Why (How) Do Analysts Make Multiple Forecasts in a Day? *

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Abstract

Analysts increasingly issue earnings forecasts for multiple firms on the same day ("forecast clustering"), accounting for 57% of one-year-ahead EPS forecasts in 2023. Because clustering is associated with lower forecast accuracy, we examine why clustering occurs and when analysts avoid it. Clustering is more prevalent when workload creates scheduling congestion, including concurrent earnings announcements, elevated news activity at other portfolio firms, and industry-wide reports. Clustering is less common for career-relevant firms and for forecasts accompanied by recommendation revisions, consistent with strategic effort allocation under capacity constraints. Firms persistently exposed to clustered forecasts exhibit wider bid–ask spreads and higher illiquidity.

JEL Classification:

Keywords: Forecast clustering, Sell-side equity analyst, Cognitive constraints, Concurrent earnings announcements, Strategic effort allocation, Information asymmetry

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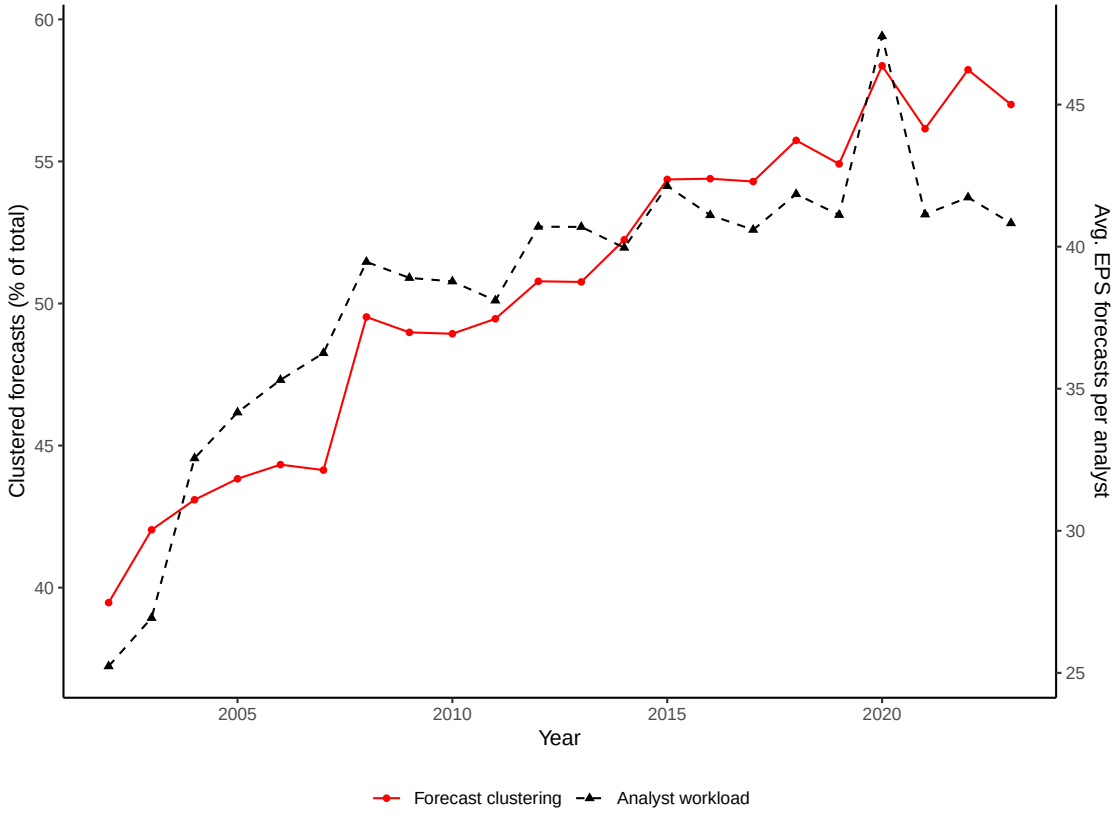
1 Introduction

We document a largely overlooked phenomenon that sell-side equity research analysts increasingly issue earnings forecasts for multiple firms on the same day, a behavior we refer to as "forecast clustering." As shown in Figure 1, the share of one-year-ahead EPS forecasts issued on days when the same analyst also issues forecasts for at least one other firm rises from 39.5% in 2002 to 57% in 2023. This trend matters because existing evidence suggests that clustering is associated with lower forecast quality: Hirshleifer et al. (2019) show that, due to decision fatigue, an analyst's accuracy declines and reliance on heuristics increases with the number of same-day forecasts, and Drake et al. (2020) find that even the first forecast on a clustered day is less accurate, less bold, and less informative.

Analysts also appear to recognize these costs. Jiao (2023) shows that analysts mitigate within-day quality deterioration by prioritizing forecasts for reputation- and career-critical firms earlier in the day. The rise of clustering therefore poses a puzzle: why do analysts increasingly cluster their earnings forecasts, knowing the potential quality costs?[1] We study this question because understanding the drivers of clustering, and how analysts manage its costs, is important for assessing the implications of clustered forecasting for firms' information environments.

[1]It is unlikely that clustering is purely unavoidable due to sheer output volume. An ordinary analyst issues one major new report and 12 company-specific notes per month (Groysberg and Healy, 2020), and in our I/B/E/S sample the average analyst issues only 38 one-year-ahead EPS forecasts per year.

Figure 1: **Trends in Forecast Clustering and Analyst Workload (2002–2023)**
This figure plots annual time trends in forecast clustering and analyst workload from 2002 to 2023. The red solid line with circular markers (left y-axis) shows the fraction of clustered one-year-ahead EPS forecasts each year. The black dashed line with triangular markers (right y-axis) shows the average number of one-year-ahead EPS forecasts issued per analyst.



We address the puzzle in three steps. First, we examine whether the rise in clustering is related to changes in analyst workload after controlling for persistent analyst work habits and brokerage practices. Second, we test whether analysts respond strategically to cognitive constraints by clustering less career-relevant firms' forecasts and by avoiding clustering when forecasts are likely to be more informative. Third, we examine whether firms that are more exposed to clustered forecasting have poorer market-based information outcomes.

To motivate the workload channel, we begin by describing long-run trends in analysts' forecasting activity. Figure 1 shows that the average number of one-year-ahead EPS forecasts issued per analyst increases by 64%, from 25 in 2002 to 41 in 2023, closely tracking the

increase in forecast clustering (time-series correlation = 0.90). The rise in forecasting activity reflects both broader coverage and more frequent updating. The average number of firms covered increases from 7.2 to 9.7, and the number of one-year-ahead forecasts per covered firm increases from 3.5 to 4.2. Workload growth is also reflected in greater timeliness: the share of forecasts issued within one day of an earnings announcement rises from 40% to 48.6%.[2]

Motivated by these macro-level patterns, we next examine clustering at the analyst-quarter level. We distinguish between the extensive margin, whether an analyst clusters any forecasts, and the intensive margin, the maximum number of forecasts the analyst issues on a single day. Analysts who cover more firms and issue more forecasts per firm are more likely to cluster. This relation remains when we include analyst fixed effects, consistent with within-analyst increases in workload predicting greater clustering. At the same time, baseline clustering propensities vary substantially across analysts and brokerages, suggesting an important role for persistent work habits and brokerage practices.

At the forecast level, we identify three workload-driven channels that reduce inter-day scheduling flexibility and increase clustering. First, as analysts cover more firms, they are more likely to face *concurrent earnings announcements* within their coverage portfolios (Driskill et al., 2020). Because forecast timeliness around earnings announcements has increased over time, analysts are more likely to respond promptly to multiple same-day announcers, mechanically bunching forecast issuance. Consistent with this mechanism, forecasts for firms whose most recent earnings announcement coincides with an earnings announcement at another firm covered by the same analyst are 21.4 percentage points more likely to be clustered, and this single indicator explains 11.0% of the variation in clustering. Second, larger coverage portfolios increase the frequency of *attention shocks* arising from major news at other covered firms. We show that such distractions increase the probability

[2]Report counts are an imperfect proxy for workload because technology can improve efficiency. At the same time, analysts' client-service and compliance responsibilities have expanded, suggesting that overall workload has likely increased.

that an analyst clusters the focal-firm forecast, whereas focal-firm information shocks attract attention and reduce clustering. Third, clustering increasingly reflects the growth of *industry/thematic reports* that combine updates across multiple firms (Drake et al., 2020). We classify a forecast as part of an industry/thematic report if it is time-stamped at the exact same *second* as another forecast by the same analyst for a firm in the same Fama–French 48 industry. The share of such forecasts rises from 8.9% in 2002 to 17.7% in 2023 and accounts for 16.8% of clustered forecasts on average, underscoring their growing prevalence.

We then assess whether analysts strategically allocate effort by clustering forecasts for less important firms. After controlling for workload-related and scheduling-pressure factors, analysts are 0.60% to 1.38% less likely to cluster forecasts for firms that are more career-relevant. We measure career relevance using the firm's relative ranking within the analyst's portfolio based on size, trading volume, and institutional ownership. Analysts are also less likely to cluster forecasts that are likely to convey more information, proxied by whether the forecast is accompanied by a recommendation revision. Forecasts accompanied by a recommendation revision are 2.92% less likely to be clustered, and the effect is concentrated among upgrades. This asymmetry suggests that additional incentives, such as managing relationships with company management by timing positive versus negative news, may also shape clustering decisions.

Finally, we examine whether clustering is associated with a broader weakening of covered firms' information environments. Using firm-year variation in exposure to clustering, measured as the fraction of clustered forecasts, we document that higher clustering is associated with poorer market-based information outcomes. Firms in the top quartile of clustering have bid–ask spreads about 3% higher and Amihud illiquidity about 18% higher relative to the sample means, consistent with greater information asymmetry and lower market liquidity. This relation is strongest among firms with relatively low institutional ownership, consistent with clustering being more consequential when the investor base is more retail and relies more on publicly disseminated analyst research, rather than on private channels such as

direct access to analysts and management.

Our paper contributes to several strands of literature. First, we contribute to research on the determinants of analyst forecasting behavior. Sell-side equity analysts are key information intermediaries (Birru et al., 2022, 2024; Keane and Runkle, 1998; Kothari et al., 2016; Loh and Stulz, 2018), and a large literature studies the forces shaping their forecasts.[3] We provide novel evidence on the increasingly common practice of forecast clustering, a behavior shown to impair forecast accuracy through cognitive constraints (Hirshleifer et al., 2019; Jiao, 2023). We identify the primary drivers of clustering, examine how analysts respond strategically to its costs, and assess its implications for the information environments of covered firms.

Second, we contribute to the literature on analysts' strategic effort allocation. Analysts are sophisticated professionals who prioritize across portfolio firms based on career incentives. Hong and Kubik (2003) and Harford et al. (2019) show that analysts issue more accurate forecasts for career-important firms, and Chiu et al. (2021) find greater effort for firms with high abnormal institutional distributions. We extend this line of research by showing that analysts manage time and attention constraints by clustering forecasts disproportionately for less important firms.

Third, we contribute to the literature on firms' information environments by linking analysts' forecast-production frictions to firm-level market liquidity and information asymmetry. Our evidence suggests that clustering is concentrated in settings with higher baseline information frictions (e.g., smaller and less liquid firms and firms with low institutional ownership) and that its association with liquidity is most pronounced when the investor base is more retail-oriented and therefore more dependent on public analyst outputs. More broadly, the findings imply that analyst capacity constraints can propagate into market-level outcomes and may widen disparities in information quality across firms and investor types.

Lastly, our finding that concurrent earnings announcements within an analyst's coverage

[3]Early work emphasizes errors and biases stemming from conflicts of interest and psychology; see Kothari et al. (2016) and Ramnath et al. (2008) for reviews.

portfolio are a primary driver of clustering connects to the literature on the causes and effects of concurrent announcements. Such concurrence has become increasingly common and has been linked to investor underreaction (Hirshleifer et al., 2009) and less timely earnings forecasts (Driskill et al., 2020). We show that even when analysts respond promptly, concurrent announcements mechanically induce clustered forecasting, which in turn reduces the quality of each forecast. This result identifies an additional channel through which concurrent earnings announcements can reduce market informativeness and suggests scope for strategic timing by firms seeking to release bad news alongside others' announcements (deHaan et al., 2015).

The remainder of the paper is organized as follows. Section 2 describes the data and empirical methodology. Section 3 examines the relation between analyst workload and forecast clustering. Section 4 studies three channels through which workload increases clustering through mechanical scheduling congestion. Section 5 investigates whether analysts strategically adjust clustering in response to cognitive constraints. Section 6 assesses whether forecast clustering is associated with a deterioration in firms' information environments. Section 7 provides additional evidence on heterogeneity in clustering across analysts and brokerages and reports robustness tests. Section 8 concludes.

2 Data and Methodology

2.1 Data Sources

We obtain analysts' earnings per share (EPS) forecasts from the Institutional Brokers' Estimate System (I/B/E/S) for 2002–2023. We start in 2002 because it is the first year in which the I/B/E/S forecast announcement date is verified (Hoechle et al., 2015). Following prior work (e.g., Gleason and Lee, 2003; Hirshleifer et al., 2019; Jiao, 2023), we focus on one-year-ahead earnings forecasts, which are the most commonly issued forecasts and are central to analysts' routine earnings updates.

We merge I/B/E/S with firm fundamentals from Compustat and stock returns and trading volume from CRSP. We obtain firm-level news from RavenPack News Analytics.

2.2 Key Variables Construction

Our main forecast-level measure of clustering is an indicator variable, $MultiForecast_{i,j,t}$, equal to one if analyst i issues earnings forecasts for more than one firm on calendar day t (including the forecast for firm j), and zero otherwise. To examine both mechanical scheduling-related and strategic drivers of forecast clustering, we construct the following explanatory variables.

Concurrent earnings announcements. To capture concurrent earnings announcements within an analyst's coverage portfolio, we define $MultiEA_{i,j,t}$ as an indicator equal to one if, on the most recent earnings announcement day of firm j on or before day t, at least one other firm covered by analyst i also announces earnings, and zero otherwise.

Distraction from other portfolio firms' information shocks. To measure distraction arising from news about other firms in the analyst's portfolio, we adapt Kempf et al. (2017) and construct three alternative measures based on (i) fundamental news coverage, (ii) abnormal trading volume, and (iii) extreme stock returns for portfolio firms other than the focal firm on day t. Specifically, distraction affecting analyst i when forecasting firm j on day t is

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

where $\omega_{i,k,t}$ is the weight assigned to portfolio firm $k \neq j$. In the main analysis we use equal weights; results are robust to weighting by market capitalization. $IS_{k,t}$ denotes an "information shock" for firm k on day t, measured in three ways. The first measure is $News_{k,t}$, the number of RavenPack fundamental news items about firm k on day t. Inspired by Ben-Rephael et al. (2023), we additionally use two market-reaction indicators: $AbnVol_{k,t}$

equals one if firm k is in the top decile of the CRSP cross-section by abnormal trading volume on day t, where abnormal volume is split-adjusted daily volume divided by the split-adjusted average volume over the prior 63 trading days; and $AbsRet_{k,t}$ equals one if firm k is in the top decile of the CRSP cross-section by absolute daily return on day t.

Strategic clustering: importance of the firm. To test whether analysts strategically cluster forecasts for less important firms, we construct portfolio-relative proxies for firm importance. Following Harford et al. (2019) and Jiao (2023), we measure firm importance for analyst i at time t using three characteristics: market capitalization, trading volume, and institutional ownership. For each characteristic, we create an indicator equal to one if firm j is in the top quartile within analyst i's portfolio (e.g., $TopSize_{i,j,t} = 1$ if firm j is in the top quartile by market capitalization measured at the prior quarter-end). We also form two composite indicators: $ImpFirmAny_{i,j,t} = 1$ if firm j is top quartile on at least one dimension, and $ImpFirmAll_{i,j,t} = 1$ if firm j is top quartile on all three dimensions.

Strategic clustering: importance of the information. To test whether analysts strategically avoid clustering when issuing more important information, we exploit simultaneous recommendation changes. Recommendation revisions are among the most informative analyst actions (Bradley et al., 2017; Loh and Stulz, 2011). We define $RecomRevision_{i,j,t} = 1$ if, on day t when analyst i issues an EPS forecast for firm j, the analyst also revises her recommendation for firm j, and zero otherwise. To examine potential asymmetries, we further partition $RecomRevision_{i,j,t}$ into upgrades ($UpGrade_{i,j,t}$) and downgrades ($DownGrade_{i,j,t}$).

Controls. Following prior literature (e.g., Hirshleifer et al., 2019; Jiao, 2023), we control for other determinants of analysts' forecasting behavior. Our controls include analyst coverage breadth (number of firms covered), brokerage size, the analyst's firm-specific experience, the analyst's overall experience, forecast age, forecast frequency, and the number of analysts covering the firm. Unless otherwise noted, we scale each control relative to the range of values

among analysts covering the same stock.[4] Table A1 reports detailed variable definitions.

Summary statistics. Table 1 reports summary statistics for the main sample. In our data, 51.4% of forecasts are clustered, underscoring the prevalence of clustering. Forecasts for firms with concurrent earnings announcements are also common (52.7% of observations). On days when analysts issue forecasts, the focal firm is mentioned in an average of five RavenPack fundamental news items. The focal firm is in the top decile of the CRSP cross-section by abnormal trading volume (absolute daily return) with probability 32.8% (23.2%), consistent with analysts issuing forecasts when information arrives and/or when their research affects trading activity. Based on our firm-importance measures, 36.4% of forecasts pertain to an "important" firm under $ImpFirmAny$, while 13.2% satisfy $ImpFirmAll$, indicating substantial overlap across the three proxies. Recommendation revisions coincide with 4.0% of forecasts, with downgrades slightly more frequent than upgrades. On average, firms in our sample are covered by about 19 analysts.

2.3 Methodology

To examine the determinants of forecast clustering, we estimate the following baseline fixed-effects model:

$$MultiForecast_{i,j,t} = \beta_1 Characteristics_{i,j,t} + \boldsymbol{\beta}_2' \mathbf{X}_{i,j,t} + \delta_{j,y} + \delta_{i,q} + \delta_t + \epsilon_{i,j,t}, \qquad (2)$$

where $MultiForecast_{i,j,t}$ is the forecast-level clustering indicator defined above. $Characteristics_{i,j,t}$ includes time-varying analyst, firm, and forecast characteristics related to workload and strategic behavior that may affect clustering. $\mathbf{X}_{i,j,t}$ denotes the set of control variables described in Section 2.2.

We include three sets of high-dimensional fixed effects: firm × year fixed effects ($\delta_{j,y}$), analyst × year-quarter fixed effects ($\delta_{i,q}$), and calendar-date fixed effects (δ_t). Firm × year

[4] All results remain qualitatively unchanged if we use the unscaled controls.

fixed effects absorb any time-varying firm-level determinants of clustering that are constant within a firm-year (e.g., firm-year disclosure policies). Analyst × year-quarter fixed effects absorb analyst-specific time variation that is common across all firms covered by analyst i within quarter q (e.g., time-varying work practices and brokerage constraints). Calendar-date fixed effects absorb all shocks common to all forecasts issued on date t (e.g., day-of-week effects and market-wide news). Because some economically relevant workload variation may operate primarily at the firm-year or analyst-quarter level, these fixed effects can partial out channels of interest; we therefore interpret estimates from the saturated specification as potentially conservative.

Because nonlinear binary-response models with many fixed effects can suffer from the incidental-parameters problem, our primary specification is a linear probability model. In robustness tests (untabulated), we re-estimate the main analyses using probit models with a more parsimonious fixed-effects structure and obtain qualitatively similar marginal effects and unchanged statistical inferences.

3 Workload and Forecast Clustering

This section examines the relation between analysts' forecast-production workload and forecast clustering. We first present time-series evidence on long-run trends in workload proxies and clustering. We then conduct analyst-quarter analyses that exploit within-analyst variation and distinguish between extensive and intensive margins of clustering.

3.1 Workload Time Trend and the Rise of Forecast Clustering

Figure 1 shows that forecast clustering and analysts' workload move closely together over the past two decades. Forecast clustering is defined as the fraction of one-year-ahead EPS forecasts issued on a day when the same analyst issues at least one additional forecast for another firm, relative to the total number of one-year-ahead EPS forecasts issued in a year.

Workload is proxied by the average annual number of one-year-ahead EPS forecasts issued per analyst. Over this period, the clustered share rises from 39.5% to 57.0%, while the number of forecasts per analyst-year increases from 25 to 41; the time-series correlation between the two series is 0.90.

Forecast output reflects both coverage breadth and forecasting intensity. Figure 2(a) shows that the average number of firms covered per analyst increases from 7.2 to 9.7. Figure 2(b) shows that the average number of one-year-ahead EPS forecasts per covered firm rises from 3.5 to 4.2, consistent with more frequent forecast updating around quarterly earnings announcements. A third dimension is timeliness. Conditional on the effort required per forecast, tighter turnaround requirements increase effective workload by compressing production schedules. Figure 2(c) shows that the fraction of forecasts issued within one day of the firm's earnings announcement increases from 40.0% to 48.6%, consistent with greater time pressure.

To assess whether the co-movement between clustering and workload holds at a finer frequency, we reconstruct the series at the year-quarter level and regress *ClusterFraction* on workload proxies. Table 2 reports the results. Column 1 shows a strong positive association between clustering and the average number of one-year-ahead EPS forecasts issued per analyst (*ReportNumTotal*). Because both clustering and workload trend upward over time, Column 2 adds a linear year-quarter time trend (*YrQtr*). The coefficient on *ReportNumTotal* declines but remains positive and highly significant, indicating that clustering is higher in quarters when analysts issue more forecasts even after controlling for smooth time trends. Columns 3–4 decompose *ReportNumTotal* into coverage breadth (*FirmsFollowed*) and forecasting intensity (*ReportNumAve*). Without time controls (Column 3), both components are positively related to clustering. With the year-quarter trend (Column 4), the association is concentrated in forecasting intensity: the coefficient on *ReportNumAve* remains positive and statistically significant, whereas the coefficient on *FirmsFollowed* becomes economically small and statistically insignificant. This pattern is consistent with average portfolio size

evolving largely as a smooth upward trend over time. Overall, the evidence is consistent with rising clustering being associated with higher workload.

3.2 Analyst-Quarter Analysis

Aggregate trends in workload and clustering could also reflect changes in analyst composition (e.g., entry and exit of analysts with systematically different coverage and forecasting practices). To address this concern and to quantify heterogeneity in clustering behavior, we conduct an analyst-quarter analysis and distinguish between extensive and intensive margins.

We construct two measures of analyst-quarter clustering. For the extensive margin, *AnyCluster* is an indicator equal to one if an analyst issues more than one forecast on any day in the quarter, and zero otherwise. For the intensive margin, *MaxClusterNum* is the log of the maximum number of forecasts the analyst issues on a clustering day within the quarter.

Table 3 reports the analyst-quarter results. Columns 1–3 present OLS estimates for *AnyCluster*, and Columns 4–6 present analogous specifications for *MaxClusterNum*. Columns 1 and 4 include no fixed effects, Columns 2 and 5 add analyst fixed effects, and Columns 3 and 6 further add year-quarter fixed effects. In line with the time-series evidence, analysts who cover more firms (*FirmsFollowed*) and who issue more forecasts per firm (*ReportNumAve*) are both more likely to cluster and, conditional on clustering, to cluster more heavily on a given day. These relations remain strong when we include analyst fixed effects (Columns 2 and 5) and persist when we additionally include year-quarter fixed effects (Columns 3 and 6), indicating that within-analyst increases in coverage breadth and forecasting intensity are associated with greater clustering and that the relation is not driven solely by compositional shifts or common time shocks.

Other analyst characteristics are also related to clustering. The number of Fama–French 48 industries an analyst covers (*IndustryCovered*) is positively associated with clustering at both margins, suggesting that broader industry scope is associated with greater bunching

of forecast activity. Employment at a top-10 brokerage firm by size (*BigBroker*) is associated with a lower likelihood of clustering at the extensive margin (Columns 1–3). This pattern suggests that analysts at large brokerage firms may face stricter forecast quality requirements that discourage clustering. In contrast, at the intensive margin, *BigBroker* is not significantly related to the number of forecasts clustered in a day once analyst fixed effects are included (Columns 5–6). Finally, general experience (*GeneralExperience*) is positively related to clustering in the specifications with analyst fixed effects (Columns 3 and 6), consistent with clustering increasing as analysts accumulate experience within their careers.

4 Workload-Driven Scheduling Constraints and Clustering

The previous section documents a strong association between analysts' forecast clustering and proxies for forecast-production workload. However, clustering is not mechanically inevitable: even in 2023, the average analyst issues only 41 one-year-ahead EPS forecasts per year. This section examines why heavier workload is nevertheless associated with more clustering. We focus on mechanisms through which higher workload compresses inter-day scheduling flexibility and increases the likelihood that analysts issue multiple forecasts on the same day in response to the timing of information events: (i) a higher incidence of concurrent earnings announcements among firms in an analyst's coverage portfolio, (ii) more frequent attention shocks arising from major news at other covered firms, and (iii) a greater prevalence of multi-firm industry/thematic updates that combine forecasts across firms.

4.1 Concurrent Earnings Announcements

We begin with concurrent earnings announcements. Earnings announcements are a primary trigger for analysts' forecast revisions, and as portfolio sizes grow, analysts are more likely to face days on which multiple covered firms announce earnings. Consistent with this intuition,

the average share of forecasts issued for a firm whose latest earnings announcement coincides with at least one other firm in the analyst's portfolio increases from 46.9% in 2002 to 59.1% in 2023. Over the same period, overall timeliness has improved (Figure 2(c)), suggesting that analysts increasingly update forecasts quickly around announcements.

A natural implication is a tighter timeliness–accuracy trade-off. Prior work argues that producing timelier forecasts can come at the expense of incorporating additional information (Cooper et al., 2001). In our setting, when multiple covered firms announce on the same day, analysts may prioritize timeliness and issue same-day updates for multiple announcers, increasing clustering. To test this hypothesis, we estimate the regression model described in Section 2.3 using *MultiEA* as the key explanatory variable. Table 4 reports the results: Column 1 presents an OLS specification, while Column 2 includes firm × year, analyst × year-quarter, and date fixed effects.

Across both specifications, *MultiEA* is strongly positively associated with clustering. In Column 2, the coefficient implies that forecasts for firms with concurrent announcements are 21.4 percentage points more likely to be clustered, which corresponds to a 41.6% increase relative to the unconditional clustering rate of 51.4%. In unreported analysis, using only *MultiEA* to predict clustering yields an R^2 of 11.0%. These results indicate that concurrent earnings announcements within an analyst's portfolio are an important source of clustering consistent with scheduling constraints around information events. Prior research links concurrent earnings announcements to investor inattention and underreaction (Hirshleifer et al., 2009) and to delays in forecast issuance (Driskill et al., 2020). Our findings highlight an additional implication: even when analysts respond promptly, concurrency is associated with more forecast clustering, potentially affecting the information environment through the analyst channel. This also suggests scope for strategic disclosure timing by firms (e.g., releasing unfavorable news alongside other firms' announcements) (deHaan et al., 2015).

4.2 Distraction from Other Portfolio Firms

Next, we examine a second workload-related driver of clustering: distractions created by news at other firms in the analyst's coverage portfolio. As an analyst covers more firms, the likelihood that at least one other covered firm experiences major news on a given day naturally increases. If analysts have limited attention and processing capacity, heightened attention demands elsewhere in the portfolio can crowd out time for the focal firm and compress inter-day scheduling flexibility, making the analyst more likely to cluster the forecast for the focal-firm.

Using the same regression framework as above, we replace *MultiEA* with the distraction measures described in Section 2.2. We also include the focal firm's own information shock measure, *IS*, to capture the focal firm's contemporaneous salience. The scheduling-constraint mechanism implies a positive coefficient on *Distraction*: greater news pressure from other portfolio firms should increase the probability that the analyst's forecast for the focal firm is clustered. By contrast, holding other demands constant, a larger focal-firm information shock should attract attention to the focal firm and reduce clustering, implying a negative coefficient on *IS*.

Columns 3–8 of Table 4 present the results. Columns 3–4 use the fundamental news-based distraction measure, Columns 5–6 use abnormal trading volume, and Columns 7–8 use absolute stock returns. Across measures and specifications, *Distraction* is positively related to clustering, while the focal firm's *IS* is negatively related to clustering. In the specifications with high-dimensional fixed effects, a one-standard-deviation increase in *Distraction* is associated with an 8.5% (absolute returns) to 13.4% (fundamental news) higher probability of clustering, while a one-standard-deviation increase in the focal firm's *IS* is associated with a 3.7% (absolute returns) to 6.6% (abnormal volume) lower probability of clustering.[5]

[5]The results remain qualitatively similar when using distraction measures (i) from day $t-1$, allowing analysts time to adjust inter-day allocation, or (ii) constructed based on all firms covered by analyst i that are not forecasted on day t.

4.3 Industry and Thematic Updates

A third channel is the growing use of multi-firm industry or thematic updates. As analysts cover more firms and face common shocks (e.g., technological change, macroeconomic conditions, or policy events), they may update forecasts for multiple firms in close succession within industry-wide or thematic research outputs (Drake et al., 2020). Operationally, we classify forecasts as part of an industry/thematic update if they are issued at the exact same *second* as another forecast by the same analyst for a firm in the same Fama–French 48 industry. This timestamp-based rule is designed to capture tightly clustered multi-firm updates, though it may also reflect mechanical batching in forecast submission systems.

Using this classification, the proportion of forecasts linked to industry/thematic updates increases from 8.9% in 2002 to 17.7% in 2023, highlighting their growing prevalence. Over the full sample period, industry/thematic updates account for 16.8% of all clustered forecasts.

In sum, we document three channels through which rising workload is associated with more forecast clustering via tighter scheduling constraints around information events. Concurrent earnings announcements substantially increase clustering, consistent with analysts responding to multiple same-day triggers under time pressure. News shocks at other portfolio firms increase clustering, while focal-firm shocks reduce it, consistent with limited attention and reallocation across covered firms. Finally, the increasing prevalence of multi-firm industry/thematic updates mechanically contributes to clustering by combining forecast revisions across firms. Together, these patterns explain a meaningful share of clustering variation even in the presence of high-dimensional fixed effects, suggesting that an important component of clustering reflects predictable responses to information-event timing under heavier workload.

5 Strategic Forecast Clustering

The preceding section documents that forecast clustering is strongly related to workload and the timing of information events that compress analysts' inter-day scheduling flexibility (e.g.,

concurrent earnings announcements, portfolio-level news shocks, and industry/thematic updates). At the same time, analysts retain discretion over how they allocate attention across the forecasts they issue within a given set of constraints. If clustering is associated with lower forecast quality, analysts may respond by prioritizing effort—and avoiding clustering—for forecasts that are more important for their careers or more salient to investors, while allowing lower-priority updates to be issued on already busy days.

We study two settings in which prioritization is most likely to appear: forecasts associated with important *firms* and forecasts associated with important *information*. First, we test whether analysts are less likely to cluster forecasts for firms that are particularly important within the analyst's portfolio, proxied by market capitalization, trading volume, and institutional ownership. Second, we test whether forecasts that coincide with recommendation revisions are less likely to be clustered. In all specifications, we control for the workload- and event-timing channels documented earlier, including concurrent earnings announcements, portfolio-level distractions, and whether the forecast is part of an industry/thematic report.

5.1 Important Firms

We first examine whether analysts avoid clustering forecasts for firms that are more important to their career. Prior research finds that analysts devote greater effort to high-priority portfolio firms (Harford et al., 2019; Jiao, 2023). As described in Section 2.2, we follow established literature and use three proxies to indicate whether one firm is important within an analyst's portfolio: firm size, trading volume, and institutional ownership. These attributes are closely related to commission generation, which can affect analysts' reputation and mobility (Groysberg et al., 2011). We also construct summary indicators capturing whether a firm meets any (or all) of the three criteria. Table 5 reports the results.

Across proxies, the coefficients on the "important firm" indicators are negative and statistically significant, implying that forecasts for high-priority firms are less likely to be clustered, conditional on workload-related controls and fixed effects. The estimated magnitudes are

modest: forecasts for important firms are approximately 0.60% (*TopVol*) to 1.38% (*TopSize*) less likely to be clustered. While small relative to the effects of workload and event timing documented earlier, the pattern is consistent with analysts allocating attention strategically by reducing clustering for forecasts tied to higher-priority firms.

5.2 Important Information

We next examine whether analysts avoid clustering when issuing forecasts that are likely to be more information-relevant. As described in Section 2.2, forecasts accompanied by recommendation revisions plausibly reflect higher-salience analyst actions and may receive greater scrutiny. We therefore test whether *RecomRevision* and its components, *UpGrade* and *DownGrade*, are associated with a lower likelihood of clustering. Table 6 presents the results.

Columns 1–2 show that forecasts accompanied by a recommendation revision are less likely to be clustered. In Column 1, the estimated effect is a 3.45 percentage point reduction in clustering probability (6.71% relative to the unconditional mean). The magnitude attenuates but remains highly significant once fixed effects are included (Column 2). Columns 3–4 separate upgrades and downgrades. The reduction in clustering is concentrated in upgrades: in Column 4, an upgrade is associated with a 5.18% lower clustering probability, whereas a downgrade is associated with a smaller 0.97% reduction.

This upgrade–downgrade asymmetry is consistent with several mechanisms. One possibility is strategic visibility management: analysts may prefer to issue upgrades on stand-alone days to attract investor attention, while clustering downgrades when attention is lower, consistent with evidence on the timing of negative recommendations (Rees et al., 2017). We view the asymmetry as suggestive evidence of prioritization and attention allocation rather than definitive evidence of intent.

6 Clustering and Firms' Information Environments

Prior research finds that forecast clustering is associated with lower forecast quality. Given the rising prevalence of clustering documented in this paper, a natural question is whether firms that are more exposed to clustered forecasts also exhibit weaker market information environments. In this section, we test whether firm-year exposure to clustering is associated with higher information asymmetry, as proxied by bid–ask spreads and stock illiquidity.

6.1 Measuring Firm-Year Exposure to Clustering

We conduct the analysis at the firm-year level. To measure a firm's exposure to forecast clustering, we define:

$$ClusterFrac_{j,t} = \frac{\#\{\text{clustered forecasts for firm } j \text{ in year } t\}}{\#\{\text{all forecasts for firm } j \text{ in year } t\}}, \tag{3}$$

where the numerator counts clustered forecasts issued by all analysts for firm j during year t, and the denominator counts the total number of forecasts for the firm in the same year.

Based on $ClusterFrac_{j,t}$, we construct two indicator variables that capture high clustering exposure. The first is a relative measure, *TopClustering*, which equals 1 if a firm's $ClusterFrac_{j,t}$ falls within the top quartile of the cross-sectional distribution in year t. The second is an absolute measure, *HighClustering*, which equals 1 if $ClusterFrac_{j,t} \geq 0.6$. We use the 0.6 threshold to identify firm-years with especially high clustering intensity in absolute terms; as of 2023, approximately 57% of all forecasts are clustered. A value of 1 on either indicator identifies firm-years that are frequently subject to clustered forecasts.

6.2 Information-Environment Outcomes

Following Harford et al. (2019), we measure a firm's information environment using two standard proxies for information asymmetry and trading frictions: the stock bid–ask spread and the Amihud illiquidity measure (Amihud, 2002). Specifically, the daily bid–ask spread is computed as

$$Spread_{j,d} = 100 \times \frac{\text{ask}_{j,d} - \text{bid}_{j,d}}{(\text{ask}_{j,d} + \text{bid}_{j,d})/2}, \tag{4}$$

using daily closing bid and ask quotes from CRSP. The daily Amihud illiquidity measure is computed as

$$Illiq_{j,d} = \frac{|Ret_{j,d}|}{DollarVol_{j,d}} \times 1{,}000{,}000, \tag{5}$$

where $DollarVol_{j,d}$ is dollar trading volume. We aggregate both measures to the firm-year level by taking the average across trading days within each year.

6.3 Controls and Empirical Specification

To isolate the association between clustering exposure and the information environment, we control for a comprehensive set of firm characteristics known to affect spreads and illiquidity. In particular, we control for firm size, trading volume, and institutional ownership, as well as their quadratic terms, to mitigate the concern that the clustering indicators merely proxy for these firm attributes. We further control for the logarithm of the number of analysts covering the firm, book-to-market ratio, leverage, the logarithm of stock price, past annual stock return, return on assets, stock return volatility, as well as firm and year fixed effects. The inclusion of firm and year fixed effects implies that the coefficients are identified from within-firm changes over time in clustering exposure, relative to the contemporaneous cross-sectional distribution. Table A2 reports summary statistics for variables used in this section.

6.4 Empirical Results

Table 7 presents the results. Panel A reports baseline estimates using the two clustering measures: Columns 1–2 use *TopClustering*, while Columns 3–4 use *HighClustering*. The coefficients on *TopClustering* and *HighClustering* are positive and statistically significant for Amihud illiquidity, and *TopClustering* is also significantly positive for bid–ask spreads. Economically, the estimates in Panel A imply that firms in the top quartile of clustered-forecast exposure experience an increase in bid–ask spreads of 1.32 basis points (about 3.1% relative to the unconditional mean spread of 42 basis points) and an 18.2% increase in the Amihud illiquidity measure. Using the absolute definition, firms with at least 60% of forecasts clustered exhibit a 1.5% increase in bid–ask spreads and a 14.9% increase in Amihud illiquidity.

6.5 Heterogeneity by Institutional Ownership

Panel B examines whether the association between clustering and the information environment varies with institutional ownership. The extent to which clustering matters for market outcomes may depend on the composition of the investor base. To the extent that retail investors rely more on publicly disseminated written research, while institutional investors can partially substitute toward private information channels (e.g., direct interactions with analysts (Groysberg and Healy, 2020)), the association between clustering and information frictions may be stronger for firms with lower institutional ownership.

To evaluate this possibility, we interact the clustering measures with *HighInsHolding*, an indicator equal to one if the firm's institutional ownership percentage is above the sample median. The interaction terms are negative and statistically significant across both liquidity proxies and for both clustering definitions, indicating that the positive association between clustering and information frictions is concentrated among firms with relatively low institutional ownership. For example, in Column 1, the coefficient on *TopClustering* is 2.59

bps, whereas the implied effect for firms with above-median institutional ownership is only $2.59 - 2.07 = 0.52$ bps. Similar patterns obtain in Columns 2–4, where the interaction terms largely offset the baseline clustering coefficients for above-median institutional ownership.

Overall, higher exposure to forecast clustering is associated with wider bid–ask spreads and higher illiquidity, and this association is materially stronger among firms with below-median institutional ownership. Combined with our earlier evidence that clustering is more prevalent among smaller and less actively traded firms and among firms with lower institutional ownership, settings typically characterized by greater information frictions, these results suggest that the increase in forecast clustering is linked to economically meaningful heterogeneity in market-level information asymmetry across firms and across investor types.

7 Additional Analysis

This section provides additional analyses of forecast clustering behavior. We (i) quantify the extent to which clustering varies persistently across analysts and brokerage firms versus over time, and (ii) assess robustness of our main inferences using refined proxies for firm importance and an alternative sample restriction motivated by analysts' within-day attention constraints.

7.1 Persistent Heterogeneity and Institutional Effects

Our main specifications include high-dimensional fixed effects. While these controls mitigate confounding, they make it harder to see how much clustering reflects persistent differences across analysts and brokerage firms versus common time variation. Panel A of Table 8 therefore reports a fixed-effects variance decomposition for the two quarterly clustering measures used in Table 3, *AnyCluster* and *MaxClusterNum*. Specifically, we report the goodness-of-fit from regressions that include only analyst fixed effects, brokerage firm fixed effects, and year-quarter fixed effects.

Analyst fixed effects explain the largest share of the variation in quarterly clustering behavior, with R^2 values of 50.3% for *AnyCluster* and 49.9% for *MaxClusterNum*. This pattern indicates that clustering propensity is highly persistent at the individual level and is consistent with stable differences in work practices or time-allocation choices across analysts. Brokerage firm fixed effects also explain a nontrivial share of the variation (18.2% for *AnyCluster* and 12.4% for *MaxClusterNum*), suggesting that clustering correlates with institutional environments that differ across employers, such as internal processes, supervisory norms, or report-production practices. In contrast, year-quarter fixed effects explain a relatively small share of the variation (0.6% and 2.6%), implying that, at the quarterly frequency, common time shocks account for less variation than persistent analyst- and brokerage-level differences. When all three sets of fixed effects are included jointly, the R^2 values increase only modestly (52.5% and 53.1%), consistent with analyst fixed effects absorbing a substantial portion of the cross-brokerage differences in clustering.

To visualize this heterogeneity, Figure 3 plots the distribution of clustering propensities across analysts and across brokerage firms. The x-axis reports the fraction of quarters in which an analyst (or brokerage firm) exhibits any clustering, and the y-axis reports the corresponding density. Both distributions are bimodal, with substantial mass near the lower and upper extremes. For example, 33.0% of analysts and 24.2% of brokerage firms never cluster in any quarter during the sample period, while 10.8% of analysts and 5.6% of brokerage firms exhibit clustering in every quarter. This polarization highlights that clustering behavior is not uniform and is instead concentrated among subsets of analysts and institutions.

Panel B of Table 8 provides additional descriptive evidence by listing the top 10 largest brokerage firms with high and low clustering behavior respectively, ranked by firm size. We classify brokerage firms as high-clustering if more than 80% of analyst-quarters involve clustering and as low-clustering if fewer than 20% involve clustering. Several large institutions (e.g., Bank of America and Barclays) fall into the high-clustering group, whereas others (e.g., Natixis and Stifel) fall into the low-clustering group. While these comparisons are descrip-

tive, they reinforce the broader point that clustering is strongly correlated with persistent analyst- and brokerage-level characteristics.

7.2 Robustness Tests

Our results remain robust across several robustness exercises. First, we refine the firm-importance proxies used in Section 5.1. To more directly capture aspects of firm importance that may be tied to commission-generating trading activity, we construct proxies based on (i) institutional (non-retail) trading volume and (ii) active institutional ownership. Institutional trading volume is measured at the firm-quarter level using TAQ data. Following Barber et al. (2024), we estimate retail trading volume and define institutional trading volume as total volume minus the retail component. We then construct *TopVolIns* and *TopVolInsMv*, indicators equal to one if institutional trading volume in shares or dollars, respectively, falls in the top quartile of the analyst's portfolio at the end of the prior quarter. To proxy for active institutional ownership, we focus on transient institutions as classified by Bushee (2001) and construct two analogous indicators, *TopTra* and *TopTraMv*, based on percentage ownership and market-value ownership by transient institutions, respectively.

Using these refined measures, we re-estimate the regression from Table 5. Table 9 reports that the coefficients on all four alternative importance indicators are negative and statistically significant. The estimates are consistent with our main conclusion that analysts are less likely to cluster forecasts for higher-priority firms, measured using proxies that emphasize institutional trading activity and active institutional ownership.

Second, given that our study is most pertinent to analysts' cognitive constraints, we narrow our sample to forecasts that are at least partially performed and released within the same day, which are directly subject to analysts' limited attention and decision fatigue (Hirshleifer et al., 2019; Jiao, 2023). Specifically, we follow Jiao (2023) and restrict the sample to forecasts issued between 9:00 a.m. and 11:00 p.m., which excludes overnight releases and reduces the influence of multi-day production cycles. Table 10 reports the results for this

restricted sample. Panel A presents estimates for the workload- and event-timing drivers of clustering, and Panel B presents estimates for the strategic-prioritization tests. The findings remain qualitatively similar to our main results, although statistical significance is weaker in some specifications, likely because this step filters out about half of the original observations.

8 Conclusion

This study provides a comprehensive analysis of forecast clustering among sell-side equity analysts, a practice that has risen markedly over the past two decades despite evidence that clustering is associated with lower forecast quality. We show that this rise tracks a sustained increase in analyst workload that compresses the time and attention available per covered firm and makes analysts' schedules more prone to congestion. As coverage responsibilities expand, the flow of information events within analysts' portfolios becomes denser and more difficult to sequence, including a higher incidence of overlapping earnings announcements, more frequent competing firm-specific news that can divert attention, and greater reliance on industry-level reports that combine updates across firms. Together, these workload-driven changes in the timing and intensity of portfolio news reduce analysts' ability to stagger forecast revisions and increase the likelihood that updates are issued in clusters.

We next examine how analysts respond to these tighter scheduling constraints. Clustering is less prevalent when the output is likely to be more visible and professionally consequential. Forecasts for firms that are more important to analysts' careers, proxied by firm size, trading volume, and institutional ownership, are less likely to be clustered. Likewise, forecasts released alongside recommendation revisions, especially upgrades, exhibit substantially lower clustering. These patterns are consistent with analysts rationing scarce attention by prioritizing forecasts with higher reputational stakes, thereby partially shielding high-salience outputs from the adverse correlates of clustering.

We then consider whether clustering is related to firms' broader market information

environments. Firms that are more frequently subject to clustered forecasts have wider bid–ask spreads and higher Amihud illiquidity, consistent with greater information frictions and weaker liquidity. The association is strongest among firms with below-median institutional ownership, a setting in which public analyst research may play a comparatively larger role in information production and dissemination. Combined with the fact that clustering is more prevalent among smaller and less actively traded firms, these results suggest that the growth of clustering is linked to economically meaningful cross-sectional heterogeneity in market-level information asymmetry, with the potential to reinforce existing disparities in market attention and information quality.

Taken together, our evidence highlights forecast clustering as an endogenous response to capacity constraints in the information-intermediation process. As analysts' portfolios become more event-intensive, clustering may help analysts cope with peak-period scheduling congestion, but it also coincides with lower forecast quality and poorer market liquidity for more exposed firms. More broadly, our findings imply that frictions internal to information intermediaries, such as limited time and attention, can shape both the timing of information releases and the distribution of information quality across firms. Future work could evaluate whether organizational practices, new technologies, or institutional and regulatory changes that reduce peak-period congestion or improve analysts' ability to sequence tasks translate into less clustering and a more even provision of high-quality information in capital markets.

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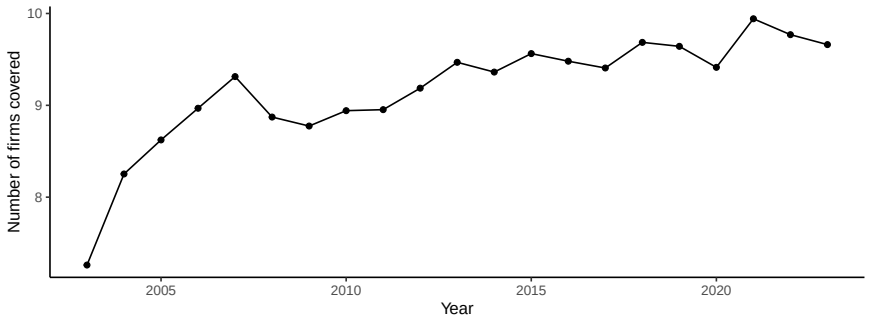
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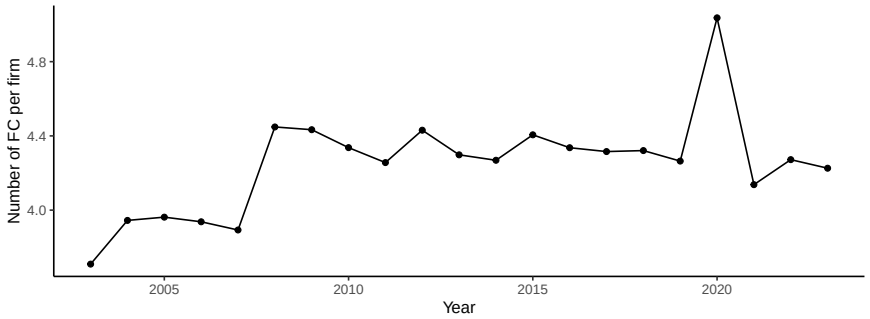
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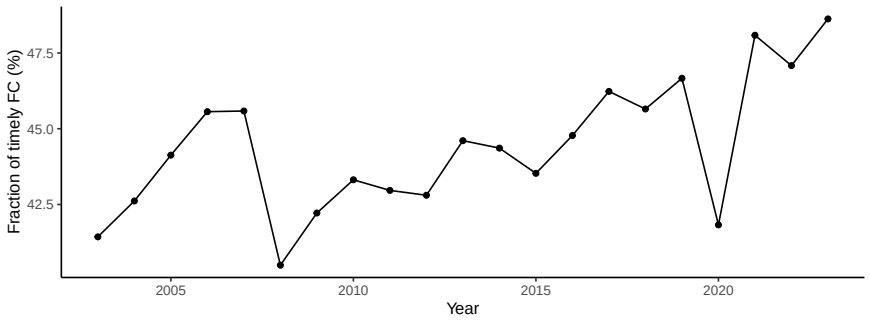
Figure 2: **Annual Trends in Analyst Coverage, Forecasting Intensity, and Timeliness**
This figure reports annual trends in three dimensions of analyst workload from 2002 to 2023. Panel (a) plots the average number of firms covered per analyst. Panel (b) shows the average number of one-year-ahead EPS forecasts (FC) issued per firm per analyst. Panel (c) reports the share of forecasts that are timely, defined as those issued on the day of or the day after the most recent earnings announcement of the forecasted firm.



(a) Average number of firms covered by each analyst

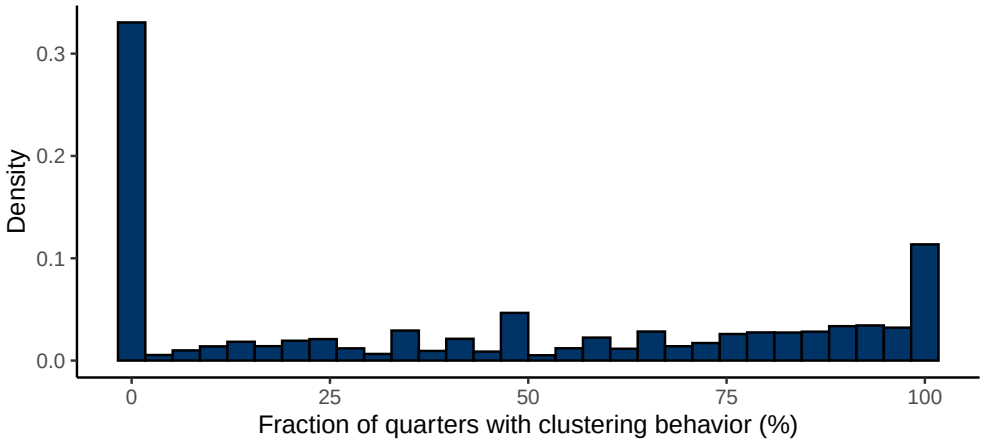


(b) Average number of one-year-ahead EPS forecasts per firm

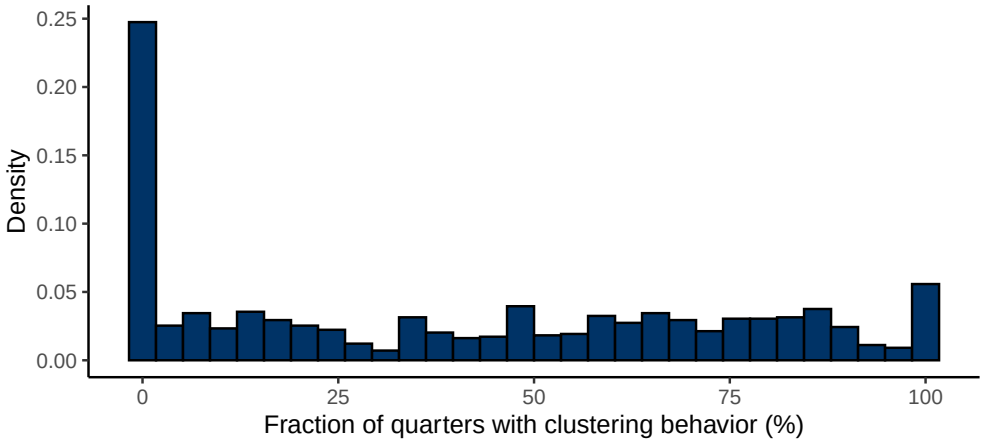


(c) Average fraction of timely forecasts

Figure 3: **Distribution of Forecast Clustering Across Analysts and Brokerages**
This figure displays the cross-sectional distribution of clustering propensities for individual analysts and brokerage firms. The x-axis reports the fraction of quarters in which an analyst (Panel (a)) or a brokerage firm (Panel (b)) exhibits any clustering behavior, and the y-axis reports the corresponding density.



(a) Distribution of forecast clustering across analysts



(b) Distribution of forecast clustering across brokerage firms

Table 1: **Summary Statistics**
This table presents the summary statistics for the variables at the forecast level in the main sample, based on I/B/E/S data from 2002 to 2023. See Table A1 for detailed variable definitions.

Name	Mean	Median	p05	p95	Std. Dev.
MultiForecast	0.514	1.000	0.000	1.000	0.500
MultiEA	0.527	1.000	0.000	1.000	0.499
IS_News	5.348	0.000	0.000	36.000	12.490
Distraction_News	0.852	0.250	0.000	3.875	1.538
IS_AbnVol	0.328	0.000	0.000	1.000	0.469
Distraction_AbnVol	0.079	0.059	0.000	0.250	0.094
IS_AbsRet	0.232	0.000	0.000	1.000	0.422
Distraction_AbsRet	0.082	0.053	0.000	0.294	0.112
IndustryReport	0.168	0.000	0.000	1.000	0.374
TopSize	0.249	0.000	0.000	1.000	0.432
TopVol	0.241	0.000	0.000	1.000	0.428
TopIO	0.247	0.000	0.000	1.000	0.431
ImpFirmAny	0.364	0.000	0.000	1.000	0.481
ImpFirmAll	0.132	0.000	0.000	1.000	0.338
RecomRevision	0.040	0.000	0.000	0.000	0.195
UpGrade	0.018	0.000	0.000	0.000	0.133
DownGrade	0.022	0.000	0.000	0.000	0.146
FirmExperience	0.396	0.294	0.000	1.000	0.350
GeneralExperience	0.436	0.348	0.000	1.000	0.343
BrokerSize	0.331	0.234	0.000	1.000	0.315
ForecastFrequency	0.587	0.600	0.000	1.000	0.299
FirmsFollowed	0.429	0.389	0.000	1.000	0.301
ForecastAge	0.546	0.533	0.036	1.000	0.302
Numest	18.548	17.000	4.000	39.000	10.796

Table 2: **Forecast Clustering and Analyst Workload: Aggregate Quarterly Trends**
This table relates forecast clustering to analyst workload using aggregate year-quarter trends from 2002 to 2023. The dependent variable is the fraction of one-year-ahead EPS forecasts issued on clustered days in year-quarter t (*ClusterFraction*). Columns 1–2 regress *ClusterFraction* on the average number of one-year-ahead EPS forecasts issued per analyst in year-quarter t (*ReportNumTotal*). Columns 3–4 replace *ReportNumTotal* with its two components: the average number of firms followed (*FirmsFollowed*) and the average number of forecasts per covered firm (*ReportNumAve*). Columns 2 and 4 include a year-quarter time trend to control for common time variation.

Dependent Variable:	ClusterFraction			
Model:	(1)	(2)	(3)	(4)
ReportNumTotal	0.0411***	0.0189***		
	(0.0030)	(0.0034)		
FirmsFollowed			0.0411***	−0.0048
			(0.0028)	(0.0078)
ReportNumAve			0.1554***	0.1683***
			(0.0524)	(0.0438)
YrQtr		0.0058***		0.0099***
		(0.0007)		(0.0016)
Constant	0.0085	−11.4055***	−0.2278**	−19.6911***
	(0.0363)	(1.3427)	(0.0899)	(3.1567)
R^2	0.6869	0.8308	0.7174	0.8055
Adjusted R^2	0.6833	0.8268	0.7107	0.7985
Observations	88	88	88	88

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: **Quarterly Forecast Clustering and Analyst Characteristics**
This table reports analyst-quarter regressions relating forecast clustering to analyst workload and other analyst characteristics. The dependent variables are *AnyCluster*, an indicator equal to one if the analyst issues forecasts for more than one firm on at least one day during the quarter (Columns 1–3), and *MaxClusterNum*, the logarithm of the maximum number of forecasts the analyst issues on a single day during the quarter (Columns 4–6). The main workload measures are *FirmsFollowed* and *ReportNumAve*. Columns 2 and 5 include analyst fixed effects, and columns 3 and 6 additionally include year-quarter fixed effects. Standard errors are two-way clustered by analyst and year-quarter and reported in parentheses.

Dependent Variables:	AnyCluster			MaxClusterNum		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
FirmsFollowed	0.0274***	0.0175***	0.0177***	0.0309***	0.0241***	0.0246***
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0007)	(0.0007)
ReportNumAve	0.2928***	0.2402***	0.2392***	0.8051***	0.5968***	0.5881***
	(0.0068)	(0.0050)	(0.0048)	(0.0204)	(0.0201)	(0.0177)
IndustryCovered	0.0374***	0.0596***	0.0588***	−0.0043	0.0214***	0.0197***
	(0.0017)	(0.0017)	(0.0016)	(0.0037)	(0.0023)	(0.0023)
BigBroker	−0.0190***	−0.0200***	−0.0192***	0.0285***	−0.0044	−0.0040
	(0.0046)	(0.0060)	(0.0060)	(0.0093)	(0.0098)	(0.0098)
GeneralExperience	0.0010***	−0.0022***	0.0158**	−0.0010*	0.0063***	0.0215**
	(0.0003)	(0.0006)	(0.0064)	(0.0005)	(0.0010)	(0.0092)
Constant	0.1235***			0.3994***		
	(0.0069)			(0.0133)		
Fixed-effects						
Analyst	No	Yes	Yes	No	Yes	Yes
YrQtr	No	No	Yes	No	No	Yes
R^2	0.4090	0.5931	0.5954	0.3244	0.6011	0.6067
Adjusted R^2	0.4090	0.5642	0.5665	0.3244	0.5724	0.5780
Observations	232,311	232,311	232,311	141,643	141,643	141,643

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: **Workload-Related (Mechanical) Drivers of Forecast Clustering**
This table examines how workload-related scheduling congestion is associated with analysts' propensity to issue clustered forecasts. The dependent variable, $MultiForecast_{i,j,t}$, equals 1 if analyst i's forecast for firm j on day t is clustered and 0 otherwise. The main variables of interest capture workload-related forces that can mechanically increase clustering, including concurrent earnings announcements within the analyst's coverage portfolio and competing information events affecting other covered firms. In Columns 1–2, the workload measure includes $MultiEA_{i,j,t}$, an indicator equal to 1 if, on the most recent earnings announcement day of firm j on or before day t, at least one other firm covered by analyst i also announces earnings. Columns 3–8 study distraction effects using three portfolio-wide proxies: the number of fundamental news events, abnormal trading volume, and absolute stock returns. We additionally include the focal firm's information shock, $IS_{j,t}$, to assess whether the focal firm's "attractiveness" affects clustering. All specifications include a standard set of controls $\mathbf{X}_{i,j,t}$ (number of companies covered, brokerage size, firm-specific experience, forecast age, forecast frequency, and the number of covering analysts; see Table A1 for definitions), as well as firm × year, analyst × year-quarter, and date fixed effects. For brevity, only coefficients of interest are reported. Standard errors are two-way clustered by analyst and date and reported in parentheses.

Dependent Variable:	MultiForecast							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MultiEA	0.3132***	0.2140***						
	(0.0029)	(0.0030)						
Distraction_News			0.0516***	0.0446***				
			(0.0013)	(0.0010)				
IS_News			−0.0028***	−0.0020***				
			(0.0001)	(0.0001)				
Distraction_AbnVol					0.6794***	0.6802***		
					(0.0150)	(0.0107)		
IS_AbnVol					−0.1451***	−0.0720***		
					(0.0036)	(0.0015)		
Distraction_AbsRet							0.4426***	0.3883***
							(0.0122)	(0.0092)
IS_AbsRet							−0.0969***	−0.0454***
							(0.0028)	(0.0012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
Firm-Year	No	Yes	No	Yes	No	Yes	No	Yes
Analyst-YrQtr	No	Yes	No	Yes	No	Yes	No	Yes
ForecastDay	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.1214	0.3668	0.0537	0.3523	0.0567	0.3530	0.0408	0.3448
Adjusted R^2	0.1214	0.2935	0.0537	0.2772	0.0566	0.2780	0.0408	0.2689
Observations	2,281,675	2,261,392	2,281,674	2,261,392	2,281,674	2,261,392	2,281,674	2,261,392

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: **Strategic Inter-day Job Allocation: Important Firms**
This table examines whether analysts are less likely to issue clustered forecasts for firms that are more important within their coverage portfolios. The dependent variable, $MultiForecast_{i,j,t}$, equals 1 if analyst i's forecast for firm j on day t is clustered and 0 otherwise. The variable of interest, $ImportantFirm_{i,j,t}$, is measured using five alternative indicators of whether firm j is important within analyst i's portfolio on day t. Specifically, *TopSize*, *TopVol*, and *TopIO* equal 1 if firm j is in the top quartile of the analyst's portfolio by market capitalization, trading volume, and institutional ownership, respectively, as of the most recent quarter-end. The composite indicators *ImpFirmAny* and *ImpFirmAll* equal 1 if any or all of these three criteria are satisfied, respectively. All specifications include the control variables $\mathbf{X}_{i,j,t}$ described in Table 4 and firm × year, analyst × year-quarter, and date fixed effects. We also control for the mechanical, workload-related factors identified earlier, including concurrent earnings announcements within the analyst's portfolio, potential distraction from news affecting other covered firms, and whether the forecast is part of an industry-wide report. For brevity, only coefficients of interest are reported. Standard errors are two-way clustered by analyst and date and reported in parentheses.

Dependent Variable:	MultiForecast				
Model:	(1)	(2)	(3)	(4)	(5)
TopSize	−0.0071***				
	(0.0011)				
TopVol		−0.0031***			
		(0.0010)			
TopIO			−0.0071***		
			(0.0011)		
ImpFirmAny				−0.0059***	
				(0.0010)	
ImpFirmAll					−0.0051***
					(0.0013)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Firm-Year	Yes	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes	Yes
R^2	0.4848	0.4848	0.4848	0.4848	0.4848
Adjusted R^2	0.4199	0.4199	0.4199	0.4199	0.4199
Observations	2,281,674	2,281,674	2,281,674	2,281,674	2,281,674

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: **Strategic Inter-day Job Allocation: Important Forecasts**
This table examines whether analysts are less likely to issue clustered forecasts when a forecast is accompanied by a recommendation revision, which proxies for the importance of the information content. The dependent variable, $MultiForecast_{i,j,t}$, equals 1 if analyst i's forecast for firm j on day t is clustered and 0 otherwise. The main explanatory variable, $RecomRevsion_{i,j,t}$, equals 1 if the forecast is issued together with a recommendation revision. To assess potential asymmetries, Columns 3–4 replace $RecomRevsion_{i,j,t}$ with two separate indicators, *UpGrade* and *DownGrade*, which equal 1 for upward and downward recommendation revisions, respectively. All specifications include the control variables $\mathbf{X}_{i,j,t}$ described in Table 4 and firm × year, analyst × year-quarter, and date fixed effects. We also control for the mechanical, workload-related factors identified earlier, including concurrent earnings announcements within the analyst's portfolio, potential distraction from news affecting other covered firms, and whether the forecast is part of an industry-wide report. For brevity, only coefficients of interest are reported. Standard errors are two-way clustered by analyst and date and reported in parentheses.

Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
RecomRevision	−0.0345***	−0.0150***		
	(0.0027)	(0.0017)		
UpGrade			−0.0468***	−0.0266***
			(0.0032)	(0.0024)
DownGrade			−0.0241***	−0.0050**
			(0.0031)	(0.0022)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm-Year	No	Yes	No	Yes
Analyst-YrQtr	No	Yes	No	Yes
ForecastDay	No	Yes	No	Yes
R^2	0.3279	0.4848	0.3279	0.4848
Adjusted R^2	0.3279	0.4200	0.3279	0.4200
Observations	2,281,674	2,281,674	2,281,674	2,281,674

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: **Forecast Clustering and the Firm's Information Environment**
This table examines the relation between forecast clustering and the information environment of firm j in year t. The dependent variable, $InformationEnv_{j,t}$, is measured alternatively using (i) the bid–ask spread (*BidAskSpread*) and (ii) Amihud illiquidity (*AmihudIlliquidity*). For the explanatory variable, we use two alternative measures to capture whether the firm experiences frequent forecast clustering during year t. Columns 1–2 use *TopClustering*, an indicator equal to 1 if the firm is in the top quartile of clustered-forecast frequency in that year. Columns 3–4 use *HighClustering*, an indicator equal to 1 if 60% or more of the forecasts issued for the firm during the year are clustered. Panel A reports the baseline specifications. Panel B includes the interaction of the clustering measures with *HighInsHolding*, an indicator equal to 1 if the firm's institutional ownership percentage is above the sample median, to examine heterogeneity by institutional ownership. All specifications include a standard set of firm-year controls $\mathbf{X}_{j,t}$: firm size, trading volume, institutional holdings (and their quadratic terms), the number of covering analysts, book-to-market ratio, leverage, log stock price, past stock return, return on assets, and stock return volatility (see Table A1 for definitions). Firm and year fixed effects are included. Standard errors are clustered at the firm level and reported in parentheses.

Panel A: Clustering and Information Environment				
Dependent Variables:	BidAskSpread	AmihudIlliquidity	BidAskSpread	AmihudIlliquidity
Model:	(1)	(2)	(3)	(4)
TopClustering	0.0132***	0.0142***		
	(0.0045)	(0.0039)		
HighClustering			0.0064	0.0116***
			(0.0047)	(0.0040)
log(Numest)	−0.0440***	−0.0161***	−0.0445***	−0.0164***
	(0.0062)	(0.0049)	(0.0062)	(0.0049)
log(MarketCap)	−0.9511***	−0.5106***	−0.9512***	−0.5103***
	(0.0507)	(0.0483)	(0.0507)	(0.0483)
log(MarketCap)^2	0.0327***	0.0181***	0.0327***	0.0180***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)
log(TradingVolume)	−0.8161***	−0.5292***	−0.8158***	−0.5285***
	(0.0535)	(0.0511)	(0.0535)	(0.0511)
log(TradingVolume)^2	0.0176***	0.0117***	0.0176***	0.0117***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
InsHolding	0.0149	0.0241	0.0154	0.0247
	(0.0452)	(0.0390)	(0.0453)	(0.0390)
InsHolding^2	0.0491	0.0466	0.0490	0.0463
	(0.0344)	(0.0294)	(0.0345)	(0.0294)
BM	0.0172*	0.0097	0.0173*	0.0096
	(0.0092)	(0.0078)	(0.0092)	(0.0078)
Leverage	0.0298	0.0158	0.0297	0.0156
	(0.0186)	(0.0144)	(0.0186)	(0.0144)
log(Price)	−0.0400***	−0.0045	−0.0402***	−0.0046
	(0.0091)	(0.0065)	(0.0091)	(0.0065)
PastRet	−0.0387***	−0.0210***	−0.0388***	−0.0211***
	(0.0038)	(0.0034)	(0.0038)	(0.0034)
ROA	−0.0624**	−0.0330	−0.0623**	−0.0331
	(0.0280)	(0.0244)	(0.0280)	(0.0244)
Volatility	4.4601***	2.3207***	4.4478***	2.3137***
	(0.3366)	(0.2769)	(0.3365)	(0.2767)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.8125	0.6103	0.8124	0.6102
Adjusted R^2	0.7883	0.5601	0.7883	0.5600
Observations	40,098	40,100	40,098	40,100

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Clustering and Information Environment by Institutional Onwership				
Dependent Variables:	BidAskSpread	AmihudIlliquidity	BidAskSpread	AmihudIlliquidity
Model:	(1)	(2)	(3)	(4)
Variables				
TopClustering	0.0259***	0.0307***		
	(0.0097)	(0.0089)		
TopClustering × HighInsHolding	-0.0207**	-0.0270***		
	(0.0098)	(0.0086)		
HighClustering			0.0307***	0.0319***
			(0.0106)	(0.0094)
HighClustering × HighInsHolding			-0.0379***	-0.0318***
			(0.0105)	(0.0090)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
R^2	0.8015	0.5732	0.8016	0.5732
Adjusted R^2	0.7785	0.5236	0.7785	0.5236
Observations	39,648	39,650	39,648	39,650

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: **Clustering, Working Habits, and Brokerage Culture**
This table investigates whether forecast clustering reflects persistent individual working patterns and institutional practices. Panel A reports the variation in analysts' quarterly clustering behavior explained by time (year-quarter), analyst, and brokerage firm fixed effects. Two measures are used: (1) *AnyCluster*, a binary indicator equal to 1 if the analyst issues clustered forecasts on at least one day in the quarter (extensive margin), and (2) $MaxClusterNum$, the logarithm of the maximum number of forecasts issued on a single clustered day within the quarter (intensive margin). Panel B lists the ten largest brokerage firms with high and low clustering intensities, based on the fraction of analyst-quarters exhibiting clustering. Firms are classified as high clustering if this fraction exceeds 0.8 and low clustering if it falls below 0.2.

Panel A: Quarterly clustering explained by fixed effects

	Time (T)	Analyst (A)	Broker (B)	A+B	T+A+B
Any Cluster					
R^2	0.006	0.503	0.182	0.516	0.525
Observations	232,311	232,311	232,311	232,311	232,311
Max Cluster Number					
R^2	0.026	0.499	0.124	0.513	0.531
Observations	141,643	141,643	141,643	141,643	141,643

Panel B: Top 10 largest brokers with high and low forecast clustering

ESTIMID	Company Name	Clustering Fraction
High Clustering		
STIFEL	Stifel, Nicolaus & Company, Incorporated	0.849
MONTSEC	Banc of America Securities LLC	0.849
FRCLAYSC	Barclays Bank PLC	0.822
WHEAT	Wells Fargo Securities, LLC	0.839
EDWARDS	A. G. Edwards & Sons, Inc.	0.803
BLAIR	William Blair & Company L.L.C.	0.807
FAHN	Oppenheimer & Co. Inc.	0.872
PIPER	Piper Sandler & Co.	0.899
STERNE	Sterne Agee & Leach Inc.	0.800
BACHE	Prudential Equity Group	0.875
Low Clustering		
JBEF	Kepler Capital Markets	0.060
CDC	Natixis S.A.	0.007
CICC	China International Capital Corporation Limited	0.182
ODDO	ODDO BHF Corporate & Markets	0.038
ALPHAV	Fairesearch GmbH & Co KG	0.030
MAINFRST	Stifel Europe	0.089
CARNEGIE	Carnegie Investment Bank AB	0.141
DANBORS	Danske Bank A/S	0.092
SANINVLC	Santander Investment Securities Inc.	0.170
JMDUTTON	Dutton Associates	0.091

Table 9: **Robustness: Alternative Measures of Firm Importance**
This table examines whether analysts are less likely to cluster forecasts for important firms, using alternative proxies for importance. The dependent variable, $MultiForecast_{i,j,t}$, equals 1 if analyst i's forecast for firm j on day t is clustered and 0 otherwise. The main explanatory variable, $ImportantFirm_{i,j,t}$, is measured using four alternative proxies for firm importance based on institutional trading activity and ownership. Two trading-based indicators, *TopVolIns* and *TopVolInsMv*, equal 1 if firm j is in the top quartile of analyst i's portfolio based on the number of shares or the dollar value of shares traded by institutional investors, respectively. Two ownership-based indicators, *TopTra* and *TopTraMv*, equal 1 if firm j is in the top quartile based on the percentage or dollar value of shares held by transient institutional investors, following the classification in Bushee (2001). All specifications include the control variables $\mathbf{X}_{i,j,t}$ described in Table 4 and firm × year, analyst × year-quarter, and date fixed effects. For brevity, only coefficients of interest are reported. Standard errors are two-way clustered by analyst and date and reported in parentheses.

Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
TopVolIns	−0.0030***			
	(0.0010)			
TopVolInsMv		−0.0052***		
		(0.0011)		
TopTra			−0.0023**	
			(0.0011)	
TopTraMv				−0.0063***
				(0.0011)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm-Year	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes
R^2	0.4848	0.4848	0.4848	0.4848
Adjusted R^2	0.4199	0.4199	0.4199	0.4199
Observations	2,281,674	2,281,674	2,281,674	2,281,674

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: **Robustness: Forecast Clustering within Analyst Working Hours**
This table replicates the main regression results from Table 4 through Table 6, restricting the sample to forecasts issued between 9:00 a.m. and 11:00 p.m., which corresponds to analysts' working hours according to Jiao (2023). Panel A reports results for workload-related, mechanical clustering channels examined in Table 4, including concurrent earnings announcements and distraction from news affecting other firms in the analyst's portfolio. Panel B presents results for strategic clustering based on firm or information importance, replicating specifications from Tables 5 and 6, respectively.

Panel A: Workload-related clustering				
Dependent Variable:	MultiForecast			
Model:	(1)	(2)	(3)	(4)
MultiEA	0.1853***			
	(0.0032)			
Distraction_News		0.0561***		
		(0.0013)		
IS_News		−0.0022***		
		(0.0001)		
Distraction_AbnVol			0.5644***	
			(0.0121)	
IS_AbnVol			−0.0711***	
			(0.0017)	
Distraction_AbsRet				0.3092***
				(0.0103)
IS_AbsRet				−0.0471***
				(0.0015)
Controls	Yes	Yes	Yes	Yes
Fixed-effects				
Firm-Year	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes
R^2	0.4654	0.4613	0.4552	0.4498
Adjusted R^2	0.3463	0.3412	0.3338	0.3272
Observations	1,013,328	1,013,328	1,013,328	1,013,328

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel B: Strategic clustering							
Dependent Variable:	MultiForecast						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TopSize	−0.0059***						
	(0.0016)						
TopVol		−0.0025					
		(0.0015)					
TopIO			−0.0054***				
			(0.0016)				
ImpFirmAny				−0.0057***			
				(0.0015)			
ImpFirmAll					−0.0029*		
					(0.0015)		
RecomRevision						−0.0167***	
						(0.0028)	
UpGrade							−0.0282***
							(0.0039)
DownGrade							−0.0071*
							(0.0038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects							
Firm-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst-YrQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ForecastDay	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5679	0.5679	0.5679	0.5679	0.5679	0.5680	0.5680
Adjusted R^2	0.4536	0.4536	0.4536	0.4536	0.4536	0.4536	0.4537
Observations	1,047,436	1,047,436	1,047,436	1,047,436	1,047,436	1,047,436	1,047,436

*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.
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.
Distraction_News	A weighted measure of IS_News for all firms in analyst i's portfolio excluding firm j on day t.
IS_News	The number of fundamental news for firm j recorded in RavenPack on day t. Fundamental news are news with a relevance score of 100 and an event similarity day equal to or larger than 100 from the following news types: news-flash, hot-news-flash, full article, and press release, excluding the following six news groups related to analysts' analysis or technical analysis: credit-ratings, analyst-ratings, price-targets, stock-picks, stock-prices, technical-analysis.
Distraction_AbnVol	A weighted measure of IS_AbnVol for all firms in analyst i's portfolio excluding firm j on day t.
IS_AbnVol	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.
Distraction_AbsRet	A weighted measure of IS_AbsRet for all firms in analyst i's portfolio excluding firm j on day t.
IS_AbsRet	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 market capitalization 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 (in thousand shares) in the previous quarter 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 institutional ownership at the last quarter-end and 0 otherwise. Institutional ownership is calculated as the percentage of equity of firm j held by all institutions, multiplied by the market capitalization at the last quarter-end.
ImpFirmAny	A dummy variable equal to 1 if TopSize, TopVol, *or* TopIO is equal to 1.

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Table A1 – *Continued from previous page*

Variable	Definition
ImpFirmAll	A dummy variable equal to 1 if TopSize, TopVol, *and* TopIO are equal to 1.
TopVolIns	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of institutional trading volume in the previous quarter and 0 otherwise. Institutional trading volume is calculated as the total trading volume minus retail trading volume, where retail trading volume is estimated using TAQ data following Barber et al. (2024).
TopVolInsMv	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of the market value of institutional trading volume in the previous quarter and 0 otherwise. Market value of institutional trading volume is computed as institutional trading volume, measured in shares, multiplied by the firm's stock price at the last quarter-end.
TopTra	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of transient institutional ownership at the last quarter-end and 0 otherwise. Transient institutional ownership is the percentage of shares owned by transient institutional investors, according to Bushee (2001)'s classification.
TopTraMv	A dummy variable equal to 1 if firm j is in the top quartile of analyst i's portfolio in terms of the market value of transient institutional ownership at the last quarter-end and 0 otherwise. Market value of transient institutional ownership is the percentage of shares owned by transient institutional investors, according to Bushee (2001)'s classification, multiplied by the market value of the firm at the last quarter-end.
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.
ForecastFrequency	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 number of analysts who cover firm j at time t.
	Information Environments Variables
BidAskSpread	The average bid-ask spread over the year, calculated as $100 \times \frac{\text{ask}-\text{bid}}{(\text{ask}+\text{bid})/2}$, using daily closing bid and ask prices from CRSP.
AmihudIlliquidity	The average ratio of the absolute stock return to the dollar trading volume, scaled by 10^6, using daily stock returns and trading volumes over the year from CRSP.
TopClustering	A dummy variable equal to 1 if a firm falls within the top quartile of the fraction of clustered forecasts across all firms in year t.
HighClustering	A dummy variable equal to 1 if at least 60% of forecasts are clustered in year t.

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Table A1 – *Continued from previous page*

Variable	**Definition**
HighInsHolding	A dummy variable equal to 1 if firm j's institutional ownership percentage is above the sample median.
TradingVolume	The annual trading volume for a firm j in year $t-1$.
InsHolding	The percentage of a firm's equity held by all institutions at the end of year $t-1$.
BM	Book value of equity in the fiscal year prior to the earnings forecast, divided by the current market value of equity.
Leverage	Long-term debt plus debt in current liabilities, divided total assets in the fiscal year prior to the earnings forecast.
PastRet	Cumulative buy-and hold returns in year $t-1$.
ROA	Return on assets, calculated as net income before extraordinary items and discontinued operations, divided by total assets in year $t-1$.
Volatility	Daily stock return volatility for firm j in year t.

Table A2: **Summary Statistics for Variables in the Information Environment Analysis** This table presents the summary statistics for the variables in the information environment analysis from 2002 to 2023. See Table A1 for detailed variable definitions.

Name	Mean	Median	p05	p95	SD
BidAskSpread	0.420	0.159	0.022	1.917	0.608
AmihudIlliquidity	0.078	0.003	0.000	0.498	0.230
Synchronicity	−1.435	−1.241	−4.241	0.611	1.400
TopClustering	0.250	0.000	0.000	1.000	0.433
HighClustering	0.244	0.000	0.000	1.000	0.429
HighInsHolding	0.500	0.500	0.000	1.000	0.500
Numest	9.708	7.000	2.000	27.000	7.995
log(MarketCap)	13.671	13.611	10.536	17.063	1.892
log(TradingVolume)	21.201	21.272	17.361	24.739	2.169
InsHolding	0.613	0.695	0.025	1.020	0.317
BM	0.552	0.444	0.090	1.444	0.415
Leverage	0.228	0.192	0.000	0.655	0.213
log(Price)	2.809	2.956	0.425	4.688	1.235
Past ret	0.115	0.065	−0.670	1.151	0.522
ROA	0.074	0.113	−0.378	0.294	0.188
Volatility	0.031	0.027	0.013	0.065	0.015