Career Concerns and Strategic Effort Allocation by Analysts

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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 strategically devoting more effort to firms that are relatively more important for their career concerns. Specifically, we find that within each analyst's portfolio, firms ranked relatively higher based on market capitalization, trading volume, or institutional ownership receive more frequent, accurate, and informative earnings forecast revisions and stock recommendation changes that contain greater information content. As a result, these firms display less information asymmetry and exhibit higher stock market liquidity and lower costs of capital. Moreover, we find that analysts who engage in a greater extent of strategic effort allocation are more likely to experience favorable career outcomes.

1. Introduction

Sell-side financial analysts are prominent information intermediaries in the financial markets. They specialize in gathering, analyzing, and disseminating firm value-relevant information to various market participants. They also facilitate investors' information production and processing efforts by arranging interactions between their institutional clients and firm management (Groysberg, Maber and Healy (2014)).[1] The information content and investment value of analyst research have been the subjects of a large body of literature.[2] In particular, prior studies have uncovered a number of analyst and firm characteristics that can explain cross-analyst or cross-firm differences in the quality of 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 (2014)).[3] However, little attention has been paid to variation across firms *within* an analyst's portfolio and whether this variation impacts the way in which analysts provide research coverage on portfolio firms. In other words, how analysts allocate their effort among firms in their respective portfolios remains largely unexplored.

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 firms' information environment.

[1] For example, analysts can organize investor conferences where firm management and institutional investors meet, take institutional clients on field trips to visit companies, and accompany firm management on non-deal road shows to meet institutional investors.
[2] For evidence on short-term stock price reactions to analyst research, please see Womack (1996) and Bradley, Clarke, Lee and Orthanalai (2014) for stock recommendation revisions, Francis and Soffer (1997) and Gleason and Lee (2003), and Ivkovic and Jegadeesh (2004) for earnings forecast revisions, and Brav and Lehavy (2003) for target stock price estimates. Stickel (1995), Jegadeesh, Kim, Krishce, and Lee (2004), and Boni and Womack (2006) document long-term abnormal returns of stocks based on analyst recommendations.
[3] 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.

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 with these constraints, analysts must be selective in allocating their attention and effort to firms in their portfolios. Therefore, we expect that as any rational economic agents would do, financial analysts will maximize their utility function defined by their career concern incentives. Importantly, firms within an analyst's research portfolio often have differential impacts on the analyst's career outcomes including 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 in *Institutional Investor* (*II*) and the allocation of buy-side investors' trade and commission across brokerage firms. 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. 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 importance for the analyst's career concerns. Based on this intuition, we develop a "strategic effort allocation" hypothesis, which contends that analysts devote more effort to researching firms that are relatively more important from their career concern perspectives. We then investigate the implications of this strategic allocation for firms and analysts.

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. Therefore, we expect firms with larger market capitalization, trading volumes, and institutional ownership to be more important for analysts' career concerns, because these three characteristics capture firms' visibility, commission revenue potential, and importance to institutional investors. We identify firms of relative high (or low) importance to analysts using a firm's relative rank in an analyst's portfolio based on these variables. 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. The "strategic effort allocation" hypothesis predicts that firms of relative high importance receive more attention from analysts. Furthermore, this pattern should be especially pronounced for analysts covering larger portfolios, because larger portfolios are more likely to hit the constraint created by analysts' limited time, energy, and resources, making it even more critical for the analysts to be strategic in their research activities.

Alternatively, rather than responding to career concern incentives, analysts as information intermediaries may choose to allocate their effort among firms based on their potential impact on the firm's information environment. For example, smaller firms or firms with 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. Based on this "incremental impact" hypothesis, we may observe just the opposite of what the "strategic effort allocation" hypothesis predicts. Specifically, to the extent that firms with larger market capitalizations, trading volume, and institutional ownership tend to have more transparent information environments, analysts may have less incentive to devote research effort to these firms.

We test these competing conjectures by analyzing the earnings forecasts and stock recommendations issued by a large sample of sell-side analysts from 1983 to 2012. Evidence from our analysis lends strong support for the "strategic effort allocation" hypothesis. Specifically, analysts provide more frequent earnings forecast revisions and more accurate earnings forecasts 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 obtained while controlling for a large array of pertinent firm and analyst characteristics. Our findings are also robust to controlling for analyst fixed effects or analyst-firm pair fixed effects. The robustness to analyst-firm pair effects is notable because we are holding the pairing constant so that variation in the importance of the firm to the analyst comes entirely from variation 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 lends further credence to our *strategic effort allocation* 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' strategic 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' strategic effort allocation. If the pattern of analyst earnings forecast behavior we document is a rational response to career concerns, we expect a favorable career outcome to be related to the degree to which the analyst engages in strategic effort allocation. We measure an analyst's engagement of strategic effort allocation by the differences in earnings forecast frequency and accuracy between the higher and lower ranked firms (based on size, trading volume, and institutional ownership) within the analyst's portfolio. Consistent with our expectation, we find that the extent of an analyst's strategic effort allocation is significantly and positively related to the probability of the analyst being voted as an "All Star". 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. This evidence provides a logical explanation for the strategic effort allocation pattern we observe.

Our study contributes to the financial analyst literature by exploring within-analyst portfolio variations in analyst behavior. This approach represents a novel departure as well as an important complement to the focus by prior studies on either cross-analyst (see, e.g., Clement (1999), Jacob, Lys, and Neale (1999), Clement, Reese, and Swanson (2003), Bradley, Gokkaya, and Liu (2014), and Jiang, Kumar, and Law (2014)) or cross-firm (e.g., Frankel, Kothari, and Weber (2006) and Ljungqvist et al. (2007)) variations. Our findings provide new insights into how analysts allocate their limited attention and resources to firms within their portfolios. They suggest that analysts do not treat all firms equally; instead, they strategically allocate more research effort to firms that are relatively more important for their career concerns.

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 for their probability of being voted an “All Star”. 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 strategic effort allocation, matters as well.

Our results also 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 unreliable. 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 accurate earnings forecasts 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 the analyst must cover.

Finally, our findings suggest that the widely used approach of treating 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.

The rest of the paper proceeds as follows. Section 2 discusses the data sources, sample, and key variables. Section 3 presents evidence of analyst strategic effort allocation based on earnings forecast frequency and accuracy. Section 4 presents further evidence of analyst strategic effort allocation based on the stock price impact of analyst research. Section 5 shows the real effects of analyst strategic effort allocation on firm information asymmetry and costs of capital. Section 6 presents results on the implication of strategic effort allocation for analyst career outcomes. 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 first 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 measure is a widely used proxy for the quantity of analyst effort in the analyst literature (e.g., Jacob, Lys, and Neale (1999) and Pandit, Willis, and Zhou (2009)). However, its caveat is that it does not directly speak to the quality of analyst research on a given firm.

Our second and primary measure of analyst effort is the accuracy of an analyst's earnings forecasts, which is based on the forecast 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 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 defined as the difference between the absolute forecast error ($AFE_{i,j,t}$) of analyst *i* for firm *j* in time *t* and the mean absolute forecast error for firm *j* at time *t*. This difference is then scaled by the mean absolute forecast error for firm *j* at time *t* ($MAFE_{j,t}$) to reduce heteroskedasticity (Clement, 1998). Specifically, $PMAFE_{i,j,t}$ is formally defined as:

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

Lower values of *PMAFE* are associated with more accurate forecasts. $PMAFE_{i,j,t}$ is an analyst's forecast accuracy *relative to* all other analysts covering the same firm during the same time period and thus controls for differences across companies, time and industry (Ke and Yu, 2006). As constructed, negative values of $PMAFE_{i,j,t}$ represent better than average accuracy, while positive values indicate worse than average accuracy.

We also construct a variety of analyst and forecast characteristics that previous research has identified as important factors explaining analyst performance. First, we include proxies for analyst ability and experience because Clement (1999) and other studies report evidence that they play important roles in explaining forecast accuracy. We include general and firm-specific forecasting experience, which are calculated 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* ($Fexp_{ij}$), respectively. We include the number of days (AGE_{ij}) between analyst *i*'s forecast for firm *j* and the firm's announcement of actual earnings as 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. Portfolio complexity is measured by the size of analyst *i*'s coverage portfolio ($PortSize_i$) and the number of 2-digit SICs followed by analyst *i* ($SIC2_i$). We also capture the resources available to an analyst by an indicator variable that is equal to one if the analyst works at a top-decile brokerage house ($Top10_i$) and zero otherwise. Appendix A provides detailed definitions of these variables.

Since the *I/B/E/S* database is left censored, it is not possible to tell 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 data set in the initial year (1983). Forecasts from 1984 are also excluded from the sample since there would be little variation in the experience variables for that year (i.e., the experience variables can take on values of only 0 or 1 in 1984).[4]

<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

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

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 mean-adjusted values. Clement (1998) finds that controlling for firm-year effects in 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 predictability of earnings changing over time. Therefore, we follow the literature and adjust these variables by their respective firm-year means in order to control for firm-year effects. We observe that these 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).

The key variables of interest in this paper are the measures which capture the relative importance of a firm in an analyst's portfolio. We first construct the measure based on the market capitalization of the firm. To capture the relative importance of analyst incentive effects in a specific firm for analysts following multiple firms (on average, an analyst follows 8.6 firms per year in our sample), we create a variable *High*, which takes the value of 1 if the 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 is an indicator variable equal to one if the firm's market capitalization is in the lower quartile of all firms the analyst covers in that year, zero otherwise. We also construct the key variables of interest 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.

3. Evidence on analyst strategic effort allocation: Earning forecast frequency and accuracy

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

3.1. Earnings forecast revision frequency

Earnings forecast update frequency is a widely used proxy for analyst effort in the analyst literature (e.g., Jacob, Lys, and Neale (1999), Pandit, Willis, and Zhou (2009)). Our 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 measure earnings forecast update frequency (*FREQ*) 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 (similar to the one used in Broysberg, Healy, and Maber (2011)). In particular, we use regression model (1) to examine the effect of relative ranking on the number of forecast revisions.

$$DFREQ_{i,j,t} = \beta_0 + \beta_1 HIGH_{i,j,t} + \beta_2 LOW_{i,j,t} + \beta_3 DGEXP_{i,j,t} + \beta_4 DFEXP_{i,j,t} + \beta_5 DAGE_{i,j,t} + \beta_6 DPORTSIZE_{i,j,t} + \beta_7 DSIC2_{i,j,t} + \beta_8 DTOP10_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

The "*D*" preceding each variable stands for de-meaned. The specific variables of interest are dummy variables *High* and *Low*, which measure the relative importance of analyst incentive effects in a specific firm for analyst following multiple firms based on their market capitalization, trading volume, or institutional holding. We expect the coefficient for *High* (or *Low*) to be positive (or negative). The standard errors are estimated by double clustering at the firm and analyst level.

The baseline regression results are reported in Panel A of Table 2. In all specifications, the coefficients on *High* are significantly positive while the coefficients on *Low* are all significantly negative.

These results suggest that firms with relatively higher (lower) rankings receive significantly more (less) frequent forecast revisions. In Panels B, C and D, we further control for analyst fixed effects, firm fixed effects, and analyst-firm pair fixed effects and our results remain robust. 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 from changes in what *other* firms are in the analyst's portfolio. This approach to identification relies on variation in a firm's high/low status within the analyst's portfolio. One concern would be that there is not enough of 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. Overall, the evidence in Table 2 is consistent with our strategic effort allocation hypothesis and suggests that analyst indeed devote more effort to firms that are relatively more important.

<Insert Table 2 Here >

3.2. Earnings forecast accuracy

In this section, we examine whether, in addition to more frequent forecasts, analysts make more accurate earnings forecasts for firms that are relatively more important in their portfolios. We regress an analyst's relative forecast accuracy on a firm ($PMAFE_{i,j,t}$) on our key explanatory variables, the *High* and *Low* dummies, along with an array of analyst and firm characteristics that previous research has identified as contributing to differences in relative forecast accuracy among analysts. More specifically, the model is specified as follows.

$$PMAFE_{i,j,t} = \beta_0 + \beta_1 HIGH_{i,j,t} + \beta_2 LOW_{i,j,t} + \beta_3 DGEXP_{i,j,t} + \beta_4 DFEXP_{i,j,t} + \beta_5 DAGE_{i,j,t} + \beta_6 DPORTSIZE_{i,j,t} + \beta_7 DSIC2_{i,j,t} + \beta_8 DTOP10_{i,j,t} + \varepsilon_{i,j,t} \quad (2)$$

where the control variables are adjusted by their respective firm-year means 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 strategic effort allocation hypothesis, we expect the coefficient of *High* (*Low*) to be negative (positive).

<Insert Table 3 Here >

Panel A of Table 3 reports the 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 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 are consistent with our hypothesis that earnings forecast errors are smaller for firms which are relatively more important in an analyst's portfolio. Economically, firms which 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, and 1.70 times the effect of working for a top-decile brokerage firm. 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. 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 stable forecasts tend to be less accurate.

In further analysis, we augment the regression model specified in equation (2) by controlling for analyst fixed effects. Doing so can help mitigate the concern that our findings are driven by some timeinvariant analysts' characteristics such as talent. Results presented in Panel B of Table 3 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 1.536% lower for relatively more important firms and 1.582% 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. 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 covered by the same analyst, the accuracy of forecasts received by the firm varies with its relative importance in the analyst's portfolio. More specifically, as the firm's relative importance rises (or drops) over time because of changes in the firm's fundamentals and/or changes in the rest of the analyst's portfolio, the analyst devote more (or less) time and resources to researching the firm, leading to higher (or lower) forecast accuracy. Overall, the results from Table 3 lend strong support to the strategic effort allocation hypothesis.

3.3. Busy analysts

The strategic effort allocation hypothesis is built on the fact that analysts have limited time, energy, and resources. Faced with these constraints, analysts strategically 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 strategic 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.

<Insert Table 4 Here >

Table 4 presents the regression results, with Panel 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.

3.4. Alternative proxy for forecast accuracy

So far our results related to analyst forecast accuracy are based on the relative forecast error measure developed by Clement (1999). As a robustness check, we also repeat our analysis using an alternative proxy for forecast accuracy suggested by Clement and Tse (2005). The forecast accuracy measure in Clementi and Tse (2005) is defined as follows.

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

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.

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

Given our evidence of analysts issuing more frequent and more accurate 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' 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.

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.

$$CAR = \beta_0 + \beta_1 FR*High + \beta_2 FR*Low + \beta_3 FR + \beta_4 High + \beta_5 Low + \beta_6 DGExp + \beta_7 DAge + \beta_8 DFExp + \beta_9 Dportsize + \beta_{10} DSIC2 + \beta_{11} DTop10 + \beta_{12} Size + \beta_{13} BM + \beta_{14} Past\ ret + \beta_{15} No\ of\ analysts + Year\ dummies + \varepsilon \quad (3)$$

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 return around a forecast revision. 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. 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 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 while *Low*FR* has a significantly negative coefficient. 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 strategic effort allocation hypothesis, which predicts greater information production effort by analysts on these firms.

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.

$$CAR = \beta_0 + \beta_1 High + \beta_2 Low + \beta_3 Gexp + \beta_4 Fexp + \beta_5 Portsize + \beta_6 SIC2 + \beta_7 Top10 + \beta_8 All\ Star + \beta_9 Lag\ recommendation + \beta_{10} Size + \beta_{11} Trading\ volume + \beta_{12} Holding + \beta_{13} BM + \beta_{14} Past\ ret + \beta_{15} No\ of\ analysts + Year\ dummies + \varepsilon \quad (4)$$

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. We run separate regressions on upgrades and downgrades because of asymmetric market reactions.

<Insert Table 6 Here >

Panel A of Table 6 presents results for upgrades. Columns (1) to (3) correspond to three different ways to rank the relative importance of firms within an analyst portfolio. The coefficients on *High* dummy variable are significantly positive in all specifications, and the coefficients on *Low* dummy variable are negative in all specifications and significant in column (2). These results indicate that the informativeness of stock recommendations is related to a firm's ranking within an analyst's portfolio.

Column (1) suggest that stock market reactions are 15.2% higher for firms with relatively high rankings, and 13.1% lower for firms with relatively low rankings. The coefficients on other control variables are consist with the literature. Market reactions are stronger to upgrade revisions to firms with more pessimistic recommendation previously, smaller size, larger trading volume, lower book-to-market ratio, higher past returns, and lower analyst coverage. Upgrade revisions from analysts with higher general experience, covering fewer firms, at top 10 brokerage houses and all-star analysts also generate higher market reactions.

Panel B of Table 6 presents results for downgrades. Consistent with the results in Panel A, we also find that market reactions are stronger (weaker) for downgrade revisions to firms with relatively higher (lower) rankings. In all specifications, the coefficients on *High* (*Low*) dummy variable are significantly negative (positive) at one percent level. The economic magnitudes are larger than those in Panel A. The coefficients in column (1) suggests that market reaction to downgrade revisions is 54.8% stronger for firms which are ranked relatively high in an analyst portfolio and 33.3% weaker for firms which are ranked relatively low in analyst portfolio.

5. The real effects of analyst strategic effort allocation on firms

The results from Section 3 and 4 are consistent with analysts devoting more effort to produce more information on relatively more important firms in their portfolios. A direct implication of our evidence is that everything else being equal, firms that on average rank high in importance in their analysts' portfolio 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 sections, we conduct tests at the analyst-firm level, and rank firms within an analyst's portfolio. In this section, we would like to run tests at the firm level. Therefore, 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 larger value of *%High* means that more effort is allocated to the firm while a larger value of *%Low* means that less effort is allocated to the firm. Therefore we should expect a firm's stock liquidity increases with *%High* and decreases with *%Low*, while the cost of capital should decrease with *%High* and increase with *%Low*.

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

We follow the literature and 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 higher 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.[5] The key independent variables are *%High* and *%Low*. We control for a wide array of variables that have been shown to affect a stock's information asymmetry. Specifically, we control directly for a firm's size and trading volume, so %High and %Low are not simply picking up large/small or high/low volume. Our regression model is specified as follows.

$$\textit{Bid-ask spread/Amihud illiquidity measure} = \beta_0 + \beta_1 \%High + \beta_2 \%Low + \beta_3 No\ of\ Analysts + \beta_4 Size + \beta_5 Size^2 + \beta_6 Log(Trading\ Volume) + \beta_7 Log(Trading\ Volume)^2 + \beta_8 Holding + \beta_9 BM + \beta_{10} Leverage + \beta_{11} Ret + \beta_{12} ROA + \beta_{13} Volatility + \varepsilon \quad (5)$$

<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 and the coefficients on %Low are significantly positive in all three specifications. These results indicate that firms which are ranked high

[5] Following the literature, we exclude firms with stock price lower than \$1 for the bid-ask spread measure, and exclude firms with a stock price lower than \$5 for the Amihud measure.

by more analysts have less information asymmetry as measured by the bid-ask spread. Economically, column (1) suggests that a firm's bid-ask spread decreases by 0.52% for a 10% increase in the number of analysts who rank it high, and increases by 0.48% for a 10% increase in the number of analysts who rank it low. Coefficients on control variables are 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 ROA, and increases with stock volatility. Panel B presents the coefficient estimates from the stock market liquidity regressions. We find that firms covered by more analysts who rank them high (low) enjoy higher (lower) stock market liquidity.

5.2. Costs of equity capital

To test the effect of analyst effort allocation on firms' costs of capital, we use the residual income valuation model developed in the 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. Our main dependent variables are *%High* and *%Low*. The control variables are based on the model in Gebhardt, Lee, and Swaminathan (2001). Our regression is specified as follows:

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

<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. The economic magnitudes are significant as well. For example, a 10% increase in the number of analysts who rank the firm high decreases the ICOC by 3.84% according to column (1). The coefficients on other control variables are largely consistent with those in the literature. For example, ICOC is lower in firms with greater analyst coverage, and higher in firms with more dispersion in analyst forecasts and stock volatility.

Overall, in this section we find that firms which are relatively more important in analysts' portfolios 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.

6. Strategic effort allocation and analyst career outcomes

The evidence presented so far in the paper suggests that analyst 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 positive career outcomes. We test this conjecture by examining the probability of an analyst being voted an "All Star". We capture the extent of an analyst's strategic effort allocation by the difference in forecast frequency and accuracy between the *high* and *low* group 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 frequency and accuracy of forecasts issued by the same analyst to firms in her portfolio. The 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 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 as follows.

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

<Insert Table 9 Here >

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 while the high-low group difference in relative forecast errors has a significant and negative coefficient. These 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.

7. Some robustness checks

In the firm information environment and costs of capital analyses, we control for % high and % low. We have confirmed that our other results (Table 2, Table 3, and Table 4) are robust to the inclusion of % high and % low. We also recognize that the % high and %low are highly persistent variables (e.g., the autocorrelation of % high and % low are about 0.81 and 0.69, respectively.)

Our results are also robust to the inclusion of investment bank relationships. We define affiliated analysts are those analysts employed by the lead underwriters or co-managers of an equity offering (IPO or SEO). We assume that the relationship lasts for two years after the equity offering. About 6.5% of the observations are followed by affiliated analysts.

Our results in Table 5 are robust to the inclusion of forecast frequency and investment bank relation, as well as the exclusion of observations if they coincide with earnings announcement dates.

8. Conclusion

We provide evidence that financial analysts treat firms in their portfolios differently and tend to 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' strategic 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.

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. 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
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*.
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*.
FREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*.
DFREQ	The number of earnings forecast revisions issued by analyst *i* for firm *j* in year *t*, minus the average number of earnings forecast revisions issued by all analysts for firm *j* in year *t*.
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.
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.
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*.
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*.
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.
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.
Size	The natural log of market capitalization of the covered firm (in $millions) by the end of the month prior to the earnings forecast.
BM	Book value of equity in the fiscal year prior to the earnings forecast divided by the current market value of equity.
Past Ret	CRSP VW-index adjusted buy-and hold abnormal returns over six months prior to the announcement date of the earnings forecast.
No. of analysts	The number of unique analysts issuing earnings forecasts for firm *j* at time *t*.
Trading volume	The annual trading volume for a firm *j* in a given year *t*
Institutional holding	The percentage of institutional holding for a firm *j* in a given year *t*
All-star	Indicator variable is one if the analyst is named to Institutional Investor's all-star team in current year, and zero otherwise.
Brokerage size	The total number of analysts working at a given analyst *i*'s brokerage house.
Bold forecasts	Indicator variable that is equal to one if an earnings forecast revision is either above or below both the consensus forecast and the previous earnings forecast issued by the same analyst on the same firm, and zero otherwise.
Herding forecasts	Indicator variable is one if earnings forecast revision is between the consensus and the previous earnings forecast issued by the same analyst on the same firm.
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%.

CAR	CRSP value-weighted market-adjusted cumulative abnormal return.
Leverage	Long term debt plus debt in current liabilities divided total assets
ROA	Return on assets, calculated as net income before extraordinary items and discontinued operations divided by total assets
Volatility	Daily stock return volatility for a firm *j* in year *t*
Bid-ask spread	Computed as 100 * (ask–bid) / [(ask+bid) / 2] using daily closing bid and ask data from CRSP
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 DFREQ	The average DFREQ 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*.

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 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.

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

Table 1, Panel C

Summary statistics by High and Low Importance

High and low importance are defined using three criteria: market capitalization, trading volume, and institutional holding. The panel presents the means of several key variables for each subsample, as well as the significance of the test for differences between the means.

	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	***
Institutinal holding	0.634	0.502	***	0.632	0.503	***	0.664	0.445	***

Table 2 – Earnings Forecast Update Frequency

This table presents OLS regression results for analyst earnings forecast update frequency for the full sample. The dependent variable is the De-meaned analyst forecast update frequency (*DFREQ*). 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. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Panel B presents analyst fixed effect regression results, and Panel C presents analyst-firm pair fixed effect regression results.

Panel A: OLS regression results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	0.055***	0.034***	0.043***
	(5.12)	(3.42)	(4.17)
Low	-0.080***	-0.049***	-0.072***
	(7.66)	(5.24)	(6.53)
DGExp	-0.011***	-0.012***	-0.011***
	(4.03)	(4.10)	(4.03)
DFExp	0.126***	0.127***	0.127***
	(28.07)	(28.13)	(28.05)
DAge	-0.011***	-0.011***	-0.011***
	(97.76)	(97.74)	(97.75)
DPortsize	0.006***	0.006***	0.006***
	(4.22)	(4.15)	(4.19)
DSIC2	-0.043***	-0.043***	-0.043***
	(9.22)	(9.13)	(9.16)
DTop10	0.162***	0.159***	0.161***
	(8.10)	(7.96)	(8.08)
All-star	0.228***	0.222***	0.227***
	(8.07)	(7.90)	(8.04)
Size	-0.015**	-0.014**	-0.015**
	(2.23)	(2.14)	(2.19)
Log(trading volume)	0.001	-0.005	0.002
	(0.19)	(0.91)	(0.50)
Institutional holding	-0.008	0.002	-0.039**
	(0.44)	(0.11)	(2.07)
BM	0.001	-0.009	-0.002
	(0.09)	(0.68)	(0.16)
Past Ret	0.006	0.007	0.006
	(0.70)	(0.71)	(0.68)
# of Analysts	0.001	0.001	0.001
	(0.80)	(0.71)	(0.61)
# of observations	529,896	529,896	529,896
R-squared	0.237	0.237	0.237

Panel B: Analyst fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	0.038***	0.031***	0.033***
	(4.73)	(3.64)	(4.23)
Low	-0.064***	-0.051***	-0.063***
	(8.61)	(6.07)	(8.11)
Controls (from Table 2)	Yes	Yes	Yes
# of observations	529,896	529,896	529,896
R-squared	0.372	0.371	0.372

Panel C: Firm fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	0.050***	0.035***	0.052***
	(4.62)	(3.29)	(4.67)
Low	-0.087***	-0.058***	-0.081***
	(8.82)	(6.31)	(8.92)
Control	Y	Y	Y
Firm dummy	Y	Y	Y
# of observations	529,896	529,896	529,896
R square	0.239	0.238	0.239

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel D: Analyst-firm (pair) fixed effect results

Variables	(1) Market cap	(2) Trading volume	(3) Holding
High	0.029**	0.025*	0.026**
	(2.01)	(1.82)	(1.98)
Low	-0.047***	-0.035***	-0.044***
	(3.84)	(2.90)	(3.59)
Controls (from Table 2)	Yes	Yes	Yes
# of observations	529,896	529,896	529,896
R-squared	0.605	0.605	0.605

Table 3 – 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*). 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. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: OLS regression results

Variables	(1) Market cap	(2) Trading volume	(3) 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)
# of Analysts	-0.075***	-0.071***	-0.071***
	(3.02)	(2.85)	(2.86)
# of observations	529,427	529,427	529,427
R-squared	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 3)	Yes	Yes	Yes
# of observations	529,427	529,427	529,427
R-squared	0.234	0.234	0.234

Panel C – Firm fixed effects

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)
Control	Y	Y	Y
Firm dummy	Y	Y	Y
# of observations	529,427	529,427	529,427
R square	0.189	0.189	0.189

Panel D – Analyst-firm pair fixed effects

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 3)	Yes	Yes	Yes
# of observations	529,427	529,427	529,427
R-squared	0.550	0.550	0.550

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. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

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 3)	Yes	Yes	Yes
# 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 3)	Yes	Yes	Yes
# 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 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. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Variables	Market cap	Trading volume	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 3	Y	Y	Y
Firm dummy	Y	Y	Y
Year dummy	Y	Y	Y
R-squared	0.150	0.150	0.150
Number 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 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 upgrade and Panel B reports analysis for recommendation downgrade. Year fixed effects are included. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: upgrade

	(1)	(2)	(3)
Variables	Market cap	Trading volume	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)
# of Analysts	-0.014***	-0.015***	-0.015***
	(2.98)	(3.01)	(2.96)
Year dummy	Yes	Yes	Yes
R-squared	0.0546	0.0546	0.0546
Number of observations	63,874	63,874	63,874

Panel B: downgrade

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)
# of Analysts	0.020***	0.020***	0.020***
	(3.15)	(3.23)	(3.20)
Year dummy	Yes	Yes	Yes
R-squared	0.0889	0.0885	0.0891
Number of observations	75,552	75,552	75,552

Table 7 – Bid-ask spread and stock illiquidity

This table reports the analysis of the impact of analysts' strategic 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 industry fixed effects are included. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Bid-ask spread

	(1)	(2)	(3)
Variables	Market cap	Trading volume	Holding
Number of Analysts	-0.005***	-0.005***	-0.005***
	(3.17)	(3.28)	(3.19)
% high	-0.052*	-0.062**	-0.049*
	(1.80)	(2.15)	(1.77)
% low	0.048**	0.062***	0.057***
	(2.48)	(3.12)	(3.02)
Size	-2.256***	-2.295***	-2.242***
	(24.96)	(26.50)	(25.20)
$Size^2$	0.075***	0.075***	0.074***
	(22.88)	(24.14)	(22.95)
log(Trading volume)	1.124***	1.208***	1.122***
	(20.63)	(21.66)	(20.65)
$\log(\text{Trading volume})^2$	-0.040***	-0.041***	-0.040***
	(17.50)	(17.99)	(17.50)
Institutional holding	-0.259***	-0.260***	-0.225***
	(6.23)	(6.28)	(5.25)
BM	0.054	0.053	0.056
	(1.32)	(1.31)	(1.37)
Leverage	-0.070	-0.063	-0.069
	(1.30)	(1.17)	(1.28)
Ret	-0.189***	-0.189***	-0.189***
	(16.31)	(16.32)	(16.29)
ROA	-1.518***	-1.509***	-1.518***
	(22.31)	(22.18)	(22.29)
Volatility	14.703***	14.667***	14.701***
	(89.97)	(89.92)	(89.98)
Observations	75,292	75,292	75,292
R-squared	0.871	0.871	0.871

Panel B: Amihud illiquidity

Variables	(1) Market cap	(2) Trading volume	(3) Holding
Number of Analysts	-0.0014***	-0.0015***	-0.0015***
	(6.09)	(6.10)	(6.07)
% high	-0.0072**	-0.0102***	-0.0087***
	(2.30)	(3.38)	(2.74)
% low	0.0038	0.0072*	0.0081*
	(1.03)	(1.84)	(1.91)
Controls (Table 7, Panel A)	Y	Y	Y
Observations	64,011	64,011	64,011
R-squared	0.722	0.721	0.722

Table 8 – Implied cost of capital

This table reports the analysis of the impact of analysts' strategic effort allocation on a firm's implied cost of capital. The dependent variable is the implied cost of capital 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 industry fixed effects are included. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 8, continued

Variables	(1) Market cap	(2) Trading volume	(3) Holding
Number of Analysts	-0.015***	-0.013**	-0.015**
	(2.59)	(2.20)	(2.57)
% high	-0.384***	-0.313**	-0.370***
	(3.20)	(2.29)	(3.17)
% low	0.169*	0.164*	0.135
	(1.89)	(1.82)	(1.48)
Size	-0.166	-0.024	-0.269
	(0.62)	(0.09)	(1.02)
$Size^2$	0.001	-0.006	0.004
	(0.11)	(0.70)	(0.43)
log(Trading volume)	0.254	0.122	0.256
	(1.35)	(0.61)	(1.36)
$\log(\text{Trading volume})^2$	-0.006	-0.005	-0.006
	(0.74)	(0.59)	(0.75)
Institutional holding	-0.208	-0.168	-0.066
	(1.47)	(1.19)	(0.44)
MAE of forecasts	0.013	0.008	0.013
	(0.19)	(0.11)	(0.19)
Earnings variability	-0.030	-0.027	-0.030
	(1.05)	(0.97)	(1.05)
Dispersion of analyst forecasts	0.811***	0.829***	0.813***
	(7.82)	(7.97)	(7.83)
BM	2.391***	2.441***	2.398***
	(14.38)	(14.68)	(14.42)
Leverage	3.655***	3.651***	3.655***
	(12.59)	(12.57)	(12.59)
Ret	0.104***	0.108***	0.106***
	(2.58)	(2.69)	(2.62)
Long-term growth	0.005	0.004	0.005
	(1.35)	(0.94)	(1.32)
Beta	-0.325***	-0.304***	-0.324***
	(7.26)	(6.78)	(7.24)
Volatility	10.796***	10.842***	10.753***
	(3.72)	(3.74)	(3.71)
Constant	8.210***	8.904***	8.972***
	(4.53)	(5.16)	(5.13)
Observations	32,470	32,470	32,470
R-squared	0.434	0.434	0.434

Table 9: Strategic effort allocation and all-star analyst status

This table presents logistic regression results for the effect of strategic effort allocation on all-star status at the analyst-year level. The dependent variable in each model is a dummy variable which is equal to 1 if the analyst is an all-star analyst in the current 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. t-statistics are in parentheses with heteroskedastic-consistent standard errors clustered at the firm and analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High and Low defined using:	Mkt Cap	Volume	Holding	Mkt Cap	Volume	Holding	Mkt Cap	Volume	Holding
Diff(High-low) in DFREQ	0.079***	0.078***	0.086***				0.072***	0.069***	0.077***
	(3.91)	(3.61)	(4.30)				(3.50)	(3.18)	(3.76)
Diff(High-low) in PMAFE				-0.107**	-0.117***	-0.136***	-0.081*	-0.093**	-0.108**
				(2.42)	(2.64)	(3.05)	(1.83)	(2.08)	(2.40)
GExp	0.009	0.009	0.010	0.008	0.008	0.009	0.009	0.008	0.010
	(1.14)	(1.07)	(1.27)	(1.04)	(1.01)	(1.14)	(1.12)	(1.03)	(1.24)
Portsize	0.017***	0.017***	0.016***	0.017***	0.017***	0.016***	0.017***	0.017***	0.016***
	(4.95)	(4.93)	(4.61)	(4.86)	(4.89)	(4.53)	(4.89)	(4.89)	(4.53)
SIC2	-0.023*	-0.023	-0.025*	-0.023	-0.023	-0.025*	-0.023	-0.023	-0.025*
	(1.65)	(1.62)	(1.78)	(1.62)	(1.64)	(1.79)	(1.64)	(1.62)	(1.79)
Brokerage size	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
	(23.44)	(23.42)	(23.50)	(23.50)	(23.52)	(23.56)	(23.40)	(23.40)	(23.48)
Average PMAFE	-0.744***	-0.739***	-0.743***	-0.714***	-0.722***	-0.705***	-0.728***	-0.730***	-0.721***
	(8.63)	(8.58)	(8.57)	(8.14)	(8.28)	(7.94)	(8.31)	(8.37)	(8.12)
Average DFREQ	0.352***	0.352***	0.349***	0.376***	0.375***	0.375***	0.353***	0.353***	0.350***
	(13.10)	(13.06)	(12.70)	(14.27)	(14.27)	(13.96)	(13.09)	(13.07)	(12.69)
Average size	0.297***	0.299***	0.290***	0.299***	0.297***	0.290***	0.295***	0.296***	0.286***
	(11.12)	(11.21)	(10.79)	(11.18)	(11.15)	(10.82)	(11.02)	(11.09)	(10.68)
Lag (All-star)	5.509***	5.511***	5.491***	5.520***	5.521***	5.506***	5.512***	5.516***	5.497***
	(70.86)	(70.89)	(70.79)	(71.06)	(71.09)	(70.95)	(70.85)	(70.89)	(70.80)
Year fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pseudo R^2	0.678	0.678	0.677	0.678	0.678	0.677	0.678	0.678	0.677
Observations	46,494	46,494	45,558	46,464	46,460	45,525	46,458	46,454	45,518