Why and How Do Analysts Make Multiple Forecasts in a Day?

Tse-Chun Lin* Chuyi Zhang†

July 31, 2024

Abstract

Recent studies find that equity research analysts face cognitive constraints, and their earnings forecasts become less accurate when they issue multiple forecasts on the same day ("forecast clustering"). Knowing such a behavior leads to lower forecast quality, it remains a puzzle why these analysts increasingly choose to cluster forecasts on the same day. We find that forecast clustering is closely related to rising workloads, the need for timely forecasts following concurrent earnings announcements, the distractions from news about other portfolio firms, and the issuance of industry reports. Forecasts for firms that are important to analysts' careers or contain significant news are less likely to be clustered, suggesting strategic effort allocation by analysts. Our findings suggest that investors who heavily rely on written research by analysts should carefully assess the quality of analyst reports produced under the current increased workload.

JEL Classification:

Keywords: Equity Research Analyst, Cognitive Constraints, Behavioral Finance

*HKU Business School, The University of Hong Kong, Email: tsechunlin@hku.hk

†HKU Business School, The University of Hong Kong, Email: chuyi.zhang@connect.hku.hk

1 Introduction

Sell-side equity research analysts and their forecasts are crucial sources of information for investors (Birru et al., 2022, 2024; Keane and Runkle, 1998; Kothari et al., 2016; Loh and Stulz, 2018) and what determines their forecasting behavior has been extensively studied in the literature.[1] Recent studies has begun to focus on the cognitive constraints faced by analysts. Drake et al. (2020) find that when analysts issue earnings forecasts for multiple firms on the same day, a behavior that we will refer to as "forecast clustering," these forecasts tend to be less accurate, less bold, and less informative. Similarly, Hirshleifer et al. (2019) find that an analyst's accuracy diminishes and reliance on heuristic decision-making increases with the number of forecasts she has issued on the same day. They attribute this decline in forecast quality to decision fatigue, the decline in decision quality after extensive decision-making.

Analysts appear aware of the negative impact of decision fatigue during forecast clustering and attempt to manage it strategically by issuing forecasts for firms more important to their reputation and career when less fatigued, as noted by Jiao (2023). Logically, one would expect an analyst to first *avoid* forecast clustering whenever possible, and then decide which firm to work on first when clustering is unavoidable.[2] However, contrary to this expectation, there has been an increasing trend in forecast clustering over time. As shown in Figure 1, the fraction of one-year-ahead EPS forecasts that are clustered increased from 40% in 2002 to 60% in 2022.

[1] Earlier literature mainly focuses on errors and biases caused by conflict of interest and psychological biases. Please see Kothari et al. (2016) and Ramnath et al. (2008) for a literature review.

[2] It is unlikely that analysts have to issue too many reports to avoid forecast clustering: an ordinary analyst issues only one major new report and 12 company-specific notes in a month (Groysberg and Healy, 2020) and in our data from I/B/E/S, an average analyst issues only 41 one-year-ahead EPS forecasts in a year.

As important financial information intermediaries, analysts play a crucial role in reducing the information asymmetry between insiders and outsiders of a firm (Harford et al., 2019). The effect of this reduction in information asymmetry varies between sophisticated and unsophisticated investors. Since sophisticated institutional investors can obtain information from analysts via other channels, such as direct phone calls or investor conferences, analysts' forecasts in written research reports are most pertinent to unsophisticated retail investors.[3] Therefore, the increasing trend of analysts clustering multiple forecasts on the same day, with compromised accuracy, raises concerns about a firm's information environment, especially regarding the information asymmetry between sophisticated and unsophisticated investors. It is crucial for investors relying on these forecasts to understand why analysts cluster forecasts to evaluate their reliability.

In this paper, we aim to explore the factors that drive analysts to cluster multiple forecasts on the same day. We begin by analyzing the overall time trend of forecast clustering at the annual level, finding that this trend is closely linked to the increasing average workload of analysts, both in terms of the number of firms they cover and the number of forecasts they issue per firm. We then explore forecast clustering behavior at each analyst-quarter at both the extensive margin (i.e., whether to cluster any forecasts) and the intensive margin (i.e., how many forecasts to cluster within a day). Our findings reveal that forecast clustering is a persistent characteristic of analysts, with analyst fixed effects accounting for around 50% of the variation in clustering behavior at both the extensive and the intensive margins. Brokerage firm fixed effects explain 12.4% to 18.2% of the variations, consistent with workplace culture and regulations. Time fixed effects contribute only around 1%, suggesting that

[3] Amiram et al. (2016) find that analyst earnings forecasts decrease information asymmetry between sophisticated and unsophisticated investors because the forecasts largely contain information new only to unsophisticated investors (Irvine et al., 2007).

the increasing trend in clustering is more likely due to changes in analyst composition with different work habits rather than individual analysts clustering more forecasts over time.

At the forecast level, we further investigate various non-strategic and strategic reasons why analysts cluster forecasts. Among the non-strategic factors, where analysts have relatively low discretion, we consider concurrent earnings announcements of portfolio firms, distractions from news about other portfolio firms, and the issuance of industry reports. We find that the need to issue timely forecasts after concurrent earnings announcements is a major driver of forecast clustering. Whether a forecast is made within one day after an earnings announcement and whether another firm the analyst covers announces earnings on the same day explains 15% of the variation in whether a forecast is clustered. This result underscores the trade-off between forecast timeliness and quality, as discussed in previous literature (Clement and Tse, 2003; Guttman, 2010; Shroff et al., 2014). Additionally, forecasts are more likely to be clustered when other firms in an analyst's portfolio experience significant news events, proxied by fundamental news from RavenPack, abnormal trading volume, or extreme absolute stock returns. This finding is consistent with the findings of Bourveau et al. (2022) that temporarily distracted analysts make less accurate and less frequent forecasts. Lastly, we find that around one third of clustered forecasts are issued at the same *second* as another forecast for a firm from the same Fama-French 48 industry, indicating that they are part of an industry report where the analyst forecasts multiple firms simultaneously.

We find that 77.7% of the clustered forecasts are related to non-strategic clustering. For the remaining 22.3% of clustered forecasts, where analysts have more discretion, we hypothesize that analysts engage in strategic inter-day job allocation by clustering less critical forecasts. Supporting this hypothesis, we find that forecasts for firms more important to analysts' careers, measured by the relative ranking of the firm in terms of size, trading volume, and institutional ownership, are less likely to be clustered. Furthermore, forecasts containing important news, as indicated by accompanying recommendation revisions, are also less likely to be clustered.

This paper is closely related to the literature on the cognitive constraints of analysts. Hirshleifer et al. (2019) and Jiao (2023) find that decision fatigue negatively impacts forecast quality when analysts cluster their forecasts. Analysts are also found to have limited attention, as Driskill et al. (2020) show that they issue less accurate forecasts when distracted by concurrent earnings announcements. Pisciotta (2023) demonstrate that analysts provide less timely forecasts when their workload increases due to an IPO assignment. Our paper contributes to this body of literature by documenting the increasing trend in forecast clustering over the past 20 years, which is closely linked to the rising workload of analysts. We also identify that approximately three-quarters of the clustering is due to "exogenous" factors, such as concurrent earnings announcements and breaking news of other portfolio firms. As forecast clustering becomes more prevalent, the cognitive constraints of analysts may pose a greater threat to the firm's information environment, especially regarding the information asymmetry between institutional and retail investors. Our finding that analysts strategically cluster forecasts that are less important to their careers further implies that the potential deterioration of the information environment may be more pronounced for firms that already suffer from poor information environments, such as those that are small, lack liquidity, and have low institutional ownership.

Our paper also contributes to the developing literature on the strategic effort allocation of analysts. Analysts are sophisticated professionals who strategically prioritize their portfolio firms based on the relative importance of these firms to their careers. Hong and Kubik (2003) and Harford et al. (2019) find that analysts issue more accurate forecasts for firms that are more important to their careers. Chiu et al. (2021) find that analysts spend more effort on portfolio firms with high abnormal institutional distributions. Our paper extends this line of research by demonstrating that analysts also allocate effort discriminately across firms by clustering less important forecasts. Methodologically, we introduce a new measure of forecast importance based on accompanying recommendation revisions, which incrementally explains analysts' forecast clustering beyond the importance measures constructed based on firm characteristics commonly used in the literature.

The remainder of this paper is organized as follows: Section 2 describes our data and methodology, Section 3 investigates different potential determinants of the forecast clustering behavior; and Section 4 concludes.

2 Data and Methodology

2.1 Data Sources

Data on analysts' earnings per share (EPS) forecasts are collected from the Institutional Brokers' Estimate System (I/B/E/S) database for the sample period from 2002 to 2022. We start from 2002 because it is the first year that the forecast announcement date in I/B/E/S is verified (Hoechle et al., 2015). Following the previous literature (e.g., Gleason and Lee, 2003; Hirshleifer et al., 2019; Jiao, 2023), we focus on one-year-ahead earnings forecasts, the most commonly issued type of forecasts. Firms' financial information and stock data are from Compustat and CRSP, respectively. We obtain firm-specific news from RavenPack News Analytics.

2.2 Key Variables Construction

Our primary measure of forecast clustering at the forecast level is a dummy variable, $MultiForecast$, which is equal to 1 if the forecast is issued on a day when the analyst releases more than one forecast, and 0 otherwise. To investigate potential determinants of forecast clustering, we construct several explanatory variables, detailed below.

First, to examine the impact of timely issuance of forecasts following concurrent earnings announcements, we define $MultiEA$ as a dummy variable equal to 1 if at least one other firm in the analyst's portfolio announces earnings on the same day, and 0 otherwise. We also construct $Timely$, a dummy variable indicating whether the forecast is issued on the day of or the day after the most recent earnings announcement of the forecasted firm, following Driskill et al. (2020)

To assess the influence of distraction by news of other portfolio firms, we adapt the method from Kempf et al. (2017) and construct three alternative measures of distraction. These measures consider fundamental news, abnormal trading volumes, and extreme stock returns for firms in the analyst's portfolio that are *not* forecasted on a specific day.[4] Specifically, the distraction faced by analyst i on day t, $Distraction_{i,t}$, is measured using the following formula:

$$Distraction_{i,t} = \sum_{j \notin FC_{i,t}} \omega_{i,j,t} \times IS_{j,t}, \tag{1}$$

where $FC_{i,t}$ is the set of all firms analyst i forecasted on day t. $\omega_{i,j,t}$ represents the weight assigned to each firm j in the analyst's portfolio. In the main analysis, we use equal weights for each portfolio firm, though our results remain consistent when weighted by

[4]Kempf et al. (2017) constructs a distraction measure for institutional investors based on extreme industry returns of unrelated part of their investment portfolios to gauge whether the institutional investors are "distracted" from the focal firm.

market capitalization. $IS_{j,t}$ stands for "information shock" that we measure in three ways. The first and most direct measure is $News_{j,t}$, which is a dummy variable equal to one if there is any fundamental news of the firm j reported in RavenPack on day t. To ensure that we capture relevant and novel news, we identify news with a relevance score of 100 and a similarity gap of 100 from the following news types: news-flash, hot-news-flash, full article, and press release. To ensure we capture fundamental news, we keep the following 13 news groups: acquisitions-mergers, analyst-ratings, assets, credit, credit-ratings, dividends, earnings, equity-actions, labor-issues, legal, marketing, products-services, and partnerships.

Inspired by Ben-Rephael et al. (2023), we supplement the information shock measure constructed from RavenPack data with two dummy variables capturing stock market reactions to new information releases. The first one, $AbnVol_{j,t}$, indicates whether stock j is in the top decile of abnormal trading volume of CRSP's cross-sectional ranking on day t. Abnormal trading volume is calculated as the split-adjusted daily stock volume divided by the split-adjusted average trading volume over the past 63 trading days. The second one, $AbsRet_{j,t}$, indicates whether stock j is in the top decile of absolute return of CRSP's cross-sectional ranking on day t.

To investigate whether analysts strategically cluster less important forecasts, we construct two types of measures of importance. The first captures important firms. Similar to Harford et al. (2019) and Jiao (2023), for each analyst i at each time t, we create a dummy variable indicating the top quartile of firms in their research portfolio based on each of the three firm importance proxies: market capitalization, institutional ownership, and trading volume. For example, $TopSize_{i,j,t}$ is equal to 1 if firm j is in the top quartile of analyst i's portfolio in the quarter in terms of market capitalization measured at the last quarter-end and 0 otherwise. We also create two dummy variables consolidating the three dimensions of importance: $ImpFirmAny_{i,j,t}$ is equal to 1 if a firm is in the top quartile in *any* dimension, while $ImpFirmAll_{i,j,t}$ is equal to 1 if a firm is in the top quartile in *all* dimensions.

In addition to important *firms*, which have been well documented to affect analysts' strategic effort allocation, we conjecture that analysts may also pay more attention to forecasts with important *information*. Inspired by Kecskés et al. (2017), we attempt to capture important information using the interaction between analysts' EPS forecasts and recommendations. It is well documented that analysts' recommendation changes contain important information (Bradley et al., 2017; Loh and Stulz, 2011). Therefore, it is reasonable to assume that forecasts in a report that contains a recommendation revision contain more important information. We construct a dummy variable, $RecomRevision$, which is equal to 1 if the forecast is accompanied by a recommendation revision on the same day by the same analyst compared with the analyst's previous recommendation. We further break down $RecomRevision$ into $UpGrade$ and $DownGrade$ to investigate whether there is any asymmetric impact between downgrade and upgrade recommendation changes.

Following previous literature (e.g., Hirshleifer et al., 2019; Jiao, 2023), we control for other determinants of analysts forecast behavior to isolate the effect of our focal variables. These control variables include the number of companies covered by the analyst, the brokerage house size, the analyst's firm-specific experience, the analyst's general experience, the age of the forecast, the forecast frequency, and the number of analysts who cover the firm. Please refer to the Appendix for detailed variable definitions.

Table 1 reports the summary statistics for data used in our main analysis. In our sample, 49.8% of the forecasts are clustered, indicating the prevalence of forecast clustering today. Timely forecasts and forecasts for firms with concurrent earnings announcements are also common, accounting for 44.0% and 51.7% of the forecasts, respectively. Among the three measures of distraction, the measure based on RavenPack news, $DistractionNews$, has the highest mean value, suggesting it may capture a wider range of news compared to the other two measures, which are based on extreme stock market reactions that likely capture only the most significant news events. The mean value of 2.69 for $Numest$ indicates that, on average, a firm is covered by 15 analysts.

2.3 Methodology

To study the various determinants of forecast clustering, our baseline fixed-effect regression model is specified as follows:

$$MultiForecast_{i,j,t} = \beta_1 Characteristics_{i,j,t} + \beta_{\mathbf{2}}' \mathbf{X_{i,j,t}} + \delta_j + \delta_{i,q} + \delta_t + \epsilon_{i,j,t} \tag{2}$$

$MultiForecast_{i,j,t}$ measures forecast clustering as previously defined. $Characteristics_{i,j,t}$ encompasses the firm, analyst, and forecast characteristics that may influence forecast clustering. $\mathbf{X_{i,j,t}}$ are control variables. δ_j, $\delta_{i,q}$, and δ_t represent firm, analyst $\times$ year-quarter, and date fixed effects, respectively. The use of high-dimensional fixed effects controls for clustering due to: 1) time-invariant firm characteristics (e.g., industry differences in earnings announcement clustering); 2) analysts' time-varying characteristics (e.g., the absolute number of firms an analyst covers in a quarter); and 3) daily differences in average clustering behaviors across analysts (e.g., weekday variations). To avoid the potential incidental parameter problem associated with logit/probit models when controlling for high-dimensional fixed effects, we utilize a linear probability model in our main analysis. As demonstrated in Section 3.5, our results remain consistent when using a probit model.

3 Determinants of Forecast Clustering

3.1 Workload Time Trend

Given the increasing trend of forecast clustering over the past 20 years, as shown in Figure 1, it is natural to investigate whether this trend is driven by an increasing workload among equity research analysts. We begin by examining the average total number of one-year-ahead EPS forecasts issued by an analyst each year. This total is then "decomposed" into two components: the average number of firms an analyst covers and the average number of reports issued per firm. The findings are presented in Figure 2. Panel A indicates that the total number of one-year-ahead EPS forecasts issued by an analyst has increased by 81%, from 27 in 2002 to 49 in 2022, aligning with the increasing trend in forecast clustering.

This significant rise in the number of reports is attributed to an increase in both the number of firms an analyst covers and the number of reports issued per firm. Specifically, Panel B shows that the number of firms covered by an analyst has grown from 8 to 11 over the past two decades. Panel C illustrates that the average number of forecasts an analyst issues for each firm in a year has increased from 3.4 to 4.4, consistent with the industry practice of updating EPS forecasts following each quarterly earnings announcement.

Given the consistent upward trends in both forecast clustering and analyst workload, it is not surprising that these two time series are strongly correlated. As demonstrated in Table 2, the proportion of clustered forecasts is positively correlated with the average total number of one-year-ahead EPS forecasts issued by an analyst annually. The R-squared of the OLS regressions reaches 0.90 and 0.88, respectively, when using the total number of reports and when breaking it down into the number of firms covered and the number of reports per firm.

These results suggest that the increasing trend in forecast clustering is closely related to the growing workload of equity research analysts over time.

3.2 Work Habit Variations and Other Analyst Characteristics

In this subsection, we first explore how much of the variation in forecast clustering behavior can be explained by time (year-quarter), analyst, and brokerage firm fixed effects. We then investigate the impact of various analyst characteristics using OLS regression. We investigate the forecast clustering behavior of an analyst at the quarterly level and construct two measures to examine both the extensive and intensive margins. To capture the extensive margin, we use a dummy variable, $AnyCluster$, which is set to 1 if an analyst issues more than one forecast on any day during the current quarter and 0 otherwise. For the intensive margin, we create a continuous variable, $MaxClusterNum$, representing the log of the maximum number of forecasts an analyst issues on days when clustering occurs within the quarter. The results are presented in Table 3.

Panel A of Table 3 reports the fixed-effect decomposition for our two measures of quarterly clustering behavior. It shows that analyst fixed effects are the most important determinant in explaining the variation in quarterly forecast clustering behavior at both the extensive and intensive margins, with R-squared values of 50.3% and 49.9%, respectively. In other words, both the decision to cluster a forecast and the number of forecasts to cluster in a day are largely individual analyst characteristics. Next, brokerage firm fixed effects explain 18.2% and 12.4% of the variation in clustering, consistent with workplace culture and regulation. Year-quarter fixed effects account for only 0.6% and 2.6% of the variation. The weak impact of time fixed effects suggests that the strong increasing time trend in average forecast clustering behavior is primarily driven by newly entering analysts who tend to cluster more forecasts (i.e., an extensive margin effect) rather than existing analysts increasing their clustering over time (i.e., an intensive margin effect). Combining all three fixed effects, the R-squared values only marginally increase to 52.5% and 53.1%, respectively, likely because that analyst fixed effects absorb a large portion of the brokerage firm fixed effects.

In Panel B, we explore how forecast clustering is related to different analyst characteristics. Columns 1 to 3 report the OLS regression results for the extensive margin with incremental time (year-quarter) and analyst fixed effects, while Columns 4 to 6 provide the results for the intensive margin. First, echoing the results in Table 2, analysts with more firms to cover ($FirmsFollowed$) and those who write more reports ($ReportNum$) are more likely to engage in forecast clustering and to cluster more forecasts in a day. The results in Columns 3 and 6, with analyst fixed effects, indicate that an analyst tends to engage in more clustering as their workload increases. After controlling for the number of portfolio firms and the number of forecasts, the number of industries an analyst covers is negatively related to forecast clustering. Intuitively, when an analyst covers fewer firms in each industry, the probability of writing industry reports in response to news affecting multiple firms simultaneously decreases. Working at a top-10 brokerage firm ($BigBroker$) is consistently associated with a lower probability of clustering forecasts across different fixed effect specifications. However, at the intensive margin, if an analyst is already clustering forecasts, whether she works at a top brokerage firm does not significantly affect the number of forecasts clustered. Another interesting result is that general work experience, proxied by the number of years recorded in I/B/E/S ($GeneralExperience$), is generally negatively related to clustering behavior at both the extensive and intensive margins, and becomes insignificant after controlling for analyst fixed effects. In other words, ceteris paribus, an analyst is not more likely to engage in clustering as her general experience increases over time. These results further confirm the implication from Panel A that the increasing clustering trend is primarily driven by changes in analyst composition with varying clustering habits.

3.3 Non-strategic Forecast Clustering

In this subsection, we focus on "exogenous factors" related to forecast clustering that analysts have relatively less discretion over and find difficult to avoid. We classify these as non-strategic clustering factors. These include two factors closely related to the increasing portfolio size of analysts: timely forecasts for firms with concurrent earnings announcements, and distractions caused by important news from other portfolio firms. Additionally, we consider the new trend of issuing industry reports.

3.3.1 Concurrent Earnings Announcements

We start with the need to issue timely forecasts following concurrent earnings announcements. As the portfolio size of analysts increases, the likelihood of encountering concurrent earnings announcements naturally rises (Driskill et al., 2020). Additionally, the timeliness of analysts' forecasts has also increased: Zhang (2008) reports that the fraction of forecasts issued on or one day after earnings announcement days grew from 26% in 1996 to almost 53% in 2002. More recently, Keskek et al. (2014) find that 47% of forecasts recorded in I/B/E/S are timely. While timeliness and accuracy are arguably the two most critical qualities of an analyst's forecast, there is a trade-off between them. To provide timely information to investors, analysts may opt to issue forecasts quickly but with less accuracy, by not waiting to consolidate more information (Cooper et al., 2001). Following this logic, we conjecture that analysts may also prioritize timeliness over accuracy when facing concurrent earnings announcements, potentially clustering forecasts for firms announcing earnings on the same day.

To test this hypothesis, we first investigate the timeliness of forecasts and the relationship between timeliness, concurrent earnings announcements, and forecast clustering. The results are shown in Figure 3. Panel A plots the cumulative distribution function (CDF) for the days between a forecast and the latest earnings announcement, up to 90 days. Consistent with the findings of Keskek et al. (2014), we find that approximately 42% of forecasts are issued within one day after the earnings announcement of the forecasted firm. After one week, the CDF up to 90 days becomes nearly linear, indicating that "untimely" forecasts are randomly distributed until the next earnings announcement. Panel B displays the distribution of clustered forecasts, double-sorted by the timeliness of the forecast and whether there is a concurrent earnings announcement for the firm. The blue bars represent forecasts that are clustered, while the orange bars represent forecasts that are not clustered. The x-axis indicates whether a forecast is for a firm with concurrent earnings announcements by other firms in the analyst's portfolio. The results show that, on average, forecasts made for firms with concurrent earnings announcements are more likely to be clustered, whereas forecasts for firms without concurrent earnings announcements are less likely to be clustered. Furthermore, when forecasts are timely, the difference in clustering probability between forecasts for firms with concurrent earnings announcements and those without becomes significantly more pronounced.

Figure 3 clearly shows that concurrent earnings announcement and timely forecast are crucial to the forecast clustering decision. We formalize and quantify this importance using the regression model specified in Section 2.3, with the explanatory variables here being $Timely_{i,j,t}$, $MultiEA_{i,j,t}$, and their interaction term. The results are reported in Table 4. Column 1 reports the simple regression on the two dummies and their interaction. Column

2 reports the results after controlling for fixed effects. Column 3 further controls for the confounding variables.

Across different specifications, the coefficients for the variables of interest, $Timely_{i,j,t}$, $MultiEA_{i,j,t}$, and their interaction term, remain persistent and significant at the 1% level. The coefficients for $Timely_{i,j,t}$ indicate that, for a firm without concurrent earnings announcements, a timely forecast is 23.5 to 25.5 percentage points less likely to be clustered compared to an untimely forecast, representing a 47.2% to 51.2% decrease relative to the unconditional probability of clustering, which is 49.8%. This result is logical, as issuing a timely forecast may require analysts to focus on the firm that just issued an earnings announcement, thereby reducing their effort to issue forecasts for other firms in their portfolio. The coefficient for $MultiEA_{i,j,t}$ indicates that among untimely forecasts, those for firms with concurrent earnings announcements are 11.0% to 35.9% more likely to be clustered. Consistent with Panel B of Figure 3, this difference in probability increases by approximately 36% for timely forecasts, as reflected by the coefficient of the interaction term. The sum of the coefficients for $Timely_{i,j,t}$ and the interaction term is positive, highlighting the trade-off between clustering (which is associated with inaccuracy) and timeliness. When there are no concurrent earnings announcements, an analyst tends to focus on issuing timely forecasts and clusters less. However, when concurrent earnings announcements occur, analysts prioritize timeliness over accuracy by issuing clustered but timely forecasts. The R-squared value in Column 1 shows that forecast timeliness and concurrent earnings announcements alone can explain 15.4% of the variation in forecast clustering at the forecast level. Thus, the need to issue timely forecasts following concurrent earnings announcements is a significant determinant of forecast clustering behavior.

3.3.2 Distraction of Other Portfolio Firms

We then investigate another potential driver of forecast clustering behavior: distraction caused by other firms in the analyst's portfolio. We conjecture that when one firm has important news, the analyst is more likely to cluster forecasts for other firms in their portfolio. This is because analysts face limited attention and may need to allocate more time and effort to processing the significant news of the focal firm, thereby leaving less time and effort to issue forecasts for other firms.

We construct three measures of distraction, as described in Section 2.2, and use the same regression model, with the variables of interest being $Distraction_{i,t-1}$ and $IS_{i,j,t-1}$. It is important to note that we also include the corresponding information shock measure, $IS_{i,j,t-1}$, for the focal firm to assess the "attractiveness" of the forecasted firm to the analyst. We expect that distraction from other portfolio firms will increase the probability of clustering; thus, the coefficient for $Distraction_{i,t-1}$ is anticipated to be positive. Conversely, an information shock for the focal firm should increase the attention the analyst pays to that firm, so we expect the coefficient for $IS_{i,j,t-1}$ to be negative. We use distraction measures from day $t-1$ to address potential endogeneity issues. The results remain qualitatively similar if we use distraction measures from day t.

The results are reported in Table 5. Columns 1 and 2 report the results using distraction proxied by fundamental news; Columns 3 and 4 report the results using abnormal trading volume; and Columns 5 and 6 report the results using absolute stock returns. Across all specifications and measures, the results are highly significant and consistent with our hypothesis. For instance, after controlling for high-dimensional fixed effects, one standard deviation increase in distraction is related to an increase in the probability of a forecast being clustered by 3.2% (absolute return) to 9.0% (trading volume) while having information shock decreases the probability of clustering by 6.6% (absolute return) to 12.3% (trading volume).

3.3.3 Industry Reports

The issuance of industry reports is another factor that mechanically causes forecast clustering. Brokerage firms are increasingly releasing these reports in response to new technologies, microeconomic conditions, and policies, which inherently affect multiple firms simultaneously (Drake et al., 2020). We classify forecasts as part of an industry or thematic report if they are issued at the exact same *second* as another forecast for a firm within the same Fama-French 48 industry by the same analyst. Using this method, we find that 33.3% of clustered forecasts are associated with industry reports, highlighting their prevalence and significance in today's market.

3.4 Strategic Forecast Clustering

Up to now, we have identified that "exogenous factors" such as concurrent earnings announcements, breaking news, and industry reports contribute to non-strategic forecast clustering. We classify clustered forecasts as related to non-strategic clustering if any of the following criteria are met: 1) the forecast is issued within one day after a concurrent earnings announcement; 2) on the day the forecast is issued, all three measures of distraction are above the median; or 3) the forecast is part of an industry report. Under this classification, 77.7% of the clustered forecasts are identified as non-strategic clustering.

We now focus on the remaining 22.3% of clustered forecasts. Why do analysts still cluster these forecasts when they have the discretion to avoid doing so? We conjecture that this behavior reflects a strategic effort allocation practice by analysts: they may prioritize forecasts that are crucial to their careers and reputations, while clustering the remaining forecasts with less effort. We investigate two types of important forecasts: those related to important firms and those involving important information. First, we examine whether analysts are less likely to cluster forecasts for firms that are important to their careers, as indicated by institutional ownership, market capitalization, or trading volume. Additionally, we explore whether forecasts containing important information are less likely to be clustered. Important information is identified by whether the forecast is accompanied by a recommendation revision.

3.4.1 Important Firms

First, we investigate whether forecasts for firms that are important to an analyst's career are less likely to be clustered. Previous research by Harford et al. (2019) and Jiao (2023) indicates that important firms in an analyst's portfolio receive more effort and result in a better information environment. The results are reported in Table 6.

Except for $TopVol$ in Column 2, the coefficients for the "important firm" dummies are negative and statistically significant at the 5% level. However, it is worth noting that the economic significance is relatively mild compared to the non-strategic clustering factors we have examined. Forecasts for important firms are 1.93% ($ImpFirmAll$) to 3.09% ($TopIO$) less likely to be clustered, compared to the unconditional probability of clustering of 18.1% in this subsample.

3.4.2 Important Information

As discussed in Section 2.2, we conjecture that forecasts accompanied by recommendation revisions contain more important information and may receive special treatment from analysts. Therefore, we investigate whether the variable *RecomRevision* and its components, *UpGrade* and *DownGrade*, effectively explain the likelihood of a forecast being clustered. The results are reported in Table 7.

Columns 1 and 2 focus on the results for all recommendation revisions. Column 1 shows that, consistent with our conjecture, the probability of a forecast being clustered decreases by 4.26% if it is accompanied by a recommendation revision. However, this coefficient becomes marginal and statistically insignificant once we control for fixed effects. This result suggests a potentially heterogeneous effect between upgrade and downgrade revisions. Consequently, Columns 3 and 4 report the results for upgrades and downgrades separately. We find that the effect is concentrated on upgrades: the probability of a forecast being clustered decreases by 4.2% if it is accompanied by an upgrade, but does not change if it is a downgrade.

This asymmetric impact between upgrades and downgrades could be explained by several factors, for instance, analysts' strong incentives to maintain good relationships with management to gain private information (Brown et al., 2015). Rees et al. (2017) found that analysts strategically time stock recommendations, disproportionately issuing more downgrade recommendations on weekends when market attention is lower. Similarly, analysts may cluster forecasts with downgrade recommendations to minimize market attention, while singling out upgrade recommendations to attract more attention. This additional asymmetric incentive could make the effect of upgrades different from downgrades.

3.5 Robustness Tests

Our results are robust across several robustness checks. First, as discussed in Section 2.3, we replace the linear probability model used in the main analysis with a probit model. The results are reported in Table 8. Panel A shows the results for non-strategic clustering, while

Panel B presents the results for strategic clustering. All findings are qualitatively consistent with our main analysis.

Second, given that our study is most pertinent to analysts' cognitive constraints, we specifically consider forecasts (partially) performed and released on the same day, which are directly subject to analysts' limited attention and decision fatigue (Hirshleifer et al., 2019; Jiao, 2023). Therefore, we redo the tests, restricting our sample to days when the analyst issues forecasts only between 9:00 a.m. and 11:00 p.m. (Jiao, 2023). The results are reported in Table 9. All results are qualitatively consistent with our main findings, although statistical significance is weaker. This weaker significance is partially due to the loss of half of the observations.

4 Conclusion

In this study, we investigated the phenomenon of forecast clustering among equity research analysts, wherein an analyst issues multiple forecasts on the same day. Despite the known negative impact of forecast clustering on the accuracy and informativeness of analysts' forecasts, we find that this practice has been increasing over the past two decades. We identified several key drivers behind this trend, including the rising workload of analysts, which lead to the increasing need for timely updates following concurrent earnings announcements, and higher probability of distractions from news about other firms in analysts portfolios. The increasing trend to issue industry reports in reaction to new economic status, technology, and policies also contributes to the clustering.

Our analysis also shows that forecast clustering is not random but rather a deliberate choice influenced by various factors. Notably, analysts are less likely to cluster forecasts for firms that are more important to their careers and those that contain significant news, indicating a strategic allocation of effort to maintain forecast quality where it matters most. This strategic behavior suggests that analysts are aware of the cognitive constraints they face and attempt to manage these limitations by prioritizing their efforts.

The implications of our findings are significant for both market participants and policymakers. For investors, understanding the determinants of forecast clustering can help in better interpreting the quality and reliability of analysts' forecasts. For firms and regulators, these insights underscore the importance of monitoring and potentially addressing the factors that contribute to forecast clustering, particularly as they relate to information asymmetry between institutional and retail investors. Future research could further explore the implications of forecast clustering on market efficiency and investor behavior, as well as potential measures to mitigate its adverse effects.

References

Amiram, D., Owens, E., and Rozenbaum, O. (2016). Do information releases increase or decrease information asymmetry? New evidence from analyst forecast announcements. *Journal of Accounting and Economics*, 62(1):121–138.

Ben-Rephael, A., Carlin, B., Da, Z., and Israelsen, R. (2023). All in a day's work: What do we learn from Analysts' Bloomberg Usage? *Working Paper*.

Birru, J., Gokkaya, S., Liu, X., and Stulz, R. (2022). Are Analyst Short-Term Trade Ideas Valuable? *The Journal of Finance*, 77(3):1829–1875.

Birru, J., Gokkaya, S., Liu, X., and Stulz, R. (2024). Are Analyst "Top Picks" Informative? *The Review of Financial Studies*, 37(5):1538–1583.

Bourveau, T., Garel, A., Joos, P., and Petit-Romec, A. (2022). When attention is away, analysts misplay: Distraction and analyst forecast performance. *Review of Accounting Studies*.

Bradley, D., Gokkaya, S., and Liu, X. (2017). Before an Analyst Becomes an Analyst: Does Industry Experience Matter? *The Journal of Finance*, 72(2):751–792.

Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2015). Inside the "Black Box" of Sell-Side Financial Analysts. *Journal of Accounting Research*, 53(1):1–47.

Chiu, P.-C., Lourie, B., Nekrasov, A., and Teoh, S. H. (2021). Cater to Thy Client: Analyst Responsiveness to Institutional Investor Attention. *Management Science*, 67(12):7455–7471.

Clement, M. B. and Tse, S. Y. (2003). Do Investors Respond to Analysts' Forecast Revisions as If Forecast Accuracy Is All That Matters? *The Accounting Review*, 78(1):227–249.

Cooper, R. A., Day, T. E., and Lewis, C. M. (2001). Following the leader: a study of individual analysts' earnings forecasts. *Journal of Financial Economics*, 61(3):383–416.

Drake, M., Joos, P., Pacelli, J., and Twedt, B. (2020). Analyst forecast bundling. *Management Science*, 66(9):4024–4046.

Driskill, M., Kirk, M. P., and Tucker, J. W. (2020). Concurrent Earnings Announcements and Analysts' Information Production. *The Accounting Review*, 95(1):165–189.

Gleason, C. A. and Lee, C. M. C. (2003). Analyst Forecast Revisions and Market Price Discovery. *The Accounting Review*, 78(1):193–225.

Groysberg, B. and Healy, P. M. (2020). *Wall Street Research: Past, Present, and Future*. Stanford University Press.

Guttman, I. (2010). The Timing of Analysts' Earnings Forecasts. *The Accounting Review*, 85(2):513–545.

Harford, J., Jiang, F., Wang, R., and Xie, F. (2019). Analyst Career Concerns, Effort Allocation, and Firms' Information Environment. *The Review of Financial Studies*, 32(6):2179–2224.

Hirshleifer, D., Levi, Y., Lourie, B., and Teoh, S. H. (2019). Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics*, 133(1):83–98.

Hoechle, D., Schaub, N., and Schmid, M. (2015). Time Stamp Errors and the Stock Price Reaction to Analyst Recommendation and Forecast Revisions.

Hong, H. and Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1):313–351.

Irvine, P., Lipson, M., and Puckett, A. (2007). Tipping. *The Review of Financial Studies*, 20(3):741–768.

Jiao, Y. (2023). Managing Decision Fatigue: Evidence from Analysts' Earnings Forecasts. *Journal of Accounting and Economics*, page 101615.

Keane, M. P. and Runkle, D. E. (1998). Are financial analysts' forecasts of corporate profits rational? *Journal of Political Economy*, 106(4):768–805.

Kecskés, A., Michaely, R., and Womack, K. L. (2017). Do Earnings Estimates Add Value to Sell-Side Analysts' Investment Recommendations? *Management Science*, 63(6):1855–1871.

Kempf, E., Manconi, A., and Spalt, O. (2017). Distracted Shareholders and Corporate Actions. *The Review of Financial Studies*, 30(5):1660–1695.

Keskek, S., Tse, S., and Tucker, J. W. (2014). Analyst information production and the timing of annual earnings forecasts. *Review of Accounting Studies*, 19(4):1504–1531.

Kothari, S., So, E., and Verdi, R. (2016). Analysts' Forecasts and Asset Pricing: A Survey. *Annual Review of Financial Economics*, 8(1):197–219.

Loh, R. K. and Stulz, R. M. (2011). When Are Analyst Recommendation Changes Influential? *The Review of Financial Studies*, 24(2):593–627.

Loh, R. K. and Stulz, R. M. (2018). Is Sell-Side Research More Valuable in Bad Times? *The Journal of Finance*, 73(3):959–1013.

Pisciotta, K. (2023). Analyst workload and information production: Evidence from IPO assignments. *Contemporary Accounting Research*, 40(3):1605–1640.

Ramnath, S., Rock, S., and Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1):34–75.

Rees, L., Sharp, N. Y., and Wong, P. A. (2017). Working on the weekend: Do analysts strategically time the release of their recommendation revisions? *Journal of Corporate Finance*, 45:104–121.

Shroff, P. K., Venkataraman, R., and Xin, B. (2014). Timeliness of Analysts' Forecasts: The Information Content of Delayed Forecasts. *Contemporary Accounting Research*, 31(1):202–229.

Zhang, Y. (2008). Analyst responsiveness and the post-earnings-announcement drift. *Journal of Accounting and Economics*, 46(1):201–215.

Figure 1: **Fraction of Clustered Forecasts by Year**

This plot presents the fraction of clustered forecasts each year. The analysis is from 2002 to 2022.

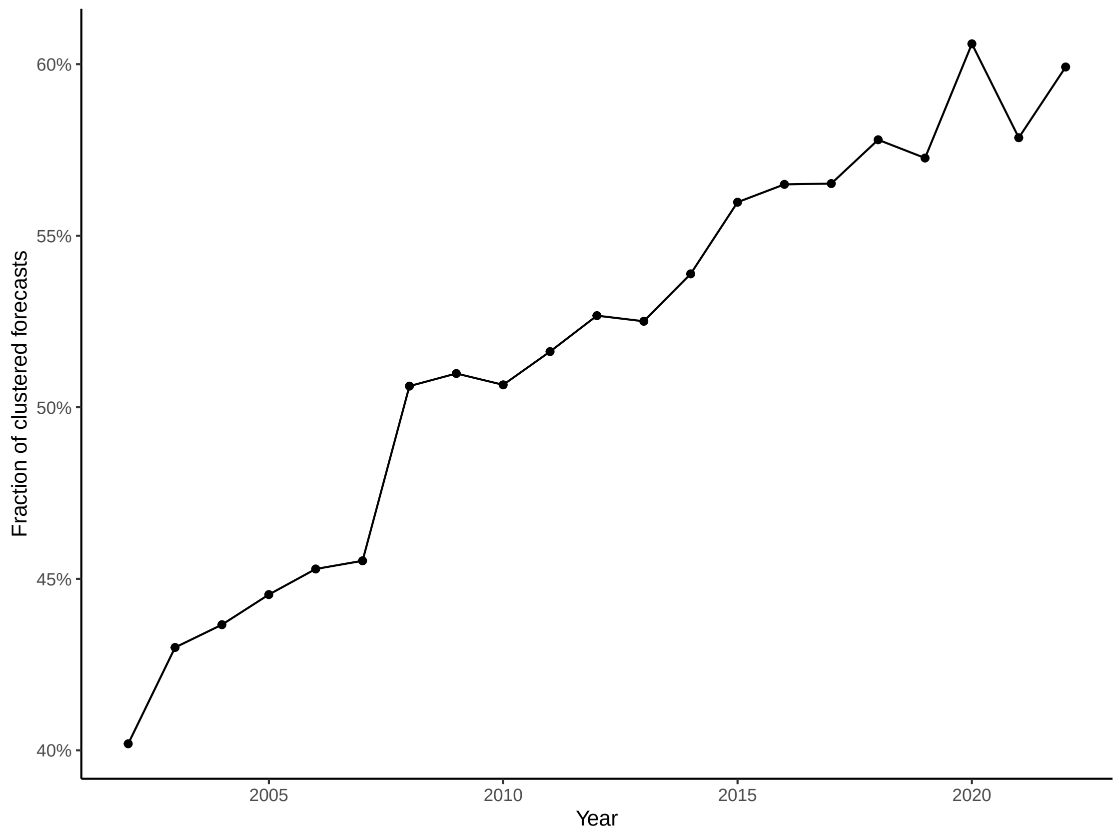


Figure 2: **Analysts' Workload by Year**
This plot presents the average number of total one-year-ahead EPS forecasts an analyst makes in a year (Panel A), and its two components: the average number of firms an analyst covers (Panel B), and the average number of forecasts an analyst issues for each firm she covers (Panel C).

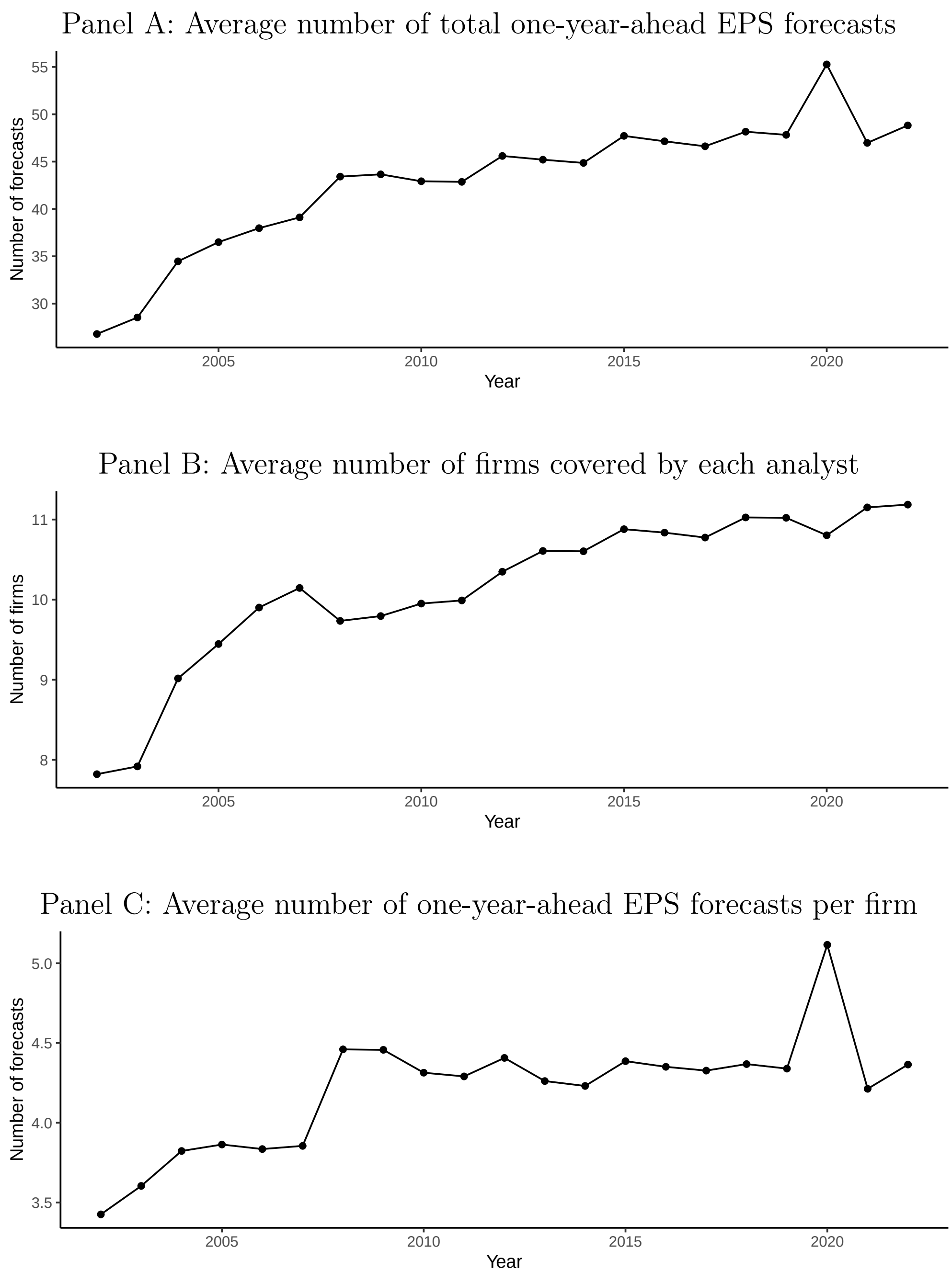
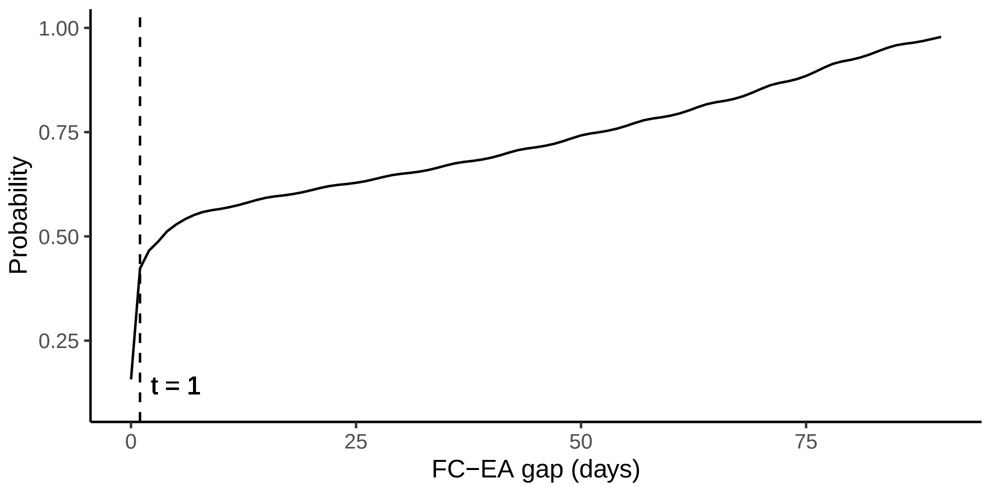


Figure 3: **Analysts Forecast Timeliness and Concurrent Earnings Announcements**
This plot presents the timeliness of forecasts and the relationship between timeliness, concurrent earnings announcements, and forecast clustering. Panel A plots the cumulative distribution function (CDF) for the days between a forecast and the most recent earnings announcement up to 90 days prior. Panel B plots the distribution of clustered forecasts, double sorted by the timeliness of the forecast and the presence of concurrent earnings announcements for the firm.

Panel A: CDF for the forecast-EA gap days



Panel B: Number of clustered forecasts, double sorted

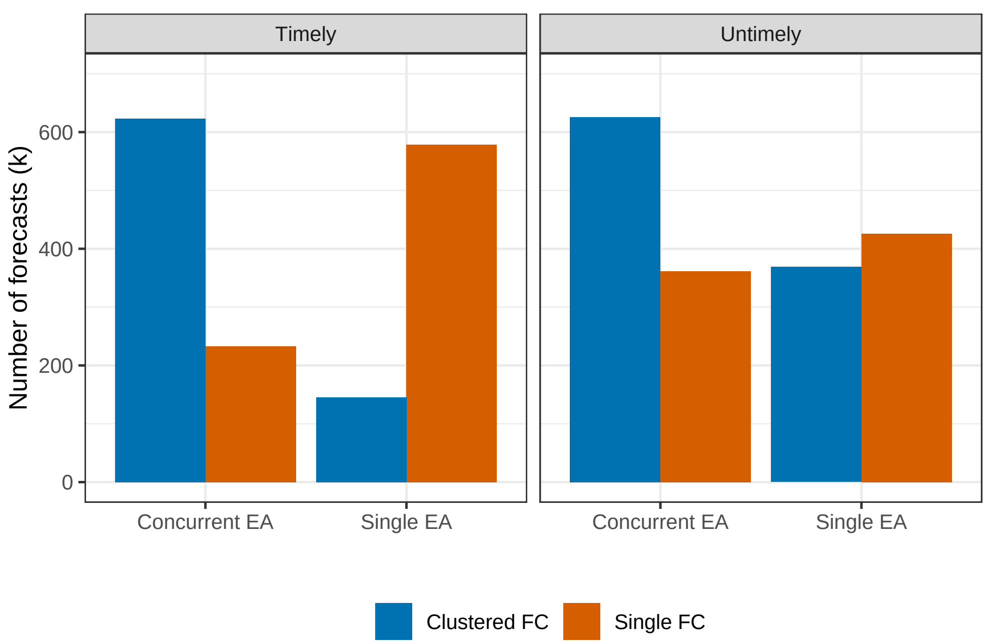


Table 1: **Summary Statistics**
This table reports the summary statistics of the variables from the main sample based on the I/B/E/S data from 2002 to 2022. See Appendix for detailed variable definitions.

Name	Mean	Median	p05	p95	Std. Dev.
MultiForecast	0.498	0.000	0.000	1.000	0.500
MultiEA	0.517	1.000	0.000	1.000	0.500
Timely	0.440	0.000	0.000	1.000	0.496
ISNews (t-1)	0.306	0.000	0.000	1.000	0.461
DistractionNews (t-1)	0.126	0.091	0.000	0.389	0.144
ISAbnVol(t-1)	0.111	0.000	0.000	1.000	0.314
DistractionAbnVol (t-1)	0.040	0.000	0.000	0.167	0.076
ISAbsRet (t-1)	0.121	0.000	0.000	1.000	0.326
DistractionAbsRet (t-1)	0.072	0.000	0.000	0.286	0.116
TopSize	0.234	0.000	0.000	1.000	0.424
TopVol	0.230	0.000	0.000	1.000	0.421
TopIO	0.232	0.000	0.000	1.000	0.422
ImpFirmAny	0.365	0.000	0.000	1.000	0.481
ImpFirmAll	0.115	0.000	0.000	1.000	0.319
RecomRevision	0.039	0.000	0.000	0.000	0.194
UpGrade	0.018	0.000	0.000	0.000	0.133
DownGrade	0.021	0.000	0.000	0.000	0.145
FirmExperience	0.500	0.500	0.000	1.000	0.384
GeneralExperience	0.669	0.824	0.000	1.000	0.367
BrokerSize	0.352	0.268	0.000	1.000	0.318
Effort	0.588	0.600	0.000	1.000	0.302
FirmsFollowed	0.435	0.393	0.000	1.000	0.299
ForecastAge	0.549	0.536	0.026	1.000	0.307
Numest	2.683	2.773	1.386	3.664	0.709

Table 2: **Correlation between Forecast Clustering and Analysts' Workload**
This table presents the correlation between forecast clustering and analysts' workload. The dependent variable is the fraction of clustered forecasts in a given year. Column 1 reports the coefficient for the average number of total one-year-ahead EPS forecasts an analyst makes annually. Column 2 includes coefficients for the average number of firms an analyst covers and the average number of forecasts an analyst issues per firm in a year. This analysis spans the years 2002 to 2022.

Dependent Variable:	ClusterFraction	
Model:	(1)	(2)
Variables		
ReportNumTtl	0.0083***	
	(0.0006)	
FirmsFollowed		0.0380***
		(0.0072)
ReportNum		0.0672***
		(0.0191)
Constant	0.1602***	-0.1501**
	(0.0273)	(0.0571)
Fit statistics		
Observations	21	21
R^2	0.90221	0.88809
Adjusted R^2	0.89706	0.87565

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: **Forecast Clustering explained by Fixed Effect and Analyst Characteristics**
This table presents the results from panel regressions of quarterly clustering on various fixed effects and analyst characteristics. We construct two measures to capture an analyst's clustering behavior each quarter. To measure the extensive margin, we use a dummy variable, $AnyCluster$, which equals 1 if an analyst issues more than one forecast on any day during the quarter and 0 otherwise. For the intensive margin, we create a continuous variable, $MaxClusterNum$, representing the logarithm of the maximum number of forecasts an analyst issues on days when clustering occurs within the quarter. Panel A reports the explained variation of the two measures by time, analyst, and brokerage firm using fixed-effect regressions. Panel B regresses the clustering measures on various analyst characteristics.

Panel A: Quarterly Clustering Explained by Fixed Effects

	Time	Analyst	Broker	A+B	T+A+B
Any Cluster					
R^2	0.006	0.503	0.182	0.516	0.525
Observations	209,842	209,842	209,842	209,842	209,842
Max Cluster Number					
R^2	0.026	0.499	0.124	0.513	0.531
Observations	127,742	127,742	127,742	127,742	127,742

Panel B: Quarterly Clustering and Analyst Characteristics

Dependent Variables:	AnyCluster			MaxClusterNum		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
FirmsFollowed	0.0048***	0.0041***	0.0009**	0.0020***	0.0018**	0.0025***
	(0.0006)	(0.0004)	(0.0004)	(0.0008)	(0.0008)	(0.0007)
ReportNum	0.2963***	0.3014***	0.2976***	0.5168***	0.5213***	0.4508***
	(0.0038)	(0.0026)	(0.0029)	(0.0122)	(0.0120)	(0.0113)
IndustryCovered	-0.0030***	-0.0023**	0.0032**	-0.0484***	-0.0481***	-0.0245***
	(0.0011)	(0.0010)	(0.0013)	(0.0029)	(0.0029)	(0.0022)
BigBroker	-0.0283***	-0.0292***	-0.0175***	0.0180	0.0163	-0.0073
	(0.0054)	(0.0051)	(0.0065)	(0.0157)	(0.0142)	(0.0112)
GeneralExperience	-0.0003	-0.0013***	0.0076	-0.0013	-0.0102***	-0.0146
	(0.0005)	(0.0005)	(0.0301)	(0.0012)	(0.0012)	(0.0327)
Constant	0.0185***			-0.0951***		
	(0.0060)			(0.0214)		
Fixed-effects						
YrQtr		Yes	Yes		Yes	Yes
Analyst			Yes			Yes
Fit statistics						
R^2	0.5538	0.5576	0.6548	0.3647	0.3796	0.6188
Observations	209,842	209,842	209,842	127,742	127,742	127,742

Clustered (Analyst & YrQtr) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: **Forecast Clustering and Timely Forecasts after Concurrent Earnings Announcements**

This table presents results from the following regression: $MultiForecast_{i,j,t} = \beta_1 Timely_{i,j,t} + \beta_2 MultiEA_{i,j,t} + \beta_3 Timely_{i,j,t} \times MultiEA_{i,j,t} + \beta_4' \mathbf{X_{i,j,t}} + \delta_j + \delta_{i,q} + \delta_t + \epsilon_{i,j,t}$. $MultiForecast_{i,j,t}$ is a dummy variable indicating whether analyst i's forecast for firm j on day t is clustered. $Timely_{i,j,t}$ is a dummy variable indicating whether the forecast is issued within one day after the most recent earnings announcement. $MultiEA_{i,j,t}$ indicates whether on the most recent earnings announcement day of firm j there are concurrent earnings announcements of other portfolio firms of analyst i. $\mathbf{X_{i,j,t}}$ are control variables including the number of companies covered, brokerage house size, firm-specific experience, age of the forecast, forecast frequency, and the number of analysts covering the firm. δ_j, $\delta_{i,q}$ and δ_t are stock, analyst $\times$ year-quarter, and date fixed effect.

Dependent Variable:	MultiForecast		
Model:	(1)	(2)	(3)
Variables			
Timely × MultiEA	0.3650***	0.3674***	0.3713***
	(0.0046)	(0.0032)	(0.0033)
Timely	-0.2554***	-0.2348***	-0.2403***
	(0.0039)	(0.0026)	(0.0027)
MultiEA	0.1785***	0.0571***	0.0550***
	(0.0037)	(0.0015)	(0.0016)
Constant	0.4363***		
	(0.0041)		
Controls			Yes
Fixed-effects			
Firm		Yes	Yes
Analyst-YrQtr		Yes	Yes
ForecastDay		Yes	Yes
Fit statistics			
R^2	0.1533	0.3819	0.3830
Observations	2,470,218	2,470,218	2,230,250

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: **Forecast Clustering and Distraction by Other Portfolio Firms**

This table presents results from the following regression: $MultiForecast_{i,j,t} = \beta_1 Distraction_{i,t-1} + \beta_2 IS_{i,j,t-1} + \beta_3' \mathbf{X_{i,j,t}} + \delta_j + \delta_{i,q} + \delta_t + \epsilon_{i,j,t}$. $MultiForecast_{i,j,t}$ is a dummy variable indicating whether analyst i's forecast for firm j on day t is clustered. $Distraction_{i,t-1}$ proxies for the distraction an analyst i faces on day $t-1$, constructed using the following equation: $Distraction_{i,t} = \sum_{j \notin FC_{i,t}} \omega_{i,j,t} \times IS_{j,t}$. $FC_{i,t}$ is the set of all firms analyst i forecasted on day t. $\omega_{i,j,t}$ is the weight of each portfolio firm. $IS_{j,t}$ stands for "information shock" of firm j on day t , which is equal to 1 according to one of the following three measures: 1) Fundamental news: the firm has fundamental news on day t recorded in RavenPack; 2) Abnormal trading: the firm is in the top decile of daily abnormal trading volume of CRSP's cross-sectional ranking; and 3) Absolute return: the firm is in the top decile of daily absolute return of CRSP's cross-sectional ranking. $\mathbf{X_{i,j,t}}$ are control variables described in Table 4. δ_j, $\delta_{i,q}$ and δ_t are stock, analyst $\times$ year-quarter, and date fixed effect.

Dependent Variable:	MultiForecast					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
DistractionNews (t-1)	0.1684***	0.3107***				
	(0.0091)	(0.0076)				
ISNews (t-1)	-0.0728***	-0.0510***				
	(0.0019)	(0.0015)				
DistractionAbnVol (t-1)			0.1768***	0.3931***		
			(0.0112)	(0.0100)		
ISAbnVol(t-1)			-0.0744***	-0.0573***		
			(0.0021)	(0.0016)		
DistractionAbsRet (t-1)					0.1847***	0.1361***
					(0.0101)	(0.0071)
ISAbsRet (t-1)					-0.0421***	-0.0307***
					(0.0017)	(0.0013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm		Yes		Yes		Yes
Analyst-YrQtr		Yes		Yes		Yes
ForecastDay		Yes		Yes		Yes
Fit statistics						
R^2	0.1713	0.3859	0.1697	0.3848	0.1695	0.3835
Observations	2,229,712	2,229,712	2,229,712	2,229,712	2,229,712	2,229,712

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: **Strategic Inter-day Job Allocation: Important Firms**
This table presents results from the following regression: $MultiForecast_{i,j,t} = \beta_1 ImportantFirm_{i,j,t} + \beta_2' \mathbf{X_{i,j,t}} + \delta_j + \delta_{i,q} + \delta_t + \epsilon_{i,j,t}$. $MultiForecast_{i,j,t}$ is a dummy variable indicating whether analyst i's forecast for firm j on day t is clustered. $ImportantFirm_{i,j,t}$ is one of the five dummy variables indicating whether firm j is important among the portfolio firms of an analyst i on day t. These variables include $TopSize$, $TopVol$, and $TopIO$ which indicates whether firm j is in the top quartile of the portfolio based on market capitalization, trading volume, and institutional ownership, respectively, as of the latest quarter end. The other two consolidated variables, $ImpFirmAny$ and $ImpFirmAll$, are equal to one if any or all of the three criteria are satisfied. $\mathbf{X_{i,j,t}}$ are control variables described in Table 4. δ_j, $\delta_{i,q}$ and δ_t are stock, analyst $\times$ year-quarter, and date fixed effect.

Dependent Variable:	MultiForecast				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
TopSize	-0.0039***				
	(0.0012)				
TopVol		-0.0015			
		(0.0012)			
TopIO			-0.0056***		
			(0.0011)		
ImpFirmDumAny				-0.0039***	
				(0.0011)	
ImpAll					-0.0035**
					(0.0015)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Firm	Yes	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes	Yes
Fit statistics					
R^2	0.3150	0.3149	0.3163	0.3158	0.3150
Observations	1,313,877	1,314,533	1,287,975	1,295,004	1,312,630

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: **Strategic Inter-day Job Allocation: Important Forecasts**

This table presents results from the following regression: $MultiForecast_{i,j,t} = \beta_1 ImportantForecast_{i,j,t} + \beta_2' \mathbf{X_{i,j,t}} + \delta_j + \delta_{i,q} + \delta_t + \epsilon_{i,j,t}$. $MultiForecast_{i,j,t}$ is a dummy variable indicating whether analyst i's forecast for firm j on day t is clustered. $ImportantForecast_{i,j,t}$ is a dummy variable indicating whether a the forecast contains important information, proxied by the presence of a recommendation revision. Column 3 and 4 further classify $ImportantForecast_{i,j,t}$ into *UpGrade* and *DownGrade* to examine the asymmetric impact of different types of recommendation revisions. $\mathbf{X_{i,j,t}}$ are control variables described in Table 4. δ_j, $\delta_{i,q}$ and δ_t are stock, analyst $\times$ year-quarter, and date fixed effect.

Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
Variables				
RecomRevision	-0.0077***	-0.0021		
	(0.0027)	(0.0019)		
UpGrade			-0.0105***	-0.0076***
			(0.0032)	(0.0026)
DownGrade			-0.0051	0.0030
			(0.0032)	(0.0025)
Constant	0.1546***		0.1546***	
	(0.0071)		(0.0071)	
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm		Yes		Yes
Analyst-YrQtr		Yes		Yes
ForecastDay		Yes		Yes
Fit statistics				
R^2	0.0080	0.3146	0.0080	0.3147
Observations	1,347,233	1,347,233	1,347,233	1,347,233

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: **Robustness Test: Probit Model**
This table presents the main results using the probit model. Panel A presents the results for non-strategic clustering. Panel B presents the results for strategic clustering.

Panel A: Non-strategic Clustering				
Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
Variables				
Timely	-0.8571***			
	(0.0092)			
MultiEA	0.1529***			
	(0.0052)			
Timely × MultiEA	1.2423***			
	(0.0122)			
DistractionNews (t-1)		1.7190***		
		(0.0399)		
ISNews (t-1)		-0.2818***		
		(0.0053)		
DistractionAbnVol (t-1)			2.0705***	
			(0.0502)	
ISAbnVol(t-1)			-0.2846***	
			(0.0060)	
DistractionAbsRet (t-1)				0.6631***
				(0.0320)
ISAbsRet (t-1)				-0.1350***
				(0.0049)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes
Fit statistics				
Pseudo R^2	0.2632	0.2054	0.2015	0.1985
Observations	2,005,770	2,018,342	2,018,342	2,018,342

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Strategic Clustering						
Dependent Variable:	MultiForecast					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
TopSize	-0.0200***					
	(0.0068)					
TopVol		-0.0040				
		(0.0063)				
TopIO			-0.0296***			
			(0.0064)			
ImpFirmDumAny				-0.0179***		
				(0.0062)		
ImpAll					-0.0162*	
					(0.0085)	
UpGrade						-0.0346**
						(0.0146)
DownGrade						0.0211
						(0.0140)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Pseudo R^2	0.1670	0.1669	0.1677	0.1675	0.1670	0.1662
Observations	758,577	758,996	742,817	747,386	757,828	778,959

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: **Robustness Test: Working Hours Samples**
This table presents the results after restricting our samples to days when the analyst issues forecasts only between 9:00 a.m. and 11:00 p.m (Jiao, 2023). Panel A presents the results for non-strategic clustering. Panel B presents the results for strategic clustering.

Panel A: Non-strategic Clustering				
Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
Variables				
Timely	-0.2160***			
	(0.0031)			
MultiEA	0.0437***			
	(0.0018)			
Timely × MultiEA	0.3312***			
	(0.0045)			
DistractionNews (t-1)		0.2945***		
		(0.0104)		
ISNews (t-1)		-0.0550***		
		(0.0017)		
DistractionAbnVol (t-1)			0.3320***	
			(0.0145)	
ISAbnVol(t-1)			-0.0518***	
			(0.0023)	
DistractionAbsRet (t-1)				0.1029***
				(0.0101)
ISAbsRet (t-1)				-0.0213***
				(0.0020)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.4726	0.4297	0.4283	0.4275
Pseudo R^2	0.4472	0.3924	0.3908	0.3898
Observations	1,007,582	1,014,750	1,014,750	1,014,750

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Strategic Clustering						
Dependent Variable:	MultiForecast					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
TopSize	-0.0028*					
	(0.0016)					
TopVol		0.0002				
		(0.0015)				
TopIO			-0.0033**			
			(0.0015)			
ImpFirmDumAny				-0.0028*		
				(0.0015)		
ImpAll					0.0004	
					(0.0020)	
UpGrade						-0.0180***
						(0.0039)
DownGrade						-0.0023
						(0.0037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
R^2	0.4242	0.4241	0.4260	0.4253	0.4242	0.4242
Pseudo R^2	0.6749	0.6746	0.6772	0.6761	0.6746	0.6717
Observations	671,907	672,217	659,117	662,530	671,306	689,030

Clustered (Analyst & ForecastDay) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix A Additional Tables

Table A1: **Variable Definition**

Variable	**Definition**
Variables of Interests	
MultiForecast	A dummy variable equal to 1 if the forecast is issued on a day when the analyst releases more than one forecast and 0 otherwise.
Timely	A dummy variable equal to 1 if the forecast is issued on the day of or the day after the latest earnings announcement of the forecasted firm and 0 otherwise.
MultiEA	A dummy variable equal to 1 if at least one other firm in the analyst's portfolio announces earnings on the same day and 0 otherwise.
DistractionNews	A weighted measure of $ISNews$ for all firms in analyst i's portfolio not forecasted on day t.
ISNews	A dummy variable equal to 1 if firm j has fundamental news recorded in RavenPack on day t and 0 otherwise.
DistractionAbnVol	A weighted measure of $ISAbnVol$ for all firms in analyst i's portfolio not forecasted on day t.

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Definition**
ISAbnVol	A dummy variable equal to 1 if stock j is in the top decile of abnormal trading volume of CRSP's cross-sectional ranking on day t and 0 otherwise.
DistractionAbsRet	A weighted measure of $ISAbsRet$ for all firms in analyst i's portfolio not forecasted on day t.
ISAbsRet	A dummy variable equal to 1 if stock j is in the top decile of absolute return of CRSP's cross-sectional ranking on day t and 0 otherwise.
TopSize	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of Size at the last quarter-end and 0 otherwise.
TopVol	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of Trading Volume at the last quarter-end and 0 otherwise.
TopIO	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of active institutional ownership at the last quarter-end and 0 otherwise. Active institutional ownership is the percentage of shares owned by transient institutional investors.
ImpFirmAny	A dummy variable equal to 1 if TopSize, TopVol, *or* TopIO is equal to 1.

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Definition**
ImpFirmAll	A dummy variable equal to 1 if TopSize, TopVol, *and* TopIO are equal to 1.
RecomRevision	A dummy variable equal to 1 if the forecast is accompanied by a recommendation issued on the same day by the same analyst for the same firm and the recommendation is an upgrade or downgrade compared to the previous one, and 0 otherwise.
UpGrade	A dummy variable equal to 1 if the forecast is accompanied by a recommendation issued on the same day by the same analyst for the same firm and the recommendation is an upgrade compared to the previous one, and 0 otherwise.
DownGrade	A dummy variable equal to 1 if the forecast is accompanied by a recommendation issued on the same day by the same analyst for the same firm and the recommendation is a downgrade compared to the previous one, and 0 otherwise.
Control Variables	

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Definition**
FirmExperience	The number of years in analyst i's forecast history for firm j minus the minimum number of years of forecast history for firm j for analysts who follow firm j in year t, and this difference is then scaled by the range of forecast history for firm j for analysts who follow firm j in year t.
GeneralExperience	The number of years in analyst i's forecast history minus the minimum number of years of forecast history for analysts who follow firm j in year t, and this difference is then scaled by the range of forecast history for analysts who follow firm j in year t.
BrokerSize	The number of analysts employed by the brokerage house that employs analyst i following firm j in year t minus the minimum number of analysts employed by brokerage houses for analysts who follow firm j in year t, and this difference is then scaled by the range of brokerage house sizes for analysts who follow firm j in year t.

Continued on next page

Table A1 – *Continued from previous page*

Variable	**Definition**
Effort	The number of forecasts issued by analyst i who follow firm j in year t minus the minimum number of forecasts issued by analysts who follow firm j in year t, and this difference is then scaled by the range of numbers of forecasts issued by analysts who follow firm j in year t.
FirmsFollowed	The number of firms followed by analyst i following firm j in year t minus the minimum number of firms followed by analysts who follow firm j in year t, and this difference is then scaled by the range of numbers of firms followed by analysts who follow firm j in year t.
ForecastAge	The number of days from analyst i's forecast date in year t to the date of the earnings announcement minus the minimum number of days from the forecast date to the date of the earnings announcement among analysts who follow firm j in year t, and this difference is then scaled by the range of days from the forecast date to the date of the earnings announcement for analysts who follow firm j in year t.
Numest	The log value of the number of analysts who cover firm j at time t.