Decomposing analyst boldness

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Abstract

This paper examines behavioural characteristics of analysts that produce earnings forecasts for UK-listed companies. The primary means of achieving this is by classifying analysts into two different types, viz., those who make use of their own private information endowment, and those who choose to ignore their private information endowment. The former group of analysts are assumed to be able to generate forecasts based on the underlying dynamics of earnings, while all other analysts are assumed to issue forecasts based on the prevailing consensus forecast. Given this framework, we are able to derive (and estimate) an econometric model of forecast boldness (as defined by Clement and Tse, 2005), which has implications regarding the determinants of analysts’ private information endowments and forecast accuracy over the forecast horizon. Specifically, using IBES Detail History files, results indicate that brokerage size, experience, past performance, and the length of the forecast horizon, are all significant determinants of analysts’ boldness, private information endowments, and forecast accuracy.

Key Words: Earnings forecasts, analysts, boldness, herding.

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1 Introduction

While herding appears to be a common feature of financial markets, some debate remains as to the extent of such behaviour.1 This debate is fuelled, in part, by the presence of genuine anti-herding behaviour in certain situations; see Levy (2004) for theoretical motivation for such behaviour. However, as herding behaviour is difficult to observe directly (and, indeed, to define concisely, Devenow and Welch, 1996), conflicting results within the literature may also be due to the vast array of herding measures available to investigators. The financial analyst forecasting literature is particularly sensitive to the second of these effects as direct observation of herding behaviour is impossible within this environment. It is to this particular debate that this paper contributes. Specifically, under a fairly general definition of (rational) herding, we decompose a commonly-used measure of analyst behaviour and demonstrate that, contrary to recent findings, the majority of analysts tend to herd.2

Analyst behaviour within the earnings forecasting literature is commonly examined by considering the proximity (and direction) of earnings forecasts with respect to the prevailing consensus forecast; see, e.g., Hong, Kubik, and Solomon (2000), and Clement and Tse (2005). Consistent with the theoretical predictions of Scharfstein and Stein (1990), and Trueman (1994), analysts that move their forecasts away from the consensus forecast (referred to as bold forecasts) are defined as anti-herders, while all other analyst activity is consistent with herding behaviour. Use of such measures often leads to the finding that bold forecasts are the modal forecast category, and hence that anti-herding is the dominant behavioural characteristic (Zitzewitz, 2001; Chen and Jiang, 2006; Bernhardt, Campello, and Kutsoati, 2006; and Naaujoks et al, 2007). However, under a set of fairly general assumptions, we demonstrate that, while bold forecasts are more likely to be produced by anti-herders, the noisiness of a typical boldness measure is such that bold forecasts can also be produced by herders. Consequently, the extent to which analysts anti-herd may have been exaggerated.

All boldness measures are motivated by the fact that anti-herding (herding) is defined as an alteration in the forecast away from (toward) the consensus forecast, and toward (away from) the analyst’s posterior belief (as dictated by their private information endowment); see, e.g., Clement and Tse (2005), Bernhardt, Campello, and Kutsoati (2006), Chen and Jiang (2006), Clarke and Subramanian (2006), and Krishnan, Lim, and Zhou (2007). However, as the posterior belief cannot be observed it must be estimated. For example, Clement and Tse (2005) assume it is given by the analyst’s previous forecast, while Krishnan, Lim, and Zhou (2007) use a statistical technique to estimate its magnitude. Irrespective of the approach taken, the boldness measure will always contain a noise component that drives

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1 See Devenow and Welch (1996), Sharma and Bikhchandani (2001), and Hirshleifer and Teoh (2003), for reviews of the theoretical and empirical issues associated with such behaviour. Also, see the following papers for specific evidence of herding behaviour amongst a variety of market participants: financial analysts (see, e.g., Stickel, 1990; Olsen, 1996; Cote and Sanders, 1997; De Bondt and Forbes, 1999; Desai, Liang, and Singh, 2000; Hong, Kubik, and Solomon, 2000; Welch, 2000; Krishnan, Lim, and Zhou, 2007; and Jagadeesh and Kim, 2008); mutual fund managers (see, e.g., Grinblatt, Titman, and Wermers, 1995; Wermers, 1999; Nofsinger and Sias, 1999; Borzenstein and Gelos, 2000; Dennis and Strickland, 2002; Lobao and Serra, 2002; Wylie, 2005; Walter and Weber, 2006; and Dass, Massa, and Putgiri, 2008); company managers (see, e.g., Bouwman, Fuller, and Nain, 2008); individual investors (see, e.g., Ivković and Weisbenner, 2007; and Barber, Odean, and Zhu, 2008); institutions investors (see, e.g., Sias, 2004); foreign investors (see, e.g., Choe, Kho, and Stulz, 1999; Chang, Cheng, and Khorana, 2000; Lobao and Serra, 2002; Oehler and Chao, 2002; and Kim and Wei, 2002); speculators (see, e.g., Golec, 1997; and DeMarzo, Kaniel, and Kremer, 2007); investment newsletters (see, e.g., Graham, 1999); banks (see, e.g., Ragan, 1994; and Luengnaruemitchai and Wilcox, 2004); and venture capitalists (see, e.g., Goldfarb, Kirsch, and Miller, 2007).

2 See Devenow and Welch (1996) for a detailed discussion of the differences between rational and irrational herding behaviour.
a wedge between observing a bold forecast and concluding that an analyst anti-herds. Such reasoning motivates the decomposition considered in this paper; specifically, boldness is broken down into two components: boldness due to anti-herding behaviour and boldness due to herding behaviour, with the weights attached to each giving a probability measure of anti-herding and herding, respectively.

The decomposition of analyst boldness considered in this paper assumes that analysts differ fundamentally with respect to their private information endowments. Specifically, in the spirit of the reputational principal-agent models of Scharfstein and Stein (1990), and Trueman (1994), we polarise analysts into two groups/types; viz., those that make use of their private information endowments, and those that find it beneficial to ignore their endowments and issue forecasts close to the prevailing consensus forecast (subject to a heterogeneous observational error). The latter category of analysts are defined as rational herders. This definition is consistent with the information cascade models of Bikhchandani, Hirshleifer, and Welch (1992), and Welch (1992), where economic agents with small private information endowments imitate the actions of superior agents (as revealed by the consensus forecast), as they cannot directly observe the private information endowments of the superior agents. It is within this framework that we decompose Clement and Tse’s (2005) measure of forecast boldness, and show that the observed levels of boldness are consistent with low usage of private information endowments, that is, infrequent anti-herding behaviour.

Another novel aspect of the approach adopted in this paper is that a structural econometric model of boldness is derived that allows the likelihood of the analyst type (i.e. herding or anti-herding) to be determined by a set of analyst-specific variables, and allows the behaviour of each type of analyst to non-linearly vary over the forecast horizon. This is achieved by making an explicit assumption regarding the mechanism by which private information endowments are used to produce forecasts, and by allowing the precision of this endowment to non-linearly vary over the forecast horizon. The latter variation is primarily motivated by the periodic reporting requirements of companies within the sample considered. As the precision of analysts’ private information endowments are likely to change in a predictable way with the provision of periodic company-specific information over the forecast horizon, we conjecture that observed analyst behaviour will also vary over this space. The results of this estimation process confirm this prediction, and also provide interesting explanations for the observed variation in analyst behaviour across the analyst-specific variables.

This paper also contains a number of predictions regarding the relative accuracy of forecasts produced by analysts that make use of their private information endowments, and those that do not. Moreover, combining these results with the previous results regarding the relationship between observed boldness and private information endowments usage, leads to a number of additional predictions regarding the relationship between forecast accuracy and boldness over the investment horizon. These predictions are then tested and examined with respect to previous literature on the determinants of forecast accuracy (see Ramnath, Rock, and Shane, 2008, for an extensive taxonomy of this literature). In doing this, we find that

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3See Brunnermeier (2001) for an overview of the theoretical herding models that have been proposed in the literature.

4Forecast accuracy has been the traditional method by which financial analyst quality has been measured; see, e.g., Hong, Kubik and Solomon (2000), and Hong and Kubik (2003), for empirical evidence regarding the relationship between forecast accuracy and (un)employment risk. However, recent studies have demonstrated that forecast boldness is recognised by the market (in varying degrees) as a desirable analyst attribute; cf. Huang, Willis, and Zang, (2005), Kadous, Mercer, and Thayer (2007), and Chiang, Lin, and Yu (2008). Indeed, the commercially-based analyst ratings provided by Starmine Professional require that forecasts be accurate and ‘bold’ (i.e., significantly different from the mean forecast), in order to achieve a high rating.
relative accuracy is greatest around the release of periodic company-specific information – a result that is consistent with more precise private information endowments around such releases. Moreover, we find that, contrary to previous findings (see, e.g., Clement and Tse, 2005), increased boldness leads to less accurate forecasts, while increased use of private information endowments gives rise to more accurate forecasts. This particular evidence implies that boldness changes that are not related to private information usage have a detrimental impact on forecast accuracy.

The above analysis is carried out using analyst forecast data pertaining to the earnings of UK-listed companies. There are two reasons for this particular choice of data. First, despite similarities over a number of dimensions (Moyes et al, 2001), the behaviour of UK analysts has been relatively less researched than their US counterparts. This is somewhat surprising given the growing importance of overseas markets (and their respective ‘local analysts’) to US institutional and individual investors (Coyles, 1995), and the significance of UK financial markets in the wider global economy. Second, unlike the data pertaining to US-listed companies, analysts of UK-listed companies tend to issue annual, rather than quarterly, earnings forecasts. This difference is ultimately due to the different accounting disclosure practices that exist in these two economies (Frost and Pownall, 1994). Most notably, in addition to annual reports, the Securities and Exchange Commission (SEC) require, inter alia, that US-listed companies submit Form 10-Q quarterly interim reports, while the Financial Services Authority (FSA) in the UK only required half-yearly interim reports. Consequently, analysts of UK-listed companies have tended to focus exclusively on annual earnings forecasts, while their US counterparts have focused on both quarterly and annual earnings forecasts. In the context of the current paper, this gives rise to a natural experiment: an examination of the relationship between periodic accounting information releases and variation in private information endowment precision over a relatively long forecast horizon. While such an investigation is possible using US analysts’ annual forecasts, the complexity of exploration would be compounded by the increased number of accounting information releases (and variation in reporting lags over different companies thereof) for each company during each year. By contrast, the investigation is much cleaner when UK data are used as analysts’ annual forecasts for each company should only be significantly affected by the release of a single burst of accounting information (as contained in the half-yearly interim report) during the forecast horizon.

The rest of the paper is organised as follows. The next section contains details of the proposed decomposition of analyst boldness, and is followed by a description of the empirical models of boldness and forecast accuracy as implied by this decomposition. Sections 4 and 5 contain details of the data used and the empirical analysis, respectively; while the final section concludes. Proofs of all propositions are provided in an appendix.

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6For instance, in 2006, 98.2% of forecasts issued for UK-listed companies had annual forecast horizons. By contrast, 39% of forecasts issued for US-listed companies were annual in nature (Source: IBES Detail History files).

7During the earlier part of the period covered by the data used in this paper, it was the International Stock Exchange of the United Kingdom and the Republic of Ireland, Ltd. (ISE), and then the London Stock Exchange (LSE) that was responsible for the periodic reporting practices of UK-listed companies.
2 The decomposition

This section is divided into four subsections. The first two subsections contain details of the assumed earnings equation employed by analysts that make use of their private information endowments, and the optimal forecasts of analysts based on this equation and the optimal forecasts of all other analysts, respectively. The third subsection contains a number of results pertaining to the ‘decomposed boldness’ of these forecasts, while the fourth subsection contains predictions regarding the relative accuracy of the two types of analysts considered in this paper.

2.1 Earnings dynamics

Assuming that earnings are released every \( h \) periods, abnormal earnings can be defined as follows:

\[
y_{t}^{a} = y_{t} - (R_f - 1)v_{t-h},
\]

where \( y_{t}^{a} \) is the abnormal earnings to the company over the time period \([t-h,t]\); \( y_{t} \) is the earnings to the company over the time period \([t-h,t]\); \( v_{t} \) is the (net) book value of the company at time \( t \); \( R_f \) is one plus the risk-free rate; and \( t = \{h, 2h, \ldots, T\} \) with \( h \in \mathbb{N} \). Furthermore, in the spirit of the residual income valuation model proposed by Ohlson (1995) (see also Ohlson and Zhang, 1999), we assume that the dynamics of abnormal earnings are given by

\[
y_{t+h}^{a} = \omega y_{t}^{a} + z_{t+h} + \epsilon_{t+h},
\]

\[
z_{t+h} = \gamma^{*} z_{t} + \eta_{t+h}^{*},
\]

where \( z_{t} \) is a measure of the ‘idiosyncratic information’ associated with abnormal earnings to the company at time \( t \); \( \epsilon_{t} \sim \text{IN}(0,\sigma^{2}) \); \( \eta_{t}^{*} \sim \text{IN}(0,a^{*}) \); and \( 0 \leq \omega < 1 \), and \( 0 \leq \gamma^{*} < 1 \).

We wish to consider the evolution of forecasts of next period abnormal earnings between each earnings announcement. To do this, we consider the \( s \) time periods between each earnings announcement, where \( s = \{1, 2, \ldots, h\} \) and \( h \) is fixed. Moreover, we assume that only idiosyncratic information is permitted to change in this dimension, with the error term in (2a) only revealed on the announcement date (i.e., at time \( t+h \)). Adopting this notation, we can rewrite (2b) as the following first-order autoregressive (AR(1)) process:

\[
z_{t+s} = \gamma z_{t+s-1} + \eta_{t+s},
\]

where \( 0 \leq \gamma \leq 1 \); the parameters, \( \gamma^{*} \) and \( \gamma \), and the error terms, \( \eta_{t}^{*} \) and \( \eta_{t} \), are related by the expressions

\[
\gamma^{*} = \gamma^{h}, \quad \eta_{t}^{*} = \sum_{\ell=0}^{h-1} \gamma^{\ell} \eta_{t-\ell};
\]

and \( \eta_{t} \sim \text{IN}(0,a) \). See Silvestrini and Veredas (2008) for a survey of issues pertaining to temporal aggregation of time series data. Furthermore, as we focus exclusively on the time period between earnings announcements, we can (without loss of generality) economise on the notational burden by suppressing the \( t \) notation in the subsequent analysis.
2.2 Earnings forecasts

Following Trueman (1994), Chen and Jiang (2006), and Clarke and Subramanian (2006), we assume that the \(i\)th analyst observes a disrupted idiosyncratic information signal. Consequently, taking conditional expectations of \(y_h\), and using (1) and (3), his or her forecast is given by

\[
F_{i,s}^{(1)} = E(y_h|\mathcal{F}_{i,s}, \kappa_i = 1) = (R_f - 1)v_0 + \omega y_0^a + \gamma^{h-s}(z_s + \nu_{i,s}),
\]

(4)

where \(\mathcal{F}_s\) is the information set available at time \(s\); \(v_0\) is the existing (net) book value of the stock; \(y_0^a\) is the existing level of abnormal earnings; \(\kappa_i\) represents the analyst type; \(\eta_s\) represents the error term in (3) with the \(t\) notation suppressed; \(\nu_{i,s} \sim \text{IN}(0, b_s)\), with \(\text{cov}(\eta_{i,s}, \nu_{i,s}) = 0\); \(i = \{1, 2, \ldots, M\}\); and with forecast revisions given by

\[
\Delta F_{i,s}^{(1)} = F_{i,s}^{(1)} - F_{i,s-1}^{(1)} = \gamma^{h-s} \eta_s + \gamma^{h-s} \nu_{i,s} - \gamma^{h-(s-1)} \nu_{i,s-1}.
\]

(5)

Henceforth, analysts that produce forecasts given by (4) are referred to as type-1 analysts. The absolute size of the error term \(\nu_{i,s}\) in (4) (and (5)) is assumed to be inversely related to analysts’ private information endowment. For instance, if the \(i\)th analyst has a high private information endowment at time \(s\), then \(\nu_{i,s}\) will be small (in absolute terms) and hence the forecast will be relatively accurate. Furthermore, we assume that type-1 analysts are homogeneous with respect to the expected private information endowment (as measured by \(b_s\)), but this endowment is allowed to vary in a systematic fashion over the forecast horizon.

In contrast to the above analysts, we also assume the presence of analysts who do not make use of their private information endowment (either because they do not have explicit knowledge of the process followed by abnormal earnings, have private information endowments that are sufficiently low to make knowledge of the process irrelevant, have private information endowments that contradict existing public information, or have no confidence in their private information endowments) – henceforth referred to as type-2 analysts. Such analysts issue forecasts that equal the lagged consensus forecast plus an error term that is specific to the \(i\)th type-2 analyst, that is,

\[
F_{i,s}^{(2)} = E(y_h|\mathcal{F}_{i,s}, \kappa_i = 2) = C_{s-1} + \zeta_{i,s},
\]

(6)

where the consensus forecast is given by the average of all type-1 forecasts made at time \(s - 1\), that is,

\[
C_{s-1} = E(F_{i,s-1}^{(1)}) = (R_f - 1)v_0 + \omega y_0^a + \gamma^{h-(s-1)} z_{s-1};
\]

(7)

\(\zeta_{i,s} \sim \text{IN}(0, c)\), with \(\text{cov}(\eta_{s-1}, \zeta_{i,s}) = 0\); with forecast revisions given by

\[
\Delta F_{i,s}^{(2)} = \Delta C_{s-1} + \Delta \zeta_{i,s} = \gamma^{h-(s-1)} \eta_{s-1} + \Delta \zeta_{i,s}.
\]

(8)

The presence of the error term \(\zeta_{i,s}\) in (6) (and (8)) allows for the fact that \(C_{s-1}\) is not directly observed (as it is based on unobservable type-1 forecasts); see Chen and Jiang (2006), and Clarke and Subramanian (2006), for similar assumptions in their models of forecast boldness.\(^8\)

\(^8\)By assuming that some analysts do not make use of their private information endowments and issue forecasts close to the consensus forecast, we are implicitly assuming that these analysts bias their own private information endowments. Such an assumption is used in many theoretical studies of analyst herding; see Trueman (1994) for a seminal example.
2.3 Analyst boldness

Forecasts within the above framework can be classified according to whether they are bold or non-bold. Specifically, following Clement and Tse (2005), these categories can be defined as follows:

\[
\text{Bold}_{i,s} = \begin{cases} 
1, & \text{if } (F^{(\kappa_i)}_{i,s} > C_{s-1} \text{ and } \Delta F^{(\kappa_i)}_{i,s} > 0) \text{ or } (F^{(\kappa_i)}_{i,s} < C_{s-1} \text{ and } \Delta F^{(\kappa_i)}_{i,s} < 0), \\
0, & \text{otherwise},
\end{cases}
\]

where \( \text{Bold}_{i,s} = 1 \) indicates that the forecast of the \( i \)th analyst at time \( s \) is bold. Use of this definition of boldness, and the assumptions contained in the previous subsections, lead to the following proposition.

**Proposition 1.** The conditional probability that an analyst of a particular type issues a bold forecast (henceforth the type-1 and type-2 boldness probability) is given by

\[
\Pr(\text{Bold}_{i,s} = 1 | \kappa_i = r) = \frac{\pi + 2 \arctan \left( \frac{\theta_{r,s}}{2\pi} \right)}{2\pi}, \quad \text{for } r = \{1, 2\},
\]

with bounds

\[
\frac{3}{4} < \Pr(\text{Bold}_{i,s} = 1 | \kappa_i = 1) < 1, \quad \text{and} \quad \frac{1}{2} < \Pr(\text{Bold}_{i,s} = 1 | \kappa_i = 2) < \frac{3}{4},
\]

where

\[
\theta_{1,s} = \frac{1}{\gamma} \sqrt{\frac{a + b_s}{b_s}}; \quad \theta_{2,s} = \sqrt{\frac{c}{a \gamma^2 (h-\gamma) + c}};
\]

and all previous notation is maintained.

**Proof.** See Appendix.

Given the expressions in Proposition 1, it is possible to decompose the unconditional probability of observing a bold forecast as follows:

\[
\Pr(\text{Bold}_{i,s} = 1) = \Pr(\kappa_i = 1) \Pr(\text{Bold}_{i,s} = 1 | \kappa_i = 1) + \Pr(\kappa_i = 2) \Pr(\text{Bold}_{i,s} = 1 | \kappa_i = 2),
\]

\[
= P \left( \frac{\pi + 2 \arctan (\theta_{1,s})}{2\pi} \right) + (1 - P) \left( \frac{\pi + 2 \arctan (\theta_{2,s})}{2\pi} \right),
\]

where \( P = \Pr(\kappa_i = 1) \) represents the proportion of type-1 analysts to type-2 analysts (henceforth the type-1 probability), which is invariant to the forecast horizon; \( \theta_{1,s} > 1 \ \forall \ s; \) and \( 0 < \theta_{2,s} < 1 \ \forall \ s. \) Furthermore, the bounds in the above proposition imply that while type-1 analysts are highly likely to produce bold forecasts, such forecasts can also be produced by

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\(^9\)If we assume that \( \gamma \) equals unity, then \( \theta_{1,s} \) and \( \theta_{2,s} \) simplify to

\[
\theta_{1,s} = \sqrt{\frac{a + b_s}{b_s}}; \quad \theta_{2} = \sqrt{\frac{c}{a + c}};
\]

where \( \theta_{1,s} > 1 \ \forall \ s; \) and \( 0 < \theta_{2} < 1 \ \forall \ s. \) See Dechow, Hutton, and Sloan (1999) for a discussion of the theoretical implications of setting \( \gamma \) to unity (and other values) within the context of Ohlson’s residual income valuation model; and Gil-Alana and Peláez (2008) for empirical evidence regarding the time-series dynamics of earnings.

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type-2 analysts. Thus, evidence of boldness does not necessarily imply the majority presence of analysts who make use of their private information endowments (i.e., anti-herding behaviour).

2.4 Analyst Accuracy

Based on the above definitions, it is possible to assess the relative accuracy of type-1 and type-2 analysts. Specifically, the following proposition describes this accuracy in terms of the mean squared forecast error (MSFE) associated with each type of analyst.

**Proposition 2.** The MSFE associated with the forecasts of an analyst of a particular type is given by

\[
E(e^2_{i,s} | \kappa_i = r) = \Theta_{r,s} + \sigma^2, \quad \text{for } s < h, \text{ and } r = \{1, 2\},
\]

where

\[
\Theta_{1,s} = a \left( \frac{1 - \gamma^2(h-s)}{1 - \gamma^2} \right) + b_s \gamma^2(h-s); \quad \Theta_{2,s} = a \left( \frac{1 - \gamma^2(h-(s-1))}{1 - \gamma^2} \right) + c;
\]

the forecast error of the \(i\)th analyst at time \(s\) (with horizon \(h\)) is defined as follows: \(e_{i,s} = y_h - F_{i,s}\); and all previous notation is maintained.

**Proof.** See Appendix.

This proposition provides predictions regarding the behaviour of forecast accuracy over the forecast horizon. Specifically, if we assume that \(b_s\) is constant over the forecast horizon (and is given by \(b\)) then

\[
\frac{\partial E(e^2_{i,s} | \kappa_i = 1)}{\partial (h-s)} = \frac{\partial \Theta_{1,s}}{\partial (h-s)} = \frac{2(a + b(\gamma^2 - 1))\gamma^2(h-s) \log \gamma}{\gamma^2 - 1}.
\]

(10)

Given the assumptions concerning the signs (and ranges) of the parameters in (10), this expression is of indeterminate sign. However, as \(\gamma\) is likely to be close to unity (and hence \(a + b(\gamma^2 - 1)\) is likely to be positive), the expression should be positive, thus accuracy is likely to increase as one shortens the forecast horizon.\(^{10}\) Regarding the accuracy of forecasts produced by type-2 analysts the results are more clear cut. Specifically, we have

\[
\frac{\partial E(e^2_{i,s} | \kappa_i = 2)}{\partial (h-s)} = \frac{\partial \Theta_{2,s}}{\partial (h-s)} = \frac{2a\gamma^2(h-s-1) \log \gamma}{\gamma^2 - 1} > 0.
\]

(11)

Thus demonstrating that forecast accuracy monotonically decreases with horizon length in this instance.

The result in Proposition 2 can also be used to deliver an expression for the relative accuracy of the analysts. This expression is given in the following proposition.

\(^{10}\)Note that we have imposed the restriction that \(b_s\) is horizon-invariant. Relaxing this assumption permits more complex relations between forecast accuracy and the horizon length. Indeed, there is ample empirical evidence that suggests that the relationship between forecast accuracy and the horizon length is complex. For example, Richardson, Toh, and Wysocki (2004) argue that analysts ‘walk down’ their forecasts over the forecast horizon, with optimistic forecasts being issued over long horizons and pessimistic forecasts being issued close to the reporting date – behaviour that implies a U-shaped relationship between forecast accuracy and the horizon length.
Proposition 3. The difference in the MSFE values associated with forecasts made by type-1 and type-2 analysts is given by

\[ E(e_{i,s}^2 | \kappa_i = 1) - E(e_{i,s}^2 | \kappa_i = 2) = (b_s - a)\gamma^{2(h-s)} - c, \quad \text{for } s < h, \]

where all previous notation is maintained.

Proof. The result follows from Proposition 2. \(\square\)

Examining Proposition 3, it is noticeable that the relative accuracy of analysts is determined by two different effects. The first, which we refer to as the lag effect is given by 

\[ -a\gamma^{2(h-s)}. \]

As this term is non-positive under the assumption that \(0 \leq \gamma \leq 1\), it implies that as type-2 analysts use lagged consensus forecasts then they are disadvantaged with respect to type-1 analysts. However, if we assume that \(0 \leq \gamma < 1\) then

\[ \lim_{h-s \to \infty} -a\gamma^{2(h-s)} = 0, \tag{12} \]

implying that the lag effect (and hence the type-2 disadvantage) disappears over long forecast horizons.

While the direction of the lag effect is unambiguous, the sign of the second effect (referred to as the noise effect and given by \(b_s\gamma^{2(h-s)} - c\)) depends on the relative magnitudes of the noise parameters, \(b_s\) and \(c\), in conjunction with the persistence parameter, \(\gamma\), and the forecast horizon, \(h-s\). However, if we assume that \(0 \leq \gamma < 1\), then

\[ \lim_{h-s \to \infty} (b_s\gamma^{2(h-s)} - c) = -c. \tag{13} \]

Thus, for long forecast horizons, the noise effect is negative, and acts in the same direction as the weak lag effect (see (12)) - a result that implies that type-2 analysts are more likely to produce less accurate forecasts particularly over long forecast horizons. By contrast, for short forecast horizons, the lag effect is relatively strong (and negative), while the noise effect is ambiguous - a result that does not preclude the possibility that type-2 forecasts could be more accurate than type-1 forecasts. Finally, if we assume that \(\gamma\) equals unity, then the relative accuracy is simply given by \((b_s - a) - c\), with no unambiguous a priori predictions about relative accuracy possible.

3 Empirical Models

This section contains (respectively) the details of the empirical model of boldness as implied by Proposition 1, and the model used to investigate the determinants of analyst accuracy using Proposition 2 as motivation.

3.1 Forecast boldness

The likelihood function for an independent sample of forecast boldness is given by

\[ L = \prod_{j=1}^{N} (\Pr(\text{Bold}_j = 1))^{\text{Bold}_j} (1 - \Pr(\text{Bold}_j = 1))^{1-\text{Bold}_j}, \tag{14} \]
where $j = \{1, 2, \ldots, N\}$. Taking logs of (14) we obtain

$$
\log L = \sum_{j=1}^{N} \left( \text{Bold}_j \log (\Pr(\text{Bold}_j = 1)) + (1 - \text{Bold}_j) \log (1 - \Pr(\text{Bold}_j = 1)) \right). \tag{15}
$$

To enable estimation of the above model, we assume that $\Pr(\text{Bold}_j = 1)$ is given by an augmented version of (9); specifically, we assume that this probability is given by

$$
\Pr(\text{Bold}_j = 1) = \beta_{0,j(i)} \left( \pi + 2 \arctan (\beta_{1,j}) \right) + (1 - \beta_{0,j(i)}) \left( \pi + 2 \arctan (\beta_{2,j}) \right), \tag{16}
$$

where $\beta_{0,j(i)}$ (the parameter that measures the type-1 probability) is assumed to be a function of a set of $i$th-specific explanatory variables,

$$
\beta_{0,j(i)} = F(\alpha_0 + \alpha_1 X_{1,j(i)} + \ldots + \alpha_q X_{q,j(i)}), \tag{17a}
$$

such that it takes values between zero and unity (inclusive); $\{X_{1,j(i)}, \ldots, X_{q,j(i)}\}$ is a set of analyst-specific explanatory variables; $\beta_{1,j}$ (the parameter that determines the type-1 boldness probability) is given by the following piecewise cubic polynomial (spline) that depends exclusively on the $j$th-specific forecast horizon:

$$
\beta_{1,j} = G \left( \sum_{l=0}^{3} \delta_{1,0,l} (h_j - s_j)^l + \sum_{k=0}^{K} \sum_{l=0}^{3} \delta_{1,k,l} ((h_j - s_j) - t_j(k))^l, \right) + \frac{(h_j - s_j) - t_j(k)}{1 + \frac{1}{\pi} \arctan (\beta_{1,j})}; \tag{17b}
$$

((h_j - s_j) - t_j(k))_+ = \left( h_j - s_j \right) - t_j(k) \text{ if } (h_j - s_j) > t_j(k), \text{ and zero otherwise}; h_j - s_j \text{ corresponds to the forecast horizon of the } j \text{th forecast; } t_j(k) \text{ is a pre-selected point on } h_j - s_j \text{ space (referred to as a knot), with } t_{j(0)} = 0; F(x) \text{ and } G(y) \text{ are suitably defined functions (see below); and } 0 \leq \beta_{0,j(i)} \leq 1 \ \forall \ j, \text{ and } \beta_{1,j} > 1 \ \forall \ j. \text{ To simplify the estimation process, we assume that } \beta_{2,j} \text{ (the parameter that determines the type-1 boldness probability) is invariant to the forecast horizon; specifically, we replace } \beta_{2,j} \text{ with } \beta_2 \text{ and assume that}

$$
\beta_2 = F (\delta_2); \tag{17c}
$$

where $0 < \beta_2 < 1$.\textsuperscript{11}

To ensure that $\beta_{0,j(i)}$ (and $\beta_2$) are appropriately bounded, we assume that $F(x)$ in (17a) (and (17c)) is given by the cumulative distribution function (CDF) of the logistic distribution (logit model).\textsuperscript{12} Moreover, we assume that the function in (17b) is given by $G(y) = 1 + \exp(y)$, thus ensuring that $\beta_{1,j} > 1 \ \forall \ j$, holds. Finally, under these assumptions, it is possible to show that the marginal effect of changes in the $i$th-specific explanatory variables is given by

$$
\frac{\partial \Pr(\text{Bold}_j = 1)}{\partial X_{j(i)}} = \phi_j f(X_{j(i),\alpha}) \alpha, \tag{18}
$$

where $\phi_j = (\arctan(\beta_{1,j}) - \arctan(\beta_{2,j}))/\pi$ is an adjustment coefficient; $X_{j(i)}$ is a $((q + 1) \times 1$)

\textsuperscript{11}Imposition of this restriction is equivalent to assuming that $\gamma$ equals unity: see Proposition 1.

\textsuperscript{12}As use of the logistic distribution in (17a) is somewhat arbitrary, we also consider the CDF of the standard normal distribution (probit model), and the CDF of the Gumbel distribution (extreme value model). However, as these models deliver similar results to the logit model we omit them from the subsequent analysis. Results pertaining to these models are available upon request.
vector of $i$th-specific explanatory variables, with corresponding coefficient vector $\alpha$; and $f(x)$ is the density function that corresponds to the cumulative function, $F(x)$.

### 3.2 Forecast accuracy

Given the results in Propositions 2 and 3, the determinants of forecasts accuracy are assessed via the following ordinary least squares (OLS) regression:

$$e^2_j = \psi_{0,j(i)} + \sum_{l=0}^{3} \delta_{0,l}(h_j - s_j)^l + \sum_{k=0}^{3} \sum_{l=0}^{K} \delta_{k,l}((h_j - s_j) - t_{j(k)})^l_+ + \sum_{l=0}^{3} \delta^*_0, l \left( \hat{\beta}_{0,j(i)} (h_j - s_j)^l \right) + \sum_{k=0}^{K} \sum_{l=0}^{3} \delta^*_{k,l} \left( \hat{\beta}_{0,j(i)} \times ((h_j - s_j) - t_{j(k)})^l_+ \right) + \nu_j, \quad (19)$$

where

$$\psi_{0,j(i)} = \psi_0 + \psi_1 X_1(j(i)) + \ldots + \psi_q X_q(j(i)); \quad (20)$$

$e_j$ is the forecast error associated with the $j$th forecast; $\nu_j$ is a suitably defined error term; and all previous notation is maintained.

The motivation for the specification of (19) and (20) is fairly straightforward. The results in Proposition 2 suggest that the relationship between forecast accuracy and horizon length may be non-linear; ergo, the presence of the piecewise cubic polynomials that span the forecast horizon in (19). Moreover, the results in Proposition 3 suggest that the relative accuracy of type-1 and type-2 analysts is functionally dependent on the forecast horizon length. For this reason, we also allow the estimated type-1 probability to non-linearly interact with the forecast horizon length in (19). Finally, given the extensive empirical evidence, we assume (via (20)) that forecast accuracy is linearly dependent on a set of analyst-specific variables.

### 4 Data

This section contains a description of the sample of data used, and explicit definitions of the dependent and explanatory variables used in the analysis.

#### 4.1 Sample selection

We use individual analysts’ earnings forecasts from the International Edition of the Institutional Brokers Estimate System (IBES) Detail History files. For each individual forecast in the dataset we track the company the forecast was made for, the individual analyst code and the broker code. Also, the dataset contains details regarding the date on which each forecast was made, the date the actual forecast was reported, the actual value of the earnings per share, and the end of the company’s fiscal year for which the forecast was provided. In addition, we follow best practise and standardise all earnings data by associated share prices observed five days prior to the earnings forecasts/realisations release dates (Thomas, 2002). These share prices were collected separately from Datastream.

The initial sample of data includes all annual earnings forecasts reported to IBES for UK-listed companies over the period, January 1, 1994 to December 31, 2006, and consists of 268,831 observations. Though we have data going back to 1986, we truncate the beginning of the sample period to avoid the problem of systematic time lags between the actual publication date and subsequent inclusion in the IBES database. Though Cooper, Day, and Lewis (2001)
point out that IBES started to update their forecasts on a daily basis starting in 1993, IBES cannot identify the exact date that these reporting changes took place. Consequently, our sample period starts on January 1, 1994.

After eliminating all forecasts with missing reported dates, actual earnings and/or analyst codes, the sample contains 229,552 observations. From this sample, we also remove 1,164 forecasts because they are issued by the same analyst, for the same company, on the same day. Moreover, we require that all the forecasts included in our sample are made for companies that are followed by at least two analysts in a particular year and are available in Datastream. After implementing these selection criteria, the sample is composed of 217,763 individual analyst forecasts.

The next stage of the data cleaning process involves the removal of outliers from the sample. Specifically, following Clement and Tse (2005), we remove all forecasts (1,247 in total) with absolute forecast errors greater than 0.4. Then, in order to be able to construct the boldness variable, we remove all forecasts that have no previous forecasts available, and/or where no consensus forecast is available. This particular procedure delivers a sample of 134,132 observations. Finally, to maintain a consistent dataset throughout the subsequent analysis, we only consider forecasts that have a lagged inaccuracy measure associated with them. These changes result in a final sample that consists of 89,032 observations.

4.2 Variable definitions

A number of analyst-specific variables are considered in this paper, which are used in the model of decomposed boldness (given by (16), (17a), (17b), and (17c)), and the model of accuracy (given by (19) and (20)). Specifically, the following explanatory variables are considered: the number of analysts employed by the analysts’ brokerage house in each year (henceforth referred to as brokerage size); the number of years of experience for an individual analyst in each year (henceforth experience); the number of industries (using the IBES classification system) followed by an individual analyst in each year (henceforth number of industries); the prior year mean absolute forecast error (MAFE) of an individual analyst following a particular company, calculated as the absolute difference between the actual earnings announced by a particular company minus the forecast made by an individual analyst for that particular company (henceforth lagged inaccuracy); a dummy variable that takes a value of one if the forecast is produced by an individual analyst, and zero if the forecast is produced by a team of analysts (henceforth individual dummy); the time period (in years) between an individual analyst’s forecast made for a particular company in each year and the previous forecast made for the same company by any analyst in each year (henceforth days elapsed); the number of forecasts produced by an individual analyst for a particular company in each year (henceforth forecast frequency); and the time period (in years) between the date of the forecast made by an individual analyst and the reported date of the actual earnings (henceforth forecast horizon).

Finally, we construct the binary boldness variable as defined in Clement and Tse (2005), with the consensus forecast for a particular company and year constructed by taking the mean of all available forecasts for that company and year – an assumption that is investigated

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13 Following Naujoks et al (2007) we retain the forecasts that are made during the respective fiscal year or they are issued after the fiscal year end, but before the earning announcement date. This choice has been made to capture the large number of forecasts (34,269 observations) released after the fiscal year-end but before the earnings announcement date.

14 The consensus forecast is constructed using at least two different previous forecasts issued during the annual forecast horizon.
in latter sections of this paper. Specifically, we repeat all of the analysis using alternative methods to construct the consensus forecasts, all of which have a theoretical motivation taken from the extant literature.

5 Empirical results

This section contains summary statistics, the empirical results pertaining to the model of decomposed boldness (given by (16), (17a), (17b), and (17c)), and the model of accuracy (given by (19) and (20)). In addition, we reexamine the predictions of these models when alternative measures of the consensus forecast are considered.

5.1 Summary statistics

Table I contains descriptive statistics associated with the variables used in this paper. Most notably, the mean forecast boldness is 0.671, indicating that the majority of forecasts are anti-herding in nature – a result that is similar to that found using US data (see Bernhardt, Campello, and Kutsoati, 2006). When comparing the boldness measure across the forecast horizon, it is evident that the highest incidence of boldness occurs for forecast horizons of medium length (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks). A similar feature is also evident when one considers the number of forecasts issued per week. In particular, Figure 1 shows that the number of forecasts peaks for forecast horizons of around six months. This peak coincides with the timing of company releases of their half-yearly interim reports.

Regarding the other analyst-specific variables, the results appear to be fairly similar to those obtained using US data (see, e.g., Clement and Tse, 2005). On average, brokerage houses employ 47.05 analysts, with each analyst following companies in 4.23 industries, having 4.85 years of experience, and making 6.04 forecast revisions each year. It is also noticeable that 83.80% of the forecasts in our sample are made by individual analysts, as opposed to a team of analysts. Finally, the distribution of forecasts appears to be fairly symmetric over the forecast horizon, as evinced by the fact that the average forecast horizon is 0.49 years; see Figure 1 for visual confirmation of this finding.

5.2 The determinants of decomposed boldness

Four model of boldness are considered in this paper, all of which are based on the specification given in (16), (17a), (17b), and (17c). The first model (denoted M0) simply assumes that the probability of boldness is constant over all observations,

\[ \text{M0: Pr(Bold}_j = 1) = F(\alpha_0), \]

where \( F(x) \) is given by the CDF of the logistic distribution (logit model) and ensures that the probability is bounded between zero and unity.\(^{15}\) To allow this probability to vary according to analyst characteristics, we consider the following model (denoted M1):

\[ \text{M1: Pr(Bold}_j = 1) = F(\alpha_0 + \alpha_1 X_{1,j(i)} + \ldots + \alpha_7 X_{7,j(i)}), \]

\(^{15}\)Use of alternative distributions gives similar results, and are available upon request.
where \( X_{1,j(i)} \) is the brokerage size variable, \( X_{2,j(i)} \) is the experience variable, \( X_{3,j(i)} \) is the number of industries variable, \( X_{4,j(i)} \) is the lagged inaccuracy variable, \( X_{5,j(i)} \) is the individual dummy variable, \( X_{6,j(i)} \) is the days elapsed variable, \( X_{7,j(i)} \) is the forecast frequency variable; and all previous notation is maintained. The next model that we consider (M2), augments M1 by introducing the forecast horizon variable (and transformations thereof) into its specification; that is,

\[
M2: \Pr(\text{Bold}_j = 1) = F(\alpha_0 + \alpha_1 X_{1,j(i)} + \ldots + \alpha_7 X_{7,j(i)} + \alpha_8 X_{8,j(i)} + \ldots + \alpha_{10} X_{10,j(i)}),
\]

where \( X_{8,j(i)} = (h_j - s_j) \) is the linear horizon variable, \( X_{9,j(i)} = (h_j - s_j)^2 \) is the quadratic horizon variable, \( X_{10,j(i)} = (h_j - s_j)^3 \) is the cubic horizon variable; and all previous notation is maintained. Finally, we consider a model of boldness (M3) that most closely resembles the model outlined in section 3; specifically,

\[
M3: \Pr(\text{Bold}_j = 1) = F(\alpha_0 + \alpha_1 X_{1,j(i)} + \ldots + \alpha_7 X_{7,j(i)} + \alpha_8 X_{8,j(i)} + \ldots + \alpha_{10} X_{10,j(i)}).
\]

The first three of the above models represent restricted versions of last model. To see this, consider the following restrictions:

\[
\arctan(\beta_{1,j}) = \frac{\pi}{2}, \quad \arctan(\beta_2) = -\frac{\pi}{2},
\]

which is equivalent to assuming that \( \Pr(\text{Bold}_j = 1|\kappa_j(i) = 1) = 1 \) and \( \Pr(\text{Bold}_j = 1|\kappa_j(i) = 2) = 0 \) (see Proposition 1). If this restriction is imposed on (21d) then one ends up with the specification given by (21b). Moreover, if one assumes that \( \alpha_1 = \alpha_2 = \ldots = \alpha_7 = 0 \) in (21b) then we have (21a). Finally, we include M2 in the analysis because, though it is not nested within the other models, it represents an augmented version of M1 that allows for non-linear horizon effects. In this respect it contains the same informational context as M3, albeit with a different specification.

Despite the obvious similarities amongst the above models, they are subtly different in terms of their interpretation. The coefficients in models M0, M1, and M2, measure the (direct) impact of analyst-specific (and horizon) factors on forecast boldness. By contrast, given the decomposition described in section 2, the coefficients \( \alpha_1, \ldots, \alpha_7, \) in M3, measure the (indirect) impact of analyst-specific factors on forecast boldness via their effect on the type-1 probability. Also, the way the forecast horizon affects forecast boldness is different for M2 and M3. The former model assumes that the effect is direct, while the latter assumes that the effect is indirect. Specifically, M3 assumes that the forecast horizon only affects boldness via its effect on the type-1 boldness probability (via the coefficients \( \delta_{1,0,0}, \delta_{1,0,1}, \delta_{1,0,2}, \) and \( \delta_{1,0,3} \)).

\(^{16}\)With reference to the model given by (16), (17a), (17b), and (17c), we have set \( K = 0 \) as this delivers the best parsimonious fit to the data.
This can most easily be seen by evoking Proposition 1, 
\[ \Pr(\text{Bold}_j = 1|\kappa_{j(i)} = 1) = \frac{\pi + 2 \arctan(\beta_{1,j})}{2\pi}, \quad \Pr(\text{Bold}_j = 1|\kappa_{j(i)} = 2) = \frac{\pi + 2 \arctan(\beta_{2})}{2\pi}, \]
and inspecting (21d).

The maximum likelihood (ML) estimates, standard errors, and measures of fit, associated with the above models are presented in Table II.\textsuperscript{17} The first notable feature of these results is the superior fit of the model of decomposed boldness proposed in this paper, viz. M3, in comparison to the other models. This superiority is not due to the use of more parameters in M3, as the Akaike and Schwarz Information Criteria (AIC and SIC, respectively) both indicate that it provides the best penalised fit to the data. Moreover, the fit of this model is significantly better (at the 1% level) than all competing models, as confirmed by the pairwise likelihood ratio tests of comparative fit.

The results also reveal how analyst-specific variables directly affect boldness (M1 and M2), or indirectly affect boldness via their effect on the type-1 probability (M3). Focusing on the latter model, the results indicate that the size of the brokerage house employing an analyst is positively related to the type-1 probability. Thus, the larger (smaller) the brokerage house, the higher (lower) the probability will be that the analyst makes use of their private information endowment. This result is consistent with the US-based evidence of Clement and Tse (2005), and Krishnan, Lim, and Zhou (2007), but not with alternative evidence that suggests that analysts working for more reputable brokerage houses are more likely to herd (Prendergast and Stole, 1996; and Jagadeesh and Kim, 2008). In a similar vein, the results also show that forecasts produced by a team of analysts have a significantly higher type-1 probability, and are thus more likely to be bold (as evinced by the coefficient on the individual analyst dummy variable).

Results pertaining to the other analyst-specific variables provide mixed evidence in terms of their consistency with previous US-based studies. While lagged inaccuracy has a significant negative effect on the type-1 probability and boldness (as in Clement and Tse, 2005), the number of industries followed by analysts and the forecast frequency of analysts have significant positive and negative effects, respectively – results that are in contrast to those found by Clement and Tse (2005). It is also noticeable that experience appears to be insignificant. This particular result contradicts the US-based evidence that shows that experience has a positive impact on boldness (Hong, Kubik, and Solomon, 2000; Kitzewitz, 2001; Clement and Tse, 2005; and Clarke and Subramanian, 2006).

The effects of the forecast horizon on a variety of boldness-related measures are most easily seen via inspection of Figure 2. This figure is divided into two panels, each of which

\textsuperscript{17}The Constrained Maximum Likelihood Estimation MT (Version 1) module run under GAUSS 7.0 is used to calculate the ML estimates in this paper. This module uses the sequential quadratic programming method, employing a routine that automatically switches between the BFGS and Newton descent algorithms (according to the value of the objective function), in combination with the STEPBT line search method. Inference is carried out using the result that for sufficiently large sample sizes,

\[ \hat{\Phi} \overset{d}{\approx} N(\Phi_0, N^{-1}\mathcal{I}^{-1}), \]

where \( \Phi_0 \) is the true parameter vector; and \( \mathcal{I} \) is the (Fisher) information matrix. We estimate this information matrix using the second-derivative estimate, that is,

\[ \hat{\mathcal{I}} = -N^{-1} \frac{\partial^2 \ell(\Phi)}{\partial \Phi \partial \Phi'} \bigg|_{\Phi = \hat{\Phi}}, \]

where \( \ell(\Phi) \) represents the log likelihood given by (15).
plots various M3 parameter-related information over the one year forecast horizon. The first panel, Panel (a), contains estimates of the type-1 probability (given by $F(\hat{\alpha}_0 + \hat{\alpha}_1 X_{1,j(i)} + \ldots + \hat{\alpha}_7 X_{7,j(i)})$, obtained from (21d)) over the forecast horizon. This plot reveals that this probability, that is, the probability of making use of private information endowments, takes values around 0.30 over the entire forecast horizon. This result implies that, contrary to recent US-based empirical findings (see, e.g., Bernhardt, Campello, and Kutsoati, 2006), the majority of UK-based analyst forecasts appear to be generated by herding-type behaviour (i.e., behaviour consistent with not making use of private information endowments).

The second panel in Figure 2, Panel (b), contains plots of the estimated conditional probabilities of being bold over the forecast horizon (as given by the estimated versions of (22)), and the implied unconditional probability of being bold (as given by the estimated version of (21d)). The first notable feature is that the estimated type-2 boldness probability is above 0.5 over the entire forecast horizon (approaching 0.6). Thus, bold forecasts are not the exclusive domain of anti-herding analysts, i.e., those that make use of their private information endowments. Indeed, it is this high type-2 boldness probability that creates the divergence between the high incidence of bold forecasts, and the low probability of anti-herding behaviour observed in Panel (a).

Another important feature of the plots in Panel (b) is that the type-1 boldness probability is highly non-linear with values close to unity, except at very short and long horizons where values approach their minimum bound (0.75). Also shown in this plot is the unconditional probability of boldness as predicted by this model. The shape of this probability plot confirms the results shown in Table I that boldness is inverted U-shaped over the forecast horizon, with the highest values occurring during the middle part of the forecast horizon. This plot also shows how this curvature is achieved. Specifically, it is caused by the non-linearity in the type-1 boldness probability. We conjecture that this non-linearity is, in turn, due to the release of accounting information around the middle part of the forecast horizon (i.e., the interim report releases of companies). Specifically, Proposition 1 predicts that as the precision of analysts’ private information endowments improve (as measured by the inverse of $b_s$) during this period, this leads to increases in the probabilities of issuing type-1 bold forecasts, and thus, higher unconditional probabilities of being bold.

### 5.3 The determinants of forecast accuracy

Previous studies have argued that because bold forecasts reflect more private information (or private information that does not conflict with public information) than non-bold forecasts, they are the more accurate forecast class (see, e.g., Clement and Tse, 2005; and Clarke and Subramanian, 2006). We test this proposition by examining the relationship between forecast (in)accuracy and a set of pertinent explanatory variables. This is achieved via use of five different regression models of forecast (in)accuracy, each of which varies with respect to the size of the explanatory information set. We supplement this analysis by examining the accuracy of forecast portfolios constructed on the basis of their boldness and type-1 probabilities.

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18 This particular result is in contrast to most previous studies that assume that boldness is linearly related to the forecast horizon (see, e.g., Clement and Tse, 2005).

19 Brown and Niederhoffer (1968), Coates (1972), Reilly, Morgenson, and West (1972), and Brown and Roseff (1979), all document the predictive value of interim reports on earnings forecast quality – evidence that is consistent with the notion that such reports improve the precision of analysts’ private information endowments.
5.3.1 Regression-based analysis

The first model we consider takes the following form:

R0: \( e_j^2 = \psi_0 + v_j \), \hspace{1cm} (23a)

where \( e_j \) is the forecast error associated with the \( j \)th forecast; \( v_j \) is a suitably defined error term; and the estimated parameter, \( \hat{\psi}_0 \), represents the MSFE associated with all forecasts. To allow analyst-specific variables into the analysis, we estimate the model,

R1: \( e_j^2 = \psi_0 + \psi_1 X_{1,j(i)} + \ldots + \psi_8 X_{8,j(i)} + v_j \), \hspace{1cm} (23b)

where \( X_{1,j(i)}, \ldots, X_{8,j(i)} \), represents the set of seven analyst-specific variables used in (21b) and (21d), augmented by the binary forecast boldness variable \( X_{8,j(i)} \); and all previous notation is maintained. Inclusion of forecast boldness in (23b) allows an examination of whether bold forecasts are more accurate than non-bold forecasts. To permit variation in forecast accuracy over the forecast horizon, we augment (23b) as follows:

R2: \( e_j^2 = \psi_0 + \psi_1 X_{1,j(i)} + \ldots + \psi_8 X_{8,j(i)} + \sum_{l=0}^{3} \delta_{0,l}(h_j - s_j)^l + v_j \), \hspace{1cm} (23c)

where all previous notation is maintained.\(^{20}\) The next model introduces the estimated type-1 probabilities (i.e., the probabilities of issuing forecasts based on private information endowments) into the above specification,

R3: \( e_j^2 = \psi_0 + \psi_1 X_{1,j(i)} + \ldots + \psi_8 X_{8,j(i)} + \sum_{l=1}^{3} \delta_{0,l}(h_j - s_j)^l + \delta_{0,1} \hat{\beta}_{0,j(i)} + v_j \), \hspace{1cm} (23d)

where \( \hat{\beta}_{0,j(i)} \) is obtained from the estimated version of M3; and all previous notation is maintained. Finally, given the results in Proposition 3 that suggest that the relative accuracy of type-1 and type-2 analysts is functionally dependent on the forecast horizon, we allow the type-1 probability to non-linearly interact with the forecast horizon as follows:

R4: \( e_j^2 = \psi_0 + \psi_1 X_{1,j(i)} + \ldots + \psi_8 X_{8,j(i)} + \sum_{l=1}^{3} \delta_{0,l}(h_j - s_j)^l + \sum_{l=0}^{3} \delta_{0,l} \left( \hat{\beta}_{0,j(i)} \times (h_j - s_j)^l \right) + v_j \), \hspace{1cm} (23e)

where all previous notation is maintained.

The ordinary least squares (OLS) estimates, standard errors, and measures of fit, associated with the above models are presented in Table III. It is apparent from these results that the basic forecast (in)accuracy model (R0) is dominated by all the other models; see the significance of the pairwise F-tests of comparative fit. Thus, the explanatory variables used in the competing models appear to be useful in describing variation in forecast accuracy. Of these models, it is the model whose specification makes full use of the results in Propositions 2 and 3 (that is, R4) that provides the best penalised fit to the data. Thus, without loss of generality, we focus attention on this model, and the best of the ‘other’ models (that is, R2).

The results in Table III also highlight a number of other interesting features. First,

\(^{20}\)As with the model given by (16), (17a), (17b), and (17c), we have set \( K = 0 \) in (19) and (20) as this delivers the best parsimonious fit to the data.
contrary to previous US-based studies (Clement and Tse, 2005), the positive (and significant) coefficient on the boldness variable indicates that bold forecasts are less accurate than non-bold forecasts. Conversely, the results associated with R4 indicate that forecast accuracy is positively (and significantly) related to the type-1 probability. Thus, the higher (lower) the probability of making use of private information endowments, the greater (lesser) the accuracy of forecasts. This difference in effects is due to the noisiness of the boldness measure. Specifically, as boldness can result from herding-like behaviour (i.e., not making use of private information endowments) then inaccurate forecasts can occur. By contrast, the type-1 probability gives a much cleaner measure of the likely use of private information endowments.

Inclusion of the type-1 probabilities also changes the sign (and significance) of the coefficients on some of the analyst-specific variables. In particular, the coefficient on brokerage size becomes significantly positive (as found by Bolliger, 1999, using European data); the coefficient on the number of industries switches from significantly negative to significantly positive (as in Clement, 1999; Jacob, Lys, and Neale, 1999; Clement and Tse, 2003, 2005; and Krishnan, Lim, and Zhou, 2007; using US data); the coefficient on forecast frequency becomes significantly negative (as in Jacob, Lys, and Neale, 1999; and Clement and Tse, 2003, 2005; using US data); and the coefficient on the individual dummy variable switches from significantly positive to significantly negative.

The reason for these changes can be explained as follows. Consider, the case of the individual dummy effect. The significant positive coefficient on this variable in R2 would appear to be composed of two competing effects. First, there is a positive (indirect) effect in operation; specifically, if an analyst becomes part of team then the type-1 probability increases (see Table II), which, in turn, has a positive effect on forecast accuracy (see Table III). However, there is also a second stronger (direct) negative impact on forecast accuracy that appears to outweigh the former effect. The net effect is evinced by the positive coefficient in R2 (see, also, the absolutely larger negative coefficient in R4).

The estimated parameters associated with R4 also indicate that there is significant variation in type-1 probability effects over the forecast horizon. This is evinced by the significance of the F-test of R4 fit over R3 fit. The nature of this variation can most easily be seen by observing the plot provided in Figure 3. This plot shows the marginal effect of changes in the type-1 probability upon forecast (in)accuracy at each point during the forecast horizon. The results indicate substantial variation in this effect over the forecast horizon, with the greatest (negative) impact occurring just after the midway point of the forecast horizon (around 20 weeks before the earnings release dates). This result can be rationalised with respect to greater precision of private information endowments around the middle of the forecast horizon ($b_s$ reduces; see Proposition 3), leading to greater improvements in relative forecast accuracy for type-1 analysts at this time.

---

21 This particular result is consistent with empirical and theoretical studies that find that herders (i.e., those that do not make use of their private information endowments) have less ability to predict earnings (see, e.g., Trueman, 1994; and Krishnan, Lim, and Zhou, 2007).

22 Results pertaining to the other analyst-specific variables are largely in line with those found in previous US-based studies. Specifically, forecast accuracy is positively (and significantly) related to analyst experience (as in Mikhail, Walther, and Willis, 1997; Clement, 1999; Jacob, Lys, and Neale, 1999; Clement and Tse, 2003, 2005; and Krishnan, Lim, and Zhou, 2007), and lagged accuracy (as in Brown, 2001; Clement and Tse, 2005; and Krishnan, Lim, and Zhou, 2007); and is negatively (and significantly) related to the days elapsed between analysts’ forecasts (as in Clement and Tse, 2003, 2005; and Krishnan, Lim, and Zhou, 2007).

23 Other effects appear to work in the same direction as each other. For instance, improvements in past performance will increase the type-1 probability, which will, in turn, improve current performance. Moreover, there also appears to be a positive direct impact, which means that the coefficient on lagged inaccuracy in R2 is larger than the associated coefficient in R4.
5.3.2 Portfolio-based analysis

To examine in more detail the relations between forecast accuracy, boldness, and type-1 probabilities, ten equally-sized portfolios sorted on type-1 probability are constructed. We construct these portfolios using bold forecasts only (Panel A), and all forecasts (Panel B), with further divisions occurring according to three different forecast horizon lengths (viz., short, medium, and long forecast horizons). The MSFE values associated with these forecast portfolios are provided in Table IV.

A number of features are noteworthy. Bold forecasts are less accurate than non-bold forecasts. This is evinced by the fact that portfolios based on bold forecasts have higher MSFE values than portfolios based on all forecasts (that is, bold and non-bold forecasts). By contrast, forecast accuracy increases as the type-1 probability increases. Moreover, the gradients of the MSFE values over the type-1 probability sorted portfolios are statistically significant. This can be seen by noting the significant differences between the MSFE values associated with the lowest and highest type-1 probability portfolios (referred to as low minus high, LMH, portfolios). These results confirm the findings of the regression-based analysis, which show that forecasts based on private information endowments are more accurate than forecasts that do not make use of private information endowments.

It is also apparent from Table IV that significant horizon effects appear to be in operation. First, forecast accuracy tends to improve as the forecast horizon shortens, with high type-1 probability bold forecasts made during short horizon periods the most accurate of all forecasts considered. However, there are exceptions to this finding. In particular, low type-1 probability forecasts appear to be at their least accurate during forecast horizons of medium length. Second, the difference in quality between high and low type-1 probability forecasts is at its greatest for forecast horizons of medium length. This confirms the results in Figure 3, and is most likely due to the greater private information endowment precision (low $b_s$ values) during this time (see Proposition 3).

5.4 Robustness checks

This subsection repeats the previous analysis under alternative measures of the consensus forecast. Specifically, six construction techniques are first described (denoted C1 to C6), and then the determinants of forecast boldness and accuracy are reexamined using these techniques.

5.4.1 Consensus construction techniques revisited

The empirical analysis has thus far assumed that the consensus forecast at the time of the current forecast is given by the equal-weighted mean of all available forecasts, where an available forecast is defined as a forecast that occurs at least one day prior to the current forecast (issued by all analysts for the same company and in the same year). Letting $k = \{F_{j,1}, \ldots, F_{j,n}\}$ represent the set of all available forecasts, then this particular weighting...
scheme can be represented as

\[ C_j = \frac{1}{n} \sum_{k=1}^{n} F_{j,k}, \]  

(24a)

where \( C_j \) is the consensus forecast associated with the \( j \)th forecast.

While the above approach is standard practise in the literature, it is problematic on three counts. First, empirical evidence from the general forecasting literature suggests that improved consensus forecasts can be obtained by using robust averages of available forecasts (see, e.g., Jose and Winkler, 2008). Therefore, we consider consensus forecasts based on trimmed and Winsorised means of all available forecasts. Specifically, we construct a trimmed consensus forecast as follows:

\[ C_2: C_j = \frac{1}{n-2i} \sum_{k=i+1}^{n-i} F_{j,k}, \]  

(24b)

where \( F_{j,[i]} \) is the \( i \)th order statistic for \( F_{j,1}, \ldots, F_{j,n} \) (and \( 0 \leq i < n/2 \)); and a Winsorised consensus forecast as follows:

\[ C_3: C_j = \left( iF_{j,[i+1]} + \sum_{k=i+1}^{n-i} F_{j,[k]} + iF_{j,[n-i]} \right) / n, \]  

(24c)

where in both cases we set \( 2i/n = 0.1 \) to achieve a 10% level of trimming and Winsorizing.

Second, previous theoretical evidence implies that the order in which forecasts are issued has implications regarding their relative importance. Specifically, within the context of a reputational principal-agent model, Trueman (1994) derives analytical results that show that more (less) recent forecasts are issued by analysts who have higher (lower) probabilities of observing the true forecast signal.\(^{25}\) This implies that more recent forecasts should receive more weight when constructing the consensus forecast; ergo, we employ the following exponential weighting scheme with weights that increase according to the timeliness of forecasts:\(^{26}\)

\[ C_4: C_j = \frac{1}{\sum_{k=1}^{n} \varrho^{h_{j,k} - s_{j,k}}} \sum_{k=1}^{n} \varrho^{h_{j,k} - s_{j,k}} F_{j,k}, \]  

(24d)

where \( h_{j,k} - s_{j,k} \) is the forecast horizon of the \( k \)th forecast; and \( \varrho \) determines the rate of timeliness decay, which we assume equals 0.98 in the current application.\(^{27}\)

Third, the equal-weighted consensus forecast does not coincide with the consensus forecast assumed in this paper (see (7)). However, the latter consensus forecast cannot be practically constructed as type-1 forecasts are unobservable. Therefore, some form of mediating assumption is required. To this end, using the fact that type-1 forecasts are more accurate than type-2 forecasts, we consider a weighting scheme that places more (less) weight on forecasts

\(^{25}\)Indeed, this is implied by the assumptions used in the current paper, whereby the consensus forecast is given by the average of all (type-1) forecasts issued in the previous period only.

\(^{26}\)See Brown (1991) and Stickel (1993) for empirical evidence regarding the benefits of using forecasting techniques that give more weight to more recent forecasts.

\(^{27}\)After some experimentation with various \( \varrho \) values, this particular value was found to deliver the most accurate consensus forecast.
with greater (lesser) lagged accuracy. Specifically,

\[ \text{C5: } C_j = \frac{1}{\sum_{k=1}^{n} \varphi_{j,k}} \sum_{k=1}^{n} \frac{1}{\varphi_{j,k}} F_{j,k}, \]  

(24c)

where \( \varphi_{j,k} \) is MAFE associated with all forecasts issued by the analyst who issues the \( k \)th forecast for the same company in the previous year. Finally, we combine the techniques in C4 and C5, such that the consensus forecast is constructed using a time/accuracy-weighting scheme; that is,

\[ \text{C6: } C_j = \frac{\sum_{k=1}^{n} \varphi_{j,k}^{h_{j,k}-s_{j,k}}}{\sum_{k=1}^{n} \varphi_{j,k}} \sum_{k=1}^{n} \frac{\varphi_{j,k}^{h_{j,k}-s_{j,k}}}{\varphi_{j,k}} F_{j,k}, \]  

(24f)

where all previous notation (and parameter assumptions) are maintained.

5.4.2 Boldness revisited

The models of boldness described in subsection 5.2 are re-estimated using the above consensus forecast measures. The penalised fit (given by the AIC) and predicted boldness (for various forecast horizon lengths) associated with these models are provided in Table V. The results indicate that the superior fit of the model of decomposed boldness introduced in this paper (M3) is robust to the technique used to construct the consensus forecast. Specifically, for all consensus forecast measures, M3 delivers the minimum AIC value; thus, demonstrating that the superiority of the model of decomposed boldness developed in this paper is robust in this respect. It is also noticeable that predicted boldness remains close to the levels obtained using the equal-weighted (C1) consensus forecast measure (around 0.65), with the inverted U-shaped pattern in boldness over the forecast horizon present irrespective of the consensus forecast measure used.

To examine more closely the robustness of the implications of the M3 model documented previously, we calculate the mean type-1 and type-2 boldness probabilities, and the mean type-1 probabilities, associated with the estimated parameters from M3, using all six consensus forecast measures and for various forecast horizon lengths. These probabilities are given in Table VI. The results confirm the evidence in Figure 2. Specifically, the mean type-1 boldness probabilities are almost equal to unity for medium length forecast horizons, with lower levels observed for short and medium length forecast horizons. By contrast, the mean type-2 boldness probabilities are constant (by construction) over the forecast horizon. Perhaps most interestingly, the mean type-1 probabilities indicate that the probability of making use of private information endowments is below 0.30. Thus, despite the fact that most forecasts are bold, they appear to be the result of the majority of analysts not using there private information endowments (i.e., herding behaviour).

Finally, to examine the robustness of the analyst-specific determinants of boldness, the marginal effects of all analyst-specific variables are estimated using all six consensus forecast measures. This is achieved via the formula given in (18), with the estimated parameters from each model of boldness used as inputs into this formula. Results pertaining to these models and measures are provided in Figure 4, with intra-horizon marginal effects shown in Figure 5. It is apparent from the former figure that the sign of the coefficient does not change over the consensus forecast measures, with marginal effects broadly similar to each

\(^{28}\)See Rapach and Strauss (2008) for empirical evidence regarding the benefits of using such a weighting scheme within a macroeconomic forecasting context.
other (ranging from zero to 0.04 in absolute terms). However, marginal effects do appear to be noticeably different when the (superior) M3 model is used – a result that implies that use of alternative (inferior) models may provide inaccurate estimates of the impact of analyst-specific variables upon boldness. Finally, the plots in Figure 5 show that there does appear to be variation in the impact of analyst-specific variables over the forecast horizon, with the greatest impact occurring during the middle of the forecast horizon, and the smallest at short forecast horizons.\textsuperscript{29}

5.4.3 Accuracy revisited

To examine the robustness of the results pertaining to the regression-based forecast accuracy analysis, we re-estimate the marginal effects of changes in the type-1 probability upon forecast (in)accuracy using each of the six consensus forecast measures described previously. These effects are calculated using the R4 measure of forecast accuracy, for small, medium, and long forecast horizon lengths. The results given in Table VII confirm the results provided in Figure 3. Specifically, marginal effects are consistently greatest during the middle of the forecast horizon, albeit with some variation in the magnitudes of these effects over the consensus forecast measures.

Finally, we reexamine the portfolio-based analysis performed previously. Specifically, the MSFE values associated with various type-1 probability portfolios (and the extreme differences between these values as indicated by the LMH portfolios) are calculated using various forecast horizon lengths and consensus forecast measures, for both bold forecasts and all forecasts. The results given in Table VIII confirm those obtained previously, and provide affirmation of the robustness of the results to variation in the consensus forecast measure. Specifically, the following results hold for all consensus forecast measures: forecast accuracy significantly improves as the forecast horizon shortens; bold forecasts are generally less accurate than non-bold forecasts; and relative performance (that is, type-1 versus type-2 performance as indicated by the LMH portfolios) is significantly positive, with maxima occurring during the middle of the forecast horizon.

6 Conclusion

The analysis carried out in this paper shows that, while forecast boldness is a desirable property (Huang, Willis, and Zhang, 2005; Kadous, Mercer, and Thayer, 2007; and Chiang, Lin, and Yu, 2008), its measurement is complicated by the requirement of knowledge of the true posterior beliefs of analysts – beliefs that cannot be observed. Moreover, we demonstrate that when simplifying assumptions are imposed (à la Clement and Tse, 2005), the measure itself becomes inherently noisy leading to potentially misleading conclusions regarding the underlying motivation for issuing such forecasts. Recognising this issue, we decompose Clement and Tse’s (2005) boldness measure to yield valuable implications regarding the issuers use (or otherwise) of their private information endowment. Specifically, using a large set of analysts’ earnings forecasts of UK-listed companies, we show that even though most forecasts are bold, the majority of forecasts appear to be the result of analysts not using their private information endowments. Instead, they tend to issue less accurate forecasts that are as close as possible to the true prevailing consensus forecast, and thus appear to exhibit herding-like behaviour.

\textsuperscript{29}This particular result is driven by intra-horizon variation in the adjustment coefficient (that is, $\phi_j = (\arctan(\beta_1) - \arctan(\beta_2))/\pi$) in (18). This, in turn, is caused by the intra-horizon variation in type-1 boldness probabilities documented previously (see Figure 3).
The results in this paper also demonstrate that the processes underlying the issuance of forecasts varies over the forecast horizon. Specifically, we document an inverted U-shaped pattern in boldness over the forecast horizon, which (via inspection of decomposed boldness) appears to be due to variation in the precision of analysts’ private information endowments over this space. Furthermore, we conjecture that the increase in this precision observed around the middle of the (annual) forecast horizon is caused by the release of accounting information contained in the interim reports of companies. This particular result, together with those described above, have practical implications regarding the list of desirable forecast properties: specifically, the conventional list of forecast accuracy and boldness, should be replaced by forecast accuracy and horizon-specific decomposed boldness (i.e., estimates of private information endowment precision and usage at each point during the forecast horizon). Market-based tests of the importance of these elements is left for future research.
Appendix

Proof of Proposition 1. Under the definition of boldness considered in this paper, it is possible to calculate the probability of a type-1 analyst producing a forecast (given by (4)) that is bold. First, note that

\[
\Pr(\text{Bold}_{i,s} = 1|\kappa_i = 1) = \Pr((F_{i,s}^{(1)} > C_{s-1}), (\Delta F_{i,s}^{(1)} > 0)) + \Pr((F_{i,s}^{(1)} < C_{s-1}), (\Delta F_{i,s}^{(1)} < 0)). \tag{A.1}
\]

Using (4), (5), and (7), the second of these probabilities can be rewritten,

\[
\Pr((F_{i,s}^{(1)} < C_{s-1}), (\Delta F_{i,s}^{(1)} < 0)) = \Pr((\Delta F_{i,s}^{(1)} + \gamma^{h-(s-1)}\nu_{i,s-1} < 0), (\Delta F_{i,s}^{(1)} < 0)). \tag{A.2}
\]

Furthermore, maintaining the assumptions that \(\eta_s \sim \text{IN}(0, a)\) and \(\nu_{i,s} \sim \text{IN}(0, b_s)\), with \(\text{cov}(\eta_s, \nu_{i,s}) = 0\), then it is possible to show that

\[
\Delta F_{i,s}^{(1)} \sim \text{IN}(0, a\gamma^{2(h-s)} + b_s\gamma^{2(h-s)}), \tag{A.3a}
\]

\[
\Delta F_{i,s}^{(1)} + \gamma^{h-(s-1)}\nu_{i,s-1} \sim \text{IN}(0, a\gamma^{2(h-s)} + b_s\gamma^{2(h-s)}), \tag{A.3b}
\]

\[
\text{corr}(\Delta F_{i,s}^{(1)}, \Delta F_{i,s}^{(1)} + \gamma^{h-(s-1)}\nu_{i,s-1}) = \frac{\sigma_{\nu_{i,s}}}{\sigma_{\Delta F_{i,s}^{(1)}}}. \tag{A.3c}
\]

The results in (A.3a) to (A.3c) can then be used to show that (for any bivariate normal distributed variables) the probability in (A.2) is given by

\[
\Pr((\Delta F_{i,s}^{(1)} + \gamma^{h-(s-1)}\nu_{i,s-1} < 0), (\Delta F_{i,s}^{(1)} < 0)) = \frac{\pi + 2\arctan\left(\frac{\rho_{\nu_{i,s}}\sigma_{\nu_{i,s}}\sigma_{\Delta F_{i,s}^{(1)}}}{\sqrt{\sigma_{\nu_{i,s}}^2\sigma_{\Delta F_{i,s}^{(1)}}^2 - (\rho_{\nu_{i,s}}\sigma_{\nu_{i,s}}\sigma_{\Delta F_{i,s}^{(1)}})^2}}\right)}{4\pi},
\]

\[
= \frac{\pi + 2\arctan\left(\frac{1}{2}\sqrt{\frac{a+b_s}{b_s}}\right)}{4\pi}. \tag{A.4}
\]

By symmetry, the first probability in (A.1) is also given by this expression, thus giving the following expression for the probability of a type-1 analyst setting a bold forecast:

\[
\Pr(\text{Bold}_{i,s} = 1|\kappa_i = 1) = \frac{\pi + 2\arctan\left(\frac{1}{2}\sqrt{\frac{a+b_s}{b_s}}\right)}{2\pi}, \tag{A.5}
\]

with \(\gamma/4 < \Pr(\text{Bold}_{i,s} = 1|\kappa_i = 1) < 1\) as \(\lim_{\theta_{i,s} \to 1} \arctan(\theta_{i,s}) = \pi/4\), and \(\lim_{\theta_{i,s} \to \infty} \arctan(\theta_{i,s}) = \pi/2\),

where \(\theta_{i,s}\) is defined in (A.5). These bounds exist because \(\theta_{i,s}\) must be greater than unity (given that \(0 \leq \gamma < 1, a > 0, \text{ and } b_s > 0 \forall s\)): a result that implies that type-1 analysts generally produce bold forecasts.

Likewise, to calculate the probability of a type-2 analyst producing a forecast (given by (6)) that is bold note that

\[
\Pr(\text{Bold}_{i,s} = 1|\kappa_i = 2) = \Pr((F_{i,s}^{(2)} > C_{s-1}), (\Delta F_{i,s}^{(2)} > 0)) + \Pr((F_{i,s}^{(2)} < C_{s-1}), (\Delta F_{i,s}^{(2)} < 0)). \tag{A.6}
\]

Using (6), (8), and (7), the second of these probabilities can be rewritten,

\[
\Pr((F_{i,s}^{(2)} < C_{s-1}), (\Delta F_{i,s}^{(2)} < 0)) = \Pr((\zeta_{i,s} < 0), (\gamma^{h-(s-1)}\nu_{i,s-1} + \Delta \zeta_{i,s} < 0)). \tag{A.7}
\]
Furthermore, maintaining the assumptions that \( \eta_s \sim \text{IN}(0, a) \), and \( \zeta_{i,s} \sim \text{IN}(0, c) \), then it is possible to show that

\[
\begin{align*}
\zeta_{i,s} &\sim \text{IN}(0, c), \\
\gamma^h(s-1)\eta_{s-1} + \Delta\zeta_{i,s} &\sim \text{IN}(0, a\gamma^{2(h-(s-1))} + 2c), \\
\text{corr}(\zeta_{i,s}, \gamma^h(s-1)\eta_{s-1} + \Delta\zeta_{i,s}) &= \frac{c}{\sqrt{\gamma^h(s-1)}}.
\end{align*}
\]

It follows that the probability in (A.7) is given by

\[
\Pr((\zeta_{i,s} < 0), (\gamma^h(s-1)\eta_{s-1} + \Delta\zeta_{i,s} < 0)) = \frac{\pi + 2 \arctan\left(\frac{c}{\sqrt{a\gamma^2(s-1)}}\right)}{2\pi},
\]

(A.9)

By symmetry, the first probability in (A.6) is also given by this expression, thus giving the following expression for the probability of a type-2 analyst setting a bold forecast:

\[
\Pr(\text{Bold}_{i,s} = 1|\kappa_i = 2) = \frac{\pi + 2 \arctan\left(\frac{c}{\sqrt{a\gamma^2(s-1)}}\right)}{2\pi},
\]

(A.10)

where \( \theta_{2,s} \) is defined in (A.10). These bounds exist because \( \theta_{2,s} \) must be greater than zero (given that \( 0 \leq \gamma \leq 1 \), \( a > 0 \), and \( c > 0 \)), but less than unity: a result that implies that type-2 analysts generally produce bold forecasts, though to a less extent than type-1 analysts.

\(\square\)

**Proof of Proposition 2.** The forecast error of the \( i \)th analyst at time \( s \) (with horizon \( h \)) is defined as follows:

\[
e_{i,s} = y_h - F_{i,s}.
\]

(A.11)

Taking expectations of the squared value of the above forecast error, and assuming that all cross-product terms equal zero, leads to the following expression for the MSFE associated with the forecasts of type-1 analysts:

\[
\begin{align*}
E(e_{i,s}^2|\kappa_i = 1) &= \sum_{\ell=s+1}^{h} \gamma^{2(h-\ell)} E(\eta^2_{\ell}|\kappa_i = 1) + \gamma^{2(h-s)} E(\nu^2_{i,s}|\kappa_i = 1) + E(e_h^2|\kappa_i = 1), \\
&= a \sum_{\ell=s+1}^{h} \gamma^{2(h-\ell)} + b_s \gamma^{2(h-s)} + \sigma^2, \\
&= a \left(1 - \frac{\gamma^{2(h-s)}}{1 - \gamma^2}\right) + b_s \gamma^{2(h-s)} + \sigma^2, \quad \text{for} \ s < h.
\end{align*}
\]

(A.12)

Similarly, using (6) and (7), and assuming that all cross-product terms equal zero, eventually leads to the following expression for the type-2 analyst MSFE:

\[
E(e_{i,s}^2|\kappa_i = 2) = a \left(1 - \frac{\gamma^{2(h-(s-1))}}{1 - \gamma^2}\right) + c + \sigma^2, \quad \text{for} \ s < h,
\]

(A.13)

where all previous notation is maintained.

\(\square\)
References


Welch, B., 1947, The generalization of “student’s” problem when several different population variances are involved, *Biometrika* 34, 28–35.


Table I: Summary statistics

This table contains the mean, standard deviation (SD), and various percentile points for the following variables: ‘Number of Forecasts’ is the number of annual forecasts issued (per week) by all analysts for all companies; ‘Boldness’ is the binary boldness variable as defined in Clement and Tse (2005); ‘Inaccuracy’ is the standardised mean squared forecast error of an individual analyst following a particular company, calculated as the squared difference between the actual earnings announced by a particular company minus the forecast made by an individual analyst for that particular company standardised by the share price five days prior to the earning announcement date; ‘Brokerage Size’ is the number of analysts employed by the analysts’ brokerage house in each year; ‘Experience’ is the number of years of experience for an individual analyst following a particular company in each year; ‘Number of Industries’ is the number of industries (using the IBES classification system) followed by an individual analyst in each year; ‘Lagged Inaccuracy’ is the prior year standardised mean absolute forecast error of an individual analyst following a particular company, calculated as the absolute difference between the actual earnings announced by a particular company minus the forecast made by an individual analyst for that particular company standardised by the share price five days prior to the earning announcement date; ‘Individual Dummy’ is a dummy variable that takes a value of one if the forecast is produced by an individual analyst, and zero if the forecast is produced by a team of analysts; ‘Days Elapsed’ is the time period (in years) between an individual analyst’s forecast made for a particular company in each year and the previous forecast made for the same company by any analyst in each year; ‘Forecast Frequency’ is the number of forecasts produced by an individual analyst for a particular company in each year; ‘Forecast Horizon’ is the time period (in years) between the date of the forecast made by an individual analyst and the reported date of the actual earnings. In addition, summary statistics associated with the ‘Number of Forecasts’ and ‘Boldness’ variables are also provided for the following forecast horizons: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Horizon</th>
<th>Mean</th>
<th>SD</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Forecasts</td>
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<td>69.189</td>
<td>71.000</td>
<td>103.000</td>
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<tr>
<td></td>
<td>Medium</td>
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<td>71.061</td>
<td>114.000</td>
<td>147.000</td>
<td>193.000</td>
</tr>
<tr>
<td></td>
<td>Long</td>
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<td>90.265</td>
<td>46.000</td>
<td>74.500</td>
<td>113.500</td>
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<tr>
<td></td>
<td>All</td>
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<td>77.250</td>
<td>119.000</td>
<td>162.000</td>
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<td>65.000</td>
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<tr>
<td>Experience</td>
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<td>3.000</td>
<td>4.000</td>
<td>6.000</td>
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<tr>
<td>Number of Industries</td>
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<td>3.000</td>
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<td>0.003</td>
<td>0.006</td>
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<td>1.000</td>
<td>1.000</td>
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<tr>
<td>Days Elapsed</td>
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<td>0.011</td>
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<td>3.000</td>
<td>5.000</td>
<td>7.000</td>
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<tr>
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<td>0.254</td>
<td>0.289</td>
<td>0.500</td>
<td>0.673</td>
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</table>
The parameters $\hat{\alpha}_0, \ldots, \hat{\alpha}_{10}$, measure the impact of analyst-specific variables upon the type-1 probability, while the parameters $\hat{\delta}_{1,0,0}, \ldots, \hat{\delta}_{2,0,3}$, allow for non-linear variation in the type-1 and type-2 boldness probabilities over the forecast horizon. Model fit is measured via the log likelihood, the Akaike Information Criterion (AIC), and the Schwarz Information Criterion (SIC). In addition, the p-values associated with various likelihood ratio (LR) tests of comparative model fit are provided. In the case of nested model comparisons (e.g., M1 v. M3), the classical Neyman-Pearson (1928) LR test is performed; while for non-nested model comparisons (e.g., M2 v. M3), the Vuong (1989) LR test is performed.

The significance of each parameter is denoted by ** (1% significance), and * (5% significance). All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

Table II: Boldness determinants

This table contains maximum likelihood (ML) parameter estimates (with standard errors in parentheses) associated with restricted and unrestricted variants of the model of decomposed boldness given by (16), (17a), (17b), and (17c).

<table>
<thead>
<tr>
<th>Parameter (Variable)</th>
<th>M0</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\alpha}_0$ (Constant)</td>
<td>0.714**</td>
<td>0.793**</td>
<td>0.669**</td>
<td>$-0.280^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.030)</td>
<td>(0.039)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>$\hat{\alpha}_1$ (Brokerage Size)</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.002**</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_2$ (Experience)</td>
<td>$-0.005$</td>
<td>$-0.004$</td>
<td>$-0.003$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_3$ (Number of Industries)</td>
<td>0.017**</td>
<td>0.016**</td>
<td>0.022**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_4$ (Lagged Inaccuracy)</td>
<td>$-0.749^{**}$</td>
<td>$-0.740^{**}$</td>
<td>$-7.714^{**}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.159)</td>
<td>(0.159)</td>
<td>(1.677)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_5$ (Individual Dummy)</td>
<td>$-0.140^{**}$</td>
<td>$-0.141^{**}$</td>
<td>$-0.198^{**}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.034)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_6$ (Days Elapsed)</td>
<td>0.240</td>
<td>0.151</td>
<td>0.161</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.138)</td>
<td>(0.129)</td>
<td>(0.244)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_7$ (Forecast Frequency)</td>
<td>$-0.007^{**}$</td>
<td>$-0.007^{**}$</td>
<td>$-0.045^{**}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_8$ (Linear Horizon)</td>
<td>0.970**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.167)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_9$ (Quadratic Horizon)</td>
<td>1.158**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.548)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\alpha}_{10}$ (Cubic Horizon)</td>
<td>1.158**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.011</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.227)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}_{1,0,0}$ (Type-1 Constant)</td>
<td></td>
<td></td>
<td></td>
<td>$-0.813$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.538)</td>
</tr>
<tr>
<td>$\hat{\delta}_{1,0,1}$ (Type-1 Linear Horizon)</td>
<td></td>
<td></td>
<td></td>
<td>19.215**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(6.899)</td>
</tr>
<tr>
<td>$\hat{\delta}_{1,0,2}$ (Type-1 Quadratic Horizon)</td>
<td></td>
<td></td>
<td></td>
<td>$-28.094$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(14.440)</td>
</tr>
<tr>
<td>$\hat{\delta}_{1,0,3}$ (Type-1 Cubic Horizon)</td>
<td></td>
<td></td>
<td></td>
<td>7.253</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(8.664)</td>
</tr>
<tr>
<td>$\hat{\delta}_2$ (Type-2 Constant)</td>
<td></td>
<td></td>
<td></td>
<td>$-1.187^{**}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.226)</td>
</tr>
<tr>
<td>Log Likelihood/1000</td>
<td>$-56.391$</td>
<td>$-56.275$</td>
<td>$-56.205$</td>
<td>$-56.155$</td>
</tr>
<tr>
<td>AIC/1000</td>
<td>112.784</td>
<td>112.566</td>
<td>112.431</td>
<td>112.336</td>
</tr>
<tr>
<td>SIC/1000</td>
<td>112.793</td>
<td>112.641</td>
<td>112.535</td>
<td>112.458</td>
</tr>
<tr>
<td>LR p-value (M0 v. M1, M2, M3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LR p-value (M1 v. M2, M3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>LR p-value (M2 v. M3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table III: Forecast accuracy determinants

This table contains ordinary least squares (OLS) parameter estimates (with standard errors in parentheses) associated with restricted and unrestricted variants of the model of forecast inaccuracy (as measured by the squared forecast error) given by (19) and (20). The parameters \( \hat{\psi}_0, \ldots, \hat{\psi}_8 \), measure the impact of analyst-specific variables upon forecast inaccuracy; the parameters \( \hat{\delta}_{0,1}, \ldots, \hat{\delta}_{0,3} \), allow for non-linear variation in forecast inaccuracy over the forecast horizon; while the parameters \( \hat{\delta}_{0,1}^{*}, \ldots, \hat{\delta}_{0,3}^{*} \), allow for non-linear variation in the impact of the type-1 probability on forecast inaccuracy over forecast horizon. Model fit is measured via the adjusted \( R^2 \) statistic, the Akaike Information Criterion (AIC), and the Schwarz Information Criterion (SIC). In addition, the p-values associated with various F-tests of comparative model fit are provided. The significance of each parameter is denoted by ** (1% significance), and * (5% significance). All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Parameter (Variable)</th>
<th>Model</th>
<th>R0</th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\psi}_0 ) (Constant)</td>
<td></td>
<td>0.118**</td>
<td>0.069**</td>
<td>0.035**</td>
<td>0.504**</td>
<td>0.424**</td>
</tr>
<tr>
<td>( \hat{\psi}_1 ) (Brokerage Size)</td>
<td></td>
<td>(0.002)</td>
<td>(0.010)</td>
<td>(0.014)</td>
<td>(0.020)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>( \hat{\psi}_2 ) (Experience)</td>
<td></td>
<td>0.000</td>
<td>-0.000</td>
<td>0.001**</td>
<td>0.001**</td>
<td>0.001**</td>
</tr>
<tr>
<td>( \hat{\psi}_3 ) (Number of Industries)</td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( \hat{\psi}_4 ) (Lagged Inaccuracy)</td>
<td></td>
<td>-0.005**</td>
<td>-0.005**</td>
<td>-0.010**</td>
<td>-0.010**</td>
<td>-0.010**</td>
</tr>
<tr>
<td>( \hat{\psi}_5 ) (Individual Dummy)</td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>( \hat{\psi}_6 ) (Days Elapsed)</td>
<td></td>
<td>-0.002*</td>
<td>-0.002**</td>
<td>0.010**</td>
<td>0.010**</td>
<td>0.010**</td>
</tr>
<tr>
<td>( \hat{\psi}_7 ) (Forecast Frequency)</td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>( \hat{\psi}_8 ) (Boldness)</td>
<td></td>
<td>0.009*</td>
<td>0.010*</td>
<td>0.015**</td>
<td>0.015**</td>
<td>0.015**</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,1} ) (Linear Horizon)</td>
<td></td>
<td>0.157</td>
<td>0.218**</td>
<td>1.041**</td>
<td>1.041**</td>
<td>1.041**</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,2} ) (Quadratic Horizon)</td>
<td></td>
<td>(0.083)</td>
<td>(0.083)</td>
<td>(0.083)</td>
<td>(0.083)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,3} ) (Cubic Horizon)</td>
<td></td>
<td>-0.344</td>
<td>-0.430*</td>
<td>-2.112**</td>
<td>-2.112**</td>
<td>-2.112**</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,0}^{*} ) (Pr(Type 1))</td>
<td></td>
<td>0.286*</td>
<td>0.306*</td>
<td>1.212*</td>
<td>1.212*</td>
<td>1.212*</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,1}^{*} ) (Pr(Type 1) × Linear Horizon)</td>
<td></td>
<td>(0.134)</td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,2}^{*} ) (Pr(Type 1) × Quadratic Horizon)</td>
<td></td>
<td>-1.474**</td>
<td>-1.474**</td>
<td>-1.474**</td>
<td>-1.474**</td>
<td>-1.474**</td>
</tr>
<tr>
<td>( \hat{\delta}_{0,3}^{*} ) (Pr(Type 1) × Cubic Horizon)</td>
<td></td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td></td>
<td>n.a.</td>
<td>2.83%</td>
<td>2.89%</td>
<td>3.91%</td>
<td>3.93%</td>
</tr>
<tr>
<td>AIC/1000</td>
<td></td>
<td>-74.034</td>
<td>-76.578</td>
<td>-76.634</td>
<td>-77.576</td>
<td>-77.586</td>
</tr>
<tr>
<td>SIC/1000</td>
<td></td>
<td>-74.025</td>
<td>-76.494</td>
<td>-76.521</td>
<td>-77.454</td>
<td>-77.436</td>
</tr>
<tr>
<td>F p-value (R0 v. R1, R2, R3, R4)</td>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>F p-value (R1 v. R2, R3, R4)</td>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>F p-value (R2 v. R3, R4)</td>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>F p-value (R3 v. R4)</td>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
</tr>
</tbody>
</table>
Table IV: Forecast accuracy and analyst type

This table contains the mean squared forecast error (MSFE) associated with various type-1 probability deciles (based on the M3 model of decomposed boldness given by (21d)), and various forecast horizon lengths. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). These MSFE values are calculated using bold forecasts only (Panel A) and all forecasts (Panel B). In addition, we provide the difference between the MSFE associated with the lowest and highest type-1 probability deciles (LMH), and the MSFE associated with all forecasts in each forecast horizon category. Welch (1947) t-tests are performed to examine three hypotheses: First, the hypothesis that the MSFE associated with each type-1 probability decile and each forecast horizon category equals the MSFE associated with all forecasts (the benchmark); and second, the hypothesis that the MSFE associated with all forecast horizon categories equals the MSFE associated with all forecasts (the benchmark); and third, the hypothesis that the LMH MSFE equals zero (the benchmark). The significance of each test is denoted by †† (1% significance), and † (5% significance), if the MSFE is significantly greater than its benchmark; §§ (1% significance), and § (5% significance), if the MSFE is significantly less than its benchmark; and ** (1% significance), and * (5% significance), if the LMH MSFE is significantly different from zero. All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Type-1 Quantile Range</th>
<th>Short</th>
<th>Medium</th>
<th>Long</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A: Bold forecasts only</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0% to 10% (low type-1 probability)</td>
<td>0.342††</td>
<td>0.408††</td>
<td>0.358††</td>
<td>0.385††</td>
</tr>
<tr>
<td>10% to 20%</td>
<td>0.139</td>
<td>0.160††</td>
<td>0.168</td>
<td>0.157††</td>
</tr>
<tr>
<td>20% to 30%</td>
<td>0.109</td>
<td>0.093††</td>
<td>0.142</td>
<td>0.105§</td>
</tr>
<tr>
<td>30% to 40%</td>
<td>0.076</td>
<td>0.080††</td>
<td>0.105§</td>
<td>0.084§</td>
</tr>
<tr>
<td>40% to 50%</td>
<td>0.091</td>
<td>0.087††</td>
<td>0.156</td>
<td>0.099§</td>
</tr>
<tr>
<td>50% to 60%</td>
<td>0.049††</td>
<td>0.091††</td>
<td>0.079§</td>
<td>0.081§</td>
</tr>
<tr>
<td>60% to 70%</td>
<td>0.053††</td>
<td>0.085††</td>
<td>0.091§</td>
<td>0.080§</td>
</tr>
<tr>
<td>70% to 80%</td>
<td>0.063††</td>
<td>0.069††</td>
<td>0.083§</td>
<td>0.070§</td>
</tr>
<tr>
<td>80% to 90%</td>
<td>0.060††</td>
<td>0.071††</td>
<td>0.109</td>
<td>0.074§</td>
</tr>
<tr>
<td>90% to 100% (high type-1 probability)</td>
<td>0.048††</td>
<td>0.059††</td>
<td>0.120</td>
<td>0.066§</td>
</tr>
<tr>
<td>LMH (low minus high)</td>
<td>0.203**</td>
<td>0.348**</td>
<td>0.238**</td>
<td>0.319**</td>
</tr>
<tr>
<td>All</td>
<td>0.105§</td>
<td>0.118</td>
<td>0.148††</td>
<td>0.120</td>
</tr>
<tr>
<td>Panel B: All forecasts</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0% to 10% (low type-1 probability)</td>
<td>0.355††</td>
<td>0.402††</td>
<td>0.355††</td>
<td>0.383††</td>
</tr>
<tr>
<td>10% to 20%</td>
<td>0.141†</td>
<td>0.182††</td>
<td>0.165</td>
<td>0.169††</td>
</tr>
<tr>
<td>20% to 30%</td>
<td>0.094</td>
<td>0.103</td>
<td>0.150</td>
<td>0.110</td>
</tr>
<tr>
<td>30% to 40%</td>
<td>0.073†</td>
<td>0.076††</td>
<td>0.100§</td>
<td>0.081§</td>
</tr>
<tr>
<td>40% to 50%</td>
<td>0.081</td>
<td>0.091††</td>
<td>0.128</td>
<td>0.095§</td>
</tr>
<tr>
<td>50% to 60%</td>
<td>0.068††</td>
<td>0.071††</td>
<td>0.082§</td>
<td>0.072§</td>
</tr>
<tr>
<td>60% to 70%</td>
<td>0.067††</td>
<td>0.084††</td>
<td>0.075§</td>
<td>0.080§</td>
</tr>
<tr>
<td>70% to 80%</td>
<td>0.061††</td>
<td>0.061††</td>
<td>0.075§</td>
<td>0.063§</td>
</tr>
<tr>
<td>80% to 90%</td>
<td>0.053††</td>
<td>0.066††</td>
<td>0.110</td>
<td>0.071§</td>
</tr>
<tr>
<td>90% to 100% (high type-1 probability)</td>
<td>0.050††</td>
<td>0.050††</td>
<td>0.115</td>
<td>0.060§</td>
</tr>
<tr>
<td>LMH (low minus high)</td>
<td>0.305**</td>
<td>0.352**</td>
<td>0.240**</td>
<td>0.323**</td>
</tr>
<tr>
<td>All</td>
<td>0.105††</td>
<td>0.116</td>
<td>0.143††</td>
<td>0.118</td>
</tr>
</tbody>
</table>
Table V: Boldness model robustness (model fit and unconditional boldness probabilities)

This table contains measures of model fit (based on the Akaike Information Criterion, AIC) and the mean fitted unconditional probability of being bold, associated with various models of decomposed boldness, various measures of the consensus forecast, and various forecast horizons. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). The numbers in parentheses associated with these horizons are the actual mean unconditional probability of being bold as given by the data. All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Construction Technique</th>
<th>Horizon</th>
<th>M0</th>
<th>M1</th>
<th>M2</th>
<th>M3</th>
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<tbody>
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<td>Panel A: Model fit (AIC/1000)</td>
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<tr>
<td>C1: Equal-weighting</td>
<td>Short</td>
<td>112.784</td>
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<td>112.361</td>
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<td>113.334</td>
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<td>113.103</td>
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<td>C2: Equal-weighting (with trimming)</td>
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<td>112.533</td>
<td>112.326</td>
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<td>Long</td>
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</tr>
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<td>112.549</td>
<td>113.334</td>
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<tr>
<td>C3: Equal-weighting (with Winsorising)</td>
<td>Short</td>
<td>112.572</td>
<td>112.361</td>
<td>112.226</td>
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<td></td>
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<td>112.549</td>
<td>113.334</td>
<td>113.179</td>
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<td>114.504</td>
<td>114.423</td>
<td>115.919</td>
</tr>
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<td>Long</td>
<td>114.705</td>
<td>114.504</td>
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</tr>
<tr>
<td></td>
<td>All</td>
<td>114.705</td>
<td>114.504</td>
<td>114.423</td>
<td>115.919</td>
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<tr>
<td>C5: Accuracy-weighting</td>
<td>Short</td>
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<td>113.334</td>
<td>113.179</td>
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<td>113.334</td>
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<tr>
<td>C6: Time/Accuracy-weighting</td>
<td>Short</td>
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<td>114.989</td>
<td>114.897</td>
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<tr>
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<td>115.187</td>
<td>114.989</td>
<td>114.897</td>
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<td>114.989</td>
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<td>Panel B: Predicted behaviour (mean unconditional boldness)</td>
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<td></td>
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<tr>
<td>C1: Equal-weighting</td>
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<td>0.663</td>
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<tr>
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<td>Medium (0.682)</td>
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<td>0.672</td>
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<tr>
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<td>Long (0.640)</td>
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<td>0.670</td>
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<td>All (0.671)</td>
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<tr>
<td>C2: Equal-weighting (with trimming)</td>
<td>Short (0.667)</td>
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<td>0.673</td>
<td>0.667</td>
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<tr>
<td></td>
<td>Medium (0.683)</td>
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<td>0.674</td>
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<td>0.672</td>
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<td>C3: Equal-weighting (with Winsorising)</td>
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<td>0.672</td>
<td>0.666</td>
<td>0.666</td>
</tr>
<tr>
<td></td>
<td>Medium (0.683)</td>
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<td>0.673</td>
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</tr>
<tr>
<td></td>
<td>Long (0.641)</td>
<td>0.673</td>
<td>0.672</td>
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<tr>
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</tr>
<tr>
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<td>Long (0.630)</td>
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<td>C6: Time/Accuracy-weighting</td>
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<td>0.639</td>
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</tr>
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<td>Medium (0.661)</td>
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</tr>
<tr>
<td></td>
<td>Long (0.627)</td>
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<td>0.626</td>
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</tr>
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<td></td>
<td>All (0.651)</td>
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<td>0.651</td>
<td>0.651</td>
<td>0.639</td>
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</table>
Table VI: Boldness model robustness (conditional boldness and type probabilities)

This table contains measures of the predicted type-1 boldness probability, the predicted type-2 boldness probability, and the predicted type-1 probability. These predicted values are generated via the M3 model of decomposed boldness given by (21d), various measures of the consensus forecast, and various forecast horizons. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

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<td>Medium</td>
<td>Long</td>
<td>All</td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Predicted behaviour (mean type-1 boldness probability)</strong></td>
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<td>C1: Equal-weighting</td>
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<td>0.833</td>
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<td>C3: Equal-weighting (with Winsorising)</td>
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<td>C4: Time-weighting</td>
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<td>0.987</td>
<td>0.917</td>
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<td>C5: Accuracy-weighting</td>
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<td>C6: Time/Accuracy-weighting</td>
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<td><strong>Panel B: Predicted behaviour (mean type-2 boldness probability)</strong></td>
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</tr>
<tr>
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<tr>
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<tr>
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<tr>
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<td>0.576</td>
<td>0.576</td>
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<tr>
<td>C6</td>
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<td>0.566</td>
<td>0.566</td>
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<td><strong>Panel C: Predicted behaviour (mean type-1 probability)</strong></td>
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<tr>
<td>C1</td>
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<td>0.286</td>
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<td>0.200</td>
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Table VII: Forecast accuracy robustness (regression-based type effects)

This table containing the partial derivative of forecast inaccuracy (as measured by the squared forecast error) with respect to the type-1 probability based on the estimated R4 model given by (23e). These estimated total impact measures are calculated for various measures of the consensus forecast, and various forecast horizons. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). In addition, we use a Welch (1947) t-test to examine whether the estimated total impact during each of these forecast horizon lengths is equal to the estimated total impact during all forecast horizons. The significance of each test is denoted by †† (1% significance), † (5% significance), if the estimated total impact during a particular forecast horizon length is significantly greater than the estimated total impact during all horizons; and §§ (1% significance), and § (5% significance), if the estimated total impact during a particular forecast horizon length is significantly less than the estimated total impact during all horizons. All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Construction Technique</th>
<th>Short</th>
<th>Medium</th>
<th>Long</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1: Equal-weighting</td>
<td>−1.429†††</td>
<td>−1.534†††</td>
<td>−1.336†††</td>
<td>−1.480‡‡</td>
</tr>
<tr>
<td>C2: Equal-weighting (with trimming)</td>
<td>−1.434†††</td>
<td>−1.552†††</td>
<td>−1.358†††</td>
<td>−1.496‡‡</td>
</tr>
<tr>
<td>C3: Equal-weighting (with Winsorising)</td>
<td>−1.408†††</td>
<td>−1.518†††</td>
<td>−1.323†††</td>
<td>−1.463‡‡</td>
</tr>
<tr>
<td>C4: Time-weighting</td>
<td>−2.723†††</td>
<td>−2.905†††</td>
<td>−2.672†††</td>
<td>−2.830‡‡</td>
</tr>
<tr>
<td>C5: Accuracy-weighting</td>
<td>−1.527†††</td>
<td>−1.644†††</td>
<td>−1.425†††</td>
<td>−1.583‡‡</td>
</tr>
<tr>
<td>C6: Time/Accuracy-weighting</td>
<td>−2.813†††</td>
<td>−2.996†††</td>
<td>−2.763†††</td>
<td>−2.920‡‡</td>
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</tbody>
</table>
Table VIII: Forecast accuracy robustness (portfolio-based type effects)

This table contains the mean squared forecast error (MSFE) associated with various type-1 probability deciles (based on the M3 model of decomposed boldness given by (21d)), various measures of the consensus forecast, and various forecast horizon lengths. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). Specifically, we provide the difference between the MSFE associated with the lowest and highest type-probability deciles (LMH), and the MSFE associated with all forecasts in each forecast horizon category. These MSFE values are calculated using bold forecasts only (Panel A) and all forecasts (Panel B). Welch (1947) t-tests are performed to examine two hypotheses: First, the hypothesis that the MSFE associated with all forecast horizon categories equals the MSFE associated with all forecasts (the benchmark); and second, the hypothesis that the LMH MSFE equals zero (the benchmark). The significance of each test is denoted by †† (1% significance), and † (5% significance), if the MSFE is significantly greater than its benchmark; §§ (1% significance), and § (5% significance), if the MSFE is significantly less than its benchmark; and ** (1% significance), and * (5% significance), if the LMH MSFE is significantly different from zero. All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

<table>
<thead>
<tr>
<th>Construction Technique</th>
<th>Type-1 QR</th>
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<th>Long</th>
<th>All</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C1: Equal-weighting</td>
<td>LMH (low minus high)</td>
<td>0.293**</td>
<td>0.348**</td>
<td>0.238**</td>
<td>0.319**</td>
</tr>
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<td>C2: Equal-weighting (with trimming)</td>
<td>0.287**</td>
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<td>0.244**</td>
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<td>0.290**</td>
<td>0.348**</td>
<td>0.242**</td>
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<td>0.257**</td>
<td>0.328**</td>
<td>0.261**</td>
<td>0.303**</td>
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<td>C5: Accuracy-weighting</td>
<td>0.312**</td>
<td>0.358**</td>
<td>0.256**</td>
<td>0.331**</td>
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<td>C6: Time/Accuracy-weighting</td>
<td>0.291**</td>
<td>0.346**</td>
<td>0.270**</td>
<td>0.322**</td>
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<td>C1 All</td>
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<td>0.105†</td>
<td>0.116</td>
<td>0.148††</td>
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<td>0.109</td>
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<td>0.148††</td>
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Panel B: All forecasts

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<th>Long</th>
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<td></td>
<td></td>
</tr>
<tr>
<td>C1: Equal-weighting</td>
<td>LMH (low minus high)</td>
<td>0.305**</td>
<td>0.352**</td>
<td>0.240**</td>
<td>0.323**</td>
</tr>
<tr>
<td>C2</td>
<td>0.308**</td>
<td>0.351**</td>
<td>0.253**</td>
<td>0.326**</td>
<td></td>
</tr>
<tr>
<td>C3</td>
<td>0.302**</td>
<td>0.346**</td>
<td>0.248**</td>
<td>0.321**</td>
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<tr>
<td>C4</td>
<td>0.254**</td>
<td>0.347**</td>
<td>0.256**</td>
<td>0.313**</td>
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<tr>
<td>C5</td>
<td>0.323**</td>
<td>0.364**</td>
<td>0.261**</td>
<td>0.338**</td>
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<tr>
<td>C6</td>
<td>0.268**</td>
<td>0.356**</td>
<td>0.268**</td>
<td>0.324**</td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>All</td>
<td>0.105†§</td>
<td>0.116</td>
<td>0.143††</td>
<td>0.118</td>
</tr>
</tbody>
</table>

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Figure 1: Intra-horizon forecast competition

This figure contains the total number of forecasts issued during each week of the forecast horizon. All information in this figure is based on 89,038 annual forecasts issued over the period, 1994 to 2006.
Figure 2: Intra-horizon behaviour

This figure is divided into two panels: Panel (a) contains type-1 probability estimates over the forecast horizon; and Panel (b) contains probability of boldness (conditional on type) estimates, and unconditional probability of boldness estimates, over the forecast horizon. All of these estimates are based on the M3 model of decomposed boldness. All information in this figure is based on 89,038 annual forecasts issued over the period, 1994 to 2006.
Figure 3: The impact of analyst type changes

This figure contains the partial derivative of forecast inaccuracy (as measured by the squared forecast error) with respect to the type-1 probability, based on the estimated R4 model given by (23e). These estimated total impact measures are calculated at each point over the forecast horizon. In addition, the average value of this estimated total impact is provided. All information in this table is based on 89,038 annual forecasts issued over the period, 1994 to 2006.
Figure 4: Marginal effects (construction technique and model variation)

This figure contains the estimated marginal effects for various analyst-specific variables (given by (18)), as implied by various models of boldness, and for various measures of the consensus forecast. All information in this figure is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

(a) Brokerage Size

(b) Number of Industries

(c) Lagged Inaccuracy

(d) Individual Dummy

(e) Forecast Frequency
Figure 5: Marginal effects (construction technique and horizon variation)

This figure contains the estimated marginal effects for various analyst-specific variables (given by (18)), as implied by the M3 model of decomposed boldness given by (21d), and for various forecast horizons. The following forecast horizons are considered: ‘Short’ (defined as horizons of less than 12 weeks); ‘Medium’ (defined as horizons greater than or equal to 12 weeks, but less than 40 weeks); and ‘Long’ (defined as horizons greater than or equal to 40 weeks). All information in this figure is based on 89,038 annual forecasts issued over the period, 1994 to 2006.

(a) Brokerage Size

(b) Number of Industries

(c) Lagged Inaccuracy

(d) Individual Dummy

(e) Forecast Frequency