecasts by business economists in its year-end issue. Accompanying the forecasts is a separate write-up on the economist whose prior-year projection was closest to the mark. The write-up, complete with photograph, also prominently lists the firm for which the economist works. Similarly, *The Wall Street Journal* rewards the most accurate participant in its survey of professional forecasters with a separate article. The publisher of *Blue Chip Economic Indicators*, a monthly newsletter compiling dozens of professional economic forecasts, holds an annual dinner at which the most accurate forecaster for the previous year is honored.[2]

In order to survive, a survey must offer benefits to all parties involved: the publication, its readers, and the participating firms. The publication gains useful data that it can share with its readers, boosting its circulation. Readers gain information about the outlook for the economy. Firms that go to the trouble of responding to a survey, offering the fruits of their labor free of charge, also gain something - media exposure. This includes the chance to receive the favorable coverage that comes from producing the best forecast in a given period. This arms-length, high-profile reporting of its forecasting expertise might even be more effective in

[2]A recent example demonstrates how significant these contests have become. When Lawrence Meyer was nominated to the Board of Governors of the Federal Reserve System in February 1996, newspaper accounts noted that his economic forecasting firm had been cited twice in recent years for having the top forecast in *Blue Chip Economic Indicators*.

attracting new clients than a paid advertisement. Because media citations also enhance a forecaster's own reputation, he will be particularly willing to help his firm by participating in these surveys.[3]

## II. The Model

We develop a model that shows how forecasters' efforts to balance the twin objectives of accuracy and publicity can lead them to produce biased macroeconomic forecasts. Heuristically, if all forecasters have similar information, the pure pursuit of accuracy will lead to forecasts that cluster tightly around a consensus. Forecasters seeking publicity, however, will not want to be in the cluster, since their forecasts would then have little or no chance of winning them widespread attention. Instead, they will select forecast values that have a reasonable likelihood of occurring but which are not already being forecast by others. As an extension of this reasoning, those who are especially publicity-conscious should be more inclined to make unconventional forecasts; those who emphasize accuracy will make projections that cluster around the most likely outcome. The following sections spell out the details.

*Timing and information structure*

Assume that there are N firms, each of which employs an economic forecaster. At date 0, the forecasters announce their predictions of next period's level of a macroeconomic variable x whose probability distribution function (pdf) is discrete.[4] Forecasters have access to two types

[3]Michael Woodford notes that just as these publications have strong incentives to publicize the most successful forecaster, they also have strong incentives *not* to publicize the poorest performers. This asymmetric media coverage is an efficient mechanism for encouraging organizations to participate, and to continue participating, in a survey.

[4]The discreteness assumption reflects the way in which widely followed macroeconomic variables are reported. For example, the real GDP growth rate and the unemployment rate are rounded to the nearest tenth of a percent even though the level of GDP and the number of people working and looking for work are measured with greater precision.

of information, on which they base their predictions of x: (1) the pdf of x, f(x); and (2) the contemporaneous distribution of forecasts made by those in the profession, denoted n(x).

By assuming the existence of a pdf on which forecasters concur, the model seeks to explain the dispersion of forecasts without appealing to differences among forecasters' information sets, methodologies, or abilities. Forecasters in fact rely on extremely similar data sources; the statistical models they use tend to produce similar near-term forecasts. While some differences of opinion among forecasters are inevitable, a strength of the model is its ability to explain how a dispersion of forecasts can occur even in the absence of these differences.

Our other key assumption is that when making their forecasts, each forecaster is aware of the distribution of contemporaneous forecasts, n(x), a function which meets the condition

$$\sum n(x) = N. \tag{1}$$

The assumption that forecasters know n(x) reflects an industry environment in which forecasters reveal and actively debate their views with one another. The forecasts that appear in the December issue of *Blue Chip Economic Indicators*, for example, are very similar to those appearing in the November issue. Even if important new information has arrived in the interim, forecasters can generally find out how others in the profession have adjusted their views through published reports, statements in the press, or personal conversations. Thus, in the model, the dispersion of published forecasts is due not to differences in information and methodologies, but to the strategic behavior of forecasters jockeying for position.

At date 1 the realized value of the variable, $x_0$, is announced. A forecaster's wage is then set based on his *ex post* performance.

*Forecasters' compensation*

A forecaster is paid according to how well he fulfills the roles of internal adviser and source of media attention. In the first role, the forecaster helps his firm decide such questions as how many workers to hire, how much to produce, and how large a stock of inventories to carry. An accurate forecast will enable the firm to plan wisely; a poor forecast will create inefficiencies and missed opportunities. More specifically, we assume that the opportunity cost L of an inaccurate forecast is a function of forecast error:

(2) $$L(x) = L(x_0 - x).$$

L represents the difference between the profits a firm actually realizes from operations and how much it would have earned had its forecaster been exactly correct. (This excludes any gains in profitability due to publicity, which are measured separately). By construction, the function L achieves a minimum value of zero when its argument is zero.

A forecaster can also contribute to his firm by enhancing its reputation. The firm whose forecaster is the one who correctly predicts the value of x receives favorable publicity worth P. But if more than one forecaster predicts this value, the publicity must be shared among all of their firms. More formally, if the realized value of the forecast variable is $x_0$, the value of publicity derived from a forecast of x equals

(3) $$A(x) = P/n(x) \qquad \text{if } x = x_0\text{; and}$$
$$A(x) = 0 \qquad \text{otherwise.}$$ [5]

Forecasters are paid for their contribution to their employers, as measured by their

[5] An additional assumption that would make the model more realistic is that if no forecaster correctly predicts the value of x, all those who come closest will equally share the publicity:

$$A(x) = P/[n(x) + n(2x_0-x)] \qquad \text{if } n(x_0) = 0 \text{ and } |x-x_0| \leq |z-x_0| \text{ for all z for which } n(z) > 0.$$

As a practical matter, this will not alter the equilibrium because, as we observe in footnote 12, every value in the range of possible outcomes will be forecast by someone.

accuracy and the advertising they generate. Assuming a linear pay structure, forecaster i earns

$$w_i = v_i - s_iL(x_i) + b_iA(x_i), \qquad i = 1,2,\ldots,n$$

where $w_i$ is forecaster i's wage, $v_i$ is a constant, $s_i \geq 0$ measures how closely forecaster i's pay is tied to his accuracy, and $b_i \geq 0$ reflects the size of the bonus he receives for making a forecast that garners publicity by being among the most accurate.

It will simplify the analysis considerably to specify L to be a quadratic loss function.[6] Thus, the wage of the $i^{th}$ forecaster, who predicts $x_i$ when the variable's realized value is $x_0$, equals

$$(4) \qquad w_i(x_i) = v_i - s_i(x_0 - x_i)^2 + b_iA(x_i), \qquad i = 1,2,\ldots,N.$$

If forecasters are assumed to be risk neutral, their optimization problem reduces to choosing the value of $x_i$ that maximizes their expected wage

$$Ew_i(x_i) = v_i - s_iE(x_0 - x_i)^2 + b_iPf(x_i)/n(x_i), \qquad i = 1,2,\ldots,N,$$

where the final term is the expected value of the forecaster's bonus for correctly predicting x. Letting $\mu = E(x_0)$, this expression simplifies to[7]

$$(5) \qquad Ew_i(x_i) = w_i^* - s_i(\mu - x_i)^2 + b_iPf(x_i)/n(x_i),$$

where $w_i^* = v_i - s_i\text{Var}(x)$. The constant $w_i^*$, which is beyond the control of forecaster i, can be interpreted as his expected base wage, absent bonus, for forecasting the value $\mu$.

The final two terms in equation (5) summarize the trade-off between accuracy and

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[6]Alternative functional forms will produce very similar results. If, for example, L were a function of absolute error instead of squared error, forecasters' expected wage would be penalized for deviations from the *median* of the pdf as opposed to its *mean*. The analysis would be essentially the same.

[7]The key step is to note that

$$E(x_0 - x_i)^2 = E[(x_0-\mu) + (\mu-x_i)]^2 = E(x_0-\mu)^2 + 2(\mu-x_i)E(x_0-\mu) + (\mu-x_i)^2.$$

The middle term is zero by definition and the first term is the variance of x. Substituting,

$$Ew_i(x_i) = v_i - s_i\text{Var}(x) - s_i(\mu-x_i)^2 + b_iPf(x_i)/n(x_i),$$

which is equivalent to (5).

publicity that a forecaster faces. At one extreme, he can simply forecast $\mu$, the expected value of x. This will minimize his expected squared error but would rule out the possibility of earning a large bonus if many others also forecast $\mu$, i.e., if $n(\mu)$ is large. Alternatively, to have a chance at winning a large bonus, he can choose a value of x for which $n(x)$ is small. Such a forecast would likely be biased, however, thereby raising his expected squared error. The choice that a given forecaster makes will depend on two factors: differences between the pdf and the distribution of forecasts, as measured by $f(x)/n(x)$, and the relative emphasis his employer places on accuracy as opposed to advertising, measured by $s_i/b_i$. Next we consider the resulting equilibrium.

## Homogeneous Incentives

In the simplest version of the model, every employer places the same emphasis on advertising and accuracy, so that the parameters $b_i$ and $s_i$ are the same for all forecasters. We can therefore omit the subscripts from our discussion. There are three possible cases.

*Case I: Only accuracy matters ($b=0$ and $s>0$).*

When only accuracy matters to employers, it follows from equation (5) that, because $b=0$, expected wage is maximized when $(\mu-x)^2$ is at a minimum. The optimal forecast of x will therefore be its expected value $\mu$. This implies that if all employers compensate their forecasters based solely on accuracy, everyone will make the same forecast.

*Case II: Only publicity matters ($b>0$ and $s=0$).*

The opposite extreme case is where forecasters are all rewarded exclusively for the publicity they generate for their employers. Since $s=0$, expression (5) implies that each forecaster will choose the value of x for which $f(x)/n(x)$ is maximized. When all forecasters try to maximize $f(x)/n(x)$, the resulting distribution of forecasts $n(x)$ will be exactly proportional to $f(x)$, the pdf of x.

This can be shown through a proof by contradiction. Suppose that the ratio $f(x)/n(x)$ were not equal to a constant in equilibrium. Then there would exist values for $x_1$ and $x_2$ such that $f(x_1)/n(x_1) > f(x_2)/n(x_2)$. This would not constitute an equilibrium. People forecasting $x_2$, commanding a lower expected wage than those forecasting $x_1$, would change their forecasts from $x_2$ to $x_1$. This migration would raise $n(x_1)$ and lower $n(x_2)$, until the discrepancy was eliminated.[8]

This general condition of proportionality and equation (1) together imply that when publicity is all that matters,

$$n(x) = Nf(x) \qquad \text{for all x.} \tag{6}$$

What is striking about this result is that even though everyone agrees on which value of x is most likely to occur, forecasters will nonetheless be drawn to distribute themselves in a fashion that mimics the pdf of x.

*Case III: Accuracy and publicity both matter (b>0 and s>0).*

Having examined the two extreme cases, we next consider the intermediate case, in which publicity and accuracy both matter. Expression (5) states a forecaster's expected wage Ew as a function of his forecast of x. For a distribution of forecasts $n(x)$ to constitute a Nash equilibrium, it must have the property that no forecaster will be able to increase his expected wage by changing his forecast. What this latter condition implies for equilibrium depends on whether or not $n(x)$ is assumed to take on only integer values. Provided that $n(x)$ can assume

[8] This argument implicitly assumes that n(x) can take on non-integer values. For further elaboration, see the next footnote.

any real value, a necessary condition for equilibrium is that all forecasts must yield the same expected wage $\hat{w}$:[9]

$$(7) \qquad Ew(x) = \hat{w} \qquad \forall x \ni n(x) > 0.$$

To simplify the analysis, we assume that the mean of f(x) is one of the discrete values that x can assume. Reparameterizing so that $\mu_x = 0$ and substituting (7) into (5) yields

$$\hat{w} = w^* - sx^2 + bPf(x)/n(x),$$

which can be solved for n:

$$(8) \qquad n(x) = \frac{Pf(x)}{k(\hat{w}) + rx^2}, \qquad \text{where } k(\hat{w}) = (\hat{w}-w^*)/b \text{ and } r = s/b.$$

The expression n(x) represents a distribution of forecasts that will cause all forecasters to have the same expected wage, $\hat{w}$. We will refer to this function as the forecasters' "iso-expected wage curve" or, more simply, their "iso-wage curve." For this expression to constitute an equilibrium, it must also satisfy equation (1), which states that there are exactly N forecasters.

There exists a unique market-clearing wage $\hat{w}$ for which equation (8) characterizes an equilibrium with N forecasters. To see why, consider the terms on the right-hand side of equation (8). The pdf f(x) is known and the parameters P (the value of publicity) and r (the relative emphasis that employers place on accuracy) have fixed values. The only variable in the expression is k, which is a positive linear function of the market expected wage $\hat{w}$. Thus, to each value of $\hat{w}$ there corresponds a distinct iso-expected wage curve, which we can label $n^{\hat{w}}(x)$ (Chart 1). Because P, f(x), and r are all non-negative, it follows from (8) that $n^{\hat{w}}(x)$ is

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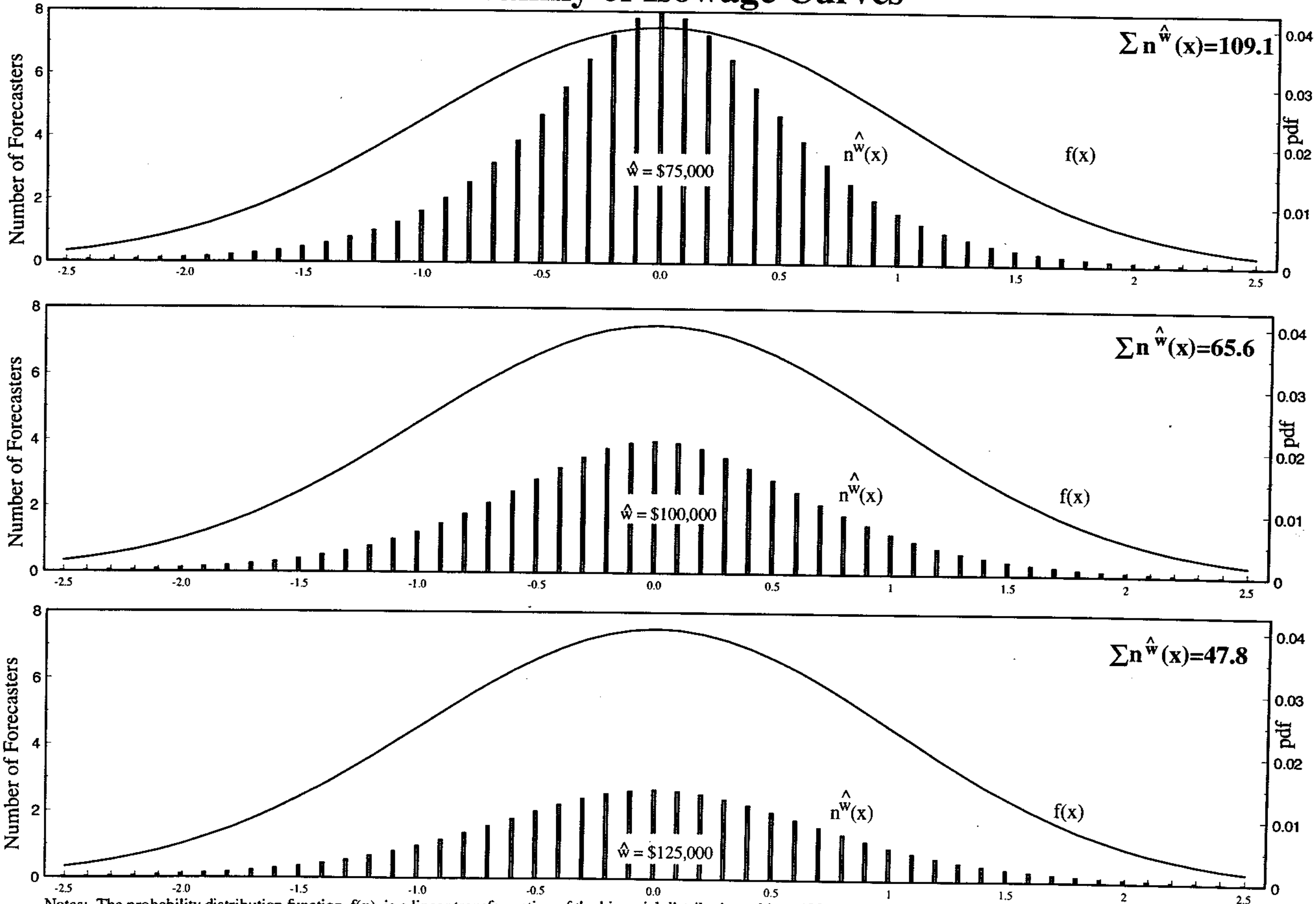
[9]If, however, n(x) is restricted to integer values, a Nash equilibrium will meet a somewhat weaker condition, namely,

$$(7') \qquad Ew(x_1+1) \leq E(x_2) \qquad \text{for all possible forecasts } x_1 \text{ and } x_2.$$

In this paper we assume that n can assume non-integer values, so that equation (7) applies. The larger the pool of forecasters, the better an approximation this is. Our analysis of the case in which n is restricted to integer values, not reported here, demonstrates that the main results continue to hold and that the resulting equilibrium is essentially the same.

Chart 1

# A Family of Isowage Curves




Notes: The probability distribution function, f(x), is a linear transformation of the binomial distribution with n=400, p=q=.5. It is scaled to have zero mean and a variance of one. While the distribution of forecasters is sketched here as a curve, it is actually discrete and takes on values at intervals of 0.1.

The isowage curves are constructed for the parameter values **[P = \$5,000,000; w* = \$50,000; s = 50,000; and b=1]**.

monotonically decreasing in $\hat{w}$.[10] Moreover, by varying $\hat{w}$, $\sum n^{\hat{w}}(x)$ can be made arbitrarily large or small.[11] This implies that for any given number of forecasters N there will exist a market clearing expected wage $\hat{w}$ and a unique equilibrium distribution n(x) that satisfies equation (1).[12]

The equilibrium will be stable because a forecaster predicting a value of x that is selected by more than n(x) forecasters will earn a substandard expected wage, prompting him to change his forecast. Conversely, a value of x chosen by fewer than n(x) forecasters will command an expected wage above the industry standard. These forces will create incentives for forecasters to change their predictions until the point where equation (8) holds.

*Comparative statics*

How does the relative emphasis that employers place on accuracy as opposed to publicity affect the equilibrium distribution of forecasters? Cases I and II illustrate the notion that the more employers reward accuracy, the greater will be the tendency for forecasters to cluster. When r=s/b is high (i.e., employers emphasize accuracy), we would expect the distribution of forecasts to cluster tightly around its mean. When r is low (i.e., publicity matters relatively more), the distribution of forecasts should be more dispersed. Proposition 1 makes the nature of this relationship more precise.

PROPOSITION 1: *If $n_1(x)$ and $n_2(x)$ each represents an equilibrium distribution of N forecasters such that $n_1$ reflects a greater relative emphasis on accuracy than $n_2$ (i.e., $r_1 > r_2$), then there exists a positive constant a so that $n_1(x) > n_2(x) \Leftrightarrow |x| < a$.*

This proposition states that an increased emphasis on accuracy will raise the number of

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[10] Intuitively, an increase in the reservation wage of forecasters will induce some to leave the business, raising the expected wage of those who remain (since there will be fewer forecasters with whom to share the available publicity).

[11] This is because: $\forall x$, $n^{\hat{w}}(x) \to 0$ as $\hat{w} \to \infty$; and $n^{\hat{w}}(0) \to \infty$ as $\hat{w} \to w^*$.

[12] Expression (8) also implies that for all values of x for which f(x) is positive, n(x) will also be positive. In other words, there will always be someone forecasting every possible value of x.

forecasts of values within a symmetric interval around 0 and will decrease the number of forecasts for values outside that interval (Chart 2).

To establish the proposition, first note that (8) implies that

$$(8') \qquad n_i(x) = \frac{Pf(x)}{k_i(\hat{w}_i) + r_i x^2}, \qquad i=1,2$$

where subscripts denote the two alternative distributions. Since by hypothesis $r_1 > r_2$, it follows from (8') that if $k_1 \geq k_2$, then $n_1(x) \leq n_2(x)$ for all x, with strict inequality holding for all nonzero values of x. This would imply that $\sum n_1(x) < \sum n_2(x)$, which violates the assumption that the two alternative distributions have the same number of forecasters. So $k_1$ must be less than $k_2$. Substituting into (8') for the values i=1,2 and simplifying gives

$$n_1(x) > n_2(x) \Leftrightarrow x^2 < (k_2-k_1)/(r_1-r_2).$$

The desired result follows from setting $a = [(k_2-k_1)/(r_1-r_2)]^{.5}$.

The central message of Proposition 1 and equation (8) is that the distribution of forecasts that we observe for a given period reflects two underlying factors -- the pdf of the variable being forecast and the relative emphasis that employers place on accuracy. If the incentives forecasters face don't vary much from year to year then we can interpret a change in the extent to which forecasters cluster as a symptom that the variable's (unobserved) pdf has changed. Conversely, secular trends in the incentives that forecasters face, as measured by r, will affect the equilibrium distribution of forecasts, even absent any changes in the forecast variable's pdf.

Another consequence of Proposition 1 is that the more employers emphasize accuracy over publicity, the lower will be the variance of forecasts.[13] But recall from our discussion of

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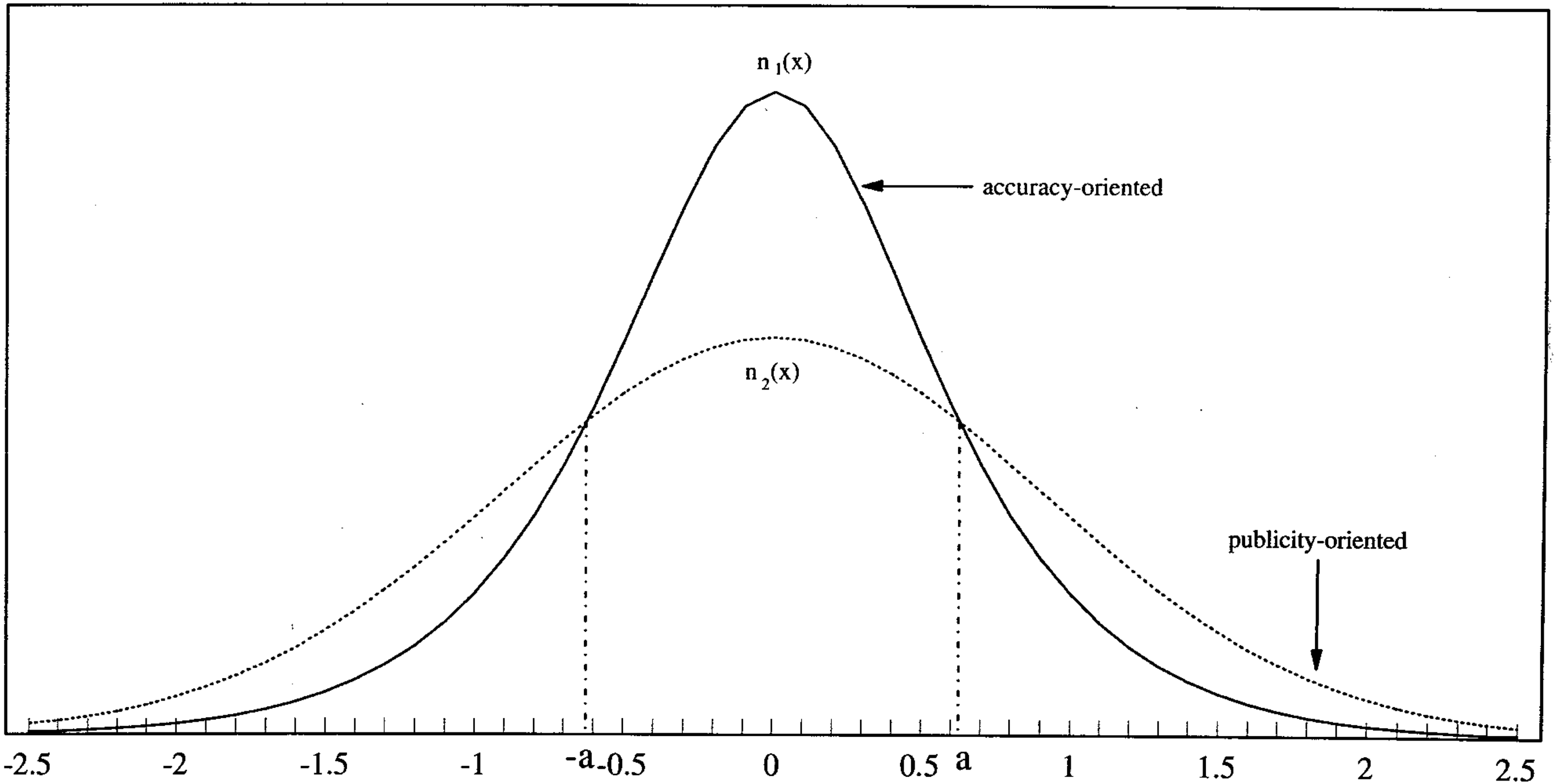
[13]This result follows from the property that, for all c, the sum $\sum(n_1(x)-n_2(x))$, when calculated for $-c \leq x \leq c$, is nonnegative. For further discussion see Mood, Graybill, and Boes (1974), pp. 74-75.

Chart 2

## Comparative Statistics: Equilibrium Distribution of Forecasters for Varying Degrees of Emphasis on Accuracy




Notes: The probability distribution function, f(x), is a linear transformation of the binomial distribution with n=400, p=q=.5. It is scaled to have zero mean and a variance of one.
The two alternative equilibrium distributions of forecasters were constructed using the parameter values:

| | |
|---|---|
| N = | 100 |
| P = | \$5,000,000 |
| $r_1$ = | 50,000 |
| $r_2$ = | 5,000 |

Thus, $n_1$ reflects more of an emphasis on accuracy than does $n_2$.
While the distributions of forecasters are sketched here as curves, they are actually discrete and take on values at intervals of 0.1.

Case II that when accuracy receives zero weight the distribution of forecasters will be identical to the pdf of x. These two statements together imply a

COROLLARY: *In equilibrium, the forecasts of a given variable will have a variance less than or equal to that of the variable itself.*

*Consensus forecast*

In this model, the predictions of individual forecasters are often biased. What about the consensus? Suppose that the pdf of x is symmetric about its mean, which is labeled zero, so that

$$f(-x) = f(x) \qquad \text{for all } x.$$

This condition together with expression (8) implies that n(x), the distribution of forecasts, will also be symmetric about 0. From this symmetry it follows that the distribution of individual forecasts of the variable will have the same mean as the variable's pdf, a result worth emphasizing:

PROPOSITION 2: *If a variable has a probability distribution function symmetric about its mean, then the consensus (mean) forecast of the variable will be unbiased.*

The intuition behind Proposition 2 is that if a large proportion of forecasters opt to make high forecasts, there will be a strong incentive for some to switch to low forecasts in order to increase their expected bonuses. This incentive will prompt forecasters to distribute themselves evenly around the mean of x. While Proposition 2 is premised on a very strong assumption - perfect symmetry - it will nonetheless hold approximately true even if f(x) is only approximately symmetric.

The unbiasedness of the consensus has an important empirical implication, namely, that the consensus forecast should have the lowest expected root mean squared error. We will return to this observation in our empirical work below.

To summarize, we have shown that in the case where all employers pays their forecasters according to a common wage function, there exists a stable, unique equilibrium distribution of forecasts. The variance of this distribution is less than that of the pdf and is an increasing function of the relative emphasis employers place on publicity. If the pdf is symmetric, the consensus will be unbiased.

Heterogeneous Incentives

Now consider the more general case, in which the wage parameters $w_i^*$, $s_i$, and $b_i$ can vary by industry. Forecasters hired to function chiefly as internal advisors have a high value of $s_i$ relative to $b_i$ because accuracy is what matters most. A forecaster employed by a manufacturer, for example, helps guide the planning process but will not benefit his firm by winning recognition as the most accurate among a panel of experts. Other employers place special emphasis on publicity and assign a much higher value to $b_i$ relative to $s_i$. The forecasts produced by an economist working at a fledgling consulting firm (perhaps his own) are a vital part of the firm's output. The publicity attached to having the best forecast among competitors can be invaluable to the efforts of such a firm to expand its client base.

The equilibrium we consider is one in which all forecasters receive the same expected wage. Expected wage is equalized *within* each industry because any wage inequality will motivate forecasters to change their forecasts until the disparity is eliminated. Expected wage will also be equalized *across* industries provided that forecasters can select the industries in which they work.[14] This is because forecasters will migrate from low-wage industries to high-

[14]The analysis readily generalizes to the case where expected wage is equalized within each industry, but not across industries.

wage industries until interindustry discrepancies disappear.

Suppose that the pdf f(x), the value of publicity P, the market-clearing expected wage $\hat{w}$, and the wage vector $\{w_i^*, s_i, b_i\}$ are known for each of m industries. Will an equilibrium distribution of forecasts exist and, if so, what will it be? In particular, how many forecasters will choose to work in each industry and what values will they forecast?

To solve for the equilibrium, we follow the same approach as in the one-industry homogeneous incentives case. The isowage curve n(x) in equation (8) states how many forecasters employed in a given industry will be prepared to forecast each value of x. Appending subscripts, we can use an analogous expression in the multi-industry case:

$$n_i(x) = \frac{Pf(x)}{k_i(\hat{w}) + r_i x^2}, \qquad i=1,\ldots,m. \tag{8'}$$

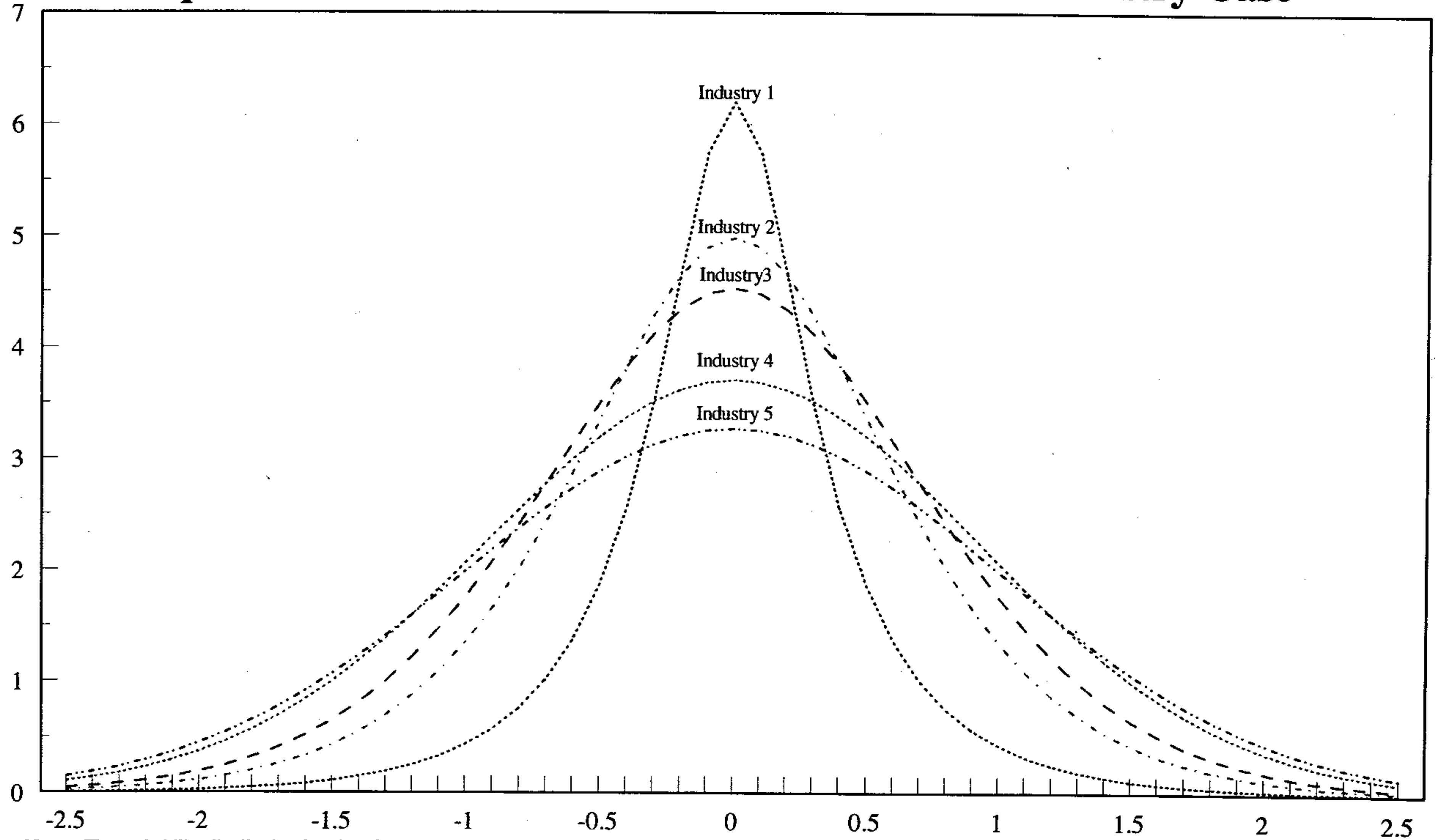
where $k_i(\hat{w}) = (\hat{w}-w_i^*)/b_i$
and $r_i = s_i/b_i$.

For any given market-clearing expected wage $\hat{w}$, we can aggregate the industry-specific isowage curves $n_i(x)$, to determine the equilibrium distribution of all forecasters. For each possible forecast value x, the expression $n_i(x)$ states how many forecasters compensated according to the industry i pay scale can predict x and still earn $\hat{w}$. It follows that, in equilibrium the only forecasters who will predict the value x will be those from the industry or industries for which $n_i(x)$ is a maximum. Forecasters from other industries will be crowded out from predicting the value x because doing so would cause them to earn an expected wage below the market rate $\hat{w}$. The aggregate distribution of forecasters n(x) will therefore be the upper envelope of the individual industry isowage curves (Chart 3a):

$$n(x) = \max_i n_i(x) \qquad i=1,\ldots m. \tag{9}$$

Chart 3a

# Equilibrium Distribution of Forecasters: Multi-Industry Case




Notes: The probability distribution function, f(x), is a linear transformation of the binomial distribution with n=400, p=q=.5. It is scaled to have zero mean and a variance of one. While the distribution of forecasters is sketched here as a curve, it is actually discrete and takes on values at intervals of 0.1.
P is set equal to $5,000,000. The values of $r_i$ and $N_i$ (the number of firms per industry) are assumed to be:

| Industry | $r_i$ | $N_i$ |
|---|---|---|
| i = 1 | 250,000 | 20 |
| 2 | 50,000 | 20 |
| 3 | 25,000 | 20 |
| 4 | 5,000 | 20 |
| 5 | 0 | 20 |

Equations (8') and (9) together determine the equilibrium distribution of forecasters for the multi-industry case. The salient characteristic of this equilibrium is the close connection between the way an industry pays its forecasters and the forecasts that they generate. This is shown in

PROPOSITION 3: *If forecaster 1 is rewarded relatively more for accuracy than is forecaster 2 ($r_1 > r_2$), then their forecasts $x_1$ and $x_2$ will be such that $|x_1| \leq |x_2|$.*

The proof of this proposition follows directly from the optimizing behavior of forecasters. The fact that forecaster 1 chooses value $x_1$ rather then $x_2$ implies that

$$Ew_1(x_1) \geq Ew_1(x_2).$$

Substituting into (5) and noting that $\mu$=0 yields

$$w_1^* - s_1x_1^2 + b_1Pf(x_1)/n(x_1) \geq w_1^* - s_1x_2^2 + b_1Pf(x_2)/n(x_2),$$

which simplifies to

(10) $$P[f(x_1)/n(x_1) - f(x_2)/n(x_2)] \geq r_1(x_1^2 - x_2^2)$$

Similarly, forecaster 2's preference for $x_2$ over $x_1$ means that

$$Ew_2(x_2) \geq Ew_2(x_1), \quad \text{or}$$

(11) $$r_2(x_1^2 - x_2^2) \geq P[f(x_1)/n(x_1) - f(x_2)/n(x_2)].$$

Combining (10) and (11) and subtracting gives

$$(r_2 - r_1)(x_1^2 - x_2^2) \geq 0.$$

The first of these two multiplicative terms is negative by hypothesis. Thus, $x_1^2 - x_2^2$ must be negative or zero. The proposition follows as a consequence.

Proposition 3 allows us to characterize the equilibrium distribution for forecasters. If the employers in each of m industries emphasize accuracy and publicity to varying degrees, we can number the industries so that

$$r_i \quad > \quad r_j \qquad\qquad \text{for } i < j.$$

The proposition implies that forecasters employed in industry 1, which places the greatest weight on accuracy, will position themselves along a symmetric interval around zero, $[-c_1,+c_1]$. Industry 2 forecasters will select values over the intervals $[-c_2,-c_1]$ and $[+c_1,-c_2]$, and so forth (Chart 3b). Finally, industry m forecasters, who receive the greatest relative rewards for attracting publicity, will position themselves along the tails of the probability distribution, at $(-\infty,-c_{m-1}]$ and $[+c_{m-1},\infty)$.[15]

We can frame the model in a slightly more realistic way. Until now, we have assumed that the industry wage parameters $\{w_i^*,s_i,b_i\}$ and the market clearing wage $\hat{w}$ are exogenous and that they induce an allocation of forecasters across industries. Another approach is to assume that each industry adjusts its pay scale to the level needed to attract its desired number of forecasters. Thus, for each industry, the parameter $r_i$ is fixed, while $k_i$ can vary. If, in equilibrium, each industry i employs $N_i$ forecasters, where

$$\sum N_i = N, \qquad\qquad i=1,\ldots,m,$$

Proposition 3 suggests an algorithm for determining the equilibrium distribution of forecasts given f(x), and the values of $r_i$ and $N_i$ for $i = 1,\ldots,m$ (Appendix 1).

To conclude, the multi-industry case of our model has a very strong empirical implication: the more an industry rewards its forecasters for generating publicity, the greater

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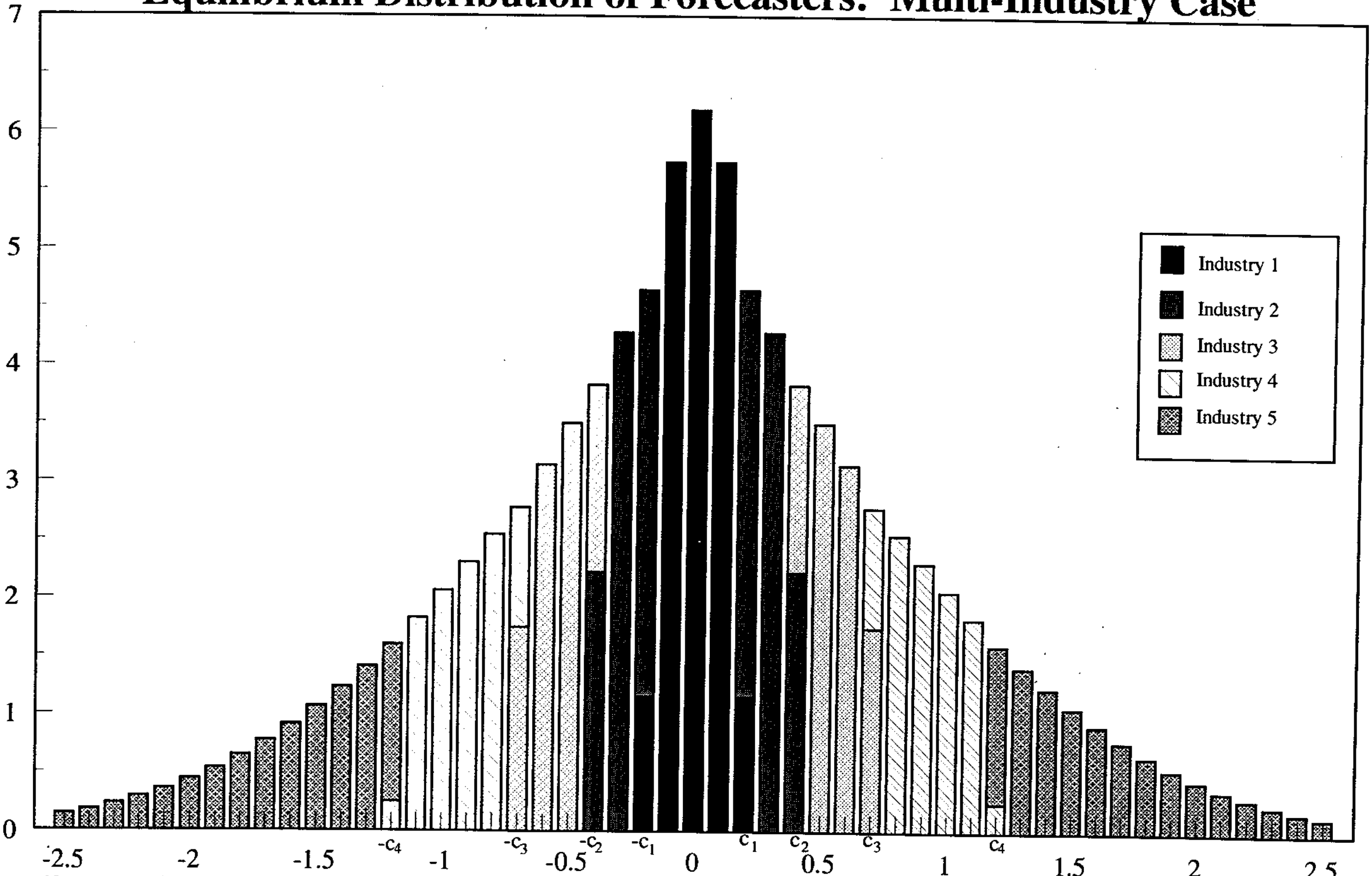
[15] There could, of course, be two or more industries for which r assumes the same value. In that case, it follows from (8') that the one with the lowest value of k will bid away the forecasters from the other industries having the same value of r. If two industries have identical values for both k and r, they can be thought of as constituting a single industry for the purposes of the model.

This discussion implicitly assumes that the wage parameters for the m industries are such that some forecasters will choose to work in each industry. If, however, the parameter $k_j$ for a particular industry j is too high (i.e., $w_j^*$ is too low), forecasters might choose not to work in that industry. Stated in terms of expression (9), this means that there does not exist a value of x for which $n_i(x)$ is at a maximum when i=j. This in no way affects our discussion. We can simply exclude all noncompetitive industries such as j from the analysis and renumber the remaining industries.

Chart 3b

# Equilibrium Distribution of Forecasters: Multi-Industry Case




Notes: The probability distribution function, $f(x)$, is a linear transformation of the binomial distribution with $n=400$, $p=q=.5$. It is scaled to have zero mean and a variance of one. P is set equal to $5,000,000. The values of $r_i$ and $N_i$ (the number of firms per industry) are assumed to be:

| Industry | $r_i$ | $N_i$ |
|---|---|---|
| i = 1 | 250,000 | 20 |
| 2 | 50,000 | 20 |
| 3 | 25,000 | 20 |
| 4 | 5,000 | 20 |
| 5 | 0 | 20 |

will be the tendency for forecasters in that industry to produce unconventional forecasts.

## III. Empirical Results

In this section we report our statistical findings, which are generally consistent with the implications of the model. Our data consist of year-ahead forecasts of U.S. real GDP (prior to 1992, GNP) growth published in *Blue Chip Economic Indicators*. Participating forecasters were categorized by industry in consultation with Robert Eggert, the newsletter's editor. These industry categories are an objective way of grouping together forecasters who work for similar types of firms and can therefore be expected to face similar incentives regarding accuracy and publicity. Before presenting our empirical results, we offer a few additional details about the data.

*Data*

*Blue Chip Economic Indicators* is a monthly newsletter that compiles several dozen professional forecasts of widely followed macroeconomic variables. The forecasts are produced by a variety of participating firms. Once a firm is invited to participate in the survey, it remains a participant as long as it continues to submit forecasts. While firms are not paid to participate, the newsletter nonetheless offers them regular public exposure.

Our data consist of the forecasts of year-ahead real GNP/GDP growth appearing in the December issues of the newsletter. During the twenty years in our sample, 1976 through 1995, the number of forecasters in the panel ranged from 32 to 81. A total of 129 firms contributed real GNP/GDP forecasts at one time or another. We divide these firms, listed in Appendix 2, into six industry categories - banks, industrial corporations, econometric modelers, independent forecasters, securities firms, and other. When analyzing how forecaster behavior is related to industry of employment we use the full panel of data, which consists of 1197 individual forecasts. When analyzing the forecasts of individual firms, however, we restrict the sample to the forty-one firms with twelve or more annual real GDP forecasts. Of these, the thirty-eight that published twelve or more year-ahead December forecasts in years prior to 1995 are used when comparing forecasts to actuals. The industry breakdown of our sample is as follows:

| Category | # in survey | # in subsample (>12 annual obs) |
|---|---|---|
| Banks | 30 | 12 |
| Securities Firms | 14 | 4 |
| Industrial Corporations | 18 | 4 |
| Independent Forecasters | 38 | 9 |
| Econometric Modelers | 12 | 5 |
| Others | 17 | 7 |
| Total | 129 | 41 |

Our analysis also uses the *Blue Chip's* consensus forecast of real GDP growth. The consensus is calculated as the mean prediction of forecasters designated as members of the "*Blue Chip* panel," rounded to the nearest tenth of a percent. Our sample includes all forecasters appearing in the newsletter, whether or not they are designated as panel members. Since the consensus forecast and the mean of our more inclusive sample never differ by more than 0.1 percent, the practical distinction between them is minimal.

The "actual" figures with which we compare the forecasts are the official figures released in the January following the year in question. For example, the year-over-year "actual" for 1986 was the Commerce Department's January 1987 measure for 1986 constant-dollar GNP, expressed as a percent change from the January 1987 measure of 1985 constant-dollar GNP, as reported in the *Survey of Current Business*. While these figures continue to be revised for several years after their initial release, we use the first-released figure. McNees (1989) convincingly argues that this is the appropriate benchmark against which to measure forecast accuracy.

*Consensus forecasts*

Researchers have found that consensus forecasts are substantially more accurate than individual forecasts. Zarnowitz and Braun (1992, Table 9), for example, compare the accuracy of individual and consensus forecasts of real GNP in the NBER-ASA quarterly surveys for the 1968-90 period. They find that, over horizons ranging from one to five quarters, the consensus forecast has a root mean square error ("RMSE") 23 to 27 percent below that of individual forecasts.

Table 1, which ranks the individual forecasters in our sample and the consensus by RMSE, shows a very similar result. The first two columns correspond to subperiods 1977-86 and 1987-95, and the third column corresponds to the entire sample period. Of thirty-eight firms, four beat the consensus in the first subperiod, as did ten in the second subperiod. Not one of the firms that outperformed the consensus in the first subperiod managed to do so again in the second. Only one firm outperformed the consensus over the entire period.[16]

The superior performance of the consensus is consistent with our model. As noted in the discussion of Proposition 2, the model suggests that the consensus forecast will be unbiased, or very nearly so. Many individual forecasters, by contrast, will find it in their interest to make biased forecasts. Our model, therefore, correctly predicts that the consensus will outperform individual forecasters. Still, the tendency of the consensus to outperform individuals constitutes at best a weak confirmation of our model. This is because there is an alternative, well-accepted explanation of why the consensus does so well: averaging the projections of individual

[16]Pairwise comparisons between individual forecasters and the consensus yield weaker results. Using a statistic proposed by Diebold and Lopez (1995) we can reject, at the 95 percent significance level, the hypothesis that an individual is as accurate as the consensus for only four of the thirty-eight forecasters. This general inability to reject the null seems to be due to the small sample size.

Table 1

# Forecasters Ranked by RMSE

| Subperiod 1: 1977-86 | | Subperiod 2: 1987-95 | | Entire Period: 1977-95 | |
|---|---|---|---|---|---|
| **Firm** | **RMSE** | **Firm** | **RMSE** | **Firm** | **RMSE** |
| ECO4 | 0.91 | BAN11 | 0.72 | ECO4 | 0.96 |
| ECO3 | 0.95 | IND4 | 0.73 | **Consensus** | **1.01** |
| BAN1 | 0.98 | OTH3 | 0.74 | OTH3 | 1.02 |
| BAN3 | 1.03 | OTH4 | 0.79 | BAN3 | 1.03 |
| **Consensus** | **1.04** | IND1 | 0.86 | BAN9 | 1.05 |
| BAN9 | 1.04 | BAN12 | 0.86 | BAN12 | 1.05 |
| OTH6 | 1.06 | BAN2 | 0.91 | OTH4 | 1.08 |
| OTH2 | 1.08 | BAN4 | 0.91 | BAN1 | 1.09 |
| SEC3 | 1.08 | BAN5 | 0.93 | BAN6 | 1.10 |
| COR3 | 1.08 | BAN10 | 0.96 | BAN11 | 1.10 |
| BAN6 | 1.11 | **Consensus** | **0.96** | BAN2 | 1.10 |
| ECO1 | 1.13 | SEC2 | 0.99 | COR3 | 1.10 |
| ECO2 | 1.15 | OTH5 | 0.99 | BAN5 | 1.11 |
| SEC1 | 1.15 | ECO4 | 0.99 | OTH6 | 1.12 |
| BAN8 | 1.18 | OTH7 | 1.00 | BAN10 | 1.12 |
| BAN12 | 1.20 | OTH1 | 1.02 | ECO1 | 1.13 |
| OTH4 | 1.21 | BAN3 | 1.03 | BAN4 | 1.13 |
| OTH3 | 1.22 | COR2 | 1.03 | ECO2 | 1.17 |
| BAN2 | 1.26 | BAN9 | 1.05 | SEC2 | 1.18 |
| BAN10 | 1.26 | IND7 | 1.06 | COR1 | 1.23 |
| BAN11 | 1.27 | BAN6 | 1.08 | SEC3 | 1.23 |
| SEC2 | 1.29 | IND9 | 1.08 | IND1 | 1.23 |
| BAN4 | 1.32 | COR1 | 1.09 | COR2 | 1.23 |
| COR2 | 1.32 | BAN7 | 1.11 | OTH2 | 1.25 |
| COR1 | 1.34 | ECO1 | 1.12 | OTH1 | 1.28 |
| BAN5 | 1.38 | COR3 | 1.14 | IND9 | 1.29 |
| IND5 | 1.48 | OTH6 | 1.18 | OTH5 | 1.32 |
| OTH1 | 1.49 | ECO2 | 1.20 | IND5 | 1.33 |
| IND8 | 1.50 | BAN1 | 1.21 | BAN7 | 1.34 |
| IND9 | 1.55 | IND5 | 1.28 | BAN8 | 1.35 |
| IND1 | 1.55 | SEC3 | 1.29 | ECO3 | 1.36 |
| IND6 | 1.58 | OTH2 | 1.43 | SEC1 | 1.39 |
| BAN7 | 1.60 | IND2 | 1.44 | OTH7 | 1.44 |
| OTH5 | 1.69 | IND6 | 1.51 | IND7 | 1.46 |
| IND3 | 1.77 | IND8 | 1.51 | IND8 | 1.51 |
| OTH7 | 1.82 | BAN8 | 1.52 | IND6 | 1.54 |
| IND7 | 1.91 | SEC1 | 1.64 | IND4 | 2.04 |
| IND4 | 2.63 | ECO3 | 1.71 | IND2 | 2.10 |
| IND2 | 2.94 | IND3 | 3.18 | IND3 | 2.53 |

Notes: Sample consists of organizations that forecasted real GDP in the December issue of the Blue Chip Economic Indicators at least twelve times between 1977 and 1995.
Forecasters are labeled by industry sector as follows:

- BAN = banks
- SEC = securities firms
- COR = industrial corportations
- IND = independent forecasters
- ECO = econometric modelers
- OTH = other miscellaneous forecasters (financial publications, industry associations, government bodies, insurance companies, and rating agencies).

The correlation coefficient between the RMSEs for the two subperiods is 0.10, not statistically significant at the 95 percent level.

Sources: *Blue Chip Economic Indicators, Survey of Current Business.*

forecasters tends to cancel out their idiosyncratic errors.

Another implication of the consensus's strong showing is what it says about forecasters and their clients. Clients comparing the accuracy of different forecasters should eventually discover (or read about) how well the consensus performs. Since the consensus forecast is inexpensive and readily available, there should be no need to hire an in-house economist or an outside consultant to forecast macroeconomic variables such as unemployment and real GDP growth.

Firms that do hire their own forecasters assign them roles beyond just making projections. Professional forecasters explain current developments and the risks they pose to their employers, provide instant analysis of just-released government statistics, and construct models to estimate the impact of alternative policy choices. Moreover, many of the variables professional forecasters predict are regional, industry-specific, or firm-specific. As such, they are not included in surveys such as the *Blue Chip*.

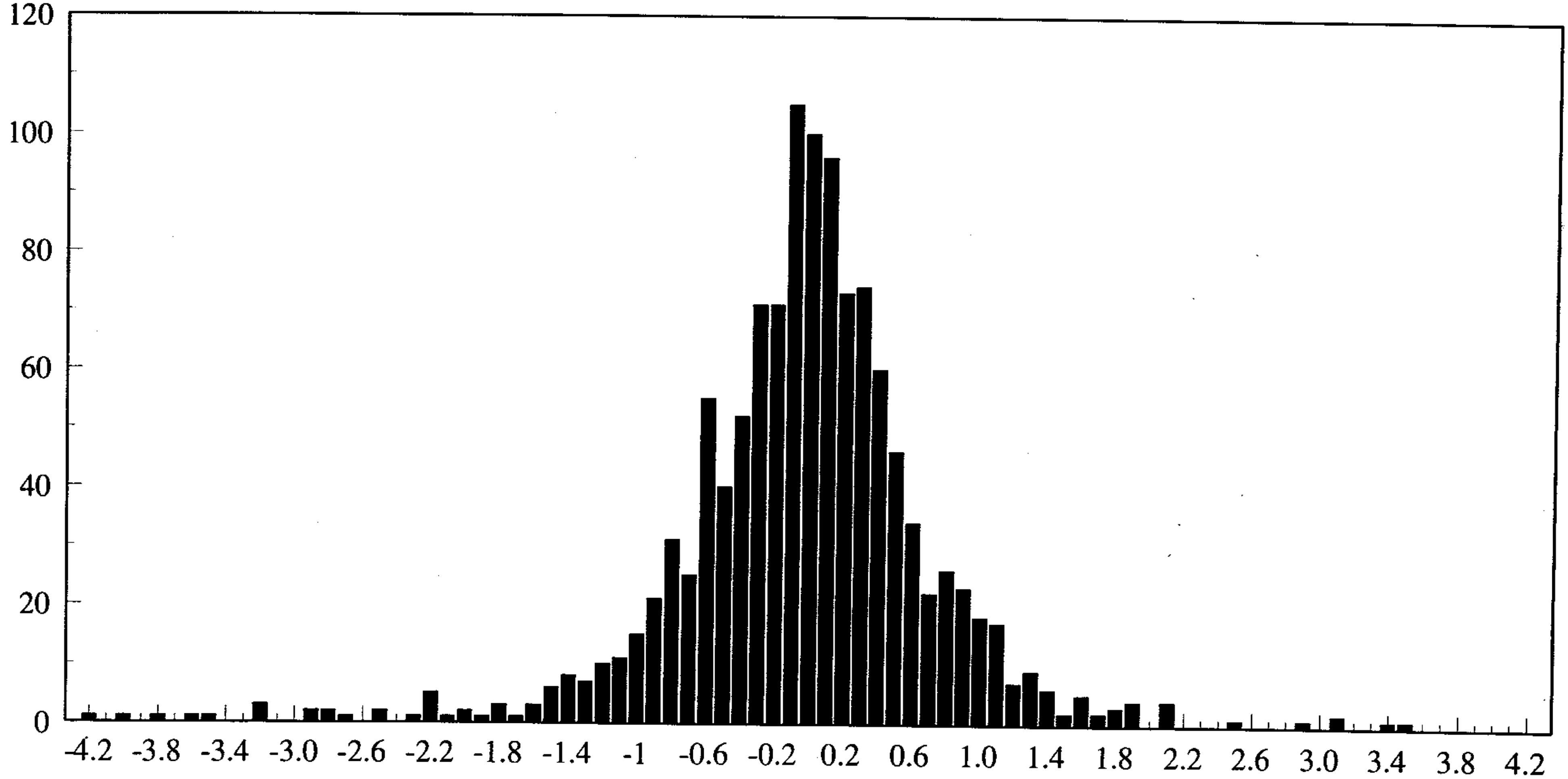
But while professional forecasters do more than just predict macroeconomic variables, those who participate in the *Blue Chip* survey must still produce some kind of forecast. Why not just copy the consensus which, as many economists know, tends to perform best over time? The standard explanation is that different forecasters have different information sets and models. Our model offers another explanation - strategic behavior in the pursuit of publicity. The next section provides some evidence that, while necessarily indirect, points to the importance of strategic behavior.

*Deviations from consensus*

Chart 4 shows the frequency distribution of the deviations of individual GDP (GNP)

Chart 4

## Distribution of Individual Year-End Real GDP/GNP Forecasts Relative to Consensus Blue Chip Indicators, 1977-1996




Source: *Blue Chip Economic Indicators*

forecasts from the consensus. Are these deviations the result of strategic behavior or do they mainly reflect idiosyncratic differences in forecast methodologies and information?

One type of bias that does *not* appear at the industry level is that predicted by the heterogenous expectations hypothesis as formulated in Ito (1990). Specifically, we do not find that forecasters' *mean* deviations from the consensus -- allowing positive and negative values to cancel -- varies systematically by industry. In Table 2 we regress the deviation of individual forecasts from the consensus on industry dummies. The OLS results, listed in the left-hand column of the table, show that five of the six industry categories have mean deviations from consensus that are less than a tenth of a percent and are statistically insignificant. The only industry category in which forecasters deviated significantly from the consensus was "other," a catch-all consisting of financial publications, government agencies, industry associations, insurance companies, and ratings agencies. When this broad grouping is broken down into its component subcategories, only the "financial publication" subcategory exhibited a significant mean deviation from the consensus (right column). All told, industry affiliation explains less than one percent of the variation in forecasters' deviations from consensus. Using an F-test, we cannot reject the null hypothesis that industry affiliation has no bearing on these deviations. In short, we find little support for the hypothesis that the GNP/GDP forecasts by the firms in our sample exhibit a consistent industry-specific bias.[17]

In contrast, the evidence supporting the rational bias theory developed in this paper appears much stronger. Chart 5 plots the mean deviation from the consensus (rounded to the

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[17]This negative result could be due to the way in which we classify firms. Whereas the profitability of Ito's importers and exporters are clearly tied to the dollar/yen exchange rate, our data set has no analogous partition between firms that benefit more or less from strong real GDP growth.

Table 2

# Regressions of Deviations from Consensus as a Function of Industry Sector

Dependent variable: (GDP(i)-Consensus)

Sample Period: 1977-1996

| Explanatory Variables: | Coefficient | t-statistic | Coefficient | t-statistic |
|---|---|---|---|---|
| Constant | -0.03 | -1.53 | -0.03 | -1.53 |
| BAN | -0.01 | -0.16 | -0.01 | -0.25 |
| COR | 0.02 | 0.52 | 0.03 | 0.62 |
| ECO | -0.03 | -0.50 | -0.03 | -0.56 |
| IND | -0.04 | -1.13 | -0.04 | -1.01 |
| SEC | -0.09 | -1.26 | -0.10 | -1.32 |
| OTH | 0.12* | 2.43 | – | – |
| FP | – | – | 0.20* | 2.00 |
| GOV | – | – | 0.33 | 1.53 |
| IA | – | – | 0.07 | 0.74 |
| RAT | – | – | 0.21 | 0.96 |
| INS | – | – | 0.03 | 0.30 |
| R-squared: | 0.007 | | 0.009 | |
| F-statistic: | 1.582 | | 1.173 | |

Notes: Regression was run using panel of 1197 individual forecasts of real GDP appearing in the December issue of Blue Chip Economic Indicators from 1977-1996.
Explanatory variables are industry sector dummies, defined as follows, with number of non-zero observations in parentheses:

BAN = banks (322)
SEC = securities firms (97)
COR = industrial corporations (163)
IND = independent forecasters (287)
ECO = econometric modelers (142)
OTH = other miscellaneous forecasters (186), consisting of:
- FP = financial publications (54)
- GOV = government agencies (12)
- IA = industry associations (57)
- INS = insurance companies (51)
- RAT = rating agencies (12)

Industry dummies are constrained to have an observation-weighted mean value of zero.
*denotes 95 percent significance; **denotes 99 percent significance.

Source: *Blue Chip Economic Indicators*

# Histogram: Average Deviation of Individual Real GDP Forecasts From Blue Chip Consensus, 1977-1996

| Scale | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| -1.7 | **I** | | | | | | | |
| -1.6 | | | | | | | | |
| -1.5 | | | | | | | | |
| -1.4 | | | | | | | | |
| -1.3 | | | | | | | | |
| -1.2 | | | | | | | | |
| -1.1 | | | | | | | | |
| -1.0 | | | | | | | | |
| -.9 | | | | | | | | |
| -.8 | | | | | | | | |
| -.7 | **I** | | | | | | | |
| -.6 | | | | | | | | |
| -.5 | **B** | | | | | | | |
| -.4 | **B** | | | | | | | |
| -.3 | **C** | **E** | i | | | | | |
| -.2 | **B** | b | b | c | e | o | s | s |
| -.1 | o | s | | | | | | |
| 0 | b | b | b | b | e | e | i | o |
| .1 | b | b | c | c | i | o | o | s |
| .2 | o | | | | | | | |
| .3 | e | o | | | | | | |
| .4 | **B** | | | | | | | |
| .5 | | | | | | | | |
| .6 | **I** | | | | | | | |
| .7 | | | | | | | | |
| .8 | **I** | i | | | | | | |
| .9 | | | | | | | | |
| 1.0 | | | | | | | | |
| 1.1 | | | | | | | | |
| 1.2 | **I** | | | | | | | |
| 1.3 | | | | | | | | |
| 1.4 | | | | | | | | |
| 1.5 | | | | | | | | |
| 1.6 | | | | | | | | |
| 1.7 | | | | | | | | |

Notes: Includes all organizations that forecasted real GDP/GNP in the December issue of the *Blue Chip Economic Indicators* at least twelve times between 1977 and 1996.
Each letter corresponds to a single forecaster.
Forecasters whose letters are bold and capitalized have a bias significant at the 95% level.

Legend: b=banks
s=securities firms
c=industrial corporations
i=independent forecasters
e=econometric modelers
o=other miscellaneous forecasters

Source: *Blue Chip Economic Indicators*

nearest tenth of a percent) of the forty-one individual forecasters for whom we have at least twelve observations. Each forecaster is identified with a letter signifying his industry; an upper case letter denotes a mean deviation significantly different from zero. What is apparent from the chart is that the independent forecasters (the "I's") tend to be more scattered than are forecasters from other categories. Indeed, the six forecasters with the largest mean deviations from consensus are all independents. This is consistent with Lamont's (1995) finding that forecasters with firms bearing their own names tend to make unconventional forecasts.

*Absolute deviations from consensus*

We next test the implications of our model more formally. The model suggests two empirical hypotheses: First, if the relative preference for accuracy versus publicity varies *across* industries but is similar *within* industries, a forecaster's *mean absolute deviation* ("MAD") from the consensus should be related to his industry. Second, we can make informed *a priori* guesses about which industries will tend to emphasize publicity most and therefore produce forecasts that deviate most from the consensus.

Nonfinancial corporations, for example, would not be expected to particularly reward publicity in the sense of having the best forecast in a year, since these firms forecast mainly for internal planning and investment purposes, activities for which accuracy counts and publicity does not. At the other extreme, a consulting firm or advisory service trying to gain publicity for its main product, economic advice, would find the media attention from having the best forecast in a given year quite valuable and would place less emphasis on forecast accuracy in the traditional sense.

Other financial firms such as banks or brokerages may welcome favorable publicity as a

Table 3

# Regressions of Absolute Deviations from Consensus as a Function of Industry Se

Dependent variable: |GDP(i)-Consensus|

Sample Period: 1977-1996

| Explanatory Variables: | Coefficient | t-statistic | Coefficient | t-statistic |
|---|---|---|---|---|
| Constant | 0.52** | 33.89 | 0.52** | 35.71 |
| BAN | -0.11** | -4.44 | -0.12** | -5.14 |
| COR | -0.15** | -3.93 | -0.13** | -3.50 |
| ECO | -0.09* | -2.16 | -0.10** | -2.59 |
| IND | 0.30** | 11.01 | 0.31** | 11.80 |
| SEC | -0.00 | -0.08 | -0.02 | -0.36 |
| OTH | -0.07 | -1.83 | -0.06 | -1.76 |
| Y1977 | – | – | -0.16 | -1.87 |
| Y1978 | – | – | -0.09 | -1.17 |
| Y1979 | – | – | 0.08 | 1.02 |
| Y1980 | – | – | 0.19* | 2.56 |
| Y1981 | – | – | 0.23** | 3.09 |
| Y1982 | – | – | 0.39** | 5.31 |
| Y1983 | – | – | 0.16* | 2.14 |
| Y1984 | – | – | -0.13 | -1.74 |
| Y1985 | – | – | -0.03 | -0.44 |
| Y1986 | – | – | 0.15* | 2.26 |
| Y1987 | – | – | 0.18** | 2.71 |
| Y1988 | – | – | 0.22** | 3.86 |
| Y1989 | – | – | -0.02 | -0.34 |
| Y1990 | – | – | 0.03 | 0.58 |
| Y1991 | – | – | 0.11* | 1.98 |
| Y1992 | – | – | -0.02 | -0.44 |
| Y1993 | – | – | -0.22** | -4.06 |
| Y1994 | – | – | -0.25** | -4.62 |
| Y1995 | – | – | -0.23** | -4.22 |
| Y1996 | – | – | -0.21** | -4.46 |
| R-squared: | 0.10 | | 0.20 | |
| F-statistic: | 25.35** | | 12.17** | |

Notes: Regression was run using panel of 1197 individual forecasts of real GDP appearing in the December issue of Blue Chip Economic Indicators from 1977-1996.

Explanatory variables are year dummies and industry sector dummies, defined as follows:

BAN = banks
SEC = securities firms
COR = industrial corporations
IND = independent forecasters
ECO = econometric modelers
OTH = other miscellaneous forecasters (financial publications, industry associations, government bodies, insurance companies, and rating agencies).

Industry dummies and year dummies are constrained to have an observation-weighted mean value of zero.

*denotes 95 percent significance; **denotes 99 percent significance.

Source: *Blue Chip Economic Indicators*

way of attracting clients, particularly to businesses such as trading services to which economic forecasting may be complementary. Econometric forecasting firms, much like the banks and securities firms, need to emphasize accuracy. But they are also under business pressure to outperform their competitors in a given year, thereby differentiating their products.

To summarize, we hypothesize that the forecasts produced by different categories of firms will differ systematically in their mean absolute deviations from the consensus and that these MADs will be relatively small for industrial corporations; large for independent forecasters; and somewhere in between for banks, securities firms, and econometric modelers.

Table 3 reports regressions that measure the MAD of forecasts produced by different categories of firms. The dependent variable is the absolute value of each forecast's deviation from the consensus. Because the equation includes a constant term, the coefficient for each industry dummy indicates whether its MAD is greater or smaller than that of the overall sample. The significance of four industry dummies supports the hypothesis that MADs differ across industry groups. In particular, industrial corporations and banks deviate least from consensus, followed by econometric modelers. The securities firms' MAD was appreciably greater. Independent forecasters, consistent with Chart 5, had the largest MAD. Summing the constant and industry dummies, we see just how compelling these differences are. The MAD for independent forecasters is 0.82, more than double what it is for industrial corporations (0.37). Overall, industry affiliation alone explains fully ten percent of the variation in absolute deviations from the consensus. An F-test strongly rejects the null hypothesis that these affiliations are unrelated to absolute deviations. When year dummies are included to control for intertemporal changes in the distribution of GDP/GNP forecasts (second column), the results are essentially the same.

## IV. Summary and Conclusion

This paper has developed a theory of rational bias in macroeconomic forecasts in which individual forecasters, hired by firms to project economic variables, have an incentive to compromise the accuracy of their forecasts in order to gain publicity for their firms. The theory relies on two key assumptions. First, forecasters are fully knowledgeable about the true probability distribution of actual outcomes. Second, individual firms assign some combination of values to statistical accuracy in the traditional sense and to the publicity that accompanies the "winning" forecast in a given year. The theory predicts that rational forecasts are distributed in a way that reflects the true probability distribution of the variable being forecast, with the degree of clustering around the consensus dependent upon the relative value placed on accuracy. The implication is that different firms with the same information and forecasting skills will produce different forecasts. The statistical evidence from the real GNP/GDP forecasts of different types of firms supports the view that there is strategic behavior in positioning forecasts relative to the consensus forecast, and that firms favoring publicity relative to accuracy will tend to produce unconventional forecasts.

The main significance of this work is in demonstrating that the observed dispersion of professional forecasts can be explained purely by strategic behavior. It is not necessary to assume any differences of fundamental views or information across forecasters. While in fact some such differences among professional forecasters are inevitable, the contribution of the theory is to demonstrate that the dispersion of forecasts does not rely on them. Indeed, the inability of individual forecasters to outperform the consensus over time supports the notion that forecasters often behave strategically when making their projections.

While we develop our theory based on the tradeoff between traditional accuracy and the publicity value of being the best among all forecasters, there may be other, not necessarily conflicting, explanations of individual forecaster bias. For example, there may be a chronic demand for well-articulated forecasts of economic sluggishness coming from bond salesmen or from journalists seeking a range of views. These would reinforce the incentives to provide outlying forecasts, in addition to the particular advertising explanation developed in this paper. Our empirical finding that deviation from the consensus is related to the type of firm for which a forecaster works is highly supportive of the notion that professional forecasting has a strong strategic component.

Overall, we conclude that it is fruitful to extend our conception of rational forecasting behavior beyond the simple notion of individual unbiased projections. Our model supports the doubts some have held about using survey or published forecast data as a measure of true individual expectations, while also explaining why the consensus forecasts well.

References

Gary S. Becker, "Irrational Behavior and Economic Theory", The Journal of Political Economy, Vol LXX No I, February 1962, pp 1-13.

Carl Bonham and Richard Cohen, "Testing the Rationality of Price Forecasts: Comment," The American Economic Review, Vol 85 No. 1, March 1995, pp 284-289.

Dean Croushore, "Inflation Forecasts: How Good Are They?," Federal Reserve Bank of Philadelphia Business Review, May/June 1996, pp. 15-25.

Francis X. Diebold and Jose A. Lopez, "Forecast Evaluation and Combination," Federal Reserve Bank of New York Research Paper #9525, Nov. 1995.

Tilman Ehrbeck and Robert Waldman, "Why Are Professional Forecasters Biased? Agency versus Behavioral Explanations," The Quarterly Journal of Economics, February 1996, pp. 21-40.

Stephen Figlewski and Paul Wachtel, "The Formation of Inflationary Expectations," The Review of Economics and Statistics, Vol LXIII, No 1, February 1981, pp 1-10.

George B. Henry, "Wall Street Economists: Are They Worth Their Salt?," Business Economics, October 1989, pp 44-48.

Takatoshi Ito, "Foreign Exchange Rate Expectations: Micro Survey Data," The American Economic Review, Vol 80 No 3, June 1990, pp 434-449.

Jinook Jeong and G.S. Maddala, "Testing the Rationality of Survey Data Using the Weighted Double-Bootstrapped Method of Moments," The Review of Economics and Statistics, May 1996, pp 296-302.

Michael P. Keane and David E. Runkle, "Testing the Rationality of Price Forecasts: New Evidence from Panel Data," The American Economic Review, Vol 80, No 4, September 1990, pp 714-735.

Michael P, Keane and David E. Runkle, "Testing the Rationality of Price Forecasts: Reply," The American Economic Review, Vol 85, No 1, March 1995, p 289.

Owen Lamont, "Macroeconomic Forecasts and Microeconomic Forecasters," NBER Working Paper 5284, October 1995.

Stephen K. McNees, "An Assessment of the "Official" Economic Forecasts," New England Economic Review, July/August 1995, pp 13-23.

Stephen K. McNees, "Forecasts and Actuals: The Trade-off between Timeliness and Accuracy," International Journal of Forecasting 5 (1989), pp 409-416.

Stephen K. McNees, "How Large are Economic Forecast Errors?," New England Economic Review, July/August 1992, pp 25-42.

Stephen K. McNees, "The 'Rationality' of Economic Forecasts," The American Economic Review, Vol 68 No 2, May 1978, pp 301-305.

Alexander M. Mood, Franklin A. Graybill, and Duane C. Boes, Introduction to the Theory of Statistics, Third Edition, New York: McGraw-Hill Book Company, 1974.

Sherwin Rosen, "The Economics of Superstars," The American Economic Review, Vol 71, No 5, December 1981, pp 845-858.

David S. Scharfstein and Jeremy C. Stein, "Herd Behavior and Investment," The American Economic Review, Vol 80, No 3, June 1990, pp 465-479.

Victor Zarnowitz and Phillip Braun, "Twenty-Two Years of the NBER-ASA Quarterly Economic Outlook Surveys: Aspects and Comparisons of Forecasting Performance,: NBER Working Paper 3965, January 1992

Jeffrey Zweibel, "Corporate Conservatism and Relative Compensation," The Journal of Political Economy, No 1, Vol 103, February 1995, pp 1-25.

**Appendix 1**. An algorithm for determining the equilibrium distribution of forecasters given $f(x)$, $\{r_i\}$, and $\{N_i\}$, for $i=1,...,m$.

First, provisionally assume a value for $n(0)$, the number of forecasters predicting the value 0. This value will determine a value of $k_i$ and an associated isowage curve $n^1(x)$ for forecasters in industry 1. Working from 0 outward, assign $n^1(x)$ forecasters to values of x until all sector 1 forecasters are exhausted, at $x=\pm c_1$. Then assign enough sector 2 forecasters to $\pm c_1$ so that the total number of forecasters predicting these two values are, respectively, $n^1(-c_1)$ and $n^1(c_1)$. The values of $n^1(-c_1)$ and $n^1(c_1)$ will then determine an isowage curve, $n^2(x)$, for sector 2 forecasters. Continuing to move away from the origin, sector 2 forecasters will distribute themselves along this isowage curve until they too are exhausted. This recursive procedure is then repeated until either all N forecasters are assigned and some values of x are unaccounted for, or the entire range of x is blanketed but some forecasters remain unassigned. In either case, another value of $n(0)$ can be chosen and the procedure repeated until a value of $n(0)$ is found for which the entire range of values of x is covered and all forecasters are assigned.

**Appendix 2**

# Forecasters Participating in the Blue Chip Economic Indicators

1976-1995

**Banks (30)**
Bank of America
Bankers Trust Co.
Brown Brothers Harriman
Chase Manhattan Bank
Chemical Banking
Citibank
Comerica
Connecticut National Bank
CoreStates Financial Corp.
First Fidelity Bancorp
First Interstate Bank
First National Bank of Chicago
Fleet Financial Group
Harris Trust and Saving
Irving Trust Company
J P Morgan
LaSalle National Bank
Manufacturers Hanover
Manufacturers National Bank of Detroit
Marine Midland
Mellon Bank
National City Bank of Cleveland
Northern Trust Company
Philadelphia National Bank/ PNC Bank
Provident National Bank
Security Pacific Bank
Shawmut National Corp.
United California Bank
U.S. Trust Co.
Wells Fargo Bank

**Securities Firms (14)**
American Express/ Shearson Lehman Company
Amhold and S. Bleichroeder
A.G. Becker/ Becker Associates
A.G. Edwards & Company
Chicago Capital, Inc.
CRT Government Securities
C.J. Lawrence, Inc.
Dean Witter Reynolds, Inc.
Goldman, Sachs Co.
Ladenburg, Thalmann, & Co.
Loeb Rhoades, Hornblower, & Co.
Morgan Stanley & Co, Inc.
NationsBanc Capital Markets Inc.
Prudential Securities, Inc.

**Industrial Corporations (18)**
B.F. Goodrich
Caterpillar
Chrysler Corporation
Conrail
Eaton Corporation
DuPont
Ford Motor Company
General Electric Company
General Motors
Machinery & Allied Products
Monsanto Company
Motorola, Inc.
Pennzoil Company
Predex Corp.
Sears Roebuck
Union Carbide
Weyerhaeuser Co.
W.R. Grace

**Independent Forecasters (38)**
Albert T. Sommers
Argus Research
Arthur D. Little
Ben E. Laden Associates
Business Economics, Inc.
Center for Study of American Business
Computer Aided Production Planning Systems, Inc.
DuPrince & Associates
DeWolf Associates
Econonoclast
Econoviews International, Inc.
Evans Economics, Inc.
George Gols
Hagerbaumer Economics
Heinemann Economic Research
Helming Group
Herman I. Leibling & Associates
InfoMetrica, Inc.
Joel Popkin & Co.
Juodeika Allen & Co.
Leonard Silk, NY Times
MAPI
Morris Cohen & Associates
Moseley, Hallgarten, & Estabrook
Oxford Economics USA
Peter L. Bernstein, Inc.
Polyconomics
Reeder Associates (Charles)
Robert Genetski and Associates, Inc.
Rutlegde & Co.
Schroder, Naess, and Thomas
Sindlinger Company, Inc.
SOM Economics, Inc.
Statistical Indicator Associates
Stotler Economics
The Bostian Group - HHG
Turning Points Micrometrics
Wayne Hummer & Company- Chicago

**Econometric Modelers (12)**
Chase Econometrics
Data Resources, Inc.
Fairmodel-Economics, Inc.
Georgia State University
Gil Heebner, Eastern College
Inforum - University of Maryland
Laurence H. Meyer & Associates
Merrill Lynch Economics
Michigan Quarterly U.S. Model
UCLA Business Forecasting
University of Illinois (B.T.)
Wharton Econometrics /WEFA Group

**Other (17)**
*Financial Publications*
Cahners Economics
Financial Times Currency Forecaster
Eggert Economics Enterprises, Inc.
Fortune Magazine

*Government Agencies*
Bush Administration
Clinton Administration
Congressional Budget Office
Office of Management and Business

*Industry Associations*
Conference Board
Mortgage Bankers Association of America
National Association of Home Builders
U.S. Chamber of Commerce

*Insurance Companies*
Equitable Life
Metropolitan Life Insurance Co.
Prudential Insurance Co.

*Ratings Agencies*
Dun & Bradstreet
Standard and Poor's Corp.