

Biases in Macroeconomic Forecasts: Irrationality or Asymmetric Loss?*

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Abstract

Survey data on expectations frequently find evidence that forecasts are biased, rejecting the joint hypothesis of rational expectations and symmetric loss. While the literature has attempted to explain this bias through forecasters' strategic behavior, we propose a simpler explanation based on asymmetric loss. We establish that existing rationality tests are not robust to even small deviations from symmetry and hence have little ability to tell whether the forecaster is irrational or the loss function is asymmetric. We propose new and more general methods for testing forecast rationality jointly with flexible families of loss functions that embed quadratic loss as a special case. An empirical application to survey data on forecasts of nominal output growth shows strong evidence against rationality and symmetric loss. There is considerably weaker evidence against rationality once asymmetric loss is permitted.

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1 Introduction

How agents form expectations and, in particular, whether they are rational and efficiently incorporate all available information into their forecasts, is a question of fundamental importance in macroeconomic analysis. Ultimately this question can best be resolved through empirical analysis of expectations data. It is therefore not surprising that a large literature has been devoted to empirically testing forecast rationality based on survey data such as the Livingston data or the Survey of Professional Forecasters (SPF).¹ Unfortunately, the empirical evidence is inconclusive and seems to depend on the level of aggregation of data, sample period, forecast horizon and type of variable under consideration.²

The vast majority of studies have tested forecast rationality in conjunction with an assumption of quadratic loss. This loss function has largely been maintained out of convenience: under quadratic loss and rationality, the observed forecast errors should have zero mean and be uncorrelated with all variables in the current information set.

A reading of the literature reveals little discussion of why forecast errors of different signs should lead to the same loss. On economic grounds one would, if anything, typically expect asymmetric losses. For example, overpredictions of sales lead to inventory holding costs while underpredictions lead to stockout costs, loss of reputation and revenues when demand cannot be met. Most often there is no reason why these costs should be identical. Concerns such as these led Granger and Newbold (1986, page 125) to write: “An assumption of symmetry for the cost function is much less acceptable [than an assumption of a symmetric forecast error density]”.³ Relaxing the assumption of symmetric loss has important consequences. If the loss function under which predictions were derived is not restricted to be symmetric,

¹See, e.g., Bonham and Cohen (1995), Fama (1975), Keane and Runkle (1990), Mankiw, Reis and Wolfers (2003), Mishkin (1981) and Zarnowitz (1979).

²The recent survey by Stekler (2002) summarizes empirical studies of rationality for inflation and output forecasts as follows: “Although there have been many evaluations of U.S. and U.K. forecasts, there is no definitive conclusion about their rationality and efficiency. The results are in conflict, with some forecasts displaying these characteristics in some periods, and not in others, and/or some forecasters able to generate unbiased and efficient forecasts while others were unable to do so” (p. 235).

³The literature makes a clear distinction between inventory and backordering costs, c.f. Arrow, Karlin and Scarf (1958), Krane (1994) and Benjaafar, Kim and Vishwanadhan (2002).

rationality no longer requires that the forecast errors are unbiased, as demonstrated by Zellner (1986) and Christoffersen and Diebold (1997).

While many studies on forecast rationality testing are aware of the limitations of symmetric loss and indicate that rejections of rationality may be driven by asymmetries, little is known about the magnitude of the problem - i.e. how much this really matters in practice. In this paper we therefore examine the theoretical and practical importance of the joint nature of tests for forecast rationality. We show that the coefficients in standard forecast efficiency tests are biased if the loss function is not symmetric and characterize this bias. Under asymmetric loss, standard rationality tests thus do not control size and may lead to false rejections of rationality. Conversely, we also find that even very large inefficiencies in forecasters' use of information may not be detectable by standard tests when the true loss is asymmetric.

In realistic applications the shape of an individual's loss function is unobserved and so rationality cannot be tested directly without placing additional structure on the problem. Building on the work of Elliott, Komunjer and Timmermann (2002), we present a more general framework for rationality testing that allows the loss function to belong to flexible families and tests rationality by means of moment conditions. The families of loss functions can be chosen such that they embed symmetric loss as special cases, thus ensuring that our framework directly generalizes the methods traditionally used in the literature.

To demonstrate these points, we revisit the Survey of Professional Forecasters (SPF) data on US output growth and examine whether the apparently high rejection rate for rationality found in this data set can be explained by asymmetric loss. We find strong evidence of bias in the forecast errors of many individual survey participants. In fact, close to 30% of the individual predictions lead to rejections of the joint hypothesis of rationality and symmetric loss at the 5% critical level. Allowing for asymmetric loss, the rejection rate is very close to 5% which is consistent with rationality. Output forecasts thus tend to be consistent with the more general loss functions, although inconsistent with symmetric loss. Furthermore, our estimates of the direction of asymmetries in loss overwhelmingly suggest that the cost of overpredicting exceeds the cost of underpredicting output growth. Using data from the

Livingston survey, we also find that these estimates vary considerably across forecasters with academics adhering closest to symmetric loss and banking and industry economists' forecasts suggesting larger degrees of asymmetry.

Asymmetric loss is by no means the only explanation of biases in forecasts. Recent work has attempted to explain biases by means of strategic behavior arising in situations where the forecaster's remuneration depends on factors other than the mean squared forecast error, c.f. Scharfstein and Stein (1990), Truman (1994), Lamont (1995) and Ehrbeck and Waldmann (1996). Common features of the models used by these authors is that forecasters differ by their ability to forecast, reflected by differences in the precision of their private signals, and that their main goal is to influence clients' assessment of their ability. Such objectives are common to business analysts or analysts employed by financial services firms such as investment banks, whose fees are directly related to their clients' assessment of analysts' forecasting ability. The main finding of these models is that the forecasts need not reflect analysts' private information in an unbiased manner. Biases in individual forecasters' predictions are related to the consensus forecast and can induce herding among forecasters. Strategic behavior can only be analyzed in the context of a specified loss function and by no means precludes asymmetric loss, so the two explanations for biases may well be complements.

The plan of the paper is as follows. Section 2 reviews the evidence against symmetric loss and rationality in forecasts of output growth from the Survey of Professional Forecasters. Section 3 contains an illustrative example which explains why forecasters may depart from symmetric loss functions. This section also introduces a new family of loss functions that contains quadratic loss as a special case and allows for asymmetries. In Section 4, we examine standard tests for forecast rationality based on quadratic loss and show how they can lead to biased estimates and wrong inference when loss is genuinely asymmetric. Construction of rationality tests under asymmetric losses is undertaken in Section 5, while Section 6 presents empirical results and Section 7 concludes with a discussion of the results. Technical proofs and details of the data set are provided in appendices at the end of the paper.

2 Bias in Forecasts of Output Growth

In this paper we will focus on forecasts of US nominal output growth - a series in which virtually all macroeconomic forecasters should have some interest. Overpredictions of output growth are likely to be associated with sales forecasts that are too large, which will lead to larger inventory costs for firms. Conversely, underpredictions of output growth will plausibly lead to shortfalls in production and larger-than-expected stock-out costs. A discussion of asymmetric loss can thus be related to asymmetries between inventory and stock-out costs, which the literature clearly distinguishes between, c.f. Arrow, Karlin and Scarf (1958), Krane (1994) and Benjaafar, Kim and Vishwanadhan (2002).

Forecasts of output growth have been the subject of many previous studies. Brown and Maital (1981) studied average GNP forecasts and rejected unbiasedness and efficiency in six-month predictions of growth in GNP measured in current prices. Zarnowitz (1985) found only weak evidence against efficiency for the average forecast, but stronger evidence against efficiency for individual forecasters. Batchelor and Dua (1991) found little evidence that forecast errors were correlated with their own past values. In contrast, Davies and Lahiri (1995) conducted a panel analysis and found evidence that informational efficiency was rejected for up to half of the survey participants.

2.1 Data

The main data used in this paper is from the Survey of Professional Forecasters (SPF) which has become a primary source for studying macroeconomic forecasts.⁴ Survey participants provide point forecasts of these variables in quarterly surveys. Surveys such as the SPF do not specify the objective of the forecasting exercise. This leaves open the question what the objective of the forecaster is. It is by no means clear that the forecaster simply minimizes a quadratic loss function and reports the conditional mean.⁵

⁴For an academic bibliography, see the extensive list of references to papers that have used this data source maintained by the Federal Reserve Bank of Philadelphia at <http://www.phil.frb.org/econ/spf/spfbib.html>.

⁵For example, in a study of predictions of interest rates, Leitch and Tanner (1991) found that commercial forecasts performed very poorly according to an MSE criterion but did very well according to a sign prediction

Survey participants are anonymous; their identity is only known to the data collectors and not made publicly available. It is plausible to expect that participants report the same forecasts that they use either for themselves or with their clients. Forecasts should therefore closely reflect the underlying loss function. Although strategic behavior may also play a role, we will abstract from this in our analysis.

Most macroeconomic time series are subject to revisions. Indeed, the nominal output series changed from GNP to GDP in the first quarter of 1992. We shall refer to the combined series as GDP. Since the data set contains both the forecasters' expectations about current-quarter and next quarter's GDP, we use both data points to compute the predicted rate of change in GDP.

The SPF data set is an unbalanced panel. Although the sample begins in 1968, no forecaster participated throughout the entire sample. Each quarter some forecasters leave the sample and new ones are included. We therefore have very few observations on most individual forecasters. We deal with this problem by requiring each forecaster to have participated for a minimum of 20 quarters. Imposing this requirement leaves us with 98 individual forecast series. The data appendix provides more details of the construction of the data.

Figure 1 shows a histogram of the average forecast errors across the 98 forecasters in the data set. The average forecast error, defined as the difference between the realized and predicted value, has a positive mean (0.16% per quarter). Out of 98 forecast errors, 80 had a positive mean, suggesting systematic underpredictions of output growth.

2.2 Rationality Tests under Quadratic Loss

Under quadratic loss - often referred to as mean squared error (MSE) loss - forecast rationality has traditionally been studied by testing one of two conditions: (1) that the forecast under consideration is unbiased and (2) that it is efficient with respect to the information set available to the forecaster at the time the forecast was made. The requirement of zero bias is a special case of the more general condition of informational efficiency. Its rejection, criterion linked more closely to profits from simple trading strategies based on these forecasts. Clearly, these forecasters did not use a quadratic loss function.

however, automatically leads to a rejection of forecast rationality under quadratic loss, which is why biasedness of macroeconomic forecasts is so often tested in practice.

Statistical tests of forecast unbiasedness are typically undertaken by means of the Mincer-Zarnowitz (1969) regression:

$$y_{t+1} = \beta_c + \beta f_{t+1} + u_{t+1}, \quad (1)$$

where y_{t+1} is the time $t + 1$ realization of the target variable - US nominal output growth in our data - which we denote by Y_{t+1} , f_{t+1} is its one-step-ahead forecast and u_{t+1} is a realization of a scalar error random variable, U_{t+1} , satisfying $E[U_{t+1}] = 0$. Under the null hypothesis of zero bias we should have $\beta_c = 0$ and $\beta = 1$. This test is commonly referred to as a test of weak rationality.

Table 1 shows the outcome of tests for bias in the forecast errors. Under quadratic loss, the null of no bias is rejected at the 1% critical level for 16 participants and gets rejected in 29 cases at the 5% level.⁶ If MSE loss is accepted, this strongly questions rationality for a large proportion of the survey participants. On the other hand, in a situation where the forecasters incur different losses from over- and underprediction, it would be rational for them to produce biased forecasts. Before developing rationality tests which allow for asymmetry, we illustrate with a simple example why forecasters' losses might indeed be asymmetric.

3 Sources of Asymmetry: An Illustrative Example

Forecasts are of interest to economic agents only in so far as they can improve their decisions. It is common to assume that an agent's utility, $U(y_{t+1}, \delta(f_{t+1}))$, depends on the realization of some target variable(s), y_{t+1} , in addition to a set of decisions or actions, $\delta(f_{t+1})$ which are functions of the forecasts, f_{t+1} . Optimal forecasts are determined so as to maximize expected utility (or profits) and must reflect both the form of the action rule mapping forecasts to decisions and the shape of the utility or (in the case of a firm) cost function. In general it is difficult to characterize the optimal forecast in closed form, so this section provides an illustrative example which motivates a broad class of loss functions.

⁶These numbers are a little higher than those reported by Zarnowitz (1985). This is likely to reflect our longer sample and our requirement of at least 20 observations which gives more power to the test.

Consider a forecaster - e.g., policy maker, firm, government, Central Bank or international organization - whose utility function at time $t + 1$ depends on some variable, w_{t+1} , representing wealth, power, reputation or publicity (see, e.g., Chadha and Schellekens 1998, Peel and Nobay 1998, Bray and Goodhart 2002, Pons-Novell 2003). For professional forecasters such as those considered here, it is reasonable to assume that the level of w_{t+1} depends on some target variable y_{t+1} - e.g., inflation rate, GDP growth, budget deficit - and on its forecast f_{t+1} . For example, the reputation (or reward) of professional forecasters is likely to depend on the accuracy with which they forecast the variable of interest. Further, suppose that the forecaster's utility only depends on w_{t+1} , and belongs to the CARA family, $u(w_{t+1}) = -\exp(-pw_{t+1})$, where $p > 0$ measures the coefficient of absolute risk aversion.

We now turn to the specification of the response function, $w(y_{t+1}, f_{t+1})$. It is natural to assume that the value of w_{t+1} decreases in the magnitude of the forecast error $e_{t+1} \equiv y_{t+1} - f_{t+1}$. This guarantees that the level of w_{t+1} is at its maximum when the forecaster has perfect foresight, in which case the forecast error is zero. For imperfect forecasts, $|e_{t+1}| > 0$ and w_{t+1} is decreasing in the absolute forecast error. The embarrassment costs to the forecaster resulting from positive as compared to negative forecast errors of the same magnitude are likely to differ. Hence, we allow w_{t+1} to be an asymmetric function of the forecast error, which we parametrize as: $w_{t+1} = w(e_{t+1}) \equiv -\ln [b|e_{t+1}|1(e_{t+1} \geq 0) + c|e_{t+1}|1(e_{t+1} < 0)]$, where b and c are positive constants. This form captures that: (1) the level of the forecaster's w_{t+1} decreases concavely with the magnitude of the forecast error; (2) the rate of decay of w_{t+1} differs depending on the direction in which the error is made: it equals b if the forecaster's error is positive and c if it is negative. Symmetry arises when $b = c$.

This specification of the response function implies that at any time $t + 1$,

$$\frac{u'(e_{t+1})}{u'(-e_{t+1})} = \left(\frac{\alpha}{1-\alpha}\right)^{\text{sgn}(e_{t+1})}, \quad (2)$$

where $\alpha \equiv b^p/(b^p + c^p)$, so that $0 < \alpha < 1$. For a given magnitude of the forecast error, the ratio of marginal utilities corresponding to a positive deviation from the target (underprediction of y_{t+1}) and a negative deviation (overprediction of y_{t+1}) is given by $\alpha/(1-\alpha)$, and is hence uniquely determined by the value of α . α thus describes the degree of asymmetry in the forecaster's loss function - values less than one half indicate that the forecaster put

higher weights on negative forecast errors than on positive ones of the same magnitude. Values of α greater than one half suggest a greater cost associated with positive forecast errors. In the symmetric case ($b = c$), α equals one half, so $\alpha/(1 - \alpha) = 1$ and the forecaster's embarrassment costs due to positive and negative forecast errors are the same.

Combining the utility and response functions, expected utility maximization requires minimizing the expected value of a loss $L(e; \alpha, p)$

$$L(e; \alpha, p) \equiv [\alpha + (1 - 2\alpha)1(e < 0)]e^p. \quad (3)$$

The optimal decision problem in equation (3) is not specific to the choice of CARA utility and logarithmic response function. Indeed, the same result can be derived for an agent with constant relative risk aversion utility function $u(w_{t+1}) = w_{t+1}^{1-\rho}$, where $\rho > 0$ measures relative risk aversion. For this case, if the response function is $w(e_{t+1}) \equiv [b|e_{t+1}|1(e_{t+1} \geq 0) + c|e_{t+1}|1(e_{t+1} < 0)]^{-1}$, we obtain the same result as in equation (3) with $p = \rho + 1$ and $\alpha \equiv b^\rho/(b^\rho + c^\rho)$.

4 Caveats in Rationality Tests under Quadratic Loss

In this section we study the behavior of standard tests for forecast rationality when the forecaster's loss function takes the form (3) and thus allows for asymmetries. An attractive feature of (3) is that it generalizes loss functions commonly used in the rationality testing literature. When $(\alpha, p) = (1/2, 2)$, loss is quadratic and (3) reduces to MSE loss. More generally, when $p = 2$ and $0 < \alpha < 1$, the family of losses L is piecewise quadratic and we call it 'Quad-Quad'. Similarly, when $p = 1$ and $0 < \alpha < 1$ we get the piecewise linear family of losses L , known as 'Lin-Lin', a special case of which is the absolute deviation or mean absolute error (MAE) loss which is obtained for $(\alpha, p) = (1/2, 1)$.

4.1 Misspecification Bias

Suppose that $p = 2$ in (3) so the forecaster's loss function

$$L(e; \alpha) \equiv [\alpha + (1 - 2\alpha)1(e < 0)]e^2, \quad 0 < \alpha < 1 \quad (4)$$

is parameterized by a single shape or asymmetry parameter, α , whose true value, α_0 , may be known or unknown to the forecast evaluator. This loss function offers an ideal framework to discuss how standard tests of rationality - derived under MSE loss ($\alpha_0 = 1/2$) - are affected if (4) is the true loss function and $\alpha_0 \neq 1/2$.

As we saw earlier, forecast errors should be unpredictable under MSE loss so it is common to test forecast rationality by means of the efficiency regression,

$$e_{t+1} = \beta' v_t + \varepsilon_{t+1}, \quad (5)$$

where e_{t+1} is the forecast error and v_t are the observations of a $d \times 1$ vector of variables (including a constant), denoted V_t , that are known to the forecaster at time t . Assuming that a sample of forecasts running from $t = \tau$ to $t = T + \tau - 1$ is available, this regression tests the orthogonality condition $E[\sum_{t=\tau}^{T+\tau-1} V_t \varepsilon_{t+1}] = 0$. In reality, if the true loss function is (4), the correct moment condition is $E[V_t \varepsilon_{t+1}] = (1 - 2\alpha_0)E[V_t | e_{t+1}]$. By misspecifying the forecaster's loss function, we omit the variable $(1 - 2\alpha_0)|e_{t+1}|$ from the linear regression and introduce correlation between the error term and the vector of explanatory variables. Hence, the standard OLS estimator $\hat{\beta} \equiv [\sum_{t=\tau}^{T+\tau-1} v_t v_t']^{-1} [\sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}]$ will be biased away from β by a quantity which we derive in Proposition 1:

Proposition 1 *Under assumptions (A1)-(A4) given in Appendix A and under Quad-Quad loss (4), the standard OLS estimator, $\hat{\beta}$, in the efficiency regression (5) has a bias that equals*

$$\text{plim } \hat{\beta} - \beta = (1 - 2\alpha_0) \Sigma_V^{-1} h_V, \quad (6)$$

where $\Sigma_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t']$ and $h_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t | e_{t+1}]$. Hence the misspecification bias depends on (i) the extent of the departure from symmetry in the loss function L , quantified by $(1 - 2\alpha_0)$; (ii) the covariance of the instruments used in the test, V_t , with the absolute value of the forecast error, $|e_{t+1}|$, h_V ; (iii) the covariance matrix of the instruments, Σ_V .⁷

⁷ Σ_V and h_V can be consistently estimated by $\hat{\Sigma}_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t v_t'$ and $\hat{h}_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t |e_{t+1}|$, respectively.

A number of positive implications can be drawn from Proposition 1, improving our understanding of standard efficiency tests when the forecaster’s loss is asymmetric ($\alpha_0 \neq 1/2$). In the usual implementation of orthogonality regressions, a constant is included in V_t and we can write $V_t = (1, \tilde{V}_t)'$. The first element of the covariance vector h_V then equals $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[|e_{t+1}|]$. Thus, when $\alpha_0 \neq 1/2$, there will always be bias in at least the constant term, unless the absolute forecast error is zero in expectation. But this can only happen in the highly unlikely situation where the forecasts are perfect so in general standard tests of forecast rationality will be biased under asymmetric loss.

A further consequence of Proposition 1 is that the bias decreases with the variability of the regressors. Indeed, if the covariance matrix Σ_V is sufficiently large, it can ‘drown out’ the bias. Moreover, whenever the matrix Σ_V is nonsingular, the bias that arises through the constant term will extend directly to biases in the other coefficients for each regressor whose mean is nonzero. This follows from the interaction of Σ_V^{-1} and the first term of h_V . Hence, even when regressors have no additional information for improving the forecasts, they may still have nonzero coefficients when the loss function is misspecified, giving rise to false rejections.

In practice, we can easily evaluate the relative biases for each coefficient in the efficiency regression (5) by simply computing the term $\Sigma_V^{-1} h_V$. For any degree of asymmetry, the latter can be estimated consistently by regressing the absolute forecast errors on V_t . Such regressions should accompany results that assume quadratic loss, especially when there are rejections. They allow us to understand how sensitive the results are to misspecifications of the loss function, at least of the form examined here.

4.2 Power Loss

Misspecification of the loss function will affect not only the probability limit of the standard OLS estimator $\hat{\beta}$ but also its asymptotic distribution. Hence, rationality tests implemented by traditional MSE regression based on the null hypothesis $\beta = 0$ might well lead to incorrect inference. To study the magnitude of this problem, we first characterize the (asymptotic) distribution of $\hat{\beta}$:

Proposition 2 *Under Assumptions (A1)-(A4) listed in Appendix A, the asymptotic distribution of $\hat{\beta}$ in the efficiency regression (5) is*

$$\sqrt{T}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, \Omega^*), \quad (7)$$

where $\beta^* \equiv \beta + (1 - 2\alpha_0)\Sigma_V^{-1}h_V$, $\Omega^* \equiv \Sigma_V^{-1}\Delta(\beta^*)\Sigma_V^{-1}$ and

$$\Delta(\beta^*) \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[u_{t+1}^2 V_t V_t'] + 2(1 - 2\alpha_0)E[u_{t+1}|e_{t+1}|V_t V_t'] + (1 - 2\alpha_0)^2 E[|e_{t+1}|^2 V_t V_t'].$$

Spurious rejections of the rationality hypothesis follow whenever the absolute value of the forecast error is correlated with V_t and the standard error of $\hat{\beta}$ is not too large.⁸ Proposition 2 allows us to construct standard errors for $\hat{\beta}$ and hence to study the power of a misspecified MSE test. We use this for the following result:

Corollary 3 *Suppose the assumptions from Proposition 2 hold. For local deviations from symmetric loss, $\alpha_0 = 1/2$, given by $\alpha_0 = \frac{1}{2}(1 - aT^{-1/2})$, and local deviations from rationality, $\beta = 0$, given by $\beta = bT^{-1/2}$, with a and b fixed, the Wald test statistic $T\hat{\beta}'\hat{\Omega}^{-1}\hat{\beta}$ based on the efficiency regression (5) is asymptotically distributed as $T\hat{\beta}'\hat{\Omega}^{-1}\hat{\beta} \xrightarrow{d} \chi_d^2(m)$, a non-central chi-square with d degrees of freedom and non-centrality parameter m given by*

$$m = a^2 h_V' \Delta(\beta^*)^{-1} h_V + b' \Sigma_V \Delta(\beta^*)^{-1} \Sigma_V b + 2ab' \Sigma_V \Delta(\beta^*)^{-1} h_V. \quad (8)$$

This implies the following: (i) for a wide range of combinations of the asymmetry parameter, $\alpha_0 \neq 1/2$, and the regression coefficient β , efficiency tests may fail to reject even for large degrees of inefficiency ($\beta \neq 0$); (ii) when the forecaster genuinely uses information efficiently ($\beta = 0$) the efficiency test will tend to reject the null provided loss is asymmetric ($\alpha_0 \neq 1/2$).

Recall that d is the number of instruments used in the test, i.e. $d = 1$ if only a constant is used. Since the power of the Wald test for $\beta = 0$ is driven entirely by the noncentrality

⁸The asymptotic covariance matrix Ω^* can be consistently estimated by $\hat{\Omega} = \hat{\Sigma}_V^{-1} \hat{\Delta}(\hat{\beta}) \hat{\Sigma}_V^{-1}$ with $\hat{\Delta}(\hat{\beta}) \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} (e_{t+1} - \hat{\beta}' v_t)^2 v_t v_t'$.

parameter m , it suffices to consider this parameter to study the power of the standard rationality test in the directions of nonzero a and b .

Non-zero values of a and b have very different interpretations: $b \neq 0$ implies that the forecasting model is misspecified, while $a \neq 0$ reflects asymmetric loss. Only the former can be interpreted as forecast inefficiency or irrationality. Yet, for given values of Σ_V , $\Delta(\beta)$ and h_V we can construct pairs of values (a, b) that lead to identical power (same m). In principle, standard efficiency tests based on (5) can therefore not tell whether a rejection is due to irrationality or asymmetric loss - i.e., lack of robustness with respect to the shape of the loss function. A large value of m can arise even when the forecaster is fully rational ($b = 0$) provided that $|a|$ is large.⁹

Conversely, suppose that the test does not reject, which would happen at the right size provided $m = 0$. This does *not* imply that the forecast is rational ($b = 0$) because we can construct pairs of non-zero values (a, b) such that $m = 0$. This will happen when the misspecification in the forecasts cancel out against the asymmetry in the loss function. The test will not have any power to identify this problem.

To demonstrate the importance of this point, Figure 2 uses Corollary 3 to plot iso- m - or, equivalently, iso-power - curves for different values of a and b , assuming a size of 5% and $V_t = 1$. For this case $\Sigma_V = 1$, Δ can be estimated by $\hat{\sigma}_u^2$ (the variance of the residuals of the regression) and h_V can be estimated by $\hat{h}_V = T^{-1} \sum_{t=\tau}^{t=T+\tau} |e_{t+1}|$. Values for $\hat{\sigma}_u$ and \hat{h}_V were chosen to match the SPF data. When $a = b = 0$, we have the case with MSE loss and informational efficiency. Positive values of a correspond to a value of α below one-half, while negative values of a represent $\alpha > 1/2$.

For any value of m we can solve the quadratic relationship (8) to obtain a trade-off between a and b : $b = -a\hat{h}_V \pm \sqrt{m}\hat{\sigma}_u$. When $m = 0$ (the thick line in the center), the test rejects with power equal to size and the trade-off between a and b is simply $b = -a\hat{h}_V$. The two $m = 0.65$ lines correspond to power of 10%, the $m = 1.96$ lines give 50% power, while

⁹When $a \neq 0$, the constant term in (5) is particularly likely to lead to a rejection even when the forecasts are truly rational. This bias will be larger the less of the variation in the outcome variable is explained (since $E[|e_{t+1}|]$ is increasing in the variation of the forecast error).

the $m = 3.24$ lines furthest towards the corners of the figure represent a power of 90%.¹⁰ The lines slope downward since a larger value of a corresponds to a smaller value of α and a stronger tendency to underpredict (yielding a positive mean of the forecast error) which will cancel out against a larger negative bias in b .

Pairs of values a, b on the $m = 0$ line are such that biases in the forecasts (non-zero b) exactly cancel out against asymmetry in loss (non-zero a) in such a way that the standard test cannot detect the bias (in the sense that power = size) even though forecasters are irrational. For nonzero values for m , we see the converse. The point where these contours cross the $b = 0$ boundary (in the centre of the graphs) gives the asymmetry parameter that if true for the forecaster would result in rejections with greater frequency than size even though the forecaster is rational for that asymmetric loss function.¹¹

5 Rationality Tests under Asymmetric Losses

Our finding that standard rationality tests are not robust to asymmetric loss suggests that a new set of tests is required. In this section we describe two such approaches. The first approach is applicable when the shape and parameters of the loss function are known. This set-up does not pose any new problems and least-squares estimation can still be adopted, albeit on a transformation of the original forecast error. The second case arises when the parameters of the loss function are unknown and have to be estimated as part of the test. This framework requires different estimation methods which we describe below.

We start by briefly discussing forecast rationality more generally. Under a loss function $L(e; \eta)$, characterized by some shape parameter η , the sequence of forecasts $\{f_{t+1}\}$ is said to be *optimal* under loss L if at any point in time t , the forecast f_{t+1} minimizes $E[L(e_{t+1}; \eta)|\Omega_t]$ - the expected value of L conditional on the information set available to the forecaster, Ω_t . If

¹⁰The range of values for a in the figure (-10, 10) ensures that $\alpha \in (0, 1)$ when $T = 100$. This range becomes more narrow (wider) for smaller (larger) sample sizes.

¹¹Only if $\hat{h}_V = 0$ would asymmetric loss not cause problems to the standard test. In this case the absolute value of the forecast error is not correlated with the instrument, V_t , there is no omitted variable bias and the iso-power curves would be vertical lines, so size would only be controlled when $b = 0$.

the forecaster's loss function L is once differentiable, this implies that, at any point in time, the optimal forecast errors $\{e_{t+1}\}$ satisfy the first order condition $E[L'_e(e_{t+1}; \eta)|\Omega_t] = 0$, where L'_e denotes the derivative of L with respect to the error e_{t+1} .

Conditional moment conditions such as these are difficult to check in practice. Instead, they are replaced by unconditional moment conditions based on the $d \times 1$ vector of instruments, V_t , that are known to the forecaster, i.e. $V_t \in \Omega_t$. We can then say that, under L , the forecasts $\{f_{t+1}\}$ are *rational* with respect to the variables V_t if the forecast errors satisfy the orthogonality conditions: $E[\sum_{t=\tau}^{T+\tau-1} L'_e(e_{t+1}; \eta) \cdot V_t] = 0$. In other words, the transformed (or 'generalized') forecast error $L'_e(e_{t+1}; \eta)$ has to be orthogonal to the vector of variables V_t .

5.1 Known Loss

When both L and η are known we can transform the observed forecast error e_{t+1} and test the orthogonality conditions by means of the generalized efficiency regression

$$L'_e(e_{t+1}; \eta) = \beta' v_t + u_{t+1}, \quad (9)$$

where u_{t+1} is a realization of a scalar error random variable U_{t+1} such that $E[\sum_{t=\tau}^{T+\tau-1} V_t U_{t+1}] = 0$. Assuming that standard regularity conditions hold, the linear regression parameter β can be consistently estimated by using the ordinary least squares (OLS) estimator $\tilde{\beta} \equiv [\sum_{t=\tau}^{T+\tau-1} v_t v_t']^{-1} [\sum_{t=\tau}^{T+\tau-1} v_t L'_e(e_{t+1}; \eta)]$. Forecast rationality is equivalent to having $\beta = 0$. Hence, under general loss a test for rationality can be performed by first transforming the observed forecast error e_{t+1} into $L'_e(e_{t+1}; \eta)$, then regressing the latter on V_t by means of the regression (9) and finally testing the null hypothesis that all the regression coefficients are zero, i.e. $\beta = 0$. Under quadratic loss, such tests of orthogonality of the forecast error with respect to all variables observed by the forecaster are commonly referred to as strong rationality tests.

To demonstrate this type of test, suppose that it is known that the forecaster has a 'Quad-Quad' loss function with known asymmetry parameter $\alpha_0 \neq 1/2$. For this case the generalized efficiency regression takes the form

$$e_{t+1} - (1 - 2\alpha_0)|e_{t+1}| = \beta' v_t + u_{t+1}. \quad (10)$$

When α_0 equals one half, the previous regression collapses to the one traditionally used in tests for strong rationality. Assuming that the forecaster's loss is quadratic, i.e. $\alpha_0 = 1/2$, amounts to omitting the term $(1 - 2\alpha_0)|e_{t+1}|$ from the regression above. Whenever the true value of α_0 is different from one half, the estimates of the slope coefficient β are biased, as already shown in Section 4. This finding is as we would expect from the standard omitted variable bias result with the difference that we now have constructed the omitted regressor.

5.2 Unknown Loss Parameters

For many applications, however, both L and η are unknown to the forecast evaluator. One way to proceed in this case is to relax the assumption that the true loss is known by assuming that L belongs to some flexible and known family of loss functions but with unknown shape parameter, η . This enlarges the null space and reduces the power of the test, yet has the advantage that problems of rejection due to the form of the loss function rather than the hypothesis of interest - that forecasters are rational - are lessened. Tests will still have power to detect violations of rationality.

Forecast rationality tests merely verify whether, under the loss, L , the forecasts are optimal with respect to a set of variables, V_t , known to the forecaster. They can therefore be viewed as tests of moment conditions, which arise from first order conditions of the forecaster's optimization problem. Traditional rationality tests, such as the one proposed by Mincer and Zarnowitz (1969), adopt a regression based approach to testing these orthogonality conditions. A natural alternative, which we propose here, is to use a Generalized Method of Moments (GMM) framework as in Hansen (1982). The benefits of the latter are easily illustrated in the 'Quad-Quad' case. If the asymmetry parameter, α_0 , is unknown it is impossible to compute the term $(1 - 2\alpha_0)|e_{t+1}|$ and hence not feasible to estimate the regression coefficient, β , in (9). However, it is still possible to test whether the moment conditions $E[\sum_{t=\tau}^{T+\tau-1} V_t((\alpha_0 - 1(e_{t+1} < 0))|e_{t+1}| - \beta'V_t)] = 0$ hold, with $\beta = 0$ and α_0 left unspecified.

The statistic suggested by Elliott, Komunjer and Timmermann (2002) for testing the null hypothesis that the forecasts are rational takes the form of a test for overidentification

in a GMM framework:

$$J_T \equiv T^{-1} \left[\sum_{t=\tau}^{T+\tau-1} v_t (\hat{\alpha}_T - 1(e_{t+1} < 0)) |e_{t+1}| \right]' \hat{S}^{-1} \left[\sum_{t=\tau}^{T+\tau-1} v_t (\hat{\alpha}_T - 1(e_{t+1} < 0)) |e_{t+1}| \right]. \quad (11)$$

Here \hat{S} is a consistent estimator of $S \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t' \cdot (1(e_{t+1} < 0) - \alpha_0)^2 \cdot |e_{t+1}|^2]$, and $\hat{\alpha}_T$ is a linear Instrumental Variable (IV) estimator of α_0 ,

$$\hat{\alpha}_T \equiv \frac{\left[\sum_{t=\tau}^{T+\tau-1} v_t |e_{t+1}| \right]' \cdot \hat{S}^{-1} \cdot \left[\sum_{t=\tau}^{T+\tau-1} v_t (1(e_{t+1} < 0)) |e_{t+1}| \right]}{\left[\sum_{t=\tau}^{T+\tau-1} v_t |e_{t+1}| \right]' \cdot \hat{S}^{-1} \cdot \left[\sum_{t=\tau}^{T+\tau-1} v_t |e_{t+1}| \right]}. \quad (12)$$

In other words, the GMM overidentification test (J-test) is a consistent test of the null hypothesis that the forecasts are rational, i.e. $\beta = 0$, even if the true value of the asymmetry parameter α_0 is unknown, and the forecast errors depend on previously estimated parameters. The test is asymptotically distributed as a χ_{d-1}^2 random variable and rejects for large values. Effectively, we exploit the first order conditions under forecast rationality, $E[V_t(\alpha_0 - 1(e_{t+1} < 0)) |e_{t+1}|] = 0$, for each observation with α_0 left unspecified. As a by-product, an estimate of the asymmetry parameter, $\hat{\alpha}_T$, is generated from equation (12).¹²

Intuitively, the power of our test arises from the existence of overidentifying restrictions. In practice, for each element of V_t we could obtain an estimate for the asymmetry parameter, α_0 , that would rationalize the observed sequence of forecasts. However, when the number of instruments, d , is greater than one, our method tests that the implied asymmetry parameter is the same for each moment condition. If no common value for α_0 satisfies all of the moment conditions, the test statistic J_T in equation (11) becomes large. This explains why the test still has power against the alternative that the forecasts were not constructed rationally and why it is not possible to justify arbitrary degrees of inefficiency in the forecasts by means of

¹²The covariance matrix S can be consistently estimated by replacing the population moment by a sample average and the true parameter by its estimated value, so that $\hat{S}(\bar{\alpha}_T) = T^{-1} \sum v_t v_t' (1(e_{t+1} < 0) - \bar{\alpha}_T)^2 |e_{t+1}|^2$, where $\bar{\alpha}_T$ is a consistent initial estimate of α_0 (obtained by setting $S = I$, for example), or by using some heteroskedasticity and autocorrelation robust estimator, such as Newey and West's (1987) estimator. Formal proofs of these results as well as a more precise statement of the underlying assumptions are provided in Elliott, Komunjer and Timmermann (2002).

asymmetric loss: if the forecasts did not efficiently use the information in V_t , then $\hat{\alpha}_T$ would be very different for each of the moment conditions and the test would reject.¹³

Although this approach does not impose a fixed value of α_0 , it still assumes that the loss function belongs to the family (3) or (4) and the test (11) provides a joint test of rationality and this assumption. The advantage of this approach is that it loses little power since only one or two parameters have to be estimated. It is possible to take an even less restrictive approach and estimate the moment conditions non-parametrically. However, this is unlikely to be a useful strategy in view of the very short data samples typically available on individual forecasters.¹⁴

6 Empirical Results

To see how asymmetric loss affects the empirical results from Section 2, derived under MSE loss, we proceed to test rationality of the output forecasts under ‘Quad-Quad’ loss. Results under four different sets of instruments, V_t , are considered, namely: (1) a constant and the lagged forecast error, (2) a constant and lagged actual GDP growth, (3) a constant, the lagged forecast error and the lagged value of GDP growth, and (4) a constant and the lagged absolute forecast error. These instruments are similar to those adopted in the literature and have power to detect predictability in forecast errors such as serial correlation.

6.1 Rationality Tests

Table 2 shows the outcomes of two separate tests for rationality. The first test is for the joint hypothesis of rationality and symmetric loss ($\alpha_0 = 1/2$). The second test is for rationality but allows for asymmetry within the context of the more general family of ‘Quad-Quad’ loss functions (4).

¹³If we were to impose a value for α in the J_T statistic (11), the resulting test would be identical to the test of $\beta = 0$ in the efficiency regression (9).

¹⁴Alternatively, one could compare results for different values of p . Our empirical results suggested that the exact functional form of the asymmetry (e.g., lin-lin with $p = 1$ versus quad-quad with $p = 2$) is less important than allowing for asymmetric loss in the first instance.

The joint hypothesis of rationality and symmetric loss is strongly rejected for many forecasters. For instance, when three instruments are used, the null is rejected at the 1% level for 20 forecasters and it gets rejected for 34 forecasters at the 5% level and 42 forecasters at the 10% level. The results are very different when we no longer impose symmetry on the loss function. For this case no rejection is found at the 1% level, while four forecasts produce a rejection at the 5% level and 11 do so at the 10% level.

Standard tests of forecast rationality thus have strong power towards detecting asymmetry in the loss function. In fact, rejections of the joint hypothesis of rationality and symmetry appear mostly to be driven by the symmetry assumption. Our rejection frequencies under asymmetric loss are almost exactly equal to the size of the test and hence suggest little evidence against the joint null of asymmetric loss and efficient forecasts.

6.2 Estimates of Loss Parameters

So far we have not discussed the α -estimates although clearly there is considerable economic information in these values which should reflect the shape of the forecasters' loss function. Figure 3 shows a histogram of the 98 α -estimates computed using (12) for $V_t = 1$. The evidence is clearly indicative of asymmetric loss. Irrespective of which set of instruments is used, the proportion of α -estimates above one-half never exceeds 20%.

Since the target variable is output growth, asymmetric loss must be related to differential inventory holding and stockout costs. Estimates of α below one-half are consistent with loss functions that penalize negative forecast errors more heavily than positive ones. Our results suggest that many individuals in the survey prefer to *underpredict* output growth, thereby creating the positive bias in the forecast error reported earlier. This is consistent with stockout costs being lower than inventory holding costs.

Importantly, the α -estimates suggested by our data do not appear to be 'extreme' and are clustered with a mode around 0.38. This corresponds to putting around twice as large a weight on positive forecast errors as on negative ones, consistent with inventory costs being twice as large as stockout costs. Such values do not appear to be implausible. We might have found α -values much closer to zero in which case the degree of asymmetry required to

explain biases in the forecasts would have to be implausibly large.

The small portion of α -estimates exceeding one-half may in part reflect sampling error. However, the direction of the bias could also differ across industries if holding and stockout costs are industry specific. For example, some industries have storage capacity constraints which can be regarded as increased inventory holding costs. In broad terms, however, we would expect similarity in the direction of the bias across industries, as indeed we find.

6.3 Bias and Type of Forecaster

The SPF data does not identify the affiliation of the forecaster. It is natural, however, to expect the extent of loss asymmetry to be different for forecasters associated with academia, banking and industry. It seems more plausible that academics have less of a reason to produce biased forecasts than, say, industry economists whose forecasts are produced for a specific firm or industry and thus - at least in theory - should put more weight on positive forecast errors if, e.g., inventory costs exceed stockout costs. It is more difficult to conjecture the size and direction of the bias for the banking forecasters. If these were produced for clients that were fully hedged with regard to unanticipated shocks to economic growth, one would expect α -estimates closer to one-half. However, if bank losses arising from over-predictions of economic growth exceed those from underpredictions, again we would expect more α -estimates below one-half than above it.

To consider this issue, we used data from the Livingston survey which lists the forecaster's affiliation. Unfortunately this data set tends to be much shorter as forecasts are only generated every six months. We therefore only required a minimum of 10 observations. This leaves us with 12 industry, five academic and 12 forecasters from the banking sector - admittedly a very small sample.

The α -estimates for these forecasters are shown in Figure 4. Academic forecasters tend to produce α -estimates closer to one-half than the forecasters from industry and banking. In fact, the joint null of rationality and $\alpha = 1/2$ is not rejected for any of the academic forecasters, while this hypothesis was rejected at the 5% level for two of the 12 industry forecasters and for five of the 12 banking forecasters. While this evidence is by no means

conclusive given the very small sample available here, it is indicative that differential costs associated with positive and negative forecast errors play a role in explaining forecast biases in macroeconomic data.

7 Summary and Discussion

Many empirical studies have found forecasts to be biased. Does this mean that forecasters genuinely use information inefficiently and hence are irrational or simply that they have asymmetric loss? We have shown in this paper that standard forecast efficiency tests often cannot distinguish between these two possible explanations. The importance of this point was validated empirically: we found that previous rejections of rationality may well have been driven by the assumption of symmetric loss since rejections occur far less frequently under asymmetric loss. Our results suggest that rejections of forecast rationality and symmetric loss reported in the existing literature are not robust to relaxing the symmetry assumption and that the power of standard tests is very much derived from their ability to reject symmetric loss. This is an important point which many previous papers have expressed concern about.¹⁵

To deal with this problem, we proposed a more general framework for rationality testing that applies to a flexible family of loss functions that allow for asymmetries and nests MSE loss as a special case. While more general loss functions than those proposed here can certainly be thought of, the advantage of our framework is that it links asymmetry to a single parameter, thus keeping the loss in the power of the test to a minimum. This is crucial in empirical analysis where only relatively short time series of individual forecasts typically is available and low power is an important concern. Furthermore, our results appear to be robust to the specific functional form maintained for the loss function, the key being to allow positive and negative forecast errors to be weighted differently.

Our generalized tests do *not* imply that any sequence of forecasts - even inefficient ones

¹⁵Keane and Runkle (1990, page 719) write “If forecasters have differential costs of over- and underprediction, it could be rational for them to produce biased forecasts. If we were to find that forecasts are biased, it could still be claimed that forecasters were rational if it could be shown that they had such differential costs.”

- can be rationalized by asymmetric loss. Quite on the contrary: each moment condition leads to a different value of the loss asymmetry parameter if the forecasts do not efficiently incorporate the information in each instrument and hence to a rejection of rationality. Only when forecasts are computed efficiently should each instrument lead to the same value of the asymmetry parameter.

Our empirical findings raise the question whether the degree of asymmetry in the loss function required for forecasts to be efficient is excessive given what is known about firms' cost function. There is, of course, a precursor for this type of question. In finance, the equity premium puzzle consists of the finding that the value of the risk aversion parameter required for mean (excess) stock returns to be consistent with a representative investor model appears to be implausibly high, c.f. Mehra and Prescott (1985). In our context, the empirical findings do not suggest that the degree of loss asymmetry required to overturn rejections of rationality needs to be very severe although, ultimately, this implication is best addressed by considering empirical (micro) data on costs.

Asymmetric loss offers an obvious explanation for the very diverse results reported in the empirical literature on rationality testing and the large dispersion in individuals' forecasts documented by Mankiw, Reis and Wolfers (2003). Loss functions reflect individuals' preferences so there are no reasons why they should be identical across individuals or even across different variables since the consequences of forecast errors may well be different for, say, inflation and output forecasts. Since the vast majority of empirical studies has maintained quadratic loss, the very mixed empirical results reported in the literature could well be consistent with varying degrees of loss asymmetry. Our findings emphasize the importance of allowing for heterogeneity in loss functions, as indicated by the differences in the estimated asymmetry parameters observed for economists with academic, banking and industry affiliations.

Heterogeneity in loss function parameters also help to explain findings in the empirical literature that would otherwise be very puzzling. Zarnowitz (1985) reports that composite group forecasts are rejected less frequently than individual forecasts. Suppose the degree of asymmetry differ across individual forecasters' loss functions. As we have shown, this may

lead to rejections of standard rationality tests for forecasters with $\alpha \neq 1/2$. However, if some α -values are below one-half while others are above, then the simple average of forecasts will be less biased than many of the individual forecasts and is less likely to lead to a rejection of rationality tests.

For sure, there are alternative explanations of forecast biases such as forecasters' strategic behavior. It is less clear whether such explanations are supported empirically. Ehrbeck and Waldmann (1996) use data on forecasts of interest rates to test both cross-sectional and time-series implications of an agency model and find that their model is rejected empirically. This leads them to question the rational expectations hypothesis. Our results indicate that such a conclusion may be premature when asymmetries in the loss function are considered.

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Data Appendix

Our empirical application uses the growth in quarterly seasonally adjusted nominal US GDP in billions of dollars before 1992 and nominal GNP after 1992. The growth rate is calculated as the difference in natural logs. Data for the actual values come from two sources. The official (revised) data is from the BEA. To avoid using revised data that was not historically available to the forecasters we also use real-time data from the Philadelphia Fed. This provides the vintages of data available in real time and takes the following form:

	<i>68.IV</i>	<i>69.I</i>	<i>69.II</i>	<i>69.III</i>	<i>69.IV</i>
<i>68.IV</i>	<i>NA</i>	887.8	887.4	892.5	892.5
<i>69.I</i>	<i>NA</i>	<i>NA</i>	903.4	908.7	908.7
<i>69.II</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>	925.1	924.8
<i>69.III</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>	942.3
<i>69.IV</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>	<i>NA</i>

Rows represent the dates corresponding to the index while columns track the vintage. So, in 1969.IV, a forecaster looked at a value of 942.3 for 69.III, 924.8 for 69.II and so on. This real-time data is used to construct real time instruments used in the rationality tests. Both the lagged forecast error and the lagged value of output growth are based on the historical vintages available in real time.

Data on the forecasts come from the Survey of Professional Forecasters, also maintained by the Philadelphia Fed. This data runs from the fourth quarter of 1968 to the first quarter of 2002. It provides the quarter, the number of the forecaster, the most recent value known to the forecaster (preceding), the value (most of the times forecasted) for the current quarter (current) and then forecasts for the next four quarters. We use the values corresponding to the current and the first forecast to calculate the one-step-ahead growth rate.¹⁶

Some forecasters report missing values while others decide to leave for a while, but then return and continue to produce forecasts. To deal with these problems we followed three steps. We eliminate individuals with less than 20 forecasts (so, from a total of 512 individuals

¹⁶A few forecasts were omitted from the data base. There were clear typos for forecaster number 12 (1989.II), forecasters 20 and 62 (1992.IV) and forecaster 471 (1997.II).

we keep 107 forecasters).¹⁷ We then eliminate forecasters with missing values. This reduces the number of individual forecasters to 98.

The Livingston data considered in Section 6.3 uses the difference in the logs of the six-month forecast (two quarters ahead) over the forecast of the current quarter and starts in the second semester of 1992 which is the time when current quarter figures start to get included. Data runs through the second semester of 2002. This data contains information on the affiliation of the forecasters. Most affiliations have very few observations, so only those corresponding to Industry, Academic and Banking were considered. Individuals with implausibly large forecast errors (greater than 5 percentage points over a six-month period) and too few observations (less than ten) were excluded from the analysis. This leaves us with five Academic forecasters, 12 Banking forecasters and 12 Industry forecasters.

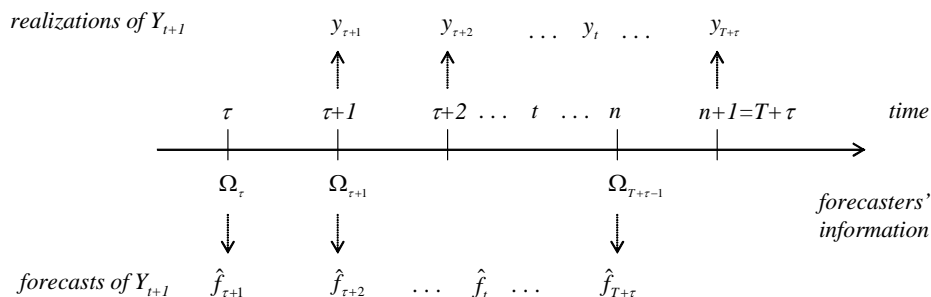
¹⁷103 out of these 107 individuals have a gap of at least one quarter in their reported forecasts. Most forecasters skip one or more quarters.

Appendix A

This appendix describes the forecasting setup and lists the assumptions used to establish Propositions 1 and 2 and Corollary 3. We use the following notations: if v is a real d -vector, $v = (v_1, \dots, v_d)'$, then $|v|$ denotes the standard L_2 -norm of v , i.e. $|v|^2 = v'v = \sum_{i=1}^d v_i^2$. If M is a real $d \times d$ -matrix, $M = (m_{ij})_{1 \leq i, j \leq d}$, then $|M|$ denotes the L_∞ -norm of M , i.e. $|M| = \max_{1 \leq i, j \leq d} |m_{ij}|$.

Forecasting scheme:

As a preamble to our proofs, it is worth pointing out that the estimation uncertainty of the observed forecasts, which we hereafter denote \hat{f}_{t+1} , gives rise to complications when testing rationality. The models used by the forecasters to produce \hat{f}_{t+1} are typically unknown to the econometrician or forecast user. Indeed, there are a number of different forecasting methods which can be used by the forecasters at the time they make their forecasts, most of which involve estimating (or calibrating) some forecasting model.



In addition to different models employed, forecasts may also differ according to the forecasting scheme used to produce them. For example, a fixed forecasting scheme constructs the in-sample forecasting model only once, then uses it to produce all the forecasts for the out-of-sample period. A rolling window forecasting scheme re-estimates² the parameters of the forecasting model at each out-of-sample point. In order to fix ideas, we assume that all

the observed forecasts are made recursively from some date τ to $\tau + T$ as depicted in the figure above, so that the sequence $\{\hat{f}_{t+1}\}$ depends on recursive estimates of the forecasting model. The sampling error caused by this must be taken into account (see, e.g., West (1996), West and McCracken (1998), McCracken (2000)). Throughout the proofs we assume that the forecasters' objective is to solve the problem

$$\min_{\{f_{t+1}\}} E\left[\sum_{t=\tau}^{\tau+T-1} \alpha |e_{t+1}|^p \mathbf{1}(e_{t+1} \geq 0) + (1 - \alpha) |e_{t+1}|^p \mathbf{1}(e_{t+1} < 0) \right], \quad (13)$$

and thus define a sequence of forecasts $\{f_{t+1}^*\}$ and corresponding forecast errors $\{e_{t+1}^*\}$. It is important to note that $\{f_{t+1}^*\}$ which minimizes the above expectation is unobservable in practice. Instead we assume the econometrician observes $\{\hat{f}_{t+1}\}$ thus taking into account that the observed sequence of forecasts embodies a certain number of recursively estimated parameters of the forecasting model.

Assumptions:

- (A1) $\beta \in B$ where the parameter space $B \subseteq \mathbb{R}^d$ and B is compact. Moreover $\beta^* \in \overset{\circ}{B}$;
- (A2) for every t , $\tau \leq t < T + \tau$, the forecast of Y_{t+1} is a measurable function of an Ω_t -measurable h -vector W_t , i.e. $f_{t+1} = f_{t+1}(W_t)$, where the function f_{t+1} is unknown but bounded, i.e. $\sup_{\theta \in \Theta} |f_{t+1}(W_t)| \leq C < \infty$ with probability one, and $\hat{f}_{t+1} = f_{t+1}^* + o_p(1)$;
- (A3) the d -vector V_t is a sub-vector of the h -vector W_t ($d \leq h$) with the first component 1 and for every t , $\tau \leq t < T + \tau$, the matrix $E[V_t V_t']$ is positive definite;
- (A4) $\{(Y_t, W_t')\}$ is an α -mixing sequence with mixing coefficient α of size $-r/(r - 2)$, $r > 2$, and there exist some $\Delta_Y > 0$, $\Delta_V > 0$ and $\delta > 0$ such that for every t , $\tau \leq t < T + \tau$, $E[|Y_{t+1}|^{2r+\delta}] \leq \Delta_Y < \infty$ and $E[|V_t|^{2r+\delta}] \leq \Delta_V < \infty$;

Appendix B

Proof of Proposition 1. In the first part of this proof we show that $\hat{\beta} \xrightarrow{p} \beta^*$, where $\beta^* \equiv (\sum_{t=\tau}^{T+\tau-1} E[V_t V_t'])^{-1} \cdot (\sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*])$. We then use this convergence result in the second part of the proof to derive the expression for the misspecification bias of $\hat{\beta}$.

Recall from Section 4 that the standard OLS estimator is $\hat{\beta} \equiv [\sum_{t=\tau}^{T+\tau-1} v_t v_t']^{-1} [\sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1}]$.

In order to show that $\hat{\beta} \xrightarrow{p} \beta^*$, it suffices to show that the following conditions hold:

(i) β^* is the unique minimum on B (compact in \mathbb{R}^d) of the quadratic form $S_0(\beta)$ with $S_0(\beta) \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[(e_{t+1}^* - \beta' V_t)^2]$; (ii) $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t v_t' \xrightarrow{p} T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t']$; (iii) $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} \xrightarrow{p} T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*]$. From the positive definiteness of $E[V_t V_t']$, for all t (assumption A3) and the continuity of the inverse function (away from zero), it then follows that $\hat{\beta} \xrightarrow{p} \beta^*$.

We start by showing (i): note that $S_0(\beta) = T^{-1} \sum_{t=\tau}^{T+\tau-1} E[(e_{t+1}^*)^2] - 2\beta' T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*] + \beta' T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t'] \beta$, so $S_0(\beta)$ admits a unique minimum at β^* if for every t , $\tau \leq t < T + \tau$, the matrix $E[V_t V_t']$ is positive definite, which is satisfied by assumption (A3). This verifies the uniqueness condition (i).

In order to show (ii) and (iii), we use a law of large numbers (LLN) for α -mixing sequences (e.g., Corollary 3.48 in White, 2001). By assumptions (A2) and (A3) we know that for every t , $\tau \leq t < T + \tau$, \hat{f}_{t+1} and V_t are measurable functions of W_t which by (A4) is an α -mixing sequence with mixing coefficient α of size $-r/(r-2)$, $r > 2$. Hence, by Theorem 3.49 in White (2001, p 50) we know that $\{(\hat{e}_{t+1} V_t', \text{vec}(V_t V_t')')'\}$, where $\hat{e}_{t+1} = Y_{t+1} - \hat{f}_{t+1}$, is an α -mixing sequence with mixing coefficient α of the same size $-r/(r-2)$, $r > 2$. For $\delta > 0$, we have $r + \delta/2 > 2$ and $r/2 + \delta/4 > 1$ so by assumption (A4)

$$\begin{aligned} E[|V_t V_t'|^{r/2+\delta/4}] &\leq E[|V_t|^{r+\delta/2}] \\ &\leq \max\{1, \Delta_V^{1/2}\} < \infty, \end{aligned}$$

for all t , $\tau \leq t < T + \tau$. Hence, by applying the results from Corollary 3.48 in White (2001) to the sequence $\{\text{vec}(V_t V_t')'\}$, we conclude that $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t v_t'$ converges in probability to its expected value $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t']$, which shows that (ii) holds.

Similarly, we know by the Cauchy-Schwartz inequality that, for all $t, \tau \leq t < T + \tau$,

$$E[|V_t \hat{e}_{t+1}|^{r/2+\delta/4}] \leq (E[|V_t|^{r+\delta/2}])^{1/2} \cdot (E[|\hat{e}_{t+1}|^{r+\delta/2}])^{1/2}.$$

Hence there exists some $n_{r,\delta} \in \mathbb{R}_*^+, n_{r,\delta} < \infty$, such that

$$\begin{aligned} E[|V_t \hat{e}_{t+1}|^{r/2+\delta/4}] &\leq \max\{1, \Delta_V^{1/2}\} \cdot (n_{r,\delta} \cdot (E[|Y_{t+1}|^{r+\delta/2}] + E[|\hat{f}_{t+1}|^{r+\delta/2}]))^{1/2} \\ &\leq \max\{1, \Delta_V^{1/2}\} \cdot n_{r,\delta}^{1/2} \cdot (\max\{1, \Delta_Y^{1/2}\} + \max\{1, C^{r+\delta/2}\})^{1/2} \\ &< \infty, \end{aligned}$$

for all $t, \tau \leq t < T + \tau$, where we have used assumptions (A2) and (A4). Hence, our previous argument applies to the sequence $\{\hat{e}_{t+1} V_t'\}$ as well, and we conclude that $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1}$ converges in probability to its expected value $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t \hat{e}_{t+1}]$. Note, however, that this does not ensure that (iii) holds, as we moreover need to show that substituting e_{t+1}^* for \hat{e}_{t+1} does not affect the result, i.e. that $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t \hat{e}_{t+1}] - E[V_t e_{t+1}^*] \xrightarrow{p} 0$. For every $t, \tau \leq t < T + \tau$, we have

$$\begin{aligned} |E[V_t \cdot (\hat{e}_{t+1} - e_{t+1}^*)]| &= |E[V_t \cdot (f_{t+1}^* - \hat{f}_{t+1})]| \\ &\leq (E[|V_t|^2])^{1/2} \cdot (E[(f_{t+1}^* - \hat{f}_{t+1})^2])^{1/2} \\ &\leq \max\{1, \Delta_V^{1/2}\} \cdot (E[(f_{t+1}^* - \hat{f}_{t+1})^2])^{1/2}. \end{aligned}$$

Since by (A2) we know that $f_{t+1}^* - \hat{f}_{t+1} = o_p(1)$, for all t , we get $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t \hat{e}_{t+1}] - E[V_t e_{t+1}^*] \xrightarrow{p} 0$. Combined with our previous result this shows that (iii) holds. Hence, we conclude that $\hat{\beta} \xrightarrow{p} \beta^*$.

We now use this convergence result to derive the bias in $\hat{\beta}$. We know from Section 4 that the parameter β in the generalized regression (9) satisfies the set of identifying constraints

$$T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t \cdot (2(\alpha_0 - 1(e_{t+1}^* < 0))|e_{t+1}^*| - \beta' V_t)] = 0,$$

so that $T^{-1} \sum_{t=\tau}^{T+\tau-1} 2E[(\alpha_0 - 1(e_{t+1}^* < 0))V_t |e_{t+1}^*|] = T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t'] \beta$. Using that $2 \cdot 1(e_{t+1}^* < 0) |e_{t+1}^*| = |e_{t+1}^*| - e_{t+1}^*$, this last equality can be written $T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*] - T^{-1} \sum_{t=\tau}^{T+\tau-1} E[(1-2\alpha_0)V_t |e_{t+1}^*|] = T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t'] \beta$ so by positive definiteness of $E[V_t V_t']$ (assumption A2) we have $\beta = (T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t'])^{-1} \cdot \{T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*] - E[(1 -$

$2\alpha_0)V_t|e_{t+1}^*|]$ }. In other words, $\beta = \beta^* - (1 - 2\alpha_0) \cdot (T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t'])^{-1} \cdot (T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t |e_{t+1}^*|])$. This shows that $\hat{\beta} \xrightarrow{p} \beta + (1 - 2\alpha_0) \Sigma_V^{-1} h_V$ with $\Sigma_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t V_t']$ and $h_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t |e_{t+1}^*|]$, which completes the proof of Proposition 1.¹⁸ ■

Proof of Proposition 2. We now show that $T^{1/2}(\hat{\beta} - \beta^*)$ is asymptotically normal by expanding the first order condition for $\hat{\beta}$ around β^* :

$$\left[\sum_{t=\tau}^{T+\tau-1} v_t(\hat{e}_{t+1} - \hat{\beta}' v_t) \right] = 0 = \left[\sum_{t=\tau}^{T+\tau-1} v_t(\hat{e}_{t+1} - \beta^{*'} v_t) \right] - \left(\sum_{t=\tau}^{T+\tau-1} v_t v_t' \right) (\hat{\beta} - \beta^*). \quad (14)$$

The idea then is to use (i) $[\sum_{t=\tau}^{T+\tau-1} v_t(\hat{e}_{t+1} - \beta^{*'} v_t)] = [\sum_{t=\tau}^{T+\tau-1} v_t(e_{t+1}^* - \beta^{*'} v_t)] + o_p(1)$, together with (ii) $T^{-1/2} \sum_{t=1}^T v_t(e_{t+1}^* - \beta^{*'} v_t) \xrightarrow{d} N(0, \Delta(\beta^*))$, where $\Delta(\beta^*) \equiv T^{-1} \sum_{t=1}^T E[(e_{t+1}^* - \beta^{*'} V_t)^2 \cdot V_t V_t']$, to show by Slutsky's theorem that

$$T^{-1/2} \sum_{t=\tau}^{T+\tau-1} v_t(\hat{e}_{t+1} - \beta^{*'} v_t) \xrightarrow{d} \mathcal{N}(0, \Delta(\beta^*)). \quad (15)$$

The remainder of the asymptotic normality proof is then similar to the standard case: the positive definiteness of Σ_V^{-1} , and the consistency of $\hat{\Sigma}_V = T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t v_t'$, $\hat{\Sigma}_V \xrightarrow{p} \Sigma_V$, ensure that the expansion (14) is equivalent to $T^{1/2}(\hat{\beta} - \beta^*) = \hat{\Sigma}_V^{-1} T^{-1/2} \sum_{t=\tau}^{T+\tau-1} v_t(\hat{e}_{t+1} - \beta^{*'} v_t)$. We then use the limit result in (15) and Slutsky's theorem to show that

$$T^{1/2}(\hat{\beta} - \beta^*) \xrightarrow{d} \mathcal{N}(0, \Sigma_V^{-1} \cdot \Delta(\beta^*) \cdot \Sigma_V^{-1}),$$

which is what Proposition 2 states.

Hence, we need to show that conditions (i) and (ii) hold: For (i) it is sufficient to show that $\sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} - \sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}^* \xrightarrow{p} 0$. By the triangular inequality

$$\left| \sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} - \sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}^* \right| \leq \left| \sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} - \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*] \right| + \left| \sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}^* - \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*] \right|.$$

¹⁸Moreover, these results ensure that $\hat{h}_V - h_V \xrightarrow{p} 0$ and $\hat{\Sigma}_V - \Sigma_V \xrightarrow{p} 0$ where $\hat{h}_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t |\hat{e}_{t+1}|$ and $\hat{\Sigma}_V \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t v_t'$, which makes the estimation of the bias components straightforward.

Recall from the proof of Proposition 1 that $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} \xrightarrow{p} T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*]$ so the first term of the right-hand side of the previous inequality converges in probability to zero. Moreover, the LLN applied to the α -mixing sequence $\{e_{t+1}^* V_t'\}$ ensures that $T^{-1} \sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}^* \xrightarrow{p} T^{-1} \sum_{t=\tau}^{T+\tau-1} E[V_t e_{t+1}^*]$, given assumptions (A2) and (A4). Therefore, we conclude that $|\sum_{t=\tau}^{T+\tau-1} v_t \hat{e}_{t+1} - \sum_{t=\tau}^{T+\tau-1} v_t e_{t+1}^*| \xrightarrow{p} 0$, which implies that (i) holds.

We now show that (ii) holds as well, i.e. that $T^{-1/2} \sum_{t=1}^T v_t (e_{t+1}^* - \beta^{*'} v_t) \xrightarrow{d} N(0, \Delta(\beta^*))$ with $\Delta(\beta^*) = T^{-1} \sum_{t=1}^T E[(e_{t+1}^* - \beta^{*'} V_t)^2 \cdot V_t V_t']$. For that, we use a central limit theorem (CLT) for α -mixing sequences (e.g. Theorem 5.20 in White, 2001): first, note that, by construction, $E[V_t(e_{t+1}^* - \beta^{*'} V_t)] = 0$. For $r > 2$, the Cauchy-Schwartz inequality and assumption (A4) imply that

$$\begin{aligned} E[|V_t(e_{t+1}^* - \beta^{*'} V_t)|^r] &\leq (E[|V_t|^{2r}])^{1/2} \cdot (E[(e_{t+1}^* - \beta^{*'} V_t)^{2r}])^{1/2} \\ &\leq \max\{1, \Delta_V^{1/2}\} \cdot (E[n_r(|e_{t+1}^*|^{2r} + |\beta^{*'}|^{2r} |V_t|^{2r})])^{1/2} \\ &\leq \max\{1, \Delta_V^{1/2}\} \cdot \max\{1, n_r^{1/2}(E[|e_{t+1}^*|^{2r}] + |\beta^{*'}|^{2r} E[|V_t|^{2r}])^{1/2}\}, \end{aligned}$$

where $n_r \in \mathbb{R}_*^+$ is a constant, $n_r < \infty$, such that $E[(\hat{e}_{t+1} - \beta^{*'} V_t)^{2r}] \leq E[n_r(|e_{t+1}^*|^{2r} + |\beta^{*'} V_t|^{2r})]$. Knowing that $E[|e_{t+1}^*|^{2r}] = E[(Y_{t+1} - f_{t+1}^*)^{2r}] \leq n_r(E[|Y_{t+1}|^{2r}] + E[|f_{t+1}^*|^{2r}]) \leq n_r(\Delta_Y + C^{2r})$, we get

$$E[|V_t(e_{t+1}^* - \beta^{*'} V_t)|^r] \leq \max\{1, \Delta_V^{1/2}\} \cdot \max\{1, n_r^{1/2}(n_r(\Delta_Y + C^{2r}) + |\beta^{*'}|^{2r} \Delta_V)^{1/2}\} < \infty,$$

by assumptions (A1) (β^* is an element of a compact set) and (A2) (boundedness of $|f_{t+1}|$). Assumption (A3) moreover ensures that the matrix $\Delta(\beta^*)$ is positive definite, so that the CLT implies $T^{-1/2} \sum_{t=1}^T v_t (e_{t+1}^* - \beta^{*'} v_t) \xrightarrow{d} N(0, \Delta(\beta^*))$. This shows that (ii) holds.

The reasoning we described at the beginning of the proof then gives $\sqrt{T}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, \Omega^*)$ with $\Omega^* \equiv \Sigma_V^{-1} \Delta(\beta^*) \Sigma_V^{-1}$. Now note that

$$\begin{aligned} \Delta(\beta^*) &= E[(e_{t+1}^* - \beta^{*'} V_t)^2 \cdot V_t V_t'] \\ &= E[\varepsilon_{t+1}^2 \cdot V_t V_t'], \end{aligned}$$

where $\varepsilon_{t+1} \equiv u_{t+1} + (1 - 2\alpha_0)|e_{t+1}^*|$ and u_{t+1} is the realization of the error term U_{t+1} in the generalized Mincer-Zarnowitz (1969) regression (9). Hence,

$$\Delta(\beta^*) = E[u_{t+1}^2 \cdot V_t V_t'] + 2(1 - 2\alpha_0)E[u_{t+1} \cdot |e_{t+1}^*| \cdot V_t V_t'] + (1 - 2\alpha_0)^2 E[|e_{t+1}^*|^2 \cdot V_t V_t'].$$

Moreover, the results above ensure that $\Delta(\beta^*)$ can be consistently estimated by $\hat{\Delta}(\hat{\beta}) \equiv T^{-1} \sum_{t=\tau}^{T+\tau-1} (\hat{e}_{t+1} - \hat{\beta}' v_t)^2 v_t v_t'$. Using that Σ_V^{-1} is positive definite, we can then show that $\hat{\Omega} \equiv \hat{\Sigma}_V^{-1} \hat{\Delta}(\hat{\beta}) \hat{\Sigma}_V^{-1}$ is a consistent estimator of the asymptotic covariance matrix of the standard OLS estimator $\hat{\beta}$, i.e. $\hat{\Sigma}_V^{-1} \hat{\Delta}(\hat{\beta}) \hat{\Sigma}_V^{-1} = \hat{\Omega} \xrightarrow{p} \Omega^* = \Sigma_V^{-1} \Delta(\beta^*) \Sigma_V^{-1}$. ■

Proof of Corollary 3. Let $\beta = bT^{-1/2}$ and $1 - 2\alpha_0 = aT^{-1/2}$ where a and b are fixed.

We can write

$$\begin{aligned} T\hat{\beta}' \cdot \hat{\Omega}^{-1} \cdot \hat{\beta} &= T^{1/2}(\hat{\beta} - \beta^*)' \cdot \hat{\Omega}^{-1} \cdot T^{1/2}(\hat{\beta} - \beta^*) \\ &\quad + T^{1/2}\beta^{*'} \cdot \hat{\Omega}^{-1} \cdot T^{1/2}\beta^* \\ &\quad + 2T^{1/2}\beta^{*'} \cdot \hat{\Omega}^{-1} \cdot T^{1/2}(\hat{\beta} - \beta^*). \end{aligned}$$

>From Proposition 2 it follows that the first term is asymptotically χ_d^2 distributed. For the second term, recall from Proposition 1 that $\beta^* = \beta + (1 - 2\alpha_0)\Sigma_V^{-1}h_V$ so $T^{1/2}\beta^* = (b + a\Sigma_V^{-1}h_V)$ and, moreover, $\hat{\Omega} \xrightarrow{p} \Omega^* = \Sigma_V^{-1}\Delta(\beta^*)\Sigma_V^{-1}$ with Ω^* nonsingular. We then have $T\beta^{*'}\hat{\Omega}^{-1}\beta^* \xrightarrow{p} m$ with

$$\begin{aligned} m &= (b + a\Sigma_V^{-1}h_V)'(\Sigma_V^{-1}\Delta(\beta^*)\Sigma_V^{-1})^{-1}(b + a\Sigma_V^{-1}h_V) \\ &= b'\Sigma_V\Delta(\beta^*)^{-1}\Sigma_V + 2ab'\Sigma_V\Delta(\beta^*)^{-1}h_V + a^2h_V'\Delta(\beta^*)^{-1}h_V. \end{aligned}$$

For the third term, application of Proposition 2 and Slutsky's theorem gives, $\hat{\Omega}^{-1/2} \cdot T^{1/2}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, I)$. Hence, $T\beta^{*'}\hat{\Omega}^{-1}(\hat{\beta} - \beta^*) \xrightarrow{d} N(0, s)$ where

$$\begin{aligned} s &= (b + a\Sigma_V^{-1}h_V)'\Omega^{*-1}(b + a\Sigma_V^{-1}h_V) \\ &= m. \end{aligned}$$

Therefore, $T\hat{\beta}'\hat{\Omega}^{-1}\hat{\beta} \xrightarrow{d} \chi_d^2 + m + N(0, m)$. Points (i) and (ii) follow from the discussion after the Corollary. ■

Figure 1

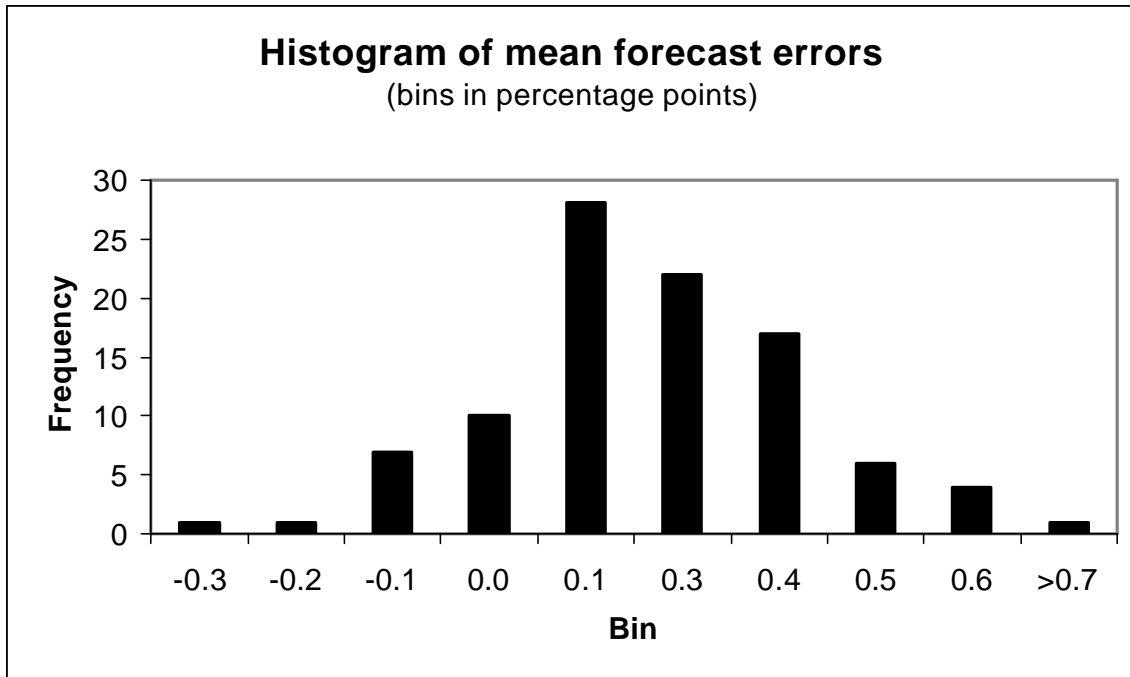


Figure 2

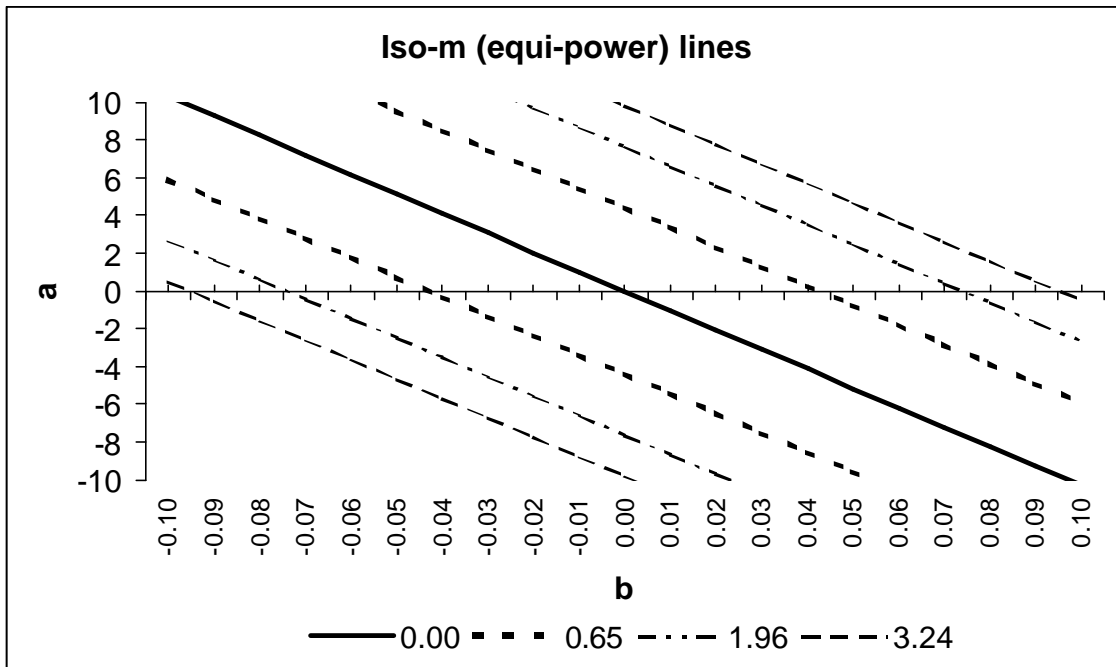


Figure 3

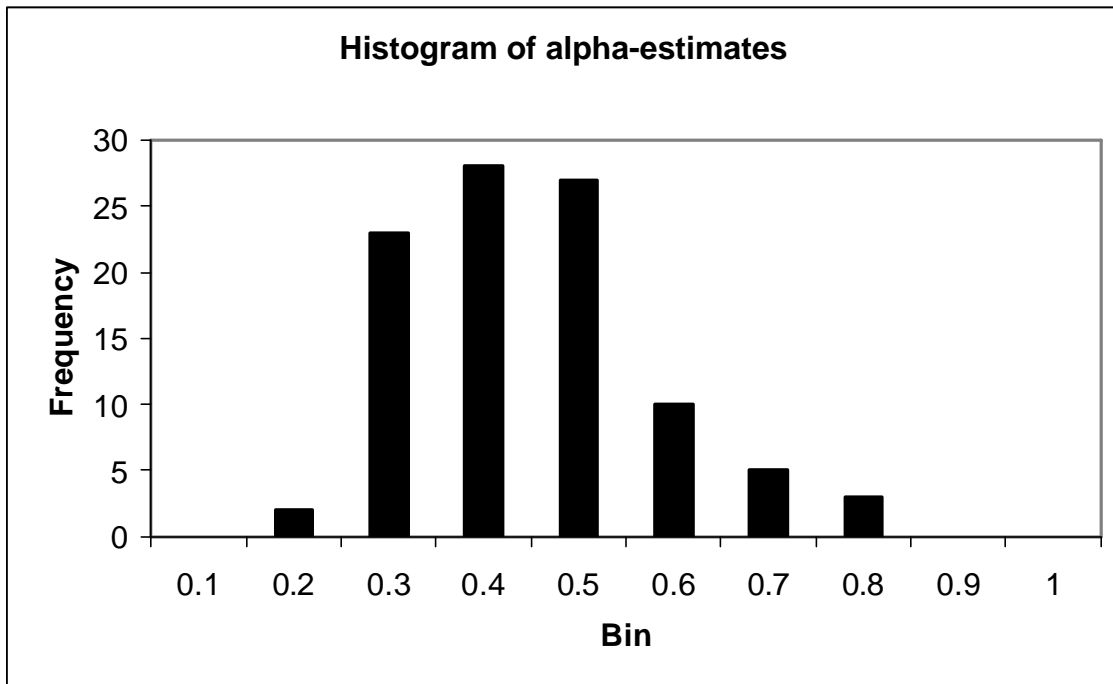


Figure 4

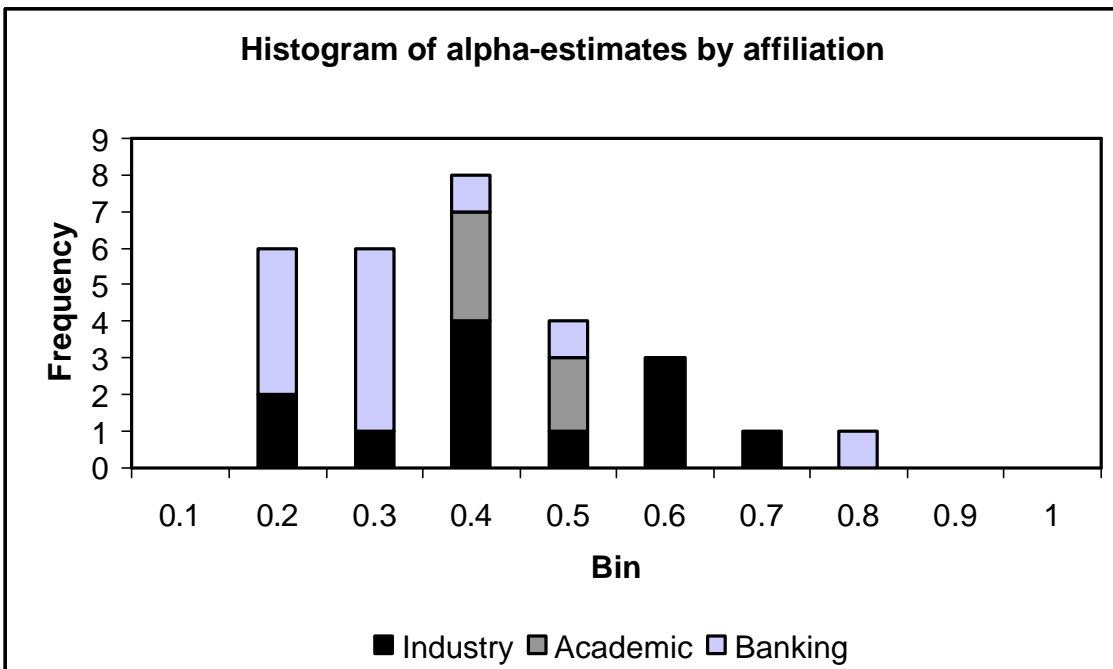


Table 1: Tests for bias under MSE loss

P-value	Quad-quad
<1%	16
<5%	29
<10%	33

Note: this table reports the number of forecasters (out of a total of 98) for whom the null of symmetric loss ($\alpha = 1/2$) could be rejected at the specified critical values.

Table 2: J-tests of rationality and symmetry of the loss function (quad-quad)

Range	Rationality and $\alpha = 1/2$			Rationality and α unconstrained		
	<1%	<5%	<10%	<1%	<5%	<10%
Inst=1	13	34	39	1	8	19
Inst=2	15	30	33	0	4	12
Inst=3	20	34	42	0	4	11
Inst=4	12	30	35	0	5	10

Note: this table reports the range for p-values up to 0.10 in J-tests of rationality and symmetry and of rationality only. The instruments are as follows:

Inst =1: constant plus lagged errors

Inst =2: constant plus lagged actual values

Inst =3: constant plus lagged errors and actual values

Inst =4: constant plus absolute lagged errors