Lured by the Consensus: Pricing Implications of Treating All Analysts as Equal

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Abstract:

We suggest a more accurate earnings forecast than the consensus by classifying analysts into high and low quality (HQ and LQ) categories based on their past forecast accuracy. We find that the market overweighs the information content of the consensus forecast and does not utilize price-relevant information in the forecasts and recommendations of the HQ analysts. The HQ analysts' recommendation changes and forecast dispersion predict the firm's stock returns and return volatility next month. Importantly, the PEAD phenomenon is present only when the HQ analysts are relatively uncertain. At the aggregate level, recommendation changes of the HQ analysts predict future industry and market returns, while the consensus recommendation changes do not, and market volatility is higher following periods of greater uncertainty among the HQ analysts. Overall, our results indicate that fixation on the consensus can lead to less accurate forecasts and inefficient prices.

Keywords: Analyst quality, Forecasts, Consensus, PEAD, recommendations

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Investors and academics alike use analysts' consensus forecasts as the measure of market expectations of the firm's future earnings. The perceived importance of consensus earnings estimates has greatly increased in the recent years, to the extent that even companies' investor relations departments tend to follow it on a continuous basis (Consensus earnings estimates report, 2013). However, a potential disadvantage of the consensus is that by construction, it gives equal weight to all analysts' estimates and, hence, ignores that analysts may have different abilities, perhaps, due to varying experience (Mikhail, Walther, and Willis, 1997; Clement, 1999; Hirst, Hopkins, and Wahlen, 2004), aptitude (Jacob, Lys and Neale, 1999), education (Maines, McDaniel, and Harris, 1997; De Franco and Zhou, 2009), brokerage house association (Clement, 1999), proximity to firm (Malloy, 2005), or work habits (Rubin, Segal, and Segal, 2017) among others. Given the overwhelming evidence on differences in analysts' ability, there is no *a priori* reason to believe that the consensus forecast is the best estimate of the market's expectations or that the consensus recommendation is the best signal to follow. The fixation on a simple average of analysts' forecasts or recommendations that disregards differences in analyst forecasting ability motivates us to examine whether it leads to less accurate forecasts and, perhaps, more importantly, to price inefficiency.

Our findings can be summarized as follows: we find that analysts persistently differ in their forecasting accuracy, which allows us to rank them based on their past forecasting performance. We define high quality (HQ) analysts as those with below the median forecast error in the previous year and show that the HQ designation is persistent over time and consistent across companies covered by the analyst. Investors, however, do not sufficiently recognize quality differences among analysts in that they focus on the consensus forecast when they react to earnings surprise. This inefficient handling of information in analysts' forecasts suggests market mispricing around earnings announcements. We illustrate this mispricing by constructing an arbitrage trading strategy using the HQ analysts' forecasts as a proxy for the actual earnings before they are announced. In additional analyses, we demonstrate the superiority of HQ analysts relative to the consensus. Specifically, we find that the HQ analysts provide superior stock recommendations that predict firms' stock returns in the month following the announcement. HQ analysts' forecasts are also relatively more informative in that the dispersion of the HQ analysts' forecasts predicts one month ahead stock return volatility for the firm. Further, the post-earnings announcement drift phenomenon takes place only when the HQ analysts are relatively uncertain (compared to all analysts) about the firm's prospective earnings. Finally, aggregating forecasts and recommendations of the HQ analysts across all firms allows for predicting the stock market and industry returns and market volatility, which is not found for aggregated forecasts and recommendations provided by all analysts.

We start by examining a key necessary condition implicit in the principle of differentiating analysts in terms of their quality—that analysts' quality measured by forecast accuracy is persistent over time. Two earlier studies (Stickel, 1992; Sinha, Brown, and Das, 1997) report the persistence in forecast accuracy in different subsamples of analysts.[1] We enhance their approach in two dimensions: by testing the persistence in the full sample of analysts and, more importantly, by analyzing persistence across all firms to determine whether analysts' persistent forecasting performance can be described as an analyst characteristic indicating their ability. We define HQ and LQ analysts as those, respectively, above and below

[1] Stickel (1992) analyzes forecast revisions by analysts who are members of the All-American Research Team, where the All-American status is based on both the past forecasts' accuracy and other criteria. Sinha, Brown, and Das (1997) rank analysts into three categories (superior, average, and inferior) based on their annual forecast errors in the previous years and find persistence for the top category. Brown (2004) finds that these two models built on past forecasting performance predict analysts' forecasting accuracy as well as a model based on analysts' individual characteristics (Clement, 1999).

the median in the accuracy ranking in the previous year.[2] We find that analysts who are categorized as HQ in a given year tend to be ranked as HQ in the following year as well, and their annual earnings forecasts are 5.7% more accurate compared to the full set of analysts following this firm. In addition, we find that analysts who are HQ in one firm are also likely to be HQ in the other firms they follow. This suggests that ranking analysts based on their past forecasting performance is a straightforward way to capture analyst quality, in particular, because it summarizes the overall analysts' individual characteristics including the unobservable ones.

These results suggest that investors should follow the HQ analysts' forecasts rather than the consensus[3] and, consequently, should react more vigorously to earnings surprises that are measured based on the average forecast of the HQ analysts. However, we find the opposite—the earnings response coefficient on the standardized unexpected earnings (SUE) based on the consensus forecast is much higher than that of SUE based on the average of the HQ analysts' estimates. This finding suggests the market pays too much attention to the consensus forecast and fails to fully incorporate the information embedded in the forecasts of the HQ analysts. Next, we find that one can exploit this inefficiency by predicting earnings surprise using the difference between the HQ analysts' average forecast and the consensus to generate abnormal returns. Taking a long (short) position in stocks where the HQ analysts' average forecast is greater (smaller) than the consensus as of one day before the announcement generates a 0.20% abnormal return over the announcement day and the following trading day.

[2] We verify that our analysis is not affected by the cutoff percentile distinguishing HQ and LQ analysts.

[3] The finding that analyst performance has a persistent component points to the question whether investors should always follow the HQ analysts and disregard the consensus which includes the forecasts by the LQ analysts. In general, there is a tradeoff between the quality and quantity of forecasts: On the one hand, the consensus includes more estimates, which is beneficial for reducing the measurement error; on the other hand, analysts who individually have more accurate forecasts produce a smaller average measurement error. Our analysis reveals that as the number of HQ analysts following the firm is four or above, the accuracy of the average of their forecasts tends to exceed the accuracy of the consensus forecasts, and our empirical procedures take into account this finding.

Our finding that analysts have different forecasting ability suggests these differences should manifest themselves in other aspects of analysts' informational output as well. First, we investigate whether analysts with more accurate forecasts should have more accurate stock recommendations.[4] We find that only the HQ analysts' recommendation revisions predict stock returns next month. Importantly, the predictive power of recommendation changes in the full sample comes from the HQ analysts only; recommendation changes by non-HQ analysts are not associated with future stock returns. Indeed, an arbitrage strategy that is long (short) in stocks where HQ analysts on average provide an upgrade (downgrade) produces a statistically significant **1.2%** return in the following month.

Second, given our finding that the forecasts by the HQ analysts are more informative about the future level of earnings than the consensus or LQ analysts' forecasts, we consider whether the second moment of the HQ analysts' forecasts is also more strongly associated with uncertainty regarding future firm performance than that of the consensus or LQ analysts' forecasts. Ajinkya and Gift (1985) report a contemporaneous relation between analysts' forecast dispersion and stock return volatility. We find a weak relation between the forecast dispersion of all analysts following the firm and its stock return volatility next month. However, when we examine the relation separately for HQ and LQ analysts we find that the dispersion of the HQ analysts' forecasts is a strong predictor of the firm's stock return volatility in the month following the annual earnings announcement month, whereas the LQ analysts' forecast dispersion is not predictive of return volatility.

The finding that it is the HQ analysts' forecast dispersion that captures the firm's uncertainty allows us to consider a possible role of analysts' forecast quality in the context of the

[4] Bradshaw (2004) provides insights into the link between analysts' forecasts and recommendations, and Loh and Mian (2006) and Ertimur, Sunder, and Sunder (2007) report a contemporaneous relation between stock recommendations produced by analysts with relatively more accurate forecasts and stock returns.

literature on the relation between forecast dispersion and the post-earnings announcement drift (PEAD). The model in Abarbanell, Lanen, and Verrecchia (1995) suggests that when forecast dispersion is high, investors delay their complete response to earnings announcements, which could lead to a greater PEAD.[5] We find that the PEAD is higher when the HQ analysts are more uncertain relative to all analysts covering the firm. Specifically, the standard PEAD strategy is that of buying (shorting) shares when SUE is positive (negative). We implement the strategy for the subsamples in which the forecast dispersion of HQ is greater (lower) than the dispersion of all analysts. We find a significantly greater PEAD (annualized 9.4% after 11 months) if the HQ analysts are relatively uncertain. During most of this forecast horizon, the PEAD is not statistically different from zero in the sample where the HQ analysts are relatively less uncertain, implying that the long-puzzling PEAD phenomenon arises only during the periods of high uncertainty among the HQ analysts. Overall, these findings indicate that the superior information in the HQ analysts' forecasts predicts not only the immediate reaction to earnings announcements but also the long-term market response. Another conclusion from our findings is that firms' information uncertainty (Diether, Malloy, and Scherbina, 2002; Zhang 2006) is better proxied by the forecast dispersion of the HQ analysts than all analysts.

Finally, having established that the HQ analysts' recommendations and forecast dispersion are better predictors than the consensus at the firm level, we next explore their predictive ability at the market-wide level. Because individual HQ analysts' recommendation changes predict their firm's returns, their average recommendation change across all firms in the market should predict the market return. The argument for the average dispersion of analysts'

[5] We are unaware of existing studies confirming this prediction. The two most closely-related studies are Zhang (2006), which finds that analysts' forecast dispersion predicts the price drift following analysts' forecasts (the relation to the PEAD is not tested), and Hung, Li, and Wang (2015), which does not study analysts' forecast dispersion but finds that reduced uncertainty due to increased disclosure leads to a lower PEAD.

forecasts predicting market volatility is similar.[6] Indeed, we find that by relying on the average recommendation changes of the HQ analysts, one can predict the market and industry returns in the following month, in contrast to the average recommendation changes of all analysts or the LQ analysts following the firm. For example, a long-short arbitrage strategy based on the direction of the HQ recommendation revisions across industries produces a 7.9% annualized return in the post-announcement month. We also find that the HQ analysts' normalized dispersion is associated with a higher market volatility as measured by the VIX next month. In contrast, analysts' forecast dispersion at the consensus level or that of the LQ analysts do not have a relation to the VIX. Given that the VIX is often interpreted as the "fear index", investors should be worried about the economy and the stock market performance when the HQ analysts become relatively uncertain compared to all other analysts.

Our paper belongs to a recent literature suggesting that the average of analysts' estimates can be misleading and can be improved upon (So, 2013; Buraschi, Piatti, and Whelan, 2017). We build on the persistence of analysts' forecasts across time, stocks, and signals to gain further insights into this issue. We find that, in contrast to the approach using the consensus forecast, our method reveals mispricing at earnings announcements. It also exposes the market's inefficient processing of other information produced by analysts, such as their stock recommendations and forecast dispersion. The high publicity of the consensus forecast and investor's fixation on the mean of analysts' forecast distribution are similar to central fixation bias, which is people's tendency to fixate their vision at the center of a group of objects and which can be optimal for the initial processing of information (Tatler, 2007). Likewise, the consensus fixation is related to

[6] It is important to note that these two conjectures neither assume nor indicate that the HQ analysts have superior macroeconomic knowledge or ability to predict market-level developments.

the limited attention literature (Hirshleifer, Lim, and Teoh, 2009) in that investors may prefer a single number of the consensus to spending their cognitive effort on analyst quality assessment.

Our findings directly contribute to the literature on the value of recommendations (Loh and Stulz, 2011; Kecskes, Michaely, and Womack, 2016; Jegadeesh et al., 2004). Our definition of HQ analysts that does not use specific analyst characteristics also allows us to extend the findings in Sorescu and Subrahmanyam (2006), who define analyst ability based on the years of experience and brokerage house. Going beyond firm-level predictability and finding predictability of relative returns for industries, is also related to Boni and Womack (2006), who do not find such predictability based on consensus recommendation changes.

Finally, the paper also contributes to the large literature that is concerned with understanding the PEAD (Bernard and Thomas, 1989; Mendenhall, 2004; Sadka, 2006) phenomenon. The relation we find between HQ analysts' forecast dispersion and the PEAD can have two different interpretations. First, we extend recent studies that argue that uncertainty tends to amplify investors' valuation mistakes due to behavioral biases (Zhang, 2006; Kumar, 2009), which in turn affects the PEAD phenomenon. On the other hand, our findings support a risk factor explanation to the PEAD, such as Abarbanell, Lanen, and Verrecchia (1995), who suggest that investors discount both good and bad earnings surprises when uncertainty is high, resulting in a PEAD.

2. Data and variables

We use the sample of annual EPS estimates[7] and earnings announcements in I/B/E/S during the period from January 1992 to December 2015 for companies with daily return data in CRSP. The starting year of 1992 is chosen because some of the analyses require analysts' recommendation data, which begins in 1993. Earnings estimates and actual earnings are adjusted for splits using the daily cumulative adjustment factor from CRSP (Glushkov and Robinson, 2006). Each year, we rank analysts based on the closest absolute forecast error, which is the absolute difference between an analyst's earnings forecast closest to the earnings announcement (but made at least one day prior to the announcement) and actual earnings, divided by the share price at the beginning of the calendar year. From the initial sample, we generate 861,349 firm-year-analyst rankings based on the closest forecast error. This number drops to 804,003 observations once we require firms to have Compustat data. Next, to avoid small sample bias in our ranking when the number of analysts following the firm is small, we exclude firm-years with less than four analysts following, which reduces the sample to 750,295 observations.[8]

In the firm-level regressions, we control for five firm characteristics—size, annual stock return, book-to-market ratio, number of analysts following, and leverage. Firm size is the market value of the firm's equity at the end of the month prior to the earnings announcement month.

[7] We focus on annual rather than quarterly earnings for two main reasons. First, fewer analysts provide quarterly than annual forecasts. Second, annual earnings announcements are typically more informative, combined with a conference call, and followed by recommendation changes.

[8] An alternative ranking procedure would be to rank analysts in a given year by averaging their forecast errors across all firms they follow. There are several advantages for this alternative ranking procedure. Analysts follow 15 firms on average, which implies that we could avoid small sample bias if a firm is followed by too few analysts and, perhaps, achieve a higher level of persistence in analyst ranking. We would also avoid losing the observations of the first year when an analyst begins covering a firm because we could rely on the analyst's ranking in the previous year in other firms. However, this year-level ranking approach also has several pitfalls. First, an aggregated ranking across firms can be misleading if analysts' ability to predict earnings is mainly firm-specific. Second, with the year-level ranking, we end up with some firms followed mostly by high or low quality analysts only, and even have just one analyst-quality type populated in some firms. This would undermine our study's objective of analyzing whether it is worthwhile to follow the average estimate of the high quality analysts or the consensus estimate. Nevertheless, we analyze the relation between an analyst's forecast accuracy in a given firm and all other firms covered by the analyst.

Annual stock return is measured based on monthly equity returns in the 12 months prior to the earnings announcement month. The book-to-market ratio is computed as stockholder equity minus preferred stock plus deferred taxes at the end of the fiscal year for which the earnings are announced divided by firm size. The number of analysts is the number of analysts who made at least one earnings forecast for this announcement. Leverage is the book values of total liabilities divided by total assets at the end of the fiscal year for which the earnings are announced. Some of the regression models also control for analyst characteristics. Overall tenure is the number of years since the analyst first appeared in the I/B/E/S file. Firm-specific tenure is the number of years since the analyst began covering the company in the I/B/E/S file. Brokerage house size is the number of analysts employed by the brokerage firm. Firm coverage is the number of firms covered by the analyst.

3. Persistence in analysts forecasting ability

3.1. Defining high and low quality analysts

This section describes how we partition analysts into the high and low quality categories based on their absolute forecast error and then analyzes whether this classification of analysts persists in the following year. To this end, we sort analysts in a given firm-year based on their absolute forecast error. In general, HQ analysts are those who are ranked in the top p percent of analysts, while LQ analysts are those in the bottom $(1-p)$ percent. We note that if analysts' forecasting performance were uncorrelated across years, the fractions of analysts who preserve their ranking in two consecutive years as HQ and LQ would be p^2 and $(1-p)^2$, respectively, or $p^2+(1-p)^2$ of all analysts.

Figure 1 plots the fraction of analysts that retain their rankings in consecutive years and the expected fraction assuming no performance correlation across years. We find that with almost all cutoff values of p, the actual fraction of persistent forecasting performance is above the expected fraction, and all these differences are statistically significant. For example, when we classify the top 10% of analysts following a firm in a given year as high quality (p=10%) and the bottom 90% as low quality, the expected fraction given random assignment is $0.9^2 + 0.1^2 = 0.82$. The figure shows that the actual fraction is greater than that at 0.843. The exception is the relaxed definition of HQ analysts as the best 95%. Nevertheless, the overall finding is that for almost all of the cutoff values, there is a sizeable persistent component, so that it makes little difference which exact cutoff value we choose to partition HQ and LQ analysts.

In the remainder of the paper, we define HQ (LQ) analysts based on whether their absolute closest forecast error for the firm-year is below (above) the median absolute forecast error for the firm-year. We choose the median as the cutoff due to its advantage that the numbers of analysts in the high and low quality groups are equal in year t-1 and relatively close in year t. However, because some analysts can stop covering the firm after year t-1 and new, thus unranked, analysts can come in, the numbers of HQ and LQ analysts in year t can become too small or their relative numbers too different, leading to small sample bias and lack of robustness in the firm-level analysis comparing the average performance of the HQ and LQ analysts as groups. To mitigate this concern, we restrict the sample to firms for which the numbers of HQ and LQ analysts are not too different in year t. Specifically, we require for the firm-level analysis (starting with Table 3) that neither of these groups exceeds 75% of all analysts in the firm, which results in having 358,917 observations comprising ranked and unranked (those who cover the firm for the first time) analysts. Analyst-level analysis (e.g., Figure 2) does not require this filter but, instead, considers analysts who appear in the data in two consecutive years for a given firm-year, reducing the sample to 485,815 observations.

3.2. Mean absolute forecast error

Figure 2 shows the mean absolute forecast errors of HQ analysts and the consensus during the 300 days prior to the earnings announcement. We observe acceleration in the reduction of the mean forecast error around quarterly earnings announcements at 90, 180, and 270 day marks. The graph shows that the mean absolute forecast error of the consensus is consistently higher than the mean forecast error of HQ analysts across all days prior to the earnings announcement. The mean absolute forecast error of the consensus (HQ analysts) decreases from 0.026 (0.0258) to around 0.012 (0.0115) one day before the earning announcement. These differences between these two sets of analysts are economically meaningful. For example, just before the earnings announcement date, the forecast based on HQ analysts is more accurate by 4.17% compared to the consensus ($\frac{0.0115}{0.0120} - 1$). The HQ analysts' accuracy 30 days before the announcement is already higher than the consensus accuracy at the announcement.

Table 1 analyzes how the classification of analysts to low or high quality is associated with various analysts' characteristics and the persistence of the classification over time. Panel A provides univariate comparisons. We find that the HQ analysts tend to be more experienced, are employed by larger brokerage firms, and cover more firms. For robustness, in untabulated tests, we distinguish between firms with many (more than 10) and few analysts, which also approximates large and small firms. All the full sample relations hold in large firms, while the HQ analysts in small firms do not to have a longer tenure in each firm and do not cover more firms. To analyze the persistence of analysts' forecast accuracy, we compare the HQ and LQ analysts' forecast errors in the year after they were ranked. The absolute forecast errors of the HQ analysts remain smaller than those of the LQ analysts—the difference is 9% (0.0081/0.0089) and statistically significant. In the last line of the panel, we find that both the HQ and LQ analysts have an optimism bias in their forecasts (the average forecast errors are significantly different from zero, with untabulated p-values<0.01), but there no statistical difference in optimism bias between them.

Panel B reports regression analyses that show that the quality classification of analysts persists. In the probit models in columns (1) and (2), the dependent variable is an indicator that equals one if the analyst is of HQ and zero otherwise. In columns (3) and (4), the dependent variable is the absolute forecast error, a continuous variable, which allows us to control for firm fixed effects in the regression. In columns (1) and (3), we control with firm characteristics, and in columns (2) and (4), we control for both firm and analyst characteristics. The main coefficient on interest is the HQ classification in year t-1. The results show that the coefficient on HQ analyst indicator (t-1) is highly significant (p-value<0.01) in all specifications, indicating that analysts' rankings and forecast accuracy are persistent in consecutive years. For example, the unconditional probability of being HQ classification is approximately[9] 50%, and accounting for the HQ status in the previous year increases this likelihood by approximately 4.1% according to columns (1) and (2). Columns 3 and 4 show that HQ analysts continue to have lower absolute forecast errors in the following year.

We next conduct cross-firm tests to examine whether forecasting performance is an analyst characteristic, in which case an analyst who performs well in one firm performs well in

[9] There are slightly fewer HQ analysts than LQ analysts in year t-1 because in firms with an odd number of analysts, the analyst at the median is designated as a LQ analyst.

the other firms he or she follows. We define an analyst's performance in the other firms as that of high (low) quality if the analyst is classified in high (low) quality category in the majority of the other firms he or she follows during the year (excluding this firm).[10] Panel A of Table 2 reports that HQ analysts in a given firm are also ranked as HQ in the other firms that they follow 54.4% of the time, which is statistically greater than the unconditional percentage of HQ analysts in a given firm, 48.3%. LQ analysts in a given firm also tend to be LQ in the other firms they follow; LQ analysts in a given firm are LQ in 57.6% of the other firms that they follow. Panel B tests whether ranking as a HQ analyst in the other firms in year t-1 can predict an analyst's forecasting performance over and above the HQ classification in the same firm. We estimate two probit models where the dependent variable is the HQ analyst indicator in firm j in year t. The independent variables include the HQ indicator of the same analyst in firm j in year t-1, and the *HQ analyst in other firms* indicator in year t-1. We find that analysts who were of HQ in the majority of other firms they followed in year t-1 are 5.1% (p-value<0.01) more likely to be HQ in a given firm in year t. The coefficient on the firm specific HQ designation in year t-1 remains positive and significant (p-value<0.01), consistent with Table 1. Hence, the cross-firm findings in Table 2 suggest that analysts' forecasting performance can be viewed as an analyst characteristic.

4. A tradeoff between the number of analysts and the quality of analysts

Our finding that a HQ analyst consistently provide more accurate earnings forecasts than the consensus leads us to a question whether investors should heed the *average* of the HQ analysts' forecasts rather than the consensus forecast. We now consider how this decision is

[10] If the number of high and low quality rankings of the analyst in the other firms is the same, this analyst-year-firm observation cannot be categorized as either high or low quality in the other firms and, thus, is excluded from this analysis.

affected by the relative numbers of HQ and LQ analysts following the firm. Intuitively, the greater the number of forecasts (analysts following), the smaller is the measurement error and, hence, the more accurate is the consensus. However, HQ analysts' forecasts have on average a smaller forecast error to begin with. This suggests that there is a tradeoff between the total number of analysts and the relative number of HQ analysts within the pool of analysts. A simple model illustrating this relation is in the Appendix. The theoretical framework tells us that as the fraction of HQ analysts increases, investors are more likely to obtain a more accurate forecast than the consensus by following the average estimate of HQ analysts. We verify this intuition in this section. Our objective is to empirically determine the smallest number of HQ analysts that allows one to heed only HQ analysts instead of the consensus.

We begin with summary statistics of the distributions of analysts in year t, which includes the HQ, LQ, and unranked analysts (those who did not follow the firm in the previous year). Table 3 reports the relative number of the three analyst types categorized by the number of HQ analysts at the firm-year level. We find that as the number of HQ analysts increases, their fraction increases as well, while the fraction of LQ analysts stays approximately the same, and the fraction of unranked analysts decreases. We do not have an affirmative explanation for this result except for the intuitive relation that, in equilibrium, a large following by HQ analysts in a firm makes other analysts (LQ and unranked newcomers) less inclined to stay and compete with them or start to follow the firm. The positive relation between the number and fraction of HQ analysts allows us to conduct our analysis by considering the number of HQ analysts as the variable of interest when deciding whether to have an earnings estimate based on the average of all analysts' estimates (i.e., the consensus) as opposed to averaging only the HQ analysts' estimates.

Table 4 provides statistical tests comparing the absolute SUE of consensus with the absolute SUE of HQ analysts. We find that as the number of HQ analysts following the firm increases, the HQ analysts as a group are becoming more accurate than the consensus, confirming the prediction of the theoretical model. When the number of HQ analysts increases and becomes four or more, investors should switch their attention from the consensus forecast to the average of the HQ analysts' estimates.[11]

5. Is the market aware of high quality analysts?

5.1 Comparing earnings response coefficients

The previous section demonstrates that with HQ analysts' earnings forecasts, one can generate an earnings forecast superior to the consensus forecast. We next test whether the market is aware of this possibility. To this end, we analyze the immediate market reaction to three earnings surprise measures based on the consensus, HQ, and LQ analysts' average forecasts. We test whether the market is aware of the superior ability of the HQ analysts as a group by examining whether the reaction to the earnings surprise based on the mean forecast of HQ analysts is greater than the earnings surprise based on the consensus forecast and, separately, surprise based on the mean forecast of LQ analysts. Given our finding in Table 4 that the average forecast of the HQ analysts is preferable to the consensus when the number of HQ analysts is sufficiently high, we also examine whether the earnings response coefficient to *SUE of HQ analysts* is greater than that of *SUE of consensus* for firms followed by four or more HQ analysts.

[11] We note that our approach that suggests ignoring the estimates of LQ analysts in order to improve on the consensus estimate is only one of many ways of generating an alternative to the consensus forecast. Other ideas may include a weighting scheme in which one gives more weight to the estimates by HQ analysts than the weight to LQ analysts or adds observable analysts' characteristics to improve the classification of HQ and LQ analysts. Nevertheless, the advantage of our approach is in its simplicity of creating a rather straightforward single yardstick that is tractable and can be directly compared to the consensus.

Table 5 reports regression results in which the dependent variable is the buy-and-hold cumulative abnormal return (BHAR) for the earnings announcement day and the following trading day, based on the 4-factor model (Fama and French, 1993; Carhart, 1997). The main variables of interest are the coefficients on the SUE based on the consensus, HQ analysts, and LQ analysts. The table shows that the reaction to the SUE of the consensus is greater than the reaction to the SUE of HQ analysts, with a highly statistically significant difference between the coefficients of 0.1031 based on the chi-squared test in the full sample and a slightly smaller difference of 0.0768 in the sample of firms with four or more HQ analysts. The coefficient on SUE of HQ analysts is greater and statistically different than the coefficient on SUE of LQ analysts, which suggests the market is aware to some extent of the accuracy differences among analysts. Overall, the results indicate that the market reacts primarily to the earnings surprise based on the consensus forecast.

5.2. Trading based on the HQ analysts' forecasts

The finding that the market does not give sufficient weight to the HQ analysts' forecasts suggests this inefficiency can be exploited. We test whether a simple trading strategy based on the difference between the HQ analysts' mean forecast and the consensus, labeled *predicted surprise*, generates positive abnormal returns. The intuition is to replace the actual earnings in the SUE formula with the HQ analysts' mean forecast, so that *predicted surprise* defined this way can be used to predict SUE of consensus. Given that HQ analysts are more accurate than the consensus and that investors react primarily to earnings surprise based on the consensus forecast, one can expect positive (negative) abnormal returns to the earnings announcement when the mean forecast of HQ analysts is greater (smaller) than the consensus. Additionally, we consider a definition for *predicted surprise* equal to the difference between the HQ and LQ analysts' mean forecasts, which also reflects the idea that the market does not sufficiently react to the HQ analysts' estimates and, thus, overweighs the LQ analysts' estimates. In both definitions, a simple trading strategy is to buy (short) the stock when the predicted surprise is positive (negative).

We report the empirical results in Table 6. The trading strategy is based on two variations of the signal based on *predicted surprise*: *Positive predicted surprise* and *Big predicted surprise* indicators. *Positive predicted surprise* is equal to one if *predicted surprise* is positive and zero otherwise. A stronger signal, *Big predicted surprise* indicator, is one (zero) depending on whether *predicted surprise* is above (below) the median of its positive (negative) values in the previous year. Using the values of *predicted surprise* in the previous year ensures our analysis is out-of-sample. We regress the two-day cumulative BHAR on each of these indicators and control variables. The coefficients on the predicted surprise indicators are positive and significant in all specifications, and the predictive ability of the predicted surprise indicators is stronger for the definition based on the difference between the HQ and LQ analysts' forecasts. The last line of the table reports the two-day abnormal returns of a trading strategy that is long if the predicted surprise indicator tested in that column is equal to 1 and short if it is equal to 0. All returns are statistically significant and reach 0.24% for *Big predicted surprise* based on the difference between the HQ and LQ analysts' forecasts. We note, however, that these returns may not be high enough relative to transaction costs (Novy-Marx and Velikov, 2016).

The overall conclusion from Tables 5 and 6 is that the market reacts to *SUE of consensus*, although HQ analysts' forecasts are more informative than the consensus. Hence, the market seems to overreact to the actual earnings' deviations from the consensus compared to deviations from the HQ analysts' average estimate. Another way to state this conclusion is that the market overreacts to the LQ analysts and underreacts to the HQ analysts. This is an easily-exploitable market inefficiency that allows for predicting announcement returns because the HQ analysts' forecast is available to investors at least one day before the actual announcement.

6. Predicting stock returns and return volatility at the firm level

We next study additional implications of the superior ability of the HQ analysts. We consider three testable predictions based on the HQ analysts' information output: one related to the first moment and the other two related to the second moment of stock returns. First, analysts with more accurate earnings forecasts are likely to produce better stock recommendations, and given that stock recommendation revisions are positively associated with future returns, recommendation revisions of the HQ analysts are likely to be strongly associated with the company's future stock returns. Second, we examine whether the HQ analysts' forecast dispersion, which the literature typically uses as a measure of uncertainty about the firm's future state, can predict the volatility of the firm's stock returns. The third testable implication is based on the theoretical and empirical literature which suggest that the PEAD anomaly should be greater during periods of high uncertainty and high analysts' forecast dispersion (Abarbanell, Lanen, and Verrecchia, 1995; Zhang, 2006; Hung, Li, and Wang, 2015). Hence, we examine whether the return to the PEAD strategy is indeed associated with the dispersion of the HQ analysts' forecasts. In all three tests, we compare the predictive ability of the HQ analysts to the LQ analysts and all analysts in the firm.[12]

[12] For these analyses (in the remainder of the paper), we use the sample in which HQ analysts' average forecast is more accurate than the consensus, i.e., firms with four or more HQ analysts in year t according to Table 5.

6.1. Stock recommendations

Table 7 reports regressions of firms' monthly stock returns on changes in individual analysts' stock recommendation for this firm made in the previous month. A recommendation is an integer between 1 and 5, where 1 is "strong buy", 5 is "strong sell", and 3 is "hold". For ease of interpretation, we measure recommendation changes as the negative of the current recommendation of the analyst minus the previous recommendation of the analyst, so that a positive (negative) recommendation change is an upgrade (downgrade). All regressions include firm fixed effects. Because most of analysts' recommendation changes take place in the month of the annual earnings announcement, the sample includes only recommendation changes made during the earnings announcement month. We also note that analyzing the returns in the month following a recommendation revision month allows for the HQ and LQ analyst classification to be of year t rather than year t-1, while ensuring that the long-short trading strategies we test are implementable. The investment delay from the revision date provides the investors with sufficient time to react to the revision and makes our return estimates conservative because such a delay reduces the returns (Barber et al., 2001).

Table 7 shows that the coefficient on all recommendation revisions and the cross-term of recommendation revisions with the HQ analyst indicator are positive and significant, while the cross-term with the LQ analyst indicator is not. The positive relation between recommendation revisions for all analysts and future returns is consistent with the literature (e.g., Jegadeesh et al, 2004). A one step recommendation upgrade by HQ analysts during the month of the earnings announcement predicts the firm's stock return will be 0.23% greater next month. Although firm fixed effects prevent us from testing the statistical difference between the coefficients on all and HQ analysts' revisions, the predictive ability of all analysts' revisions is economically smaller by half. A similar conclusion is reached based on a long-minus-short strategy, in which the long (short) position is in the firms for which the mean recommendation revision is positive (negative) during the earnings announcement month. This trading strategy yields 0.36% in the month following the earnings announcement for recommendations by all analysts; however, using the HQ analysts' recommendation revisions, the resulting return almost doubles, to 0.85%. Further, trading based on LQ analysts' recommendation revisions does not generate statistically significant returns. Overall, we find that the predictability relation between analyst recommendation revisions and equity returns in the subsequent month is driven by the recommendations of the HQ analysts.

6.2. Analysts' forecast dispersion

Next, we consider whether the HQ analysts' forecast dispersion is associated with future equity returns volatility. There has been relatively few studies on the relation between forecast dispersion and return volatility (Ajinkya and Gift, 1985; Lobo and Tung, 2000). In general, high forecast dispersion implies that analysts are uncertain about the firm's future performance. This suggests that the risk associated with the firm performance is relatively high, and we test whether the HQ analysts are relatively more aware of this risk, which would be reflected in the relation between their forecast dispersion and stock return volatility. Table 8 reports regression results of the standard deviation of daily stock returns during the month following the firm's annual earnings announcement month on the standard deviation of analysts' forecast errors close to earnings announcements (the forecast was given during the 60 days prior to the earnings announcement). We consider separately the dispersion of forecasts for all analysts, the HQ analysts, and the LQ analysts and seek to find out whether only the HQ analysts' forecast dispersion has the predictive power.

Table 8 provides regression results without and with firm fixed effects. Because volatility and dispersion are known to be persistent at the firm-level, finding that dispersion is correlated with volatility in the-cross section would not be too surprising; however, adding firm fixed effects allows us to test a predictive relation over time, which is a rather high bar to cross. In the first three columns (without firm fixed effects), we observe that the coefficients on all three variables are positive and significant. Chi-squared tests indicate that the coefficient on the dispersion of HQ analysts is greater than the coefficients on the dispersion of all analysts and the LQ analysts, with the p-values of 3.1% and 0.3%, respectively. Next, we add firm fixed effects to the regressions in the last three columns of the table, and the results change. The only strongly statistically significant variable is the HQ analysts' forecast dispersion. The LQ analysts' forecast dispersion becomes not significant, indicating its predictive power is only firm-specific, and the dispersion for all analysts is relatively weakly significant. Although firm fixed effects preclude us from testing for the statistical differences, the coefficient on dispersion for HQ analysts is now much greater than that for all analysts. These findings suggest that only the HQ analysts' forecasts capture variation in uncertainty across firms which results in future equity volatility.

6.3. Post-earnings announcement drift

In this sub-section, we report the results of tests on the relation between analysts' uncertainty and the PEAD. We present the findings in Figure 3 and Table 9. We calculate the PEAD using the calendar-time approach. To make our PEAD results comparable with the standard PEAD measurement in the literature, we use the consensus earnings surprise to assign announcing stocks to the long (short) portfolio each month if earnings surprise is positive (negative). The stocks are then held in the portfolios for horizons from 1 to 11 months to avoid overlapping with the following annual earnings announcement. Recent studies show that the PEAD is largely driven by relatively illiquid stocks (Sadka, 2006; Ng, Rusticus, and Verdi, 2008) and limits to arbitrage (Chung and Hrazdil, 2011), which together with the discussion of calendar-time analysis in Novy-Marx and Velikov (2016), motivates using value-weighted portfolio returns.[13] The monthly PEAD is the alpha from regressing the monthly portfolio returns on the four Fama-French-Carhart factors. The cumulative PEAD is the monthly alpha multiplied by the number of months for which the stock is held in the long or short calendar time portfolio.

Figure 3 reports the returns of the long minus short portfolios for the sample of announcements with high uncertainty, defined as announcements for which the HQ analysts' forecast dispersion is greater than that of all analysts, the full sample, and the low uncertainty sample, in which the HQ analysts have lower forecast dispersion than all analysts. The high uncertainty PEAD is clearly above the full-sample PEAD, and the low uncertainty PEAD is below the full sample PEAD. Table 9 reports the statistical significance of the returns on long, short, and long minus short strategies for the subsamples with high and low uncertainty announcements. We find that the low uncertainty PEAD (approximately 60% of the announcements) is not significant except for the 11-month horizon and is only weakly significant for the long-minus-short portfolio there. In contrast, when the forecast dispersion of HQ analysts is greater than dispersion of all analysts the long-minus-short PEAD is highly significant for all horizons except for 4- and 5-month horizons, and especially significant for the long portfolio. Overall, the findings for the PEAD based on the HQ analysts' information output are consistent

[13] We obtain similar results when using equal-weighted portfolios.

with our findings related to the immediate reaction to earnings surprise; the market is unaware of the superior ability of HQ analysts, and the PEAD is produced primarily during periods of high information uncertainty, which can be determined based the relation between forecast dispersions of the HQ analysts' and all analysts.

7. Predicting market and industry returns and volatility

Given our findings about the firm-level predictive ability of the HQ analysts of future equity returns (via recommendation revisions) and future volatility (via forecast dispersion), we now consider whether these relations can be aggregated to the industry and market levels. In Table 7, we find that recommendation changes by the HQ analysts predict stock returns at the firm level, so that averaging the change in recommendations across firms results in a testable relation between average recommendation changes and future market returns. The aggregation argument works similarly for forecast dispersion. In Table 8, a relatively high forecast dispersion of the HQ analysts implies they are uncertain about the firm's prospects, and aggregating analysts' dispersion across all firms in the market results in a dispersion measure that reflects the degree of uncertainty in the market.

In Table 10, Panel A, we report the estimation results on the relation between revisions in stock recommendations and *future* industry and market returns, respectively, in the first three and last three columns. To this end, each month, we average recommendation changes of the HQ, LQ, and all analysts in each firm and then across all firms in each 2-digit SIC industry (resulting in an industry-month panel) and across all firms (resulting in a monthly time series). The dependent variables are the monthly value-weighted industry and market returns in the month following the month with the earnings announcement. *All analysts' mean recommendation change* is the mean of all recommendation changes of all analysts who provided a recommendation change during the month in which the firm's earnings are announced. *HQ (LQ) mean recommendation change* are analogous variables that are based only on recommendation changes of the HQ (LQ) analysts. In addition, we control for the previous month's industry or market return to account for the possibility of a momentum in these returns.

The regression results in columns (1)-(3) reveal that the recommendation revisions by HQ analysts is associated with future industry returns, while the revisions by the LQ analysts do not predict future industry returns. Specifically, the coefficient on HQ analysts' recommendation revision is positive and significant (p-value<0.01) indicating that the recommendation revision by HQ analysts are not fully internalized by the market because they are predictive of the industry return in the following month. A cross-industry arbitrage strategy which has a long (short) position in the industries for which the HQ analysts' mean recommendation revision is positive (negative) yields a highly statistically significant average return of 0.66% in the month following the announcement month. The strategy based on the LQ analysts does not yield a statistically significant return. The predictive power of the HQ analysts' recommendation revisions is strong enough to produce a statistically significant coefficient for revisions by the full set of analysts and a statistically significant long-short industry strategy return. Finally, we report results on calendar-time alphas based on regressions of these long-minus-short monthly returns on the market index. Only the HQ analysts' recommendation revisions generate a statistically significant alpha of 0.51% per month. Together, these findings suggest that it is the HQ analysts that have ability to predict industry returns.

In the last three columns of Panel A, we repeat this analysis at the market level. The estimated coefficients are very similar to the industry ones. In the regressions of market returns on mean recommendation revisions, the mean HQ analysts' recommendation revisions predict the market return next month, while the LQ analysts' coefficient is not statistically significant. The coefficient on all analysts is statistically significant, albeit smaller than the HQ analysts' coefficient, because it combines recommendations by both HQ and LQ analysts. We also provide the results of a trading strategy in the market index based on mean recommendation revisions. Because the market-level data is a monthly time series, the long and short trading signal is based on time-series variation in monthly mean recommendation changes. If the mean recommendation revision across all firms in a given month is above (below) the median of the distribution of monthly mean recommendation revisions during the previous 24 months[14] we buy (short) the market value-weighted index and hold it for one month. We regress the monthly returns of this strategy on the market return and report the alphas for all, HQ, and LQ analysts' recommendation revisions. Only the HQ analysts' recommendations produce a statistically significant alpha, 0.51% per month. These findings suggest that the HQ (LQ) analysts' recommendations are (are not) informative about the future state of the market. Note that market efficiency implies that all recommendation changes are expected to be internalized by the market quickly, in the same month they are released, and hence no subset of recommendation changes should be predictive of the market return.

Finally, in Panel B of Table 10, we examine the second market-level aggregate relation—whether the HQ analysts' forecast dispersion aggregated across all firms is associated with uncertainty about the economy and, thus, with current and/or future market volatility, which

[14] The results are unaffected by selecting a longer window up to five years. The shorter, 24-month window minimizes the number of months lost to initialize this out-of-sample analysis while providing enough observations for a robust distribution of monthly mean recommendation changes.

we measure with the VIX index. Because the HQ analysts' forecast dispersion is firm-specific, it needs to be normalized to make it comparable across firms and years and, thus, usable as a measure of market uncertainty.[15] We define a dispersion ratio for the HQ analysts equal to the standard deviation of the HQ analysts' forecasts divided by the standard deviation of all analysts' forecasts (i.e., the consensus). The dispersion ratio for the LQ analysts is defined analogously. A market-level measure of analyst uncertainty is created by firm value-weighting the forecast dispersion or dispersion ratios across firms each month.

Panel B reports regressions of monthly VIX returns (percentage changes in the VIX)[16] on the dispersions of all, HQ, and LQ analysts' forecasts and the HQ and LQ analysts' dispersion ratios measured before the earnings announcement in the previous month. The results indicate that a higher dispersion ratio for the HQ analysts predicts a greater VIX return in the following month. Forecast dispersions, which are not normalized, are not associated with the VIX because of their firm-specific component. The LQ dispersion ratio also does not capture the level of uncertainty in the market. The last line of Panel B reports the performance of a trading strategy for the VIX index identical in design to the trading strategy for the market index. If the forecast dispersion or dispersion ratio in the corresponding column in a given month is above (below) the median of its distribution during the previous 24 months, we buy (short) the VIX index and record its percentage change over the next month. To benchmark the performance of this strategy, we regress its return on the market return and report the alphas. The only statistically significant (p-value<0.01) abnormal return is for the trading signal based the HQ analysts' dispersion ratio; the strategy yields a 3.32% alpha per month. We conclude that when the HQ

[15] In the panel regression model in Table 8, we control for the firm-specific component using firm fixed effects.
[16] We obtain very similar results using the values of the VIX in place of returns on the VIX.

analysts on average tend to be more uncertain than all analysts about the prospects of firms they follow, investors should expect an increase in market-wide uncertainty and volatility.

8. Conclusion

We find that when firms are followed by sufficiently many HQ analysts the consensus forecast is less accurate than the average estimate of the HQ analysts. Our results show that analysts' forecasting ability tends to persist for the firm and across firms. Therefore, it can be considered an analyst characteristic, and disregarding LQ analysts' forecasts and other information they generate, such as stock recommendations and forecast dispersion, can be beneficial for investors. However, the market does not seem to be aware of these shortcomings of the consensus because it reacts much stronger to deviations from the consensus earnings estimate than to analyst subsamples sorted by forecasting ability. A simple trading strategy for the immediate market reaction based on the HQ analysts' forecasts underlines that the market is inefficient in ignoring them. Following the principle that acknowledges differences in analyst ability allows for uncovering other mispricing phenomena using stock recommendations and forecast dispersion. Just as parsimonious models tend to perform well out-of-sample (e.g., DeMiguel et al. (2009) on the underperformance of the mean-variance optimization analysis relative to equal investment across assets), our analyst quality measure allows for uncovering predictive relations for analysts. The HQ analysts' stock recommendations and forecast dispersion predict the first two moments of firm and stock market performance.

Overall, our findings suggest that the market is not justified in focusing only at the consensus forecasts and can utilize the forecasts and other information output of the HQ analysts. Investors giving less or no weight to LQ analysts may lead to improvements not only in the price efficiency but also in the security analyst market. The more talented analysts would have additional incentives to exert more effort, while the less talented analysts would move to activities in which they add value. The accuracy of forecasts and informativeness of recommendations can improve as a result.

Appendix

Let there be n_G analysts of type G (high quality) and n_B analysts of type B (low quality) following the firm. Each analyst receives an unbiased noisy signal about the true earnings μ. Analysts of type G receive signal $S_i^G = \mu + \varepsilon_i^G$, where ε_i^G are i.i.d. $N(0, \sigma_G)$, while analysts of type B receive signal $S_i^B = \mu + \varepsilon_i^B$, where ε_i^B are i.i.d. $N(0, \sigma_B)$, and $\sigma_G < \sigma_B$. Analysts' forecasts are equal to their signals.

To obtain a more accurate forecast, closer to the true earnings μ, one would prefer the average forecast of type G analysts and ignore the forecasts of type B analysts if and only if the dispersion of the average signal of high quality analysts is less than that of low quality analysts:

$$var\left(\frac{1}{n_G}\sum \varepsilon_i^G\right) < \ var\left(\frac{1}{n_B}\sum \varepsilon_i^B\right) \tag{A.1}$$

This simplifies to

$$\frac{\sigma_G^2}{n_G} < \frac{\sigma_B^2}{n_B} \tag{A.2}$$

This means if a firm has relatively few high quality analysts and relatively many low quality analysts, the average forecast of the low quality analysts can be more accurate than the average forecast of the high quality analysts despite $\sigma_G < \sigma_B$. As the relative number of the high quality analysts increases, we will eventually prefer their average forecast over the low quality analysts' average forecast.

A similar logic applies to the consensus forecast, which averages across both low and high quality analysts. We should follow the average forecast of type G analysts rather than the consensus if and only if the dispersion of the average signal of high quality analysts is less than that for all analysts combined. This implies

$$\frac{\sigma_G^2}{n_G} < var\left(\frac{1}{n_G+n_B}\left(\sum \varepsilon_i^G + \sum \varepsilon_i^B\right)\right) \tag{A.3}$$

This simplifies to the following condition:

$$\sigma_G^2(2 + \frac{n_B}{n_G}) < \sigma_B^2 \tag{A.4}$$

Hence, as the number of *G* analysts increases or as the number of *B* analysts decreases, the inequality is more likely to hold, so that we would prefer to consider the signals of only *G*-type analysts. The left-hand-side monotonically declines with n_G. Because the signal variances are unobserved, the model's testable predictions are based on the relative numbers of high and low quality analysts in the firm. Hence, this framework shows that as the fraction of high quality analysts increases, the condition for considering only high quality analysts' estimates is more likely to be satisfied, which would make it optimal to ignore the low quality analysts' and the consensus estimates.

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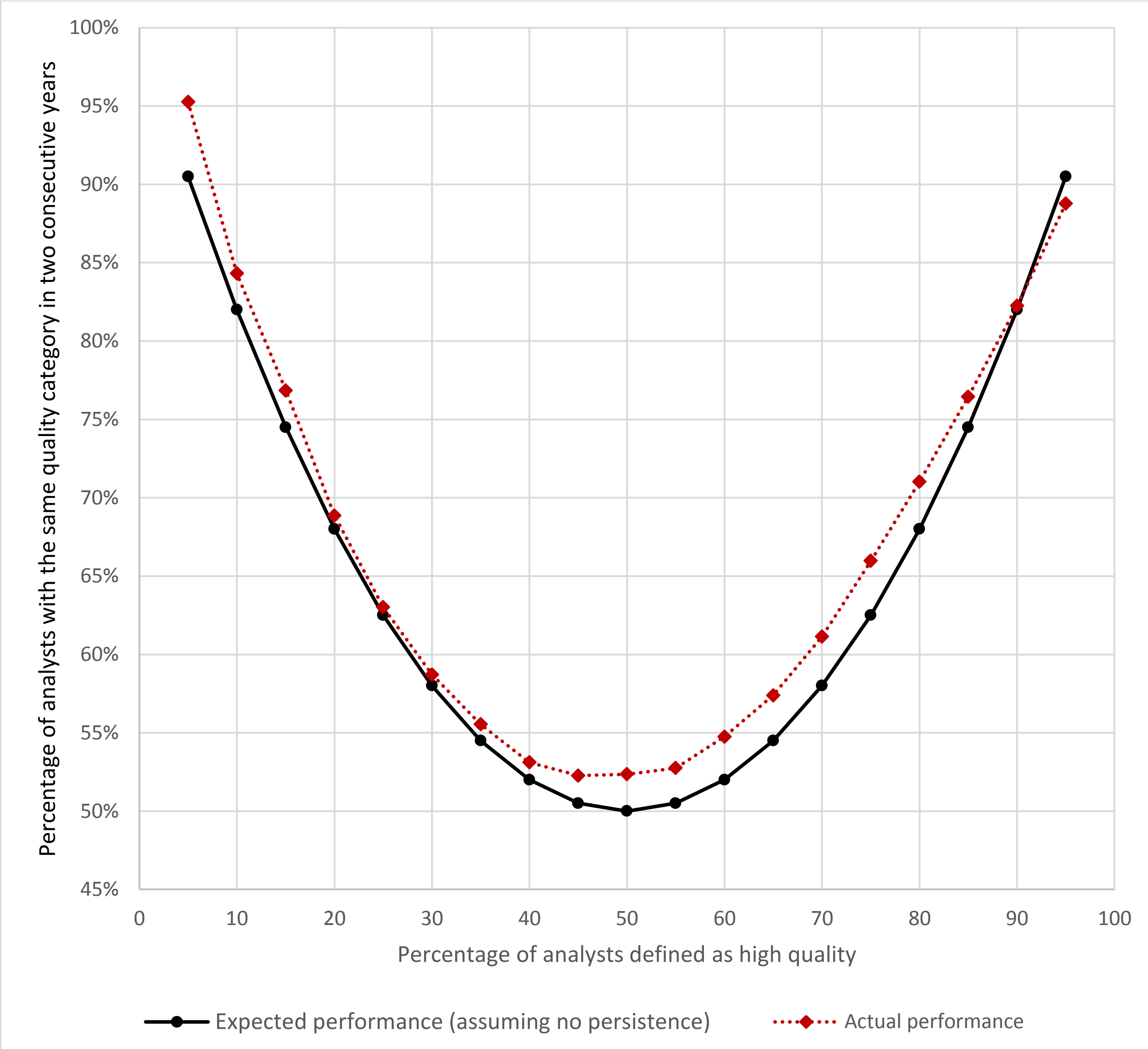

Figure 1: Persistence in analysts' forecasting performance. The figure depicts how the fraction of analysts retaining their ranking of either high or low quality of forecast accuracy in two consecutive years depends on the cutoff percentile in the definition of high quality analysts. High quality analysts are those whose closest absolute forecast errors are below the absolute forecast error at the cutoff percentile (horizontal axis) of the distribution of forecast errors for the firm's annual earnings announcement in year t-1. The closest absolute forecast error is the absolute difference between an analyst's forecast estimate closest to the earnings announcement prior to the announcement day and actual annual earnings, divided by the share price at the beginning of the calendar year. To rank analysts up to the decile precision, the sample of analysts ranked in consecurive years is constrained here only to firms that are followed by ten or more analysts. Expected performance assuming no persistence is the fraction of analysts who have the same forecast performance category in two consecutive years if their performance were uncorrelated between years.

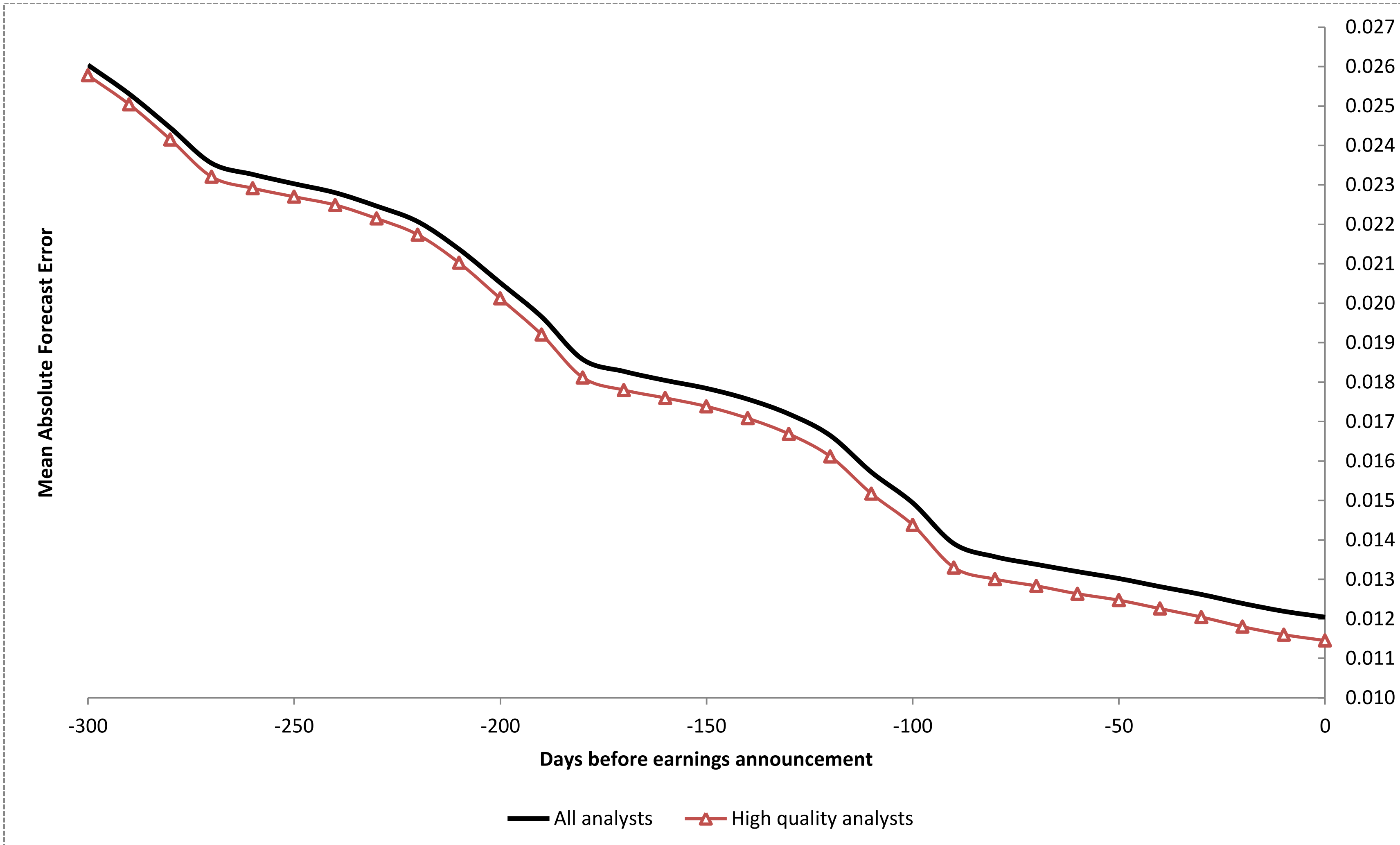

Figure 2: Absolute forecast error of analysts' estimates starting 300 days before the earnings announcement day. High quality analysts and absolute forecast errors are defined in Table 1. Absolute forecast errors at date t is calculated as the mean forecast error based on all forecasts outstanding as of day t prior to the earnings announcement date, averaged across firm-years and then averaged across firms for each pre-announcement day during 300 days prior to the announcement day.

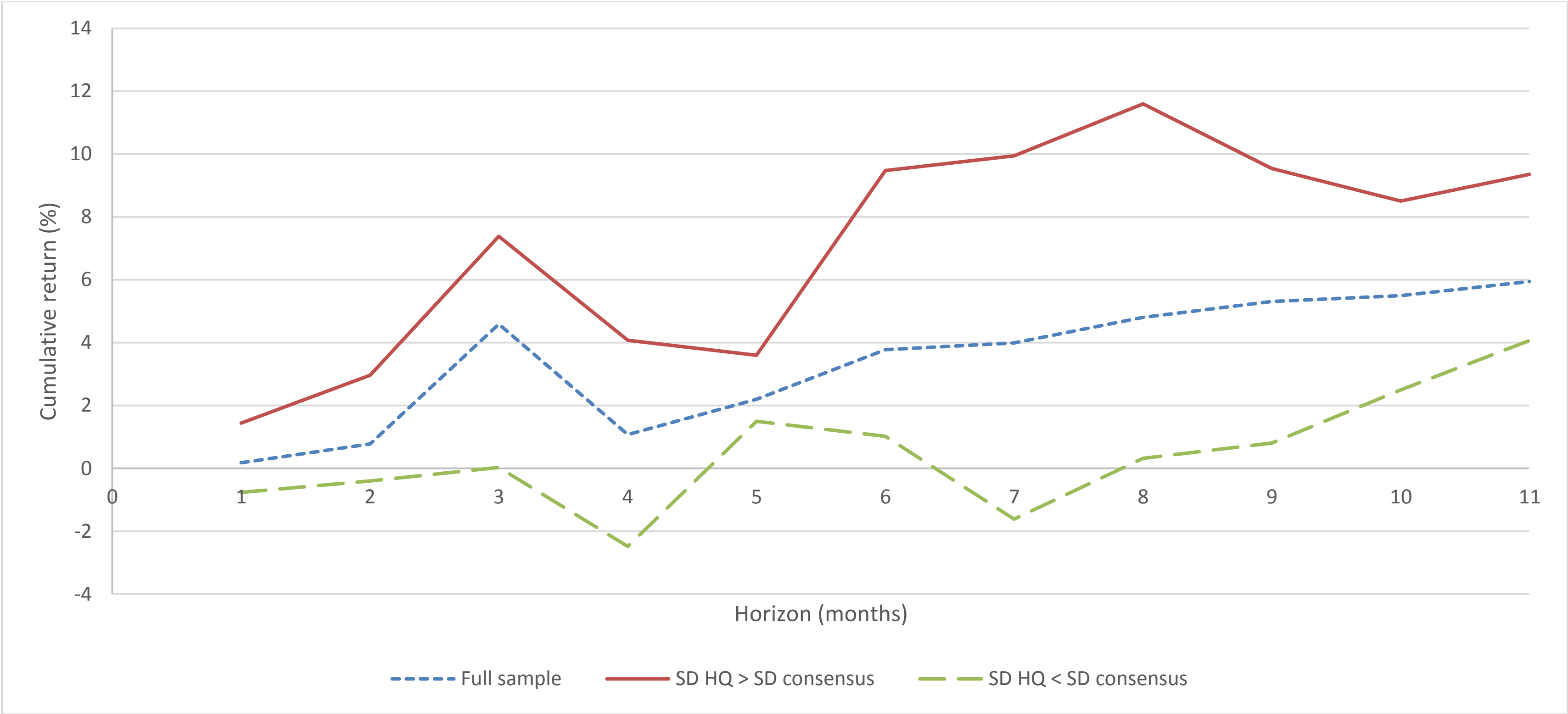

Figure 3. Cumulative post-announcement drifts depending on analysts' uncertainty
The figure shows the cumulative drift for 1 to 11-month horizons following earnings announcements. The horizontal axis is the drift's holding horizon, which is the number of months a stock is held in the calendar-time portfolios. Each month stocks enter a calendar-time long (short) portfolio depending on whether their earnings surprise is positive (negative), where earnings surprise is defined based on the consensus estimate. The long-minus-short value-weighted portfolio return is regressed on the four Fama-French-Carhart factors, and the intercept (monthly alpha) is multiplied by the portfolio's horizon to obtain the cumulative drift on the vertical axis. The graphs are for the full sample and two subsamples of firms in which the standard deviation of high quality analysts' forecasts (SD HQ) is greater or smaller than that of all analysts' forecasts (SD consensus). The high quality analysts are defined in Table 1.

Table 1: Analyst characteristics and forecast accuracy persistence

Panel A conducts univariate analysis for high and low quality (HQ and LQ) analysts. HQ (LQ) quality analysts are those whose closest absolute forecast errors are below (at or above) the median closest absolute forecast error for the firm's earnings announcement. The closest *absolute forecast error* is the absolute difference between an analyst's forecast estimate closest to the earnings announcement prior to the announcement day and actual annual earnings, divided by the share price at the beginning of the calendar year. The rankings in all panels and the sample in Panel A are based on firms that have at least four analysts in year t-1. *Overall tenure* is the number of years since the analyst first appeared in the I/B/E/S file. *Firm-specific tenure* is the number of years since the analyst began covering the specific firm in the I/B/E/S file. *Brokerage house size* is the number of analysts in the analyst's brokerage house. *Firm coverage* is the number of firms covered by the analyst. Panel B reports probit model results for the *HQ analyst indicator* that equals one if the analyst is of high quality and zero otherwise (columns (1) and (2)) and regressions for the analyst's closest absolute forecast error in columns (3) and (4). *Firm size* is the log of the firm's market value of equity equal to the stock price times the number of shares outstanding at the end of the month prior to the annual earnings announcement. *Annual return* is the annual return of the firm's equity over the 12 months prior to earnings announcement month. *Leverage* is the book value of total liabilities divided by the book value of total assets, and *Book-to-market* is the book value of common equity divided by the market value of equity at the end of the fiscal year. *Number of analysts* is the number of analysts following the firm. All independent variables are measured prior to the announcement date. The probit coefficients are marginal probability effects. All models include the intercept. Robust standard errors are clustered by firm. *z*- and *t*-statistics are in parentheses in the first two and last two columns of Panel B, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. HQ and LQ analyst characteristics

Analyst or announcement characteristic	HQ analysts	LQ analysts	Difference (t-statistic)
Overall tenure	7.07	7.00	0.07^{***} (4.73)
Firm-specific tenure	3.04	2.97	0.07^{***} (8.61)
Brokerage house size	65.76	63.04	2.72^{***} (19.14)
Firm coverage	17.60	17.55	0.05^{*} (1.79)
Absolute forecast error	0.0081	0.0089	-0.08^{***} (-12.83)
Forecast error	0.00185	0.00181	0.00004 (0.66)

Panel B. Predicting analysts' forecasting performance

	HQ analyst indicator		Absolute forecast error	
	(1)	(2)	(3)	(4)
HQ analyst indicator (t-1)	0.0414***	0.0407***	-0.00073***	-0.00072***
	(25.54)	(25.13)	(-16.14)	(-15.91)
Firm size	0.0034***	0.0011***	-0.00611***	-0.00612***
	(10.52)	(3.11)	(-25.12)	(-25.15)
Annual return	-0.0003	0.0005	-0.00086***	-0.00086***
	(-0.50)	(0.88)	(-5.68)	(-5.67)
Leverage	0.0006	0.0003	0.00573***	0.00570***
	(0.37)	(0.20)	(6.58)	(6.55)
Book-to-market	0.0001	0.00003	0.00002	0.00002
	(1.40)	(0.54)	(1.48)	(1.48)
Number of analysts	0.0007***	0.0007***	0.00022***	0.00022***
	(12.40)	(14.52)	(10.78)	(10.69)
Overall tenure		0.0007***		-0.00004***
		(4.33)		(-7.12)
Firm-specific tenure		0.0023***		0.00001
		(9.66)		(1.45)
Brokerage house size		0.0001***		-0.00000
		(10.63)		(-0.26)
Firm coverage		-0.0007***		0.00003***
		(-12.32)		(8.40)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects			Yes	Yes
Observations	485,815	485,815	485,815	485,815
Adj. R-squared			0.344	0.344

Table 2: Analyst quality across firms

The table reports how analysts' forecasting quality in one firm is related to their quality in other firms covered by the analyst in the same year, with Panel A showing the contemporaneous and Panel B showing the predictive relations. High and low quality (HQ and LQ) analysts are defined in Table 1. *HQ (LQ) indicator* is one if the analyst is ranked HQ (LQ) and is zero otherwise. *High (low) quality analyst in other firms* equals one (zero) if the analyst is of high (low) quality in the majority of the other firms the analyst follows during the year; analysts who have equal numbers of other firms with HQ and LQ performance rankings are excluded (9% of the sample). Panel B reports probit regressions predicting the HQ analyst indicator in a given firm based on analysts' HQ status indicator in the other firms in the previous year. The other independent variables are defined in Table 1. All independent variables are measured prior to the announcement date, and all specifications include the intercept. The reported coefficients are marginal probability effects. Robust standard errors are clustered by firm. *z*-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. HQ and LQ analysts' forecasting performance in other firms

		Performance in other firms		Full sample	t-statistic HQ vs. Full sample
		HQ	LQ		
Performance in this firm	HQ	54.4%	42.4%	48.3%	70.6***
	LQ	45.6%	57.6%	51.7%	

Panel B. Probit model predicting the HQ analyst status in a given firm

	HQ analyst in other firms, year t-1	HQ analyst in this firm, year t-1	Overall tenure	Firm-specific tenure	Brokerage house size	Firm coverage	Number of obs.
Marginal probability (z-statistic)	0.0531*** (32.95)	0.0387*** (23.14)					443,262
Marginal probability (z-statistic)	0.0514*** (31.83)	0.0382*** (22.84)	0.0002 (1.12)	0.0030*** (12.90)	0.0001*** (7.23)	-0.0005*** (-8.63)	443,262

Table 3: Distribution of analysts of different types

The table reports the average number of high quality, low quality, and unranked analysts in the earning announcement year. High and low quality (HQ and LQ) analysts are defined in Table 1. Unranked analysts are those who did not provide annual forecasts for the firm in the previous year.

HQ analysts		LQ analysts		Unranked analysts	
Number	Fraction	Number	Fraction	Number	Fraction
1	0.265	1.659	0.399	1.908	0.336
2	0.371	2.083	0.346	2.123	0.283
3	0.405	2.695	0.327	2.560	0.268
4	0.403	3.672	0.349	2.969	0.249
5	0.419	4.315	0.340	3.365	0.240
6	0.432	4.945	0.336	3.682	0.232
7	0.432	5.782	0.342	4.092	0.226
8	0.439	6.449	0.342	4.367	0.218
9	0.448	7.011	0.337	4.700	0.214
10 or more	0.461	9.201	0.337	5.715	0.202

Table 4: The number of HQ analysts and improvement in forecast accuracy

The table compares the accuracy of the average forecast of the high quality (HQ) analysts and the consensus sorted by the number of HQ analysts following the firm in a given year. High quality analysts are defined in Table 1. SUE of Consensus (SUE of HQ analysts) is the difference between the actual earnings and the average forecast provided by all analysts (HQ analysts) normalized by the stock price at the beginning of the year. *Accuracy improvement* is the percentage reduction from the absolute SUE of the consensus to the absolute SUE of HQ analysts. *t*-statistics is for the difference in means between the absolute SUE of consensus and HQ analysts.

Number of HQ analysts	Absolute SUE of Consensus	Absolute SUE of HQ analysts	Accuracy improvement	t-statistics Abs. SUE difference
1 or more	0.00656	0.00678	-3.31%	-8.63***
2 or more	0.00589	0.00595	-1.08%	-3.19***
3 or more	0.00514	0.00513	0.19%	0.54
4 or more	0.00461	0.00455	1.17%	2.99***
5 or more	0.00422	0.00415	1.52%	3.51***
6 or more	0.00404	0.00396	1.96%	3.95***
7 or more	0.00386	0.00377	2.35%	4.47***
8 or more	0.00377	0.00367	2.69%	4.60***
9 or more	0.00355	0.00346	2.61%	3.91***
10 or more	0.00346	0.00337	2.59%	3.44***

Table 5: Immediate Reaction to Earnings News

The table reports the earnings response coefficients for measures of earnings surprise based on all analysts' forecasts and on the forecasts of the high and low quality (HQ and LQ) analysts defined in Table 1. The dependent variable is the buy-and-hold abnormal return (based on the four-factor Fama-French-Carhart model) for the earnings announcement day and the following trading day. SUE of Consensus and SUE of HQ and LQ analysts are defined in Table 4. All other variables are defined in Table 1. Columns (1) - (3) use the entire sample of earnings announcements, and columns (4) - (6) use the sample of earnings announcements by firms followed by at least four HQ analysts. All independent variables other than SUE are measured prior to the announcement date. The intercept and year fixed effects are included in all regressions. Robust standard errors are clustered by firm. *t*-statistics are provided in parentheses. The last two lines report p-values for chi-squared tests of the equality of the coefficients on SUE measures for the three analyst groups. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Full Sample			4 or more HQ analysts		
	(1)	(2)	(3)	(4)	(5)	(6)
SUE of Consensus	0.7245***			0.7251***		
	(13.62)			(3.50)		
SUE of HQ analysts		0.6211***			0.6483***	
		(12.93)			(3.37)	
SUE of LQ analysts			0.5691***			0.5704***
			(12.78)			(3.16)
Firm size	-0.0003	-0.0002	-0.00014	-0.00071	-0.00069	-0.00069
	(-0.71)	(-0.55)	(-0.37)	(-1.04)	(-1.01)	(-1.02)
Annual return	-0.00064	-0.00057	-0.00057	0.00173	0.00178	0.00176
	(-0.98)	(-0.89)	(-0.87)	(1.54)	(1.56)	(1.56)
Leverage	0.00597***	0.00570***	0.00571***	0.00186	0.00165	0.00166
	(3.73)	(3.55)	(3.56)	(0.62)	(0.55)	(0.55)
Book-to-market	0.00002	0.00001	0.00001	-0.00065	-0.00068	-0.00065
	(0.38)	(0.29)	(0.28)	(-1.17)	(-1.21)	(-1.17)
Number of analysts	0.00002	0.00002	0.00001	-0.00010	-0.00010	-0.00011
	(0.25)	(0.28)	(0.08)	(-1.09)	(-1.06)	(-1.10)
Observations	44,709	44,709	44,709	15,544	15,544	15,544
Adjusted R-squared	0.0153	0.0134	0.0125	0.0092	0.0082	0.0074
p-value (SUE of HQ analysts vs. SUE of consensus)		0.000			0.008	
p-value (SUE of HQ analysts vs. SUE of LQ analysts)			0.02			0.04

Table 6: Abnormal return on earnings announcement day

The dependent variable is the buy-and-hold abnormal return (based on the four-factor Fama-French-Carhart model) for the earnings announcement day and the following trading day. High and low quality (HQ and LQ) analysts are defined in Table 1. *Predicted surprise* is equal to (HQ analysts' average forecast minus the consensus forecast) in columns (1) and (2) and (HQ analysts' average forecast minus LQ analysts' average forecast) in columns (3) and (4), normalized by the stock price at the beginning of the year. *Positive predicted surprise* indicator equals one if *Predicted surprise* is positive and zero if it is negative. *Big predicted surprise* equals one if *Predicted surprise* is greater than the median of positive values of *Predicted surprise* and zero if *Predicted surprise* is smaller than the median of negative values of *Predicted surprise* in year t-1. All independent variables are measured prior to the announcement date, and the regressions include the intercept and year fixed effects. Robust standard errors are clustered by firm. *t*-statistics are provided in parentheses. The last line of the table provides the two-day holding returns of a trading strategy that is long if the predicted surprise indicator variable in that column is equal to 1 and short if it is equal to 0. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Surprise: HQ average – Consensus		Surprise: HQ average – LQ average	
	(1)	(2)	(3)	(4)
Positive predicted surprise	0.0015*		0.0019**	
	(1.92)		(2.48)	
Big predicted surprise		0.0007*		0.0008**
		(1.71)		(1.98)
Firm size	0.00029	-0.00002	0.00028	-0.00002
	(0.76)	(-0.03)	(0.75)	(-0.04)
Annual return	-0.00016	-0.00061	-0.00016	-0.00102
	(-0.25)	(-0.67)	(-0.24)	(-1.15)
Leverage	0.0040**	0.0071***	0.0040**	0.0072***
	(2.45)	(2.89)	(2.45)	(2.90)
Book-to-market	0.00000	0.00001	0.00000	0.00000
	(0.03)	(0.15)	(0.03)	(0.11)
Number of analysts	-0.00000	-0.00006	-0.00000	-0.00002
	(-0.02)	(-0.51)	(-0.04)	(-0.15)
Observations	44,709	20,999	44,709	20,605
Adj. R-squared (%)	0.086	0.078	0.171	0.230
Two-day long-short strategy	0.14*	0.20*	0.19**	0.24*
returns (%)	(1.88)	(1.64)	(2.52)	(1.94)

Table 7: Recommendation revisions predicting returns

The analysis considers all recommendation revisions made in the month when the annual earnings announcement is made by the firm. The dependent variable is the firm's stock return next month. A recommendation is an integer from 1 to 5, where 1 is strong buy, 5 is strong sell, and 3 is hold. A recommendation revision is the negative of the difference between the current and the previous recommendations of an analyst, so that a positive (negative) recommendation revision is an upgrade (downgrade). Other indepedent variables are defined in Table 1 and measured prior to the earnings announcement. Robust standard errors are clustered by firm. The last line reports long-minus-short portfolio returns where the long (short) position is in the firms for which the mean recommendation revision is positive (negative) during the earnings announcement month, and the returns are for the next month. *t*-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Recommendation revision	0.00129**		
	(2.05)		
Recommendation revision × HQ indicator		0.00230***	
		(2.97)	
Recommendation revision × LQ indicator			-0.00001
			(-0.01)
Lagged dependent variable	0.00499	0.00504	0.00662
	(0.35)	(0.35)	(0.46)
Firm size	-0.02321***	-0.02321***	-0.02312***
	(-6.33)	(-6.32)	(-6.31)
Leverage	-0.01480	-0.01468	-0.01477
	(-1.04)	(-1.03)	(-1.04)
Book-to-market	-0.00005	-0.00005	-0.00005
	(-1.62)	(-1.63)	(-1.60)
Number of analysts	-0.00085***	-0.00085***	-0.00086***
	(-3.00)	(-2.99)	(-3.02)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	39,944	39,944	39,944
Adjusted R-squared	0.251	0.251	0.251
One month long-short strategy returns (%)	0.36	0.85***	0.14
	(1.61)	(3.11)	(0.49)

Table 8: Forecast dispersion predicting return volatility

The dependent variable is the standard deviation of the firm's daily returns in the month following the annual earnings announcement month. Forecast dispersion is the standard deviation of forecast errors defined in Table 1 and based on analysts' closest forecasts issued during 60 days prior to the earnings announcement. The other independent variables are defined in Table 1 and measured prior to the announcement date. All regressions include the intercept. Robust standard errors are clustered by firm. *t*-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Forecast dispersion of all analysts	0.1452***			0.0731*		
	(5.02)			(1.64)		
Forecast dispersion of HQ analysts		0.1802***			0.1315**	
		(5.18)			(2.55)	
Forecast dispersion of LQ analysts			0.0852***			0.0340
			(3.22)			(0.79)
Lagged dependent variable	0.5207***	0.5193***	0.5261***	0.5179***	0.5141***	0.5206***
	(21.34)	(21.56)	(21.40)	(12.69)	(12.82)	(12.63)
Firm size	-0.0009***	-0.0009***	-0.0009***	-0.0007	-0.0006	-0.0008*
	(-6.06)	(-6.21)	(-6.24)	(-1.59)	(-1.40)	(-1.73)
Annual return	0.0010***	0.0010***	0.0009***	0.0002	0.0002	0.0002
	(2.99)	(3.04)	(2.80)	(0.53)	(0.56)	(0.46)
Leverage	-0.00198***	-0.00204***	-0.00162**	-0.00065	-0.00068	-0.00052
	(-2.75)	(-2.82)	(-2.28)	(-0.29)	(-0.31)	(-0.23)
Book-to-market	0. 0002	0.0002	0. 0002*	0.0015	0.0016	0.0015
	(1.34)	(1.42)	(1.68)	(1.25)	(1.41)	(1.16)
Number of analysts	0.000064***	0.000066***	0.000066***	-0.000038	-0.000043	-0.000035
	(4.19)	(4.34)	(4.33)	(-1.22)	(-1.40)	(-1.13)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects				Yes	Yes	Yes
Observations	4,812	4,812	4,812	4,812	4,812	4,812
Adj. R-squared	0.631	0.633	0.628	0.691	0.693	0.691

Table 9: Post-earnings announcement drift and analysts' relative uncertainty

The table reports the cumulative drift for 1 to 11-month horizons following annual earnings announcements. Announcements are divided into two subsamples in which the standard deviation of the firm's HQ analysts' forecast errors is greater (the *high uncertainty* sample) or smaller (the *low uncertainty* sample) than the standard deviation of forecast errors for all analysts following the firm. Each stock is held in a calendar-time portfolio for the length of the horizon. The monthly value-weighted portfolio returns are regressed on the four Fama-French-Carhart factors to obtain the drift, which is the intercept of the regression (monthly alpha). A stock is assigned to the long or short portfolio depending on whether its earnings surprise is positive or negative, respectively, where earnings surprise is defined based on the consensus estimate. The high quality analysts are defined in Table 1. *, **, *** represent 10%, 5%, 1%, significance based on the regression *t*-statistics, respectively.

Drift horizon (months)	High uncertainty			Low uncertainty		
	Long	Short	Long-Short	Long	Short	Long-Short
1	1.09	-0.35	1.44*	-0.46	0.30	-0.76
2	1.36***	-0.12	1.48**	0.13	0.33	-0.20
3	1.87***	-0.58	2.46***	0.20	0.19	0.01
4	1.06***	0.04	1.02	-0.27	0.35	-0.62
5	0.90***	0.18	0.72	-0.05	-0.35	0.30
6	1.19***	-0.40	1.58***	-0.03	-0.20	0.17
7	0.97***	-0.35	1.42***	-0.16	0.07	-0.23
8	0.97***	-0.48*	1.45***	-0.18	-0.22	0.04
9	0.50***	-0.56**	1.06***	-0.14	-0.22	0.09
10	0.42***	-0.44**	0.85***	-0.08	-0.33	0.25
11	0.41***	-0.44**	0.85***	0.03	-0.4**	0.37*

Table 10: HQ analysts predicting returns and volatility at the aggregate level

The dependent variables are value-weighted returns in 2-digit SIC industries (columns (1)-(3) of Panel A), value-weighted market returns (columns (4)-(6) of Panel A), and the VIX index return (Panel B) in the month following the month with the earnings announcement. Panel A uses recommendation revisions during the announcement month defined in Table 7, and Panel B uses the dispersion of analysts' forecasts defined in Table 8. The HQ and LQ analysts are defined in Table 1. The *mean recommendation revision* variables are averages across all analysts in a given industry (columns (1)-(3)) and the entire market (columns (4)-(6)). A monthly industry return is included if there is more than one recommendation change for a firm in the industry during the month. *Dispersion* variables are firm-level value-weighted averages of analysts' forecast error dispersions with the firm's market capitalization as the weights. *Dispersion ratio for HQ (LQ) analysts* is the firm value-weighted average of the ratio of *Dispersion of HQ (LQ) analysts* to *Dispersion of all analysts*. The models use robust standard errors clustered by industry in the industry specifications, Newey-West standard errors with three lags in the market specifications, and Huber-White robust standard errors in Panel B. Industry specifications also report long-minus-short portfolio returns where the long (short) position is in the industries for which the mean recommendation revision is positive (negative). The last line in in Panel A reports the alphas from a market model regressions obtained as follows. In the industry specifications, industries whose mean recommendation revisions are positive (negative) are assigned to the long (short) portfolio each month, and the portfolio returns are value-weighted to produce a long-minus-short monthly return, which is then regressed on the market value-weighted return. In the market specifications, the market return is multiplied by 1 (-1) if the mean recommendation revision this month is above (below) the median of mean recommendaton revisions during the previous 24 months. The last line in Panel B provides the alphas from regressing a VIX trading strategy return on the market value-weighted return, where the VIX strategy return is the VIX return during the month following the announcement month multiplied by 1 (-1) if the column's *Dispersion* or *Dispersion ratio* that month is above (below) the median of *Dispersion* or *Dispersion ratio* during the previous 24 months. *t*-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Predicting Industry and Market Returns

	Industry returns			Market returns		
	(1)	(2)	(3)	(4)	(5)	(6)
All analysts' mean	0.002**			0.015*		
recommendation revision	(2.22)			(1.83)		
HQ analysts' mean		0.003***			0.017**	
recommendation revision		(2.60)			(2.24)	
LQ analysts' mean			-0.000			0.005
recommendation revision			(-0.03)			(0.90)
Lagged dependent variable	0.068**	0.068***	0.068***	0.072	0.073	0.070
	(7.71)	(7.73)	(7.74)	(0.93)	(0.95)	(0.90)
Constant	0.009**	0.009***	0.009***	0.009***	0.010***	0.008***
	(26.58)	(26.66)	(26.46)	(3.42)	(3.57)	(2.77)
Observations	16,445	16,445	16,445	265	265	265
Adj. R-squared (%)	0.47	0.49	0.45	0.85	1.75	-0.1
One month long-short industry	0.51**	0.66***	0.36			
returns (%)	(2.30)	(2.81)	(1.49)			
Monthly alpha (%)	0.05	0.51*	-0.14	0.43	0.51*	0.34
	(0.19)	(1.89)	(-0.48)	(1.48)	(1.72)	(1.15)

Panel B: Predicting VIX Index Return

	(1)	(2)	(3)	(4)	(5)
Dispersion of all analysts	1.105				
	(0.21)				
Dispersion of HQ analysts		3.883			
		(0.54)			
Dispersion of LQ analysts			1.243		
			(0.21)		
Dispersion ratio for HQ analysts				0.091*	
				(1.69)	
Dispersion ratio for LQ analysts					-0.005
					(-0.15)
Lagged dependent variable	-0.111	-0.113	-0.112	-0.100	-0.109
	(-1.13)	(-1.16)	(-1.12)	(-1.01)	(-1.11)
Constant	0.007	0.002	0.007	-0.066	0.014
	(0.39)	(0.12)	(0.36)	(-1.52)	(0.39)
Adj. R-squared (%)	0.201	0.418	0.205	1.660	0.180
Monthly alpha (%)	1.85	2.04	-0.57	3.32***	-0.56
	(1.34)	(1.60)	(-0.40)	(2.68)	(-0.41)
Obs. in Long portfolio	115	124	74	141	64
Obs. in Short portfolio	97	88	138	71	148