Did You See What I Saw? Interpreting Others’ Forecasts When Their Information Is Unknown*

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Abstract

We conduct a forecasting experiment to examine whether people properly account for potential differences between their information and others’. Subjects first choose whether to observe a firm’s costs or revenues, after which they issue initial forecasts for the firm’s earnings. Subjects are then informed whether a randomly chosen partner observed good news or bad news about the firm, and they issue revised forecasts. We find that unless their partner’s information directly contradicts the information they observe, subjects generally revise their forecasts as though they naïvely assume their partner observes the same information as them.

Keywords: Forecasting, Financial Analysts, False Consensus Effect

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1 Introduction

In almost any economic setting where information may be aggregated, it is useful for people to know what information others rely on to form their beliefs. For example, consider two financial analysts covering a particular firm. If one analyst believes the firm will have high earnings, and he observes that the other analyst also believes the firm will have high earnings, it is important for him to know whether the other analyst is optimistic for the same reason as him. If their optimism is based on the same information, there is little reason for the analyst to update his beliefs about the firm’s earnings upon observing that the other analyst is also optimistic. If, on the other hand, the other analyst’s optimism is based on different information, then the analyst should become even more optimistic about the firm’s earnings upon learning that the other analyst is optimistic.

In the case of financial markets, it is rational for traders to incorporate market prices, which can convey information about others’ valuations. Consider the case of a firm’s earnings announcement. Each trader who analyzes the earnings report will likely update his beliefs about the firm’s future operating performance, which will affect his valuation for the firm. While all traders may examine the same report, they may arrive at different conclusions based upon differing expertise, limited attention, or bounded rationality. For example, given the length and detail of earnings reports, it is likely that some traders simply ‘skim’ the report and may focus their attention on different areas of the report. A trader can also observe the market reaction to the earnings announcement, which may provide him with information about whether other traders became more or less optimistic about the firm’s future performance. The market reaction, however, does not reveal why other traders become more or less optimistic about the firm. If the change in an individual trader’s valuation is not similar to the change in the firm’s market value, that trader might infer that others are unaware of something that he knows, or he is unaware of something that others know. If, on the other hand, the market response is similar to the trader’s, it is unclear whether the trader should further update his beliefs. If other market participants updated their valuations for the same reasons as the trader, then the trader should not update his beliefs further. However, if the other traders updated their valuations for different legitimate reasons, the trader should take this information into account and
become even more optimistic regarding the firm.

The problem is that in this and many other situations people cannot know for sure whether others are optimistic (or pessimistic) for the same or different reasons; therefore people must form subjective beliefs about the sources of others’ information. Joint optimism can come from observing the same information or different optimistic information. Any trader who recognizes this uncertainty should become at least modestly more optimistic upon learning that others also became more optimistic. However, if a trader’s subjective beliefs are inconsistent with reality, he may fail to respond adequately to the market response (e.g., he overestimates the similarity of his information to others’) or he may overreact to the market response (e.g., he overestimates the differences between his information and others’).

While information aggregation and transmission have been studied extensively theoretically and experimentally when the sources of information are taken to be common knowledge, there is relatively little research examining the persistent real world problem of ambiguity of information sources. This study aims to provide insights into this problem by conducting a controlled forecasting experiment where in addition to uncertainty regarding economic fundamentals (the firm’s earnings) there is an added level of uncertainty regarding the source of information for other participants. We then examine whether this added level of uncertainty creates systematic biases in the decisions of real human decision makers.

The context of our experiment is a simple financial forecasting exercise. Subjects are asked to provide forecasts for a hypothetical firm’s earnings, equal to revenues minus costs, plus a random noise term.\(^1\) Revenues and costs each take one of two values, each with 50% probability. Revenues and costs are independent of each other (and the noise term). Subjects first choose whether to observe revenues or costs; they cannot choose to observe both. After they are shown the realization of their chosen earnings component, they are asked to provide an initial forecast for the firm’s earnings. Next, each subject is informed whether his randomly assigned partner observed “good news” (which can represent either high revenues or low costs) or “bad news” (low revenues or high

\(^1\)The random noise term can be thought of as an unpredictable earnings readjustment term, or more generally, a component of revenues or costs that is unknowable at a given point in time.
costs). Subjects are not informed whether their partner chose to observe revenues or costs. Subjects are then asked to issue revised forecasts for the firm’s earnings.

We find that subjects generally issue optimal initial forecasts that correctly account for the remaining uncertainty in earnings. Also, when information of the partner is in the opposite direction from their own, the subjects appear to understand the implications and generally revise their forecast to reflect the aggregated information. On the other hand, subjects frequently fail to correctly incorporate the information of others when it is in the same direction (e.g. both good news or both bad news). While there is heterogeneity in subject responses, many subjects appear to suffer from a “false consensus effect” and behave as if the other subject definitely saw the same piece of information. A much smaller proportion of the subjects suffered from a “false uniqueness effect” and behaved as if the other subject definitely saw a different piece of information. We find that these systematic biases are stable over time so are likely to persist even with experience.

Much of the related literature is in psychology. Psychologists have long been interested in whether people overestimate their similarity to others. Their studies are primarily based on surveys that ask respondents: (i) whether they engage in a certain activity (e.g., watch television at least 30 hours a month), hold a certain belief (e.g., whether nuclear weapons will be used in warfare during the next 20 years), have a certain preference (e.g. prefer wheat bread or white bread), etc., and (ii) to estimate the percentage of the general population that engages in the activity, holds the belief, or has the preference. The general finding from this literature is that people do tend to overestimate their similarity to others, a finding known as the “false consensus effect” (FCE). For more discussion of this literature, see Krueger (1998), Krueger (2000), or Williams (2013). This literature, however, does not examine how people update their beliefs upon learning that others observed good news or bad news when there is uncertainty about others’ sources of information,

\footnote{As Dawes and Mulford (1996) note, it is rational for Bayesians to update their beliefs based on a sample of one (e.g., their own type). In other words, rationality is consistent with individuals’ preferences being correlated with their estimates of the preference in the general population. Some researchers have responded by defining a “truly false consensus effect” (TFCE) to occur if respondents weight their own responses more heavily than the response of a randomly chosen individual. Engelmann and Strobel (2000) and Engelmann and Strobel (2012) analyze whether this form of a truly false consensus effect arises when there are monetary incentives; they find that it arises only if mental effort is required to infer others’ decisions.}
which is the focus of this study.

The related literature in economics, finance, and accounting is small, primarily because (to our knowledge) economists have largely ignored the issue of whether people have biased beliefs regarding the similarity of their information to others’. Williams (2013) models sequential forecasting with differential information. Drawing from the psychological evidence described in the previous paragraph, he assumes that the forecasters overestimate the correlation of their private signal errors. Using financial analysts’ earnings forecasts, he empirically confirms a testable prediction of his model, namely, that the likelihood of an analyst underreacting in his forecast revision is increasing in the number of analysts who issue forecasts between the time of the analyst’s earlier forecast and his revised forecast.

Compared to the field, the laboratory is advantageous because it allows us to cleanly identify possible biases in information processing. By examining behavior in the experimental laboratory we have the ability to control for a number of factors that makes it difficult to make conclusions with empirical data. For example, we are able to observe the information sources of all participants as well as how their decisions (forecasts) related to that information. The complexities, lack of control of incentives, and unobservability of actual information sources makes drawing firm conclusions using naturally occurring data nearly impossible. However, the experimental laboratory can provide evidence that certain biases are likely to be driving factors in real world decision processes that closely parallel the setting created in the laboratory.

Our findings have obvious implications for the analyst forecasting literature. Our evidence suggests that financial analysts may overestimate the likelihood that other analysts observe the same information as them, lending additional support for the model of Williams (2013). Moreover, Elliott, Philbrick, and Wiedman (1995) document that analysts underreact to firms’ recent stock returns when issuing earnings forecasts. Our experiments suggest that analysts may overestimate the likelihood that market participants are observing the same information as them, which would

\[3\] In practice, analysts endogenously choose whether, and when, to issue earnings forecasts. The lab allows us to avoid such endogeneity problems. Moreover, it is not clear that financial analysts’ forecasts equal their true beliefs. There is a large literature suggesting that they may have incentives to issue forecasts that differ from their true beliefs. See, e.g., Trueman (1990), Trueman (1994), and Ottaviani and Sørensen (2006).
explain why analysts insufficiently react to the firm’s recent stock returns.

Our findings also have important implications regarding how financial markets aggregate information. Two types of equilibrium concepts dominate this literature: difference of opinion (DO) and rational expectations (RE). In DO models, investors do not learn from price—they treat the equilibrium price as completely uninformative, despite the fact that it reveals useful information about others’ signals. In RE models, investors fully understand the distribution of everyone’s signals as well as the equilibrium pricing function that maps investors’ signals to the equilibrium price. They use this knowledge of their environment to update their beliefs about the asset’s value upon observing the equilibrium price—their posterior beliefs are a function of the equilibrium price and their private signal.4

Our experiments suggest that a more appropriate model for information aggregation may lie between these two polar equilibrium concepts. In our experiments, subjects recognize that others’ signals are informative, but only when it is obvious that others observed a different signal. This suggests that a more appropriate model of information aggregation is one where investors learn from price (as in RE models) when the equilibrium price clearly reveals that others observed private signals that differ from their own. However, when the equilibrium price is somewhat consistent with an investor’s private signal, he naively assumes other investors observed the same information as him, so he treats the equilibrium price as incrementally uninformative (as in DO models). Choi and Williams (2013) introduce such an equilibrium concept in their model of trading around earnings announcements. They show that such an assumption naturally leads to post-earnings announcement drift and high trading volume around earnings announcements with extreme (high or low) earnings surprises and returns, consistent with the empirical evidence.

The paper is outlined as follows. We provide a detailed description of the experiment in Section 2. Section 3 contains our empirical analysis of subjects’ behavior, and Section 4 concludes.

4Often, the equilibrium price makes their own private signal incrementally uninformative, and all agents ignore their own signals.
2 Experimental Environment

All experimental subjects participated in the same forecasting decision process for 30 independent periods. In each period, subjects were randomly matched with a partner. Each pair of matched subjects faced the same task of forecasting a hypothetical firm’s earnings, $X$. The firm’s earnings were determined by its uncertain revenues, $R$, costs, $C$, and a random noise component, $\epsilon$, as follows:

$$X = R - C + \epsilon.$$ 

Revenues were distributed according to $P(R = $20) = 0.5$ and $P(R = $10) = 0.5$, costs were distributed according to $P(C = $0) = 0.5$ and $P(C = $10) = 0.5$, and $\epsilon$ was distributed uniformly on $[-$1, $1]$. Revenues, costs, and $\epsilon$ were independently distributed across pairs and across periods, so each firm’s unconditional expected earnings was $10:


Each independent experimental period proceeded in a series of two distinct stages: an initial forecast stage and a revised forecast stage. In the initial forecast stage, each subject was first given the option to observe either the revenues realization, $R$, or the cost realization, $C$.$^5$ Upon selecting only one of the realizations, subjects were informed of the realization in the following manner: they were told that they had observed either “good news” or “bad news,” and they were told the exact realization associated with such news. In the case of revenues, good news was associated with high revenues ($R = $20), and bad news was associated with low revenues ($R = $10). For costs, good news was associated with low costs ($C = $0), and bad news was associated with high costs ($C = $10).

Subjects were then asked to submit an initial forecast, $f^0$, for the firm’s earnings, $X$, and they

$^5$The order of the buttons for selecting either revenues or costs was randomized on the computer screen to avoid potential issues with biases for subjects to select the top button. See the experimental results section for a description of the frequency of choice of revenues or costs realizations.
were compensated according to the following proper scoring rule:

\[
\text{Compensation} = 6 - 0.04(f^0 - X)^2. \tag{1}
\]

Since the mean is the best predictor under square loss, subjects could maximize their expected compensation by issuing forecasts equal to their conditional expectations of \(X\).\(^6\)

Given the information structure described above, the expectation of earnings in the initial stage depends only on whether the subject has observed good news or bad news (and not on whether revenues or costs were observed):

\[
\begin{align*}
E[X|\text{good news}] &= 15, \quad \text{and} \\
E[X|\text{bad news}] &= 5.
\end{align*}
\tag{2, 3}
\]

Therefore, we would expect a risk neutral, expected utility maximizer to report either $5 or $15 in the initial forecasting stage. We refer to the forecast consistent with risk neutral, expected utility maximization as the “optimal” forecast henceforth.

In the revised forecast stage, the subjects were informed of whether their partner observed good or bad news but not whether their partner observed the revenue or cost realization. The subjects were not aware of the identity of their partner in any period.\(^7\) Subjects were then asked to submit a revised forecast, \(f^R\). Their compensation for their revised forecasts is given by the same proper scoring rule described in (1).\(^8\)

If the signal \(i\)'s partner observes (good news or bad news) is not consistent with \(i\)'s signal, then it is obvious that the subjects observed different earnings components, and that the expected earnings conditional on their information is $10. Hence, \(i\)'s revised forecast (after observing whether

\(^6\)Since the object of this study was not compliance with a proper scoring rule, the experimental instructions provided guidance in this regard. Subjects were informed that they would maximize their expected compensation by issuing forecasts equal to what they think earnings would be on average given all the information they have observed. We formally verify the incentive properties of the scoring rule in Appendix A.

\(^7\)The subjects were not informed of the forecast of their partner to avoid potential uncertainties created by initial forecasts that did not conform to risk neutral expected utility maximization. They were, however, informed of the forecast such a person would have submitted (e.g. $5 or $15 as described above).

\(^8\)Simply replace the \(f^0\) in (1) with \(f^R\).
his partner observed good news or bad news) should be $10. Note that in this case the only remaining uncertainty is the small residual noise created by $\epsilon$. Thus, an obvious test of comprehension of the experimental environment is that, when this situation arises, nearly all subjects should report revised forecasts very close to $10$.

The more interesting case is when the signal $i$’s partner observes is consistent with $i$’s signal. In other words, both subjects observe either good or bad news. Subject $i$’s optimal revised forecast will depend on whether or not his partner observed the same information as him. For example, in the case of good news, if $i$ and his partner observe the same component of earnings, then $i$ gains no incremental information upon observing that his partner also observed good news, so the expected earnings conditional on the total information the two subjects observed is $15$. If, on the other hand, $i$’s partner observed that the other component of earnings conveyed good news, then there is additional information value in her signal, and the expected earnings conditional on the total information the subjects observed is $20$.

Since the subjects are unaware of the earnings component observed by their partner (or the population in general), their optimal revised forecast will be a function of their subjective probability that their partner observed the same earnings component. Let $q$ denote a subject’s prior probability that his partner observes the same earnings component (revenues or costs) as him. It is straightforward to verify that

$$P(\text{partner observes the same component | their signals are consistent}) = \frac{2q}{1 + q},$$

from which it follows that

$$P(\text{partner observes the other component | their signals are consistent}) = \frac{1 - q}{1 + q}.$$

Hence, the optimal revised forecast (after observing that his partner also observed good news) is
given by

\[ f^R = \mathbb{E}[\text{earnings} \mid \text{both subjects observe good news}] \]

\[ = \left( \frac{2q}{1+q} \right) \$15 + \left( \frac{1-q}{1+q} \right) \$20. \tag{4} \]

Since subjects are uninformed of the component choices of their partners, it might be reasonable to posit that \( q = 0.5 \). In this case, the optimal revised forecast is \$16\frac{2}{3} \). By symmetry, if \( q = 0.5 \) and both subjects observe bad news, then the optimal revised forecast should be \$3\frac{1}{3} \).

The primary objective of this study is to examine the implied prior, \( q \), of the subject population—in particular, to examine whether \( q \) systematically differs from the empirical distribution of component observation choices. Assuming the subjects are risk neutral utility maximizers, (4) implies there is a one-to-one relationship between a subject’s prior probability that his partner chooses to observe the same earnings component as him, \( q \), and the subject’s revised forecast when the news his partner observes (good or bad) is consistent with the news he observes, \( f^R \). Hence, in these cases we can solve for the implied prior, \( q \), as a function of the subject’s revised forecast, \( f^R \):

\[ q = \begin{cases} \frac{\$20 - f^R}{\$10 - f^R} & \text{if both subjects observe good news} \\ \frac{f^R}{\$10 - f^R} & \text{if both subjects observe bad news} \end{cases} \tag{5} \]

If the subject’s revised forecast equals his initial forecast, then his implied \( q \) is equal to 1. We say such forecasts are consistent with an extreme form of a “false consensus effect,” where the subject assumes everyone chooses to observe the same earnings component as him.\(^9\) We say that forecast revisions implying that \( q \) is equal to 0 are consistent with an extreme form of a “false uniqueness

\(^9\)It is puzzling why subjects’ revised forecasts would ever equal their initial forecasts, because if a subject is certain his partner will choose a certain earnings component, then he should choose to observe the opposite component. For example, a subject who believes everyone else is choosing to observe revenues should rationally decide to observe costs so that his revised forecast will be fully informed (except for the noise component).
effect,” where the subject assumes everyone chooses to observe the opposite earnings component as him.

While we use risk neutral utility maximization as our primary benchmark, our subjects might exhibit risk aversion, in which case drawing such clear inferences about $q$ might be more difficult. It is worth noting that many of the qualitative predictions survive even in the case of risk aversion. When subjects observe consistent news, their revised forecasts should not equal their initial forecasts even if they are extremely risk averse. Consider a risk averse utility maximizer who is initially uncertain whether his partner chooses to observe the same earnings component as him ($q \in (0, 1)$), and suppose (without loss of generality) that he observes good news (e.g., high revenues). Then his posterior subjective distribution of the firm’s earnings will shift in the sense of first order stochastic dominance upon observing that his partner also observed good news. We show in Appendix A that any risk averse decision maker will respond to such a shift by issuing a revised forecast that is greater than his initial forecast. (See Proposition 3.) Further, an examination of CRRA preferences (which are typically assumed in economics experiments) for typical risk aversion attitudes reveals that the shift in the revised forecast is similar to that predicted by risk neutrality. For example, if $q = 0.5$ and both subjects observe good news, the optimal revised forecast for risk averse subjects is still above $16$ (the optimal revised forecast for a risk neutral subject is $16\frac{2}{3}$). Importantly, risk aversion does not predict equality of initial and revised forecasts.

At the end of each forecast period, subjects were informed of the actual earnings realization and their potential compensation (given by (1)) from both the initial and revised forecasting stages. They were not informed of the compensation, earnings component observed, or identity of their partner. Subjects were then randomly rematched with a partner and began the next period with a new, independent earnings realization. This proceeded for 30 periods, and the duration of the experiment was common knowledge amongst the subjects.

At the end of the 30 periods, one period for each subject was randomly chosen for compensation based upon their initial forecast for that period, and one period for each subject was random chosen for compensation based upon their revised forecast. We chose to pay for one random period for each
forecasting stage to minimize potential period choice dependencies and the possibility of hedging across stages.

All sessions were conducted at the Pennsylvania State University in the Laboratory for Economics Management and Auctions. All experiments were conducted utilizing the Ztree software (Fischbacher (2007)); a copy of the instructions provided to the subjects at the beginning of the experiment are included in Appendix B.

All subjects were undergraduate or graduate students, and each subject participated in only one session. Two sessions were conducted with 16 and 22 subjects for a total of 38 subjects. Average earnings per subject were $15.18 inclusive of the $5 show up fee. No session lasted longer than 90 minutes. At the end of the session, subjects were asked to provide basic demographic information. There were 20 male subjects, 17 female subjects, and one subject did not answer the gender question. Business majors comprised the majority of the sample (22 out of 38 subjects).

3 Results

We begin by analyzing subjects' initial forecasts. Recall from (2) and (3) that these forecasts should be $15 ($5) if the subject observes good (bad) news, regardless of whether the subject observes revenues or costs. We plot the distribution of subjects' initial forecasts (rounded to the nearest dollar) in Figures 1 and 2. It is apparent from these figures that most of the initial forecasts are consistent with risk neutral utility maximization—723 out of the 1,140 initial forecasts (63.4%) equal the expectation of the firm's earnings conditional on the subject's information. The mean forecast across all subjects and periods was $15.03 for good news and $6.10 for bad news. While the mean forecast is not significantly different than the optimal forecast of $15 in the event of good news ($t = 0.42$), the mean is significantly greater than $5 in the event of bad news ($t = 3.04$), but this was largely due to a few subjects who consistently issued high forecasts after observing bad news (above $10$). Because the individual subject is arguably the smallest independent unit of observation, we compute t-stats by first taking the averages within subject, and then analyzing these averages across subjects. Therefore, the sample size is the number of subjects, and the reported means, which are taken at the forecast level, may differ slightly from the

10
i.e., subjects who are most likely to fully understand the forecasting environment.

After issuing his initial forecast, each subject is informed whether his partner observed good news or bad news about the firm’s earnings, where good (bad) news corresponds to either high revenues or low costs (low revenues or high costs).\textsuperscript{11} After observing this additional information, subjects are asked to issue revised forecasts.

When paired subjects observe contrasting news about the firm’s profits, the firm’s expected earnings conditional on each subject’s information at the time of the revised forecast is $10:

\[
\begin{align*}
\mathbb{E}[X|\text{good news and bad news}] &= \mathbb{E}[X|R = \$20, C = \$10] \\
&= \mathbb{E}[X|R = \$10, C = \$0] \\
&= \$10.
\end{align*}
\]

In Figure 3, we plot the distribution of subjects’ revised forecasts for the 290 instances in which the subject’s partner observed information that conflicted with what the subject observed. 229 of the 290 revised forecasts (79.0\%) equal $10, and the average forecast is $10.28, which is not statistically different than $10 (t = 1.01). This suggests that subjects generally understand how to properly incorporate their partner’s information when it conflicts with what they have observed.

The more interesting scenarios, which are the focus of this study, arise when the subject’s partner observes information that is consistent with what the subject has observed—i.e., when both partners observe good (or bad) news. In these scenarios, the subject cannot know with certainty

\textsuperscript{11}Recall that subjects are not informed which earnings component their partner chose to observe.
whether his partner observed the same information as him. If the subject were initially uncertain whether his partner would choose to observe the same earnings component as him, he should realize that it is possible his partner observed the opposite earnings component, in which case the subject’s posterior beliefs should be shifted towards $20 (in the case of good news) or $0 (in the case of bad news). For any finitely risk averse subject, this shift in beliefs should cause his revised forecast to differ from his initial forecast.

We find that most subjects’ revised forecasts are identical to their initial forecasts in these scenarios—out of the 850 revised forecasts in these scenarios, 443 (52.1%) are identical to the subject’s initial forecast. This suggests that subjects tend to assume their partner chose to observe the same information as them unless they are presented with evidence to the contrary. We plot the distribution of subjects’ revisions, defined as the difference between their revised forecast and their initial forecast, in Figure 4.

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We plot the distribution of subjects’ revisions, defined as the difference between their revised forecast and their initial forecast, in Figure 4.

[INSERT FIGURE 4 HERE]

It is difficult to explain this behavior within a rational paradigm. There are two possibilities: either (i) subjects tend to choose to observe the same earnings component, in which case it is rational (at the time of the revised forecast) to issue a revised forecast that equals the initial forecast, or (ii) subjects overestimate the likelihood their partner is observing the same information as them. Note that the first possibility is not consistent with a subgame perfect Nash equilibrium: if a subject were certain that his partner would choose to observe a certain component, then he should choose to observe the opposite component, because doing so would provide him full information (except for the random noise term) at the time of the revised forecast.13 Empirically distinguishing these two possibilities is straightforward. 613 out of 1,140 times (53.8%) subjects choose to observe revenues,

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12 A well-known phenomenon in experimental data is what is commonly termed an ‘experimenter demand effect’ whereby subjects respond to stimuli simply because they believe the experimenter wants them to respond. Taking this into account, the fact that so many of our subjects resisted change is particularly striking.

13 It is straightforward to verify that in the (unique) symmetric Nash equilibrium, subjects mix evenly between choosing to observe revenues and costs, implying \( q = 0.5 \).
suggesting that the subjects whose revised forecasts equal their initial forecasts behave suboptimally at the revised forecast stage, not in a tendency to choose to observe the same earnings component in the initial forecast stage.

For the remainder of our analysis, we restrict attention to the instances in which the subject’s initial forecast is optimal—$15 if he observed good news, and $5 if he observed bad news. This reduces our sample of revised forecasts from 1,140 observations to 723. We restrict attention to this sample for two reasons. First, these subjects are most likely to understand the game, so our findings will be less likely to be driven by subjects’ misunderstanding of the experiment. Second, this restriction will allow us to use the Bayesian framework of (4)-(5) to estimate subjects’ implied prior probabilities that their partner chooses to observe the same earnings component as them.

We plot the distribution of revised forecasts (rounded to the nearest dollar) among this population when both partners observe good news (bad news) in Figure 5 (Figure 6). Subjects’ tendency to issue revised forecasts that equal their initial forecasts is apparent even when the sample is restricted to subjects whose initial forecast is optimal.

[INSERT FIGURES 5 AND 6 HERE]

Consider Figure 5, which plots subjects’ revised forecasts when both partners observed good news and the subject’s initial forecast is $15. The mean revised forecast is $16.05, which is lower than the predicted optimal forecast of $16.67 ($t = -1.65$). Most of the revised forecasts (190 out of 290, 65.5%) are $15, the same as the subject’s initial forecast. This is consistent with a Bayesian’s posterior mean if he were certain that his partner chose to observe the same earnings component as him ($q = 1$). Some of the revisions are consistent with Bayesian updating from an uncertain prior—47, i.e., 16.2%, of the revised forecasts lie in the open interval ($15, 20$). This is where a Bayesian’s posterior mean would lie if his prior that his partner chooses the same earnings component as him is in the open interval (0, 1). There are other revisions implying that the subject was certain his partner chose to observe the opposite earnings component ($q = 0$): 45, i.e., 15.5% of the revised
forecasts equal $20. Note that unlike the majority of the subjects, whose revised forecast is $15, these subjects’ behavior is consistent with forward looking behavior. For example, if a subject were certain his partner would choose to observe revenues, he should choose to observe costs in order to maximize his expected compensation in the revised forecast stage.\textsuperscript{14}

Revised forecasts when both partners observe bad news, depicted in Figure 6, exhibit similar tendencies. The mean revised forecast is $4.12, which is significantly greater than the predicted optimal forecast of $3.33 (t = 2.95), and 160 out of the 256 (62.5%) revised forecasts are identical to the initial forecast of $5, 59 (23.0%) are strictly between $0 and $5, and 26 (10.2%) are equal to $0.

A natural question is how subjects’ implied $q$’s compare to the actual percentage of subjects who choose to observe revenues and costs, and how the relationship between these variables evolves over time. To address this, we start with the 723 ($f^0, f^R$) pairs such that the initial forecast ($f^0$) is equal to the firm’s expected earnings conditional on the subject’s information at the time of the initial forecast ($15$ if good news, $5$ if bad news). Then, we restrict this sample to the 546 observations in which the subject and partner observed consistent news (i.e., both good or both bad).\textsuperscript{15} Finally, we restrict this sample to the 527 forecasts that are consistent with Bayesian updating, i.e., revised forecasts in the closed interval [$15, $20] in the case where both subjects observe good news, and [$0, $5] in the case where both subjects observe bad news. For each of these 527 ($f^0, f^R$) pairs, we compute the subject’s prior that his partner chooses to observe the same earnings component as him, $q$, via (5). Note that our filters ensure that each such $q$ lies in the closed interval [0, 1].

We plot the average $q$, the median $q$, and the proportion of subjects choosing to observe revenues, by period, in Figure 7. The mean $q$ is higher than the proportion of subjects choosing revenues or costs in 29 of the 30 periods, and the median $q$ is higher than the proportion of subjects choosing revenues or costs in every period. Clearly, subjects’ revised forecasts imply that subjects overestimate the likelihood their partner observes the same information as them, consistent with a false consensus effect.

\textsuperscript{14}We cannot explain the 7 revised forecasts that are less than $15 or the 1 revised forecast that is greater than $20.

\textsuperscript{15}Note that this is the combined sample used to generate Figures 5 and 6.
A puzzling feature of Figure 7 is that there is little evidence that subjects learn over the course of the experiment. The median $q$ is equal to 1 for every period from Period 13 to Period 30, and the mean $q$ actually rises from Period 1 to Period 30. Though we did not inform subjects whether their partner chose to observe revenues or costs, they could infer their partner’s choice (ex post) whenever the firm’s revenues and costs were both high or both low (i.e., when the firm had good news and bad news).

We report the results of basic regressions in Table 1. In these regressions, the sample consists of the 527 forecast revisions for which we can estimate the subject’s implied prior that his partner chooses to observe what he does, $q$. The dependent variable in the regressions is the implied prior, $q$, minus 0.5. Column 1, which includes no explanatory variables, documents that the average implied $q$ is 0.75, and that it is significantly greater than 0.5. Note that 0.5 may not be the appropriate baseline prior since subjects choose to observe revenues a majority (53.8%) of the time. Since the standard error of the intercept is only 0.046, it is clear that the average implied $q$ is statistically greater than baseline $q$’s that are greater than 0.538.

In Column 2, we regress the implied $q$ onto $Period$, which is defined as the period number minus 15.5. The coefficient of $Period$ is actually positive, suggesting that not only do subjects fail to correct their false consensus tendencies over time, these tendencies are exacerbated by experience. Finally, in Column 3, we explore gender differences. We find that the coefficient on $Female$ is negative, suggesting that the females in our sample exhibited less of a false consensus effect, although the difference between their implied $q$’s and males’ implied $q$’s is not statistically significant.

A possible alternative explanation for subjects’ tendency to issue revised forecasts that equal their initial forecasts is inattention—perhaps subjects simply ignore whether their partner observed
good or bad news. To rule out this possibility, we start with the 723 observations with optimal initial forecasts, and restrict that sample to the 177 observations in which the partner’s information conflicts with the subject’s information. If subjects are ignoring the information about their partner’s news, then we should expect their revised forecasts to equal their initial forecast in this sample. Figure 8 shows this distribution for the 92 cases in which the subject observes good news and his partner observes bad news, and Figure 9 shows the distribution for the 85 cases in which the partner observes bad news and his partner observes good news.\textsuperscript{16} In each scenario, subjects overwhelmingly choose $10 for their revised forecast even though their initial forecasts are either $15 (Figure 8) or $5 (Figure 9).\textsuperscript{17}

We now consider cross-sectional differences in subjects’ forecast revision tendencies. Do subjects vary in their tendencies to exhibit a false consensus effect?

To obtain meaningful measures of subjects’ priors at the subject level, we restrict our sample to the 21 subjects who have at least 15 periods satisfying the following conditions: (i) the subject’s initial forecast in the period is optimal ($5 if he observed bad news, $15 if he observed good news), (ii) the subject’s partner observed the same directional news (good news or bad news) as him, and (iii) the subject’s revised forecast can be explained within a Bayesian framework, i.e., the revised forecast is in the closed interval [$15, $20] if the partners observed good news, and in the closed interval [$0, $5] if the partners observed bad news.\textsuperscript{18} For each of the 21 subjects’ revised forecasts satisfying (i)-(iii), we estimate the implied prior that the partner observes the same information as the subject, $q$, using (5). For each subject, note that we have at least 15 such implied $q$’s. We

\textsuperscript{16}These two sets are unequal in size because our initial sample of 723 observations was restricted to ones where the subject’s initial forecast is optimal.

\textsuperscript{17}The results in these figures are not necessarily implied by Figure 3 because the samples differ.

\textsuperscript{18}Our qualitative results do not depend on the requirement that there be at least 15 periods satisfying (i)-(iii) above. Moreover, the subjects who remain after the filter are arguably the most rational subjects because they must have many periods with optimal initial forecasts. Hence, any systematic biases among this population is of particular interest.
compute the mean and median of these implied \( q \)'s for each of the 21 subjects. The distribution of the subjects' median \( q \)'s is plotted in Figure 10, and the distribution of subjects' mean \( q \)'s is plotted in Figure 11.

From Figure 10, it is clear that a large number of subjects consistently issue revised forecasts that are identical to their initial forecasts: 13 of the 21 subjects have a median implied \( q \) equal to 1. These subjects exhibit a false consensus effect in that they tend to update their beliefs as though they are absolutely certain their partner chooses to observe the same information as them. The median implied \( q \) for 6 of the 21 subjects is consistent with Bayesian updating starting from an uncertain prior \( (q \in (0, 1)) \). A false uniqueness is exhibited by two of the subjects—these subjects tend to revise their forecasts as though they are uncertain their partner observed the opposite earnings component as them. The mean of subjects' median implied \( q \)'s is 0.74, which is significantly greater than 0.5 \( (t = 3.92) \).

Not surprisingly, the distribution of subjects’ mean \( q \)'s is less disperse, since an outlier forecast revision has a larger impact on a subject’s mean \( q \) than on his median \( q \). Nevertheless, we still see a large mass of subjects near \( q = 1 \): 5 of the 21 subjects have a mean \( q \) in the interval \([0.95, 1]\), and 6 of the 21 subjects have a mean \( q \) in the interval \([0.85, 0.95]\). The mean of subjects' mean implied \( q \)'s is 0.70, which is significantly greater than 0.5 \( (t = 4.79) \).

### 4 Conclusion

Through a controlled laboratory experiment, we have demonstrated that people frequently fail to correctly account for potential differences between their information and others’. In particular, many subjects appear to exhibit a form of an extreme false consensus effect whereby they fail to revise their forecast when other subjects have observed news that is directionally similar (“good” or “bad”) to what they have observed. This is despite the fact that for any realistic beliefs about
the other subject’s information source, a subject who observes good news should become more optimistic about earnings upon learning that the other subject also observed good news. On the other hand, a few subjects appear to treat the information of other subjects as completely different and exhibit a false uniqueness effect. The facts that (i) most initial forecasts are optimal, and (ii) most revised forecast are optimal when it is possible for the subject to infer with certainty that the other subject observed different information suggests our results are not driven by a lack of subject comprehension or a lack of control by the experimenter. Further, the persistence of the effect over the course of the experiment demonstrates that even experienced subjects are likely to exhibit such biases.

In a broad context, we have demonstrated that the psychological tendency to assume others are similar to oneself will translate to an economic decision making environment where the uncertainty and incentives are well controlled. The model of Williams (2013), which translates this psychological effect to analyst decision making, is supported by these results. We speculate that such a bias may have an impact in many real world setting where there is uncertainty and the source of individuals’ private signals is unclear.
A Theory

In this section we establish some properties of incentives created by the scoring rule examined in the experiment. Throughout let $G$ be the distribution of the random variable $X$, when there is the possibility of confusion we denote the expectation of $X$ with respect to this distribution by $E_G(X)$. We assume agents have twice differentiable, strictly increasing, concave Bernoulli utility functions $u$ with $u' > 0$ and $u'' \leq 0$. Upon receiving some information, agents are asked to provide a forecast $f$ of $X$ and are compensated according to the proper scoring rule:

$$s(f, x) = \alpha - \beta (f - x)^2$$

where $\alpha, \beta > 0$ and $x$ is the realized value of the random variable. Note that the partial derivatives of the scoring function are given by

$$s_f(f, x) = -2\beta (f - x)$$

and

$$s_x(f, x) = 2\beta (f - x)$$

which differ only in sign.

We begin by establishing two rather obvious results related to the scoring rule.

**Proposition 1.** If a decision maker is risk neutral, then the optimal forecast $f^* = E(X)$.

**Proof.** If a decision maker is risk neutral they will want to select a forecast to maximize the expected
value of the scoring rule yielding the following first order condition:

\[
E(s_f(f^*, X)) = 0 \\
E(-2\beta (f^* - X)) = 0 \\
E(-2\beta f^*) - E(-2\beta X) = 0 \\
-2\beta f^* + 2\beta E(X) = 0 \\
f^* = E(X).
\]

When there is no uncertainty, any risk averse decision maker should prefer to report the known value of \(X\).

**Proposition 2.** Consider a decision maker with preferences that are strictly increasing in payoffs \((u' > 0)\). If the distribution of \(X\) is degenerate at \(x\), then the optimal forecast is \(f^* = x\).

**Proof.** The agent will select a forecast to maximize the (certain) utility from the scoring rule yielding the following first order condition:

\[
u'(s(f^*, x))s_f(f^*, x) = 0 \\
-u'(s(f^*, x))2\beta (f^* - x) = 0
\]

which is only satisfied if \(f^* = x\). It is straightforward to verify that the second order condition at the optimal solution is given by \(-2\beta u'(s(f^*, x))\) so \(u' > 0\) ensures this is a maximum.

Finally, we demonstrate that shifts in the distribution in terms of first order stochastic dominance will result in more optimistic forecasts by any risk averse decision maker. A distribution \(H\) is said to first order stochastically dominate \(G\) if for all \(x\), \(G(x) \geq H(x)\) meaning that higher values
are ‘always’ more likely for the distribution $H$ than $G$. We use $f_H$ and $f_G$ to denote the forecast made by the decision maker under the different distributions.

**Proposition 3.** If $H$ first order stochastically dominates $G$, then for any risk averse decision maker the optimal forecasts will be such that $f_H^* \geq f_G^*$.

**Proof.** Prove by contradiction. Assume the forecasts are optimal but $f_G^* > f_H^*$. In order for each forecast to be optimal, they must satisfy the following first order conditions:

$$E_H (u'(s(f_H^*, X) s_f (f_H^*, X))) = 0$$
$$E_G (u'(s(f_G^*, X) s_f (f_G^*, X))) = 0.$$

Also, consider the derivative of the function inside the expectation with respect to $x$, which is given by

$$-u''(s(f, x))(2\beta)^2 (f - x)^2 + u'(s(f, x))2\beta.$$

Since $u'' \leq 0$ and $u' > 0$, we have this function is strictly positive, or the function inside the expectation is an increasing function of $x$. Similarly, it follows that (taking the derivative of the function with respect to $f$) the function inside the expectation is a strictly decreasing function of $f$.

Assuming optimality of $f_H^*$ we have

$$E_H (u'(s(f_H^*, X) s_f (f_H^*, X))) = 0$$

but since $H$ first order stochastically dominates $G$ and the function inside the expectation is increasing, it must be that

$$E_H (u'(s(f_H^*, X) s_f (f_H^*, X))) \geq E_G (u'(s(f_H^*, X) s_f (f_H^*, X)))$$

and, since $f_G^* > f_H^*$ and the function is strictly decreasing in $f$

$$E_G (u'(s(f_H^*, X) s_f (f_H^*, X))) > E_G (u'(s(f_G^*, X) s_f (f_G^*, X))).$$
However, putting these three inequalities together we have that

$$E_G \left( u' \left( s(f_G^* X) s_f (f_G^*, X) \right) \right) < 0$$

which contradicts the assumption that $f_G^*$ is optimal.
B Experimental Instructions

You are about to participate in an experiment in economics of individual decision-making. If you follow these instructions carefully and make good decisions you will earn additional money that will be paid to you in cash at the end of the session. If you have a question at any time, please raise your hand and the experimenter will answer it. We ask that you not talk with one another for the duration of the experiment.

The experiment will continue for a number of periods. Each period is independent of the other in the sense that the outcomes of one period do not directly influence the outcomes of another. In each period you will participate in the forecasting exercise described below.

How you earn money

This is an experiment on financial forecasting. Each period, you will forecast a firm’s earnings and you will be compensated based on your forecast accuracy—the more accurate you are, the more money you will earn. Your compensation from any one forecast is given by:

\[
\text{Compensation} = 6 - 0.04(\text{Your Forecast} - \text{Actual Earnings})^2.
\]

You can maximize your expected compensation by issuing forecasts that are equal to the expected (average) earnings given the information you have observed. For example, if you think it’s 50% likely a firm’s earnings are $10, and 50% likely the firm’s earnings are $20, you would maximize your expected compensation by issuing a forecast equal to $15 [because $0.5(10) + 0.5(20) = 15].

How firm earnings are determined

A firm’s earnings are equal to its revenues minus its costs, plus a random noise term. In other words,

\[
\text{Actual Earnings} = \text{Revenues} - \text{Costs} + \text{Noise}.
\]
At the time of issuing your forecast, the firm’s actual earnings will not be known to you. However, you will have the opportunity to obtain information that might help you issue a more accurate forecast.

Revenues are either $10 or $20, each with 50% probability. High revenues ($20) are considered “good news,” and low revenues ($10) are considered “bad news.” Costs are either $0 or $10, each with 50% probability. Low costs ($0) are considered “good news,” and high costs ($10) are considered “bad news.” The noise term can take any value between -$1.00 and $1.00, and each value is equally likely. Note that on average, revenues are $15, costs are $5, and the noise term is $0.

Revenues and costs are independent of each other. In other words, regardless of whether the firm’s revenues are good or bad, there’s a 50% chance its costs will be good, and regardless of whether the firm’s costs are good or bad, there’s a 50% chance its revenues will be good. Revenues and costs are also independent across time. In other words, in every period there is a 50% chance revenue will be good, and a 50% chance costs will be good, regardless of previous periods’ costs and revenues. The noise term is independent of revenues and costs. That is, whether revenues and costs are high or low does not affect whether the noise term is unusually high or low.

**Initial Forecasts**

At the beginning of each period, you must choose whether to observe the firm’s revenues or costs—you may observe one, but not both. After observing that information, you will be asked to place your Initial Forecast.

**Revised forecast opportunity**

Each period, you will be randomly assigned a partner. After issuing your Initial Forecast, you will be informed whether your partner observed “good news” or “bad news.” Recall that “good news” corresponds to either high revenues ($20) or low costs ($0), and “bad news” corresponds to either low revenues ($10) or high costs ($10). (Similarly, your partner will see whether the news you observed was “good” or “bad.”) You will not be told whether your partner chose to observe
revenues or costs. After observing whether your partner observed good news or bad news, you will be asked to issue a Revised Forecast for the firm’s earnings that period.

Your partner observes information about the same firm as you. In other words, the revenues and costs are the same for your firm as they are for his or her firm. (Subjects who are not your partner, e.g., your neighbor, may observe revenues or costs from a different firm.)

Note that you will generally be assigned a different random partner each period.

Results and earnings determination

At the end of the each period, the firm’s actual earnings will be announced and your forecast compensation from both your Initial Forecast and Revised Forecast will be displayed.

After all the periods have been completed, one period will be randomly chosen as your Initial Forecast compensation period (i.e., you will be compensated based on the accuracy of your initial forecast that period), and one period will be randomly chosen as your Revised Forecast compensation period (i.e., you will be compensated based on the accuracy of the forecast you issue after observing your partner’s initial forecast). Your total compensation will be the sum of your compensation from these two forecasts and the $5 show up fee.
References


We plot the distribution of 591 initial forecasts when the subject observes good news and should forecast $15. Forecasts are rounded to the nearest dollar.

We plot the distribution of 549 initial forecasts when the subject observes bad news and should forecast $5. Forecasts are rounded to the nearest dollar.
Figure 3: Distribution of Revised Forecasts when Partner’s News ("Good" or "Bad") is not Consistent with the Subject’s

We plot the distribution of 290 revised forecasts when the partner’s news is not consistent with the subject’s news. Forecasts are rounded to the nearest dollar.

Figure 4: Distribution of Forecast Revisions ($f^R - f^0$) when Partner’s News ("Good" or "Bad") is Consistent with the Subject’s

We plot the distribution of 850 forecast revisions, defined as the difference between the subject’s initial forecast and revised forecast, when the subject is informed whether or not his partner observed good or bad news, and the partner’s news is consistent with the subject’s news. Revisions are rounded to the nearest dollar.
Figure 5: Distribution of Revised Forecasts when both Subjects Observe Good News

We plot the distribution of the 290 revised forecasts when both subjects observe good news. This sample is restricted to (subject, period) pairs \((i, t)\) such that \(i\)'s initial forecast in Period \(t\) is $15 (the optimal initial forecast given he observed good news). Forecasts are rounded to the nearest dollar.

Figure 6: Distribution of Revised Forecasts when both Subjects Observe Bad News

We plot the distribution of the 256 revised forecasts when both subjects observe bad news. This sample is restricted to (subject, period) pairs \((i, t)\) such that \(i\)'s initial forecast in Period \(t\) is $5 (the optimal initial forecast given he observed bad news). Forecasts are rounded to the nearest dollar.
Figure 7: Average Implied Prior and Proportion of Subjects Choosing to Observe Revenues/Costs, by Period

We plot the percentage of subjects (out of the total 38) who choose to observe revenues and costs each period. Among the \{subject, period\} pairs such that (i) the initial forecast was optimal ($5 if the subject observed bad news, $15 if good news), and (ii) the revised forecast was between (inclusive) the subject’s initial forecast and the nearest pole ($0 or $20), we plot the average $q$ by period, where $q$ is the subject’s prior probability that his partner chose to observe the same earnings component as him (which is implied by his revised forecast).

Figure 8: Distribution of Revised Forecasts when the Subject Observes Good News and the Subject’s Partner Observes Bad News

We plot the distribution of the 92 revised forecasts in which the subject observes good news and his partner observes bad news. This sample is restricted to (subject, period) pairs \((i, t)\) such that $i$’s initial forecast in Period $t$ is $15 (the optimal initial forecast given he observed good news). Forecasts are rounded to the nearest dollar.
We plot the distribution of the 85 revised forecasts in which the subject observes bad news and his partner observes good news. This sample is restricted to (subject, period) pairs \((i, t)\) such that \(i\)'s initial forecast in Period \(t\) is $5 (the optimal initial forecast given he observed bad news). Forecasts are rounded to the nearest dollar.

We consider the 21 subjects whose forecast revision tendencies can be reasonably estimated. Specifically, we restrict our attention to subjects \((i)\) such that there were at least 15 periods \((t)\) such that: (i) \(i\)'s initial forecast in period \(t\) is optimal ($5 if he observed bad news, $15 if he observed good news), (ii) \(i\)'s partner observed the same directional news (good news or bad news) as him in period \(t\), and (iii) the revised forecast can be explained within a Bayesian framework (i.e., has an implied \(q \in [0, 1]\)). For each of these subjects, we restrict attention to the periods satisfying (i)-(iii) above, and we compute the median \(q\) (defined in (5)) for the subject. We round each subject’s median \(q\) to the nearest 0.1, and we plot the distribution of the rounded median \(q\)'s.
We consider the 21 subjects whose forecast revision tendencies can be reasonably estimated. Specifically, we restrict our attention to subjects (i) such that there were at least 15 periods (t) such that: (i) i’s initial forecast in period t is optimal ($5 if he observed bad news, $15 if he observed good news), (ii) i’s partner observed the same directional news (good news or bad news) as him in period t, and (iii) the revised forecast can be explained within a Bayesian framework (i.e., has an implied $q \in [0, 1]$). For each of these subjects, we restrict attention to the periods satisfying (i)-(iii) above, and we compute the mean q (defined in (5)) for the subject. We round each subject’s mean q to the nearest 0.1, and we plot the distribution of the rounded mean q’s.
Table 1: Implied Prior Probability (q − 0.5) Regressions

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The dependent variable in these regressions is the implied q minus 0.5, where q is the subject’s prior belief that his partner chooses to observe the same earnings component as him. This implied prior is revealed by the subject’s revised forecast. (For the formal mathematical definition of q, see (5)). The sample is restricted to ($f^0_i, f^{Ri}$) pairs such that: (i) i’s initial forecast in period t is optimal ($5 if he observed bad news, $15 if he observed good news), (ii) i’s partner observed the same directional news (good news or bad news) as him in period t, and (iii) $f^{Ri}$ is consistent with a prior in the closed unit interval (i.e., $f^{Ri} \in [\$15, \$20]$ if the partners observed good news, and $f^{Ri} \in [\$0, \$5]$ if the partners observed bad news). We normalize Period so that it has mean 0: Period is defined as the period number minus 15.5. Female is a dummy for whether the subject is female. Column (3) has 7 fewer observations than Columns (1) or (2) because one subject did not answer the gender question. Robust standard errors are clustered by subject and presented in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.