Long-Horizon Forecasts

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Abstract

Why do some analysts reveal their long-horizon forecasts, while many others do not? We find evidence consistent with these decisions being driven by an accuracy-publicity tradeoff faced by analysts' employers; analysts' efforts to signal their ability do not appear to be a primary driver of these decisions. Analysts who work for brokerages where a larger fraction of revenue comes from trading fees are more likely to reveal their long-horizon forecasts. Further, sell-side analysts are much more likely to issue these forecasts than buy-side analysts, consistent with analysts using long-horizon forecasts to attract new clients. Analysts who issue long-horizon forecasts and work for brokerages that value publicity are less likely to lose their jobs but also less likely to move to top brokerages. We provide novel evidence on the influence of brokerages' incentives on the information revelation decisions of their analysts.

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1. Introduction

Sell-side analysts typically cover ten to twenty firms and periodically publish earnings forecasts, investment recommendations, and price targets for each firm. When revising their recommendations and price targets, analysts rely not only on their forecasts of near-term earnings, but also on their forecasts of distant earnings (Brown, Call, Clement, and Sharp, 2015). Analysts inform these estimates of firms' distant earnings through a variety of ongoing information gathering activities. For example, in addition to being experts in understanding how news events affect the firms they cover, analysts also frequently interact with executives and investors to refine their understanding of these events and how they affect firms' long-term investment opportunities. As a result, almost all analysts maintain dynamic, internal estimates of firms' distant earnings. Importantly though, only some analysts reveal these estimates to their clients. In particular, only around 50% of analysts each year reveal forecasts for earnings two years into the future, and only 15% reveal forecasts for earnings three years into the future.[1] This divergence in information revelation strategies across analysts is important because the information analysts choose to release affects prices and firm decisions but is nonetheless a puzzle that is not well understood.

One common explanation for the variation in analysts' information revelation strategies, which follows Jung, Shane, and Yang (2012)'s study of long-term growth (LTG) forecasts, is ability signaling. However, our evidence indicates that ability signaling is unlikely to be a primary driver of analysts' issuance of long-horizon forecasts for several reasons. For one, unlike LTG forecasts, in expectation long-horizon earnings forecasts directly impair analysts' forecasting records. Second, we find that brokerages are a bigger driver of the variation in revelation strategies than analysts, which is inconsistent with an ability signaling framework. Lastly, we show that decisions to issue long-horizon forecasts tend to create a ceiling on analysts' careers, reducing the likelihood that they

[1] By "reveal," we mean an analyst's dissemination of their forecast through *I/B/E/S* to clients. We also use forecasts disseminated through an alternative platform, *Estimize*, for some of our analysis. Our primary definition of *long-horizon* forecasts is those with horizons of at least three years, but our results are robust to using alternative cutoffs such as two or two and a half years.

end up at top brokerages. This result directly conflicts with a signaling explanation.

Instead, our evidence is more consistent with an alternative explanation. Specifically, our evidence suggests that a primary driver of analysts' decisions to reveal their long-horizon forecasts is a trade-off, particularly for analysts' employers, between accuracy and publicity. The intuition for how a trade-off between accuracy and publicity might drive analysts' decisions to reveal their long-horizon forecasts stems from the rational bias model of Laster, Bennett, and Geoum (1999).

Analysts' employers value forecast accuracy because accurate forecasts improve the forecaster's reputation, and improvements in the forecaster's reputation increase demand for the employer's research and other services. Analysts' employers, however, also value forecast publicity because high publicity forecasts attract new forecast users. A natural question is, how can analysts increase the publicity of their research? One way is that analysts can issue more extreme forecasts (i.e.,"bold" forecasts), which have lower expected accuracy than if their employer did not value publicity but stand out if they end up being accurate (Laster et al., 1999). We argue analysts can also increase the publicity of their research by issuing long-horizon forecasts (i.e., "early" forecasts). Like bold forecasts, long-horizon forecasts have lower expected accuracy than the analysts' other forecasts (40–50% less accurate on average). Also like bold forecasts, they stand out if they end up being accurate (Cooper, Day, and Lewis, 2001). Further, inaccuracy for these forecasts results in significant reputational penalties.[2] In this paper, we use analysts' long-horizon forecast issuance as a setting to examine motives other signaling for analysts' information revelation strategies. In particular, we explore the extent to which an accuracy-publicity trade-off explains why some analysts reveal their long-horizon forecasts and some do not.

We test several predictions of the accuracy-publicity trade-off that are based on the basic

[2]One might argue that if the market perfectly understands how forecast timing relates to accuracy, analysts should not care about issuing long-horizon forecasts that end up being inaccurate. However, there is evidence across a variety of settings that investors have trouble interpreting publicly-available information (e.g., Tetlock, 2011) and separating skill from luck (e.g., Bertrand and Mullainathan, 2001). As a result, they may not be able to perfectly separate the influence of timing from forecasting ability. Additionally, the greater noise associated with long-horizon forecasts can make it difficult to form reasonable estimates of the influence of forecast timing on accuracy.

intuition that analysts are more likely to issue long-horizon forecasts when the relative rewards from generating publicity to their employers are higher. First, since the incentive weight that a brokerage places on publicity is driven by the marginal benefit to their firm from generating additional publicity, we expect analysts are more likely to reveal long-horizon forecasts when they work for a brokerage that is more reliant on attracting new clients and trading revenue. Second, we also expect the weight that a brokerage places on publicity is moderated by firm and analyst characteristics. Specifically, high-publicity brokerages will emphasize publicity more for portfolio firms that have a higher expected sensitivity of client demand to publicity, and an analyst's personal publicity incentives will interact with the incentives that they internalize from their employer. Finally, we predict that if revealing long-horizon forecasts can attract attention and trading activity to analysts' employers, early forecast issuance is rewarded by investors and employers who value publicity. However, because publicity incentives are not uniform across employers and, specifically, are less important to the most prestigious employers, we expect that long-horizon forecast issuance reduces the likelihood that analysts are promoted to top brokerages. As mentioned above, the signaling and publicity-tradeoff frameworks offer distinct predictions for this test.

Using several measures to capture the weight that brokerages place on publicity incentives, such as brokerages' affiliations with top investment banks, we show that analysts working for brokerages with high publicity incentives are 3–4 percentage points more likely to reveal their long-horizon forecasts than other analysts. This effect represents approximately a 50% increase in issuance likelihood relative to the unconditional mean. We next use dataset containing crowd-sourced earnings forecasts from both buy-side and sell-side analysts to exploit more stark differences in employer incentives across analysts. Sell-side brokerages publish forecasts to attract forecast users, while buy side firms do not. We use analysts' affiliations with buy-side or sell-side firms to test the prediction that analysts working for firms that put emphasis on attracting additional forecast users are more likely to issue long-horizon forecasts.[3] We find that sell-side analysts are

[3]Using a much smaller sample of analysts working for different types of employers, Laster et al. (1999) similarly test

overwhelmingly more likely to issue long-horizon forecasts. These results support the idea that analysts are more likely to publicly reveal their long-horizon forecasts when their employers benefit more from publicity-generating forecasts.

It important to note that because employer status can serve as a sufficient signaling statistic, the results above are consistent with both an ability signaling and a publicity trade-off framework. To help separate these two explanations, we examine the relative importance of brokerage and analyst effects in explanation the aggregate variation in long-horizon forecast decisions. We find that the percent of variation explained by analyst effects is 51%, while the percent of variation explained by brokerage effects is 67%. This result undermines ability signaling as a primary driver of long-horizon forecast decisions because mandates or incentives by brokerages, particularly those of smaller brokerages, often conflict with analysts' career concern motives. Instead, this result supports the notion that the reason analysts employed by brokerages with higher publicity incentives issue more long-horizon forecasts is because analysts' revelation strategies are responsive to the publicity motives of their employers.

We next show that incentives specific to each portfolio firm, and analysts' personal incentives, interact with the incentives of analysts' employers. Analysts who work for publicity-focused brokerages are more likely to reveal a long-horizon forecast for firms that offer higher expected rewards from generating publicity and a better opportunity for analysts to stand out. Also, analysts who work for brokerages with low publicity incentives, who themselves have low personal incentives to generate publicity, are particularly unlikely to publish long-horizon forecasts. These results are also consistent with both frameworks.

Last, we examine how issuing long-horizon forecasts affects analysts' careers. We find evidence

whether independent economic forecasters are more likely to issue bold GDP forecasts than industrial corporation forecasters. According to Laster et al. (1999), the *"industry categories are an objective way of grouping together forecasters who work for similar types of firms and can therefore be expected to face similar incentives ... consulting firms and advisory services seeking additional clients might be prepared to trade off long-term forecast accuracy for a greater chance at media attention."* (pp. 309–310). They find that independent forecasters issue much bolder forecasts on average.

most consistent with an accuracy-publicity trade-off. First, accuracy for longer horizon forecasts affects promotion opportunities. In other words, the market does not give analysts a pass for being inaccurate on longer horizon forecasts. Second, analysts working for brokerages that value publicity who issue long-horizon forecasts are less likely to be demoted or terminated from their current employer than other analysts working for these brokerages that do not issue long-horizon forecasts. We confirm this result using the setting of brokerage mergers, where often an analyst from one of the merging brokerages is unexpectedly let go. However, long-horizon forecast issuance by these analysts reduces the likelihood they are promoted to more prestigious brokerages, which is consistent with there being reputational costs to issuing inaccurate long-horizon forecasts and brokerages with low publicity incentives discouraging their dissemination. And third, consistent with analysts revealing their long-horizon forecasts to generate attention, we find that analysts who reveal their long-horizon forecasts garner stronger investor reactions in the future.

Our paper's most important contribution is that, despite several prior papers discussing the value that early forecasts provide to clients (Ball and Brown, 1968; Cooper et al., 2001), we are the first to study the curiously wide variation in analysts' decisions to reveal their long-horizon forecasts. In doing so, we contribute to prior studies using long-horizon forecasts in their analyses (Brown, Foster, and Noreen, 1985; Bandyopadhyay, Brown, and Richardson, 1995) and to prior studies examining analysts' long-term growth (LTG) forecasts (Jung et al., 2012). Jung et al. (2012) provide evidence that analysts issue LTG forecasts to signal their ability. This result is intuitive, and ability signaling likely plays some role in analysts' decisions to reveal long-horizon forecasts. However, several aspects of these decisions are inconsistent with an ability signaling framework. First, long-horizon EPS forecast decisions and LTG forecast decisions are essentially uncorrelated. Second, while it is not clear how LTG forecasts impose any risk on analysts' careers, long-horizon forecasts have a direct negative impact on analysts' performance record and career outcomes. Third, long-horizon forecasts are heavily driven by the incentives of analysts' employers, which is inconsistent with analyst-specific efforts to signal their ability. Lastly, using horse race analyses, we show that all of our results are above and beyond the effects attributable to the drivers of LTG forecasts. Instead, we believe we provide novel evidence of how accuracy-publicity trade-offs affect analysts' information revelation decisions. Our evidence uniquely aids our understanding of the incentives analysts face to strategically reveal certain modeling information but not others.

We also contribute to prior studies examining analysts' decisions of whether to provide investors with supplementary forecast information. Ertimur, Mayew, and Stubben (2011) show that analysts with low reputations are more likely to issue disaggregated revenue and expense forecasts and that these disaggregation decisions affect analysts' subsequent career outcomes. Our study is the first to focus on analysts' decisions to reveal their long-horizon forecasts, which involves a more direct trade-off with accuracy than their revelation of supplementary information, such as revenue and expense forecasts. We show that disaggregated forecasts are issued four-to-five times more often than long-horizon forecasts, and the decision to issue disaggregated forecasts is only weakly correlated with the decision to issue long-horizon forecasts, indicating that the two information revelation problems are unique. Further, for the reasons discussed above, our findings are also distinct from Ertimur et al. (2011), who focus on ability signaling. We also use a supplementary sample of crowd-sourced forecasts that includes forecasts issued by both buy-side and sell-side analysts to provide further evidence that the publicity incentives of analysts' employers influence analysts' information revelation decisions. Last, we provide the first evidence that analysts' decisions to reveal certain supplementary information could hurt their ability to advance to more reputable brokerages.

We also contribute to the literature on analyst career outcomes. Prior literature shows that analysts' career prospects are highly dependent on their perceived forecasting ability.[4] Additionally, Harford, Jiang, Wang, and Xie (2019) show that analysts' strategic allocations of effort among their

[4] For evidence of the effect of analyst forecast accuracy on career prospects, see Mikhail, Walther, and Willis (1999); Hong, Kubik, and Solomon (2000); Hong and Kubik (2003); Groysberg, Healy, and Maber (2011); and Altınkılıç, Balashov, and Hansen (2019). For evidence of the effect of stock price impact on career prospects, see Balashov (2018). For evidence of the effect of forecast consistency on career prospects, see Hilary and Hsu (2013).

relatively more important firms is rewarded in the labor market. We contribute to this literature by showing that analysts' responses to the marketing incentives of their employer — through revealing their less accurate but potentially attention-grabbing and useful long-horizon forecasts — can protect against termination risk. It has become increasingly important over time to understand how analysts create value for their clients, especially given recent changes in the sell-side industry following the Markets in Financial Instruments Directive (MiFID II) that require clients to explicitly define the value proposition. Our evidence suggests that analysts can shift the demand curve for their services and one way they can achieve this is by issuing extremely early forecasts.

2. Hypothesis Development

Brokerages and their analysts face an information revelation decision problem. On the one hand, a brokerage's analysts produce a significant amount of information, and publishing this information offers benefits to the brokerage: investors trade more through the brokerage when analysts release information (Juergens and Lindsey, 2009). Thus, brokerages have an incentive to reveal all the information their analysts' produce. On the other hand, brokerages want to manage the perceived quality of the signals that they provide to clients. That is, because research service is an experience good, whereby a brokerage's clients constantly learn about the quality of the brokerage's analysts through the information revealed to the clients, and a brokerage's revenue is increasing in the perceived quality of their analysts, the brokerage has an incentive to manage the information flowing from their analysts to their clients. Brokerages weigh these competing incentives when deciding how much information to reveal to their clients.

One way this information revelation problem relates specifically to analysts' earnings forecasts is that the brokerage must decide which forecasts to reveal to their clients.[5] The brokerage's analysts continually produce and update forecasts for both near-term and distant earnings periods. Crucially though, although all analysts reveal their forecasts for near-term earnings periods, only

[5] Although analysts might have a say in this decision, because the brokerage firm is in charge of resource allocation across their analysts and sets analysts' financial incentives through their wage contract, the brokerage's incentives play a primary role in governing this decision.

some analysts reveal their forecasts for distant earnings periods. The question we ask in this paper is why some analysts reveal their long-horizon forecasts, while other analysts do not. The competing incentives brokerages face between revealing more and less information must differ across brokerages, but how? Prior studies of analysts' information release (e.g., Ertimur et al., 2011; Jung et al., 2012) argue that analysts release supplemental information to signal their ability. However, (i) forecasts for distant earnings are not supplemental, but rather, a direct component of analysts' earnings forecast record; (ii) long-horizon forecasts, on average, damage outside perceptions of analysts' ability; and (iii) an ability signaling framework ignores the role of brokerages in setting analysts' incentives for which information to reveal. To help fill this gap in understanding, we consider the rational bias model of Laster et al. (1999) as an alternative framework for thinking about this problem.

In Laster et al. (1999), a forecasting firm (e.g., a brokerage) determines their optimal forecast for a macro variable. The firm has an incentive to issue the forecast with the highest expected accuracy because accurate forecasts boost the firm's reputation. However, the firm may also have an incentive to issue a forecast with lower expected accuracy, if that forecast has the potential to attract new forecast users (i.e., generate "publicity"). An important assumption underlying this claim is that some of the firm's clients only perform a cursory analysis of the firm's forecasting track record. The trading decisions of these clients in any particular period are thus a function of which forecasts stand out to them. Depending on the proportion of the firm's current and prospective clients that the firm thinks will be responsive to forecasts that stand out, the brokerage will weight publicity and accuracy differently in their analysts' wage contracts. Consequently, even when analysts of different forecasting firms have the same private information, they can issue forecasts that deviate substantially from one another because some analysts have more incentive than others to produce forecasts that can stand out and generate publicity. In the model, an analyst may issue a particularly radical (i.e., "bold") forecast because radical forecasts increase the probability that the analyst is correct when no other analysts are correct, even though the radical forecast has significantly lower accuracy in expectation.

This framework has important implications for brokerages' information revelation decision problems. In particular, an alternative way that brokerages can try to generate publicity and attract new users is through the strategic release of certain information, information that hurts their analysts' forecasting record in expectation but has the potential to stand out from other brokerages' information. One such type of information is long-horizon forecasts — regular earnings forecasts that are nonetheless issued much earlier than most other analysts' forecasts. That is, in additional to radical forecast estimates, brokerages might motivate their analysts to issue forecasts with radical timing. These long-horizon forecasts increase the probability that the analyst correctly predicts earnings before other analysts, which brokerages can market to prospective clients, even though these forecasts have much lower accuracy in expectation.

Thus, the central proposition in our paper is that an analyst's decision to reveal a long-horizon forecast — in particular, a forecast that is issued at least three years before the earnings date — is guided by an accuracy-publicity trade-off faced by their brokerage. For one, there is an obvious conflict between revealing a long-horizon forecast and maintaining a high quality forecasting record. Although much of the evidence in prior literature focuses on small differences in timing, early forecasts have been shown to be less accurate than late forecasts (Lim, 2001; Ke and Yu, 2006). As we discuss below, we estimate the reduction in expected accuracy to be between 40 and 50% between short- and long-horizon forecasts. Additionally, as we show in Section 4, the market does not give analysts a pass for being less accurate when issuing long-horizon forecasts. Investors pay attention to the issuance of long-horizon forecasts and forecast accuracy even at longer horizons affects analysts' labor market outcomes. For another, there are several reasons that issuing early forecasts can generate publicity. Cooper et al. (2001) show that early forecasts are valued by clients. Similarly, Laster et al. (1999) argue that since clients can form their own unbiased consensus of forecasts at any point during the earnings period, the default preference is for analysts to reveal the complete set of their forecasts as early as possible, regardless of forecast noise. Last, there exists wide variation across analysts in their decisions to reveal their long-horizon forecasts. We thus form several testable hypotheses around this central proposition.

We first examine the extent to which an analyst's decision to reveal a long-horizon forecast comes at the expense of accuracy. We predict that an analyst is significantly less accurate when they issue a long-horizon forecast relative to the other forecasts that they issue for the same portfolio firm later during the same earnings period. Importantly, this prediction distinguishes our analysis from that of other studies that analyze other information revelation problems faced by brokerages, such as Ertimur et al. (2011)'s study of disaggregated revenue and expense forecasts and Jung et al. (2012) study of long-term growth (LTG) forecasts. Revealing these forecasts does not conflict with accuracy incentives. We argue that revealing a long-horizon forecast *directly* conflicts with a brokerage's incentives to manage the accuracy of the signals they provide to clients. To test the accompanying hypothesis that the reduction in accuracy of long-horizon forecasts *matters*, we adapt prior models examining the relation between analysts' forecast accuracy and their career outcomes (e.g., Hong and Kubik, 2003; Altınkılıç et al., 2019) to examine how forecast accuracy at longer horizons affects analysts' career prospects, after controlling for the accuracy of their shorter horizon forecasts.

We next examine whether brokerages are more likely to encourage their analysts to issue long-horizon forecasts when the relative benefits to the brokerage from generating publicly are higher. In Laster et al. (1999), the relative benefits from generating publicity are represented by the expected emphasis that the brokerage places on attracting new clients.[6] Given our primary focus on the sell-side analyst industry, which lacks variation in whether forecasting firms publish their research to attract clients, we estimate the relative benefits from generating publicity using variation in the

[6]They estimate this fraction using variation in the industries of the forecasting firms (e.g., independent forecasting firms vs. industrial corporations). They predict that an independent forecasting firm places greater weight on publicity incentives and they provide evidence that these firms issue bolder forecasts.

relative importance of trading revenue across the brokerages. Smaller brokerages tend to be more reliant on attracting trading activity via their research services than larger brokerages (Flood, 2021); larger brokerages tend to have affiliated investment banking and wealth management divisions that generate fees that can help offset the costs of research services. Additionally, larger brokerages tend to have larger and more lucrative client lists, with most large buy-side investors subscribing to the research services of at least one of the largest brokerages, if not most of them. Thus, larger brokerages have weaker incentives to attract publicity through their analysts' forecasts. We therefore predict that analysts that work for smaller, less prestigious brokerages are more likely to publish their long-horizon forecasts. In additional analysis using a relatively novel sample of crowd-sourced forecasts that includes forecasts submitted by both buy-side and sell-side analysts, we are able to more directly measure the relative emphasis that analysts' employers place on attracting new clients. We expect that analysts working for sell-side firms, who publish their research to attract clients, are more likely to reveal their long-horizon forecasts than analysts working for buy-side firms, who do not publish research to attract clients.

We then explore whether brokerages place more emphasis on publicity for certain firms and whether analysts' personal incentives for publicity interact with the publicity incentives of their employers. We expect that a brokerage's incentives for accuracy versus publicity vary across the firms that their analysts cover. However it is unclear how firm characteristics relate to brokerages' incentives. On the one hand, firms in the analysts' portfolios that have relatively more trading activity and analyst coverage (i.e., client demand or "importance") have higher expected rewards from generating publicity. On the other hand, it is likely harder for their analysts to stand out and generate publicity for these firms. It is thus an empirical question whether an analyst working for a brokerage that values publicity-generating forecasts is more or less likely to issue a long-horizon forecast for their relatively more important portfolio firms than for their relatively less important firms. Analysts' personal reputations also likely affect how they respond to the incentives set by their employer. Given that analysts care not only about their current wage contract, but also their expected future wages, we predict that analysts who work for brokerages that place less emphasis on publicity and who themselves have strong personal forecasting reputations to maintain are particularly unlikely to publish long-horizon forecasts.[7]

In our final analysis, we examine the labor market benefits and costs that accrue to analysts from publishing their long-horizon forecasts. Under the assumption that publicity is particularly valued by some brokerages, we predict that analysts who work for these brokerages and who publish their long-horizon forecasts reduce their termination risk. Given the accuracy-publicity trade-off and that publicity is not uniformly valued in the industry, we also hypothesize that revealing a long-horizon forecast makes it more difficult for analysts to graduate to more prestigious forecasting firms. Last, under the assumption that publicity-generating forecasts increase the size of a brokerage's client list particularly when issued by forecasting firms that derive more of their revenue from trading activities, we predict that analysts that reveal their long-horizon forecasts in the current period experience larger market responses to their forecasts in the subsequent period.

3. Data

We collect all annual forecasts from the I/B/E/S U.S. Detail file from 1994 to 2016.[8] We begin the sample in 1994 because forecasts before then were often delivered to I/B/E/S with inaccurate dates (Hilary and Hsu, 2013). We then merge forecasts with financial information from Compustat and stock price information from CRSP. The initial sample collection yields 8,610,527 annual forecasts issued by 22,473 analysts. We then drop (i) forecasts produced by analysts who cover more than 40 firms in a year, which is an indicator of analyst teams (Kini, Mian, Rebello, and Venkateswaran, 2009); (ii) forecasts announced after the end of the forecast period; and (iii)

[7]Forecasting reputation is presumably not the only type of reputation an analyst cares about. However, (i) forecasting reputation is the most likely to be harmed by issuing an inaccurate long-horizon forecast, and (ii) as Hong et al. (2000) note, an analyst's ability to provide services other than high quality forecasts in the long run depends *"in part on her perceived forecasting ability"* p. 122.

[8]We focus on annual forecasts because they are produced far more frequently than quarterly forecasts (e.g., Hong et al., 2000; Hong and Kacperczyk, 2010) and because using annual forecasts better enables us to partition on forecast horizon within analyst-firm-earnings period groups.

duplicate forecasts issued on the same day by the same analyst for the same firm and earnings period. The final sample consists of 6,762,870 forecasts, 841,826 analyst-firm-years, and 93,893 analyst-years.[9] Table A1 in Appendix A reports our sample filters and the resulting effect of each on our sample size. Table 1 presents summary statistics for our sample of analyst forecasts, partitioned by forecast horizon.

Analysts predominantly submit forecasts for earnings periods less than three years in the future (i.e., forecast horizons of three years or less). Analysts derive forecasts for most distant earnings periods to inform their price targets, recommendations, and report content, but only some analysts choose to reveal these longer-horizon forecasts. From Column (3) of Panel A of Table 1, the average analyst in our sample produces 34 forecasts each calendar year with horizons under one year, 27.9 forecasts with horizons between one and two years, 10.1 forecasts with horizons greater than two years, and 2.7 forecasts with horizons greater than three years. From Columns (4) and (5), a similar distribution is evident when analyzing the number of forecasts produced per firm-calendar year and per analyst-firm-calendar year. The number of forecasts that a firm typically receives with a horizon of at least three years is approximately 2.3 out of the 61.16 total forecasts received. On average, analysts produce 0.3 forecasts with a horizon of at least three years for each firm in their portfolio each calendar year.

To compare the issuance of long-horizon forecasts with the issuance of LTG forecasts and disaggregated revenue and cost forecasts, in Panel B of Table 1, we report the unconditional likelihoods an analyst issues a long-horizon forecast, an LTG forecast, or a disaggregated forecast in a given year. In Panel C, we report the correlations between these likelihoods. Panel B shows that the likelihoods of issuing LTG forecasts or disaggregated forecasts, 42% and 62%, respectively, are far higher than the likelihood of issuing long-horizon forecasts, just 14%. This evidence is consistent with long-horizon forecast issuance posing greater risks to brokerages. Panel C shows that there is little overlap between analysts issuing LTG or disaggregated forecasts and analysts issuing long-

[9] Due to our inclusion of fixed effects, our regression sample is slightly smaller.

horizon forecasts, with correlation coefficients of 0.02 and 0.18, respectively. Thus, long-horizon forecast issuance is a phenomenon distinct from these other forecast decisions believed to be primarily driven by analyst-specific ability signaling motives.

Figure 1 shows that the probability of analysts revealing one of their long-horizon forecasts increases over time. The average forecast horizon increases from approximately 350 days in the late 1990s to approximately 500 days in 2016. Additionally, the fraction of forecasts with horizons greater than three years grows sharply between 2003 and 2007 and then stays roughly flat for the rest of the sample period. One plausible explanation for the increase in average forecast horizon is that increasing competition in the sell-side analyst industry has forced analysts to attract clients in ways other than through forecast accuracy, one of which might be releasing forecasts earlier. This is only a working theory, however; we defer a deeper analysis of this question to future research.

4. Empirical Analysis

4.1. Accuracy and Publicity Trade-off of Long-Horizon Forecasts

As described in Section 2, we hypothesize that an analyst's decision of whether to reveal a long-horizon forecast for a distant earnings period is driven by a trade-off between the accuracy and publicity incentives of their brokerage. This hypothesis depends on four assumptions: (i) long-horizon forecasts are less accurate than their shorter-horizon counterparts, (ii) long-horizon forecasts generate publicity, (iii) there are penalties to issuing inaccurate long-horizon forecasts, (iv) and publicity is valued by at least some brokerages. For the last assumption, we rely on evidence in Laster et al. (1999), which shows that at least some brokerages value publicity. For the second assumption, in addition to empirical evidence in Cooper et al. (2001) suggesting clients value early forecasts, we also provide evidence consistent with this assumption in Section 4.3.2 using subsequent investor reactions to analysts' research after issuing long-horizon forecasts. We analyze the plausibility of the first and the third assumption next.

For the first assumption, prior research documents that forecast accuracy is negatively related to forecast horizon, albeit while almost exclusively focusing on only small differences in forecast timing within the last year of the earnings period (e.g., Clement, 1999; Lim, 2001; Ke and Yu, 2006). To confirm the validity of the first assumption, we estimate the amount by which an analyst's forecast accuracy changes as a result of issuing a long-horizon forecast. To estimate the relative change in accuracy, we estimate a forecast-level regression of the following form:

$$Accuracy_{ijpt} = \beta_0 + \beta_1 \boldsymbol{\mathit{Long\text{-}Horizon}}_{ijpt} + \alpha_{ijp} + \epsilon_{ijpt}, \tag{1}$$

where i represents analysts, j represents portfolio firms, p represents earnings periods, and t represents forecast issuance dates. *Long-Horizon*, our primary measure of long-horizon forecasts, is an indicator variable equal to one if the forecast is issued at least three years before the end of the earnings period. Although our horizon cutoff of three years is somewhat ad hoc, our results are robust to using alternative cutoffs of 2, 2.5, and 3.5 years. *Accuracy* is the absolute difference between an analyst's forecast and actual earnings (times negative one), scaled by the absolute value of actual earnings. Given that this measure is missing when actual earnings is zero, in untabulated results we also estimate Equation (1) using the unscaled absolute difference between an analyst's forecast and actual earnings and find similar results. Our inclusion of analyst-firm-earnings period fixed effects (α_{ijp}) means that the regressions compare the accuracy of an analyst's long-horizon forecasts with subsequent forecasts issued by the same analyst for the same firm and earnings period. If encouraging the release of long-horizon forecasts is costly in the form of significantly lower expected forecasting accuracy, we expect $\beta_1 < 0$.

We report the results from regressions estimated using Equation (1) in Table 3. Whether we measure long-horizon forecasts as those issued at least three years before the end of the earnings period (Column (1)) or at least two years before the end of the earnings period (Column (2)), long-horizon forecasts are substantially less accurate than their shorter-horizon counterparts. From Column (1), forecasts issued at least three years before the end of the earnings period are on average 49.4 percentage points less accurate (as a percentage of actual earnings) than other forecasts issued by the same analyst for the same firm and earnings period. This evidence is consistent with the first assumption described above that brokerages face a trade-off when deciding whether to encourage their analysts to reveal their long-horizon forecasts. Revealing long-horizon forecasts means revealing forecasts that are substantially less accurate than analysts' other forecasts.

For the third assumption, prior research finds strong evidence that analysts' forecast accuracy positively affects their career prospects (Mikhail et al., 1999; Hong and Kubik, 2003; Altınkılıç et al., 2019). Thus, one cost to analysts of a poor forecasting record is reduced job security, which implies that brokerages bear costs from the poor accuracy of their analysts as well. However, prior literature focuses almost exclusively on the accuracy of forecasts issued within the last six months of the earnings period. To validate our third assumption, we augment commonly-used analyst labor market movement models to test whether the accuracy of an analyst's longer-horizon forecasts positively affects their career prospects. Specifically, we compare the brokerages that an analyst works for at the end of years t and $t+1$ as a function of the analyst's forecast accuracy during year t. We assign brokerages into deciles each year based on the number of analysts employed by the brokerage; if the analyst moves from a lower to a higher decile brokerage during the year, we classify such a movement as positive and vice versa.[10] We classify an analyst as having departed the industry for negative reasons in the year $t+1$ if they stop producing reports after year t.[11]

Table 4 provides labor market movement statistics throughout our sample period. From Column (6), 31% of analysts switch jobs each year — a trend that reached a high of 42% around the time of a series of regulatory changes in 2002 and a low of 24–25% in recent years. From Column (5), 17% of analysts leave the industry each year. Columns (3) and (4) show that of the 31% who change

[10] Our results are robust to several alternative measurements of promotion and demotion movements across brokerages. For example, our results are qualitatively similar when we focus on an analyst's promotions and demotions to/from (i) the top 25 brokerages (based on the number of employed analysts) (Altınkılıç et al., 2019); (ii) brokerages that employ at least 25 analysts (Hong et al., 2000; Jung et al., 2012); (iii) our set of bulge banks explored in Table 6; (iv) brokerages that appear on *II*'s annual All-America Ranking (Hong and Kubik, 2003); and (v) banks with the highest Carter–Manaster ranking. Additionally, our results are similar when we re-compute the job-movement variable to include only an analyst's movements between brokerages that are different in size by at least ten analysts.

[11] This definition of negative turnover follows Mikhail et al. (1999) — who show that turnover in the analyst industry is mostly involuntary — and Hong et al. (2000) —who provide evidence that the probability of analysts leaving the industry for better job prospects, such as to become mutual fund managers, is quite low.

jobs each year, 5% move to higher-decile brokerages, and 5% move to lower-decile brokerages. The average tenure that an analyst has with the same employer is around two years (untabulated). We also present the unconditional annual probability that an analyst is voted as an *All-Star*, a status awarded to the top three vote-getters in *Institutional Investor*'s annual poll of buy-side investors. The average likelihood of receiving this award in our sample is 5%. The estimates in Table 4 are in line with prior research (e.g., Balashov, 2018) and support the notion that the analyst labor market is characterized by high turnover and frequent departures.

We create three separate forecast accuracy measures, one for the accuracy of the analyst's short-horizon forecasts (i.e., six months or less), one for the accuracy of the analyst's medium-horizon forecasts (six to twelve months), and one for accuracy of the analyst's longer-horizon forecasts (12 to 18 months). Even though our main definition of long-horizon forecasts is those with horizons of three years or more, we focus on forecasts with horizons of between 12 to 18 months here to limit sampling issues. In particular, as Table 1 shows, only 14% of analysts issue forecasts with a horizon of at least three years each year, and thus we lose over 80% of our sample in these regressions by requiring the analyst to have a measure of accuracy for forecasts with horizons more than three years. Furthermore, it is empirically challenging to construct measures of relative forecast accuracy for forecasts with horizons of two or three years because (i) there are often no peer analysts covering the same firm that also issue forecasts with a similar horizon, and (ii) the accuracy of those forecasts are not realized for at least two years into the future. Thus, we make a simplifying assumption for tractability that the relative labor market consequences of forecasts with horizons between 12 and 18 months compared with shorter horizon forecasts is informative about the relative consequences of forecasts with longer horizons. We predict in these tests that even after controlling for the accuracy of an analyst's short-horizon forecasts, the accuracy of the analyst's longer-horizon forecasts (i.e., 12–18 months) has an incremental positive impact on the analyst's career prospects.

We estimate analyst-year level regressions of the following form:

$$\begin{aligned} \textit{Labor Market Outcome}_{i,t+1} &= \beta_0 + \beta_1 \textit{Accuracy}_{0-6m,it} + \beta_2 \textit{Accuracy}_{6-12m,it} \\ &\quad + \beta_3 \boldsymbol{Accuracy}_{12-18m,it} + \delta X_{it} + \alpha_i + \gamma_t + \epsilon_{i,t+1}, \end{aligned} \tag{2}$$

where i represents analysts and t represents years. $\textit{Accuracy}_{0-6,it}$ is the average relative accuracy of analyst i's forecasts during year t, conditional on the forecasts being issued less than six months before the end of the earnings period; $\textit{Accuracy}_{6-12,it}$ and $\textit{Accuracy}_{12-18m,it}$ are measured the same way as $\textit{Accuracy}_{0-6,it}$, but are conditional on the forecasts being issued between 6 and 12 months before the end of the earnings period and between 12 and 18 months before the end of the earnings period, respectively. We compute our measures of relative accuracy by first ranking analysts following the same firm during year t based on the percentage absolute deviation of the forecast estimates and actual earnings per share ($\textit{Accuracy} = -\frac{|F-A|}{|A|}$) for forecasts within the respective horizon groups, and then compute an aggregate score for each analyst covering each firm during year t using the following equation: $\textit{Score} = 1 - \left[\frac{rank-1}{\#\ of\ analysts}\right]$. We then take the mean value of *Score* across all firms that analyst i covers that year. The computation of this measure follows Hong et al. (2000), Hong and Kubik (2003), and Altınkılıç et al. (2019).

$\textit{Labor Market Outcome}_{i,t+1}$ represents a series of variables we use to capture analyst labor market movements and award recognition. Our primary measure of labor market movements, $\textit{Career Outcome}_{i,t+1}$, is an ordinal variable with three levels increasing in more positive labor market movements. The variable takes a value of 1 if the analyst moves to a larger brokerage decile in year *t+1*; a value of 0 if the analyst remains at the same brokerage or moves within the same size decile; and a value of -1 if the analyst (i) moves to a smaller brokerage decile or (ii) leaves the profession. We also examine the likelihood of analysts moving down to a lower decile brokerage (*Moves Down*). X_{it} represents a set of control variables that previous research shows relate to analyst career prospects. We follow the model used in Altınkılıç et al. (2019), which includes controls for analysts' forecast optimism, experience, and piggybacking activity during year

t.[12] Analyst fixed effects, α_i, and calendar year fixed effects, γ_t, absorb the effect of innate analyst characteristics and annual market conditions. We predict $\beta_1 > 0$.

We report the results from regressions estimated using Equation (2) in Table 5. Columns (1) and (2) show that the relative accuracy of analysts' longer-horizon forecasts positively predicts their labor market outcomes. Columns (3) and (4) show that the effect of forecast accuracy on demotion likelihood for forecasts with horizons between 12 and 18 months is almost twice as strong as the effect of forecast accuracy for forecasts with horizons between 6 and 12 months. The results support the assumption that analysts do not get a pass from investors or employers if they are inaccurate when issuing longer-horizon forecasts. Analysts continue to face reduced job security and promotion prospects when issuing less accurate longer-horizon forecasts, even after controlling for the accuracy of their shorter-horizon forecasts. The results in this section indicate that revealing longer horizon forecasts imposes real costs on analysts and their employing brokerages.

4.2. Do Analysts Reveal their Long-Horizon Forecasts to Attract Publicity?

4.2.1. Brokerage Incentives

The prior section provides evidence that there are costs to analysts and their employers from revealing inaccurate long-horizon forecasts, which is consistent with brokerages facing an accuracy-publicity trade-off. We next examine whether analysts are more likely to reveal their long-horizon forecasts when their employers place more weight on publicity. To test this prediction, we exploit variation in the relative benefits from generating publicity across brokerages, and estimate analyst-year regressions of the following form:

$$Long - Horizon_{it} = \beta_0 + \beta_1 \boldsymbol{x}_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{3}$$

where again i represents analysts and t represents years. $Long - Horizon_{it}$ is an indicator variable equal to one if an analyst issues at least one forecast during calendar year t with a horizon of at

[12] In untabulated analysis, we estimate the alternative specification used by Altınkılıç et al. (2019) by replacing controls for optimism and piggybacking with controls for forecast boldness and herding and find similar results.

least three years. The independent variable x represents a series of variables meant to capture the relative weight that a brokerage places on publicity. α_i and γ_t represent analyst and calendar year fixed effects, which absorb the influence of time-invariant analyst characteristics and annual market conditions. If analysts who work for brokerages that place greater relative emphasis on publicity are more likely to reveal their long-horizon forecasts, we expect $\beta_1 > 0$.

As discussed in Section 2, we estimate the relative importance of generating publicity across brokerages by proxying for the fraction of the brokerage's revenue that comes from trading commissions based on the brokerage's size and prestige. To do so, we employ three measures of brokerages' size/prestige. Our primary measure of brokerage size/prestige is an indicator variable equal to one if the analyst's employer is not one of the six "bulge bracket" banks listed in Cowen, Groysberg, and Healy (2006) (plus JP Morgan). Two alternative measures we use are indicator variables equal to one if (i) the analyst's employer does not have a top Carter Manaster (CM) ranking (*Low-Prestige Brokerage*) — where a higher CM ranking signifies that the affiliated investment bank of the analyst's employer has a higher capital markets reputation — and (ii) the analyst's employer is not one of the ten largest brokerages that calendar year based on the number of analysts employed by the brokerage (*Small Brokerage*). We report the results from these tests in Table 6.

We find that analysts working for brokerages that derive a greater fraction of their revenue from trading commissions are more likely to reveal their long-horizon forecasts. Column (1) shows that an analyst working for a non-bulge bracket bank is nearly 11% more likely to reveal a long-horizon forecast in a given year. Columns (2) and (3) show that analysts working for firms that do not have a top-ranked investment bank or are not one of the ten largest brokerages are 5.2% and 1.7% more likely to reveal a long-horizon forecast. In Table A2 in Appendix A, we find nearly identical results when controlling for whether the analyst also issues a LTG forecast or disaggregates their earnings forecasts into revenue and expense forecasts during the year, suggesting that the publicity incentives of the analyst's employer incrementally predicts long-horizon forecast issuance above the determinants of these other forecast decisions. The results in Table 6 and Table A2 are consistent with the notion that when research services makes up a larger fraction of a bank's overall revenue, the bank is more likely to encourage their analysts to publish their long-horizon forecasts.

Building on the idea that brokerages that derive more value from generating publicity motivate their analysts to issue long-horizon forecasts, we expect that buy-side analysts are less likely to release their long-horizon forecasts than sell-side analysts. The intuition for this prediction follows Laster et al. (1999), who compare the propensity to issue bold forecasts across analysts working for different types of forecasting firms (though they do not have data on buy-side firms). Using a sample of crowd-sourced EPS forecasts issued by forecasters with a variety of backgrounds, we investigate this hypothesis by comparing the relative likelihoods of issuing long-horizon forecasts between buy-side and sell-side analysts.

The sample of crowd-sourced forecasts comes from *Estimize*, which collects quarterly earnings and revenue forecasts from a range of forecasters via an online platform. Prior research shows that these forecasts provide incremental information to Wall Street's consensus and affect equity returns (e.g., Jame, Johnston, Markov, and Wolfe, 2016; Adebambo, Bliss, and Kumar, 2016; Da and Huang, 2020). Conveniently, *Estimize* provides professional background information for each forecaster that submits a forecast. Table A3 in Appendix A shows the distribution of forecasts across professional backgrounds, as well as the average forecast error and horizon of each group. The top three most represented groups are all financial professionals, comprised of analysts working for independent research firms, buy-side firms, and sell-side brokerages. The least represented groups are non-financial professionals working in the utilities, telecommunication, and energy industries. Forecasters that work for sell-side brokerages are on average the least accurate, but they also tend to submit their forecasts much farther away from the earnings periods than other forecasters.

Using forecasters' professional background information, we run forecast-level OLS regressions that estimate the relative probability of long-horizon forecast issuance between buy-side and sell-side analysts.[13] The sample period begins in January 2011 (the first month with available data) and ends in March 2021. Unfortunately, because horizons of two years or more are extremely rare in *Estimize* (i.e., $< .02\%$), we are forced to use horizons shorter than our primary definition in these tests. We use two dependent variables; (i) $\textit{Long-Horizon}_{1yr}$, which is an indicator variable equal to one if the forecast has a horizon of at least one year, and (ii) $\textit{Long-Horizon}_{1.5yrs}$, which is an indicator variable equal to one if the forecast has a horizon of at least a year and a half. The main explanatory variable is an indicator variable equal to one if the forecaster works for a sell-side brokerage and zero if the forecaster works for a buy-side firm. We include firm-earnings period fixed effects to isolate comparisons between buy-side and sell-side analysts forecasting the same earnings results. We predict that sell-side analysts are more likely to issue long-horizon forecasts. We report the results of these tests in Table 7.

From Column (1), sell-side analysts are almost 26 percentage points more likely to issue forecasts with horizons greater than one year, which is an 159% increase relative to the unconditional probability of 16% (untabulated). Column (2) shows that sell-side analysts are 8.5 percentage points more likely to issue forecasts with horizons of at least a year and a half, which is a 156% increase relative to the unconditional probability of 5.4%. These results provide direct evidence that analysts employed by forecasting firms that place more emphasis on attracting new clients through their research are more likely to reveal their long-horizon forecasts.

4.2.2. Portfolio Firm Incentives

We next examine whether brokerages consider differences in the relative benefits of generating publicity across the firms their analysts cover when designing publicity incentives. It is possible that brokerages employ uniform incentives across firms. In Table A4, we show that the percent of variation in long-horizon forecast issuance explained by brokerage effects (i.e., the interclass correlation coefficient) is 67%, while the percent of variation explained by analyst effects is 51%

[13] Following Da and Huang (2020), we exclude forecasts that *Estimize* flags as unreliable. We also exclude erroneous duplicate forecasts, forecasts issued on or after the earnings announcements dates, and forecasters with missing professional background information.

and the percent explained by firm effects is 27%. This evidence supports the notion that brokerage incentives are most binding in the information revelation problem, which is intuitive given that brokerages design analysts' incentives to meet the brokerage's objectives. It also represents some of our strongest evidence that ability signaling motives are unlikely to be the primary driver of long-horizon forecast decisions; strong brokerage-level effects are inconsistent with analyst-specific efforts to signal their ability to evaluate long-term prospects. Last, this evidence also suggests firm-specific incentives play a relatively small role in the information revelation problem. It is thus possible that brokerages with high publicity incentives indiscriminately encourage long-horizon forecast issuance.

Alternatively, brokerages that place more emphasis on publicity may vary the weight they place on their analysts' publicity incentives based on the firm's trading volume or other measures of portfolio firm "importance" (Harford et al., 2019).[14] The theoretical relation between portfolio firm importance brokerages' publicity incentives is, however, unclear. On the one hand, the amount of revenue that can be generated from attracting new clients is increasing in the trading volume and analyst following of a portfolio firm. On the other hand, the costs of issuing less accurate forecasts are also increasing in portfolio firm importance. Furthermore, it is difficult for lesser-known brokerages that value publicity to compete for attention on firms with more trading volume and analyst following. It is thus an empirical question how brokerages consider the importance and potential trading activity of a covered firm when designing publicity incentives. Using the following regression equation estimated at the analyst-firm-year level, we examine whether analysts working for brokerages that place more emphasis on publicity are more or less likely to release long-horizon forecasts for portfolio firms with relatively more trading activity and analyst competition:

$$\begin{aligned} Long-Horizon_{ijt} = \beta_0 + \beta_1 \boldsymbol{\textit{Non-Bulge Bracket Bank}}_{ijt} \times \boldsymbol{\textit{Importance}} \\ + \beta_2 \textit{Non-Bulge Bracket Bank}_{ijt} + \beta_3 \textit{Importance} + \alpha_b + \gamma_{jt} + \epsilon_{ijt}. \end{aligned} \tag{4}$$

[14] Harford et al. (2019) introduce several ways to measure portfolio firm "importance," based on the idea that analysts care more about the firms in their portfolios that offer higher rewards to research effort. They show that a firm's relative trading volume, size, and analyst following help capture the marginal return to an analyst's effort.

$Long-Horizon_{ijt}$ is an indicator variable equal to one if analyst i reveals at least one forecast with a horizon of at least three years for firm j during calendar year t. α_b represents broker fixed effects, and γ_t represents firm fixed effects. *Non-Bulge Bracket Bank* is an indicator variable equal to one if the analyst's employer is not one of the seven bulge bracket banks defined above, and *Importance* represents one of two indicator variables: *High Trading Volume*, which is equal to one if firm j is ranked in the top quartile among firms that analyst i covers during year t in terms of the firm's trading volume during year *t-1*, and *High Analyst Following*, which is equal to one if firm j is ranked in the top quartile among firms that analyst i covers during year t in terms of the number of analysts covering each firm that year.[15] If publicity-oriented brokerages encourage their analysts to issue publicity-generating forecasts among firms with more trading activity and analyst competition, we expect $\beta_1 > 0$. If publicity-oriented brokerages instead encourage their analysts to issue publicity-generating forecasts among firms where there is greater ability to stand out and the costs of being inaccurate are lower, than we expect $\beta_1 < 0$.

We report the results for regressions estimated using Equation (4) in Table 8. In Panel A, we examine variation in the propensity to reveal forecasts with horizon of at least three years. Because the unconditional probability of revealing a forecast with a horizon of more than three years is low, in Panel B, we examine variation in the propensity to reveal forecasts with horizons of at least two years. Regardless of how we measure long-horizon forecasts or relative portfolio firm publicity incentives, we find that β_1 is negative and significant. From Panel A, a publicity-oriented brokerage is 0.3 percentage points less likely to reveal a long-horizon forecast for a firm that has high trading activity and 0.5 percentage points less likely to reveal a long-horizon forecast for a firm with high analyst competition. These estimates translate to reductions of 4.7% and 7.8% relative to the mean probability of 6.4%. Panel B shows that the economic magnitude of the effect is similar when focusing on forecasts with horizons of at least two years. These results suggest

[15] We find similar results when we replace *Non-Bulge Bracket Bank* with *Low-Prestige Brokerage* or *Small Brokerage* from Table 6.

that analysts working for brokerages with strong publicity incentives are more likely to reveal long-horizon forecasts for firms where these forecasts are more likely to attract new brokerage clients. This evidence does not align well with an ability signaling framework, under which analysts have incentives to target firms where their forecasts reach more clients.

4.2.3. Analyst Personal Incentives

We next examine the influence of analysts' personal incentives on their decisions to reveal their long-horizon forecasts. We expect that analysts respond to the financial incentives provided by their brokerage, which we provide evidence of in Section 4.2.1. However, we also expect that analysts respond to personal career concerns. Because analysts who work for publicity-oriented brokerages are unlikely to have much discretion on publicity-generating decisions, to test the extent to which analysts' personal career concerns drive their issuances of long-horizon forecasts, we exploit variation in analyst career concerns among analysts who work for high-prestige brokers. Specifically, we test whether analysts who work for brokerages that place less emphasis on publicity (i.e., high-prestige brokerages) are less likely to issue long-horizon forecasts when they have strong personal reputations in the industry and thus have less to gain from generating publicity. We use *All-star* status, past forecast accuracy, and number of years in the industry to proxy for analysts' personal reputations. We estimate analyst-year level regressions of the following form:

$$\begin{aligned} Long-Horizon_{it} = \beta_0 &+ \beta_1 \boldsymbol{Bulge\ Bracket\ Bank_{it}} \times \boldsymbol{High\ Analyst\ Reputation} \\ &+ \beta_2 Bulge\ Bracket\ Bank_{it} + \beta_3 High\ Analyst\ Reputation + \alpha_i + \gamma_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where $Long-Horizon_{it}$ again is an indicator variable equal to one if the analyst issues at least one forecast with a horizon of three years or more during year t, and α_i and γ_t are analyst and calendar year fixed effects. *Bulge Bracket Bank* is an indicator variable equal to one if the analyst's employer is one of the seven bulge bracket banks defined above. *High Analyst Reputation* represents one of three variables: (i) *All-Star*, an indicator variable equal to one if analyst i is voted to one of *Institutional Investor*'s *All America* research teams during the previous three years; (ii) *Forecasting Reputation*, analyst i's lagged relative forecast accuracy; and (iii) *General Experience*, the natural logarithm of the number of years analyst i has been submitting forecasts to I/B/E/S. Our computation of *Forecasting Reputation* follows our computation of the *Accuracy* measures in Table5, except we use only the shortest-horizon forecasts of each analyst here and lag the measure one year. If an analyst's personal reputation reinforces the publicity incentives that they internalize from their employer, we expect that $\beta_1 < 0$. We report the results from these tests in Table 9.

We find that analysts who work for brokerages with low publicity incentives *and* who have high personal forecasting reputations are particularly unlikely to publish long-horizon forecasts. From Column (1), a non-*All-Star* analyst who works for a bulge bracket bank is 10.4 percentage points less likely than other non-*All-Star* analysts to publish a long-horizon forecast. An *All-Star* analyst at a bulge bracket bank is an additional 4.7 percentage points (or 73% relative to the unconditional mean) less likely to publish a long-horizon forecast. Columns (2) and (3) indicate that conditional on working for a bulge bracket bank, analysts with high forecast reputations and experience are also particularly unlikely to publish long-horizon forecasts. These results suggest that analysts' personal publicity incentives reinforce the publicity incentives they internalize from their banks. An analyst who benefits little from additional publicity, who works for a bank that benefits little from additional publicity, is extremely unlikely to reveal his/her long-horizon forecasts.

4.3. Career Implications of Revealing Long-Horizon Forecasts

The accuracy of analysts' forecasts matters for their careers. Analysts that issue more accurate forecasts obtain better career outcomes (Mikhail et al., 1999; Hong and Kubik, 2003). In Section 4.1, we provide evidence that analysts' career prospects are affected not only by the accuracy of their short-horizon forecasts, but also the accuracy of their longer-horizon forecasts. Thus, analysts have incentives to protect their reputation for forecasting accurately at both short and long horizons. However, as we have argued throughout, analysts may also face incentives to forecast in ways that, in expectation, hurt their reputations for forecasting accuracy if doing so helps attract new clients to their brokerages. If analysts face such incentives, then we expect analysts to be rewarded by their brokerages for endeavoring to attract new clients.

In this section, we shed light on this assertion by examining whether publishing long-horizon forecasts increases analysts' job security. That is, we test whether analysts' decisions to reveal long-horizon forecasts are associated with reduced likelihoods of demotion or termination.[16] We also examine analyst upward labor market movements. Because brokerages vary in how much emphasis they put on publicity-generating forecasts, one cost of publishing long-horizon forecasts could be that it reduces analysts' marketability to top brokerages; issuing long-horizon forecasts, on average, reduces analysts' reputations for forecasting accurately, and top brokerages put less emphasis on generating publicity. Thus, we predict that analysts' decisions to reveal long-horizon forecasts are associated with reduced likelihoods of moving to top brokerages. Last, we use investor reactions to analysts' future forecasts to test the hypothesis that long-horizon forecasts generate publicity.

4.3.1. Labor Market Movements and Award Recognition

Similar to our analysis in Section 4.1, we study analyst labor market movements across brokerages and industry departures to examine how analysts' decisions to reveal their long-horizon forecasts affect their career prospects. We again assess movements across brokerages by comparing the brokerages that analysts work for at the end of years t and $t+1$. We also test whether analysts' decisions to reveal their long-horizon forecasts increase the likelihood they are voted as *All-Stars*. Prior research shows that *All-Star* votes are less related to analysts' forecast accuracy than they are to the analysts' popularity among clients Emery and Li (2009). If revealing long-horizon forecasts generates publicity, then issuing these forecasts should increase the chances of being voted an *All-Star*. We limit our analysis to analysts working for non-bulge bracket banks since we do not have predictions for how revealing long-horizon forecasts affects the careers of analysts working for

[16] Ideally, we would also examine analyst compensation. Unfortunately, analyst compensation information is unavailable.

brokerages that place less emphasis on publicity; however, we find similar results when estimating the career effects of long-horizon forecast issuance among all analysts.

To study analyst labor market movements and industry award recognition, we estimate analyst-year level regressions of the following form:

$$\textit{Labor Market Outcome}_{i,t+1} = \beta_0 + \beta_1 \boldsymbol{\textit{Long-Horizon}}_{it} + \delta X_{it} + \alpha_i + \gamma_t + \epsilon_{i,t+1}, \tag{6}$$

where i indexes analysts, t indexes years, α_i and γ_t represent analyst and calendar year fixed effects. Our primary measures of labor market movements are again *Career Outcome*$_{i,t+1}$, an ordinal variable with three levels increasing in more positive labor market movements, and *Moves Down*, an indicator variable equal to one if the analyst moves down to a lower decile brokerage. We also examine the likelihoods of analysts leaving the profession in year *t+1* (*Leaves*) and moving to a higher decile brokerage (*Moves Up*).[17] Our measure of award recognition, *All-Star*, is an indicator variable equal to one if the analyst is elected to an All-America research team in year *t+1*. We control for the same characteristics as in Equation (2), which again includes controls for analysts' relative forecast performance, forecast optimism, experience, and piggybacking during year *t*. We also include a control for *All-Star* status during year *t* in regressions analyzing analysts' selection to all-star teams during year *t+1*.[18] We report the results from these regressions in Table 10.

Columns (1) shows that analysts' decisions to reveal long-horizon forecasts are associated with more positive labor market movements during the following year.[19] Columns (2) and (3) show that the more positive labor market movements are driven by reductions in the likelihoods that these analysts move down to a lower brokerage or leave the industry. The decision to reveal a long-horizon forecast reduces the probability of departing the industry during year *t+1* by 6.6

[17] In untabulated analyses, we find similar results when we use indicators for moving to a bulge bracket bank or moving to an bank with a top Carter Manaster ranking.

[18] Due to data limitations, we only have *All-Star* information for the years 2001–2012. We thus only control for lagged *All-Star* status in tests predicting future *All-Star* status. However, controlling for lagged *All-Star* status in all regressions estimated using Equation (6) does not alter our conclusions.

[19] We exclude analysts employed by brokerages in the bottom and top deciles in Column (1), analysts employed by brokerages in the bottom decile in Column (2), and analysts employed by brokerages in the top decile in Column (5), since the movement of these analysts is censored. Results are similar when including these analysts.

percentage points (or 39% relative to the mean). In Column (4), we restrict our sample to analysts working for brokerages that merge with another brokerage during year t. We use a combination of the brokerage mergers reported in Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012) that are completed during our sample period. We report the annual distribution of mergers during our sample period in Panel A of Table A5 in Appendix A and the individual brokerage mergers that we use in Panel B of Table A5. We find that, in the context of unexpected departures from the industry in which such decisions are at least partly driven by downsizing as opposed to an analyst taking a better job outside the industry, analysts' decisions' to reveal long-horizon forecasts are associated with reduced likelihoods of departing the industry during the following year. These results are consistent with employers rewarding their analysts for generating publicity for their firms, particularly the employers that depend more heavily on generating publicity through their firms' research services.

In Column (5), we show that analysts' decisions to publish their long-horizon forecasts are associated with increased likelihoods they are voted *All-Stars* during the subsequent year. Although there are a number of factors that influence how buy-side investors vote for *All-Stars*, our results suggest that analysts' decisions to reveal their long-horizon forecasts expand their recognition with buy-side investors. In Column (6), we provide evidence that one cost analysts face when revealing their long-horizon forecasts is a reduced probability of moving to more prestigious brokerages. More prestigious brokerages place less emphasis on generating publicity through forecast issuance than smaller brokerages. Analysts can improve their fit with their current employer by revealing their long-horizon forecasts but appear to worsen their fit with more prestigious brokerages. These results directly conflict with an ability signaling explanation, which argues that the primary reason analysts reveal these forecasts is to improve their attractiveness to more reputable employers.

4.3.2. Market Impact

We examine here whether analysts who publish their long-horizon forecasts garner higher market reactions to their forecasts during the following period. Investors cannot immediately impound all of the information associated with an analyst's report into prices, such as the analyst's incentives, conflicts of interest, and quality. Consequently, an analyst's reputation and investor recognition help determine the impact of their research. Greater recognition with investors increases the sensitivity of investors' responses to the analyst's research. This relation underpins why brokerages create incentives for analysts to generate publicity: through producing forecasts that stand out, analysts can increase their recognition with investors, and the increased recognition can increase investor demand for the brokerage's trading and research services. We thus predict that analysts who reveal their long-horizon forecasts garner larger market reactions to their forecasts in the future.

The model we use to assess market reactions to analysts' forecasts follows the models of Jung et al. (2012), Hilary and Hsu (2013), and Shroff, Venkataraman, and Xin (2014). We estimate the following forecast-level regression equation:

$$\begin{gathered} MAR(0,+2)_{ijt} = \beta_0 + \beta_1 \Delta \,\boldsymbol{Value}\ \mathbf{x}\ \boldsymbol{Long\text{-}Horizon}_{ijt} + \beta_2 \Delta Value + \beta_3 First_{ijt} + \\ \theta Controls + \delta \Delta Value \times Controls + \alpha_i + \gamma_{jt} + \epsilon_{it}, \end{gathered} \tag{7}$$

where $\Delta Value$ is the difference between analyst i's current forecast for firm j and the analyst's most recent forecast for the same firm and earnings period.[20] *Long-Horizon* is an indicator variable equal to one if the analyst issues at least one forecast with a horizon of three years or more during the prior calendar year. α_i represents analyst fixed effects, γ_{jt} represents firm-calendar year fixed effects, and β_1 is our coefficient of interest. The intuition of the regression model is that to account for the fact that forecasts by themselves do not have an implied direction like recommendations, $\Delta Value$ estimates the direction and magnitude of the revision in earnings expectations. Higher $\Delta Value$

[20]Results are robust to using the outstanding consensus forecast instead of analyst i's most recent forecast, where consensus is the average of the most recently issued forecasts by peer analysts forecasting the same firm and earnings period. Empirically, within-analyst changes in forecast estimates have a larger impact on prices than changes in the outstanding consensus.

predicts higher market reactions. We confirm this relation in Column (1) of Table 11, where we regress three-day market-adjusted returns (*MAR(0,+2)*) surrounding forecast announcements (in percentage terms) on the revision in earnings expectations, $\Delta Value$.[21] A one standard deviation increase in $\Delta Value$ (\$0.58) increases three-day abnormal market reactions by 31 basis points.

The regression model then interacts $\Delta Value$ with all of the explanatory variables (including controls) to assess the relative impact that these variables have on the relation between $\Delta Value$ and *MAR(0,+2)*. For example, one of the controls is an indicator for whether the forecast is a negative revision (*Downgrade*). Prior evidence shows that negative news generates larger market reactions than positive news of similar magnitude (Skinner, 1994; Kothari, Shu, and Wysocki, 2009; Ho, Strong, and Walker, 2018). This evidence predicts a positive coefficient on the interaction between $\Delta Value$ and *Downgrade*. We confirm this relation in Column (2), which shows that downgrades move prices by an additional 22 basis points.[22] In Columns (3) and (4), we examine whether analysts that recently publish long-horizon forecasts generate relatively larger market reactions to their forecasts during the subsequent period. Our control variables include controls for the number of firms the analyst covers during the year, the number of forecasts the analyst issues that year, the analyst's relative forecast accuracy during the prior year, whether the analyst works for a top investment bank, the analyst's length of forecasting experience, an indicator for whether the analyst initiated coverage of the firm that year, the horizon of the forecast itself, and the number of upgrade and downgrade forecasts (separately) produced by peer analysts during the return window.[23]

The results in Columns (3) and (4) show that analysts' decisions to publish their long-horizon forecasts predict higher market reactions to their subsequent research. Revealing a long-horizon forecast is associated with an increase in the market impact of the analyst's forecasts by 12.2 basis

[21] We winsorize *MAR(0,+2)* at + and − 200%. Our results are insensitive to winsorizing at + and − 100% and to not winsorizing at all.

[22] We include the main effects (i.e., uninteracted variables) in all of the regressions but, to conserve space, we do not report them.

[23] We sum the number of upgrade and downgrade forecasts announced during the window beginning two days before the announcement and ending two days after the announcement to account for overlapping (0,+2) return windows.

points. These results provide further support for the idea that analysts use long-horizon forecasts to generate publicity and doing so boosts interest in their research and their employer's services.

5. Conclusion

Although all analysts produce forecasts of cash flows for distant earnings period, only some analysts reveal these forecasts to clients. We propose that the decision of whether to reveal such long-horizon forecasts is the product of a trade-off for the analyst and their brokerage between, on the one hand, carefully managing the accuracy of the forecasts they issue and, on the other hand, revealing forecasts that have the potential to generate publicity. We produce several pieces of evidence that support this hypothesis.

First, we document that analysts' long-horizon forecasts are approximately 50% less accurate than their shorter-horizon forecasts, and being accurate at longer horizons matters for analysts' careers almost as much as being accurate at shorter horizons. There is thus a clear trade-off between revealing long-horizon forecasts and maintaining a quality forecasting record. Second, we find that analysts presumably facing stronger incentives from their employer to generate publicity are more likely to reveal their long-horizon forecasts. This effect is particularly stark when examining differences in long-horizon forecast issuance between buy-side and sell-side analysts: buy-side analysts essentially never reveal their long-horizon forecasts, which is consistent with brokerages encouraging the release of long-horizon forecasts to attract new users and boost trading revenue. Third, we show that much more of the variation in long-horizon forecast issuance is explained by brokerage effects, compared with either analyst or portfolio firm effects. This result is more consistent with a publicity explanation than an ability signaling explanation. Last, we find that although issuing long-horizon forecasts appears to reduce termination risk, there are also career costs: analysts who reveal their long-horizon forecasts experience reduced likelihoods of moving to more prestigious brokerages. Despite a large literature studying the influence of analysts' forecasting reputations, effort, and other characteristics on their career prospects, we are the first to document how analysts' responses to their employers incentives potentially worsens their fit with other brokerages.

Notably, our tests do not causally identify the effect of analysts revealing their long-horizon forecasts. It is possible that analysts' decisions to reveal their long-horizon forecasts are correlated with unobservable characteristics that more generally relate to the analysts' abilities to serve their clients' needs and it is those characteristics that are rewarded by the analysts' employers and financial markets. Nevertheless, understanding analysts' incentives and what drives their forecasting decisions is important because their research helps form consensus expectations in financial markets, and investors use analysts' signals to set prices. Despite prices likely being more efficient if all analysts revealed all of their forecasts for all earnings periods, we provide the first evidence that the sample of long-horizon forecasts that investors observe disproportionately comes from brokerages that depend more heavily on generating trading revenue and attracting new clients.

Future research can help address additional questions relating to analysts' decisions of whether to reveal their longer-horizon forecasts, including questions regarding the usefulness of long-horizon forecasts, the relative impact of long-horizon forecasts on firm information asymmetry, and the drivers of the dramatic rise in long-horizon forecast production over time.

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Figure 1: Analyst Forecast Horizon Over Time

This figure plots both the annual average forecast horizon—i.e., the time between the forecast announcement and the forecast period end-date (FPE)—for all forecasts in our sample (solid line, left axis) and the annual unconditional probability of the issuance of a forecast with a horizon of at least three years (dashed line, right axis).

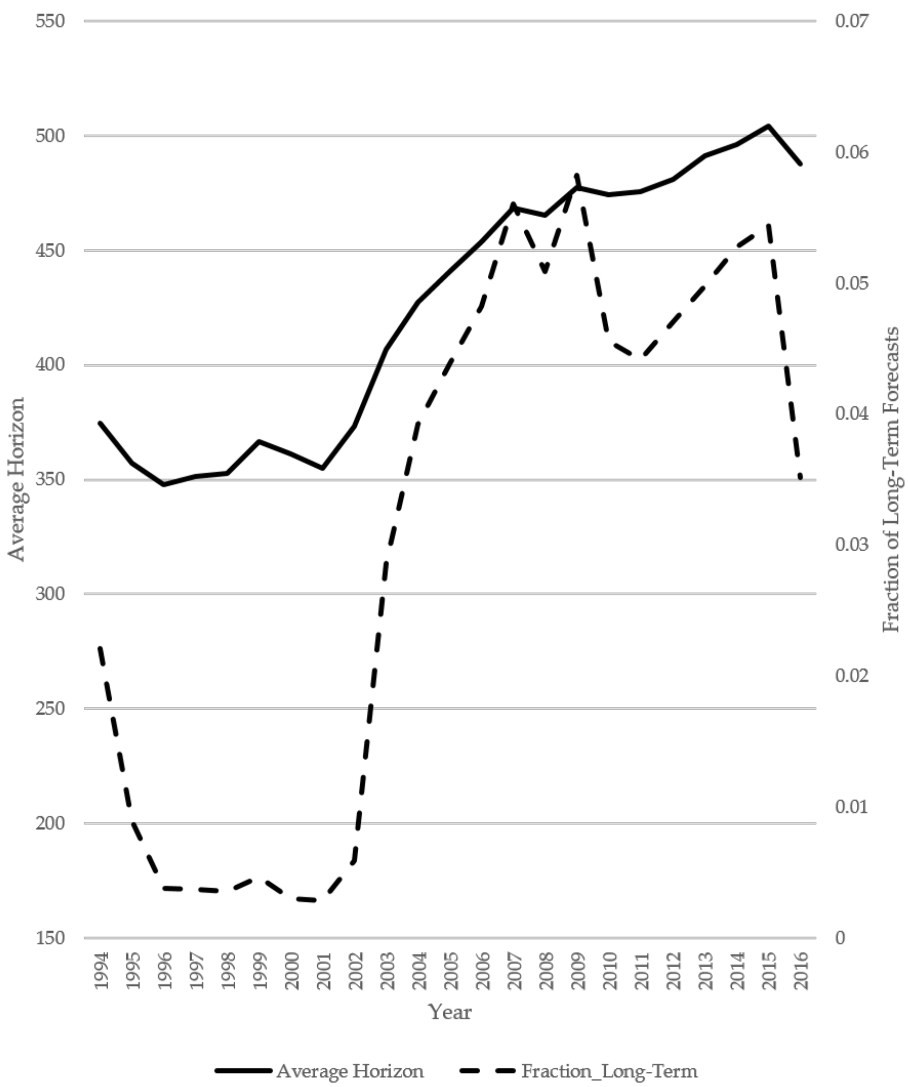

Table 1: Descriptive Statistics of Forecast Sample

Panel A reports the distribution of annual EPS forecasts across varying forecast horizons. Forecast horizon is computed as the time between the forecast announcement date and the forecast period end-date (FPE). The sample of forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. Variable definitions are presented in Table B1 in Appendix B. Panel B reports the unconditional probabilities that analysts issue forecasts of varying horizons, long-term growth (LTG) forecasts, and disaggregated revenue and expense forecasts each year. Panel C reports the correlation between analysts' decisions to reveal at least one long-horizon forecast, one LTG forecast, and one disaggregated forecast each year.

Panel A: Long-Horizon Forecast Issuance

Horizon	**Total**	**Mean N per Analyst-Year**	**Mean N per Firm-Year**	**Mean N per Analyst-Firm-Year**
Between 0 and 0.5 years	1,646,858	17.54	14.89	1.96
Between 0.5 and 1 years	1,545,001	16.48	13.99	1.84
Between 1 and 1.5 years	1,408,251	14.98	12.72	1.67
Between 1.5 and 2 years	1,212,805	12.92	10.97	1.44
Between 2 and 2.5 years	456,578	4.85	4.12	0.54
Between 2.5 and 3 years	243,321	2.59	2.20	0.29
Between 3 and 3.5 years	88,111	0.94	0.80	0.10
Between 3.5 and 4 years	66,539	0.71	0.60	0.08
Between 4 and 4.5 years	45,938	0.49	0.42	0.05
Between 4.5 and 5 years	33,382	0.36	0.30	0.04
Over 5 years	16,086	0.17	0.15	0.02
Full Sample	6,762,870	72.03	61.16	8.03

Panel B: Unconditional Likelihoods of Long-Horizon, LTG, and Disaggregated Forecasts

Variable	**Mean**	**Median**	**Std Dev**	**N**
Analyst-Year				
Horizon 0–1 Yr	0.98	1.00	0.13	93,893
Horizon 1–2 Yr	0.95	1.00	0.22	93,893
Horizon 2+ Yr	0.52	1.00	0.50	93,893
Long-Horizon Forecast (i.e., Horizon $\geq$ 3 Yrs)	0.14	0.00	0.35	93,893
LTG Forecast	0.42	0.00	0.49	93,893
Disaggregated Forecast	0.62	1.00	0.49	93,893

Panel C: Correlations Between Long-Horizon, LTG, and Disaggregated Forecasts

	Long-Horizon	LTG	Disaggregated
Long-Horizon	1.000		
LTG	0.020	1.000	
Disaggregated	0.181	0.083	1.000

Table 2: Descriptive Statistics of Forecast Horizon Measures

This table reports means, medians, inner quartiles, and standard deviations of our explanatory variables. The unit of observation is either analyst-firm-year or analyst-year. Our sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. Variable definitions are presented in Table B1 in Appendix B.

Variable	Mean	Q1	Median	Q3	Std Dev	N
Brokerage Characteristics						
Non-Bulge Bracket Bank	0.81	1.00	1.00	1.00	0.39	820,437
Low-Prestige Bank	0.82	1.00	1.00	1.00	0.38	794,810
Small Brokerage	0.74	0.00	1.00	1.00	0.44	820,437
Analyst Characteristics						
All-Star Analyst	0.11	0.00	0.00	0.00	0.28	565,453
High Forecast Reputation	0.10	0.00	0.00	1.00	0.30	668,335
Relative Forecast Performance	0.49	0.38	0.50	0.60	0.21	78,696
General Experience	5.82	3.00	6.00	8.00	2.73	78,696
Optimism	0.48	0.31	0.50	0.64	0.27	78,696
Piggybacking	0.46	0.26	0.48	0.66	0.27	78,696
Lagged All-Star	0.06	0.00	0.00	0.00	0.24	40,829
Number of Companies	10.27	3.00	9.00	15.00	7.64	78,696

Table 3: Long-Horizon Forecast Issuance and Forecast Accuracy

This table reports the results of forecast-level OLS regressions examining the impact of analysts' decision to issue long-horizon forecasts on their forecast accuracy. The dependent variable, *Accuracy*, is defined as the absolute value of the difference between analyst i's EPS forecast and realized EPS, scaled by the absolute value of realized EPS. $Long\text{-}Horizon_{3yr}$ is an indicator variable equal to one if the forecast is the forecast has a horizon of at least three years (i.e., 1095 days). $Long\text{-}Horizon_{2yr}$ is an indicator variable equal to one if the forecast is the forecast has a horizon of at least two years (i.e., 730 days). *Accuracy* is winsorized at the extreme 5% to mitigate the influence of outliers and noise. *Analyst-Firm-FPE FE* represents analyst-firm-forecast period end date fixed effects. Variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Accuracy	(2) Accuracy
Long-Horizon$_{3yr}$	−0.495*** (−26.91)	
Long-Horizon$_{2yr}$		−0.422*** (−42.79)
Analyst-Firm-FPE FE	Yes	Yes
Adj. R-squared	0.772	0.777
Observations	6,384,477	6,384,477

Table 4: Summary Statistics for Analyst Career Outcomes

This table reports annual job turnover frequencies among our sample of analysts. Each year, brokerage houses are assigned to deciles based on the number of analysts that they employ, with approximately an equal number of analysts in each decile. An analyst moves up (down) in year *t+1* if they change an employer during that year and are employed by a brokerage house that is assigned to a higher (lower) decile at the end of year *t+1* than the brokerage house by which they were employed during year *t*. An analyst is classified as leaving the profession in year *t* if they are in the I/B/E/S U.S. Detail file during year *t*, but are not in this database in any of the following years afterward. The analyst is classified as an *Institutional Investor* (II) *All-Star* if they are on one of *Institutional Investor*'s All-America teams that year (any ranking). The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described Table A1 in Appendix A. *All-Star* rankings are from *Institutional Investor*'s All-America ranking 2001-2012.

Year	Total	Move Up		Move Down		Leave		All Job Switches		All-Star	
(1)	(2)	(3)		(4)		(5)		(6)		(7)	
1994	3,045	266	*9%*	234	*8%*	325	*11%*	1,064	*35%*		
1995	3,177	228	*7%*	299	*9%*	376	*12%*	1,105	*35%*		
1996	3,440	266	*8%*	272	*8%*	407	*12%*	1,164	*34%*		
1997	3,680	244	*7%*	218	*6%*	413	*11%*	1,050	*29%*		
1998	4,197	309	*7%*	272	*6%*	615	*15%*	1,453	*35%*		
1999	4,555	373	*8%*	274	*6%*	732	*16%*	1,644	*36%*		
2000	4,583	408	*9%*	282	*6%*	835	*18%*	1,737	*38%*		
2001	4,897	208	*4%*	378	*8%*	1,054	*22%*	1,972	*40%*	278	*6%*
2002	4,673	213	*5%*	321	*7%*	1,221	*26%*	1,983	*42%*	279	*6%*
2003	4,445	225	*5%*	189	*4%*	1,046	*24%*	1,642	*37%*	205	*5%*
2004	4,085	155	*4%*	178	*4%*	742	*18%*	1,237	*30%*	184	*5%*
2005	4,051	140	*3%*	171	*4%*	706	*17%*	1,156	*29%*	191	*5%*
2006	4,015	149	*4%*	130	*3%*	697	*17%*	1,075	*27%*	169	*4%*
2007	4,088	163	*4%*	256	*6%*	739	*18%*	1,292	*32%*	171	*4%*
2008	3,952	160	*4%*	267	*7%*	756	*19%*	1,292	*33%*	196	*5%*
2009	3,801	176	*5%*	151	*4%*	546	*14%*	1,017	*27%*	208	*5%*
2010	4,051	142	*4%*	123	*3%*	535	*13%*	960	*24%*	234	*6%*
2011	4,230	110	*3%*	141	*3%*	681	*16%*	1,064	*25%*	246	*6%*
2012	4,121	97	*2%*	133	*3%*	711	*17%*	1,078	*26%*	258	*6%*
2013	4,137	165	*4%*	89	*2%*	645	*16%*	1,007	*24%*		
2014	4,334	105	*2%*	110	*3%*	786	*18%*	1,078	*25%*		
2015	4,257	59	*1%*	107	*3%*	843	*20%*	1,037	*24%*		
Average	4,082	205	*5%*	214	*5%*	694	*17%*	1,278	*31%*	218	*5%*

Table 5: Impact of Longer-Horizon Forecast Accuracy on Analyst Career Prospects

This table presents analyst-year OLS regressions examining the labor market market implications of analyst forecast accuracy for forecasts with different horizons. Brokerages are sorted into deciles each year based on the number of analysts that they employ (in descending order); larger brokerages are considered more prestigious employers. Each decile includes approximately the same number of analysts. The dependent variable in Columns (1) and (2), *Career Outcome (t+1)*, is an ordinal variable with three levels: -1 if the analyst moves down to a worse brokerage decile or leaves after year t, 0 if the analyst for stays or moves within the same decile, and 1 if the analyst moves up to a better brokerage decile. The dependent variable in Columns (3) and (4), *Moves Down (t+1)*, is an indicator variable equal to one if analyst i moves down to a lower decile in year $t+1$. Deciles 1 and 10 are excluded from the regressions in Columns (1) and (2). The bottom decile is excluded from the regressions in Columns (3) and (4). $Accuracy_{0m-6m}$ is the standardized average accuracy of analyst i's forecasts issued during calendar year t that had a horizon of less than six months. $Accuracy_{6m-12m}$ is the standardized average accuracy of analyst i's forecasts issued during calendar year t that had a horizon of at least six months but less than one year. $Accuracy_{12m-18m}$ is the standardized average accuracy of analyst i's forecasts issued during calendar year t that had a horizon of at least one year but less than 18 months. Standardized accuracy for a given forecast horizon range is computed by first ranking analysts following the same firm during year t based on the percentage absolute deviation of the forecast estimates from actual earnings per share using forecasts with horizons in the given range ($Accuracy = -\frac{|F-A|}{|A|}$) and then computing an aggregate score for the given horizon range across all firms that the analyst covers during year t using the following equation: $Score = 1 - \left[\frac{rank-1}{\#ofanalysts}\right]$. All variables are defined Table B1 in Appendix B. The sample of forecasts includes 6,762,870 annual EPS forecasts issued for US firms from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Career Outcome (t+1)	(2) Career Outcome (t+1)	(3) Moves Down (t+1)	(4) Moves Down (t+1)
$\text{Accuracy}_{\text{0m–6m}}$	0.197***	0.204***	−0.046***	−0.048***
	(11.74)	(12.32)	(−5.91)	(−6.05)
$\text{Accuracy}_{\text{6m–12m}}$	0.084***	0.084***	−0.013*	−0.013*
	(5.82)	(5.88)	(−1.90)	(−1.87)
$\text{Accuracy}_{\text{12m–18m}}$	0.108***	0.099***	−0.028***	−0.026***
	(7.00)	(6.46)	(−3.98)	(−3.72)
General Experience		−0.045***		0.001
		(−15.93)		(0.68)
Optimism		−0.111***		0.024***
		(−10.80)		(4.59)
Piggybacking		−0.132***		0.059***
		(−7.70)		(6.65)
Constant	−0.493***	0.027	0.066***	0.013
	(−31.04)	(0.91)	(8.88)	(0.82)
Analyst FE	Yes	Yes	Yes	Yes
Broker FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.128	0.141	-0.017	-0.015
Observations	55,257	55,257	59,147	59,147

Table 6: Brokerage Publicity Incentives and Long-Horizon Forecasts

This table reports the results of analyst-year OLS regressions examining the influence of a brokerage's publicity incentives on their analysts' decisions to reveal their long-horizon forecasts. The dependent variable, *Long-Horizon*, is an indicator variable equal to one if analyst i issues at least one forecast during year t that has a horizon of at least three years (i.e., 1095 days). *Non-Bulge Bracket Bank* is an indicator variable equal to one if the analyst's brokerage is not one of the six "bulge bracket" banks listed in Cowen et al. (2006) (plus JP Morgan). *Low-Prestige Brokerage* is an indicator variable equal to one if the investment bank affiliated with the analyst's employer does not have a top Carter-Manaster ranking in the calendar year of the forecast. *Small Brokerage* is an indicator variable equal to one if the analyst's brokerage is not one of the top ten largest brokerages in the calendar year of the forecast, where brokerage size is determined based on the number of analysts employed by the brokerage during that year. All variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Long-Horizon	(2) Long-Horizon	(3) Long-Horizon
Non-Bulge Bracket Bank	0.109***		
	(12.77)		
Low-Prestige Brokerage		0.052***	
		(7.01)	
Small Brokerage			0.017***
			(3.05)
Analyst FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes
Adj. R-squared	0.410	0.407	0.406
Observations	89,779	89,779	89,779

Table 7: Sell-Side vs. Buy-Side Analysts

This table reports the results of forecast-level OLS regressions examining the influence of a forecaster's professional background on their decision to submit a long-horizon forecast to the crowd-sourced *Estimize* platform. The dependent variable in Column (1), $\textit{Long-Horizon}_{1yr}$, is an indicator variable equal to one if the forecast has a horizon of at least one year (i.e., 365 days). The dependent variable in Column (2), $\textit{Long-Horizon}_{1.5yrs}$, is an indicator variable equal to one if the forecast has a horizon of at least a year and and a half (i.e, 548 days). Horizon is defined as the number of days between the date that the forecast was submitted to *Estimize* and the date of the earnings announcement. *Sell-side* is an indicator variable equal to one if the forecaster's user bio describes the forecaster as a financial professional employed by a sell-side broker. Only forecasts issued by financial professionals in either the sell-side or buy-side analyst industries are included in the regressions. Each regression includes firm-forecast period fixed effects. All variables are defined in Table B1 in Appendix B. The sample of forecasts includes quarterly EPS forecasts submitted to *Estimize* between January 2011 and March 2021. *t*-statistics are reported in parentheses, with standard errors clustered at the forecaster level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Long-Horizon$_{1yr}$	(2) Long-Horizon$_{1.5yrs}$
Sell-side	0.255***	0.084***
	(19.48)	(17.25)
Firm-FPE	Yes	Yes
Adj. R-squared	0.318	0.184
Observations	387,345	387,345

Table 8: Portfolio-Firm-Level Publicity Incentives and Long-Horizon Forecasts

This table reports the results of analyst-firm-year OLS regressions examining analysts' decisions to reveal their long-horizon forecasts. The dependent variable in Panel A, *Long-Horizon*, is an indicator variable equal to one if analyst i issues at least one forecast for firm j during year t that has a horizon of at least three years (i.e., 1095 days). The dependent variable in Panel B is an indicator variable equal to one if analyst i issues at least one forecast for firm j during year t that has a horizon of at least two years (i.e., 730 days). *Non-Bulge Bracket Bank* is an indicator variable equal to one if the analyst's brokerage is not one of the six "bulge bracket" banks listed in Cowen et al. (2006) (plus JP Morgan). *High Trading Volume* is an indicator variable equal to one if the portfolio firm is ranked in the top quartile of all firms that the analyst covers during calendar year t, in terms of each firm's trading volume during the prior calendar year. *High Analyst Following* is an indicator variable equal to one if the portfolio firm is ranked in the top quartile of all firms that the analyst covers during calendar year t, in terms of the number of unique analysts covering the firm that year. All variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Long-Horizon – 3 Years

	(1) Long-Horizon	(2) Long-Horizon
Non-Bulge Bracket Bank*High Trading Volume	−0.003*	
	(−1.74)	
Non-Bulge Bracket Bank*High Analyst Following		−0.005***
		(−2.99)
High Trading Volume	−0.002	
	(−1.29)	
High Analyst Following		0.000
		(0.15)
Broker FE	Yes	Yes
Firm FE	Yes	Yes
Adj. R-squared	0.242	0.264
Observations	781,510	831,047

Panel B: Long-Horizon – 2 Years

	(1) Long-Horizon	(2) Long-Horizon
Non-Bulge Bracket Bank*High Trading Volume	−0.016***	
	(−5.48)	
Non-Bulge Bracket Bank*High Analyst Following		−0.013***
		(−4.24)
High Trading Volume	0.015***	
	(4.55)	
High Analyst Following		0.005
		(1.46)
Broker FE	Yes	Yes
Firm FE	Yes	Yes
Adj. R-squared	0.276	0.282
Observations	781,510	831,047

Table 9: Analysts Publicity Incentives and Long-Horizon Forecasts

This table reports the results of analyst-year OLS regressions examining analysts' decisions to reveal their long-horizon forecasts. The dependent variable, *Long-Horizon*, is an indicator variable equal to one if analyst i issues at least one forecast during year t that has a horizon of at least three years (i.e., 1095 days). *Bulge Bracket Bank* is an indicator variable equal to one if the analyst's brokerage is one of the six "bulge bracket" banks listed in Cowen et al. (2006) (plus JP Morgan). *All-Star* is an indicator variable equal to one if the analyst was elected to one of *Institutional Investors*' All-America research teams in the previous year. *High Forecast Reputation* is an indicator variable equal to one if the analyst was in the top 10 percentile of the sample distribution of annual forecast accuracy during the prior calendar year. We compute annual forecast accuracy by first ranking analysts who follow the same firm during the year based on the percentage absolute deviation of forecast estimates from actual earnings per share ($Accuracy = -\frac{|Forecast-Actual|}{|Actual|}$), and then computing an aggregate score among the analysts forecasting the same firm in the same year using the following equation: $Score = 1 - \left[\frac{rank-1}{\#of analysts}\right]$. Relative forecast performance for analyst i during year t is the mean value of *Score* across the firms that they cover. All variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. The sample period in Column (1) is limited to 2001-2015, since our access to *All-Star* rankings information is limited to the period 2001-2012. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Long-Horizon	(2) Long-Horizon	(3) Long-Horizon
Bulge Bracket Bank*All-Star	−0.047**		
	(−1.98)		
Bulge Bracket Bank*Forecasting Reputation		−0.025**	
		(−2.25)	
Bulge Bracket Bank*Forecasting Experience			−0.015***
			(−4.23)
Bulge Bracket Bank	−0.104***	−0.094***	−0.042**
	(−8.18)	(−8.66)	(−2.41)
All-Star	0.065***		
	(3.65)		
Forecasting Reputation		0.030***	
		(4.90)	
Forecasting Experience			0.006***
			(2.68)
Analyst FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R-squared	0.443	0.430	0.410
Observations	50,630	75,682	89,708

Table 10: Impact of Long-Horizon Forecast Issuance on Analyst Careers

This table presents analyst-year OLS regressions examining the labor market market implications of analysts' decisions to reveal their long-horizon forecasts. Brokerages are sorted into deciles each year based on the number of analysts that they employ (in descending order); larger brokerages are considered more prestigious employers. Each decile includes approximately the same number of analysts. The dependent variable in Column (1), *Career Outcome (t+1)*, is an ordinal variable with three levels: -1 if the analyst moves down to a worse brokerage decile or leaves after year t, 0 if the analyst for stays or moves within the same decile, and 1 if the analyst moves up to a better brokerage decile. The dependent variable in Column (2), *Moves Down (t+1)*, is an indicator variable equal to one if analyst i moves down to a lower decile in year *t+1*. The dependent variable in Columns (3) and (4), *Leaves (t+1*, is an indicator variable equal to one if analyst i is in the I/B/E/S U.S. Detail file during year t, but is not in this database in any of the following years. The dependent variable in Column (5), *All-Star*, is an indicator equal to one if analyst i is on one of *Institutional Investor*'s All-America teams in year *t+1* (any ranking). The dependent variable in Column (6), *Moves Up (t+1)*, is an indicator variable equal to one if analyst i moves up to a higher decile in year *t+1*. Deciles 1 and 10 are excluded from the regression in Column (1). The bottom decile is excluded from the regression in Column (2) and the top decile is excluded from the regression in Column (6). Column (4) is restricted to analysts that work for either the acquiring or target brokerage during the year in which a merger between two brokerages occurs. The main explanatory variable in each column, *Long-Horizon*, is an indicator variable equal to one if the analyst issued at least one forecast in the prior calendar year that had a forecast horizon of at least three years. All variables are defined in Table B1 in Appendix B. The sample of forecasts includes 6,762,870 annual EPS forecasts issued for US firms from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. The sample period in Column (5) is restricted to 2001-2012, since our access to *All-Star* rankings information is limited to these years. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Career Outcome (t+1)	Moves Down (t+1)	Leaves (t+1)	Merger Leaves (t+1)	All-Star (t+1)	Moves Up (t+1)
Long-Horizon	0.063***	−0.011***	−0.066***	−0.077**	0.012***	−0.011**
	(8.08)	(−2.63)	(−14.44)	(−2.11)	(3.25)	(−2.41)
Relative Forecast	0.175***	−0.032***	−0.157***	−0.116	0.014***	−0.024***
Performance	(12.70)	(−4.97)	(−17.30)	(−1.63)	(3.36)	(−3.90)
General Experience	−0.062***	−0.003**	0.071***	−0.020***	0.009***	0.002
	(−21.28)	(−2.14)	(38.31)	(−3.95)	(4.80)	(1.20)
Optimism	−0.150***	0.031***	0.136***	0.161***	−0.006*	0.016***
	(−14.45)	(6.23)	(20.18)	(2.72)	(−1.79)	(3.31)
Piggybacking	−0.068***	0.057***	0.008	−0.195***	0.005	0.008
	(−4.13)	(7.07)	(0.78)	(−2.76)	(1.01)	(1.05)
Lagged All-Star					0.215***	
					(8.93)	
Constant	0.270***	0.048***	−0.284***	0.481***	−0.034***	0.045***
	(13.31)	(4.59)	(−22.05)	(6.96)	(−2.70)	(4.64)
Analyst FE	Yes	Yes	Yes	No	Yes	Yes
Broker FE	No	No	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.071	0.011	0.163	0.215	0.581	0.022
Observations	49,335	49,447	55,796	1,034	27,374	49,447

Table 11: Market Impact of Subsequent Research

This table presents forecast-level OLS regressions of investor market reactions to an analyst forecasts, as a function of the analyst's past decisions to reveal their long-horizon forecasts. The dependent variable in Columns (1)–(4), *MAR(0,+2)*, is the cumulative market-adjusted return of the firm being forecasted over the three-day window beginning the day of the forecast announcement, where market-adjusted returns are computed as the firm's daily return minus the return of the CRSP value-weighted market index on the same day. The regressions include interactions between $\Delta Value$ — i.e., the signed difference between the analyst's current forecast and their most recent forecast for the same firm-earnings period — and every other explanatory variable. The main effects of each variable are included in the regressions, but are suppressed to conserve space. The main explanatory variable (that is interacted with $\Delta Value$) in Column (3), *Long-Horizon*$_{3yr}$, is an indicator variable equal to one if the analyst issued at least one forecast in the prior calendar year that had a forecast horizon of at least three years; the main explanatory variable (that is interacted with $\Delta Value$) in Column (4), *Long-Horizon*$_{2yr}$, is an indicator variable equal to one if the analyst issued at least one forecast with a horizon of at two years. All variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) MAR(0,+2)	(2) MAR(0,+2)	(3) MAR(0,+2)	(4) MAR(0,+2)
Δ Value	0.540***	0.093**	−0.554***	−0.623***
	(22.98)	(2.36)	(−2.76)	(−2.96)
Δ Value x Downgrade		0.218***	−0.044	−0.043
		(4.27)	(−0.58)	(−0.57)
Δ Value x (Lagged) Long-Horizon$_{3yr}$			0.122**	
			(2.25)	
Δ Value x (Lagged) Long-Horizon$_{2yr}$				0.082**
				(1.98)
Δ Value x Ln(Number of Companies)			0.035	0.034
			(0.88)	(0.84)
Δ Value x Ln(Forecasts per Company)			−0.226***	−0.217***
			(−4.24)	(−4.06)
Δ Value x (Lagged) Relative Forecast Performance			0.338**	0.332**
			(2.57)	(2.54)
Δ Value x High Reputation Bank			0.032	0.014
			(0.62)	(0.27)
Δ Value x General Experience			−0.006	−0.006
			(−0.78)	(−0.73)
Δ Value x Initiation			−0.050	−0.063
			(−0.13)	(−0.16)
Δ Value x Ln(Horizon)			0.075***	0.081***
			(4.49)	(4.53)
Δ Value x Ln(Number Confounding Upgrades)			0.117***	0.119***
			(3.19)	(3.22)
Δ Value x Ln(Number Confounding Downgrades)			0.392***	0.391***
			(10.33)	(10.29)
Ln(Horizon)			0.022***	0.023***
			(4.67)	(4.79)
Analyst FE	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.152	0.155	0.175	0.175
Observations	2,386,307	2,386,307	1,984,595	1,984,595

A. Sample Filters and Additional Analysis

Table A1: Sample Construction

This table reports the sample filters that we apply to reach our final sample of short and long-horizon EPS forecasts from the I/B/E/S U.S. Detail file.

Sample Filter	Observations	N Analysts
Annual EPS forecasts between 1994 and 2016 with *usfirm*= 1, and analyst codes not equal to "0" or "1"	8,610,527	22,473
Forecasts with *report_curr* = "USD" and *curr_act* = "USD"	7,149,627	19,567
Remove observations that represent duplicate EPS forecasts by the same analyst for the same firm and day, with the same forecast estimate value	7,148,933	19,567
Remove analyst-years in which analysts cover more than for 40 distinct firms	6,965,281	19,566
Remove observations with missing forecast estimates	6,965,070	19,555
Restrict observations to those with horizon greater or equal to 0	6,762,870	19,490

Table A2: Brokerage Publicity Incentives and Long-Horizon Forecasts

This table reports the results of analyst-year OLS regressions examining the influence of a brokerage's publicity incentives on their analysts' decisions to reveal their long-horizon forecasts. The dependent variable, *Long-Horizon*, is an indicator variable equal to one if analyst i issues at least one forecast during year t that has a horizon of at least three years (i.e., 1095 days). *Non-Bulge Bracket Bank* is an indicator variable equal to one if the analyst's brokerage is not one of the six "bulge bracket" banks listed in Cowen et al. (2006) (plus JP Morgan). *Low-Prestige Brokerage* is an indicator variable equal to one if the investment bank affiliated with the analyst's employer does not have a top Carter-Manaster ranking in the calendar year of the forecast. *Small Brokerage* is an indicator variable equal to one if the analyst's brokerage is not one of the top ten largest brokerages in the calendar year of the forecast, where brokerage size is determined based on the number of analysts employed by the brokerage during that year. *LTG* is an indicator variable equal to one if analyst i issues a long-term growth forecast during calendar year t. *Disaggregation* is an indicator variable equal to one if analyst i issues a revenue and/or expense forecast accompanying their earnings forecast during year t. All variables are defined in Table B1 in Appendix B. The sample of EPS forecasts includes 6,762,870 annual forecasts from 1994 to 2016 from the I/B/E/S U.S. Detail file, as described in Table A1 in Appendix A. t-statistics are reported in parentheses, with standard errors clustered at the analyst level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Long-Horizon	(2) Long-Horizon	(3) Long-Horizon
Non-Bulge Bracket Bank	0.103***		
	(12.16)		
Low-Prestige Brokerage		0.041***	
		(5.48)	
Small Brokerage			0.014**
			(2.45)
LTG	0.032***	0.031***	0.031***
	(9.11)	(8.83)	(8.79)
Disaggregation	0.065***	0.067***	0.070***
	(16.11)	(16.21)	(17.14)
Analyst FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes
Adj. R-squared	0.414	0.411	0.411
Observations	89,779	89,779	89,779

Table A3: Summary Statistics of Estimize Sample

This table reports summary statistics for the full sample of crowd-sourced quarterly EPS forecasts from *Estimize* over the period January 2011 to March 2021. *Forecast Error* is the absolute value of the difference between the forecaster's EPS forecast and the firm's actual EPS. *Forecast Horizon* is the number of days between the date that the forecast was submitted to *Estimize* and the earnings announcement date.

Professional Background	N	Forecast Error	Horizon
Professionals			
Buy-side Analysts	183,083	0.150	36.80
Independent	252,310	0.152	39.07
Sell-side Analysts	190,584	0.219	254.47
Non-Professionals			
Academia	41,176	0.163	34.27
Consumer Discretionary	26,274	0.187	37.42
Consumer Staples	15,668	0.172	55.76
Energy	11,538	0.161	40.99
Financials	137,060	0.160	24.46
Health Care	29,561	0.176	26.77
Industrials	46,904	0.185	37.85
Information Technology	174,010	0.170	42.00
Materials	19,441	0.184	52.73
Other	106,505	0.179	26.37
Student	106,942	0.156	31.06
Telecommunication Services	8,474	0.165	31.85
Utilities	4,270	0.187	42.09

Table A4: Interclass Correlation Coefficients

This table reports interclass correlation coefficients (ICCs) of brokerage, analyst, and firm effects on the probability of publishing a long-horizon forecast. A long-horizon forecast is defined as an earnings forecast with a horizon of at least three years.

Effects	ICC
Brokerage	0.67
Analyst	0.51
Firm	0.27

Table A5: Brokerage Mergers

Panel A reports the annual distribution of brokerage mergers that we use in Column (4) of Table 10. Panel B reports our sample of brokerage mergers. The sample of mergers comes from a combination of the samples reported in Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), conditional on the mergers being completed during our sample period of 1994–2016.

Panel A: Brokerage Mergers Completed per Year

Year	N Mergers
1994	1
1997	3
1998	3
1999	1
2000	6
2001	7
2002	1
2005	3
2006	1
2007	3
2008	1

Panel B: List of Sample Broker Mergers

Target Brokerage	Acquiroring Brokerage	Date
Kidder Peabody & Co.	PaineWebber Group, Inc.	Dec., 1994
Dean Witter Discover & Co.	Morgan Stanley	May, 1997
Furman Selz	ING	Sep., 1997
Salomon Brothers	Smith Barney	Nov., 1997
Principal Financial Securities	EVEREN Capital Corp.	Jan., 1997
Jensen Securities	DA Davidson & Co.	Feb., 1998
Wessels Arnold & Henderson LLC	Dain Rauscher Corp	Apr., 1998
EVEREN Capital Corp.	First Union Corp	Oct., 1999
JC Bradford & Co.	PaineWebber Group, Inc.	June, 2000
Schroders	Salomon Smith Barney/Citigroup	Apr., 2000
Donaldson, Lufkin & Jenrette Securities	Credit Suisse First Boston	Oct., 2000
Paine Webber & Co	UBS	Nov., 2000
R.J. Steichen & Co.	Miller, Johnson & Kuehn	Dec., 2000
JP Morgan	Chase Manhattan	Dec., 2000
Wasserstein Perella & Co.	Dresdner Bank	Feb., 2001
ING Financial Markets	ABN Amro Holdings NV	May, 2001
Epoch Partners, Inc.	Goldman Sachs	June, 2001
SunTrust Equitable Securities	Robinson-Humphrey Co	Aug., 2001
Josephthal Lyon & Ross	Fahnestock & Co.	Sep., 2001
Wachovia Securities	First Union Securities	Oct., 2001
Tucker Anthony Sutro Capital Markets	RBC Dain Rauscher Corp	Nov., 2001
Sutro & Co	Sanders Morris Harris	Jan., 2002
Parker/Hunter Inc	Janey Montgomery Scott LLC	May, 2005
Advest, Inc.	Merrill Lynch	Dec., 2005
Legg Mason Wood Walker, Inc	Citigroup	Dec., 2005
Petrie Parkman & Co.	Merrill Lynch	Dec., 2006
Ryan Beck & Co.	Stifel Financial Corp	Jan., 2007
Cochran, Caronia Securities, LLC	Fox-Pitt Kelton Inc	Sept., 2007
A.G. Edwards & Sons	Wachovia	Oct., 2007
CIBC World Markets	Oppenheimer	Jan., 2008

B. Variable Definitions

Table B1: Variable Definitions

Variable Name	Variable Definition
Accuracy_{0_6}	The relative accuracy of analyst i's forecasts issued during year t conditional on the forecasts having horizons between 0 and 180 days, relative to peers analysts forecasting the same firm and annual forecast period that year. We first rank analysts following the same firm during year t based on the percentage absolute deviation of the forecast estimates and actual earnings per share ($Accuracy = -\frac{\|F-A\|}{\|A\|}$), and then compute an aggregate score among these analysts using the following equation: $Score = 1 - \left[\frac{rank-1}{\#of analysts}\right]$. The measure is computed similarly for Accuracy_{6_12} and Accuracy_{12_18}, except that the forecasts are required to have horizons between 180 and 360 days and between 360 and 540 days, respectively.
All-Star	An indicator variable equal to one if the analyst is on one of *Institutional Investor*'s All-America research teams (top three) during the prior three years, and zero otherwise.
Bulge Bracket Bank	An indicator variable equal to one if analyst i's employer in year t is one of the six "bulge" banks listed by Cowen et al. (2006) (plus JP Morgan), and zero otherwise.
General Experience	The decile rank of the number of months that analyst i has been in the I/B/E/S database by the time of the forecast (starting in 1983). Ranks are assigned each calendar year.
High Analyst Following	An indicator variable equal to one if the portfolio firm is ranked in the top quartile of all firms that the analyst covers during calendar year t, where firms are ranked based on the number of unique analysts covering them that year.
High Forecast Reputation	An indicator variable equal to one if the analyst was in the top 10 percentile of the sample distribution of annual forecast accuracy during the prior calendar year. We compute annual forecast accuracy by first ranking analysts who follow the same firm during the year based on the percentage absolute deviation of forecast estimates from actual earnings per share ($Accuracy = -\frac{\|Forecast-Actual\|}{\|Actual\|}$), and then computing an aggregate score among the analysts forecasting the same firm in the same year using the following equation: $Score = 1 - \left[\frac{rank-1}{\#of analysts}\right]$. Relative forecast performance for analyst i during year t is the mean value of *Score* across the firms that they cover.
High Visibility Firm	An indicator variable equal to one if the portfolio firm is ranked in the top quartile of all firms that the analyst covers during calendar year t, where firms are ranked based on their trading volume during the prior calendar year.
High Visibility (Market Cap)	An indicator variable equal to one if the portfolio firm is ranked in the top quartile of all firms that the analyst covers during calendar year t, where firms are ranked based on their market capitalization as the end of the prior calendar year.
Horizon	The number of days between the day of the forecast and the forecast period end date.
Initiation	An indicator variable equal to one if the forecast is the first one ever issued by analyst i for firm j.
Leaves	An indicator variable equal to one if analyst i is in the I/B/E/S database in year t, and not in the database in any of the following years.
Long-Horizon	Our primary measure is an indicator variable equal to one if analyst i issues at least one annual forecast for firm j with a horizon of least three years during year t. We report robustness results using an indicator variable equal to one if analyst i issues at least one annual forecast for firm j with a horizon of least two years during year t.

Continued on next page

Table B1 – continued from previous page

Variable Name	Variable Definition
Low-Prestige Brokerage	An indicator variable equal to one if the investment bank affiliated with the analyst's employer does not have a top Carter-Manaster ranking (i.e., ranking = 9) in the calendar year of the forecast. Investment bank Carter Manaster rankings come from Jay Ritter's webpage.
MAR(0,+2)	The cumulative daily market-adjusted stock return over the three trading days beginning on the day of a forecast announcement by analyst i. The daily market-adjusted stock return is computed as the difference between the daily stock return of firm j and daily return of the CRSP value-weighted market index.
Moves Down	An indicator variable equal to one if analyst i changes employers between year t and year $t+1$ and the brokerage that the analyst is employed by in year $t+1$ is ranked in a lower size decile than the brokerage that the analyst was employed by in year t. Brokerages are ranked based on the number of analysts that they employ, and are sorted into deciles each year.
Moves Up	An indicator variable equal to one if analyst i changes employers between year t and year $t+1$ and the brokerage that the analyst is employed by in year $t+1$ is ranked in a higher size decile than the brokerage that the analyst was employed by in year t. Brokerages are ranked based on the number of analysts that they employ, and are sorted into deciles each year.
Number Confounding Upgrades (Downgrades)	The number of upgrade (downgrade) forecasts issued by peer analysts during the period beginning two days before the announcement of analyst i's forecast and ending two days after the announcement of analyst i's forecast. A forecast is considered an upgrade (downgrade) if it is higher (lower) than the analyst's most recent previous forecast for the same firm-forecast period.
Number of Companies	The total number of firms for which analyst i issues annual forecasts during year t.
Optimism	The fraction of all forecasts issued by analyst i during year t that are above the most recent consensus forecast for the same firm-forecast period.
Piggybacking	The fraction of all forecasts issued by analyst i during year t that piggyback on public news. A forecast is considered piggybacking on public news if it follows a key event or a large return within three days. This definition follows Altınkılıç et al. (2019).
Relative Forecast Performance$_{t-1}$	A measure of the accuracy of analyst i's shortest horizon forecasts in the prior year, relative to peers analysts forecasting the same firm and annual forecast period. We first rank analysts following the same firm during year *t-1* based on the percentage absolute deviation of the forecast estimates and actual earnings per share ($Accuracy = -\frac{\lvert F-A \rvert}{\lvert A \rvert}$), and then compute an aggregate score among these analysts using the following equation: $Score = 1 - \left[\frac{rank-1}{\#of analysts}\right]$.
Upgrade	An indicator variable equal to one if the current forecast estimate is higher than the analyst's most recent previous forecast for the same firm-forecast period.
Δ Value	The signed difference between the analyst's current forecast and their most recent forecast for the same firm-earnings period, winsorized at the top and bottom 1% tails.
Sell-side	An indicator variable equal to one if the forecaster's user bio in the *Estimize* database describes the forecaster as a financial professional employed by a sell-side broker.
Small Brokerage	An indicator variable equal to one if the analyst's brokerage is not one of the top ten largest brokerages in calendar year t, where brokerage size is determined based on the number of analysts employed by the brokerage during that year.