**Speed and Expertise in Stock Picking: Older, Slower, and Wiser?**

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**Abstract**

There are significant differences among sell-side analysts in how frequently they revise recommendations. We show that much of this variation is an analyst-individual trait. Analysts who change their recommendations more slowly make recommendations that are more influential and generate better portfolio returns. Examining the sources of differing investment value, we find that recommendations of slower-revising analysts are more likely to “lead the pack,” and revised following corporate disclosures that are harder to assess by non-stock experts. Analysts tend to change recommendations less frequently as their career progresses; however, recommendation speed-style is the only robust predictor of their recommendation value.

1. **Introduction**

“All of us would be better investors if we just made fewer decisions.”

–— Daniel Kahneman[[1]](#footnote-1)

Two decades of academic research support the view that sell-side analysts play an important role in collecting, digesting, and disseminating value-relevant market knowledge to investors.[[2]](#footnote-2) As information processing agents who are surely monitored by their own firms and their clients, these analysts have incentives to be accurate and to predict the future corporate activities and stock prices of their target firms. And, as documented in an important stream of the literature, analysts’ attention to their own reputations and career concerns affect their decisions (Hong and Kubik, 2003; Clement and Tse, 2005; Hilary and Hsu, 2013).

This study examines speed as an important decision-making-process choice of individual analysts. All else equal, one might hypothesize that reputation would be enhanced by “getting there first,” i.e. beating industry competitors by reacting quicker to new information. Even in more traditional information-based investing, virtually all event-based trading rules are less profitable if the decision maker’s reaction to the event is delayed. But there is another side to the speed story. Warren Buffet’s famous line, “Wait for the fat pitch,” is a decision maxim urging investors *not* to be in a hurry because there are many investment opportunities, but not many good ones. There may also be other cogent reasons for slower decision-making. If an analyst is really talented, his previous recommendations will remain accurate longer. Thus, a truly talented analyst should have less need to change them frequently.

Several factors could affect when analysts revise their recommendations. Intuitively, an analyst would change a stock recommendation when his assessment of the stock value (*V*) sufficiently deviates from the current share price (*P*). If the ratio of an analyst’s stock valuation to price (*V/P*) exceeds or falls below a certain threshold, then a recommendation is triggered. Under this framework, variations in the timing of recommendation changes can come through four channels. The first is the arrival of new information that alters an analyst’s assessment of the stock value *(V).* This new information could be in the form of public news about the company (e.g., earnings announcements) or news about the industry. Also, the information that analysts acquire need not be publicly observable but arrive through private channels such as their interaction with firm managers. The second channel for which variations in the recommendation speed can arise is through the publicly traded share price (*P*). For instance, a sudden stock price jump can trigger a recommendation change which can occur with news arrival, as well as in its absence. The third channel that can explain variations in recommendation-change speed relates to the nature of a new recommendation that the analyst is evaluating. This includes the magnitude of recommendation changes that the analyst is contemplating, as well as the current recommendation level.

Finally, the fourth channel that can explain variations in the recommendation-speed is the analyst-person characteristic. This may be due to the speed at which some analysts collect and absorb information, as well as the difference in their valuation approaches (Kahneman, 2011). The speed at which analysts revise their recommendations may also be a strategic choice. As shown in Bernhardt, Wan and Xiao (2016), frictions in recommendation revisions can arise through the threshold in the valuation-to-price ratio (*V/P)* that an analyst requires to exceed or fall below before a new recommendation is warranted. This “revision threshold” is likely to differ across analysts.

In this paper, we show that variations in the speed at which analysts revise their recommendations is substantially explained by the “speed-style” of individual analysts. After, we analyze the investment value of the differing, inherent, decision-speed styles employed by stock experts.

We introduce a methodology to identify an analyst’s propensity to update his recommendations on the spectrum of fast to slow, relative to his competitors covering a similar portfolio of firms. We denote this speed-style as the “recommendation turnover,” representing how often the analyst *overturns* his recommendation opinions. The method builds on a simple Binomial test and accounts for firm characteristics that may influence the revision frequency, and the number of stocks that the analyst covers. At the beginning of each calendar year, we use detailed recommendation history up until the end of the previous year to classify analysts into three recommendation turnover groups: (1) Slow, (2) Average, (3) Fast. We repeat this process yearly from 1996 to 2013. As a result, our method provides an *out-of-sample* estimate of analysts’ recommendation decision-speed types from 1996 to 2013. On average, we find that *fast-turnover* analysts change their recommendations every 6 months, while *slow-turnover* analysts typically change their recommendations every 20 months.

We provide strong evidence that much of the variation in the speed at which analysts revise their recommendations is an inherent-individual trait. We illustrate this by estimating a hazard rate model for the probability that each recommendation will be revised in relation to analysts’ recommendation speed-styles identified from the previous year. We control for a host of observable signals that may trigger or delay recommendation revisions and our modeling approach allows for unobserved heterogeneity across analysts (i.e., private information) that may affect their revision speed. Estimation results indicate that analysts’ past recommendation speed-style strongly predicts the speed at which they will revise their next recommendations. The economic magnitude is large. The model estimates imply that on any given week, fast-turnover analysts are about 2 times more likely to revise their recommendations relative to slow-turnover analysts.

We next examine the *value* of recommendations made by analysts with different decision-speed styles. We find that recommendation changes made by slow-turnover analysts significantly outperform recommendation changes by fast-turnover analysts. The immediate stock market reaction to recommendation changes of slow-turnover analysts is 46–76 basis points greater in magnitude relative to those of fast-turnover analysts. This magnitude difference is after controlling for various analyst and firm characteristics that have been shown to affect the stock price reaction to recommendation revisions.

We further confirm the differing investment values between fast- and slow-turnover analysts by forming investable real-calendar-time portfolios in the style of Barber et al. (2001). We form a portfolio that invests (and sells) one dollar on the upgraded (downgraded) stock at the closing-day price after the recommendation change. This method makes the strategy implementable for ordinary investors. Overall, we find 5–10% differences in annualized portfolio alphas from investing following slow- versus fast-turnover analysts’ recommendation changes.

We examine analyst characteristics that are associated with different recommendation speed-styles. An important aspect we observe is that during the course of a career, there is a strong tendency for all surviving analysts to change their recommendations less frequently. In fact, results from the logit model show that analysts’ career tenure, i.e., experience, is the most significant determinant of their decision-speed style. Other aspects that are highly associated with slower-revising analysts include their likelihood of being awarded the All-star status by the *Institutional Investor* magazine and the size of their brokerage house. These aforementioned characteristics, however, do not explain the investment value of slower decision-speed style. At this point, we reemphasize that our method of identifying analysts’ recommendation speed-style is an *out-of-sample* approach, and importantly, the investment value identified through the speed-style classification dominates those identified through other analysts’ ex-ante characteristics such as their career tenure, All-star status, prior earnings forecasts precision, and brokerage house size.

The above results beg the following important questions: Why are analysts who make less-frequent recommendations better stock pickers? What do cues they use? Obviously, it is difficult, if not impossible, to see into the mind of these decision makers, but we do observe valuable clues. First, we find that slower (faster) recommendation-revising analysts are more likely to lead (follow) others in recommendation changes as measured by the leader-follower ratio of Cooper, Day and Lewis (2001). In other words, slow-turnover analysts tend to issue recommendations that “lead the pack” even though they revise them less frequently. Second, we find that analysts with different decision-speed styles take cues from different news types when updating their recommendations. Recent studies find that analysts’ recommendations are valuable because they help investors interpret the contents of corporate disclosures.[[3]](#footnote-3) Motivated by these studies, we examine the value of fast- versus slow-turnover analysts in facilitating the price discovery of corporate disclosures.

We obtain a comprehensive news database from Capital IQ that provides a very fine classification of news categories and uncover distinct patterns in the type of news that fast- vs. slow-turnover analysts tend to follow. We find that fast-revising analysts are likely to update their recommendations following verifiable and less ambiguous corporate disclosures such as scheduled earnings announcements, or security issuances (e.g., debt issuance). On the other hand, analysts who revise their recommendations more slowly tend to do so following corporate news with potentially ambiguous price impact such as news about the product market competition, operation strategy, management forecasts, and legal issues. These news announcements are mostly unscheduled and tend to carry forward-looking information about their underlying firm value, which we believe are harder to intepret by non-stock experts. We further corroborate this finding by manually reading 2,052 recommendation reports downloaded from Investext and reach a similar conclusion.

This paper contributes to the sell-side analyst literature by identifying the decision speed-style of stock experts based on the recommendations they change, and by considering the differing investment value implications thereof. Our work relates to studies that estimate models for how analysts make recommendation changes. For instance, Conrad et al. (2006) models how analysts change recommendations after large stock movements and find that they are “sticky” in one direction, with analysts more reluctant to downgrade.

A recent study by Bernhardt, Wan and Xiao (2016), which estimates the model for how an analyst revises recommendations is perhaps the closest to ours. Their study finds that analysts strategically introduce frictions when updating their recommendations to avoid frequent revisions, and as argued by the authors, this is because customers would question the ability of an analyst who repeatedly revises recommendations. Our study differs from Bernhardt, Wan and Xiao (2016) on several aspects. Their study documents frictions in the recommendation decision of a *representative* analyst in the sell-side industry. We show that there are significant differences among analysts in the degree of frictions they apply to their recommendations and that this variation is an analyst characteristic. Importantly, our method is designed to identify analysts who are predictably quicker (or slower) to revise their recommendations in an out-of-sample fashion. This enables us to study their differing investment-value implications and implement them in practice. We also provide evidence that reputation concern influences analysts to make less frequent recommendation changes. Specifically, we show characteristics that are associated with the slower speed-style are those that reflect positively on analysts’ reputation such as All-star status, employment at a top brokerage (Hong and Kubik, 2003), and career longevity (Prendergast and Stole, 1996).

Hobbs, Kovacs and Sharma (2012) find superior portfolio performance formed following recommendations of faster-revising analysts, suggesting that quantity trumps quality; a conclusion that differs from ours. However, their study measures analysts’ recommendation frequency using only recommendations that are revised within 12 months. This approach would eliminate about half of recommendation changes from the sample because the median time between revisions is 11.2 months. This implies that their study focuses on analysts who are already in the faster-extreme of recommendation speed-style, or on a subset of stocks that require frequent recommendation changes.[[4]](#footnote-4)

This paper is organized as follows. Section 2 describes the data and the methodology we use to identify analysts’ decision*-*speed style. Section 3 provides evidence that the decision-speed style is an analyst individual trait. Section 4 discusses the investment value of differing decision*-*speed styles. Section 5 examines the sources behind superior value of slower recommendation-speed style. Finally, Section 6 concludes.

1. **Data and methodology**
   1. ***Data and filters***

We obtain analyst recommendations and earnings forecasts data from I/B/E/S. We restrict our attention to equity analysts that appear in both the detailed recommendation and forecast I/B/E/S files from 1993 to 2013.[[5]](#footnote-5) This initial sample contains 629,400 recommendations made by 14,242 unique analysts. Security returns data and firm-level information are obtained from CRSP and COMPUSTAT, respectively. We identify “star analysts” based on *Institutional Investor*’s annual ranking of All-American team (see Fang and Yasuda, 2009, 2013).[[6]](#footnote-6) The gender of analysts is identified using their full names collected from the *Institutional Investor* magazine and verified against multiple sources (see Kumar, 2010; and Law, 2013).[[7]](#footnote-7)

We apply various filters to the I/B/E/S recommendation data file. We require that firms in our sample have records on the CRSP daily database and have CRSP share code of 10 or 11. We remove 19,809 anonymous recommendations in I/B/E/S since it is not possible to track which analysts issue these recommendations. We require that an analyst issues at least one forecast and one recommendation change on a given stock for the analyst-stock pair to be in our sample. Each recommendation in the I/B/E/S database is coded with the rating scale between 1 and 5, ranging from “strong buy” to “strong sell”, respectively.[[8]](#footnote-8) We characterize each revision as an upgrade or downgrade. We do not consider initiations and reiterations in our empirical analysis.

Kadan et al. (2009) document a significant number of mechanical recommendation changes due to the migration of a five-tier rating system to a three-tier rating system in 2002 following the National Association of Securities Dealers (NASD) Rule 2711. We follow the method described in Loh and Stulz (2011) for identifying these mechanical recommendation changes and remove them from the sample. Up to this point, our recommendation change sample contains 204,874 observations over 20 years, where 92,341 are upgrades.

We define a recommendation as outstanding according to Ljungqvist, Malloy, and Marston (2009). We remove recommendations that have been dropped by each broker using I/B/E/S Stopped File. We further remove stale recommendations that have been neglected by analysts without being officially dropped by their broker. If an analyst’s recommendation has been outstanding for more than one year without a reiteration and if this analyst also makes less than one earnings forecast per year on the stock, we consider his outstanding recommendation to be stale. We find 54,226 recommendations to have been outstanding for more than one year, and we classify 3,533 of them as stale.

For each recommendation revision, we calculate the *time a recommendation is in place* defined as the number of days between the current and prior recommendation revision. Our final sample contains 196,074 recommendation changes made by 8,185 distinct analysts, where 88,248 are upgrades.

* 1. ***Sample descriptive***

We focus on analysts who actively issue recommendations during the period 1996–2013. Although I/B/E/S recommendation file begins in 1993, we start our analysis in 1996 in order to allow analysts’ recommendation history file to sufficiently develop.

In each year from 1996 to 2013, we calculate various characteristics for each analyst. The number of analysts in our sample is updated yearly. We require that an analyst provides active recommendation coverage on at least three stocks. We consider that an analyst has initiated an active coverage of a stock if he has issued at least two recommendation changes on the firm. The final sample consists of 4,563 unique analysts who provide active recommendation coverage during 1996–2013, resulting in 25,678 analyst-year observations.

Table 1 summarizes characteristics of analysts that are in the final sample. All variables are defined in Appendix A. We provide explanation for the construction of selected variables in the Online Appendix, Section A. The mean general experience for analysts in our sample is 6.78 years, while the median is 6 years. The variable *Breadth* measures the number of stocks that an analyst actively provides recommendations. On average, the number of stocks in an analyst recommendation portfolio is 6.93. The descriptive statistics of analyst characteristics reported in Table 1 are in line with the literature.

The average *Months recommendation is in place* is 11.92 months, with a median of 11.19 months. This key variable reflects the time that a recommendation by an analyst remains outstanding in monthly units. Importantly, we find the standard deviation and the percentile distribution of this key variable shows a significant variation.

* 1. ***Methodology for identifying analysts’ recommendation speed-style***

We classify analysts into different recommendation speed-style groups on a yearly basis from 1996 to 2013. The method is an *out-of-sample* classification. For instance, when classifying the speed of analysts in the year 2000, we use I/B/E/S recommendations history only up until December 1999. As for the year 2001, we extend the history file to include an additional year of recommendation-change records.[[9]](#footnote-9) The methodology for classifying analysts into different speed-style groups consists of the following three steps, which we discuss next.

***Step 1: Estimating the time between revisions for each analyst-stock pair***

At the end of each calendar year starting in 1995, we calculate the average number of days between recommendation revisions for each *analyst-stock* pair. One concern associated with the annual updating is the right-truncation bias, which we illustrate in Figure 1. In this example, we want to calculate the average time between recommendation revisions for an analyst-stock pair at the end of 1999. This particular analyst initiates the coverage in 1996. Based on December 31st 1999, this analyst has revised his recommendation three times with the last revision in 1998, which is 790 days after his coverage initiation. A naïve calculation would suggest that this analyst revises his recommendation on this stock approximately every 263 (~790/3) days. However, there is a 380-day gap between his 1998 revision and when we truncate the sample on Dec 31st 1999. Therefore, an exclusion of this 380-day truncation gap will result in an underestimation of the time between recommendation revisions. We adjust for this right-truncation bias when we calculate the average number of days between recommendation revisions for each analyst-stock pair. We discuss the procedure in Section B of the Online Appendix.

***Step 2: Ranking analysts’ revision times stock by stock***

We control for firm characteristics that may influence analysts to revise recommendations on the same stock more (or less) frequently over a similar period. To do so, we sort all analysts covering the *same stock* into quartiles based on their average revisions time, i.e. from fastest (top 25th percentile) to slowest (bottom 25th percentile). The sorting is done annually using the biased-adjusted time between revisions that we calculated in Step 1.

More formally, consider the ranking of analysts’ revision speed on stock *j* in year 2000. Here, we use analysts’ biased-adjusted time between recommendation revisions that were calculated in December 1999. Let denote the bias-corrected average revision time of analyst *a* on stock *j*, and assuming that there are *Aj* analysts covering this stock *j*. We sort across *Aj* analysts into four equal groups from smallest (fastest) to largest (slowest). We repeat this procedure for all the stocks *j* annually from 1996 to 2013. As we move forward each year, an additional year of recommendation-change records is added to the ranking method. As a result, we have out-of-sample revision-speed rankings (from fastest to slowest quartiles) of all analyst-stock pairs in the sample.

***Step 3: Identifying the speed-style of each analyst***

Using the revision-speed ranking results from Step 2, we statistically test, for each analyst, whether he exhibits a distinct recommendation-speed pattern (i.e., fast or slow) *across* all the stocks that he covers. The logic of our test is as follows: If an analyst does not exhibit a distinct recommendation-revision speed, he should be equally represented in all four speed quartiles. In other words, the likelihood that his revision speed on any particular stock falls in the first (or the fourth) speed quartile should be one-fourth. This is the null hypothesis that we test.

For instance, consider an analyst covers 8 stocks and does not have an extreme speed-style preference, we expect probabilistically that 1/4×8 = 2 of his stock-revision speeds are equally observed in one of the four quartiles from the first (fastest) to the fourth (slowest). However, if we find 7 out of 8 stocks in his portfolio are ranked in the fastest revisions quartile, it is likely that this analyst has a revision speed-style that is faster than the average analyst. But according to this example, is 7 out of 8 a sufficient cut-off to confidently classify that this analyst is “fast”? Importantly, analysts do not usually cover the same number of stocks. What if this analyst covers 12 stocks instead of 8? What should the cut-off for the minimum number of stocks that are in the fastest quartile be before we can decidedly classify him as a “fast” analyst? We address this issue by applying the standard Binomial test. This method helps us define the cut-offs that we can use to conclusively classify an analyst as being distinctly “fast” or “slow” using the same statistical criteria (0.05 p-value) regardless of the number of stocks that he covers. Specifically, we test each of the following null hypotheses:

***H0 (fast):*** The probability that stocks in an analyst’s portfolio are ranked in the fastest revisions quartile is not greater than 25%.

***H0 (slow):*** The probability that stocks in an analyst’s portfolio are ranked in the slowest revisions quartile is not greater than 25%.

A rejection of the above hypothesis *H0 (fast)* at the 5 percent significant level allows us to confidently classify an analyst as faster at revising recommendations relative to peers.[[10]](#footnote-10) Similarly, a rejection of *H0 (slow)* at the 5 percent significant level would lead us to conclude that the analyst is slower at revising recommendations relative to peers. Finally, we assign analysts into three groups: (1) *Slow-turnover analyst*, (2) *Average-turnover analyst,* and (3) *Fast-turnover analyst*. Analysts for whom we can reject neither of the two null hypotheses are classified as average-turnover analysts. Figure 2 illustrates examples of slow- versus fast-turnover analysts’ recommendation patterns on Bank of New York Mellon Corporation (top panel), and Sunoco (bottom panel). Here, we pick two analysts with different recommendation turnover groups who revise their recommendations on the same stock over a similar period.

Panel A of Table 2 reports the number of analysts in each recommendation turnover group from 1996 through 2013. There are 521 distinct analysts in the sample in 1996, which is due to the relatively short recommendation history available in I/B/E/S for identifying eligible analysts.However, the number of analysts that enter the sample increases steadily each year to 1,714 in the year 2004. Panel B reports summary statistics for the bias-adjusted time between recommendations. There is a clear difference in the time between recommendation revisions between the slow-turnover group (median of 19.4 months) and the fast-turnover group (median of 6.0 months). About 68% of analysts in the sample are classified in the average-turnover group.

1. **Is recommendation speed-style an analyst’s individual trait?**

In this section, we provide evidence that recommendation speed-style is an analyst characteristic. We start by discussing factors that could trigger analysts to revise their recommendations. Then, we show that after controlling for various recommendation triggers, much of the variation in the speed at which analysts revise their recommendations is an analyst-individual trait. Finally, we end this section by examining analyst characteristics that are associated with slower and faster recommendation-speed styles.

* 1. ***Triggers of recommendation revisions***

Intuitively, we expect an analyst to upgrade (or downgrade) a stock when the ratio of his own stock valuation to its current price (*V/P*) exceeds (or falls below) a certain threshold. In this framework, several factors can speed up or delay analysts from issuing a new recommendation. We group them into the following four channels. These channels need not be mutually exclusive.

The first channel is the arrival of new information, which affects analysts’ assessment of the *stock value* (*V),* and thereby, can trigger recommendation revisions.The information that analysts uncover may be public, such as corporate disclosures. Analysts may also acquire information privately through their interactions with firm managers or from their own research. In the latter case, the new information that analysts uncover is not publicly observable and hence is unknown to econometricians. We expect that the speed at which analysts revise their recommendations is increasing with the intensity of information arrival.

The second channel that affects the ratio of an analyst’s valuation-to-price ratio is through the publicly traded *share price* (*P*). An increase (or fall) in the share price lowers (raises) analysts’ own valuation-to-price ratio (*V/P*), which may trigger an upgrade (or a downgrade) stock recommendation. Changes in stock price can occur gradually or suddenly (i.e., price jumps). Such price changes may be due to the arrival of news, and thus in this case, the price channel is not mutually exclusive from the arrival of new information (Conrad et al. 2006). However, sudden price changes can occur without the arrival of news. This out-of-the-blue price adjustment can be transitory, e.g., a short-term liquidity-related shock, or permanent, e.g., a delayed market response to an existing information. A recommendation revision also needs not depend only on the price of a security under which an analyst is evaluating. Analysts may benchmark their stock recommendations against share prices of other firms in the industry (i.e., the industry benchmark) or the aggregate stock market; see Kadan et al. (2012). Relatedly, fluctuations in the share price can affect analysts’ recommendations. When the stock price is highly volatile, analysts’ estimates of their valuation-to-price ratio (*V/P*) are less precise and could potentially delay their recommendations.

Third, the speed at which analysts revise their recommendation may depend on the *type of recommendation* that analysts are evaluating. For instance, a recommendation change by multiple notches may take longer time to execute (i.e., from “sell” to “buy”) than a one-notch upgrade (i.e., from “hold” to “buy”) because a multiple-notch change would reflect a more drastic update in the analysts’ valuation-to-price ratio. Additionally, the current recommendation level that an analyst places on the firm can affect the speed that he will revise it. An analyst may be more reluctant to put a firm on a “strong sell” for an extensive period in fear of being shunned by the firm’s management. On the other hand, an analyst may be more comfortable with leaving his stock recommendation on “hold” for an extended period until he uncovers fresh-new information to warrant a “buy” or “sell” recommendation.

Finally, the fourth channel that can explain variations in the speed of analysts’ recommendations is the analyst-person characteristic. One can expect certain analysts to make their decisions more quickly, while others are slower and more methodic in their valuation approaches; see Kahneman (2011) for a summary of literature on the speed of human decision-making. Further, variations in the speed at which analysts update their recommendations may be a strategic choice. As shown in Bernhardt, Wan and Xiao (2016), sell-side analysts strategically introduce frictions in their recommendation decisions in order to avoid frequent revisions because investors would otherwise question their ability.

* 1. ***Predicting the time to the next recommendation change***

We next provide evidence that much of the variations in the speed at which analysts revise their recommendations is an analyst-level characteristic. To demonstrate this, we show that the recommendation speed-style that we identified using analysts’ *past* recommendation patterns can predict the speed at which they will revise *future* recommendations after controlling for various recommendation triggers.

We estimate the Cox Proportional Hazard (Cox PH) model for the hazard rate at which an analyst will revise his future recommendations in any given week. The Cox PH model is commonly used in survival analysis and we prefer it over the logistic model because it can handle censored outcome variables (e.g., right-truncation bias as shown in Figure 1).

Let denote the hazard ratethat an outstanding recommendation on stock *j* by an analyst *a* will be revised in week *t*, we assume that follows a log-linear model:

(1)

We estimate the above model at the recommendation-week level, and separately for upgrades and downgrades. For each recommendation, we create a weekly panel where each observation corresponds to a distinct week *t,* starting from when this recommendation became outstanding until when it is revised. The weekly (rather than daily) frequency choice is motivated by computational practicality and because a recommendation change that occurs within one week is extremely rare, i.e., 0.06% of all revisions. There are about 8.5 million weekly panel observations created from 158,210 recommendation revisions over the 1996−2013 period, where approximately 3.5 million of them are upgrades. We estimate the model using maximum likelihood.[[11]](#footnote-11)

Our independent variables of interests are the two dummy variables *Slow* and *Fast,* indicating the recommendation speed-style of each analyst that was identified from the previous year. *Slow* (*Fast*) is equal to 1 if the analyst was classified as the slow-turnover (fast-turnover) type in the previous year, and 0 otherwise. Year-fixed effects and previous recommendation-level fixed effects are included in the model.

We include a series of firm-level, industry-level, and recommendation-level controls in the Cox PH model. They are represented by in equation (1). The baseline hazard rate function in equation (1) is assumed to be firm specific and denoted by for firm *j*. We allow for unobserved heterogeneity across analysts in the Cox PH model by including analyst-random effects. This is represented by the term in equation (1). This modeling approach is known as the frailty model, which helps control for unobserved analyst characteristics that may affect recommendation speed such as their private information about the firms that they cover.

1. ***Baseline estimation results***

Table 3 reports the results. Panels A and B report estimates for the hazard-rate model that the current recommendation will be upgraded and downgraded, respectively. A positive value on the coefficient estimate indicates that an increase in the corresponding independent variable will increase the rate at which a recommendation will be revised, while a negative coefficient estimate would indicate the otherwise.

Column (1) in Panel A and Column (4) in Panel B report the baseline model estimates for upgrades and downgrades, respectively. Here, we include an indicator variable *Concurrent with earnings*, which controls for the well-known fact that analysts often revise their recommendations around earnings announcements, and fixed effects that control for the previous recommendation level.

We find that the coefficient estimate on *Slow* is negative, while the coefficient estimate on *Fast* is positive. This finding indicates that an analyst with a history of slow (fast) recommendation-revising pattern is likely to revise his next recommendation more slowly (quickly) than an average-turnover analyst, which is the reference group. We can interpret the economic magnitude of each coefficient estimate by looking at its corresponding hazard ratio, which is the exponent of each estimate. The hazard ratios are reported under the column titled “HR” next to their estimates. Each hazard ratio represents the relative increase (or decrease) in the likelihood that a recommendation will be revised for a one-unit change in the independent variable.

Column (1) shows the hazard ratio for *Fast* is 1.35, and for *Slow* is 0.83. This implies that on any given week, a fast-turnover analyst is 1.35 times more likely to upgrade a stock, on any given week, relative to an average-turnover analyst, while for a slower-turnover analyst, the likelihood is 0.83 times lower. We can also compare the speed of recommendation changes between slow- vs. fast-turnover analysts using their hazard ratios, i.e., 1.35/0.83 ≈ 1.62. This suggests that on any given week, a fast-turnover analyst is 1.62 times more likely to upgrade his recommendation relative to that of a slow-turnover analyst. We find a similar economic magnitude for downgrades. Column (4) suggests that a fast-turnover analyst is 1.41/0.82 ≈ 1.72 times more likely than a slow-turnover analyst to downgrade a stock on any given week.

The statistical importance of including the two *Slow* and *Fast* indicator variables in the Cox PH model is large. We illustrate this by reporting the log-likelihood ratio (LLR) comparing the likelihood of the unrestricted model that includes the two speed-style indicators versus the likelihood of the null model that does not. The LLR for each model specification is reported near the bottom of Panels A and B. Columns (1) and (4) show the LLR are 688 and 916, respectively. These values are extremely large as the critical cut-off for rejecting the null model at the 0.001 p-value is 13.82.[[12]](#footnote-12)

As expected, we find the estimate on *Concurrent with earnings* to be positive and highly significant. We find that the probability that an analyst will revise a recommendation is almost four times higher when there is a concurrent earnings announcement in the same week. We include previous-recommendation fixed effects in Table 3 using indicator variables *Last recom*. The reference level for the previous-recommendation fixed effects is “hold.” Panel A shows the coefficients on *Last recom* for upgrades are mostly positive. This suggests that upgrades out of a “hold” recommendation are stickier than upgrades out of a “strong sell” or a “sell.” In Panel B, we find that downgrades out of a “strong buy” recommendation takes a longer time than downgrades out of other recommendation levels.

1. ***Speed-style under various controls for recommendation triggers***

We next show that our main regression results hold after including various sets of control variables for recommendation triggers. For brevity, we leave discussions on how coefficient estimations on these control variables are related to analysts’ recommendation speed-style in relation to the framework that we outlined in Section 3.1 to the Online Appendix.

Columns (2) and (5) of Table 3 report the estimation results with a more extensive set of control variables. Where applicable, all control variables are lagged by one week, as they are potential triggers of future recommendation revisions. We include a large set of controls for changes in the publicly traded share prices *(P).* This includes an upward or a downward stock price momentum relative to the aggregate market, i.e., *Market-adjusted stock return*, or to an industry benchmark, i.e. *Industry-adjusted stock return.* Large changes in share price can also occur abruptly, and they are often referred to as jumps. We therefore include two indicator variables *Positive stock price jump* and *Negative stock price jump*.[[13]](#footnote-13) We also include *Stock Volatility* as a control because high volatility may lower analysts’ ability to precisely estimate their stock valuation-to-price ratio (*V/P*). Finally, we include the stock price ratio relative to its 52-week high because previous research has shown that the 52-week high price serves as a reference point for the decisions of traders (e.g., George and Huang, 2004). This control is represented by *Price relative to 52-week high*.

In Columns (3) and (6) of Table 3, we introduce an additional variable *News intensity*, which is the number of firm-specific news observed in the previous week. It proxies for the arrival of new information that affects an analyst’s stock valuation (*V*). We obtain data on news releases from Capital IQ, a comprehensive database of company-specific news collected from over 20,000 public news sources. They include firm- and non-firm initiated news found in newswire services. News coverage in the Capital IQ database was relatively thin until the end of 2002. As a result, the sample that we use to estimate the Cox PH model in Columns (3) and (6) is from 2003 to 2013.[[14]](#footnote-14)

The time it takes an analyst to revise his recommendation can depend on the magnitude of the recommendation change that he is evaluating. We control for this effect in Table 3 using *# level up/down*, which is defined as the absolute value of the difference between the new and previous recommendation levels.

Overall, we find that the coefficient estimates on *Slow* and *Fast* remain strongly significant and are in the expected direction after more controls for recommendation triggers are added to the model. Importantly, these estimates are similar in magnitude relative to their baseline estimates in Columns (1) and (4). For instance, the proportion of hazard ratios for *Slow* and *Fast* in Column (6) is 1.47/0.77 ≈ 1.9. This implies that on any given week, a fast-turnover analyst is almost twice more likely to revise his recommendation relative to a slow-turnover analyst. These findings indicate that analysts’ past revision-speed patterns is a robust predictor of the rate at which they will revise future recommendation.

* 1. ***Recommendation speed-style and analyst characteristics***

We next examine which analyst characteristics are associated with different recommendation speed-styles. We estimate three logit models. In the first model, the dependent variable is an indicator function that is equal to 1 if the analyst in year *t* belongs to the *Slow-turnover* group, and 0 otherwise. Similarly, in the second and third specifications, the dependent variable is an indicator function that is equal to 1 if the analyst on year *t* belongs to the *Average-turnover* and *Fast-turnover* group, respectively, and zero otherwise.[[15]](#footnote-15)

Table 4 reports the results. All independent variables are analyst-level characteristics and are defined in Appendix A. We first examine the set of variables that are related to analysts’ career outcomes. Looking at Column (1), we find that *General Experience (*the number of years since an analyst’s first recommendation), *All-star* (a dummy equal to one if the analyst is currently elected to the *Institutional Investor’s* All-American annual ranking), and *Top Broker* (a dummy equal to if the analyst’s brokerage ranks in the top decile by size in a given year) are positively and significantly associated with the probability that an analyst is identified with the slow-turnover group. This finding indicates that slow-turnover analysts tend to have better career outcomes in the sense that they have a longer career, more likely to attain the All-star status, and work for a top brokerage firm. Among these three career-outcome variables, *General Experience* has the strongest association with slow-turnover analysts with a t-statistic of 27. Looking at the results in Columns (2) and (3) for the average- and fast-turnover group, we find the coefficients on the three variables *General Experience*, *All-star*, and *Top Broker* become negative. In particular, the magnitude of the coefficients and their statistical significance are the largest and strongest for the fast-turnover group. Put together, those results show that slower decision-speed style is associated with positive outcomes.

We next turn to the characteristics of stock recommendations that analysts with different recommendation-speed styles make. Columns (1) and (3) of Table 4 show the *Leader-follower ratio (LFR)*, which measures the average timeliness of an analyst’s recommendation change, to be positively associated with slow-turnover analysts, but negatively with fast-turnover analysts.[[16]](#footnote-16) This implies that recommendation changes of slower-revising analysts tend to “lead the pack,” in the sense that they often front-run recommendation changes of faster-revising analysts. Relatedly, we find that recommendations of fast-turnover analysts tend to be less bold, i.e., they herd more towards the consensus. This is seen in Column (3) which shows that *Recommendation boldness* is negative and significant at the 5 percent level. Overall, these findings lead to two important insights on the type of recommendations that less frequent updaters issue; they are timelier and less likely to herd.

We find the number of forecasts per quarter, *Forecast frequency*, to be negatively associated with the probability of being classified as a fast-turnover analyst. Thus, even though fast-turnover analysts make more frequent recommendation changes, they tend to revise their forecasts less frequently. This finding suggests that the decision-making of slow- and fast-turnover analysts are inherently different. An interpretation that one can make from these results is that slower-revising analysts are more reluctant to revise their recommendations despite being more active at updating their stock valuation-to-price ratio (*V/P*), on which they base their decisions. This is, perhaps, due to the difference in thresholds that slow- vs. fast-turnover analysts require their stock valuation-to-price ratio to exceed (or fall below) before a new recommendation is warranted.

Finally, controlling for all other characteristics, we find *Breadth* —the number of stocks covered–to be negatively associated with slow-turnover analysts but positively correlated with fast-turnover analyst. However, in the univariate analysis (untabulated), we find that slow*-*turnover analysts cover more stocks than fast-turnover analysts do, although the difference is economically small.

1. **Investment value implications** 
   1. ***Stock price reaction to recommendation revision***

Our objective is to quantify the difference in immediate market reactions to recommendation changes made by slow- versus fast-turnover analysts after controlling for various factors. We estimate the following regression model:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

where is the buy-and-hold abnormal return (BHAR) centered on the recommendation revision made by analyst *i* on stock *s* at time *t*.[[17]](#footnote-17) The BHAR from days to day relative to the recommendation date *t* is calculated as follows:

where is the raw return on stock *s* on day , and is the return of a benchmark portfolio with the same size, book-to-market (B/M), and momentum characteristics as the stock defined following Daniel, Grinblatt, Titman, and Wermers (1997), DGTW hereafter.

Table 5 reports the results. For this analysis, we include only recommendation changes that are made by slow- and fast-turnover analysts. Our variable of interest here is , which is an indicator variable equal to 1 if analyst *i* is a slow-turnover type, and 0 if he is otherwise a fast-turnover type. Therefore, measures the difference in market reaction to recommendation changes of slow-turnover analysts relative to those of fast-turnover analysts. We include various characteristics of the stocks on which the recommendations are issued, as well as analyst-level characteristics (*All*–*star, Male, and Breadth)*. We also include firm brokerage, industry and year-fixed effects in the regression, and cluster standard errors at the firm level.

Column 1 of Table 5 presents results for upgrade recommendations. We find that, on average, an upgrade made by a slow-turnover analyst generates a 45 basis points higher immediate market reaction than that of a fast-turnover analyst. Column 2 presents results for downgrade recommendations. Similarly, we find the market reacts significantly more to a recommendation downgrade made by a slow-recommendation revising analyst; the difference in magnitude is about 76 basis points.

Interestingly, we find that *General Experience* positively affects market reaction to downgrades and that the coefficient on upgrades is not significant. Therefore, all else equal, we find that the market does not react more strongly to recommendation changes of more experienced analysts. Among various analyst characteristics, we find that an analyst’s earnings forecast precision predicts the immediate price impact of his recommendation changes. This is seen from the statistically significant estimate on *High EPS precision* for both upgrades and downgrades. Consistent with prior literature (e.g., Jackson, 2005; Loh and Mian, 2006), we find that analysts who previously issued more precise earnings forecasts have greater ability to move prices. Nevertheless, *High EPS precision* does not erode the strong predictability of the recommendation speed-style.

Additionally, we find that our main conclusion holds after controlling for characteristics that are specific to each recommendation revision. We include dummies for recommendation revisions that occur one week before (*Pre-earnings)*, one week after (*Earnings-related*), and around the day of an earnings announcement (*Concurrent with earnings*) because the timing of the recommendation revision relative to earnings news conveys information (Ivkovic and Jegadeesh, 2004). We include a dummy variable for revisions that herd toward the consensus (*Away from consensus*) ad defined in Jegadeesh and Kim (2010). We also control for the magnitude of the recommendation change (*# level up/down*), and the recommendation level before it is revised (*Initial level*). Overall, we find the predictive ability of recommendation speed-style is economically large and significant, and more importantly, it dominates other ex-ante analyst characteristics that have been linked to analysts’ ability to move prices.[[18]](#footnote-18)

* 1. ***Real****-****calendar****-****time portfolio strategy***

We examine real-time investment value of recommendation revisions made by fast- vs. slow-turnover analysts. We build a trading strategy that follows recommendations issued by different analyst turnover groups. Specifically, in the spirit of Barber, Lehavy and Trueman (2007), we design a trading strategy that invests $1 on upgraded stocks and sells $1 on downgraded stocks.

We assume that the stock is transacted at the closing-day price *after* the recommendation change. This ensures that the strategy is implementable by *ordinary investors* without private access to analysts’ recommendations, i.e., before recommendation changes are made public. We carefully adjust for after-trading-hour recommendation releases using their timestamps recorded in the I/B/E/S database. For instance, a recommendation change recorded after the market closes on Friday is pushed to the next trading day, and the strategy is to buy/sell the stock using the Monday’s closing-day price.  We also assume that if the recommendation is released in the last 15 minute of the current trading day (after 3:45pm EST), it is pushed to the next trading day. This is because IBES recommendation timestamps are often delayed (Bradley et al., 2014), and such consideration helps make the strategy more implementable for ordinary investors.

We create a daily portfolio that invests one dollar in each upgraded stock and sells one dollar in each downgraded stock. Once added to the portfolio, the stock is held for a fixed number of trading days: 30, 60, and 120. Two distinct long-short portfolios are formed separately for the strategy that follows fast-turnover and slow-turnover analysts. For each portfolio, we compute the value-weighted portfolio return following Barber, Lehavy and Trueman (2007). We calculate the risk-adjusted returns using the CAPM, the Fama-French three-factor model, and the Carhart four-factor model.

Table 6 presents our results with annualized alphas. For the 30-day holding period, the difference in alphas is between 8.5–9.5% per year, and statistically significant at the one percent level. This confirms that analysts in the slow-turnover group generate a greater investment value in spite of issuing fewer recommendations. The difference in alphas generated from the long-short trading strategy that follows fast-turnover and the slow-turnover analysts’ recommendations remains stable for 60-trading day holding period, and decrease to about 5% for the 120-trading day holding period. Nevertheless, the difference in alphas is statistically significant at the one percent level. Appendix Table A2 provides detailed results on the long (“buy”) and short (“sell”) sides of the portfolio strategy at the daily level. We find that the strategy based on slow-turnover analysts dominates on both long and short sides, suggesting that the superior value of recommendations made by slower-revising analysts is not a result of short-sell constraint. In the Online Appendix Table IA3, we provide a comparison of our real-calendar time portfolio alphas against prior studies. Here, we find that our strategy yields excess returns with magnitude that are comparable with those previously documented.[[19]](#footnote-19) Overall, we conclude that slow-turnover analysts are able to generate investment returns for ordinary investors that are well beyond analysts who make more frequent recommendation revisions.

1. **Understanding the source of differing investment values**

We approach this in two ways. First, we ask, what types of corporate news do fast- versus slow-turnover analysts react to when they make recommendations? Second, we examine the contents of analysts’ recommendation reports and distinguish between different rationales on which they base their decision.

* 1. ***Reaction to news and recommendation speed-style***

Analysts often update their recommendations following corporate news (Ivkovic and Jegadeesh 2004, Li et al. 2015). In this case, recommendation revisions can add value by facilitating price discovery of the publicly observed information signal, consistent with the general idea that sell-side analysts play an important role of information interpreter in the financial markets (Livnat and Zhang 2012, Rubin, Segal, and Segal 2017).

Given that the majority of recommendations are made after corporate news releases (Li et al. 2015), the value of a recommendation revision depends on its incremental information beyond what market participants could learn from the preceding disclosure. In particular, news that are not based on hard figures or those containing forward-looking information about a company (e.g., merger and acquisitions, corporate strategy, management forecasts) are harder to interpret by investors who do not follow the firm professionally. Thus, recommendations that are made following these new releases are more likely to be valuable to investors because they significantly facilitate price discovery. In other words, these recommendations carry greater investment value because they simplify the news contents into an unambiguous signal — “Buy”, “Hold”, or “Sell.”

On the other hand, recommendations that are revised after less ambiguous–verifiable corporate disclosures (e.g., earnings announcements) should be less valuable because their incremental information relative to the preceding corporate disclosures is small. For instance, Ivkovic and Jegadeesh (2004) find that recommendation revisions are least informative in the week after earnings announcements. Based on this logic, we ask: Which types of corporate news do slow- and fast-turnover analysts tend to follow when they revise recommendations?

In order to study the different types of news that analysts follow when making their recommendations, it is critical to obtain a fine classification of news. For this reason, our main source for news flows is the Capital IQ (CIQ) ‘key developments’ dataset, which is a comprehensive dataset of firm-level news. Importantly for our purpose –and in contrast to other news datasets, the CIQ dataset provides a very fine news classification.[[20]](#footnote-20) For comprehensiveness, we supplement the CIQ dataset with earnings announcements and management forecasts from I/B/E/S. The merged database contains 98 distinct news items from1.14 million news. To make the interpretation easier, we aggregate these items into 14 broader topics.[[21]](#footnote-21) Appendix Table A3 provides the mapping of news items into the 14 news topics. After removing topics that make up less than 1% of the dataset, there are 9 news topics that we consider: *Earnings announcements; Product market & Operation; Management forecasts; Executive turnover; M&A; Payout policy; Security trading; Securities issuance;* and *Legal issues.* [[22]](#footnote-22)

We denote a recommendation change as being related to a specific news if it occurs within a [0; +15] day-window after the news release. For instance, we consider a recommendation change to be potentially triggered by a new product announcement if it occurs within 15 days after its announcement date. We choose the 15-day window because some news may take analysts longer to distill their contents as well as channel checking their sources.[[23]](#footnote-23)

We study the probability of observing recommendation revisions made by slow-turnover or fast-turnover analysts in relation to news flows. For *slow-turnover* analysts, we estimate the following logit model using all recommendation changes in the 2003–2013 sample:

(3)

where the dependent variable in the logit function is equal to 1 if the recommendation change is made by a slow-turnover analyst, and 0 otherwise. We include 9 dummy variables each indicating whether the recommendation change is preceded by one of the 9 news topics that we consider. For *fast-turnover* analysts, we estimate a logit model similar to that in Equation (3), but with the dependent indicator variable equal to 1 if the recommendation change is made by a fast-turnover analyst, and 0 otherwise. Year and industry-fixed effects are included in the model. Table 7 reports the estimation results. Columns (1) and (2) report results for slow- and fast-turnover analysts, respectively.

We observe a distinct pattern in the type of corporate news that fast- versus slow-turnover analysts follow when they make recommendations revisions. We find strong evidence that fast-turnover analysts tend to revise recommendations following earnings announcements, while slow-turnover analysts do not. In general, earnings announcements are pre-scheduled and contain quantitatively verifiable information about the firm’s past performance. On the other hand, Table 7 shows that slow-turnover analysts are likely to revise recommendations following news about *Product market & Operation, Management forecasts, M&A,* and *Legal issues*, while fast-turnover analysts do not. These four news types are often unscheduled and tend to convey information about the firm’s future performance.

We believe that the contents of news that tend to precede recommendations of slow-turnover analysts are not as easily interpretable by non-stock experts. For instance, the change in product market strategy (e.g., new product launch, new corporate alliance) can affect the firm’s value in different ways over the long run. Similarly, certain companies issue management forecasts. While these forecasts help guide investors about the firm’s future earnings or sales, they are estimates and made at the discretion of the management team. On the contrary, the contents of earnings announcements (i.e., EPS), which fast-turnover analysts tend to follow, can be easily compared against analysts’ prior consensus, therefore making their impact on stock valuation easier to quantify.

Overall, the findings in this section shed light on why analysts who revise their stock recommendation less frequently tend to make better stock picks. That is, recommendations of slower-revising analysts are more likely revised following harder-to-interpret corporate disclosures. This pattern in the type of information that slower-revising analysts take cue from allows their recommendations to greater facilitate price discovery, and thus have better investment value.

* 1. ***Rationales behind stock recommendations: Evidence from Investext***

We provide further evidence to support the conclusion in Table 7 by analyzing the contents in analysts’ recommendation reports downloaded from Thomson One’s Investext.

For this analysis, we construct a matched sample of fast-turnover and slow-turnover analysts and study their recommendation reports. The main objective for constructing the matched sample is to mitigate potential biases that could arise due to coverage choice of analysts and brokerage houses in Investext. Additionally, the matched sample helps reduce the number of recommendation reports. This is advantageous because we employ a labor-intensive approach of reading analysts’ reports, and identifying rationales and information sources behind each report. In particular, all reports are cross-read by three researchers in order to mitigate errors from misidentifying their contents. The final sample consists of 2,052 reports from 50 fast-turnover analysts and 50 slow-turnover analysts. These reports cover 310 distinct firms. Due to space consideration, we summarize our findings below and leave details about the methodology and further discussions to Section G of the Online Appendix.

The results from reading analyst recommendation reports are supportive of our findings in Table 7, which suggest that fast- versus slow-turnover analysts tend to follow different information signals when making their recommendations. That is, faster-revising analysts are more likely to use earnings based valuation to make their recommendations. On the other hand, slower-revising analysts are more likely to base their recommendations on news that reflect changes in the firm’s operating strategy, and product market competition.

Finally, we examine whether the superior recommendation value of slower-turnover analysts derive from their better access to management, and thus, their ability to discover novel information. To test this, we identify the source of information that sell-side analysts reference in their report to support each of their recommendation rationales. While we find that slow-turnover analysts are more likely to acquire new information through private interactions with the firm’s senior managers, the result is not statistically significant. We provide further discussions of this analysis in Section G of the Online Appendix.

1. **Concluding remarks**

We document significant variation in how frequently sell-side security analysts change their recommendation opinions. We develop a simple method for identifying analysts who revise their recommendation distinctly more frequently (versus more slowly) than their peers. We find that recommendations issued by fast-revising analysts are heavily discounted by investors and generate significantly less risk-adjusted investment return. Less frequent recommendation revisers are more likely to be elected to All-star status, work at top brokerage house, and have better career longevity.

Albeit updating their stock picks less frequently, we find that slower-revising analysts tend to issue new recommendations that lead those of others, i.e., “lead the pack.” Further, recommendations of slower-revising analysts are often revised after corporate disclosures with harder-to-interpret information, suggesting that they play a greater role in facilitating price discovery. While we find a strong evidence that sell-side analysts are slower to change their recommendations as their career tenure increases, decision-speed is the only characteristic that predicts the investment value of analysts’ recommendations. In other words, older and more experienced analysts are “wiser” only if they are willing to stand by to their recommendations longer.

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**Figure 1**

***Correction for bias due to right–truncation***

December 31st1999

1996 1997 1998 1999 2000 Timeline

Initiation

790 days 380 days

This figure illustrates the importance of adjusting for the right-truncation bias when calculating the average time between recommendation revisions. In this example, the objective is to calculate an analyst’s average time to revise his recommendation on a stock as viewed on December 31st, 1999. Stock coverage is initiated in 1996, and we observe three revisions by the end of 1999. However, this figure shows that on December 31st, 1999, there is an outstanding recommendation, which will not be revised until the following year. Therefore, if we ignore this outstanding recommendation, one would conclude that the average time between revisions is 790/3 ≈ 263 days. This method of calculation is, however, downward-biased due to the exclusion of the 380 days associated with the outstanding recommendation. We refer to this as the right***–***truncation bias. In the Online Appendix, Section B, we show how to adjust for the right***-***truncation bias by estimating a Poisson***-***likelihood model.

**Figure 2**

***Slow vs. Fast recommendation turnover analysts: Examples***

****

This figure illustrates an example of recommendation revision made on two stocks by two different types of analysts: (1) slow-turnover analyst (solid line), and (2) fast-turnover analyst (dashed line). Slow (fast) turnover analysts are those that revise their recommendations significantly less (more) often than their comparable peers do. We classify analysts in our sample at the end of the calendar year from 1996 through 2013. See text for more details. The *x*-axis represents the number of years elapsed since an analyst made his first recommendation on that stock.

**Table 1**

***Analyst characteristics***

This table reports a sample descriptive of analyst characteristics. The sample consists of analysts that provide active recommendations coverage between 1996 through 2013. Recommendations and earnings forecasts data are obtained from I/B/E/S. We require that an analyst provides active recommendation coverage on at least three stocks to remain the sample each year. Details of filters used to construct the sample can be found in the main text. The sample consists of 4,563 unique analysts providing active recommendation coverage in 1996–2013, resulting in 25,678 analyst-year observations. We summarize analyst characteristics calculated at the analyst-year level. Most of the variables are defined in Appendix **A**. *General experience* is the number of years since the analyst’s first recommendation appears in the I/B/E/S database. *Breadth* is the number of stocks for which an analyst provides active recommendation coverage.  *All–star* is the indicator variable equal to one if analyst is elected to the *Institutional Investor’s* annual All-American team (Fang and Yasuda, 2014). *Male* is the indicator variable equal to one if analyst is a male. *Top broker* is the indicator variable equal to one if analysts are working for the largest brokerage house defined as those in top tenth size decile measured by the number of analysts employed in a given year. *Recommendation boldness* is the indicator variable equal to one if an analyst’s recommendation revision is away from the consensus as defined by Jegadeesh and Kim (2010). *Recommendation* *optimism* is the indicator variable equal to one if an analyst’s recommendation is more optimistic than the prevailing consensus (Clement, 1999). *EPS optimism* is the indicator variable to one if an analyst’s quarterly earnings forecast is more optimistic than the prevailing consensus*. EPS precision* is the average earnings forecast error made by an analyst on all quarterly forecasts (Clement and Tse, 2005). *Forecast frequency* is the average number of earnings forecasts made per quarter by an analyst on all the stocks that she actively covers. *Lead*−*follower ratio (LFR)* measures the timeliness of an analyst recommendation revision relative to others analysts (Cooper, Day, and Lewis, 2001). A higher LFR ratio implies that an analyst issues more timely recommendations. *Herfindahl-Hirschman index (HHI)* measures the industry concentration of an analyst’s portfolio. *Months a recommendation is in place* is the number of months between recommendation revisions issued during the current year and when they were last revised.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Mean | Median | Std. dev. | Min. | 25th pct | 75th pct | Max. |
| General experience | 6.78 | 6.00 | 3.99 | 0.00 | 4.00 | 9.00 | 19.00 |
| Breadth | 6.93 | 6.00 | 3.94 | 3.00 | 4.00 | 9.00 | 40.00 |
| All-Star | 0.16 | 0.00 | 0.36 | 0.00 | 0.00 | 0.00 | 1.00 |
| Male | 0.89 | 1.00 | 0.31 | 0.00 | 1.00 | 1.00 | 1.00 |
| Top broker | 0.40 | 0.00 | 0.49 | 0.00 | 0.00 | 1.00 | 1.00 |
| Recommendation boldness | 0.51 | 0.50 | 0.20 | 0.00 | 0.39 | 0.63 | 1.00 |
| Recommendation optimism | 0.42 | 0.42 | 0.22 | 0.00 | 0.28 | 0.56 | 1.00 |
| EPS optimism | 0.49 | 0.49 | 0.15 | 0.00 | 0.39 | 0.58 | 1.00 |
| EPS precision | 0.00 | 0.03 | 0.26 | -9.08 | -0.10 | 0.14 | 1.00 |
| Forecast frequency | 1.79 | 1.84 | 0.36 | 1.00 | 1.60 | 2.05 | 2.50 |
| Leader-follower ratio (LFR) | 2.18 | 1.07 | 2.55 | 0.04 | 0.51 | 2.50 | 8.00 |
| Industry concentration (HHI) | 6.45 | 1.88 | 13.07 | 0.22 | 1.00 | 5.06 | 85.00 |
| Months a recommendation is in place | 11.92 | 11.19 | 5.38 | 0.83 | 7.94 | 14.97 | 46.30 |

**Table 2**

***Descriptive of Recommendation Turnover Classification***

This table summarizes the distribution of analysts after their speed-style classification. We classify analysts by how fast they revise their recommendations relative to their peers. The classification is done at the analyst-year level. The sample consists of analysts that provide active recommendations coverage in 1996–2013. For each year from 1996 through 2013, we assign analysts into three groups: (1) *Slow-turnover analyst*, (2) *Average-turnover analyst,* and (3) *Fast-turnover analyst*. Slow (fast) turnover analysts are those that revise their recommendations distinctly slower (faster) than their comparable peers. Average-turnover analysts are those that cannot be distinctly classified as either a fast- or slow-turnover type. We use analysts’ past recommendation patterns up to the previous year to identify their current-year recommendation speed-style. Panel A reports the number (and percentage) of analysts in each recommendation turnover group. Panel B reports summary statistics for the time between recommendations revisions for the overall sample, as well as for each analyst turnover group. We express time between revisions in unit months corrected for the right-truncation bias. See text for more details.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A.** Distribution of analysts across three recommendation-turnover groups | | | | | | | | | | | | | | | | | |  |
| Year | Total | |  | (1) Slow-turnover | | | |  | | (2) Average-turnover | | | |  | (3) Fast-turnover | | | |
|  | # | | % | |  | | # | | % | |  | # | | | % |
| 1996 | 521 | |  | 69 | | 13% | |  | | 391 | | 75% | |  | 61 | | | 12% |
| 1997 | 816 | |  | 138 | | 17% | |  | | 591 | | 72% | |  | 87 | | | 11% |
| 1998 | 934 | |  | 193 | | 21% | |  | | 651 | | 70% | |  | 90 | | | 10% |
| 1999 | 1106 | |  | 241 | | 22% | |  | | 765 | | 69% | |  | 100 | | | 9% |
| 2000 | 1297 | |  | 293 | | 23% | |  | | 868 | | 67% | |  | 136 | | | 10% |
| 2001 | 1327 | |  | 281 | | 21% | |  | | 909 | | 69% | |  | 137 | | | 10% |
| 2002 | 1336 | |  | 269 | | 20% | |  | | 942 | | 71% | |  | 125 | | | 9% |
| 2003 | 1602 | |  | 285 | | 18% | |  | | 1104 | | 69% | |  | 213 | | | 13% |
| 2004 | 1714 | |  | 282 | | 16% | |  | | 1204 | | 70% | |  | 228 | | | 13% |
| 2005 | 1692 | |  | 306 | | 18% | |  | | 1186 | | 70% | |  | 200 | | | 12% |
| 2006 | 1704 | |  | 348 | | 20% | |  | | 1175 | | 69% | |  | 181 | | | 11% |
| 2007 | 1699 | |  | 365 | | 21% | |  | | 1184 | | 70% | |  | 150 | | | 9% |
| 2008 | 1650 | |  | 411 | | 25% | |  | | 1113 | | 67% | |  | 126 | | | 8% |
| 2009 | 1638 | |  | 374 | | 23% | |  | | 1117 | | 68% | |  | 147 | | | 9% |
| 2010 | 1654 | |  | 377 | | 23% | |  | | 1091 | | 66% | |  | 186 | | | 11% |
| 2011 | 1650 | |  | 390 | | 24% | |  | | 1094 | | 66% | |  | 166 | | | 10% |
| 2012 | 1702 | |  | 423 | | 25% | |  | | 1101 | | 65% | |  | 178 | | | 10% |
| 2013 | 1636 | |  | 417 | | 25% | |  | | 1044 | | 64% | |  | 175 | | | 11% |
| Overall | 25678 | |  | 5462 | | 21% | |  | | 17530 | | 68% | |  | 2686 | | | 10% |
| **Panel B.** Bias-adjusted time between recommendation revisions (in months) | | | | | | | | | | | | | | | | | | | |
|  | | Nobs | | | Mean | | Median | | Std. dev. | | Min. | | 25th pct | | | 75th pct | Max. | | |
| All analysts | | 25,678 | | | 13.1 | | 12.2 | | 6.0 | | 1.0 | | 8.8 | | | 16.3 | 55.9 | | |
| *Grouped by turnover classification* | | | | | | |  | |  | |  | |  | | |  |  | | |
| (1) Slow turnover | | 5,462 | | | 20.2 | | 19.4 | | 6.0 | | 5.1 | | 16.2 | | | 23.4 | 55.9 | | |
| (2) | | 17,530 | | | 11.9 | | 11.5 | | 3.9 | | 2.3 | | 9.1 | | | 14.4 | 34.0 | | |
| (3) Fast turnover | | 2,686 | | | 6.2 | | 6.0 | | 2.3 | | 1.0 | | 4.5 | | | 7.5 | 20.1 | | |

**Table 3**

***Hazard model for predicting time to the next recommendation change***

This table reports results from estimating the Cox proportional hazard model for predicting time to the next recommendation change. The model is estimated for upgrade and downgrade revisions, separately. Panel A reports results for upgrade revisions, while Panel B reports results for downgrade revisions. The rate at which each outstanding recommendation on stock *j* by an analyst *a* will be revised in week *t* is determined by the hazard rate. We assume the hazard rate at which each recommendation will be revised follows a log-linear model:

The model is estimated at the recommendation-week level. We report the hazard ratio next to each estimated under the column labeled “HR”. The main variable of interests are indicator variables *Slow* and *Fast,* indicating the recommendation speed-style of the analyst obtained from the previous year. For instance, *Slow* (*Fast*) is equal to 1 if the analyst was classified as the slow-turnover (fast-turnover) type in the previous year, and 0 otherwise. We let the baseline hazard be firm specific, and denoted by for firm *j*. We include firm-level, industry-level, and recommendation-level controls in the model; they are represented by in the log-linear hazard rate model. We allow for unobserved heterogeneity in the hazard-rate model at the analyst level by including analyst-random effects. This is represented by , which is normally distributed. Year-fixed effects are included in all regressions. *Concurrent with earnings* is an indicator variable equal to 1 if there is an earnings announcement in the current week *t*, and 0 otherwise. All other independent variables are lagged by one period. *News intensity* is the number of firm-specific news observed in the previous week. We obtain news database from the Capital IQ’s Key developments database and the sample period begins in 2003. Therefore, regression specifications with *News intensity*, i.e., Columns (3) and (6), are estimated using recommendation observations from 2003 through 2013. All other regression specifications are estimated using observations from 1996 through 2013. *Positive stock price jump* (*Negative stock price jump*)is equal to 1 if there is a positive (negative) stock price change in the previous week, and 0 otherwise. We follow the method in Loh and Stulz (2011) and define jump as a visibly large stock price change that cannot be explained by the current stock volatility level. *Market-adjusted stock return* is the cumulative one-month buy-and-hold stock return relative to that of the CRSP value-weighted index return observed in the previous week. *Industry-adjusted stock return* is the cumulative one-month buy-and-hold stock return relative to that of the industry portfolio return observed in the previous week. We classify firms into different industries following the Global Industry Classification Standard (GICS*)*. *Stock volatility* is the standard deviation of daily stock return calculated over each week. *Stock volume* and *Industry volume* are log of total trading volumes on the stockand on the industry observed over the week, respectively. *Price rel. to 52-week high* is the ratio of the stock price to its 52-week high price. *# level up/down* is the absolute magnitude of the recommendation scale change as defined in IBES. Previous-recommendation-level fixed effects are represented by indicator variables *Last recom*. The estimate and the hazard ratio for *Last recom* variables are relative to the reference “hold” recommendation level, i.e., 3 in the I/B/E/S code. *No observations* report the number of recommendation-week observations used in the estimation. *No recomm changes* report the number of recommendation revisions present in the estimation. Near the end of each column, we report the log-likelihood ratio comparing the unrestricted model (reported model) against to the null model that restrict *Slow* and *Fast* indicators to be 0. Standard error is reported in parentheses below each estimate. \*\*\*, \*\*, and \* correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A.** Hazard model for time to an ***upgrade*** revision | | | | |  |  |  |  |  |
|  | (1) | |  | (2) | |  | (3) | | Prediction |
|  | 1996–2013 | |  | 1996–2013 | |  | 2003–2013 | |
|  | Estimate | HR |  | Estimate | HR |  | Estimate | HR |
| *Previous year speed-style* |  |  |  |  |  |  |  |  |  |
| Slow turnover | -0.190\*\*\* | 0.83 |  | -0.211\*\*\* | 0.81 |  | -0.261\*\*\* | 0.77 | ( − ) |
|  | (0.015) |  |  | (0.018) |  |  | (0.024) |  |  |
| Fast turnover | 0.298\*\*\* | 1.35 |  | 0.280\*\*\* | 1.32 |  | 0.385\*\*\* | 1.47 | ( + ) |
|  | (0.016) |  |  | (0.019) |  |  | (0.025) |  |  |
| *Control variables* |  |  |  |  |  |  |  |  |  |
| Concurrent with earnings | 1.336\*\*\* | 3.80 |  | 1.310\*\*\* | 3.71 |  | 1.181\*\*\* | 3.26 | ( + ) |
|  | (0.011) |  |  | (0.013) |  |  | (0.017) |  |  |
| News Intensity |  |  |  |  |  |  | 0.194\*\*\* | 1.21 | ( + ) |
|  |  |  |  |  |  |  | (0.005) |  |  |
| Positive stock price jump |  |  |  | -0.142\*\*\* | 0.87 |  | -0.262\*\*\* | 0.77 | ( ? ) |
|  |  |  |  | (0.017) |  |  | (0.024) |  |  |
| Negative stock price jump |  |  |  | 0.024 | 1.02 |  | -0.042 | 0.96 | ( ? ) |
|  |  |  |  | (0.019) |  |  | (0.027) |  |  |
| Market-adjusted stock return |  |  |  | 0.960\*\*\* | 2.61 |  | 1.022\*\*\* | 2.78 | ( + ) |
|  |  |  |  | (0.051) |  |  | (0.071) |  |  |
| Industry-adjusted stock return |  |  |  | 0.182\*\*\* | 1.20 |  | 0.140\*\*\* | 1.15 | ( + ) |
|  |  |  |  | (0.039) |  |  | (0.052) |  |  |
| Stock volatility |  |  |  | -0.141\*\*\* | 0.87 |  | -0.391\*\*\* | 0.68 | ( − ) |
|  |  |  |  | (0.045) |  |  | (0.063) |  |  |
| Stock volume (log) |  |  |  | 0.291\*\*\* | 1.34 |  | 0.293\*\*\* | 1.34 | ( + ) |
|  |  |  |  | (0.007) |  |  | (0.013) |  |  |
| Industry volume (log) |  |  |  | 0.002 | 1.00 |  | -0.001 | 0.00 | ( + ) |
|  |  |  |  | (0.003) |  |  | (0.004) |  |  |
| Price relative to 52-week high |  |  |  | 0.304\*\*\* | 1.36 |  | 0.239\*\*\* | 1.27 | ( + ) |
|  |  |  |  | (0.025) |  |  | (0.034) |  |  |
| # level up/down |  |  |  | -0.076\*\*\* | 0.93 |  | -0.062\*\*\* | 0.94 | ( − ) |
|  |  |  |  | (0.013) |  |  | (0.017) |  |  |
| *Previous recommendation level* |  |  |  |  |  |  |  |  |  |
| Last recom. = 2 ("Buy") | 0.112\*\*\* | 1.12 |  | 0.103\*\*\* | 1.11 |  | 0.037 | 1.04 |  |
|  | (0.013) |  |  | (0.014) |  |  | (0.027) |  |  |
| Last recom. = 4 ("Sell") | 0.362\*\*\* | 1.44 |  | 0.298\*\*\* | 1.35 |  | 0.343\*\*\* | 1.41 |  |
|  | (0.015) |  |  | (0.015) |  |  | (0.021) |  |  |
| Last recom. = 5 ("Strong sell") | 0.432\*\*\* | 1.54 |  | 0.507\*\*\* | 1.66 |  | 0.539\*\*\* | 1.71 |  |
|  | (0.019) |  |  | (0.020) |  |  | (0.028) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Year-fixed effects | Yes | |  | Yes | |  | Yes | |  |
| Analyst-random effects | Yes | |  | Yes | |  | Yes | |  |
| Log-like ratio: unrestricted vs. null | 688 | |  | 592 | |  | 502 | |  |
| No observations | 3,514,094 | |  | 2,771,067 | |  | 1,669,989 | |  |
| No of recomm changes | 71,533 | |  | 62,327 | |  | 36,011 | |  |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel B.** Hazard model for time to a ***downgrade*** revision | | | | | | | | | |
|  | (4) | |  | (5) | |  | (6) | | Prediction |
|  | 1996–2013 | |  | 1996–2013 | |  | 2003–2013 | |
|  | Estimate | HR |  | Estimate | HR |  | Estimate | HR |
| *Previous year speed-style* |  |  |  |  |  |  |  |  |  |
| Slow turnover | -0.204\*\*\* | 0.82 |  | -0.204\*\*\* | 0.82 |  | -0.285\*\*\* | 0.75 | ( − ) |
|  | (0.013) |  |  | (0.017) |  |  | (0.023) |  |  |
| Fast turnover | 0.347\*\*\* | 1.41 |  | 0.350\*\*\* | 1.42 |  | 0.484\*\*\* | 1.62 | ( + ) |
|  | (0.014) |  |  | (0.018) |  |  | (0.024) |  |  |
| *Control variables* |  |  |  |  |  |  |  |  |  |
| Concurrent with earnings | 1.343\*\*\* | 3.83 |  | 1.291\*\*\* | 3.64 |  | 1.212\*\*\* | 3.36 | ( + ) |
|  | (0.010) |  |  | (0.012) |  |  | (0.017) |  |  |
| News Intensity |  |  |  |  |  |  | 0.214\*\*\* | 1.24 | ( + ) |
|  |  |  |  |  |  |  | (0.005) |  |  |
| Positive stock price jump |  |  |  | -0.018 | 0.98 |  | -0.032 | 0.97 | ( ? ) |
|  |  |  |  | (0.016) |  |  | (0.023) |  |  |
| Negative stock price jump |  |  |  | -0.213\*\*\* | 0.81 |  | -0.283\*\*\* | 0.75 | ( ? ) |
|  |  |  |  | (0.017) |  |  | (0.025) |  |  |
| Market-adjusted stock return |  |  |  | -1.844\*\*\* | 0.16 |  | -1.496\*\*\* | 0.22 | ( − ) |
|  |  |  |  | (0.049) |  |  | (0.075) |  |  |
| Industry-adjusted stock return |  |  |  | -0.235\*\*\* | 0.79 |  | -0.424\*\*\* | 0.65 | ( − ) |
|  |  |  |  | (0.030) |  |  | (0.046) |  |  |
| Stock volatility |  |  |  | -0.338\*\*\* | 0.71 |  | -0.373\*\*\* | 0.69 | ( − ) |
|  |  |  |  | (0.036) |  |  | (0.056) |  |  |
| Stock volume (log) |  |  |  | 0.301\*\*\* | 1.35 |  | 0.319\*\*\* | 1.38 | ( + ) |
|  |  |  |  | (0.007) |  |  | (0.012) |  |  |
| Industry volume (log) |  |  |  | -0.007\*\* | 0.99 |  | -0.007 | 0.99 | ( + ) |
|  |  |  |  | (0.003) |  |  | (0.004) |  |  |
| Price relative to 52-week high |  |  |  | -0.504\*\*\* | 0.60 |  | -0.355\*\*\* | 0.70 | ( − ) |
|  |  |  |  | (0.026) |  |  | (0.039) |  |  |
| # level up/down |  |  |  | -0.088\*\*\* | 0.92 |  | -0.013 | 0.99 | ( − ) |
|  |  |  |  | (0.012) |  |  | (0.018) |  |  |
| *Previous recommendation level* |  |  |  |  |  |  |  |  |  |
| Last recom. = 1 ("Strong buy") | -0.059\*\*\* | 0.94 |  | -0.048\*\*\* | 0.95 |  | -0.016 | 0.99 |  |
|  | (0.013) |  |  | (0.016) |  |  | (0.022) |  |  |
| Last recom. = 2 ("Buy") | 0.042\*\*\* | 1.04 |  | 0.097\*\*\* | 1.10 |  | 0.016 | 1.02 |  |
|  | (0.013) |  |  | (0.016) |  |  | (0.021) |  |  |
| Last recom. = 4 ("Sell") | 0.394\*\*\* | 1.48 |  | 0.441\*\*\* | 1.56 |  | 0.449\*\*\* | 1.57 |  |
|  | (0.056) |  |  | (0.066) |  |  | (0.079) |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Year-fixed effects | Yes | |  | Yes | |  | Yes | |  |
| Analyst-random effects | Yes | |  | Yes | |  | Yes | |  |
| Log-like ratio: unrestricted vs. null | 916 | |  | 690 | |  | 607 | |  |
| No observations | 4,982,311 | |  | 3,785,808 | |  | 2,154,161 | |  |
| No of recomm changes | 86,677 | |  | 73,793 | |  | 39,706 | |  |

**Table 4**

***Analyst characteristics and recommendation speed-style***

We report estimation results from a logistic model examining characteristics that are associated with an analyst being classified into each of the three speed-style groups (1) *Slow* to (2) *Average* to (3) *Fast*. The logit model is estimated at the analyst-year level. For each year from 1996 through 2013, we assign analysts into three groups: (1) Slow-turnover analyst, (2) Average-turnover analyst, and (3) Fast-turnover analyst. The dependent indicator variables in Columns (1), (2), and (3) are equal to 1 if the analyst is identified with the slow-, average-, and fast-turnover group, respectively, in that year. All analyst characteristics are calculated yearly for each analyst; see Appendix A for definitions. Year fixed effects are included in the estimation. Robust standard error clustered at the brokerage-year level is reported in parenthesis below each estimate. Each regression model contains 25,678 analyst-year observations. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
|  | *Logit model for the likelihood that the analyst is related with the following recommendation speed-style* | | |
|  | (1)  Slow | (2)  Average | (3)  Fast |
| General experience | 0.188\*\*\* | −0.035\*\*\* | −0.304\*\*\* |
|  | (0.007) | (0.006) | (0.013) |
| All-star | 0.506\*\*\* | −0.204\*\*\* | −0.858\*\*\* |
|  | (0.056) | (0.050) | (0.107) |
| Top broker | 0.265\*\*\* | −0.017 | −0.388\*\*\* |
|  | (0.052) | (0.038) | (0.058) |
| Breadth | −0.031\*\*\* | 0.007 | 0.060\*\*\* |
|  | (0.005) | (0.005) | (0.007) |
| Recomm optimism | −0.154\* | 0.044 | 0.243\*\* |
|  | (0.093) | (0.073) | (0.104) |
| Recomm boldness | 0.002 | 0.130 | −0.417\*\*\* |
|  | (0.108) | (0.084) | (0.108) |
| EPS optimism | 0.012 | 0.015 | −0.068 |
|  | (0.123) | (0.102) | (0.146) |
| EPS precision | 0.045 | 0.046 | −0.178\*\* |
|  | (0.077) | (0.056) | (0.074) |
| Lead/follow ratio (LFR) | 0.026\*\*\* | 0.006 | −0.064\*\*\* |
|  | (0.007) | (0.006) | (0.011) |
| Forecast frequency | 0.102 | 0.086 | −0.383\*\*\* |
|  | (0.067) | (0.056) | (0.086) |
| Male | 0.023 | −0.019 | 0.009 |
|  | (0.055) | (0.046) | (0.072) |
| Industry concentration (HHI) | −0.001 | 0.000 | 0.000 |
|  | (0.001) | (0.001) | (0.002) |
| Year-fixed effects | Yes | Yes | Yes |
| Broker-year clustering | Yes | Yes | Yes |
| Nobs. | 25,678 | 25,678 | 25,678 |

**Table 5**

***Stock Price Reaction to Recommendation Changes: Regression analysis***

The sample consists of recommendation changes issued by slow-turnover and fast-turnover analysts from 1996 through 2013. All control variables are defined in Appendix **A.** Standard errors are clustered at the firm level. ∗, ∗∗, and∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

|  |  |  |
| --- | --- | --- |
|  | *Dependent Variable: BHAR( −1,+1)* | |
|  | (1) Upgrade | (2) Downgrade |
| *Recommendation turnover* |  |  |
| **Slow Analyst** | **0.464\*\*** | **−0.758\*\*\*** |
|  | (0.218) | (0.205) |
| *Stock-level characteristics* |  |  |
| Size | −0.799\*\*\* | 0.454\*\*\* |
|  | (0.093) | (0.065) |
| Volatility | 0.250\*\*\* | −0.239\*\*\* |
|  | (0.071) | (0.060) |
| Institutional investor (quartiles) | −0.591\*\*\* | −0.547\*\*\* |
|  | (0.222) | (0.145) |
| Stock return | −2.021\*\* | 0.999\*\*\* |
|  | (0.999) | (−2.020) |
| Market return | 6.356\*\*\* | 2.062\*\*\* |
|  | (2.062) | (3.080) |
| *Analyst characteristic* |  |  |
| General experience | 0.003 | 0.100\*\*\* |
|  | (0.025) | (0.032) |
| All-star | 0.551 | −0.012 |
|  | (0.556) | (0.258) |
| Male | 0.154 | 0.297 |
|  | (0.223) | (0.293) |
| Breadth | −0.009 | 0.015 |
|  | (0.012) | (0.014) |
| High EPS precision | 0.396\*\* | −0.269 |
|  | (0.179) | (0.177) |
| High EPS optimism | −0.162 | 0.219 |
|  | (0.207) | (0.174) |
| *Recommendation-level characteristic* |  |  |
| # level up/down | 1.124\*\*\* | −1.226\*\*\* |
|  | (0.195) | (0.231) |
| Initial level | −0.372\*\*\* | 0.168 |
|  | (0.122) | (0.156) |
| Concurrent with earnings announ. | 0.987\*\*\* | −2.491\*\*\* |
|  | (0.281) | (0.308) |
| Earnings-related revision | −0.830\*\*\* | 0.694\*\* |
|  | (0.251) | (0.297) |
| Pre-earnings revision | 0.584 | 0.773 |
|  | (0.382) | (0.605) |
| Away from consensus | 0.462\*\* | −1.279\*\*\* |
|  | (0.186) | (0.234) |
| Industry, Year, and Broker-fixed effects | Yes | Yes |
| Firm-level clustering | Yes | Yes |
| Nobs | 15,328 | 17,657 |
| Adjusted R-squared | 13.6% | 14.5% |

**Table 6**

***Real***-***calendar time Portfolio Results***

This table presents annualized risk-adjusted returns of calendar-time portfolios earned by investors trading on analyst recommendations. We report annualized alphas of 30, 60, and 120-day holding period returns earned by an investor who invests $1 on a stock at the closing-day price *after* the recommendation upgrade and sells $1 on a stock at the closing-day price *after* the recommendation downgrade. The sample consists of recommendation changes issued by slow and fast*-*turnover analysts in our classification sample (see Table 2) from 1996 through 2013. Portfolios are formed over the 1996–2013 period and their returns are calculated daily. We report results for three holding periods: 30, 60, and 120 trading days. We report portfolio alphas from the trading strategy that follows two groups of analysts: *Slow-turnover analyst*, and *Fast-turnover analyst*. Abnormal returns are calculated using three benchmarks: CAPM, the Fama-French three-factor model, and the Carhart four-factor model. For each model, we report the constant alpha expressed in annualized percentage terms together with its *t*–stat. The rows labeled “Slow vs. Fast” report the difference in annualized alphas from portfolios earned by investing following recommendation changes of slow-turnover analysts minus fast-turnover analysts.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Analyst turnover type |  | Holding period (trading days) |  | Annualized portfolio alpha (%) | | | | | | | |
|  |  | CAPM | *t-*stat |  | Fama-French  three-factor | *t-*stat |  | Carhart  four-factor | *t-*stat |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Slow |  | 30 |  | 27.9 | 9.95 |  | 27.7 | 7.32 |  | 25.8 | 7.57 |
| Fast |  | 30 |  | 18.4 | 7.48 |  | 18.5 | 7.51 |  | 17.3 | 7.14 |
| **Slow vs. Fast** | | **30** |  | **9.5** | **2.54** |  | **9.2** | **2.47** |  | **8.5** | **2.35** |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Slow |  | 60 |  | 22.0 | 10.45 |  | 21.9 | 10.39 |  | 20.1 | 10.09 |
| Fast |  | 60 |  | 9.9 | 7.15 |  | 13.1 | 7.14 |  | 11.9 | 6.68 |
| **Slow vs. Fast** | | **60** |  | **12.2** | **4.35** |  | **8.8** | **3.14** |  | **8.3** | **3.09** |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Slow |  | 120 |  | 14.7 | 9.47 |  | 14.7 | 9.50 |  | 13.2 | 9.19 |
| Fast |  | 120 |  | 9.9 | 7.25 |  | 9.8 | 7.21 |  | 8.7 | 6.73 |
| **Slow vs. Fast** | | **120** |  | **4.8** | **2.35** |  | **5.0** | **2.42** |  | **4.6** | **2.36** |
|  |  |  |  |  |  |  |  |  |  |  |  |

**Table 7**

***Analyst Reaction to News***

We report estimation results from a logistic model for the probability that a recommendation change is issued by a *Slow*-turnover analyst (Column (1)) or a *Fast*-turnoveranalyst (Column (2)). The sample consists of recommendation changes by analysts across different recommendation speed-style from 2003–2013. The dependent variable is equal to 1 when the recommendation change is from a slow-turnover analyst (or fast-turnover analyst). All independent variables are indicator functions for various news type. Each independent variable is equal to 1 if its corresponding news was issued in the [−15, 0] calendar-day window before the recommendation change, and 0 otherwise. We consider 9 different types of news leading to a recommendation change: *Earnings announcement*; *Product market & Operation*; *Management forecasts*; *M&A*; *Payout policy*; *Securities issuance*; *Legal issues*; *Security trading*; *Executive turnover*. Earnings announcements and earnings guidance are from the I/B/E/S actual and guidance files, respectively. All other news events are from the Capital IQ “key development” dataset. See Appendix Table A3 for a definition of news from Capital IQ. Industry and year-fixed effects are included in the estimation. Robust standard error clustered at the firm level is reported in parenthesis below each estimate. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

|  |  |  |
| --- | --- | --- |
| News leading recommendation | Probability that the recommendation change is from: | |
| Slow-turnover analyst | Fast-turnover analyst |
| (1) | (2) |
| Earnings announcement | −0.079\*\*\* | 0.045\*\* |
|  | (0.027) | (0.022) |
| Product market & Operation | 0.097\*\*\* | −0.065\*\* |
|  | (0.025) | (0.033) |
| Management forecasts | 0.067\*\* | −0.124\*\*\* |
|  | (0.028) | (0.034) |
| M&A | 0.046\* | −0.084\*\* |
|  | (0.028) | (0.035) |
| Legal issues | 0.122\*\*\* | −0.116\*\* |
|  | (0.044) | (0.057) |
| Executive turnover | 0.057\* | −0.002 |
|  | (0.031) | (0.036) |
| Payout policy | −0.095\*\*\* | 0.028 |
|  | (0.031) | (0.034) |
| Securities issuance | 0.025 | 0.201\*\*\* |
|  | (0.049) | (0.051) |
| Security trading | −0.016 | 0.072 |
|  | (0.063) | (0.069) |
| Industry & Year-fixed effects | Yes | Yes |
| Firm-level clustering | Yes | Yes |
| Nobs. | 76,229 | 76,229 |
| No. of dependent var. = 1 | 11,650 | 10,499 |
| Pseudo R-squared | 2.02% | 4.54% |

**Appendix A:** List of Variables

|  |  |  |
| --- | --- | --- |
| **Variable** | **Definition** | **Source** |
| **Analyst–level variables** | |  |
| *General experience* | The number of years since an analyst’s first recommendation in the database to the current recommendation. | I/B/E/S |
| *Recommendation optimism*  *Recommendation boldness* | Average annual number of an analyst’s new recommendation changes that are above, i.e. more optimistic than, the consensus. See Clement (1999), and Hong and Kubik (2003). For more details, see Online Appendix, Section A.  The average number of recommendation changes that move away from the consensus. The recommendation consensus is calculated as the mean of outstanding recommendations issued on each stock, excluding the analyst’s own recommendation. See Jegadeesh and Kim (2010). For more details, see Online Appendix, Section A. | I/B/E/S  I/B/E/S |
| *All–star* | Dummy variable equal to one if an analyst is currently elected to the *Institutional Investor’s* All-American team annual rankings. This dummy is updated annually as the new ranking is announced. | Fang and Yasuda (2014) |
| *Male* | Dummy variable equal to one if the analyst is a male and zero otherwise. | Law (2013), Kumar (2010) |
| *Forecast frequency* | Number of earnings forecasts made by an analyst per stock per quarter, averaged across all stocks an analyst covers in a given year. See Clement and Tse (2005). | I/B/E/S |
| *Top broker* | Dummy variable equal to one if the analyst’s brokerage house in a given year is in the top tenth size-percentile measured by the number of analysts employed in a given year. See Clement (1999). | I/B/E/S |
| *Breadth* | Number of stocks an analyst provides active recommendation coverage in a given year. | I/B/E/S |
| *EPS optimism* | The average number of quarterly earnings forecasts that is above the consensus, excluding the analyst’s own previous forecast level. For more details, see Appendix B. | I/B/E/S |
| *EPS precision* | The difference between the absolute forecast error of analyst *i* forecasting firm *j’*s fiscal quarter *Q* earnings and the average absolute forecast error across all analyst forecasts of firm *j’*s fiscal quarter *Q* earnings, divided by the average absolute forecast error across all analyst forecasts of firm *j*’s fiscal quarter *Q* earnings. This figure is multiplied by (−1) and averaged across all stocks an analyst covers in a given year. a higher value of this variable indicates higher precision of an analyst’s forecasts. See Clement and Tse (2005) and Bae, Stulz and Tan (2008). For more details, see Online Appendix, Section A. | I/B/E/S |
| **Appendix A:** List of Variables (Continued…) | | |
| **Variable** | **Definition** | **Source** |
| **Analyst–level variables (continued…)** | |  |
| *Leader–follower ratio (LFR)* | The ratio of expected arrival times of other analysts’ recommendations during the pre- and post-recommendation periods issued by an analyst. This ratio measures the average timeliness of an analyst recommendation relative to others. A higher value of LFR indicates that the analyst is a leader in revising recommendations. See Cooper, Day, and Lewis (2001). See Online Appendix, Section A for further details. | I/B/E/S |
| *Industry concentration (HHI)* | Herfindahl–Hirschman index (HHI) measuring industry concentration of an analyst’s portfolio. A higher value of HHI indicates that the analysts’ coverage is more dispersed across industries. The first digit of SIC code is used for industry classification (see Sonney, 2007). See Online Appendix, Section A for further details. | CRSP |
| **Stock–level variables** | |  |
| *Size* | The logarithm of market capitalization | CRSP |
| *Volatility* | Standard deviation of residuals from the Cahart 4–factor model estimated using daily returns over [−60,−5] period relative to event date. | CRSP |
| **Recommendation–level variables** | |
| *Days a recommendation is in place*  *Log (#days since last recommendation)* | Number of calendar days between the current recommendation revision and when it was last revised.  Log of number of calendar days since the recommendation was revised to the current date. | I/B/E/S  I/B/E/S |
| *Initial level* | The level of the recommendation before the revision. | I/B/E/S |
| *# level up/down* | The difference between the final and the initial recommendation level | I/B/E/S |
| *Concurrent with earnings* | Dummy variable equal to one for a recommendation change that occurs on days [−1,+1] relative to earnings announcement. | I/B/E/S |
| *Earnings–following revision* | Dummy variable equal to one for a recommendation change that occurs on days [+2, +7] relative to earnings announcement. | I/B/E/S |
| *Earnings–leading revision* | Dummy variable equal to one for a recommendation change that occurs on days [−7, −2] relative to earnings announcement. | I/B/E/S |
| *Away from consensus* | Dummy variable equal to one for a recommendation change that moves away from the consensus. Recommendation consensus is calculated as the mean of outstanding recommendations issued on each stock, excluding the analysts’ own recommendation level. | I/B/E/S |

**Appendix Table A1**

***Recommendation turnover Vs. Other ex-ante measures of analyst ability***

This table reports immediate stock price reactions to recommendation changes. We sorted the results with respect to recommendation turnover groups, analysts’ career tenure (i.e., general experience), and their All-star status in the annual *Institutional Investor’*s ranking. We measure immediate price reaction using cumulative buy-and-hold abnormal returns (BHAR) from day −1 to +1 relative to the recommendation change date. The sample consists of recommendation changes issued by analysts in our classification sample (see Table 2) from 1996 through 2013. BHAR is calculated relative the DGTW benchmark. Panels A and B report average BHAR(−1, +1) for upgrades and downgrades, respectively. Within each panel, we report two sets of double-sorted results: (1) *Recommendation turnover* vs. *General experience*, and (2) *Recommendation turnover* vs. *All-star* status. *General experience* is the number of years since the analyst’s first recommendation appears in the I/B/E/S database. We sort analysts annually into three equal groups based on their general experience, i.e. number of years in their career tenure: Low, Mid-career, and High. *All–star* is the indicator variable equal to one if an analyst is elected to the *Institutional Investor’s* annual All-American team (Fang and Yasuda, 2014). *Recommendation turnover* corresponds to our classification of analysts’ recommendation speed-style, which is based on how quickly (or slowly) they revise their recommendations relative to their peers (speed-style turnover status). Heteroscedasticity-adjusted standard error and the number of observation are reported below each estimate. The last row in each panel reports the difference and p–value of BHAR(−1, +1) between slow turnover and fast turnover. The column labeled “Older – Younger” (“All-star – Non-star”) reports the difference and p–value of BHAR(−1,+1) between older versus younger (All-star versus non-All-star) analysts. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

**Appendix Table A1. *Recommendation turnover Vs. Other ex-ante measures of analyst ability***

***turnover (continued…)***

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A.** Upgrades: Buy-and-hold abnormal returns (BHAR) from day −1 to +1 | | | | | | | | |
|  | *Sorted by General experience* | | | |  | *Sorted by All-star status* | | |
|  | Low | Mid-career | High | High – Low |  | Non-star | All*-*star | All-star – Non-star |
|  | *p–*value |  | *p–*value |
| All analysts | 2.82%\*\*\* | 3.17%\*\*\* | 2.91%\*\*\* | 0.08% |  | 2.90%\*\*\* | 3.32%\*\*\* | 0.42%\*\*\* |
| Std. error | (0.001) | (0.001) | (0.001) | 0.397 |  | (0.000) | (0.001) | 0.000 |
| Nobs. | 16,788 | 14,625 | 15,826 |  |  | 40,412 | 6,827 |  |
| *Sorted by analysts' turnover* | |  |  |  |  |  |  |  |
| (1) Slow-turnover | 3.64%\*\*\* | 3.70%\*\*\* | 3.14%\*\*\* | −0.50% |  | 3.33%\*\*\* | 3.56%\*\*\* | 0.23% |
| Std. error | (0.002) | (0.002) | (0.002) | 0.182 |  | (0.001) | (0.004) | 0.2748 |
| Nobs. | 1,431 | 1,811 | 3,746 |  |  | 2,727 | 1,840 |  |
| (2) Average-turnover | 3.22%\*\*\* | 3.17%\*\*\* | 2.92%\*\*\* | −0.30%\*\*\* |  | 3.06%\*\*\* | 3.31%\*\*\* | 0.25%\*\* |
| Std. error | (0.001) | (0.001) | (0.001) | 0.007 |  | (0.000) | (0.001) | 0.0112 |
| Nobs. | 10,126 | 11,169 | 10,928 |  |  | 27,648 | 4,575 |  |
| (3) Fast-turnover | 1.84%\*\*\* | 2.62%\*\*\* | 2.01%\*\*\* | 0.17% |  | 1.98%\*\*\* | 2.59%\*\*\* | 0.60% |
| Std. error | (0.001) | (0.002) | (0.002) | 0.447 |  | (0.001) | (0.003) | 0.116 |
| Nobs. | 5,231 | 1,645 | 1,152 |  |  | 7,497 | 531 |  |
| Slow − Fast | 1.80%\*\*\* | 1.08%\*\*\* | 1.13%\*\*\* |  |  | 1.34%\*\*\* | 0.97%\*\* |  |
| *p–*value | 0.001 | 0.005 | 0.001 |  |  | 0.001 | 0.049 |  |
| **Panel B.** Downgrades: Buy-and-hold abnormal returns (BHAR) from day −1 to +1 | | | | | | | | |
|  | *Sorted by General experience* | | | |  | *Sorted by All*-*star status* | | |
|  | Low | Mid-career | High | High– Low |  | Non-star | All*-*star | All-star – Non-star |
|  | *p–*value |  | *p–*value |
| All analysts | −3.28%\*\*\* | −3.54%\*\*\* | −3.16%\*\*\* | 0.12% |  | −3.28%\*\*\* | −3.55%\*\*\* | −0.27%\*\* |
|  | (0.001) | (0.001) | (0.001) | 0.219 |  | (0.000) | (0.001) | 0.012 |
|  | 19,477 | 16,355 | 17,227 |  |  | 45,516 | 7,543 |  |
| *Sorted by analysts' turnover* | |  |  |  |  |  |  |  |
| (1) Slow-turnover | −4.18%\*\*\* | −3.87%\*\*\* | −3.39%\*\*\* | 0.79%\*\* |  | −3.61%\*\*\* | −3.97%\*\*\* | −0.36%\*\*\* |
| Std. error | (0.003) | (0.002) | (0.001) | 0.026 |  | (0.001) | (0.002) | 0.005 |
| Nobs. | 1,853 | 2,170 | 4,165 |  |  | 6,137 | 2,051 |  |
| (2) Average-turnover | −3.76%\*\*\* | −3.58%\*\*\* | −3.18%\*\*\* | 0.58%\*\*\* |  | −3.51%\*\*\* | −3.48%\*\*\* | 0.04% |
| Std. error | (0.001) | (0.001) | (0.001) | 0.00 |  | (0.001) | (0.001) | 0.320 |
| Nobs. | 11,964 | 12,322 | 11,804 |  |  | 31,151 | 4,939 |  |
| (3) Fast-turnover | −1.97%\*\*\* | −2.87% | −2.20% | −0.23% |  | −2.16%\*\*\* | −2.69% | −0.53% |
| Std. error | (0.001) | (0.002) | (0.002) | 0.341 |  | (0.001) | (0.003) | 0.482 |
| Nobs. | 5,660 | 1,863 | 1,258 |  |  | 8,228 | 553 |  |
| Slow − Fast | −2.21%\*\*\* | −1.00%\*\*\* | −1.19%\*\*\* |  |  | −1.44%\*\*\* | −1.27%\*\*\* |  |
| *p–*value | 0.001 | 0.0015 | 0.001 |  |  | 0.001 | 0.001 |  |

**Appendix Table A2**

***Real***-***calendar time Portfolio Strategy: Detailed Results***

This table presents risk-adjusted returns of real-calendar time portfolios earned by investors trading following analyst recommendations. We report daily portfolio returns and alphas earned by buying (selling) $1 on a stock at the closing-day price *after* the recommendation upgrade (downgrade). We report results for three holding periods: 30, 60, and 120 trading days. Panels A and B report results for the portfolio strategy that follows recommendation changes issued by slow-turnover analysts and fast*-*turnover analysts, respectively, from 1996 through 2013. Analyst turnover classification are shown in Table 2. Portfolios are formed over the 1996–2013 period and their returns are calculated daily. For each holding period, we report results for a long only, short only, and a long-short portfolio strategy. For a long (short) only strategy, only recommendation upgrades (downgrades) are considered. We report t-statistic next to each alpha estimate. Abnormal returns are calculated using three benchmarks: CAPM, Fama-French three-factor model, and Carhart four-factor model.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Holding period |  | Portfolio type |  | Average daily  number of firms | Number of  daily return observations | Raw return (%) |  | Daily portfolio alpha (%) | | | | | | | |
|  |  |  | CAPM | *t*-stat |  | Fama French  three-factor | *t*-stat |  | Carhart  four-factor | *t*-stat |
| **Panel A.** Slow-turnover analyst | | | | | | | | | | | | | | | |
| 30 days |  | Long |  | 62 | 4,280 | 0.072 |  | 0.047 | 5.17 |  | 0.040 | 5.09 |  | 0.044 | 5.57 |
|  |  | Short |  | 79 | 4,280 | −0.038 |  | −0.064 | −5.80 |  | −0.070 | −6.84 |  | −0.059 | −6.33 |
|  |  | **Long−Short** |  | **141** | **4,280** | **0.111** |  | **0.111** | **9.95** |  | **0.110** | **9.89** |  | **0.102** | **9.53** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 60 days |  | Long |  | 124 | 4,280 | 0.046 |  | 0.020 | 2.58 |  | 0.013 | 2.12 |  | 0.016 | 2.60 |
|  |  | Short |  | 156 | 4,280 | −0.041 |  | −0.067 | −7.13 |  | −0.074 | −8.89 |  | −0.064 | −8.67 |
|  |  | **Long−Short** |  | **279** | **4,280** | **0.088** |  | **0.087** | **10.45** |  | **0.087** | **10.39** |  | **0.080** | **10.09** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 120 days |  | Long |  | 245 | 4,280 | 0.032 |  | 0.005 | 0.74 |  | 0.002 | 0.32 |  | 0.001 | 0.10 |
|  |  | Short |  | 304 | 4,280 | −0.027 |  | −0.053 | −6.36 |  | −0.060 | −8.86 |  | −0.052 | −8.64 |
|  |  | **Long−Short** |  | **549** | **4,280** | **0.058** |  | **0.058** | **9.47** |  | **0.059** | **9.50** |  | **0.053** | **9.19** |
| **Panel B.** Fast-turnover analyst | | | | | | | | | | | | | | | |
| 30 days |  | Long |  | 71 | 4,279 | 0.058 |  | 0.031 | 2.98 |  | 0.022 | 2.48 |  | 0.027 | 3.07 |
|  |  | Short |  | 81 | 4,280 | −0.016 |  | −0.042 | −3.88 |  | −0.051 | −5.26 |  | −0.042 | −4.62 |
|  |  | **Long−Short** |  | **152** | **4,279** | **0.073** |  | **0.073** | **7.48** |  | **0.073** | **7.51** |  | **0.069** | **7.14** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 60 days |  | Long |  | 142 | 4,279 | 0.025 |  | 0.012 | 1.27 |  | 0.003 | 0.38 |  | 0.007 | 0.95 |
|  |  | Short |  | 159 | 4,280 | −0.014 |  | −0.041 | −4.12 |  | −0.049 | −5.80 |  | −0.040 | −5.19 |
|  |  | **Long−Short** |  | **301** | **4,279** | **0.039** |  | **0.052** | **7.15** |  | **0.052** | **7.14** |  | **0.047** | **6.68** |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 120 days |  | Long |  | 280 | 4,279 | 0.025 |  | −0.002 | −0.28 |  | −0.011 | −1.64 |  | −0.008 | −1.25 |
|  |  | Short |  | 312 | 4,280 | −0.014 |  | −0.041 | −4.58 |  | −0.050 | −6.60 |  | −0.043 | −6.07 |
|  |  | **Long−Short** |  | **593** | **4,279** | **0.039** |  | **0.039** | **7.25** |  | **0.039** | **7.21** |  | **0.034** | **6.73** |

**Appendix Table A3. Capital IQ–I/B/E/S News Dictionary**

This table provides the mapping between the Capital IQ’s Key Development items and I/B/E/S news to our 14 news categories. The Capital IQ dataset classifies news into various items with a label and numeric code. We supplement the Capital IQ database with I/B/E/S earnings announcements and management forecasts data. We group various news items into 14 categories: *Earnings announcement*; *Management forecasts*; *Product market & Operations*; *Payout policy*; *Executive turnover*; *Securities issuance*; *M&A*; *Restatement and auditing*; *Agenda communication*; *Legal issues*; *Shareholder activism*; *Bankruptcy*; *Security trading*; and *Other*.

|  |  |
| --- | --- |
| News Category | Sources: I/B/E/S datasets and Capital IQ’s Key development labels |
| Earnings announcements | I/B/E/S actual file *anndats\_act* variable  Announcements of Earnings (28) |
| Management forecasts | I/B/E/S global estimates file *announce\_dt* variable  Corporate Guidance - Lowered (26), Corporate Guidance - Raised (27), Corporate Guidance - New/Confirmed (29) |
| Product market & Operation | Discontinued Operations/Downsizings (21), Strategic Alliances (22), Client Announcements (23), Business Expansions (31), Business Reorganizations (32), Product-Related Announcements (41), Labor-related Announcements (44), Considering Multiple Strategic Alternatives (63), Announcements of Sales/Trading Statement (138) |
| Payout policy | Buybacks (36), Dividend Affirmations (45), Dividend Increases (46), Dividend Decreases (47), Special Dividend Announced (94), Dividend Cancellation (213), Dividend Initiation (214), Preferred Dividend (215), Buyback Update (151), Potential Buyback (152) |
| Executive turnover | Executive/Board Changes - Other (16), Executive Changes - CEO (101), Executive Changes - CFO (102) |
| Securities issuance | Debt Financing Related (42), Private Placements (83), IPOs (85), Follow-on Equity Offerings (86), Fixed Income Offerings (87), Derivative/Other Instrument Offerings (88), Structured Products Offerings (135), Public Offering Lead Underwriter Change (136) |
| M&A | Seeking to Sell/Divest (1), Seeking Acquisitions/Investments (3), M&A Calls (52), M&A Rumors and Discussions (65), M&A Transaction Announcements (80), M&A Transaction Closings (81), M&A Transaction Cancellations (82), Spin-Off/Split-Off (137) |
| Restatement & Auditing | Restatements of Operating Results (43), Impairments/Write Offs (73), Auditor Going Concern Doubts (59), Auditor Changes (150) |
|  | |
|  | |
| **Appendix Table A3. (Continued…)** | |
| News Category | Sources: I/B/E/S datasets and Capital IQ’s Key development label |
| Agenda communication | Notification of Earnings Calls (48), Notification of Guidance/Update Calls (49), Notification of Shareholder/Analyst Calls (50), Notification of Company Conference Presentations (51), Notification of Earnings Release Date (55), Notification of Delayed Earnings Announcements (61), Notification of Special/Extraordinary Shareholders Meeting (97), Notification of Sales/Trading Statement Calls (139), Notification of Sales/Trading Statement Release Date (140), Announcements of Conferences (149), Announcements of Analyst/Investor Day (192), Announcements of Special Calls (194), Notification of Annual General Meeting (62), Notification of Board Meeting (78) |
| Legal issues | Regulatory Agency Inquiries (24), Lawsuits & Legal Issues (25), Legal Structure Changes (76), Changes in Company Bylaws/Rules (77), Regulatory Authority - Regulations (205), Regulatory Authority - Compliance (206), Regulatory Authority - Enforcement Actions (207) |
| Shareholder activism | Investor Activism - Proposal Related (156), Investor Activism - Activist Communication (157), Investor Activism - Target Communication (160), Investor Activism - Proxy/Voting Related (163), Investor Activism - Agreement Related (164), Investor Activism - Nomination Related (172), Investor Activism - Financing Option from Activist (177), Investor Activism - Supporting Statements (187) |
| Bankruptcy | Bankruptcy - Filing (89), Bankruptcy - Conclusion (90), Bankruptcy - Emergence/Exit (91), Bankruptcy - Asset Sale/Liquidation (153), Bankruptcy - Financing (154), Bankruptcy - Reorganization (155), Bankruptcy - Other (7), Debt Defaults (74) |
| Security trading | Delayed SEC Filings (11), Delistings (12), Exchange Changes (57), Ticker Changes (58), Index Constituent Drops (75), Index Constituent Adds (95), End of Lock-Up Period (92), Shelf Registration Filings (93) |
| Other | Seeking Financing/Partners (5), Name Changes (56), Address Changes (60), Fiscal Year End Changes (79), Potential Privatization of Government Entities (99), Composite Units Offerings (134) |

1. Nobel laureate in economics, in Jason Zweig, “Do You Sabotage Yourself?” Money Magazine, May, 2001, p. 78.

   [↑](#footnote-ref-1)
2. For some evidences, see Womack (1996), Clement (1999), Barber et al. (2001), Frankel, Kothari and Weber (2006), and Fang and Yasuda (2009). For a survey, see Bradshaw (2011). [↑](#footnote-ref-2)
3. See for examples, Livnat and Zhang (2012), and Rubin, Segal, and Segal (2017). [↑](#footnote-ref-3)
4. We reconcile the difference between our finding and their study in the Online Appendix. [↑](#footnote-ref-4)
5. Ljungqvist, Malloy, and Marston (2009) document a significant number of additions, deletions, and alterations between snapshots of the *I/B/E/S* recommendation history on different dates. According to Wharton Research Data Services, the data distributor of I/B/E/S, the issues have been corrected as of September 2007. [↑](#footnote-ref-5)
6. We thank Lily Fang and Ayako Yasuda for sharing with us their Institutional Investor’s analyst ranking data. [↑](#footnote-ref-6)
7. We thank Alok Kumar and Kelvin Law for providing us with data on analyst gender. [↑](#footnote-ref-7)
8. Some brokerage firms use a 3-tier rating system instead of a 5-tier rating system. [↑](#footnote-ref-8)
9. Our main conclusions are unaffected when using a 7-year, 5-year, or 3-year rolling window of recommendation history, instead of all past history, to classify our analysts. Section D in the Online Appendix reports robustness-check results using different rolling windows of recommendation history. [↑](#footnote-ref-9)
10. Consider our prior example, where 7 out of 8 stocks in an analyst’s portfolio are in the fastest revisions quartile. According to a Binomial distribution, the probability that 7 or more stocks (out of 8) are in the fastest revision quartile, given that the null probability is 25% is less than 0.001. [↑](#footnote-ref-10)
11. It can take up to 24 hours to estimate each Cox PH model specification on the SAS WRDS-Cloud server with this weekly panel data over the 1996–2013 period. [↑](#footnote-ref-11)
12. The log-likelihood ratio (LLR) converges to a Chi-squared distribution with two degree of freedoms. [↑](#footnote-ref-12)
13. We apply the method of Loh and Stulz (2011) to detect daily stock returns that are outliers, in a sense that they cannot be explained by the firm’s current volatility level. For each day *t*, we flag the security as experiencing a positive (or negative) jump if its 1-day buy-and-hold adjusted return exceeds 1.96 × (or falls below −1.96 × ), where is the idiosyncratic volatility calculated using the Carhart 4-factor model over the [−60, −5] days relative to day *t.* We use 1.96 as the cut-off value in detecting return outliers, which corresponds to the 5 percent detection rate for a standard normal distribution. [↑](#footnote-ref-13)
14. See Section 5.1 for a detailed description of the Capital IQ database [↑](#footnote-ref-14)
15. We opt for this approach rather than an ordered-logit (or an ordered-probit) model because the log-likelihood-ratio test rejects the parallel regression assumption (see Long and Freese, 2014). [↑](#footnote-ref-15)
16. We measure the timeliness of recommendation change in the spirit of Cooper, Day, and Lewis (2001) who developed the *LFR* to quantify the timeliness of an analyst’s forecasts. We apply their method to analysts’ recommendation revisions. A larger value of value indicates the analyst, on average, issues more timely recommendation changes. See Appendix A in the Online Appendix for details. [↑](#footnote-ref-16)
17. We obtain similar conclusions if we measure the immediate price impact using the event windows [0, +1] or [0, 0] relative to the recommendation change date. [↑](#footnote-ref-17)
18. Appendix Table A1 further verifies our results in a univariate setting by directly comparing stock price reactions to recommendations of different analysts’ speed-style groups against their experience, as well as against their All-star status. [↑](#footnote-ref-18)
19. For instance, Barber et al. (2006) finds annualized alpha from a four-factor model in the [4.03; 10.08] range for the long side and [-11.09; -5.54] for the short side. [↑](#footnote-ref-19)
20. Recent studies that take advantage of this feature in Capital IQ’s key development database include Edmans et al. (2016), Livnat and Zhang (2012), Nichols (2009), and Cohn, Gurun and Moussawi (2014). [↑](#footnote-ref-20)
21. CIQ items are naturally grouped into broader category based on their topic code. For instance, code 31 is “Business Expansion”, and code 32 is “Business reorganization”; they are naturally grouped together. [↑](#footnote-ref-21)
22. Section F of the Online Appendix provides details about the database construction. [↑](#footnote-ref-22)
23. Our conclusions are qualitatively unaffected when using a shorter one-week window and a longer four-week window. [↑](#footnote-ref-23)