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Analyst effort allocation and firms' information environment

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Analyst Career Concerns, Effort Allocation, and Firms' Information Environment*

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Abstract

Because analysts strategically allocate more effort to portfolio firms that are relatively more important for their career concerns, a firm's information environment is impacted by other firms covered by its analysts. Controlling for analyst and firm characteristics, firms ranked relatively higher within each analyst's portfolio based on market capitalization, trading volume, or institutional ownership receive more accurate, frequent, and informative earnings forecasts and recommendations from that analyst. Firms' relative ranks vary widely across analysts, and thus are not firm characteristics. Firms have more transparent information environments when a larger proportion of their analysts consider them as relatively more important. Analysts who engage in a greater extent of career concerns-driven effort allocation are more likely to experience favorable career outcomes.

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1. Introduction

What determines the amount and quality of coverage a stock receives from an analyst? Prior research has identified many analyst and firm characteristics that affect analyst research (e.g., Clement (1999), Jacob, Lys, and Neale (1999), Clement, Reese, and Swanson (2003), Frankel, Kothari, and Weber (2006), Ljungqvist et al. (2007), Du, Yu, and Yu (2013), Bradley, Gokkaya, and Liu (2016), and Jiang, Kumar, and Law (2016)).[1] But the reality of analyst coverage portfolios is that analysts face competing demands for their time from the stocks they cover. As a result, how much coverage a stock receives from an analyst should depend not only on its own characteristics, but also on the characteristics of other stocks followed by the analyst. However, we know little about how the variation in stock characteristics *within* an analyst's portfolio impacts the way in which analysts provide research coverage on portfolio firms, and whether analysts' response to intra-portfolio firm differences has real consequences.

We aim to fill this void by examining how analysts allocate their effort among firms and whether their effort allocation decisions affect firm-level research quality and information transparency as well as their career outcomes. These are important questions that can lead to a more complete understanding of how analysts fulfill their information intermediary role, and of the constraints and incentives shaping their behavior. Answers to these questions can also provide new insights into the determinants of corporate transparency and improve empirical approaches to estimating the impact of an analyst on a firm's information environment.

Our investigation is built on the premise that financial analysts, like any economic agent, have limited time, energy, and resources (Kahneman (1973)), a notion that is consistent with extant evidence in the literature. For example, Clement (1999) shows that portfolio complexity measured by portfolio size has an adverse impact on analyst earnings forecast accuracy, and Cohen, Lou, and Malloy (2014) find that analysts with larger portfolios are less likely to ask questions on firms' earnings conference calls. Faced

[1] These variables include, e.g., the analyst's forecasting experience, portfolio complexity, employer size, employment history, cultural background, and political view and the firm's potential for generating investment banking business and trading commission and its institutional ownership.

with these constraints, analysts must be selective in allocating their attention and effort to firms in their portfolios in order to maximize their utility function as determined by career concern considerations.

Analysts' compensation and upward mobility in the labor market depends on their reputation and ability to generate commission revenue for their brokerage houses and win favorable ratings from buy-side institutional clients (Groysberg, Healy, and Maber (2011)). Importantly, firms within an analyst's research portfolio can have differential impacts on the analyst's compensation, reputation, and mobility. For example, firms with large trading volumes and institutional ownership represent more lucrative sources of commission fee revenue for brokerage houses (Frankel, Kothari, and Weber (2006)). In addition, institutional investors participate in annual evaluations of sell-side analysts, and their assessments form the basis of the selection of "All-Star" analysts and the allocation of buy-side investors' trades and commissions across brokerage firms (Maber, Groysberg, and Healy (2014) and Ljungqvist et al. (2007)). In a similar vein, because large firms are more visible in the capital market, generating large trading activities and attracting significant institutional following, an analyst's performance in researching these firms may also have a larger impact on her compensation and reputation in the labor market (Hong and Kubik (2003)).

Given the heterogeneity along these dimensions among firms within an analyst's portfolio, the quality of the analyst's research services for each firm is likely to vary with the firm's relative importance for the analyst's career concerns. Based on this intuition, we develop a "career concerns" hypothesis, which contends that analysts devote more (less) effort to researching firms that are relatively more (less) important from their career concern perspectives. Following from the argument above, we identify firms of relatively high (or low) importance to analysts using a firm's relative rank in an analyst's portfolio based on market capitalization, trading volume, and institutional ownership. Importantly, because a firm's relative rank is determined by not only its own characteristics but also those of other firms in an analyst's portfolio, there is wide variation in a firm's relative rank across analysts covering the firm. Aggregating the research efforts a firm receives from all of its analysts, the "career concerns" hypothesis further predicts that firms whose relative rank is high (or low) in a larger proportion of its analysts' portfolios are associated with more (less) transparent information environment and less (more) information asymmetry. This implies that a firm's information environment and hence cost of capital can be influenced by the characteristics of the *other* firms that its analysts follow. We note that while our discussion here focuses on the benefits of coverage effort to analysts, we do not assume that analysts face the same cost of coverage across firms. Consequently, we address coverage costs in the empirical analysis.

Of course, as information intermediaries, analysts will consider their potential impact on a firm's information environment when allocating effort. The nature of the equilibrium will depend on how effort translates into accuracy for each stock and the relative reward for accuracy on stocks with higher versus lower institutional interest. Our analysis will uncover the extent to which career concerns affect analyst effort allocation, and hence the information environment of firms. Empirically, we test whether analyst effort allocation is consistent with career concerns dominated by institutional investor interest, or by incentives to add the most information to under-followed stocks.

We begin by analyzing the earnings forecasts and stock recommendations issued by a large sample of sell-side analysts from 1983 to 2012.[2] Evidence from our analysis supports the conclusion that the dominant career concerns incentive is to exert more effort on firms that—within the context of their own portfolio—are more important to institutional investors. Specifically, analysts provide more accurate earnings forecasts and more frequent earnings forecast revisions for firms ranked higher based on market capitalization, trading volume and institutional ownership relative to other firms in the same analyst's portfolio. It is worth noting that these results are robust to controlling for a large array of pertinent firm and analyst characteristics. Our findings are also robust to controlling for analyst fixed effects, firm fixed effects, or analyst-firm pair fixed effects. The robustness to analyst-firm pair effects is especially notable because we are holding the pairing constant so that variation in the importance of the firm to the analyst

[2] Our examination of earnings forecasts and stock recommendations does not imply that they are the sole metrics based on which analysts are assessed and rewarded. In fact, institutional investors and brokerage houses evaluate analysts more broadly based on their knowledge and understanding of firms and industries and their activities of producing value relevant information or helping institutional clients obtain such information (Brown et al. (2015), Groysberg, Healy, and Maber (2011), and Maber, Groysberg, and Healy (2014)). We assume that the properties of earnings forecasts and stock recommendations are signals of the effort and resources devoted by analysts to all of these activities related to a given firm.

comes largely from variations in the *other* firms that the analyst covers. In addition, we find that the impact of a firm's relative importance on earnings forecast behavior is stronger for "busy" analysts, i.e., those covering larger portfolios. This evidence is consistent with the intuition that larger portfolios are more likely to hit the constraint created by analysts' limited time, energy, and resources, making it even more critical for the analysts to be strategic in their research activities. As such, it lends more credence to our "career concerns" hypothesis.

Further analyses suggest that the stock market recognizes the effort allocation incentives of analysts. Specifically, we find that earnings forecast revisions and stock recommendation changes issued by analysts on firms that are relatively more important in their portfolios elicit stronger stock price reactions, indicative of analyst research on these firms conveying greater information content.

We then extend our investigation to study the effects of analysts' career concerns-driven effort allocation on firms' information environment. Our results show that firms where a larger proportion of their analysts consider them relatively more important are associated with lower bid-ask spreads, higher stock market liquidity, and lower costs of capital. This is consistent with the interpretation that analysts commit more effort to research and information production for these firms, thereby contributing to more transparent information environments. We also exploit exogenous losses of analyst coverage due to brokerage house closures and mergers and find that firms losing coverage by analysts who rank them as relatively more important experience greater declines in information transparency, compared to firms losing coverage by analysts who rank them as relatively less important. Thus, analysts' effort allocation decisions have real consequences for firms and investors.

Finally, we examine the career outcome implications of analysts' effort allocation. If the pattern of analyst effort allocation we document is a rational response to career concerns, we expect favorable career outcomes to be related to the degree to which analysts engage in such effort allocation. We measure an analyst's engagement of career concern-based effort allocation by the differences in earnings forecast accuracy and frequency between the higher and lower ranked firms within the analyst's portfolio. Consistent with our expectation, we find that the extent of an analyst's career concern-based effort allocation is significantly and positively related to the probability of the analyst being voted as an "All Star" and moving to more prestigious brokerage houses. The explanatory power of the differential forecast frequency and accuracy between high and low ranked firms is incremental to the analyst's average forecast frequency and accuracy for her portfolio. These results provide a logical explanation for the analyst effort allocation pattern we observe.

Our study makes several contributions that advance our understanding of the determinants of analyst behavior and firms' information environment. First, we contribute to the sell-side analyst literature by exploring within-analyst portfolio variations in analyst behavior. This approach represents a novel departure from, as well as an important complement to, prior studies focusing on either cross-analyst or cross-firm variations. It enables us to provide new insights into how analysts allocate their limited attention and resources to firms within their portfolios. Specifically, our findings go beyond the average effect of analyst and firm attributes and highlight the fact that the same analyst does not treat all firms in her portfolio equally and that the same firm does not receive equal amounts of attention and effort from all the analysts covering it. Instead, analysts strategically allocate more research effort to firms that are relatively more important for their career concerns.

In addition, we show that a firm's aggregate relative importance across its analysts has an effect on its information environment incremental to firm and analyst characteristics. Given that a firm's relative rank in an analyst's portfolio is partly determined by characteristics of other firms in the portfolio, our finding suggests that the quality of a firm's information environment is not entirely a function of its own attributes but also those of firms with which it shares analyst coverage.

Our results also suggest that the common approach of using the number of analysts following a firm as a measure of the firm's information environment can benefit from incorporating the firm's average relative importance in its analysts' portfolios. A larger number of analysts covering a firm does not necessarily translate into more information production and a more transparent information environment for the firm if it often finds itself at the bottom of its analysts' priority lists and thus receives little research attention.

Finally, our investigation sheds new light on factors that influence analysts' career outcomes. Specifically, our evidence suggests that the way in which analysts allocate their effort among portfolio firms is an important determinant of their labor market outcomes. Prior research finds that an analyst's average earnings forecast accuracy has a significant impact on her career prospects (e.g., Mikhail, Walther, and Willis (1999) and Hong and Kubik (2003)). We show that an analyst's forecasting performance differential between the high and low ranked firms within her portfolio, which captures the extent of the analyst's career concern-based effort allocation, matters as well.

2. The determination of analyst portfolios

Before we move on to the empirical part of the paper, it is important to discuss the determination of an analyst's portfolio and whether it affects our research question and findings. The size and composition of an analyst's portfolio are driven by many factors, some of which are outside analysts' or brokerage firms' control, such as the number of firms in an industry, the industry's complexity, major players, the level of competiveness and the broader competitors of a given firm (Hsu, Li, Ma and Phillips, 2017). For example, by virtue of their size, dominant position, and interest from institutional investors, some companies, such as Apple Inc., are likely to be in the portfolios of most, if not all, of the analysts covering their industries. To the extent that analyst portfolios are determined mainly by exogenous forces, it is a fairly straightforward question and empirical exercise with respect to whether/how analysts allocate their efforts trying to maximize their utility function defined by career concern considerations.

However, brokerage firms and analysts typically have at least some discretion over how many and which firms an analyst covers. For example, conversations with sell-side analysts, confirmed by our sample descriptive statistics, suggest that more seasoned analysts with higher quality and better reputation have more control over their research portfolios and tend to cover more firms. To the extent that analyst portfolios are endogenously determined, the incentives that affect analyst effort allocation may also play a role in determining which firms an analyst covers. In particular, our "career concerns" hypothesis would imply that, given the choice, analysts would choose to cover firms which are more important to their career development. This tendency will bias against finding evidence of analysts playing favorites among portfolio firms, because the portfolio consists only of "favorites". In the extreme case where firms in an analyst's portfolio are equally important to the analyst's career outcomes, we would not expect to observe any differential treatment of firms by the analyst. However, given the degree of heterogeneity across firms in a typical industry, and the lack of complete control over coverage choices, there will be variation in the relative importance of firms within an analyst's portfolio. As such, our "career concerns" hypothesis will continue to be relevant. In fact, we find stronger evidence of career concerns-driven effort allocation when the firms in the analyst's portfolio are more heterogeneous.

Additionally, analyst coverage decisions may also by motivated by considerations related to competition among analysts and firms' current information environments. For example, an analyst may prefer to cover firms that are smaller, with low trading volume, analyst coverage, and institutional interest, either because there is less competition from other analysts or because they believe their research can have a larger marginal impact on these firms' information environments. While some analysts may follow this strategy, it is unlikely to be sustainable in the long run. Given that the brokerage industry primarily serves institutional investors, it is difficult for brokerage houses to support analysts covering small and thinly traded stocks with low institutional interest. The compensation schemes for sell-side analysts also provide disincentives for covering these firms, because a large component of analysts' compensation is determined by the ratings they receive from institutional clients and the order flow they can generate. In addition, if analysts indeed actively apply this strategy – i.e. prefer covering firms with poorer information environment, then in equilibrium the result would be similar information environments across all firms. However, in reality, extant evidence establishes that different firms tend to have very different analyst coverage and information environments, suggesting that this strategy does not play a major role in determining analyst coverage decisions. Rather, given the incentives they face, it is more likely that within the group of career-critical firms an analyst covers, the analyst will further adjust effort to equate the value of outcomes across those firms. The net result of these forces is an equilibrium where the value-weighted information environment impact is equalized across firms.

The equilibrium forces notwithstanding, empirically we are able to hold constant firm-level characteristics, such as having a weaker information environment, analyst-level characteristics, such as being inherently more skilled than other analysts, as well as analyst-firm pair characteristics, such as analysts being better at covering a specific firm. Our identification relies on changes in the relative importance of a firm in an analyst's portfolio, due to changes in the *other* firms the analyst covers.

3. Sample description, variable construction, and summary statistics

The dataset used in our study is constructed from multiple sources. Analyst earnings forecasts and stock recommendations are from Institutional Broker Estimate System (*I/B/E/S*). Firm characteristics and stock returns are obtained from COMPUSTAT and CRSP. Information on institutional ownership is from the Thomson 13F database. Our sample period is from 1983 to 2012. Following prior literature, e.g., Clement (1999), we restrict the sample to earnings forecasts made during the first 11 months of a fiscal year, i.e., with a minimum forecast horizon of 30 days, although our results are not sensitive to this restriction.

Our primary measure of analyst effort is the accuracy of an analyst's earnings forecast for a firm, which is based on the forecast made by the analyst that is closest to the firm's fiscal year end. We construct the analyst forecast accuracy measure by comparing an analyst's absolute forecast error on a firm to the average absolute forecast error of other analysts following the same firm during the same time period. This measure is initially developed by Clement (1999) to remove firm-year effects in analyst forecast accuracy and is widely adopted in the literature (e.g., Malloy, 2005; Clement et al., 2007; De Franco and Zhou, 2009; Horton and Serafeim, 2012; Bradley, Gokkaya, and Liu, 2016). Specifically, the relative earnings forecast accuracy ($PMAFE_{i,j,t}$) is computed as the absolute forecast error ($AFE_{i,j,t}$) of analyst i for firm j in year t minus the mean analyst absolute forecast error for firm j at year t ($MAFE_{j,t}$), then scaled by the mean absolute forecast error for firm j at year t to reduce heteroskedasticity (Clement, 1998). Specifically, $PMAFE_{i,j,t}$ is formally defined as:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - MAFE_{j,t}}{MAFE_{j,t}}$$

$PMAFE_{i,j,t}$ is an analyst's forecast accuracy *relative to* all other analysts covering the same firm during the same time period and thus filters out differences across companies, year and industry (Ke and Yu, 2006). Lower values of *PMAFE* correspond to more accurate forecasts.

Our second measure of analyst effort is the frequency of earnings forecast updates, which is equal to the number of annual forecasts made by an analyst for a firm during a fiscal year with a minimum forecast horizon of 30 days. This variable has been used by prior studies to measure the amount of analyst effort (e.g., Jacob, Lys, and Neale (1999) and Merkley, Michaely, and Pacelli (2016)). However, its caveat is that it does not directly speak to the quality of analyst research on a given firm.

We construct a number of analyst and forecast characteristics that previous research has identified as important factors explaining analyst performance. Specifically, we control for analyst experience because Clement (1999) shows that it is related to forecast accuracy. We consider both general and firm-specific forecasting experience, which are calculated, respectively, as the total number of years that analyst *i* appeared in *I/B/E/S* ($Gexp_i$) and the total number of years since analyst *i* first provided an earnings forecast for firm *j* ($Fexp_{ij}$). We measure the resources available to an analyst using an indicator variable that is equal to one if the analyst works for a top-decile brokerage house ($Top10_i$) based on the number of analysts employed, and zero otherwise. This variable can also serve as an indicator for analyst ability, to the extent that larger brokerage houses attract more talented analysts. We also measure the complexity of an analyst's portfolio by the number of firms in analyst *i*'s portfolio ($PortSize_i$) and the number of 2-digit SICs represented by these firms ($SIC2_i$). Finally, we control for the number of days (AGE_{ij}) between analyst *i*'s forecast for firm *j* and the firm's fiscal year end. Clement (1999) and Clement and Tse (2005) find that *AGE* is positively related to relative forecast errors, emphasizing the need to control for timeliness. Appendix A provides detailed definitions of these variables.

Because the *I/B/E/S* database is left censored, we cannot determine how much experience analysts have prior to the first year of available data. To mitigate this problem, we follow Clement (1999) to exclude analysts who appear in the first year of the database (1983). Forecasts made in 1984 are also excluded from our analysis because there would be little variation in the experience variables for that year (i.e., the experience variables can take on the value of only 0 or 1 in 1984).[3]

Table 1 provides summary statistics on the main variables used throughout this paper. Panel A presents the unadjusted values. The median absolute forecast error is 0.07, and the median frequency of forecast revisions in a year is 3. The median analyst in our sample has been providing forecasts for 4 years, and covering the typical firm in our sample for 2 years. The median number of days between forecasts and the fiscal year end is 73. The median analyst covers 14 firms each year, which represents 3 distinct 2-digit SIC codes. Approximately 49% of forecasts are issued by analysts working for a top-decile brokerage house based on the number of analysts employed by each brokerage. These values are comparable to those in prior studies (Clement and Tse, 2005; Clement, Koonce, and Lopez, 2007; Bradley, Gokkaya, and Liu, 2016).

Panel B of Table 1 presents firm-year-mean-adjusted values. Clement (1999) finds that removing firm-year effects from dependent and independent variables improves the likelihood of identifying performance differences across sell-side analysts compared to a model that includes firm and year fixed effects. This is due to a firm's earnings predictability varying over time. We observe that the median values in Panel B are comparable to those reported in prior studies (e.g. Clement, 1999; Clement, Koonce, and Lopez, 2007; Bradley, Gokkaya, and Liu, 2016).

Our key explanatory variables are the measures that capture the relative importance of a firm in an analyst's portfolio. We first construct the measures based on the firm's market capitalization at the previous year end. To capture the relative importance of a specific firm for analysts following multiple firms, we create a dummy variable *High*, which takes the value of 1 if a firm's market capitalization is in the top quartile of all firms the analyst covers in that year, and zero otherwise. We also create a dummy variable *Low*, which takes the value of 1 if a firm's market capitalization is in the bottom quartile of all

[3] Our results are robust to the inclusion of those observations in 1983 and 1984.

firms the analyst covers in that year, and zero otherwise.[4] We also construct the *High* and *Low* indicators based on a firm's trading volume in the prior year and institutional ownership at the previous year end. Our goal here is not to take a stand on which measure of relative importance is most accurate. Rather, by using three different metrics, we hope to ensure that whatever pattern of analyst effort allocation we find is robust across alternative measures.

There is considerable variation in a firm's relative ranking across analysts. For example, using a firm's market capitalization to capture its relative importance, we find that conditional on a firm being ranked as high by at least one analyst, only 37% of the other analysts covering the firm rank it as high. Conditional on a firm being ranked as low by at least one analyst, the firm is ranked low by 56% of other analysts.

Panel C of Table 1 provides a comparison of several analyst forecast and firm characteristics between firms in the *High* and *Low* portions of analyst portfolios. Not surprisingly, we find that compared to firms in the *Low* group, firms in the *High* group are larger, more actively traded, and receive more institutional investment. They also receive more frequent and more accurate earnings forecasts from analysts, providing some preliminary support for our career concerns hypothesis.

4. Evidence on how analysts allocate effort

In this section, we examine how analysts allocate their effort across firms in their portfolios. We measure analyst effort using the earnings forecast accuracy and revision frequency.

4.1. Earnings forecast accuracy

Our career concerns hypothesis predicts that analysts make more accurate earnings forecasts for firms that are relatively more important in their portfolios. To test this prediction, we regress an analyst's relative forecast accuracy on a firm ($PMAFE_{i,j,t}$) on our key explanatory variables, the *High* and *Low* indicators, along with an array of analyst characteristics that previous research has identified as related to

[4] We require analysts covering at least four firms in a given year. Our results still hold without this requirement.

differences in relative forecast accuracy among analysts.[5] More specifically, the model is specified as follows.

$$PMAFE_{i,j,t} = \beta_0 + \beta_1 High_{i,j,t} + \beta_2 Low_{i,j,t} + \beta_3 DGexp_{i,j,t} + \beta_4 DFexp_{i,j,t} + \beta_5 DAge_{i,j,t} + \beta_6 DPortsize_{i,j,t} + \beta_7 DSIC2_{i,j,t} + \beta_8 DTop10_{i,j,t} + \beta_9 All\text{-}star_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

The "*D*" preceding some variables indicates that these variables are de-meaned at the firm-year level to remove firm-year fixed effects. The standard errors are estimated by double clustering at the firm and analyst level. Note that while our test is stated in terms of forecast accuracy, the dependent variable in this regression is an analyst's relative forecast error. Lower relative forecast errors indicate higher forecast accuracy. Based on the career concerns hypothesis, we expect the coefficient of *High* (*Low*) to be negative (positive).

Panel A of Table 2 reports the baseline regression results. In column (1), the relative importance of a specific firm in an analyst portfolio is measured using its equity market capitalization. As predicted, the coefficient on *High* is negative and statistically significant at the 1% level, while the coefficient on *Low* is positive and statistically significant at the 1% level. These results indicate that analysts make more accurate earnings forecasts for firms that are relatively more important in their portfolios and are consistent with the prediction of our career concerns hypothesis that analysts devote more resources to researching these firms. Economically, firms that belong to the relatively more important group receive earnings forecasts that are on average 1.928% more accurate than firms not in that group. Similarly, firms that belong to the relatively less important group receive earnings forecasts that are on average 1.594% less accurate. The average difference in earnings forecast accuracy between the high and low groups of firms is 3.522% (=1.594-(-1.928)). To put this effect into context, we compare it to the effects of some

[5] Because the dependent variable by construction is free of firm-year effects, there is no need to control for firm characteristics. Not surprisingly, we obtain very similar results if we include a set of firm characteristics, such as a firm's size, trading volume, institutional holding, book-to-market ratio, past stock returns, and analyst coverage, as additional controls. This provides further assurance that the *High* and *Low* indicators do not simply pick up the effects of the variables they are based on.

other determinants of forecast accuracy. We find that the high-low accuracy differential is equivalent to the effect of over 13 years of general forecasting experience, over 5 years of firm-specific forecasting experience, 1.34 times the effect of working for a top-decile brokerage firm and about the same as the effect of being an all-star analyst. We obtain very similar results when we measure the relative importance of a firm by trading volume in column (2) or by institutional ownership in column (3).

The coefficients on control variables are mostly consistent with previous studies (e.g., Clement (1999)). For example, analysts with more general or firm-specific forecasting experience issue more accurate earnings forecasts, while analysts covering more industries issue less accurate forecasts. Analysts employed by the largest brokerage houses have better forecasting performance, which could be due to more resources being available at large brokerage houses or analysts working for large brokerage houses being more talented. More stale forecasts tend to be less accurate.[6]

In further analysis, we augment the regression model specified in equation (1) by controlling for analyst fixed effects.[7] Doing so can help us focus on the within-analyst variations in the *High* and *Low* indicators and mitigate the concern that our findings are driven by some time-invariant analysts' characteristics such as experience, talent or personal cost of coverage effort. Results in Panel B of Table 2 show that the coefficient on *High* continues to be significantly negative while the coefficient on *Low* remains significantly positive. The magnitude of the coefficients is slightly different from that in Panel A. For example, based on equity market capitalization, the relative earnings forecast error is 1.566% lower for relatively more important firms and 1.302% higher for relatively less important firms. These results indicate that for the same analyst, firms that are more important in her portfolio receive more accurate earnings forecasts than firms that are less important in her portfolio.

In Panel C, we replace the analyst fixed effects with firm fixed effects and in Panel D, we replace them with analyst-firm pair fixed effects. These alternative specifications serve two important purposes.

[6] Our results are also robust to controlling for how long an analyst has covered a firm's industry and whether there is investment banking relationship between a firm and an analyst's employer. We identify investment banking relationships based on whether the analyst's employer has been a lead underwriter or co-manager of the firm's equity offering (IPO or SEO).

[7] Our sample includes about 7,200 unique analysts, 10,500 unique firms, and 200,500 analyst-firm pairs.

First, they accentuate the within-firm variations or variations within each analyst-firm pair. Second, they allow us to further control for the costs faced by analysts in covering a firm, which may affect their effort allocation decisions. To the extent that certain firm characteristics are related to how difficult or costly it is for analysts to cover the firm, our firm fixed-effects will absorb all of these characteristics. If some analysts are particularly good at covering a particular industry or firm, this effect will be absorbed by our analyst-firm fixed effects. Thus, while we recognize that the cost of covering firms is not equal, our firm and analyst-firm pair fixed effects justify our focus on the relative benefits of coverage, which, given our empirical approach, should also rank firms on relative net benefits.

We find that the coefficients on the *High* and *Low* indicators retain their signs and statistical significance. These results suggest that for the same firm (as in Panel C) or the same firm covered by the same analyst (as in Panel D), the accuracy of forecasts received by the firm varies with its relative importance in the analyst's portfolio. The fact that the results are robust to analyst-firm pair fixed effects is particularly reassuring because in these regressions, the variation in relative rankings comes primarily from changes in what *other* firms are in the analyst's portfolio, as well as changes in the subject firm over time *after* it was originally added. This identification approach relies on time-series variation in a firm's high/low status within the analyst's portfolio. One concern would be that there is not enough such variation. It turns out, however, that changes in the composition of an analyst's portfolio are frequent enough that conditional on a firm being ranked high (low) by an analyst, this firm has an 18% (25%) probability of being ranked non-high (non-low) in the following year by the same analyst. Finally, the analyst-firm fixed-effect results also help us address another potential concern, which is that the most important firms only get added to the best analysts' portfolios. If so, then the most important firms would enter a portfolio as high and stay high, being absorbed by the pairing fixed-effect. The results in this specification are based on within-portfolio variation over time.

Gormley and Matsa (2014) show that de-meaning variables may produce inconsistent estimates and distort the results, and suggest using the raw values of variables and controlling for fixed effects instead. Therefore, we estimate an alternative specification of model (1), in which we control for firm-year pair fixed effects in lieu of de-meaning the dependent variable as well as some of the independent variables. Table 3 presents the regression results. We continue to find a significantly negative coefficient for the *High* indicator and a significantly positive coefficient for the *Low* indicator, allowing us to conclude that de-meaning variables does not have a material impact on statistical inferences in our context. Therefore, we use the de-meaned specification as our main model to be consistent with the prior literature on analysts, and when necessary show robustness to the non-demeaned specification. Overall, the results from Tables 2 and 3 lend strong support to the career concerns hypothesis.[8]

An analyst could further adjust his or her effort to equalize incremental impact within the career-critical firms (the *High* group). If so, then if we sort the *High* group by standard information environment variables such as size, we will find no difference in forecast error across firms within the *High* group. In untabulated analysis, we do just that and find that the forecast errors for the larger firms within the *High* group are not different from those for the small firms within the *High* group. From this we conclude that an analyst first identifies and focuses on the firms within his or her portfolio that are relatively most important to his or her career, and then further adjusts effort to equalize the incremental impact of his or her effort across those career-critical firms.

4.2. Earnings forecast revision frequency

Earnings forecast update frequency is another widely used proxy for analyst effort in the literature (e.g., Jacob, Lys, and Neale (1999) and Merkley, Michaely, and Pacelli (2016)). Based on the career concerns hypothesis, we expect firms of relatively high importance within an analyst's portfolio to receive more frequent earnings forecast updates. We reestimate equation (1) in Section 4.1 while replacing the dependent variable with the earnings forecast update frequency (*DFREQ*), measured as the number of annual forecasts issued by an analyst each year during the 360 to 30 days prior to a covered

[8] We also examine the likelihood of an analyst being a leader or follower in issuing earnings forecasts for a firm. Untabulated results show that analysts are neither more likely to be leaders nor followers when making forecasts on their most important firms in their portfolio, but there is some evidence that they are more likely to be followers when it comes to their least important firms. These findings are consistent with analysts devoting less effort to the least important firms.

company's fiscal year end minus the average number of earnings forecast revisions issued by all analysts for that firm in that year (Groysberg, Healy, and Maber (2011)). Appendix B presents the results. Consistent with our hypothesis, we find that analysts update earnings forecasts more frequently for firms that are relatively more important in their portfolios. With a median frequency of 3 and an interquartile range of 2 to 5, there is less variation in frequency to explain, yet, the results are still economically meaningful. The average difference in the earnings forecast frequency between the high and low groups of firms based on their equity market capitalization is equivalent to the effect of about 5.3 years of general forecasting experience, 0.63 years of firm-specific forecasting experience, half as big as the effect of being employed at a top-decile brokerage firm and about 40% of the effect of being an all-star analyst. Our results are also robust to controlling for analyst fixed effects, firm fixed effects, and analyst-firm pair fixed effects.

4.3. Busy analysts

The career concerns hypothesis is built on the fact that analysts have limited time, energy, and resources. Faced with these constraints, analysts devote more effort to collecting and analyzing information for relatively more important firms in their portfolios. When analysts cover many firms, these constraints would be more binding and have a larger impact on analyst behavior. Therefore, we expect to observe stronger patterns of effort allocation among "busy" analysts, i.e., those who cover a large portfolio of firms. To formally test this prediction, we define "busy" analysts as those whose portfolio size in a given year is greater than the sample median and classify the other analysts as "non-busy". We then re-estimate the forecast accuracy regression for busy and non-busy analysts separately. We expect that the difference in forecast accuracy between the high and low groups of firms is more pronounced for busy analysts. On the other hand, a countervailing effect may also be at work. In particular, we find that analysts with larger portfolios tend to have significantly longer general forecasting experience and are more likely to be all-stars and employed by the largest brokerage houses.[9] To the extent that "busy" analysts have more experience, higher ability, and more resources at their disposal, there may be a lesser need for them to ration efforts to firms of low importance so as to devote more attention to firms of high importance.

Table 4 presents the regression results, with Panels A and B for busy and non-busy analysts, respectively. We find that for non-busy analysts, the coefficients on the *High* and *Low* dummies continue to be negative and positive respectively, but their statistical significance is relatively low, with the *High* dummy's coefficient only significant in one out of three models. In contrast, for busy analysts, the coefficients on the *High* and *Low* dummies are highly significant with the expected signs in all models. Moreover, when we compare the coefficients between the subsamples, we find that the coefficient on the *High* dummy is always more negative for busy analysts than for non-busy analysis (with the *p*-value for the between-subsample difference being 0.016, 0.005, and 0.014 across the three models), and that the coefficient on the *Low* dummy is always more positive for busy analysts than for non-busy analysis (with the *p*-value for the between-subsample difference being 0.011, 0.026, and 0.018). As a result, the high-low coefficient difference is much larger for busy analysts (ranging from 4.37% to 4.67%) than for non-busy analysts (from 1.57% to 1.82%). This is consistent with our conjecture that busy analysts face greater time and resource constraints and thus engage in more strategic effort allocation among firms in their portfolios.[10]

4.4. Further evidence on analyst effort allocation: Stock price impact of analyst research

Given our evidence of analysts issuing more accurate and frequent earnings forecasts for relatively more important firms in their portfolios, we next investigate the stock market reactions to their earnings forecast revisions and stock recommendations. If investors recognize that analysts allocate time

[9] In our sample, an analyst's portfolio size is significantly and positively related to the analyst's general forecasting experience, whether the analyst works for a top broker, and whether the analyst is an all-star, with the correlation coefficients being 0.239, 0.065, and 0.115, respectively.
[10] We find similar results when defining analyst "busyness" based on the number of industries (based on 2-digit SIC) they cover.

strategically across firms, we expect stronger market reactions to analysts' research on relatively more important firms in their portfolios. Analyzing the stock market reactions to analyst research can also address a potential caveat with using the earnings forecast accuracy measure. Specifically, analysts can potentially produce more accurate earnings forecasts by piggybacking on the information produced by other analysts and revealed through their published research including earnings forecasts. If an analyst's earnings forecast largely reflects the information contained in previously published research by other analysts, it would carry little new information content even though it may be more accurate. Therefore, we would expect its stock price impact to be muted at best. On the other hand, if the analyst's forecast indeed carries significant information content, its release should generate stronger stock market reactions.

4.4.1. Stock price reactions to analyst earnings forecast revisions

We first examine the market reaction to forecast revisions. We expect to observe more pronounced market reaction to forecast revisions issued by analysts for their relatively more important firms. To test this prediction, we estimate the following regression model.

$$\begin{aligned} CAR_{i,j,t} = {} & \beta_0 + \beta_1 FR{*}High_{i,j,t} + \beta_2 FR{*}Low_{i,j,t} + \beta_3 FR_{i,j,t} + \beta_4 High_{i,j,t} + \beta_5 Low_{i,j,t} + \beta_6 Gexp_{i,j,t} \\ & + \beta_7 Fexp_{i,j,t} + \beta_8 Age_{i,j,t} + \beta_9 Portsize_{i,j,t} + \beta_{10} SIC2_{i,j,t} + \beta_{11} Top10_{i,j,t} + \beta_{12} All\text{-}star_{i,j,t} \\ & + \beta_{13} Size_{j,t} + \beta_{14}\, Log(Trading\ Volume)_{j,t} + \beta_{15} Institutional\ Holding_{j,t} + \beta_{16} BM_{j,t} + \beta_{17} Past\ Ret_{j,t} \\ & + \beta_{18} No.\ of\ Analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \qquad (2) \end{aligned}$$

This model is similar to that used by Bradley, Gokkaya and Liu (2016). The dependent variable is the cumulative market-adjusted abnormal stock returns over a 3-day event window (-1, 1) around a forecast revision.[11] The key independent variables are the forecast revision (*FR*) and its interaction terms with *High* and *Low*. We control for other analyst and firm characteristics as in equation (1) as well as year

[11] The abnormal stock returns are denominated in percentage points, and we exclude analyst forecast revisions as well as stock recommendation changes that coincide with firms' earnings announcement dates.

fixed effects, and adjust standard errors for clustering at the firm and analyst level. We define forecast revision *(FR)* as the difference between the new forecast and the old forecast, scaled by the absolute value of the old forecast.[12] A positive *FR* represents an upward revision, and a negative *FR* represents a downward revision.

Table 5 presents the regression results. Columns (1)-(3) are based on using the market capitalization, trading volume, and institutional ownership to measure the relative importance of firms. We find that the coefficient on forecast revision *(FR)* is significantly positive. This suggests that the stock market responds positively to upward revisions and negatively to downward revisions, and larger forecast revisions elicit greater stock price reactions. More relevant for our purpose are the interaction terms between forecast revision and the *High* and *Low* indicators. We find that *High*FR* has a significantly positive coefficient in two out of three models while *Low*FR* has a significantly negative coefficient in all three model specifications. These results indicate that conditional on the direction and magnitude of forecast revisions, the stock market reacts more strongly to forecast revisions issued by analysts for relatively more important firms in their portfolios. In other words, the forecast revisions received by relatively more important firms in an analyst's portfolio tend to be more informative. This is again consistent with the career concerns hypothesis, which predicts greater information production effort by analysts on these firms.

4.4.2. Stock price reactions to stock recommendations

Next we examine the market reaction to stock recommendation revisions. Loh and Mian (2006) find that analysts who have superior forecast accuracy also issue more informative stock recommendations. Brown et al. (2015) document that analysts' top motivation for issuing accurate forecasts is to use these forecasts as inputs for their corresponding stock recommendations. Therefore, we expect stronger market reactions to stock recommendations issued by analysts on their relatively more important firms. We estimate the following regression model to test our prediction.

[12] Our results are robust if we deflate the forecast revision by stock price.

$$CAR_{i,j,t} = \beta_0 + \beta_1 High_{i,j,t} + \beta_2 Low_{i,j,t} + \beta_3 Gexp_{i,j,t} + \beta_4 Fexp_{i,j,t} + \beta_5 Portsize_{i,j,t} + \beta_6 SIC2_{i,j,t} + \beta_7 Top10_{i,j,t} + \beta_8 All\ star_{i,j,t} + \beta_9 Lag\ recommendation_{i,j,t} + \beta_{10} Size_{j,t} + \beta_{11} Log(Trading\ Volume)_{j,t} + \beta_{12}\ Institutional\ Holding_{j,t} + \beta_{13} BM_{j,t} + \beta_{14} Past\ Ret_{j,t} + \beta_{15} No.\ of\ Analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \quad (3)$$

The dependent variable is the cumulative 3-day market-adjusted abnormal stock return around a stock recommendation revision. The key explanatory variables are the *High* and *Low* indicators which capture the relative importance of a firm in an analyst's portfolio. We control for year fixed effects and adjust standard errors for clustering at the firm and analyst level. Following prior literature (e.g., Kecskes, Michaely, and Womack (2016)), we run separate regressions on recommendation upgrades and downgrades because of the asymmetric market reactions they elicit. Specifically, investors consider downgrades more credible and informative than upgrades, because the latter may be driven by analysts' conflicts of interest, namely, their incentive to please firm management and drum up order flow.

Panel A of Table 6 presents results for downgrades. Columns (1) to (3) correspond to the three different ways of ranking the relative importance of firms within an analyst's portfolio. We find that market reactions are stronger (weaker) for downgrades issued by analysts on their relatively more (less) important firms. In all specifications, the coefficients on *High* (*Low*) are significantly negative (positive) at the 1% level. In terms of economic significance, the coefficients in column (1) suggest that market reactions to downgrades are 54.8 basis points stronger for firms ranked relatively high in an analyst's portfolio and 33.3 basis points weaker for firms ranked relatively low in an analyst's portfolio. These results indicate that the informativeness of stock recommendations is related to a firm's ranking within an analyst's portfolio.

Panel B of Table 6 presents results for upgrades. The coefficients on *High* are significantly positive in all specifications, and the coefficients on *Low* are negative in all specifications but significant only in column (2). As a gauge of economic significance, the coefficients in column (1) indicate that stock market reactions are 15.2 basis points higher for firms with relatively high rankings, and 13.1 basis points lower for firms with relatively low rankings. The relatively weaker statistical and economic significance of the results for upgrades are likely due to their generally lower information content compared to downgrades.

5. The real effects of analyst career concerns on firm information environment

The results from Section 4 are consistent with analysts devoting more effort to information production for relatively more important firms in their portfolios. A direct implication of our evidence is that everything else being equal, firms that on average are ranked high in relative importance across their analysts' portfolios should have more transparent information environments. In this section, we test this conjecture by examining the effects of analyst effort allocation on firms' information asymmetry and costs of equity capital.

Different from the previous section, where we conduct tests at the analyst-firm-year level, the analysis in this section is at the firm-year level. We construct two variables to capture a firm's average relative ranking across all of its analysts. Specifically, we define *%High* (*%Low*) as the proportion of a firm's analysts who rank the firm high (low) in their portfolios. A higher value of *%High* implies that collectively more analyst effort is allocated to the firm while a higher value of *%Low* implies that collectively less analyst effort is allocated to the firm. Therefore, we expect a firm's information asymmetry and costs of capital to decrease with *%High* and increase with *%Low*. Appendix C reports the summary statistics of the dependent and independent variables used in this section. Panels A and B are based on two different samples, one for the information asymmetry analysis and the other for the costs of capital analysis.

5.1. Information asymmetry: Bid-ask spread and stock market liquidity

We follow the literature to measure a firm's information asymmetry in two ways. First, we compute a stock's bid-ask spread as a percentage of the stock price. A lower bid-ask spread implies lower information asymmetry. Second, we compute the Amihud (2002) stock illiquidity measure, which is defined as the natural log of one plus the ratio of the absolute stock return to the dollar trading volume and scaled by 1,000,000.[13] The key independent variables are *%High* and *%Low*. We control for a wide array of variables that have been shown to affect firms' information asymmetry. In particular, we control for firm size, trading volume, and institutional holding and their quadratic forms to ensure that *%High* and *%Low* are not simply picking up the effects of these firm characteristics. Our regression model is specified as follows.

$$\begin{aligned}&\textit{Bid-ask spread or Amihud illiquidity measure}\\&= \beta_0 + \beta_1\%High + \beta_2\%Low + \beta_3 No.\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume)\\&+ \beta_7 Log(Trading\ Volume)^2 + \beta_8\ Institutional\ Holding + \beta_9\ Institutional\ Holding^2 + \beta_{10} Log(Stock\ Price)\\&+ \beta_{11} BM + \beta_{12} Leverage + \beta_{13} Past\ Ret + \beta_{14} ROA + \beta_{15} Volatility + Year\ FE + Firm\ FE + \varepsilon \qquad (4)\end{aligned}$$

Panel A of Table 7 presents the results from the bid-ask spread regressions. Consistent with our conjecture, the coefficients on *%High* are significantly negative in all three specifications and the coefficients on *%Low* are significantly positive in two specifications. These results indicate that a firm which is ranked high by a larger proportion of its analysts has lower information asymmetry as measured by the bid-ask spreads. Economically, the coefficient estimates in column (1) suggest that, for a one standard deviation increase in *%High*, a firm's bid-ask spread on average decreases by 2.86 basis points (= -0.118×0.242×100) or 2.40% (=2.86/119).[14] Similarly, for a one standard deviation increase in *%Low*, a firm's bid-ask spread increases by 1.40 (=0.039×0.359×100) basis points or 1.17% (=1.40/119). As a comparison, for a one standard deviation increase in *No. of Analysts*, a firm's bid-ask spread on average

[13] Following prior literature, we exclude firms with stock prices below $5.
[14] The standard deviation of *%High* (*%Low*) in our sample is 0.242 (0.359). The mean value of bid-ask spread in our sample is 119 basis points. Please see Panel A of Appendix C.

decreases by 1.97 basis points (=-0.003×6.557×100) or 1.66% (=1.97/119).[15] Therefore, the economic significance of *%High* and *%Low* is on par with that of *No. of Analysts*.

Coefficients on control variables are generally consistent with the literature. For example, the bid-ask spread decreases with the number of analysts covering a firm, firm size, trading volume, stock return, and increases with stock volatility.

Panel B of Table 7 presents the results from the regressions of the Amihud illiquidity measure. We find that firms covered by more analysts who rank them high (low) enjoy higher (lower) stock market liquidity. Our results in Table 7 are robust to an alternative specification in which we replace *%High* (or *%Low)* with a dummy variable equal to one if a majority of a firm's analysts rank the firm high (or low) in their portfolios.

5.2. Costs of equity capital

To examine the effect of analyst effort allocation on firms' costs of equity capital, we use the residual income valuation model developed by Gebhardt, Lee, and Swaminathan (2001) to estimate the implied cost of capital (ICOC). The basic premise of the residual income model is that the ICOC is the internal rate of return that equates the current stock price to the present value of the expected future sequence of residual incomes or abnormal earnings. As in equation (5), the key explanatory variables are *%High* and *%Low* and we control for the raw values of firm size, trading volume, and institutional holding and their quadratic forms. The other control variables are from Gebhardt, Lee, and Swaminathan (2001). The regression model is specified as follows:

$$
\begin{aligned}
ICOC = {} & \beta_0 + \beta_1 \%High + \beta_2 \%Low + \beta_3 No\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume) \\
& + \beta_7 Log(Trading\ Volume)^2 + \beta_8\ Institutional\ Holding + \beta_9\ Institutional\ Holding^2 + \beta_{10} MAE\ of\ forecasts \\
& + \beta_{11} Earnings\ variability + \beta_{12} Dispersion\ of\ analyst\ forecasts + \beta_{13} BM + \beta_{14} Leverage + \beta_{15} Past\ Ret \\
& + \beta_{16} Long\text{-}term\ growth + \beta_{17} Beta + \beta_{18} Volatility + Year\ FE + Firm\ FE + \varepsilon \qquad (5)
\end{aligned}
$$

[15] The standard deviation of *No. of Analysts* in our sample is 6.557.

Table 8 presents the regression results. We find that a firm's ICOC decreases with the percentage of analysts that rank the firm high in their portfolios and increases with the percentage of analysts that rank the firm low in their portfolios. The coefficients on *%High* are all significantly negative and the coefficients on *%Low* are positive and significant in two out of three specifications. Economically, the coefficient estimates in column (1) suggest that, for a one standard deviation increase in *%High* or *%Low*, a firm's implied cost of capital on average decreases by 1.08% (=-0.259×0.274/(0.0654×100)) or increases by 0.89% (=0.193×0.303/(0.0654×100)).[16] As a comparison, for a one standard deviation increase in *No. of Analysts*, a firm's implied cost of capital on average decreases by 0.99% (=-0.009×7.158/ (0.0654×100)). Therefore, the economic impact of *%High* and *%Low* is similar to that of *No. of Analysts.*

Overall, our analysis in this section shows that a firm that is considered relatively more important by a larger proportion of its analysts has lower information asymmetry, better stock market liquidity, and a lower cost of capital. These results are consistent with analysts producing more information for relatively more career-important firms in their portfolios, and suggest that when evaluating the impact of analyst coverage on a firm's information environment, it is important to consider not only the number of analysts providing coverage but also the firm's average relative importance in the analysts' portfolios.

5.3. The effects of exogenous losses of analyst coverage

For a sharper identification of the effects of analyst effort allocation on firm information environments, we exploit exogenous losses of analyst coverage due to brokerage house closures and mergers as a quasi-natural experiment. Kelly and Ljungqvist (2012) document that information asymmetry increases following analyst coverage termination caused by brokerage house closures and mergers. We examine if the effect is stronger (or weaker) for firms losing coverage by an analyst who ranks the firm high (or low).

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[16] The mean implied cost of capital for our sample firms is 0.0654. Please see Panel B of Appendix C.

There are 38 brokerage house closures and mergers during our sample period.[17] We first identify firms that experienced losses of analyst coverage caused by brokerage closures or mergers. For broker mergers, we focus only on analyst coverage terminations where a stock was covered by an analyst from both the acquirer and target brokers before the merger, and by only one surviving analyst after the merger (e.g., Kelly and Ljungqvist (2012) and Derrien and Kecskes (2013)). To remove the common factors that affect the information environment of similar firms at the same time, we follow Kelly and Ljungqvist (2012) and Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) to construct a control group for each treatment firm. Specifically, for each firm experiencing analyst coverage losses, a control group is formed by selecting stocks with the same size and book-to-market quintile assignment in the month of June prior to the analyst loss, subject to the conditions that control firms (1) were covered by one or more analysts in the three months before the event; and (2) were not themselves subject to a coverage termination in the quarter before and after the event. We select up to five control stocks that are closest to the treatment stock in terms of the relevant pre-event information asymmetry measure. We then employ a difference-in-differences (DiD) approach to compare the change in the information environment of control firms to treatment firms. We further split the treatment firms into *High* and *Low* groups based on each treatment firm's ranking (high or low) in the lost analyst's portfolio in the year before the brokerage house closures and mergers. Based on market capitalization, we have 463 treatment firms in the *High* group and 214 treatment firms in the *Low* group.

Table 9 reports the differences in the mean DiD between the *High* and *Low* groups for the bid-ask spread and Amihud illiquidity measures. Following Kelly and Ljungqvist (2012), we compute the changes in a firm's bid-ask spread and stock illiquidity from three (or six) months before an analyst coverage loss to three (or six) months afterwards. Specifically, we calculate the average bid-ask spread and stock illiquidity using daily stock price and returns data over a three- (or six-) month estimation window ending ten days before a termination event and a three- (or six-) month estimation window starting ten days after the termination event.

[17] Our sample of brokerage house mergers and closures comes from Wang, Xie, and Zhang (2016).

Results in Panel A show that the differences in the mean DiD between the *High* and *Low* groups of treatment firms are positive and statistically significant in all cases. This suggests that firms losing coverage from an analyst who ranks them high experience significantly larger increases in bid-ask spreads compared to firms losing coverage from an analyst who ranks them low. In Panel B, firms in the *High* group also experience larger increases in the Amihud illiquidity measure due to analyst coverage losses, and the differences in the mean DiD between the *High* and *Low* groups are statistically significant when firms are ranked by market capitalization and institutional ownership. Overall, results in this section provide further support for our conjecture that analysts devote more effort to information production for relatively more important firms in their portfolios, helping to create more transparent information environments for these firms.[18]

6. Strategic effort allocation and analyst career outcomes

The evidence presented so far in the paper suggests that analysts respond to career concern incentives in strategically allocating their effort among portfolio firms. A question that naturally arises from our finding is whether the extent of analysts' strategic effort allocation has any impact on their career outcomes. Specifically, if an analyst indeed devotes more effort to, and produces higher-quality research for, firms with greater visibility, more institutional following, and greater brokerage commission potential, we expect the analyst to experience more favorable career outcomes. We test this conjecture by examining two measurable career outcomes – being voted an "All Star," and moving up to a more prestigious brokerage firm. We expect that a higher degree of career concern-based effort allocation increases the likelihood of both outcomes.

We capture the extent of such effort allocation by the difference in forecast frequency and accuracy between the *High* and *Low* groups of firms in an analyst's portfolio. The rationale behind this

[18] The identification strategy used in this section is less well suited for the implied cost of capital measure, because its estimation is based on many inputs that are unlikely to change much over our short event windows, such as the historical dividend yield, expected earnings per share, and the long-term GDP growth rate.

approach is that in the absence of strategic effort allocation we should not expect to observe any difference in the relative frequency and accuracy of forecasts issued by the same analyst to firms in her portfolio. This is because an analyst's forecast behavior for each firm is measured relative to other analysts covering the same firm in the same year, effectively removing firm-year effects from our forecast frequency and accuracy measures. Therefore, analyst effort allocation is the only logical explanation for any observed difference in these measures between the high and low groups of firms within an analyst's portfolio.

We estimate a logit regression to investigate how strategic effort allocation affects the probability of an analyst being voted an "All Star". We extract the annual list of "All Star" analysts from the October issues of *Institutional Investor* magazine. The dependent variable is a dummy variable that is equal to one if an analyst is named an "All Star" in a particular year and zero otherwise. The key independent variables are the differences in relative forecast frequency and accuracy between the high and low groups within each analyst's portfolio. We include the analyst's general forecasting experience, portfolio size, number of industries covered, average forecast frequency and accuracy for portfolio firms, average portfolio firm size, as well as whether the analyst was an "All Star" in the previous year. Our model is specified as follows.

$$Pr(Voted\ All\text{-}star) = \beta_0 + \beta_1(Diff(High\text{-}Low)\ in\ DFREQ) + \beta_2(Diff(High\text{-}Low)\ in\ PMAFE) + \beta_3 GExp + \beta_4 Portsize + \beta_5 SIC2 + \beta_6 Brokerage\ Size + \beta_7 Average\ PMAFE + \beta_8 Average\ DFREQ + \beta_9 Average\ Firm\ Size + \beta_{10} lag(All\ star) + Year\ FE + \varepsilon \quad (6)$$

Panel A of Table 10 presents the regression results. For each specification, we have separate regressions using market capitalization, trading volume, and institutional ownership to define the high vs. low groups. We find that in all model specifications, the high-low group difference in relative forecast frequency has a significant and positive coefficient and the high-low group difference in relative forecast errors has a significant and negative coefficient. Note that for analysts who strategically allocate their efforts, we expect a positive difference in the relative forecast frequency and a negative difference in forecast errors between high and low groups. Thus, our results suggest that analysts who engage in a greater extent of strategic effort allocation are more likely to be voted “All Star”. This is consistent with our earlier conjecture and provides a rational justification for the analyst effort allocation pattern we observe in the data.

With respect to the control variables, their coefficients are largely in line with extant evidence in the literature. For example, analysts who cover larger portfolios with larger firms, work for larger brokerage firms, issue more frequent and more accurate earnings forecasts for average portfolio firms are more likely to be voted “All Stars”. There is also significant evidence of persistence in analysts being named “All Star” in consecutive years.[19]

Next, we investigate the effect of strategic effort allocation on the likelihood of an analyst being promoted. Following Hong and Kubik (2003), we define analyst promotion as cases in which an analyst moves from a low-status brokerage house to a high-status one. Each year we classify the top ten brokerage houses employing the most analysts as high-status and the rest as low-status.[20] We find that during our sample period, 9.77% of the analysts switch brokerage houses each year. Of those analysts that switch employers, 14.29% of them move from a low-status brokerage house to a high-status one, a frequency that is comparable to that reported by Hong and Kubik (2003). Following Hong and Kubik (2003), we measure analyst performance over a 3-year period. Therefore, in the regression model specified below, *Diff(High-Low) in DFREQ*, *Diff(High-Low) in PMAFE*, *Average DFREQ*, and *Average PMAFE* are calculated as the averages over the previous 3 years.

$$
\begin{aligned}
Pr(\text{Being Promoted}) = {} & \beta_0 + \beta_1(\text{Diff(High-Low) in DFREQ}) + \beta_2(\text{Diff(High-Low) in PMAFE}) + \beta_3 \text{GExp} \\
& + \beta_4 \text{Portsize} + \beta_5 \text{SIC2} + \beta_6 \text{Brokerage Size} + \beta_7 \text{Average PMAFE} \\
& + \beta_8 \text{Average DFREQ} + \beta_9 \text{Average Firm Size} + \text{Year FE} + \varepsilon \qquad (8)
\end{aligned}
$$

[19] We also examine the probability of an analyst being a first-time all-star and obtain qualitatively similar results. The probability of an analyst being a first-time all-star in our sample is 1.85%.

[20] We also make sure that an analyst’s promotion is not driven by a brokerage house’s status change. That is, we require that the analyst’s former employer is a low-status brokerage house in both year t and year t+1, and her new employer is a high-status one in both year t and year t+1.

Panel B of Table 10 reports the regression results.[21] Similar to the results in Panel A, the high-low group difference in relative forecast frequency has a significant and positive coefficient and the high-low group difference in relative forecast errors has a significant and negative coefficient in two out of three specifications. These results suggest that analysts who engage in a greater extent of strategic effort allocation are more likely to move up to more prestigious brokerage houses.

7. Additional Analysis

7.1. Heterogeneity among firms within an analyst's portfolio

Some analyst portfolios are characterized by large differences between their high and low firms, while other analysts cover relatively similar firms, so that there is not as much of a difference, and hence less incentive for strategic effort allocation. The idea is that in analyst portfolios with large variations in market capitalization, trading volume, or institutional ownership, the high and low designations are likely to be more meaningful indicators of firms' relative importance to analyst career concerns and thus more powerful predictors of analyst effort allocation. To test this conjecture, we first compute the standard deviation of market capitalization, trading volume, and institutional ownership for each analyst portfolio in each year and partition our sample into subsamples based on whether the within-portfolio variation along a particular dimension is above or below the sample median. We then repeat our analysis in Section 4 in these subsamples. In untabulated results, we find that analysts covering portfolios with larger variations in market capitalization, trading volume, or institutional ownership indeed engage in a greater extent of strategic effort allocation.

[21] The sample used for the promotion analysis is smaller because this test is conditional on an analyst working at a low-status brokerage house in the base year t and we require each analyst to have at least three years of earnings forecast data.

7.2. Alternative measure for analyst forecast accuracy

We repeat the analyst forecast accuracy analysis using an alternative measure of forecast accuracy suggested by Clement and Tse (2005), which is defined as follows.

$$Accuracy_i = \frac{\mathrm{Max(AFE)} - \mathrm{AFE}_i}{\mathrm{Max(AFE)} - \mathrm{Min(AFE)}}$$

This alternative proxy increases with forecast accuracy, while *PMAFE* decreases with forecast accuracy. In untabulated results, we continue to find that analysts issue more (less) accurate forecasts for firms that are relatively more (less) important within their portfolios.

7.3. Coverage termination

We examine analysts' decision to terminate coverage on a firm as another indicator of effort allocation. Our career concerns hypothesis predicts that analysts are less (more) likely to stop providing research coverage for firms that are relatively more (less) important in their portfolios. We define coverage termination as instances in which an analyst does not issue earnings forecasts for a firm for an entire year but she did so in the previous year. In our sample, the unconditional probability of a firm being dropped by an analyst is 15.3%, and the likelihood decreases to 12.9% if the analyst ranks the firm high and increases to 19.5% if the analyst ranks the firm low. For more reliable inferences, we estimate a logistic regression where the dependent variable is equal to one if a firm loses coverage by an analyst in a given year and the key explanatory variables are the *High* and *Low* indicators reflecting a firm's relative importance in the analyst's portfolio. We control for firm and analyst characteristics included in previous tables, the analyst's prior forecast accuracy for the firm, and analyst-firm pair fixed effects. Untabulated results show that an analyst is more likely to stop coverage for a firm that is ranked low in her research portfolio, and this is especially the case when her prior forecast accuracy is poor for the firm. These findings provide further support for the career concerns hypothesis.

8. Conclusion

We provide evidence on how financial analysts treat firms in their portfolios differently and the implications this has for the information environment of the firms they follow. Analysts devote more effort to researching firms that are more important for their career concerns. Specifically, within each analyst's portfolio, firms ranked relatively higher based on market capitalization, trading volume, or institutional ownership receive more frequent earnings forecast revisions and more accurate earnings forecasts. These findings are robust to controlling for firm and analyst characteristics and the inclusion of firm fixed effects, analyst fixed effects, and, importantly, analyst-firm pair fixed effects. Earnings forecast revisions and stock recommendation changes issued by analysts for the relatively more important firms in their portfolios also generate significantly stronger stock price reactions. This pattern of analysts strategically allocating their effort among portfolio firms is especially strong when they have larger research portfolios.

Analysts' career concern-based effort allocation also carries real consequences for firms. Specifically, firms covered by more analysts who rank them as more important in their portfolios have, on average, more transparent information environments, characterized by lower bid-ask spreads, stock market illiquidity, and costs of equity capital. Thus, the information environment of a firm is determined in part by what other firms its analysts cover. The marginal impact of a new analyst on a firm's spreads, liquidity and cost of capital varies with the firm's relative rank within the new analyst's portfolio. Researchers studying the impact of analysts on firms should take into account these analyst portfolio effects.

Finally, as a logical justification for the observed effort allocation pattern, we find that analysts who engage in a greater extent of strategic effort allocation are more likely to be voted "All Stars" by institutional investors and move up to more prestigious brokerage houses. Overall, our entire body of evidence is consistent with the hypothesis that driven by career concerns, analysts strategically allocate their effort among firms in their portfolios, which is reflected in the frequency, accuracy, and informativeness of their research.

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Appendix A: Variable Definitions

Variable	Definition
%High	The percentage of a firm's analysts who rank the firm high in their portfolios in year *t*.
%Low	The percentage of a firm's analysts who rank the firm low in their portfolios in year *t*.
AFE	The absolute forecast error of analyst *i* for firm *j*, calculated as the absolute value of the difference between analyst *i*'s earnings forecast for firm *j* and the actual earnings reported by firm *j*
Age	The age of analyst *i*'s forecast (*Age*) is defined as the number of days between analyst *i*'s forecast for firm *j* and the firm's fiscal year end.
All-star	Indicator variable is one if the analyst is named to Institutional Investor's all-star team in current year, and zero otherwise.
Amihud illiquidity	The natural log of one plus the ratio of the absolute stock return to the dollar trading volume and scaled by 10^6.
Average DFREQ	The average DFREQ of all the firms covered by analyst *i* in year *t-1*.
Average PMAFE	The average PMAFE of all the firms covered by analyst *i* in year *t-1*.
Average firm size	The average size of the all the firms covered by analyst *i* in year *t-1*.
Beta	Market beta of a firm based on a five-year rolling regression using monthly data and the value-weighted CRSP index.
Bid-ask spread	Computed as 100 * (ask–bid) / [(ask+bid) / 2] using daily closing bid and ask prices from CRSP
BM	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
Brokerage size	The total number of analysts working at a given analyst *i*'s brokerage house.
CAR	Three-day CRSP value-weighted market-adjusted cumulative abnormal return. Values are multiplied by 100.
DAge	The age of analyst *i*'s forecast (Age) minus the average age of forecasts issued by analysts following firm *j* at year *t*, where age is defined as the age of forecasts in days at the minimum forecast horizon date.

DFExp	The total number of years since analyst *i*'s first earnings forecast for firm *j* (FExp) minus the average number of years I/B/E/S analysts supplying earnings forecasts for firm *j* in year *t*.
DFREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*, minus the average number of earnings forecast revisions issued by all analysts for firm *j* in year *t*.
DGExp	The total number of years that analyst *i*'s appeared in *I/B/E/S* (*GExp*) minus the average tenure of analysts supplying earnings forecasts for firm *j* in year *t*.
Diff(High-Low) in DFREQ	The average DFREQ of firms in the high group of an analyst's portfolio minus the average DFREQ of firms in the low group of the analyst's portfolio in year *t-1*.
Diff(High-Low) in PMAFE	The average PMAFE of firms in the high group of an analyst's portfolio minus the average PMAFE of firms in the low group of the analyst's portfolio in year *t-1*.
Dispersion of analyst forecasts	The coefficient of variation of the current FY1 forecast.
DPortsize	The number of firms followed by analyst *i* for firm *j* in year *t* (*Portsize*) minus the average number of firms followed by analysts supplying earnings forecasts for firm *j* in year *t*.
DSIC2	Number of 2 digit SICs followed by analyst *i* in year *t* (*SIC2*) minus the average number of 2-digit SICs followed by analysts following firm *j* in year *t*.
DTop10	Indicator variable is one if analyst works at a top decile brokerage house (*Top10*) minus the mean value of top decile brokerage house indicators for analysts following firm *j* in year *t*.
Earnings variability	The coefficient of the variation of annual earnings over the previous five years.
FExp	The total number of years since analyst *i*'s first earnings forecast for firm *j* in year *t*.
FREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*.
FR	Analyst forecast revision following Ivkovic and Jegadeesh (2004). The difference between an analyst's revised forecast and the previous forecast scaled by the absolute value of the previous forecast. The denominator is set equal to .01 if the absolute value of the previous forecast is smaller. Values are multiplied by 100 and are truncated between -50% and 50%.
GExp	The total number of years that analyst *i*'s appeared in I/B/E/S in year *t*.

High	A dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise.
Institutional holding	The percentage of a firm's equity held by all institutions at the end of year *t-1*.
Institutional ownership	The dollar amount of institutional investment in firm *j*, calculated as firm *j*'s market capitalization at the end of year *t-1* multiplied by the percentage of equity held by all institutions.
Leverage	Long term debt plus debt in current liabilities divided total assets
Long-term growth	Long-term growth in earnings; the mean long-term earnings growth rate from I/B/E/S.
Low	A dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise.
MAE of forecasts	The average mean absolute error of the last five annual I/B/E/S consensus forecasts
No. of analysts	The number of unique analysts issuing earnings forecasts for firm *j* in year *t*.
Past Ret	CRSP VW-index adjusted buy-and hold abnormal returns over six months prior to the announcement date of the earnings forecast.
PMAFE	The proportional mean absolute forecast error calculated as the difference between the absolute forecast error (AFE) for analyst *i* on firm *j* in year *t* and the mean absolute forecast error (MAFE) for firm *j* in year *t* scaled by the mean absolute forecast error for firm *j* in year *t*.
Portsize	The number of firms followed by analyst *i* in year *t*.
ROA	Return on assets, calculated as net income before extraordinary items and discontinued operations divided by total assets
SIC2	The number of 2-digit SICs represented by firms followed by analyst *i* in year *t*.
Size	The natural log of market capitalization of the covered firm (in $thousands) at the end of year *t*-1.
Top10	Indicator variable that is equal to one if an analyst works at a top decile brokerage house in year *t*.

Trading volume	The annual trading volume (in thousand shares) for a firm *j* in year *t-1*
Volatility	Daily stock return volatility for firm *j* in year *t*

Appendix B: Earnings Forecast Update Frequency

This table presents OLS regression results for analyst earnings forecast update frequency for the full sample. The dependent variable is the de-meaned analyst forecast update frequency (*DFREQ*) in all regressions. The primary variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	0.027***	0.022***	0.024***
	(4.75)	(3.96)	(4.04)
Low	-0.058***	-0.041***	-0.054***
	(9.46)	(7.62)	(9.30)
DGExp	-0.016***	-0.016***	-0.016***
	(5.54)	(5.58)	(5.55)
DFExp	0.134***	0.134***	0.133***
	(32.61)	(32.66)	(32.60)
DAge	-0.011***	-0.011***	-0.011***
	(95.52)	(95.52)	(95.54)
DPortsize	0.006***	0.006***	0.006***
	(3.78)	(3.73)	(3.76)
DSIC2	-0.045***	-0.045***	-0.045***
	(9.36)	(9.32)	(9.34)
DTop10	0.169***	0.168***	0.169***
	(8.21)	(8.13)	(8.20)
All-star	0.232***	0.233***	0.232***
	(8.68)	(8.70)	(8.70)
# of observations	529,896	529,896	529,896
R^2	0.236	0.236	0.236

Appendix C: Summary Statistics for Variables in the Information Environment Analysis

This table reports descriptive statistics of the variables used in information environment analysis. Panel A reports the summary statistics of 64,011 firm-year observations in Table 7 and Panel B report the summary statistics of 34,219 firm-year observations in Table 8.

Panel A: Summary statistics for Table 7

Variables	Mean	Q1	Median	Q3	Std
Bid-ask spread	1.194	0.128	0.768	1.814	1.370
Amihud illiquidity	0.100	0.001	0.007	0.046	0.290
% high (market cap)	0.134	0.000	0.000	0.182	0.242
% low (market cap)	0.325	0.000	0.200	0.556	0.359
% high (trading volume)	0.127	0.000	0.000	0.167	0.238
% low (trading volume)	0.346	0.000	0.222	0.625	0.368
% high (ownership)	0.129	0.000	0.000	0.167	0.235
% low (ownership)	0.321	0.000	0.200	0.500	0.356
No. of Analysts	7.704	3.000	6.000	10.000	6.557
Size	13.701	12.490	13.547	14.773	1.635
Log(trading volume)	11.766	10.506	11.732	12.948	1.770
Institutional holding	0.530	0.329	0.541	0.734	0.251
BM	0.689	0.480	0.713	0.911	0.269
Leverage	0.223	0.054	0.196	0.343	0.192
Price	27.426	13.200	22.726	36.088	19.033
Past Ret	0.177	-0.112	0.115	0.381	0.521
ROA	0.038	0.011	0.042	0.084	0.106
Volatility	0.027	0.018	0.024	0.034	0.013

Appendix C, Panel B: Summary statistics for Table 8

Variables	Mean	Q1	Median	Q3	Std
Implied cost of capital	0.065	0.044	0.066	0.085	0.031
% high (market cap)	0.189	0.000	0.000	0.286	0.274
% low (market cap)	0.233	0.000	0.100	0.375	0.303
% high (trading volume)	0.180	0.000	0.000	0.263	0.271
% low (trading volume)	0.254	0.000	0.111	0.429	0.316
% high (ownership)	0.185	0.000	0.000	0.286	0.267
% low (ownership)	0.223	0.000	0.091	0.333	0.294
No. of Analysts	10.005	5.000	8.000	14.000	7.158
Size	14.343	13.197	14.252	15.390	1.571
Log(trading volume)	12.360	11.178	12.348	13.505	1.696
Institutional holding	0.605	0.444	0.628	0.786	0.225
MAE of forecasts	0.107	0.028	0.061	0.140	0.320
Earnings variability	0.390	0.170	0.279	0.504	0.931
Dispersion of analyst forecasts	0.166	0.036	0.080	0.183	0.246
BM	0.683	0.485	0.704	0.894	0.253
Leverage	0.225	0.078	0.211	0.340	0.173
Past Ret	0.171	-0.094	0.113	0.348	0.442
Long-term growth (%)	14.484	9.682	13.000	17.800	8.237
Beta	1.086	0.631	1.003	1.410	0.647
Volatility	0.025	0.016	0.022	0.031	0.012

Table 1: Summary Statistics

This table reports descriptive statistics of analyst characteristics of our main variables used throughout this paper. Earnings forecast accuracy (*PMAFE*) is defined as the difference between the absolute forecast error for analyst i for firm j and the mean absolute forecast error at year t scaled by the mean absolute forecast error for firm j at year t. See Appendix A for a description of control variables. Analyst data are from I/B/E/S from 1983 to 2012, stock price data are from CRSP, and firm characteristics are obtained from Compustat. In Panel C, the notation *** indicates statistical significance at the 1% level.

Panel A: Summary statistics

Variables	Mean	Q1	Median	Q3	Std
AFE	0.25	0.02	0.07	0.21	0.60
FREQ	3.59	2	3	5	2.38
AGE	114.70	60	73	154	83.39
GEXP	5.05	2	4	7	4.37
FEXP	3.20	1	2	4	2.68
PORTSIZE	17.01	10	14	20	13.49
SIC2	4.17	2	3	5	3.13
TOP10	0.49	0	0	1	0.50

Panel B: De-meaned summary statistics

Variables	Mean	Q1	Median	Q3	Std
PMAFE	0	-0.57	-0.15	0.24	0.86
DFREQ	0	-1.05	0.00	1.00	1.75
DAGE	0	-45.81	-17.67	26.25	72.81
DGEXP	0	-2.42	-0.33	1.88	3.62
DFEXP	0	-1.27	-0.21	0.84	2.16
DPORTSIZE	0	-5.00	-0.97	3.27	8.93
DSIC2	0	-1.19	-0.29	0.75	2.09
DTOP10	0	-0.43	0.00	0.42	0.44

Panel C: Comparison between firms in the high and low groups

	Market Cap			Trading Volume			Institutional Ownership		
Variables	High	Low	Diff	High	Low	Diff	High	Low	Diff
FREQ	3.821	3.377	***	3.876	3.337	***	3.787	3.315	***
DFREQ	0.005	-0.046	***	0.003	-0.031	***	0.008	-0.041	***
AFE	0.225	0.293	***	0.243	0.260	***	0.231	0.285	***
PMAFE	-0.026	0.009	***	-0.026	0.012	***	-0.026	0.010	***
Log(market cap)	16.231	12.933	***	15.873	13.304	***	16.225	13.010	***
Log(trading volume)	13.932	11.683	***	14.216	11.298	***	13.900	11.621	***
Log(ownership)	15.515	11.717	***	15.153	12.111	***	15.544	11.649	***

Table 2: Analyst Earnings Forecast Accuracy

This table presents OLS regression results for analyst earnings forecast accuracy for the full sample. The dependent variable is the proportional mean absolute forecast error *PMAFE* (multiplied by 100). The primary variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Panel B presents analyst fixed effect regression results, Panel C presents firm fixed effect regression results, and Panel D presents analyst-firm pair fixed effect regression results.

Panel A: OLS regression results

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-1.928***	-1.816***	-1.734***
	(6.91)	(6.24)	(6.35)
Low	1.594***	1.407***	1.512***
	(5.73)	(5.14)	(5.33)
DGExp	-0.257***	-0.256***	-0.258***
	(3.38)	(3.37)	(3.39)
DFExp	-0.696***	-0.697***	-0.696***
	(7.67)	(7.67)	(7.66)
DAge	0.519***	0.519***	0.519***
	(85.72)	(85.70)	(85.71)
DPortsize	0.123**	0.122**	0.123**
	(2.01)	(1.99)	(2.01)
DSIC2	0.834***	0.842***	0.832***
	(5.89)	(5.95)	(5.87)
DTop10	-2.622***	-2.605***	-2.620***
	(5.08)	(5.05)	(5.07)
All-star	-4.361***	-4.271***	-4.275***
	(8.05)	(7.89)	(7.96)
# of observations	529,427	529,427	529,427
R^2	0.186	0.186	0.186

Panel B – Analyst fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-1.566***	-1.540***	-1.446***
	(5.27)	(5.22)	(4.87)
Low	1.302***	1.329***	1.420***
	(4.52)	(4.78)	(4.81)
Controls (from Panel A)	Y	Y	Y
Analyst FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.234	0.234	0.234

Panel C – Firm fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-2.535***	-2.576***	-2.220***
	(6.80)	(6.92)	(6.08)
Low	2.028***	2.155***	1.928***
	(6.23)	(6.44)	(5.99)
Controls (from Panel A)	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.188	0.188	0.188

Panel D – Analyst-firm pair fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-2.151***	-1.579**	-2.008***
	(3.13)	(2.42)	(3.03)
Low	1.621**	1.303**	1.620***
	(2.49)	(2.08)	(2.58)
Controls (from Panel A)	Y	Y	Y
Analyst-firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.551	0.551	0.551

Table 3: Analyst Forecast Accuracy: Absolute Forecast Error

The dependent variable is the absolute forecast error (AFE, multiplied by 100) rather than the proportional mean forecast error as in Table 2. The explanatory variables of interest are *High* and *Low*. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-0.229***	-0.272***	-0.226***
	(3.44)	(3.87)	(3.52)
Low	0.342***	0.369***	0.315***
	(4.75)	(5.19)	(4.62)
GExp	-0.025**	-0.025**	-0.025**
	(2.20)	(2.18)	(2.19)
FExp	-0.080***	-0.081***	-0.081***
	(6.11)	(6.11)	(6.12)
Age	0.064***	0.064***	0.064***
	(53.98)	(53.96)	(53.97)
Portsize	0.015	0.015	0.015
	(1.26)	(1.26)	(1.27)
SIC2	0.085***	0.087***	0.085***
	(2.96)	(3.01)	(2.94)
Top10	-0.380***	-0.377***	-0.378***
	(5.14)	(5.11)	(5.11)
All-star	-0.674***	-0.675***	-0.672***
	(6.67)	(6.68)	(6.64)
Firm-year FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.798	0.798	0.799

Table 4: Busy Analysts vs. Non-busy Analysts

This table presents results from OLS regressions of earnings forecast accuracy for "busy" and "non-busy" analysts, where "busy" analysts are defined as those whose portfolio size in a given year is greater than the sample median. The dependent variable is the proportional mean absolute forecast error (PMAFE) defined as the difference between the absolute forecast errors for analyst i for firm j and the mean absolute forecast error at year t scaled by the mean absolute forecast error for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional ownership) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization (or trading volume, institutional ownership) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: "Busy" analysts

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-2.395***	-2.365***	-2.158***
	(6.77)	(6.81)	(6.02)
Low	2.277***	2.129***	2.215***
	(7.05)	(6.84)	(6.86)
Controls (from Table 2)	Y	Y	Y
# of observations	349,933	349,933	349,933
R-squared	0.163	0.163	0.163

Panel B: "Non-busy" analysts

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High	-0.975**	-0.683	-0.736
	(2.06)	(1.39)	(1.60)
Low	0.845*	0.884*	0.872*
	(1.84)	(1.91)	(1.88)
Controls (from Table 2)	Y	Y	Y
# of observations	179,494	179,494	179,494
R-squared	0.227	0.227	0.227

Table 5: Stock Market Reactions to Forecast Revision

This table reports the market reaction to analysts' revisions of earnings forecasts. The dependent variable is the cumulative 3-day market adjusted return (multiplied by 100) around the announcement of forecast revision by analyst i for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (column (1), trading volume (2) or institutional ownership (3) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization, trading volume or institutional ownership is in the lower quartile of all firms the analyst covers in that year, zero otherwise. Forecast revision (FR) is the ratio of the difference between the new forecast and the old forecast to the absolute value of the old forecast. See Appendix A for a description of control variables. Analyst data are from I/B/E/S from 1983 to 2012, stock price data are from CRSP, and firm characteristics are obtained from Compustat. Year fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
High*FR	0.007*	0.006*	0.004
	(1.89)	(1.72)	(1.01)
Low*FR	-0.008***	-0.006**	-0.010***
	(2.77)	(2.04)	(3.47)
FR	0.082***	0.082***	0.083***
	(31.68)	(31.78)	(32.58)
High	0.049	0.011	0.028
	(1.37)	(0.27)	(0.75)
Low	-0.072	-0.058	-0.061
	(1.61)	(1.47)	(1.48)
Controls from Table 2	Y	Y	Y
Year FE	Y	Y	Y
R-squared	0.150	0.150	0.150
# of observations	350,488	350,488	350,488

Table 6: Stock Market Reactions to Recommendation Updates

This table reports the market reaction to analysts' recommendation updates. The dependent variable is the cumulative 3-day market adjusted return (multiplied by 100) around the announcement of recommendation update by analyst i for firm j at year t. *High* is a dummy variable which takes the value of 1 if the firm's market capitalization (column (1), trading volume (2), or institutional ownership (3) is in the top quartile of all firms the analyst covers in that year, zero otherwise. *Low* is a dummy variable which is an indicator variable equal to one if the firm's market capitalization, trading volume or institutional ownership is in the lower quartile of all firms the analyst covers in that year, zero otherwise. Panel A reports analysis for recommendation downgrade and Panel B reports analysis for recommendation upgrade. Year fixed effects are included. See Appendix A for a description of control variables. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Downgrades

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	-0.548***	-0.501***	-0.583***
	(5.76)	(5.21)	(5.87)
Low	0.333***	0.324***	0.372***
	(3.08)	(3.02)	(3.35)
Gexp	-0.036**	-0.033**	-0.037***
	(2.58)	(2.30)	(2.62)
Fexp	0.066***	0.061***	0.066***
	(4.19)	(3.88)	(4.19)
Portsize	0.009	0.009	0.009
	(1.28)	(1.36)	(1.34)
SIC2	0.082***	0.073***	0.079***
	(3.99)	(3.59)	(3.89)
Top10	-0.859***	-0.809***	-0.871***
	(8.88)	(8.28)	(9.03)
All-star	-0.341**	-0.281*	-0.345***
	(2.32)	(1.93)	(2.36)
Lag recommendation	-0.145***	-0.121**	-0.146***
	(2.67)	(2.23)	(2.70)
Size	1.532***	1.433***	1.526***
	(27.88)	(28.67)	(27.97)
Log(trading volume)	-0.902***	-0.966***	-0.905***
	(18.13)	(17.00)	(18.18)
Institutional holding	-0.543***	-0.521**	-0.319
	(2.64)	(2.53)	(1.51)
BM	2.052***	2.096***	2.062***
	(13.36)	(13.53)	(13.41)
Past Ret	3.943***	3.956***	3.943***
	(21.92)	(21.99)	(21.96)
No. of Analysts	0.020***	0.020***	0.020***
	(3.15)	(3.23)	(3.20)
Year FE	Y	Y	Y
R-squared	0.0889	0.0885	0.0891
# of observations	75,552	75,552	75,552

Panel B: Upgrades

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
High	0.152**	0.174**	0.167**
	(2.13)	(2.38)	(2.27)
Low	-0.131	-0.162*	-0.105
	(1.52)	(1.85)	(1.16)
Gexp	0.023**	0.023**	0.023**
	(2.26)	(2.22)	(2.28)
Fexp	-0.019	-0.019	-0.019
	(1.41)	(1.37)	(1.42)
Portsize	-0.016***	-0.016***	-0.016***
	(3.99)	(3.91)	(4.00)
SIC2	-0.015	-0.013	-0.016
	(1.01)	(0.89)	(1.03)
Top10	0.828***	0.823***	0.832***
	(11.65)	(11.63)	(11.72)
All-star	0.601***	0.592***	0.604***
	(5.75)	(5.67)	(5.78)
Lag recommendation	-0.335***	-0.337***	-0.332***
	(7.81)	(7.91)	(7.78)
Size	-0.794***	-0.792***	-0.802***
	(20.92)	(22.89)	(21.67)
Log(trading volume)	0.373***	0.398***	0.373***
	(9.74)	(9.21)	(9.72)
Institutional holding	-0.062	-0.085	-0.067
	(0.36)	(0.49)	(0.38)
BM	-0.244**	-0.231**	-0.237**
	(2.38)	(2.24)	(2.30)
Past Ret	2.231***	2.229***	2.234***
	(16.08)	(16.06)	(16.10)
No. of Analysts	-0.014***	-0.015***	-0.015***
	(2.98)	(3.01)	(2.96)
Year FE	Y	Y	Y
R-squared	0.0546	0.0546	0.0546
# of observations	63,874	63,874	63,874

Table 7: Bid-ask spread and stock illiquidity

This table reports the analysis of the impact of analysts' effort allocation on a firm's bid-ask spread and stock illiquidity. The dependent variable is bid-ask spread in Panel A and Amihud illiquidity measure in Panel B. *%High* is the ratio of the number of analysts ranking the firm high in their portfolio to the total number of analysts covering the firm in a year, and *%Low* is the ratio of the number of analysts ranking the firm low in their portfolio to the total number of analysts covering the firm in a year. See Appendix A for a description of control variables. Year and firm fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Bid-ask spread

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Ownership
% high	-0.118***	-0.169***	-0.120***
	(4.10)	(5.69)	(4.20)
% low	0.039*	0.036*	0.030
	(1.87)	(1.75)	(1.39)
No. of Analysts	-0.003*	-0.003**	-0.003*
	(1.87)	(1.97)	(1.83)
Size	-1.332***	-1.247***	-1.305***
	(12.93)	(12.39)	(12.71)
$Size^2$	0.051***	0.048***	0.050***
	(13.93)	(13.37)	(13.72)
Log(trading volume)	-0.242***	-0.259***	-0.243***
	(3.87)	(4.02)	(3.87)
$Log(trading volume)^2$	0.005**	0.007***	0.005**
	(2.04)	(2.70)	(2.04)
Institutional holding	-0.197	-0.185	-0.185
	(1.61)	(1.52)	(1.47)
Institutional $holding^2$	0.255**	0.237**	0.260**
	(2.50)	(2.33)	(2.52)
BM	0.062	0.062	0.06
	(1.59)	(1.59)	(1.53)
Leverage	0.223***	0.226***	0.222***
	(3.94)	(4.00)	(3.93)
Log(price)	-0.346***	-0.343**	-0.348***
	(14.85)	(15.16)	(14.80)
Past Ret	-0.067***	-0.066***	-0.067***
	(9.32)	(9.19)	(9.31)
ROA	0.042	0.051	0.045
	(0.66)	(0.78)	(0.70)
Volatility	5.373***	5.233***	5.388***
	(7.36)	(7.17)	(7.38)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	64,011	64,011	64,011
R-squared	0.813	0.813	0.813

Panel B: Amihud illiquidity

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
% high	-0.0112***	-0.0137***	-0.0109***
	(2.81)	(3.28)	(2.72)
% low	0.0063	0.0086*	0.0087*
	(1.27)	(1.79)	(1.81)
No. of Analysts	-0.0011***	-0.0011***	-0.0011***
	(4.36)	(4.41)	(4.35)
Controls (Table 7, Panel A)	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	64,011	64,011	64,011
R-squared	0.758	0.758	0.758

Table 8: Implied costs of equity capital

This table reports the analysis of the impact of analysts' effort allocation on a firm's implied cost of capital. The dependent variable is the implied cost of capital (multiplied by 100) in Gebhardt, Lee, and Swaminathan (2001). *%High* is the ratio of the number of analysts ranking the firm high in their portfolio to the total number of analysts covering the firm in a year, and *%Low* is the ratio of the number of analysts ranking the firm low in their portfolio to the total number of analysts covering the firm in a year. See Appendix A for a description of control variables. Year and firm fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Variables	(1) Market cap	(2) Trading volume	(3) Ownership
% high	-0.259**	-0.241**	-0.243**
	(2.29)	(2.01)	(2.11)
% low	0.193**	0.142*	0.108
	(2.34)	(1.78)	(1.22)
No. of Analysts	-0.009*	-0.009*	-0.009*
	(1.67)	(1.69)	(1.70)
Size	-0.099	-0.113	-0.223
	(0.25)	(0.30)	(0.57)
$Size^2$	0.008	0.006	0.012
	(0.60)	(0.47)	(0.86)
Log(trading volume)	-0.082	-0.116	-0.085
	(0.38)	(0.54)	(0.39)
$Log(trading volume)^2$	0.003	0.003	0.003
	(0.29)	(0.39)	(0.29)
Institutional holding	-0.322	-0.340	-0.156
	(0.68)	(0.72)	(0.33)
Institutional $holding^2$	0.225	0.236	0.165
	(0.57)	(0.60)	(0.42)
MAE of forecasts	-0.052	-0.050	-0.051
	(0.36)	(0.35)	(0.36)
Earnings variability	0.075	0.075	0.075
	(0.92)	(0.91)	(0.91)
Dispersion of analyst forecasts	0.182*	0.181*	0.183*
	(1.89)	(1.90)	(1.90)
BM	1.766***	1.678***	1.764***
	(8.75)	(8.05)	(8.73)
Leverage	1.621***	1.672***	1.681***
	(5.35)	(4.59)	(4.60)
Past Ret	-0.084*	-0.079*	-0.083*
	(1.86)	(1.76)	(1.85)
Long-term growth	0.009***	0.009***	0.009***
	(3.23)	(3.15)	(3.22)
Beta	0.019	0.019	0.019
	(0.41)	(0.40)	(0.40)
Volatility	4.404*	4.277	4.310*
	(1.68)	(1.63)	(1.65)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	34,219	34,219	34,219
R-squared	0.716	0.716	0.716

Table 9: Coverage termination and information asymmetry

This table reports the average differences in difference-in-difference (DiD) for firm-level information environment measures between *High* and *Low* groups. We compute the effect of coverage terminations on changes in 3- and 6-month bid-ask spreads (Panel A) and Amihud's illiquidity measures (Panel B). For each treatment firm, we first follow Kelly and Ljungqvist (2012) and Daniel, Grinblatt, Titman, and Wermers (1997) to construct a control group. For each treatment stock, we choose up to five stocks that are closest in terms of the relevant pre-event information asymmetry measure. We then employ a difference-in-difference (DiD) approach to compare the change in the information environment of control firms to treatment firms. We further split the affected firms into *High* and *Low* groups based on the firms' rankings (high or low) in the analysts' portfolios in the year before the brokerage house closures and mergers and report the mean differences in DiD for firm-level information environment measures between *High* and *Low* groups. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Difference in DiD between the High and Low groups		
High and low based on	Market cap	Trading volume	Ownership
Panel A: bid-ask spread			
3 month window	0.137***	0.125**	0.136***
6 month window	0.120**	0.102*	0.118**
Panel B: Amihud illiquidity measure			
3 month window	0.011*	0.007	0.012**
6 month window	0.018**	0.009	0.017**

Table 10: Analysts' effort allocation and labor market outcomes

This table presents logistic regression results for the effect of analysts' effort allocation on their labor market outcomes. The dependent variable is a dummy variable that is equal to 1 if an analyst is named an all-star analyst (Panel A) or promoted (Panel B) in a given year. The variables of interest are the Diff(High-low) in DFREQ and PMAFE. These variables capture the analyst-specific difference in his/her revision frequency and forecast error for high vs. low stocks in his/her portfolio. The greater this difference, the more strategically is the analyst allocating effort. All control variables are lagged by one year. See Appendix A for a description of control variables. Year fixed effects are included. In parentheses are t-statistics based on heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: All-star analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
High and Low based on:	Market cap	Trading volume	Ownership	Market cap	Trading volume	Ownership
Diff(High-low) in DFREQ	0.079***	0.078***	0.086***			
	(3.91)	(3.61)	(4.30)			
Diff(High-low) in PMAFE				-0.107**	-0.117***	-0.136***
				(2.42)	(2.64)	(3.05)
GExp	0.009	0.009	0.01	0.008	0.008	0.009
	(1.14)	(1.07)	(1.27)	(1.04)	(1.01)	(1.14)
Portsize	0.017***	0.017***	0.016***	0.017***	0.017***	0.016***
	(4.95)	(4.93)	(4.61)	(4.86)	(4.89)	(4.53)
SIC2	-0.023*	-0.023	-0.025*	-0.023	-0.023	-0.025*
	(1.65)	(1.62)	(1.78)	(1.62)	(1.64)	(1.79)
Brokerage size	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
	(23.44)	(23.42)	(23.50)	(23.50)	(23.52)	(23.56)
Average PMAFE	-0.744***	-0.739***	-0.743***	-0.714***	-0.722***	-0.705***
	(8.63)	(8.58)	(8.57)	(8.14)	(8.28)	(7.94)
Average DFREQ	0.352***	0.352***	0.349***	0.376***	0.375***	0.375***
	(13.10)	(13.06)	(12.70)	(14.27)	(14.27)	(13.96)
Average firm size	0.297***	0.299***	0.290***	0.299***	0.297***	0.290***
	(11.12)	(11.21)	(10.79)	(11.18)	(11.15)	(10.82)
Lag (All-star)	5.509***	5.511***	5.491***	5.520***	5.521***	5.506***
	(70.86)	(70.89)	(70.79)	(71.06)	(71.09)	(70.95)
Year FE	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.678	0.678	0.677	0.678	0.678	0.677
# of observations	46,494	46,494	45,558	46,464	46,460	45,525

Panel B: Move-up analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
High and Low based on:	Market cap	Trading volume	Ownership	Market cap	Trading volume	Ownership
Diff(High-low) in DFREQ	0.206**	0.232**	0.187**			
	(2.24)	(2.47)	(2.05)			
Diff(High-low) in PMAFE				-0.477**	-0.242	-0.408**
				(2.41)	(1.13)	(2.04)
GExp	-0.058***	-0.060***	-0.062***	-0.056***	-0.056***	-0.059***
	(2.72)	(2.82)	(2.83)	(2.61)	(2.64)	(2.71)
Portsize	0.003	0.003	0.005	0.003	0.002	0.005
	(0.31)	(0.37)	(0.56)	(0.33)	(0.23)	(0.53)
SIC2	-0.154***	-0.154***	-0.149***	-0.155***	-0.153***	-0.149***
	(4.27)	(4.26)	(4.14)	(4.31)	(4.25)	(4.13)
Brokerage size	0.042***	0.041***	0.043***	0.042***	0.042***	0.043***
	(8.22)	(8.15)	(8.33)	(8.22)	(8.27)	(8.37)
Average PMAFE	-0.818*	-0.787*	-0.903**	-0.721*	-0.799*	-0.954**
	(1.94)	(1.89)	(2.13)	(1.70)	(1.91)	(2.20)
Average DFREQ	-0.075	-0.098	-0.088	-0.048	-0.047	-0.049
	(-0.86)	(1.10)	(0.98)	(0.56)	(0.56)	(0.56)
Average firm size	0.135**	0.137**	0.127**	0.134**	0.141**	0.129**
	(2.41)	(2.46)	(2.22)	(2.39)	(2.54)	(2.29)
Year FE	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.092	0.094	0.095	0.093	0.092	0.094
# of observations	14,654	14,655	14,413	14,638	14,630	14,387