Analyst Effort Allocation and Firms' Information Environment*

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Abstract

We examine how sell-side analysts allocate their effort among firms in their research portfolios and the consequences of their effort allocation decisions. We show that analysts play favorites among portfolio firms by devoting more effort to firms that are relatively more important for their career concerns. Specifically, controlling for analyst and firm characteristics, we find that within each analyst's portfolio, firms ranked relatively higher based on market capitalization, trading volume, or institutional ownership receive more accurate, frequent, and informative earnings forecast revisions and stock recommendation changes that contain greater information content. As a result, even with explicit controls for firm characteristics, firms whose relative rank based on these dimensions is high in more analysts' portfolios display less information asymmetry and have higher stock market liquidity and lower costs of capital. Moreover, we find that 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 (2014), and Jiang, Kumar, and Law (2016)).[1] But the reality of analyst coverage portfolios suggests that analysts face competing demands for their time from the stocks they cover, and 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 the analyst follows. 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 most economic agents, 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.

Analysts as information intermediaries may choose to allocate their effort among firms based on their potential impact on a firm's information environment. For example, smaller firms with thinly traded stocks and less institutional following may be associated with more opaque information environments and thus are more difficult for outside investors to understand and evaluate. Therefore, investors as well as the firms themselves can benefit from more information production and dissemination by analysts. As a result, analysts may expend more effort researching these firms. We term this conjecture the "incremental impact" hypothesis.

Alternatively, analysts' career concerns may push them in a different direction. 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. We identify firms of relative high (or low) importance to analysts using a firm's relative rank in an analyst's portfolio based on market capitalization, trading volumes, 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.

To test these competing conjectures, 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 lends strong support to the "career concerns" hypothesis. 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 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

[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.

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 forecasts 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 covered by more analysts who consider them relatively more important are associated with lower bid-ask spreads, higher stock market liquidity, and lower costs of capital, consistent with these analysts committing more effort to research and information production for these firms and contributing to more transparent information environments. Thus, analysts' allocation of effort for strategic career concerns has real effects 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.

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 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 to all the analysts covering it has an effect on its information environment that is 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 investigation also 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.

Our results carry several implications that advance our understanding of the determinants of analyst behavior and firm information environment. First and most directly, they suggest that firms covered by the same analyst can in fact receive very different levels of research effort. Therefore, assessing the quality of a firm's analyst coverage based on analyst characteristics alone is insufficient. For example, despite the prevailing notion that analysts employed by large brokers have more resources at their disposal to produce higher-quality research, it is entirely possible that a firm followed by analysts all from top brokers receive less research coverage than another firm covered by analysts from smaller brokers, if the first firm's relative importance in its analysts' portfolios is much lower than that of the second firm.

Second, our evidence implies that the amount of analyst attention and effort received by firms is determined by not only their own characteristics but also the characteristics of other firms in the analyst's portfolio. As such, the same firm may be subject to very different coverage intensity by its analysts depending on what other firms each analyst also covers.

Finally, our findings 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.

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 a multitude of factors, some of which are outside analysts' or brokerage firms' control, such as the number of companies, complexity, and major players in an industry. 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 influence over their research portfolios and tend to cover more firms. To the extent that analyst portfolios are determined entirely by exogenous forces and analysts or brokers do not have any discretion, it is a fairly straightforward question and empirical exercise with respect to how analysts allocate their efforts trying to maximize their utility function defined by career concern considerations. Alternatively, if analysts have full control over which firms are included in their portfolios and only cover firms that are important to them in some respect, e.g., trading commission or investment banking business, then ex ante it will be less likely for us to find analysts playing favorites among portfolio firms. However, even with the endogenous determination of analyst portfolios, our career concerns hypothesis would continue to be relevant as long as there is variation in the relative importance of firms within an analyst's portfolio. In fact, we find stronger evidence of career concerns-driven effort allocation when there are larger variations in firms covered by an analyst. In addition, the endogenous selection of portfolio firms implies that our findings represent a lower bound of the extent of strategic effort allocation by analysts, because firms of the least importance are likely not even included in analyst portfolios.

The rest of the paper proceeds as follows. Section 2 discusses the data sources, sample, and key variables. Section 3 examines analysts' earnings forecasts and stock recommendations and presents evidence of analysts allocating efforts based on career concerns. Section 4 shows the real effects of analyst effort allocation decisions on firm information asymmetry and costs of capital. Section 5 presents results on the implication of analysts' strategic effort allocation for their career outcomes. Section 6 reports some additional analyses. Section 7 concludes the paper.

2. 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, 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.

Our primary measure of analyst effort is the accuracy of an analyst's earnings forecasts, which is based on the forecast made by each analyst that is closest to the 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, 2014). 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 time t minus the mean analyst absolute forecast error for firm j at time t ($MAFE_{j,t}$), then scaled by the mean absolute forecast error for firm j at time 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, time 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 announcement of actual earnings. Clement (1999) shows that relative forecast errors are positively associated with the number of days between the forecast and announcement of actual earnings date, 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 from 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]

<Insert table 1 here >

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 earnings announcements 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, 2014).

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, 2014).

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

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 market capitalization of the firm at the end of prior year. 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 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 end of prior year. 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 more heavily held by institutional investors. They also receive more frequent and more accurate earnings forecasts from analysts, providing some preliminary support for our career concerns hypothesis.

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

3.1. 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 contributing to differences in relative forecast accuracy among analysts. To ensure that the *High* and *Low* indicators do not simply pick up the effects of the variables they are based on, we also control for a set of firm characteristics, even though the dependent variable by construction is free of firm-year effects.[5] More specifically, the model is specified as follows.

$$\begin{aligned} PMAFE_{i,j,t} = {} & \beta_0 + \beta_1 HIGH_{i,j,t} + \beta_2 LOW_{i,j,t} + \beta_3 DGEXP_{i,j,t} + \beta_4 DFEXP_{i,j,t} + \beta_5 DAGE_{i,j,t} + \beta_6 DPORTSIZE_{i,j,t} \\ & + \beta_7 DSIC2_{i,j,t} + \beta_8 DTOP10_{i,j,t} + \beta_9 All\text{-}star_{i,j,t} + \beta_{10} Size_{j,t} + \beta_{11}\, Log(trading\ volume)_{j,t} \\ & + \beta_{12} Institutional\ holding_{j,t} + \beta_{13} BM_{j,t} + \beta_{14} Past\ Ret_{j,t} + \beta_{15} No.\ of\ Analysts_{j,t} + \varepsilon_{i,j,t} \qquad (1) \end{aligned}$$

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 regression above examines analysts' relative forecast errors. Lower relative forecast errors indicate a higher level of accuracy. Based on the career concerns hypothesis, we expect the coefficient of *High* (*Low*) to be negative (positive).

<Insert Table 2 Here >

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 by its equity market capitalization. As predicted, the

[5] Our results are robust without controlling for firm characteristics.

coefficient on *High* is negative and statistically significant at 1% level, while the coefficient on *Low* is positive and statistically significant at 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 2.383% more accurate. Similarly, firms that belong to the relatively less important group receive earnings forecasts that are on average 1.905% less accurate. Therefore, the average difference in earnings forecast accuracy between these two groups of firms is 4.288% (=1.905-(-2.383)). To put this effect into context, we compare it to the effects of some other determinants of forecast accuracy. We find that the high-low accuracy differential is equivalent to the effect of over 17 years of general forecasting experience or over 6.8 years of firm-specific forecasting experience, 1.70 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 holding 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.[6] 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.[7]

In further analysis, we augment the regression model specified in equation (1) by controlling for analyst fixed effects.[8] Doing so can help us focus on the within-analyst variations in the *High* and *Low*

[6] Our results are also robust to controlling for how long an analyst has covered a firm's industry.

[7] Our results in this table as well as other sections of the paper are robust to controlling for investment banking relationships between analysts' employers and the firms they cover. We define affiliated analysts as those analysts employed by the lead underwriters or co-managers of an equity offering (IPO or SEO).

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

indicators and mitigate the concern that our findings are driven by some time-invariant analysts' characteristics such as experience or talent. 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 1.582% lower for relatively more important firms and 1.536% higher for relatively less important firms. The high-low coefficient difference, however, is roughly the same as in Panel A. 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. First, they accentuate the within-firm variations or variations within each analyst-firm pair. Second, they allow us to control, at least indirectly, 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 / 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 fixed effects justify our focus on the relative benefits of coverage, which, given our empirical approach, should also rank firms on relative net benefit.

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 is 18% (25%) likely to be ranked non-high (non-low) in the following year by the same analyst.

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. The economic magnitude of the *High* minus *Low* difference is also very similar to that in Panel A of Table 2. It appears that de-meaning variables does not have a material impact on statistical inferences in our context. Therefore, we use the de-meaned specification as the main analysis 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.

3.2. Earnings forecast revision frequency

Earnings forecast update frequency is another widely used proxy for analyst effort in the analyst literature (e.g., Jacob, Lys, and Neale (1999) and Merkley, Michaely, and Pacelli (2016)). The career concerns hypothesis predicts that an analyst should exert more effort on relatively more important firms in his/her portfolio. Thus we expect that firms with better ranks should receive more frequent earnings forecast updates. We repeat (but do not tabulate) our analysis from section 3.1 to examine the earnings forecast update frequency (*FREQ*), measured as the number of annual forecasts issued by an analyst each year during the 360 to 30 days prior to a covered company's earnings announcement (Groysberg, Healy, and Maber (2011)). Consistent with our hypothesis, we find that analysts update earnings forecasts more frequently for firms that are relatively more important in their portfolios. For example, economically, the average difference in earnings forecast frequency between the high and low groups of firms based on their equity market capitalization is equivalent to the effect of about 12.3 years of general forecasting experience, 1.07 years of firm-specific forecasting experience, 0.83 times of the effect of being employed at a top-decile brokerage firm and 0.60 times of the effect of being an all-star analysts. Our results are also robust to controlling for analyst fixed effects, firm fixed effects, and analyst-firm pair fixed effects.

3.3. 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 most important and the least important 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.

<Insert Table 4 Here >

[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.

Table 4 presents the regression results, with Panels A and B presenting 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 0.041, 0.003, and 0.011 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 0.001, 0.013, and 0.001). As a result, the high-low coefficient difference is much larger for busy analysts (ranging from 3.7% to 5.8%) than for non-busy analysts (from 1.4% to 2.0%). 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]

3.4. 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 strategically across firms, then it is plausible that investors are more likely to listen to analysts when they release new information on relatively more important firms. Analyzing the stock market reactions to analyst research can also address a potential caveat with using the earnings forecast accuracy measure. Specifically, analysts may be able to produce more accurate earnings forecasts by deciphering and incorporating the information contained in other analysts' published research along with their earnings forecasts. If an analyst's earnings forecast largely reflects the information produced by other analysts'

[10] We find similar results when defining analyst "busyness" based on the number of industries they cover.

recently published research and carries little new information content, 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, the stock market should respond more to its release.

3.4.1. Stock price reactions to analyst earnings forecast revisions

We first examine the market reaction to forecast revisions. We expect that the market reaction to forecast revisions for relatively more important firms should be more pronounced. In particular, we use the following regression model to test this prediction.

$$\begin{aligned} CAR_{i,j,t} = {} & \beta_0 + \beta_1 FR{*}High_{i,j,t} + \beta_2 FR{*}Low_{i,j,t} + \beta_3 FR_{i,j,t} + \beta_4 HIGH_{i,j,t} + \beta_5 LOW_{i,j,t} + \beta_6 GEXP_{i,j,t} \\ & + \beta_7 FEXP_{i,j,t} + \beta_8 AGE_{i,j,t} + \beta_9 PORTSIZE_{i,j,t} + \beta_{10} SIC2_{i,j,t} + \beta_{11} TOP10_{i,j,t} + \beta_{12} All\text{-}star_{i,j,t} \\ & + \beta_{13} Size_{j,t} + \beta_{14}\, Log(trading\ volume)_{j,t} + \beta_{15} Institutional\ holding_{j,t} + \beta_{16} BM_{j,t} + \beta_{17} Past\ Ret_{j,t} \\ & + \beta_{18} No.\ of\ Analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \qquad (3) \end{aligned}$$

The empirical model is similar to that used by Bradley, Gokkaya and Liu (2014). The dependent variable is the cumulative 3-day market adjusted abnormal stock returns around a forecast revision.[11] On the right hand side, we control for forecast revision (*FR*), its interaction terms with *High* and *Low*, and other analyst and firm characteristics as in equation (1). Year fixed effects are included, and standard errors are clustered at the firm and analyst level. Forecast revision *(FR*) is defined 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.

<Insert Table 5 Here >

Table 5 presents the regression results. Columns (1)-(3) report results of using the equity 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, suggesting that the market response is positively associated with the forecast revision. On average, the stock market responds

[11] The abnormal stock returns are denominated in percentage points, and we exclude analyst forecast revisions that coincide with firms' earnings announcements.
[12] Our results are robust if we deflate the forecast revision by stock price.

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.

3.4.2. Stock price reactions to stock recommendations

Next we examine the market reaction to stock recommendations. Loh and Mian (2006) find that analysts who have superior forecast accuracy also issue more informative stock recommendations. Brown et al. (2014) document that analysts' top motivation for issuing accurate forecasts is to use these forecasts as inputs into their corresponding stock recommendations. Given that analysts issue more accurate forecasts to relatively more important firms in their portfolios, we should expect a stronger market reaction to stock recommendations issued on those firms. In particular, we use the following regression model to test this prediction.

$$
\begin{aligned}
CAR_{i,j,t} = {} & \beta_0 + \beta_1 High_{i,j,t} + \beta_2 Low_{i,j,t} + \beta_3 Gexp_{i,j,t} + \beta_4 Fexp_{i,j,t} + \beta_5 Portsize_{i,j,t} + \beta_6 SIC2_{i,j,t} + \beta_7 Top10_{i,j,t} \\
& + \beta_8 All\ Star_{i,j,t} + \beta_9 Lag\ recommendation_{i,j,t} + \beta_{10} Size_{j,t} + \beta_{11} Log(trading\ volume)_{j,t} \\
& + \beta_{12} Holding_{j,t} + \beta_{13} BM_{j,t} + \beta_{14} Past\ ret_{j,t} + \beta_{15} No.\ of\ analysts_{j,t} + Year\ FE + \varepsilon_{i,j,t} \qquad (4)
\end{aligned}
$$

The dependent variable is the cumulative 3-day market-adjusted abnormal stock return around a stock recommendation. On the right hand side, we control for *High* and *Low* dummies which capture the relative ranking of a firm in an analyst's portfolio. We also control for other analyst and firm characteristics as in equation (1). Year fixed effects are included, and standard errors are clustered 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 asymmetric market reactions. 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 generate order flow.

<Insert Table 6 Here >

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 on 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.

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

The results from Sections 3 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 importance in 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 capital.

In previous section, we conduct tests at the analyst-firm level, and rank firms within an analyst's portfolio. In this section, the analysis is at the firm-year level. We construct two variables to capture a firm's overall ranking across analysts. Specifically, we define *%High* as 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* as 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. 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 should expect a firm's information asymmetry and costs of capital to decrease with *%High* and increase with *%Low*.

4.1. 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) 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 of interest 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 ownership and their quadratic forms to ensure that *%High*

[13] Following prior literature, we exclude firms with stock prices below $5.

and *%Low* are not simply picking up the effects of these firm characteristics. Our regression model is specified as follows.

$$\begin{aligned}&\textit{Bid-ask spread or Amihud illiquidity measure}\\&= \beta_0 + \beta_1\%High + \beta_2\%Low + \beta_3 No.\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume)\\&+ \beta_7 Log(Trading\ Volume)^2 + \beta_8 Holding + \beta_9 Holding^2 + \beta_{10} Log(Stock\ price) + \beta_{11} BM + \beta_{12} Leverage +\\&\beta_{13} Past\ Ret + \beta_{14} ROA + \beta_{15} Volatility + Year\ FE + Firm\ FE + \varepsilon \qquad (5)\end{aligned}$$

<Insert Table 7 Here >

Results are presented in Table 7. Panel A presents results on the bid-ask spreads. 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 firms which are ranked high by more analysts have 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 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, institutional ownership, stock return, and increases with stock volatility.

Panel B presents the coefficient estimates using Amihud illiquidity measure. We find that firms covered by more analysts who rank them high (low) enjoy higher (lower) stock market liquidity. Our

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

results in Table 7 are robust to an alternative specification by replacing *%High* (or *%Low)* with a dummy variable equal to one if majority of analysts rank the firm high (or low) in their portfolios.

4.2. Cost of equity capital

To test the effect of analyst effort allocation on firms' costs of 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 ownership and their quadratic forms. The rest of control variables are from Gebhardt, Lee, and Swaminathan (2001). Our regression is specified as follows:

$$ICOC = \beta_0 + \beta_1 \%High + \beta_2 \%Low + \beta_3 No\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume) + \beta_7 Log(Trading\ Volume)^2 + \beta_8 Holding + \beta_9 Holding^2 + \beta_{10} MAE\ of\ forecasts + \beta_{11} Earnings\ variability + \beta_{12} Dispersion\ of\ analyst\ forecasts + \beta_{13} BM + \beta_{14} Leverage + \beta_{15} Past\ Ret + \beta_{16} Long\text{-}term\ growth + \beta_{17} Beta + \beta_{18} Volatility + Year\ FE + Firm\ FE + \varepsilon \quad (6)$$

<Insert Table 8 Here >

Results are presented in Table 8. 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 0.86% (=-0.246×0.242/(0.0696×100)) or increases by 0.93% (=0.180×0.359/(0.0696×100)).[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 1.13% (=-0.012×6.557/(0.0696×100)). Therefore, the economic impact of *%High* and *%Low* is similar to *No. of Analysts.*

Overall, in this section we find that firms which are relatively more important in analysts' portfolios due to career concerns enjoy lower information asymmetry, better stock market liquidity, and lower costs of capital. These results are consistent with analysts producing more information for relatively more 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 relative importance in the analysts' portfolios.

5. 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 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 the analyst's portfolio. The rationale behind this approach is that in the absence of strategic effort allocation we do not expect to observe any difference in the relative frequency and accuracy of forecasts issued by the same analyst to firms in her portfolio. The

[16] The mean implied cost of capital for our sample firms is 0.0696.

reason is that we measure an analyst's forecast behavior for each firm relative to other analysts covering the same firm in the same year, thereby effectively removing firm-year effects from our forecast frequency and accuracy measures and leaving analyst effort as the only logical explanation for any observed difference in these measures.

We first 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 in our logit regression 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 forecast frequency and accuracy between the high and low groups within an 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.

$$Pr(\textit{An analyst is voted an all-star}) = \beta_0 + \beta_1(\textit{Diff(High-Low) in DFREQ}) + \beta_2(\textit{Diff(High-Low) in PMAFE}) + \beta_3(\textit{GExp}) + \beta_4(\textit{Portfolio size}) + \beta_5(\textit{SIC2}) + \beta_6(\textit{Brokerage size}) + \beta_7(\textit{Average PMAFE}) + \beta_8(\textit{Average DFREQ}) + \beta_9(\textit{Average Firm Size}) + \beta_{10}(\textit{lag(All star)}) + \textit{Year FE} + \varepsilon \qquad (7)$$

<Insert Table 9 Here >

Panel A of Table 9 presents the regression results. For each specification, we have separate regressions using firm size, volume and institutional holdings 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.[17]

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 to a high-status brokerage house. Each year we classify the top ten brokerage houses employing the most analysts as high-status and the rest as low-status. The model specification is as follows:

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

Panel B of Table 9 reports the regression results. 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 all 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.

[17] We also limit our analysis to 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%.

6. Additional Analysis

6.1. 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 firm size, 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 firm size, 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 3 in these subsamples. The results suggest that analysts covering portfolios with larger variations in firm size, trading volume, or institutional holding engage in strategic effort allocation to a greater extent.

6.2. 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). The Clementi and Tse (2005) measure is defined as follows.

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

It is worth noting that 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.

6.3. 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 drops 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 also estimate a logistic regression where the dependent variable that is equal to one if a firm loses coverage by an analyst in a certain 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 was poor for the firm. These findings provide further support for the career concerns hypothesis.

7. 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 both analyst fixed effects and, importantly, analyst-firm pair fixed effects. 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, higher stock market liquidity, and lower costs of capital. Thus, the information environment of a firm is determined in part by the other firms that its analysts cover. The marginal impact of a new analyst on a firm's spreads, liquidity and costs of capital will vary according to that 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: Variable Definitions

Variable	Definition
%High	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.
%Low	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.
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's *i* forecast (*Age*) is defined as the age of forecasts in days at the minimum forecast horizon date.
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 PMAFE	The average PMAFE of all the firms covered by analyst i at time t-1.
Average size	The average size of the all the firms covered by analyst i at time 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 data 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's i forecast (Age) minus the average age of forecasts issued by analysts following firm j at time 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's i first earnings forecast for firm j (FExp) minus the average number of years I/B/E/S analysts supplying earnings forecasts for firm j at time 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's *i* appeared in *I/B/E/S* (*GExp*) minus the average tenure of analysts supplying earnings forecasts for firm *j* at time *t*.
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 at time t (*Portsize*) minus the average number of firms followed by analysts supplying earnings forecasts for firm j at time t.
DSIC2	Number of 2 digit SICs followed by analyst i at time t (*SIC2*) minus the average number of 2-digit SICs followed by analysts following firm j at time 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 at time t.
Earnings variability	The coefficient of the variation of annual earnings over the previous five years.
FExp	The total number of years since analyst's i first earnings forecast for firm j at time 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 at time t and the previous forecast at time t-1 scaled by the absolute value of the forecast at t-1. 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's i appeared in I/B/E/S at time t.
High	A dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional holding) is in the top quartile of all firms the analyst covers in that year, zero otherwise.
Institutional holding	The percentage of institutional holding for a firm j in a given year t

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 holding) 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 at time 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 and the mean absolute forecast error (MAFE) for firm j at time t scaled by the mean absolute forecast error for firm j at time t.
Portsize	The number of firms followed by analyst i at time t.
ROA	Return on assets, calculated as net income before extraordinary items and discontinued operations divided by total assets
SIC2	Number of 2 digit SICs followed by analyst i at time t.
Size	The natural log of market capitalization of the covered firm (in $millions) by the end of the month prior to the earnings forecast.
Top10	Indicator variable is one if analyst works at a top decile brokerage house at time t.
Trading volume	The annual trading volume for a firm *j* in a given year *t*
Volatility	Daily stock return volatility for a firm *j* in year *t*

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 time t scaled by the mean absolute forecast error for firm j at time t. See the Appendix 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 Holding		
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	***
Institutional holding	0.634	0.502	***	0.632	0.503	***	0.664	0.445	***

Table 2 – Analyst Earnings Forecast Accuracy

This table presents OLS regression results for analyst earnings forecasts 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 holding) 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 holding) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix 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	Holding
High	-2.383***	-1.712***	-2.029***
	(6.74)	(5.38)	(5.96)
Low	1.905***	1.511***	1.791***
	(6.39)	(5.13)	(6.02)
DGExp	-0.242***	-0.238***	-0.242***
	(3.17)	(3.11)	(3.16)
DFExp	-0.635***	-0.642***	-0.637***
	(6.73)	(6.80)	(6.75)
DAge	0.509***	0.509***	0.509***
	(84.16)	(84.14)	(84.14)
DPortsize	0.133**	0.133**	0.133**
	(2.01)	(2.01)	(2.02)
DSIC2	0.710***	0.711***	0.705***
	(4.44)	(4.44)	(4.41)
DTop10	-2.522***	-2.478***	-2.512***
	(5.07)	(4.98)	(5.05)
All-star	-4.325***	-4.169***	-4.292***
	(7.25)	(7.00)	(7.18)
Size	0.452***	0.399***	0.443***
	(3.05)	(2.72)	(3.01)
Log(trading volume)	-0.341***	-0.078	-0.389***
	(3.02)	(0.59)	(3.47)
Institutional holding	-0.236	(0.551)	0.686
	(0.45)	(1.05)	(1.26)
BM	0.262	0.579*	0.345
	(0.86)	(1.92)	(1.14)
Past Ret	-0.374*	-0.414*	-0.366*
	(1.74)	(1.93)	(1.70)
No. of Analysts	-0.075***	-0.071***	-0.071***
	(3.02)	(2.85)	(2.86)
# of observations	529,427	529,427	529,427
R^2	0.188	0.188	0.188

Panel B – Analyst fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	-1.582***	-1.371***	-1.392***
	(4.29)	(3.74)	(3.85)
Low	1.536***	1.579***	1.624***
	(4.65)	(4.53)	(4.82)
Controls (from Table 2)	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) Holding
High	-2.083***	-1.989***	-1.811***
	(4.46)	(4.23)	(3.86)
Low	1.848***	2.120***	1.834***
	(4.29)	(4.81)	(4.37)
Controls (from Table 2)	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.189	0.189	0.189

Panel D – Analyst-firm pair fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	-2.060***	-1.545**	-2.056***
	(2.93)	(2.32)	(3.02)
Low	1.866***	1.338**	1.597**
	(2.94)	(2.10)	(2.57)
Controls (from Table 2)	Y	Y	Y
Analyst-firm FE	Y	Y	Y
# of observations	529,427	529,427	529,427
R^2	0.550	0.550	0.550

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. Here, we present regression results without de-meaning the variables but controlling for firm-year pair fixed effects. 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 holding) 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 holding) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. See Appendix 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.

Variables	(1) Market cap	(2) Trading volume	(3) Holding
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 time t scaled by the mean absolute forecast error for firm j at time t. High is a dummy variable which takes the value of 1 if the firm's market capitalization (or trading volume, institutional holding) 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 holding) is in the lower quartile of all firms the analyst covers in that year, zero otherwise. 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	Holding
High	-2.848***	-1.945***	-2.506***
	(6.06)	(4.59)	(5.52)
Low	2.920***	1.747***	2.715***
	(7.22)	(4.47)	(6.85)
Controls (from Table 2)	Y	Y	Y
# of observations	349,933	349,933	349,933
R-squared	0.165	0.165	0.165

Panel B: "Non-busy" analysts

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Holding
High	-1.112**	-0.905	-0.562
	(2.05)	(1.62)	(1.03)
Low	0.819*	1.115**	0.898*
	(1.67)	(2.27)	(1.76)
Controls (from Table 2)	Y	Y	Y
# of observations	179,494	179,494	179,494
R-squared	0.229	0.230	0.230

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 time 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 holding (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 holding 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 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	Holding
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 time 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 holding (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 holding 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. 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) Holding
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) Holding
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 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

Variables	(1) Market cap	(2) Trading volume	(3) Holding
No. of Analysts	-0.003*	-0.003**	-0.003*
	(1.87)	(1.97)	(1.83)
% 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)
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) Holding
No. of Analysts	-0.0011***	-0.0011***	-0.0011***
	(4.36)	(4.41)	(4.35)
% 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)
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 cost of 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 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) Holding
No. of Analysts	-0.012*	-0.012*	-0.012*
	(1.72)	(1.73)	(1.70)
% high	-0.246**	-0.258**	-0.283**
	(2.09)	(2.06)	(2.27)
% low	0.180**	0.146*	0.107
	(2.00)	(1.73)	(1.15)
Size	0.397	0.351	0.215
	(0.80)	(0.72)	(0.43)
Size^2	-0.012	-0.012	-0.006
	(0.69)	(0.69)	(0.36)
log(Trading volume)	-0.491*	-0.473	-0.486*
	(1.69)	(1.59)	(1.67)
log(Trading volume)^2	0.017*	0.018*	0.018*
	(1.76)	(1.81)	(1.78)
Institutional holding	-0.228	-0.22	-0.123
	(0.40)	(0.39)	(0.22)
Institutional holding^2	0.06	0.081	0.032
	(0.13)	(0.18)	(0.07)
MAE of forecasts	-0.415*	-0.411*	-0.413*
	(1.73)	(1.71)	(1.72)
Earnings variability	0.075	0.075	0.075
	(0.92)	(0.91)	(0.91)
Dispersion of analyst forecasts	0.620***	0.654***	0.622***
	(3.90)	(4.11)	(3.91)
BM	1.766***	1.678***	1.766***
	(8.75)	(8.05)	(8.75)
Leverage	1.682***	1.672***	1.681***
	(4.60)	(4.59)	(4.60)
Past Ret	-0.084*	-0.065	-0.084*
	(1.86)	(1.46)	(1.86)
Long-term growth	0.025***	0.024***	0.025***
	(4.93)	(4.87)	(4.92)
Beta	-0.012	-0.013	-0.01
	(0.19)	(0.21)	(0.17)
Volatility	4.232	3.272	4.288
	(1.34)	(1.04)	(1.36)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
# of observations	32,470	32,470	32,470
R-squared	0.702	0.702	0.702

Table 9: 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. All control variables are lagged by one year. See Appendix 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 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 defined using:	Market cap	Trading volume	Holding	Market cap	Trading volume	Holding
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 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 defined using:	Market cap	Trading volume	Holding	Market cap	Trading volume	Holding
Diff(High-low) in DFREQ	0.191**	0.204**	0.213***			
	(2.37)	(2.54)	(2.83)			
Diff(High-low) in PMAFE				-0.352**	-0.191	-0.308**
				(2.16)	(1.24)	(2.00)
GExp	-0.041**	-0.043**	-0.044**	-0.040**	-0.041**	-0.043**
	(2.08)	(2.17)	(2.20)	(2.00)	(2.08)	(2.13)
Portsize	0.011	0.011	0.012	0.01	0.01	0.011
	(1.29)	(1.29)	(1.42)	(1.23)	(1.17)	(1.30)
SIC2	-0.157***	-0.157***	-0.154***	-0.158***	-0.156***	-0.155***
	(4.53)	(4.50)	(4.44)	(4.54)	(4.49)	(4.41)
Brokerage size	0.028***	0.028***	0.028***	0.028***	0.028***	0.029***
	(6.54)	(6.48)	(6.63)	(6.54)	(6.62)	(6.69)
Average PMAFE	-0.499	-0.478	-0.635*	-0.409	-0.52	-0.578*
	(1.54)	(1.47)	(1.90)	(1.23)	(1.58)	(1.70)
Average DFREQ	-0.082	-0.084	-0.087	-0.039	-0.037	-0.039
	(1.10)	(1.12)	(1.14)	(0.55)	(0.53)	(0.54)
Average size	0.127**	0.131**	0.122**	0.130**	0.138***	0.129**
	(2.46)	(2.55)	(2.32)	(2.52)	(2.71)	(2.48)
Year FE	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.083	0.083	0.085	0.082	0.081	0.082
# of observations	14,654	14,655	14,413	14,638	14,630	14,387