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

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This version: December 2016

For helpful comments, we thank Daniel Bradley, Jonathan Clarke, Lily Fang, Jose Guedes, Heiko Jacobs, Jennifer Jordan, Ohad Kadan, Stefan Lewellen, Roger Loh, Jay Ritter, Maria Rotundo, Richard Thaler, David Veenman, and Frank Zhang. We especially thank Alok Kumar and Kelvin Law for providing us with data on analysts' gender, and thank Lily Fang and Ayako Yasuda for providing us with *Institutional Investor's* all-star analyst data. This paper has benefited from comments by conference and seminar participants at EFA 2015, ESSEC, Frontiers in Finance 2014, EAA 2015, MIT-Asia 2015, NFA 2015, FMA 2015, NTU, HKUST, Singapore Management University, University Paris-Dauphine, University of Alberta, University of Arizona, University of Oklahoma, and University of Florida. Romain Boulland is at Essec Business School. Chay Ornthanalai is at the Rotman School of Management, University of Toronto. Kent Womack was affiliated with the Rotman School of Management, University of Toronto. Please send correspondence to Chay Ornthanalai at 105 St. George Street, Toronto, ON, M5S 3E6, Canada; chay.ornthanalai@rotman.utoronto.ca. We are responsible for all inadequacies.

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Abstract

We document significant differences among sell-side security analysts in how frequently they change their minds in making stock recommendations and find that this characteristic strongly predicts their recommendations' value. Analysts who revise their decisions more slowly make more influential recommendations and generate better portfolio returns than those who do not. We find that slower-revising analysts issue more timely recommendation changes and are less likely to herd on the consensus. Their decision speed-style is associated with positive career outcomes. Further, we find a strong tendency for analysts to change their recommendations more slowly throughout their career. While analysts' decision-speed style and their career tenure correlate, the former is the only characteristic that robustly predicts their recommendations' value. We link our findings to the role that reputation and experience play in individual decision making and support the notion that a deliberate, slower-decision style trumps a "beat the crowd" mentality.

1. Introduction

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

—— Daniel Kahneman[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] To the extent that markets are quasi-efficient in a Grossman–Stiglitz (1976) sense, analysts fit the profile of the compensated information snoopers, assisting in moving the market towards efficiency. As information processing agents who are surely monitored by their own firms and their clients, these agents 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; Fang and Yasuda, 2009; Hilary and Hsu, 2013).

This study examines speed as an important decision-making-process choice of individual analysts throughout their careers. Speed as a decision-choice of analysts' recommendation revisions may enhance or lessen their reputations. 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. In many arenas of investing and trading markets, decision and transaction speed is critical and has obvious benefits. In the last decade, for example, competitive improvements in high frequency trading have been built around faster algorithms and digital infrastructure to get decisions to the electronic central marketplace lightning fast. Even in more traditional information-based investing, where relatively efficient markets prevail, when news breaks, prices should and, for the most part do, respond quite rapidly. In that environment, not surprisingly, virtually all event-based trading rules are less effective and less profitable if the decision maker's reaction to the event is delayed. Again, speed wins; slowness loses.

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, presumably because

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

[2] For some evidences, see Womack (1996), Clement (1999), Barber et al. (2001), and Frankel, Kothari and Weber (2006). For a survey, see Bradshaw (2011).

there are many investment opportunities, but not many good ones. The explanation for not rushing to judgment might be that there are benefits to waiting for the right timing or, alternatively, observing more market information before acting. There may also be other cogent reasons for slower decision making. If an analyst is really talented, his previous recommendation will remain accurate longer. Therefore, a truly talented analyst will have less need to change his mind frequently.

In this paper, we analyze the investment value of the differing, inherent, decision-speed styles employed by stock experts. Unlike high frequency trading, the institutional setting is not one in which traders pick off the best bid or offer for a penny less, but rather where investor-followers of analysts hope their stock experts' recommendations outperform the industry or market across weeks or months. We obtain detailed recommendation data from I/B/E/S covering the period from January 1993 to December 2012. After applying various filters to remove recommendations that are erroneous, stale, or obsolete, we find the average time a recommendation opinion stays in place is about 12.4 months.[3] More importantly for our study, there is significant variation in this length of time, with an interquartile range of 8 to 15 months.

We show that much of this observed variation can be explained by the "speed-style" of the individual analyst-decision-maker, i.e. some analysts are predictably quicker to change their minds, while others are predictably slower. We denote this speed-style of each analyst as his "recommendation turnover," representing how often the analyst *overturns* his recommendation opinions. We introduce a methodology to classify an analyst's propensity to update his recommendations on the spectrum of fast to slow, relative to his competitors. First, we sort analysts covering the same stock based on their recommendation change frequency from slowest (1st quartile) to fastest (4th quartile). The sorting of analysts at the stock level controls for firm characteristics that may influence the revision frequency. After, we examine the fraction of stocks covered by the analyst that are ranked in the slowest (or fastest) quartile. In order to make a statistical inference about each analyst's recommendation speed-style, we employ a Binomial test. The null hypothesis is that if the analyst does not have extremely fast (slow) preference in recommendation speed, we expect a quarter of stocks that he covers to be ranked in the fastest (slowest) quartile. Rejection of

[3] An important filter that we applied is the removal of mechanical recommendation changes due to brokerage houses' response to Global Settlement in 2002 (see Kadan et al., 2009).

this null hypothesis would, otherwise, suggest that the analyst revises his recommendation decisions too fast (or too little).

Starting in 1996, we use the recommendation history up until December 31, 1995, to classify analysts into three recommendation turnover groups: (1) Slow, (2) Average, (3) Fast. The recommendation history file is then updated at the end of each calendar year, and we reclassify analysts into one of the three recommendation turnover groups for each following year.[4] As a result, our method provides an *out-of-sample* estimate of analysts' recommendation decision-speed types from 1996 to 2012.

We find that *fast-turnover* analysts, on average, change their opinions every 6 months, while *slow-turnover* analysts typically change their minds about every 20 months. Importantly, we find that an analyst's recommendation speed-style is persistent through time, suggesting that the speed at which analysts revise their recommendations is an inherent or strategic trait. Using the Cox Proportional Hazard model, we estimate the hazard rate that each recommendation will be revised in relation to the analyst's decision speed-style identified from the previous year (or from the multiple years before). In doing so, we control for various firm-, industry-, and recommendation-level factors that could trigger or delay recommendation revisions. Results from this analysis overwhelmingly show that the recommendation speed-style robustly predicts the speed at which analysts will revise their future recommendations. We conclude that the decision-speed at which analysts revise their recommendations appears to be an inherent trait.

We find that recommendation changes made by slow-turnover analysts significantly outperform recommendation changes by fast-turnover analysts. In the first five months after the opinion change, the risk-adjusted excess returns are 1.93% higher for upgrades and –1.23% lower for downgrades by slow-turnover analysts relative to fast-turnover analysts. Both differences are strongly significant. We reemphasize that our approach of classifying analysts' recommendation speed-style is an out-of-sample approach. Our classification method is able to predict a difference in analysts' immediate recommendation values in the order of 100 basis points or more. Importantly, the recommendation value identified based on recommendation speed-style dominates those identified through other analysts' ex-ante characteristics such as their career tenure, All-star status, prior earnings

[4] Our identification method assumes that investors form and update their beliefs about the decision–speed style of each analyst as more revisions issued by him and his peers become available.

forecasts precision, and brokerage house size.

We further confirm the differing investment values between fast- and slow-turnover analysts result 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. The stocks are added to the portfolio at the closing-day price after the recommendation change, which 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.

The above results beg the following important questions: When do analysts decide to announce new recommendation opinions? What cues do they use? Obviously, it is difficult, if not impossible, to see into the mind of these decision makers, but we do observe valuable clues. 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). We also examine the timing of analysts' recommendation relative to price-relevant news in the stock market. We find strong evidence that recommendations of slower-revising analysts tend to front-run significant news arrivals as measured by visibly large stock price changes (see Loh and Stulz, 2011). Relatedly, we find their recommendation revisions tend to be bolder, i.e., away from consensus (see Jegadeesh and Kim, 2010). Therefore, albeit being slower to update their stock pick, slow-revising analysts make more timely recommendations and their decisions are less likely to herd on the consensus level.

An important aspect we observe is that during the course of a career, there is a strong tendency for all surviving analysts to become more deliberate (i.e., slower). In fact, results from the multivariate probit model show that analysts' career tenure, i.e., experience, is the most significant determinant of their decision-speed style. This finding suggests that analysts' experience influences their decision-making speed. But why? A possible explanation is drawn from the theoretical model of Prendergast and Stole (1996), which examines the decision-making process of an agent who is aware that the decisions he makes reflect his competence. Their main prediction interpreted under the analyst framework is as follows. Initially, a young analyst will revise his recommendations too often to show that he is quick to react to new information. However, after he has made several stock recommendations, i.e. after some period, any changes that he subsequently makes are an indication of the quality of both his previous and current information. As a result, the analyst will change his recommendations less frequently because such action would suggest that his previous recommendation was wrong.

Alternatively, studies in behavioral psychology find that speed and dexterity of workers often decline with age and experience (Sparrow and Davies, 1988; Avolio, Waldman, and McDaniel, 1990). However, we do not believe this conclusion applies in our case. Slow-turnover analysts make superior and timelier investment decisions relative to fast-turnover analysts, suggesting the decrease in their decision-speed is not due to their decline in dexterity or skill. We conclude that our findings on the relationship between analysts' experience and their decision speed-style are more consistent with the reputation-concern theory predicted by Prendergast and Stole (1996).[5]

Our study contributes to the sell-side analyst literature by identifying the decision speed-style of stock experts based on the entire portfolio of stocks they follow and recommendations they change, and by considering the differing investment value implications thereof. Numerous research studies have confirmed the connection between earnings precision, recommendation accuracy, and career concerns (i.e., All-star status) success (Hong, Kubik, and Solomon, 2000; Fang and Yasuda, 2009). "Getting it right," in the long run, leads to greater job retention, higher pay, and additional reputational benefits predicted by information and labor economics. While many of these decision outcomes that lead to success are acknowledged and documented, the decision-making *processes* that create those outcomes are less well understood. We hope to contribute to this literature by focusing on the decision-speed exercised by these stock experts.

Our study is related to two recent empirical studies which measure recommendation change frequency, although differently from our approach. Jegadeesh and Kim (2010) find that slow recommendation changers are more likely to herd when making stock recommendations. We emphasize that their conclusion cannot be compared to ours because they measure recommendation frequency of each analyst-stock pair while we measure it at the *individual* analyst level. In the second study, Hobbs, Kovacs and Sharma (2012) find superior portfolio performance formed following recommendations of faster-revising analysts, opening the debate of "quantity versus quality." However, they measure how

[5] We also explore other explanations for the differing decision speed-styles employed by sell-side analysts such as trade-generating motives and analysts' inattention and find no evidence for their support.

frequently an analyst changes his recommendations using only recommendations that have been revised within 12 months. This approach eliminates almost half of recommendation-change observations from the sample because the median analysts' recommendations, on average, remain in place for 11.2 months.[6] This suggests that their study focuses on analysts who are already in the faster-extreme of recommendation speed-style, or on stocks that require frequent recommendation changes. We reconcile the difference between our findings and those in Hobbs, Kovacs and Sharma (2012) in Section 4.3.

In Section 2, we describe our data in detail and the methodology we use to measure recommendation frequency and identify analysts' decision-speed style. Section 3 presents our results. Section 4 links our findings to the existing literature. Section 5 concludes.

2. Data and methodology

2.1 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 2012.[7] This initial sample contains 526,792 recommendations made by 11,074 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).[8] 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).[9]

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. This eliminates REITS, ADRs, and closed-end funds from the sample. We remove

[6] Jegadeesh and Kim (2010) also measures recommendation frequency using recommendation changes that has occurred in the last calendar year.

[7] 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.

[8] We thank Lily Fang and Ayako Yasuda for providing us with Institutional Investor's analyst ranking data.

[9] We thank Alok Kumar and Kelvin Law for providing us with data on analyst gender.

analysts coded as anonymous by I/B/E/S, since it is not possible to track their recommendation revisions. 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.[10] We characterize each revision as an upgrade or downgrade by comparing the revised recommendation with the previous outstanding recommendation for the stock by the revising analyst. Recommendation revisions that do not result in a rating scale change are marked as reiterations. We do not consider initiations and reiterations in our empirical analysis. Nevertheless, we keep track of initiations and reiterations in a separate database in order to calculate an analyst's stock experience as well as identify stale recommendations.

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-year 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 265,116 observations over 20 years, where 118,302 are upgrades.

We define a recommendation as outstanding according to Ljungqvist, Malloy, and Marston (2009). We detect non-outstanding recommendations, i.e. recommendations that have been dropped, using I/B/E/S Stopped File. A recommendation that has not been confirmed by the analyst (in the I/B/E/S review date field) within the last twelve months and has been stopped by the broker is considered non-outstanding. We further identify stale recommendations using analysts' earnings forecasts data. We refer to stale recommendations as those 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, we check whether the same analyst also issues earnings forecasts regularly on the stock. If we find that this analyst makes less than one earnings forecast per year, his outstanding recommendation is flagged as stale, and it is noted that he has dropped recommendation coverage on the firm. We find 64,240

[10] Some brokerage firms use a 3-tier rating system instead of a 5-tier rating system.

recommendations to have been outstanding (without reiteration) for more than one year, and 4,775 of them are classified 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.[11] Even though we have removed mechanical recommendation changes as well as corrected for stale recommendations, we still observe some outliers. The shortest time between revisions is less than a day, and the longest is 11 years. We believe that these extreme observations are associated with human errors, i.e. key-punching errors in I/B/E/S records, and duplicate reports disseminated by sell-side analysts. We eliminate these potentially erroneous observations by truncating the *time a recommendation is in place* variable at the 1st and the 99th percentiles.[12] Our final recommendation change sample contains 240,957 recommendation changes made by 8,526 distinct analysts, where 107,334 are upgrades.

2.2 Sample descriptive

We focus on analysts who actively issue recommendations during the period 1996–2012. Although I/B/E/S recommendation file begins in 1993, we begin our analysis in 1996 in order to allow analysts' revision history to sufficiently develop.

In each year from 1996 to 2012, we calculate various characteristics for each analyst appearing in the analyst classification sample. The number of analysts that enter the sample is updated yearly. We require that an analyst provides active recommendation coverage on at least three stocks to be in the sample. 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 1996–2012, resulting in 24,042 analyst-year observations.

Table 1 summarizes various characteristics of analysts that are in the final sample. All variables are defined in Appendix A. We provide detailed explanation for selected variable constructions in Appendix B. The mean general experience for analysts in our sample is

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[11] We use the date reported in the Stopped File as the date when the recommendation is no longer applied. For recommendations that have been outstanding for more than one year without a reiteration and a regular earnings forecast made by the analyst, i.e. stale, we consider the stop date to be when the recommendation was last revised.

[12] The 1st and 99th percentiles correspond to 3 days and 5.19 years that a recommendation is in place. We verify that our important empirical results are robust to the inclusions of these outliers.

6.57 years, while the median is 6 years. On average, the number of stocks in an analyst recommendation portfolio is 6.91. This value is consistent with previous studies, which report that analysts typically cover about 7 firms (see He and Tian, 2013). The minimum number of stocks covered by analysts in our sample is three by construct. Overall, descriptive of analyst characteristics reported in Table 1 are in line with the literature.

Table 1 shows that the average *time a recommendation is in place* is 12.36 months, with a median of 11.2 months. This variable reflects the number of days that a recommendation by an analyst remains outstanding and is divided by 30 to express it in monthly units. Importantly, we find the standard deviation and the percentile distribution of this key variable shows a significant variation.

2.3 Identifying analysts' recommendation speed-style

Our methodology consists of three steps: 1) Estimating the average recommendation revision time of each analyst on each stock; 2) Benchmarking the revision time of each analyst-stock pair against other analysts covering the same stock; 3) Identifying a distinct speed-behavior of each analyst across all the stocks in his portfolio.

2.3.1 Estimating the time between recommendation revisions

We assume that investors update their belief about each analyst's recommendation speed-style as more revisions issued by him and his peers become available. For instance, when classifying the speed of analysts in the year 2000, we use all recommendations history up until December 1999.[13] We exclude revisions made in the current year, i.e. 2000, in order to ensure that our measure is an ***out-of-sample*** identification method.

The method for identifying fast and slow-turnover analysts is as follows: On December 31st of each 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. To see this more clearly, we illustrate the effect of right-truncation bias in Figure 1.

[13] Our main conclusions are similar when using a five-year rolling window of recommendation history, instead of all past history, to classify our analysts.

[Insert Figure 1 about here]

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, 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 by assuming the probability of an analyst revising a recommendation on a stock follows a Poisson distribution. The estimated mean parameter of the Poisson distribution is used as the bias-adjusted average time between revisions for each analyst-stock pair. When the right-truncation gap is relatively small, the mean revision time estimated from the Poisson distribution is equal to that of a naïve averaging method. We discuss the procedure in detail in Appendix C.

2.3.2 Sorting of analysts at the stock level

How often an analyst revises his recommendation on a stock can be related to firm's characteristics. For instance, stocks with intrinsically more news flows may trigger more recommendation changes from analysts. To control for firm-level characteristics, we sort all analysts covering the *same stock* into quartiles based on the average revisions time, i.e. from fastest (top 25th percentile) to slowest (bottom 25th percentile). More formally, let $\tau_{a,j}$ denote the bias-corrected average revision time of analyst a on stock j. Assuming there are A_j analysts covering stock j, we sort $\tau_{a,j}$ across A_j analysts into four equal groups from smallest to largest. This procedure is repeated for all the stocks j in the sample. As a result, we have rankings (from fastest to slowest quartiles) of all analyst-stock pairs in the sample.

2.3.3 Identifying speed-style

Finally, for each analyst, we test whether he exhibits a distinct decision-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. This is the null hypothesis that we test. In this case, the likelihood that his revision speed on a stock falls in the first (or the fourth) speed quartile is one-fourth. For instance, if an analyst covers 8 stocks and does not have an extreme speed-style preference in his recommendation, we expect probabilistically that 2 of his revisions will be in the fastest quartile, while two more will be in the slowest quartile. 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 recommendation speed-style that is faster than the average population. In order to conclusively classify an analyst as being distinctly "fast" or "slow" at revising recommendations, we apply the standard Binomial test to identify whether an analyst significantly revises his recommendations slower (or faster) than the average population. Specifically, we test each of the following null hypotheses:

H_0 (fast): The probability that stocks in an analyst's portfolio are ranked in the fastest revisions quartile is not greater than 25%.

H_0 (slow): The probability that stocks in an analyst's portfolio are ranked in the slowest revisions quartile is not greater than 25%.

Rejection of the above hypotheses at the 5 percent significant level allows us to confidently classify an analyst as faster (or slower) at revising recommendations relative to peers.[14] Finally, we assign analysts in the following calendar year into three groups: (1) *Slow-turnover analyst*, (2) *Average-turnover analyst,* and (3) *Fast-turnover analyst*. For those analysts where we can reject neither of the two null hypotheses, they 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). In each of these two cases, we pick two analysts who revise their recommendations on the same stock over a similar period, but have different recommendation turnover speeds.

[Insert Figure 2 about here]

[14] 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.

Panel A of Table 2 reports the number of analysts in each recommendation turnover group from 1996 through 2012. 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. From 2004 to 2012, the number of analysts in the sample remains relatively stable.

Panel B reports summary statistics for the bias-adjusted time between recommendations. On average, we find the bias-adjusted time between recommendations is 13.4 months with a median of 12.4 months. There is a clear difference in the time between recommendation revisions between the slow-turnover group (median of 19.8 months) and the fast-turnover group (median of 6.2 months). About 69% of analysts in the sample are classified in the average-turnover group.

In Panel C, we report the transition probability matrix of an analyst being classified in any of the three turnover groups from: Year t to Year $t+1$, and Year t to Year $t+3$. The results show that analysts' decision speed-style is persistent over time. We find that slow-turnover analysts tend to be reclassified in the same slow-turnover group in the following year (i.e., about 72.5%) or after three years (i.e., about 62.4%). Similarly, average-turnover analysts tend to be reclassified in the same group in the following year (i.e. about 84.3%), and after three years (i.e. about 70.1%). These results suggest that analysts' decision-speed appears to be an inherent or calculated trait that does not change abruptly. As for fast-turnover analysts, we find that their decision speed-style is somewhat persistent from one year to the next (i.e. about 50.1%). However, after three years, 24.8% remained in the fast-turnover group. This suggests that while analysts' recommendation speed-style is quite persistent, analysts tend to revise their recommendations more slowly as their career tenure progresses.

[Insert Table 2 about here]

2.4 Recommendation speed-style as an analysts' individual trait

Panel C of Table 2 shows that the recommendation speed-style exercised by each sell-side analyst is quite persistent from one year to the next, suggesting that such decision-making process is an analyst's calculated trait. We test this conjecture directly in this section.

If the speed at which analysts revises their recommendations is an individual trait, we expect the recommendation speed-style identified from their past revision patterns to explain the speed at which they will revise their future recommendations. To test this, we apply the Cox Proportional Hazard (Cox PH) model that is commonly used in survival analysis to estimate the rate at which an analyst will revise his recommendation. In doing so, we control for several factors that may trigger analysts to revise their recommendations, e.g., news arrivals, stock price momentum, as well as recommendation-level characteristics that may cause an outstanding recommendation to be "stickier" than the others, e.g., current recommendation level.

We estimate the hazard rate that each recommendation will be revised at the weekly frequency. We denote $\lambda(t)$ as the hazard rate at which an outstanding recommendation on stock j by an analyst a will be revised in week t. We assume the hazard rate that a recommendation will be revised follows a log-linear model:

$$\lambda(t) = \lambda_{0,j}(t)\exp\left(\alpha_{Slow}Slow_a + \alpha_{Fast}Fast_a + \Sigma_i\ \beta_i X_{i,j}(t)\right). \tag{1}$$

The above hazard-rate model is estimated 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, from when this recommendation became outstanding until when it is revised, i.e., either upgraded or downgraded. There are about 8.5 million recommendation-week observations created from 158,210 recommendation changes (upgrades and downgrades) from 1996–2012, where approximately 3.5 million of these observations correspond to upgrades.

We estimate the model using maximum likelihood. Our independent variables of interests are dummy variables *Slow* and *Fast,* indicating the recommendation speed-style of the analyst obtained 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.[15] We include a series of firm-level, and industry-level controls at the weekly frequency, which are represented by $\Sigma_i \ \beta_i X_{i,j}(t)$ in equation (1). We discuss these control variables below. Year-month fixed effects and previous recommendation-level fixed effects are included in the model. The baseline hazard rate function in equation (1) is assumed to be firm specific and denoted by $\lambda_{0,j}(t)$ for firm j. This can be thought of as allowing for the time-varying firm-fixed effects for the hazard rate at which a recommendation will be revised. We do not need to specify the functional form for $\lambda_{0,j}(t)$ as this term disappears when estimating the model's log-likelihood function, which is an advantage of the Cox PH model.

Table 3 reports the results. Panels A and B report estimates for the hazard-rate 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 indicates the otherwise.

Columns (1) and (4) report the baseline model estimates for upgrades and downgrades, respectively. Here, we include an indicator variable *Concurrent with earnings*, which is equal to 1 if there is an earnings announcement on firm j in the current week t, and 0 otherwise. This controls for the well-known fact that analysts tend to revise their recommendations around corporate earnings announcements. We do not lag the indicator for earnings announcements because such events are pre-scheduled and thus known in advance to the analyst. We find the coefficient estimate on *Slow* is negative, while the coefficient estimate on *Fast* is positive. These estimates are statistically significant at greater than 1 percent confidence level. 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 significance of each coefficient estimate by calculating its corresponding hazard ratio, which is simply the exponent of the reported estimate. The hazard ratio is reported under the column titled "HR" next to its estimate. For instance, Column (1) shows the hazard ratio for *Fast* is 1.57, and for *Slow* is 0.76. This implies that on any given week, the probability that a fast-turnover analyst will revise his recommendation is 1.57 times higher relative to an average-turnover analyst, while for a slower-turnover

[15] We obtain qualitatively the same conclusion when using analysts' recommendation speed-style identified from the two-year prior (and the three-year prior) to the current recommendation-week observation.

analyst, it is 0.76 times lower. We can also compare the probability of that, on any given week, a fast-turnover analyst will revise his recommendation relative to that of a slow-turnover analyst from their hazard ratios, i.e., 1.57/0.76 = 2.06.

As expected, we find the estimate on *Concurrent with earnings* to be positive and highly significant. Column (1) reports its hazard ratio of 3.73 for upgrade, and Column (4) reports its hazard ratio of 3.58 for downgrade. Thus, 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. This finding is consistent with prior studies. For instance, Bradley et al. (2014) reports that about a quarter of recommendation changes occur within 3-day around earnings announcements.

The level of previous recommendation is potential factor that may make one recommendation "stickier" than the others. We control for previous-recommendation fixed effects using indicator variables *Last recom* and their estimates are reported in Table 3. The reference level for the previous-recommendation fixed effects is "hold", i.e., recommendation code = 3 in IBES. As a result, the estimate and the hazard ratio for each *Last recom* fixed-effect variable should be interpreted relative to the "hold" recommendation. We find that most of the coefficient estimates for *Last recom* in Columns (1) and (4) are positive and statistically significant. This finding suggests that, all else equal, a recommendation change out of "hold" usually takes a longer time than a recommendation change towards it.

Columns (2) and (5) report results with a more extensive set of control variables. Several factors may trigger analysts to revise their recommendations at different times. For instance, analysts may revise their recommendation following an upward or a downward stock price momentum. We control for this using *Stock return*, which is the cumulative one-month buy-and-hold stock return in the previous week. As discussed in Kadan et al. (2012), industry expertise is an important aspect of sell-side research. Analysts might change their recommendation at a different time, depending on the industry benchmark they use for stock recommendations. We control for industry momentum using *Industry return*, which is the cumulative one-month buy-and-hold return of an equally-weighted industry portfolio that the stock belongs to in the previous week. We follow Kadan et al. (2012) and group firms into group firms into 68 industries using the Global Industry Classification Standard (GICS), which is widely adopted by investment banks as an industry classification system. If analysts use the industry return as a benchmark for their stock, we expect a strong positive industry momentum, ceteris paribus, to trigger analysts to downgrade the stock due to its relatively lower valuation. A similar argument would hold for a strong negative industry momentum, where we expect it to trigger an upgrade recommendation.

Besides the recent stock price momentum and its industry benchmark performance, Columns (2) and (5) include other control variables that may trigger analysts to revise their recommendations. They include the stock trading volume, the stock return volatility, and the last stock price value relative to its 52-week high value. These control variables are lagged by one week as they are potential triggers of a future recommendation revision, and also to avoid the endogenous effect of a recommendation change. We expect the hazard rate that a recommendation will be revised is increasing with the stock trading volume since it signals an increasing investors' attention to trade on the security. Our prior on the effect of stock return volatility is somewhat mixed. High volatility may signal an increase in information flow, which may trigger analysts to react by revising their recommendations. On the other hand, high volatility also raises the level of uncertainty and noises in analysts' ability to distill information, thereby, potentially delaying a recommendation revision. We include the stock price ratio relative to its 52-week high to the list of the control variables 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). We control for the magnitude of the new recommendation change using *# level up/down*. This is to reflect the empirical fact that an upgrade revision by 2 notches from "hold" to "strong buy" occurs less often than a 1-notch upgrade from "hold" to "buy". We define *# level up/down* as the absolute value of the difference between the new and previous recommendation levels. Finally, *Breadth* controls for the number of stocks that the analyst is actively covering.

We find the coefficient estimates on *Slow* and *Fast* in Columns (2) and (5) of Table 3 remain highly significant, and are in the expected direction. Importantly, these estimates are very similar in magnitude relative to their baseline estimates in Columns (1) and (4). This finding indicates that the recommendation speed-style that we identified using analysts' past revision patterns is a robust predictor of the rate at which an analyst will revise his future recommendation.

Columns (3) and (6) report results for the hazard-rate model where we add an additional control variable to account for the possibility that analysts revise their recommendations in reaction to public news releases. The control variable that we add here is *News intensity*, which is the number of firm-specific news observed in the previous week. We obtain data on news releases related to firms in our sample from Capital IQ, which tags the company name to each news release. Such news articles include business press, company's earnings guidance, newspaper coverage, and newswires. The news database begins in 2000 but news coverage in Capital IQ was relatively thin until the end of 2002. The recommendation sample that we use in Columns (3) and (6) is therefore from 2003 to 2012. With the addition of *News intensity* variable and a shorter sample period, we find the coefficient estimates on *Slow* and *Fast* remain strongly significant, and have the expected signs. In fact, the hazard ratios show a greater distinction between the rates at which slow- versus fast-turnover analysts revise their recommendations. For instance, the proportion of hazard ratios for *Slow* and *Fast* in Column (6) is 1.79/0.72 ≈ 2.5. This implies that on any given week, a fast-turnover analyst is 2.5 times more likely to revise his recommendation relative to a slow-turnover analyst.

We find the coefficient estimates on *News intensity* in Columns (3) and (6) are positive and strongly significant. The hazard ratios corresponding to this variable are 1.21 and 1.24, respectively. This implies that an increase of one news article reported in the previous week is likely to increase the probability that an analyst will revise his recommendation by about 1.2 times, or about a 20 percent increase.

Looking at the coefficient estimates on *Stock return* in Table 3, we find that it significantly predicts the likelihood of a recommendation revision. A positive (negative) stock price momentum subsequently induces an analyst to upgrade (downgrade) the stock. The effect of stock price momentum is much stronger for downgrades than upgrades. That is, an analyst is quicker to respond to a string of negative stock price decline than a positive stock price increase. For instance, Column (2) of Table 3 shows the hazard ratio on *Stock return* is 2.98, suggesting that a unit (i.e., 100%) increase in stock return over the last month increases the probability of an upgrade revision by about 3 times. As for downgrades, Column (5) shows the hazard ratio on *Stock return* is 0.16, indicating that a 100% decrease in stock return over the last month increases the probability of a downgrade revision by about 1/0.16 = 6.25 times.

The coefficient estimates on *Industry return* in Table 3 are strongly significant. The sign of these estimates are consistent with our expectation that analysts often benchmark their covered stock relative to the industry. That is, a strong performance in the industry portfolio return lowers the relative valuation of the stock that it is benchmarked against, thereby, triggering a downgrade recommendation. This finding is observed in Panel B where we find a positive and statistically significant estimate on *Industry return*. Similarly, Panel

A shows that the estimate on *Industry return* is negative, suggesting that a week industry performance increases the relative stock valuation, thereby increasing the probability of an upgrade revision.

Consistent with our prediction, Table 3 shows that an increase in trading volume raises the probability of a recommendation for both upgrades and downgrades. In term of economic magnitude, hazard ratios for *Stock volume* indicate that when the stock trading volume doubles over one week, the probability that an analyst will revise his recommendation in the subsequent week increases by about 1.3–1.4 times. We find that an increase in stock volatility reduces the likelihood that a recommendation will be revised in the subsequent week. This is seen from the negative and strongly significant coefficient estimates on *Stock Volatility* across all regression specifications.

We find that the magnitude of the recommendation change, i.e., # *level up/down*, is negatively related to the speed of a recommendation revision. This is consistent with previous research which shows that multiple-level recommendation changes occur less frequently than one-level recommendation changes (e.g., Loh and Stulz (2011)). Table 3 also shows the coefficient estimate on *Breadth* to be positive and significant, suggesting that analysts are quicker to revise their recommendations if they are actively covering more stocks. Nevertheless, the economic significances as interpreted through the hazard ratios of # *level up/down* and *Breadth* are quite small.

Overall, results in Table 3 show that analysts' recommendation speed-style is a robust predictor of the speed at which they will revise their future recommendations. This conclusion is robust to inclusions of a host of potential factors that can affect the speed of a recommendation revision. We thus conclude that recommendation speed-style that we identified using the method introduced in this paper appears to be an analyst-level characteristic that is persistent and predictable.

2.5 Decision speed-style and the cumulative probability of a recommendation revision

A useful way to interpret estimates from the Cox PH model is to plot the cumulative probability that an event (i.e., a recommendation revision) will occur over the time horizon. This analysis provides us with a visual illustration on the difference in speeds at which fast-versus slow-turnover analysts will revise their future recommendations. Figure 3 plots the results.

Let τ denote the time when the current recommendation will be revised since it has been outstanding. The Cox PH model allows us to write the probability that the current recommendation will have been revised after h weeks since it has been outstanding as:

$$\Pr(\tau \leq \mathrm{h}) = 1 - \int_0^h exp\big(-\lambda(s)\big)\,ds, \tag{2}$$

where $\lambda(s)$ is the hazard-rate function shown in equation (1). The above equation is the cumulative probability of a recommendation revision after h weeks. Using the estimates from the hazard rate model in Columns (2) and (5), we can calculate the cumulative probability of a recommendation upgrade and downgrade for each firm in our sample, respectively. For brevity, we plot results for the following three example firms in Figure 3: Bank of New York Mellon (BK), Sunoco (SUN), and Home Depot (HD). Panel A plots the results for upgrades, while Panel B plots the results for downgrades. In each panel, we plot the results for three distinct groups of analysts: (1) Slow-turnover, (2) Average-turnover, and (3) Fast-turnover. Firm- and industry-level control variables are set equal to their time-series averages.

Figure 3 strikingly illustrates the difference in how analysts with different recommendation speed-styles will revise their future recommendations. The cumulative probability that a fast-turnover analyst will revise his recommendation after a certain number of weeks have passed is significantly higher than that relative to other analyst-turnover groups. For instance, the probability that a fast-turnover analyst will have upgraded Sunoco (SUN) after 50 weeks has passed is close to 80 percent, while for a slow-turnover analyst, it is slightly less than 50 percent.

We emphasize that the recommendation speed-style that we use to plot the results in Figure 3 are identified using analysts' past (not the currently observed) recommendation patterns. Thus, these findings are not mechanically generated due to the endogenous relationship between the current revision speed and the current analyst's speed-style type. An analyst that was identified as a fast-revising analyst is much more likely to revise his future recommendation quicker than an analyst who was identified as a slow-turnover analyst. Overall, results in Table 3 together with the visual representation in Figure 3 indicate that analysts' recommendation speed-style is a person-specific characteristic.

3 Empirical results

3.1 Determinants of an analyst's recommendation speed-style

This section explores the observable characteristics that relate to the decision-speed style utilized by different analysts.

We examine the determinants of analysts' recommendation speed-style in a multivariate context. This approach allows us to control for brokerage and year fixed effects. Specifically, we estimate an ordered probit model where the dependent variable is the probability of j analyst being classified in the recommendation turnover type $i = \{1, 2, 3\}$ on year t. The dependent variable, analysts' turnover type, takes on an increasing value from 1 (slow turnover) to 3 (fast turnover). Table 4 reports the results. All independent variables are analyst-level characteristics and are defined in Appendix A. A positive (negative) and significant coefficient estimate on the independent variable would suggest that this analyst characteristic is positively related to analysts with faster (slower) decision-speed style.

Controlling for brokerage fixed effects and other characteristics, we find *General experience*, *Top broker*, and *All–star* are negatively and significantly associated with the probability that an analyst is in the fast-turnover group. The strongest predictor of the decision-speed style is *General experience*, with a t-statistic of –30.12.

The number of forecasts per quarter is negatively associated with the speed of recommendation revisions and statistically significant at the 10 percent level. This shows that slower recommendation-revising analysts tend to revise their forecasts more frequently (rather than more slowly). Existing studies use forecast frequency as a measure of analyst efforts. Jacob, Lys, and Neale (1999) find that analysts' forecast frequency is strongly associated with higher forecast accuracy, suggesting that it proxies for analyst effort to incorporate the latest information into forecasts. Our finding that the coefficient on *Forecast frequency* is negative in Table 4 suggests that slower recommendation-revising analysts put more effort into their earnings forecasts.

We find the *Leader–follower ratio (LFR)*, which measures the average timeliness of an analyst's recommendation change, is strongly significantly and negatively associated with the recommendation speed-style.[16] Therefore, recommendation changes of slower-revising analysts tend to lead those of faster-revising analysts. We also find that recommendation changes made by slower-revising analysts tend to be bolder, i.e., away from consensus. Table 4 shows that *Recommendation boldness* is negative and significant at the 5 percent level. Overall, the multivariate analysis provides two important insights into the type of recommendations that slow-revising analysts make relative to fast-revising analysts; they are timelier, and less likely to herd on the consensus.

[Insert Table 4 about here]

3.2 Buy–and–hold abnormal returns: Univariate results

We examine whether the recommendation turnover classification that we have introduced predicts how the stock market reacts to analyst's future recommendation changes. We measure the price impact of recommendation changes using buy-and-hold abnormal return (BHAR) starting on the day of the revisions.

We calculate *H*–day buy-and-hold abnormal return (BHAR) from time t to time t+H as follows:

$$BHAR_i(t, t+H) = \prod_{\tau=t}^{t+H}(1+R_{\mathrm{i},\tau}) - \prod_{\tau=t}^{t+H}(1+R_{\mathrm{DGTW},\tau}),$$

where $R_{\mathrm{i},\tau}$ is the raw return on stock i on day τ, and $R_{\mathrm{DGTW},\tau}$ 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, Titmans, and Wermers (1997), DGTW hereafter.

[Insert Table 5 about here]

Table 5 reports cumulative BHAR following recommendation revisions. Panels A and B report average BHAR for upgrades and downgrades, respectively. Within each panel, we report BHAR grouped by analyst turnover group. Heteroskedasticity-adjusted standard error is reported in parenthesis below each estimate. The last two rows in each panel report the difference and p–value of BHAR between slow- and fast-turnover analysts.

[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 *LFR* value indicates the analyst, on average, issues more timely recommendation changes. See Appendix B for details.

There is a clear difference in BHAR across the three analyst classification groups. The magnitude of market reactions appears to decrease as we move from slow-turnover analysts to fast-turnover analysts. This finding holds for both upgrades (Panel A) and downgrades (Panel B), as well as at all horizons. The differences in BHAR between the slow and fast-turnover analysts are all significant at less than one percent confidence level. Overall, we find strong evidence that the stock market reacts significantly different to recommendations made by analysts with different recommendation speed-styles. More importantly, fast-turnover analysts who revise their recommendations, on average, every 6.4 months (Panel B or Table 2) command significantly lower stock market reactions.

3.3 Stock price reaction to recommendation revision: Regression analysis

Results in Table 4 show that analysts' recommendation speed-style is related to a number of observable characteristics that proxy for analysts' ability. For instance, slower-revising analysts tend to be All-star analysts, have longer career tenures, and are employed by top brokerage firms. Therefore, it can be argued that these ex-ante characteristics explain why investors react more strongly to recommendation changes of slower-revising analysts than those of faster-revising analysts. We show that this is not the case using a multivariate regression. The results are reported in Table 6.

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. The dependent variable is the buy-and-hold abnormal return (BHAR) calculated over the [–1;+1] window centered on the recommendation change date made by slow-turnover and fast-turnover analysts. We estimate the following regression model:

$$\begin{aligned} &BHAR[-1;+1]_{s,i,t} \\ &\quad = Slow\ vs.Fast\ analyst_i + \beta Analyst\ Controls_{i,t} + \gamma Revision\ Controls_{s,t} \\ &\quad + \delta Stock\ Controls_{s,t} + \varepsilon_{s,i,t}, \end{aligned} \tag{3}$$

where $BHAR[-1;+1]_{s,i,t}$ indicates for a recommendation revision made by analyst i on stock s at time t.[17] Our variable of interest, $Slow\ vs. Fast\ analyst_i$, is an indicator variable equal to one if analyst i is identified in the slow-turnover group when the recommendation is made. Therefore, the estimate on $Slow\ vs. Fast\ analyst_i$ measures the difference in market reaction to recommendation changes of slow-turnover analysts relative to fast-turnover analysts. We control for a number of factors that have been associated with the market reaction to recommendation revisions. See Appendix A for their descriptions. We include brokerage, industry and year-fixed effects in the regression, and cluster standard errors at the firm level.

[Insert Table 6 about here]

Column 1 of Table 6 presents results for upgrade recommendations. We find that, on average, an upgrade made by a slow-turnover analyst generates 52 basis points higher in immediate market reaction than an upgrade made by a fast-turnover analyst. Column 2 presents results for downgrade recommendations. Similarly, we find the market reacts significantly less to a recommendation downgrade made by a fast-recommendation revising analyst; the difference in magnitude is about 76 basis points.

Our finding that recommendation changes made by fast-turnover analysts are heavily discounted is robust after controlling for a host of potential factors. We include characteristics of the stocks on which the recommendations are issued, namely size, volatility, and institutional ownership. We also control for analyst-level characteristics (*All–star, Male, and Breadth)*, all of which do not appear statistically significant.

Interestingly, we find that *General Experience* negatively affects market reaction to upgrades and positively affects market reaction to downgrades; however, only the coefficients on downgrades are 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 examined in Table 6, we find that an analyst's earnings forecast precision predicts the immediate price impact of his recommendation

[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.

changes. This is seen from the statistically significant estimate on *High EPS precision* for both upgrades and downgrades. This variable is an indicator variable equal to one if the analyst's *EPS precision* level is ranked above the sample median in the previous year, and zero otherwise. 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, this analyst characteristic does not erode the strong predictability of the recommendation speed-style.

Finally, Table 6 shows that our main conclusion holds after conservatively controlling for characteristics that are specific to each recommendation revision. We include dummies for recommendation revisions that occur one week before (*Earnings–leading)*, one week after (*Earnings–following*), 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*) because they are known to be more influential (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. Importantly, it dominates other ex-ante analyst characteristics that have been linked to analysts' ability to move prices.[18]

3.4 Investment value: Real-calendar-time portfolio strategy

One concern arises from the previous analysis of stock price reaction to recommendation revisions: Fast-turnover analysts make recommendations in greater quantity than slow-turnover analysts. Therefore, even though recommendation revisions of fast-turnover analysts are less influential, in aggregate, they may yield greater investment value. To address this issue, 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

[18] In the Appendix Table A1, we further verify 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.

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' recommendation decisions, 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 initially invests one dollar in each upgraded stock and sells one dollar in each downgraded stock. Let $x_{s,t}$ be the daily compounded return of stock s from the date of revision through date t, and $R_{s,t}$ is the gross return of stock s on date t. The equally-weighted portfolio return on date t is:

$$\frac{\sum_{s=1}^{n_t} x_{s,t-1} R_{s,t}}{\sum_{s=1}^{n_t} x_{s,t-1}}, \tag{4}$$

where n_t is the number of stocks in the portfolio on date t. 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. Each portfolio yields a daily return $R_{p,t}$. We calculate the risk-adjusted returns using the CAPM, the Fama-French three-factor model, and the Carhart four-factor model.

Table 7 presents our results with annualized alphas. For the 30-day holding period, the difference in alphas is around 10% 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 decreases to about 9% and 5% for 60- and 120-trading day holding period, respectively. Nevertheless, the difference in alphas is statistically significant at the one percent level. Overall, we conclude that slow-turnover analysts are able to generate investment returns for ordinary investors that are well beyond analysts who make more recommendation revisions.

[Insert Table 7 about here]

3.5 Timing of a recommendation revision with respect to news arrival

This section investigates the source of differing investment values between slow versus fast recommendation-revising analysts. We focus on when analysts' recommendation decisions are made relative to news arrival. We are motivated by the finding in Table 5 that slower-revising analysts tend to be a leader in recommendation changes. Instead of which analysts lead (or follow) others in recommendation changes, we examine whether their recommendations tend to front-run news, influence news, or piggy-back on news.

When analysts revise their stock recommendations greatly matters for investors who follow their stock experts' decisions. In virtually all event-based trading rules, the strategy becomes less profitable if the decision maker delays in reacting to the event. Therefore, one might hypothesize that analysts' stock picking ability is determined by how quickly they react to news. However, Altinkiliç and Hansen (2009) argue that analysts who revise their recommendations following news are simply piggy-backing on public information, which make them falsely appear to be informative. Therefore, a truly talented analyst should not need to rely on public information when revising his stock recommendations, but rather, his decisions should precede or influence the news in the stock market.

We identify news arrival that is value-relevant to the stock market as the day when stock price change is visibly large, i.e., when stock price "jumps". Formally, we apply the method of Loh and Stulz (2011) to detect daily returns of each security that are outliers, in a sense that they cannot be explained by the firm's current volatility level.

For each day t, the security is marked as having a news arrival if the magnitude of its 1-day buy-and-hold DGTW-adjusted returns exceeds $1.96 \times \sigma_\varepsilon$, where σ_ε is the idiosyncratic volatility calculated using the Carhart 4−factor model over the $[-60, -5]$ days relative to day t. Following Loh and Stulz (2011), 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. The scaling of daily return by its volatility level controls for firm-level uncertainty that could be responsible for large price fluctuations. The procedure is repeated for all stocks in our sample and for all valid trading days between 1996−2012. Using this method, we observe, on average, one news-arrival-day per month for each security.

We examine whether analysts' recommendations tend to front-run news, influence news, or piggy-back on news using a probit model. Table 8 reports the results. Our independent variable of interest here is *Recommendation Speed-style*, which classifies each analyst annually from 1996–2012 as either a (1) Slow-turnover analyst, (2) Average-turnover analyst, or (3) Fast-turnover analyst.

In the first specification, we estimate the likelihood that a recommendation change *leads* news arrivals. The dependent variable is an indicator function that is equal to one if we observe a news arrival, i.e., "jump", in the (+2, +7) days after the recommendation date, and zero otherwise. We find the coefficient on *Recommendation Speed-style* is negative and highly significant (t-stat of −14.7). This suggests that slower-revising analysts are more likely to revise their recommendations before news arrivals, which could explain why their recommendations generate a larger real-time portfolio alpha as reported in Table 7. We do not find that analyst's *All-star* status and *General experience* are associated with the likelihood that his recommendations will front-run news. However, we find the coefficient on the dummy variable *Downgrade* to be negative and significant. This suggests that on average, a recommendation upgrade is more likely to precede large stock price changes rather than a recommendation downgrade.

[Insert Table 8 about here]

In the second specification, we estimate the likelihood that a recommendation change *influences* news arrivals. The dependent variable is an indicator function that is equal to one if we observe a stock price jump in the (0, +1) days relative to the recommendation date, and zero otherwise. In this case, we interpret a recommendation change to be influential because it generates visibly large immediate stock market reaction (Loh and Stulz, 2011). The row labeled *No. of events* in Table 8 indicates the number of recommendation changes that are accompanied by news (or "jumps"). Out of 145,252 recommendations, we find that 30,306 of them are influential, which translates to about 20%. This finding is in line with Bradley et. al (2014). We find the coefficient on *Recommendation Speed-style* is negative and significant. Therefore, recommendations of slower-revising analysts are more influential and likely to influence news than those of faster-revising analysts. Consistent with Loh and Stulz (2011), we also find that All-star analysts are more influential.

The third specification in Table 8 examines the likelihood that a recommendation change *follows* news arrivals. We do not find that analysts' recommendation speed-style determines the likelihood that their recommendations will piggy-back on news.

Overall, Table 8 shows that slow-turnover analysts generate greater investment values for investors because their recommendations are likely to lead other price-relevant news, i.e., front-run news. Further, recommendation changes of slow-turnover analysts are more influential in a sense that they carry more pricing-relevant new information to the market.

4. Understanding analysts' decision-speed style

In this section, we link our results to existing literature. We examine in more details the role of analysts' experience on their decision-speed style. After, we explore alternative explanations for the decision-speed choice of sell-side analysts. Finally, we reconcile our results with the existing literature.

4.1 Recommendation speed and experience

Results from the multivariate probit model in Table 4 show that among analyst various characteristics, *General Experience* is the most significant determinant of their decision-speed style. We argue that this strong result is consistent with the prediction in Prendergast and Stole (1996).

Prendergast and Stole (1996) show that when individuals (e.g., sell-side analysts) worry that the decisions they make reflect their ability to learn, they will initially overreact by responding too much to new information to show that they are quick learners. However, after some period, they will revise their decisions less often, or too little, because such revisions suggest that their previous decision was wrong. In the analyst context, their study would predict that an analyst will revise his recommendations too often at the start of his career, but this decision-speed would decrease as his career tenure increases. The key distinction between the early- and late-career periods is that in the latter period, the analyst has already made previous (and several) stock recommendations. Therefore, any recommendation changes that he subsequently makes are an indication of the quality of both his previous and current information. In other words, an analysts with longer career tenure is more likely concerned that by revising his decisions too quickly, h indicating that his previous decisions were often wrong.

We examine the empirical predictions of Prendergast and Stole (1996) in Table 9. In Panel A, we sort analysts annually into three equal groups based on their career tenure ("Young", "Mid-career", and "Old") and report cross-sectional snapshots of their speed-style distribution at four different time points: 1996, 2000, 2005, and 2010.

[Insert Table 9 about here]

Panel A shows the probability that "young" analysts are classified to the fast-turnover group is between 22.1–25.7%, while the probability that "young" analysts are classified to the slow-turnover group is only between 3.3–8.0%. We therefore find that younger (older) analysts are always disproportionately classified to the fast-turnover (slow-turnover) group. This evidence shows that analysts usually begin their career with a fast decision-speed style, and that the results hold at different points in our sample period. In other words, our findings are not driven by business-cycle or when analysts begin their career.

We next show that analysts will make slower recommendation decisions as their career tenure increases. Panel B of Table 9 reports the results. Here, we consider a survival-bias-free panel of 189 analysts who were ranked in the least general-experience tercile in 1996 (i.e., young analysts) and consecutively appear in our classification until 2005. We label these 189 analysts as "Then–young" in the year 1996. We report their distribution grouped by recommendation turnover type (i.e., fast, average, or slow). We follow these analysts over the next ten years and report their distribution again in year 2000, during their "Mid-career," and again in year 2005, when they are "Now-old." Overall, using a control sample of analysts that consecutively appear in the data, Panel B shows a tendency for analysts to become slower recommendation-changers as their career tenure increases. Overall, the results in Table 9 support the empirical predictions of Prendergast and Stole (1996).

Although we find strong evidence that experience drives analysts to make slower decisions, analysts' experience does not predict their ability to move prices. We explore the difference in investment value of analysts' decision-speed style versus their career tenure in the Appendix Table A1. Here, we report BHAR(−1,+1) relative to the date of recommendation changes. Panels A and B report results for upgrades and downgrades, respectively. Looking at the results of all analysts sorted by their *General experience*, we find no distinct pattern between analysts' experience and their recommendation's influence. We further double-sort analysts based on their experience and decision-speed style into 3–by–3 groups. We find very robust results that recommendations issued by fast-turnover analysts are heavily discounted regardless of their experience level. The differences in BHAR(−1,+1) between fast- vs. slow-turnover analysts are all greater than 100 bps. On the other hand, among the average-turnover analysts, which correspond to those that do not have extreme decision-speed style, we find that more experienced analysts have less ability to move prices.[19] This finding echoes the result in Table 5 which finds that, all else equal, *General experience* negatively affects the stock market reactions to recommendation changes.

Overall, we find that experience significantly drives analysts' decision speed, which is consistent with the prediction in Prendergast and Stole (1996). However, while these two characteristics strongly correlate, we emphasize that decision-speed is the only characteristic that robustly predicts the investment value of analysts' recommendations. In other words, older and more experienced analysts provide better stock recommendations only if they also take more time between recommendation decisions.

4.2 Alternative hypotheses

Besides the reputational effects that may cause an analyst's revision speed-style to decrease over time, prior research in behavioral organization (Sparrow and Davies, 1988; Avolio, Waldman, and McDaniel, 1990) shows that speed and dexterity of non-managerial workers often decline with age and experience. Therefore, declining mental dexterity could explain why older analysts make slower recommendation decisions. We do not believe this hypothesis holds in our case. Slow-turnover analysts make superior and timelier investment decisions relative to fast-turnover analysts. They also tend to issue more frequent earnings forecasts on their covered firm. These results suggest the decrease in their recommendation speed is not due to a decline in dexterity or skill.

Another potential factor affecting analysts' recommendation speed-style is the trade-generating motive. Jackson (2005), and Cowen, Groysberg, and Haley (2006) argue that besides underwriting activities, sell-side analysts are incentivized by their ability to

[19] Loh and Stulz (2011) also find that recommendations issued by more experienced analysts are less likely to be influential as measured by their ability to generate visibly large price movement.

generate trading commissions for their brokerage firms. While we cannot directly measure an analyst's trade-generating motive, Jackson (2005) shows that trade-generating incentive is most positively correlated with analysts' optimism. Table 4 shows that the coefficients related to analysts' optimism, i.e., *Recommendation optimism* and *EPS optimism*, are not significant. These results suggest that analysts' decision speed-style is not driven by their incentives to generate trading commissions.

Finally, a possible explanation to why an analyst may revise his recommendation more slowly is due his *increasing inattention* associated with a larger number of stocks that he actively covers. We reject this hypothesis because we find in Table 4 that, all else equal, slower recommendation-revising analysts cover significantly less stocks than fast recommendation-revising analysts.

4.3. Reconciliation with the literature

There exist few studies examining the investment value of analysts' recommendation speed-style. Hobbs et. al (2012) is the closest study to ours because they study recommendation frequency of individual analyst. In contrast to our results, they find superior portfolio performance formed following faster-revising analysts relative to slower-revising analysts. We discuss the difference between our method and theirs, which leads to opposite conclusions.

Our method for classifying analysts' decision speed-style differs from Hobbs et al. (2012) in two important aspects. First, their study measures analysts' decision-speed using only recommendations that are revised within 12 months. This filter eliminates about half of valid recommendation observations from the sample because the median recommendation, on average, remains in place for 11.20 months (see Table 1). This practice narrows down the sample to analysts who already revise their recommendations faster than the average population, or on stocks requiring frequent recommendation revisions. In fact, the average recommendation revision time in their sample is about five months, which is shorter than the 6.4 months revision time of fast-turnover analysts that we find in Table 2. Second, they identify recommendation speed-type of each analyst by averaging the time between his recommendation revisions *across all* the covered stocks. This simple averaging does not account for firm-level differences that may require analysts, in general, to revise their recommendation on each stock more quickly (or less often) than the other stocks. In contrast, our method sorts the time between recommendation revisions at the stock level before aggregating the results to compute the decision-speed style of each analyst.

We replicate the methodology in Hobbs et al. (2012) and find about 10% correlation between our speed-style measure and theirs. We also calculate the transition probability matrix of being classified to their (1) Slowest, (2) Average, and (3) Fastest recommendation-speed groups. Table A2 in the Appendix reports the results. We find the speed-type classification of Hobbs et al. (2012) is significantly less persistent than ours. For instance, looking at the 3-year transition probability, a slow-revising analyst in Year t can turn into a fast-revising analyst after 3 years with a probability of 24%—the same chance of being reclassified to the fast-revising speed group (23.9%). We further analyze the determinants of their recommendation speed-type and do not find that it is related to analysts' ex-ante measure of ability such as *General experience*, *All-star*, or *Breadth*. Panel B of Appendix Table A2 reports these results.

Using the classification method in Hobbs et al. (2012), we replicate the real-calendar time portfolio strategy over their sample period 1997–2007 and obtain a similar conclusion as theirs. That is, the portfolio formed following fastest-revising analysts' recommendations outperforms the portfolio formed following recommendations of slower-revising analysts by about 50 bps in risk-adjusted returns per month. Hobbs et al. (2012) explain why they find analysts who frequently revise their stock recommendations outperform those who do not. They show that much of their advantage derives from reacting quickly to abnormal trading activity.[20] In other words, analysts in the fastest group identified by their methodology are those who are quickest to piggy-back on abnormal trading news, suggesting that their recommendations generate value from the subsequent price drifts. In an additional test, we find faster-revising analysts are more likely to make recommendations following a jump in stock prices, i.e., news arrival. In summary, analysts who frequently revise their stock recommendations in Hobbs et al. (2012) appear to outperform those who do not because they are quick to piggy-back on abnormal trading activity (see also Altinkiliç and Hansen, 2009).

Concluding remarks

In this paper, we document significant variation in how frequently sell-side security

[20] See Table 9 in Hobbs et al. (2012).

analysts change their minds in issuing 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. We examine the determinants of analysts' decision-speed style and find strong evidence suggesting that it is related to analysts' ability. Less frequent recommendation revisers are more likely to be elected to All-star status, less likely to be terminated, and less likely to herd on the recommendation consensus. Although slower to revise their stock picks, recommendations of slower-revising analysts tend to lead other recommendation changes and front-run large stock price moves. These findings suggest the slower-decision style reflects analysts' ability to make more "deliberate" and better recommendation decisions.

We find strong evidence suggesting that analysts' career tenure affects their decision-speed style consistent with the prediction in Prendergast and Stole (1996). While we find that security experts are slower to change their opinions as they become more experienced, 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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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 data base.	I/B/E/S
Recommendation optimism	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 Appendix B.	I/B/E/S
Recommendation boldness	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 Appendix B.	I/B/E/S
All–star	Dummy variable equal to one if an analyst is elected to the *Institutional Investor's* All-American team annual rankings.	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 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
Coverage redundancy	The number of distinct analysts covering a stock on a given year, averaged over all stocks an analyst covers that year. The larger value indicates that his stocks coverage is more redundant.	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 Appendix B.	I/B/E/S

Appendix A: List of Variables

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 Appendix B 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 Appendix B 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	Number of calendar days between the current recommendation revision and when it was last revised.	I/B/E/S
Log (#days since last recommendation)	Log of number of calendar days since the recommendation was revised to the current date.	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 B: Variable constructions for selected analyst characteristics

Recommendation boldness measures the fraction of recommendation changes that move away from the consensus in the spirit of Jegadeesh and Kim (2010). A recommendation is considered to be away from the consensus if its rating scale changes in the direction away from the recommendation consensus. We calculate recommendation consensus as the mean of outstanding recommendations issued on each stock, excluding an analyst's own recommendation level. We calculate the boldness of an analyst using all recommendation changes from January to December of each year. In few situations when an analyst makes less than four recommendation changes in the year, we extend the sample back by one year to increase the sample size.

Recommendation optimism is the average number of an analyst's new recommendation changes in each calendar year that are above the consensus. Following prior literature such as Hong and Kubik (2003), and Malmendier and Shanthikumar (2014), we consider a recommendation that is above the consensus to be optimistic. We exclude analyst's own recommendation level on a stock when calculating its recommendation consensus. To calculate *Optimism* at the analyst-year level, we assign a dummy variable equal to one to each new recommendation that is optimistic, and zero otherwise. We then calculate the average value of all recommendation-level optimism dummies associated for each analyst during the calendar year.

EPS Precision is defined following Clement and Tse (2005), and Bae, Stulz and Tan (2008). It measures the accuracy of an analyst's earnings forecasts relative to other analysts providing forecasts on the same firm–quarter. EPS Precision of an analyst i on firm j for the fiscal quarter Q is calculated as

$$EPS\ Precision_{i,j,Q} = -1 \times \frac{AFE_{i,j,Q} - \overline{AFE_{j,Q}}}{\overline{AFE_{j,Q}}},$$

where $AFE_{i,j,Q}$ is the absolute forecast error of analyst i forecasting firm j's fiscal quarter Q earnings, and $\overline{AFE_{j,Q}}$ is the average absolute forecast error across all analyst forecasts of firm j's fiscal quarter Q earnings. As explained in Clement (1999), we subtract $AFE_{i,j,Q}$ by $\overline{AFE_{j,Q}}$ to adjust for the firm–year effect. The difference is then deflated by $\overline{AFE_{j,Q}}$ to correct for heteroskedasticity in forecast error distribution. After, we multiply this figure by (-1) so that a higher value of this variable indicates higher precision of an analyst's forecasts.

EPS optimism is the average number of quarterly earnings forecasts of an analyst that are above the consensus, excluding the analysts' own previous forecast level (Malmendier and Shanthikumar, 2014). We assign a dummy variable equal to one to each forecast made by an analyst that is optimistic, and zero otherwise. We first calculate *EPS optimism* at the analyst–stock–year level using all his quarterly forecasts in a given year. After, we average the results across all stocks that analyst i covers to produce *EPS optimism* at the analyst–year level.

Leader–follower ratio (LFR) measures the average timeliness of an analyst's 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 the method that they developed to analysts' recommendation revisions. *LFR* is calculated as the ratio of the cumulative lead-time, T_0, over the cumulative follow-time, T_1, for the K recommendation changes made by a given analyst. The cumulative lead-time and the cumulative follow-time for K recommendation changes are calculated as:

$$T_0 = \sum_{k=1}^{K} \sum_{i=1}^{L_k} t_{ik}^{0}\ ; \quad \text{and} \quad T_1 = \sum_{k=1}^{K} \sum_{i=1}^{F_k} t_{ik}^{1}.$$

We let t_{ik}^0 and t_{ik}^1 denote the number days by which the k^{th} recommendation change of the selected analyst is either preceded or followed by the recommendation i of another analyst. We denote L_k and F_k as the number of recommendations that lead and follow the k^{th} recommendation change of the selected analyst, respectively. In order to exclude revisions that are earnings-news motivated, we remove recommendation changes of the selected analyst that are made within +/–15 calendar days of the firm's earnings announcements. Further, when a recommendation of the selected analyst is the same day as a recommendation of another analyst, it is excluded because we cannot precisely determine which ones come first. These two filters eliminated about 35% of recommendation changes from the sample. Finally, for the calculations of T_0 and T_1, we use only recommendations made by other analysts that are within +/–7 calendar days with respect to the k^{th} recommendation change of the selected analyst. The larger the value of T_0, and the smaller the value T_1, indicate that recommendation changes made by the selected analyst are not likely to follow other recommendations, but are followed by other analysts, i.e., the analyst is a recommendation leader. Therefore, a large value of $LFR = T_0 / T_1$ indicates the analyst, on average, issues more timely recommendation changes. We calculate the *LFR* for each analyst at the end of each year using all recommendation changes from the current and previous year. Finally, the *LFR* values are winsorized at the 1st and the 99th percentile to limit outliers.

Herfindahl-Hirschman index (HHI) is a measure of the industry concentration of an analyst's portfolio. Following Sonney (2007), we use the first digit SIC code to classify industries. An *HHI* score of one indicates that all stocks covered by an analyst's portfolio are from the same industry, and a higher value of *HHI* indicates that the analysts' coverage is more dispersed across industries. *HHI* is calculated for each analyst as $\sum_i (N_i/N)^2$, where N_i is the number of stocks covered in industry i and N is the total number of stocks covered. The squared ratio, $(N_i/N)^2$, is summed over all industries.

Appendix C: Bias–corrected time between recommendation revisions

Let y_i for i = 1...n represent the time between an analyst's $i-1$and i recommendation revisions. We assume that y_i follows a Poisson distribution with the density

$$f(y_i) = \frac{\lambda^{y_i} e^{\lambda}}{y_i!},$$

where λ is the intensity of time between revisions. Intuitively, the intensity parameter represents the expected time between revisions. The cumulative probability of observing n revisions, each with a revision time of y_i is then given by $F(n) = \sum_{i=1}^{n} f(y_i)$.

Let c be the time from the last observation to the right truncation point. The probability of *not* observing any recommendation change from the n^{th} revision to the right truncation time is

$$Pr(y_{n+1} > c) = \sum_{j=c}^{\infty} f(y_{n+1} = \mathrm{j})$$
$$= 1 - \sum_{j=0}^{c-1} f(y_i) = 1 - F(c-1).$$

The log–likelihood of observing n recommendation changes, with times between revisions of $y_1, y_2, \ldots y_n$ followed by an idle time c between the n^{th} revision and the right–truncated time point is

$$\mathcal{L}(\lambda) = \sum_{j=1}^{n} f(y_i) + log(1 - F(c-1)).$$

Maximizing the above log–likelihood equation with respect to the intensity parameter λ yields the following solution

$$\lambda = \frac{\sum_{j=1}^{n} y_i}{n} + \frac{c}{n} \cdot \frac{f(c)}{1 - F(c-1)}. \qquad \text{(A.1)}$$

Note that when c is equal to zero, there is no right–truncation issue. In this case, the expected time between recommendation revisions λ is simply the total time from the coverage initiation to the last recommendation revision, $\sum_{j=1}^{n} y_i$, dividing by the number of revisions made. However, when there is a significant idle time c between the last observed recommendation revision and the right truncation point, the expected time between revisions will be greater than the naïve calculation of $\frac{1}{n}\sum_{j=1}^{n} y_i$.

In this paper, we estimate λ for all analyst–stock pairs in the sample at the end of each year using equation (A.1). The estimates of λ are then used as the average times between recommendation revisions.

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 2012. 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. *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). Heteroskedasticity-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*		
	Younger	Mid-career	Older	Older – Younger p–value	Non-star	All-star	All-star – Non-star 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*		
	Younger	Mid-career	Older	Older – Younger p–value	Non-star	All-star	All-star – Non-star 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

Recommendation change Frequency: Hobbs et al. (2012) method

We replicate the method of classifying analysts' recommendation frequency following Hobbs et al. (2012). The two panels below summarize analysts. Groups (1) and (3) refer to analysts ranked in the slowest and fastest quintiles. Group (2) refers to analysts ranked in the second, third and fourth quintiles based on recommendation frequency. Panel A reports probability transition matrices of the analysts' recommendation-speed type. Panel B reports estimates from ordered probit model for the determinants of analysts' recommendation-speed type based on Hobbs et al. (2012). All independent variables in Panel B are defined in Appendix A.

Panel A. Transition matrix based on the Hobbs et al. (2012) classification

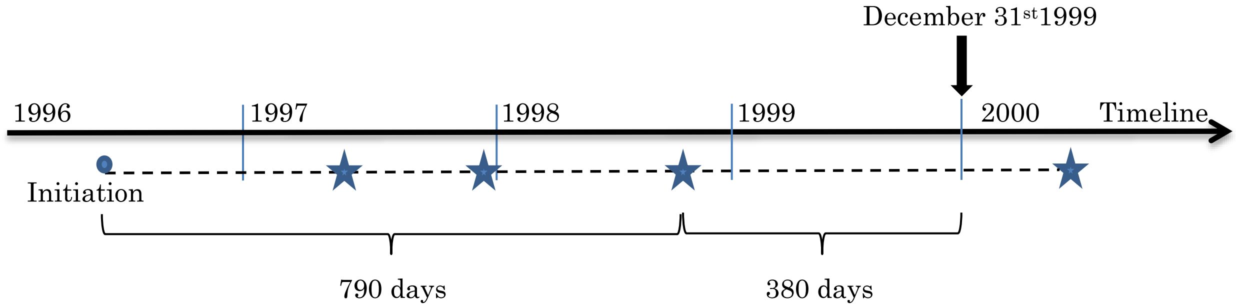
		Speed type: Year t+1			Speed type: Year t+3		
		(1) Slowest	(2) Middle	(3) Fastest	(1) Slowest	(2) Middle	(3) Fastest
Speed Type:	(1) Slowest	40.7%	42.4%	16.9%	23.9%	52.1%	24.0%
Year t	(2)	18.6%	63.9%	17.4%	21.5%	56.8%	19.8%
	(3) Fastest	14.2%	47.6%	38.1%	22.2%	55.9%	21.9%

Panel B. Ordered probit model of analyst recommendation frequency based on Hobbs et al. (2012)

	Dependent variable: Probability of being classified as Slow (1) to Fast (3) Recommendation changer
General experience	0.000
	(0.003)
Breadth	0.004
	(0.003)
All-star	0.017
	(0.030)
Male	−0.001
	(0.029)
Top broker	−0.058**
	(0.027)
Recomm boldness	−0.065
	(0.051)
Recomm optimism	0.041
	(0.047)
EPS optimism	−0.008
	(0.008)
EPS precision	0.012
	(0.008)
Forecast frequency	−0.157***
	(0.034)
Lead/follow ratio (LFR)	−0.009**
	(0.004)
Industry concentration (HHI)	−0.001**
	(0.001)
Year fixed effects	Yes
Brokerage fixed effects	Yes
Pseudo R-square	45.3%
Nobs.	17,566

Figure 1

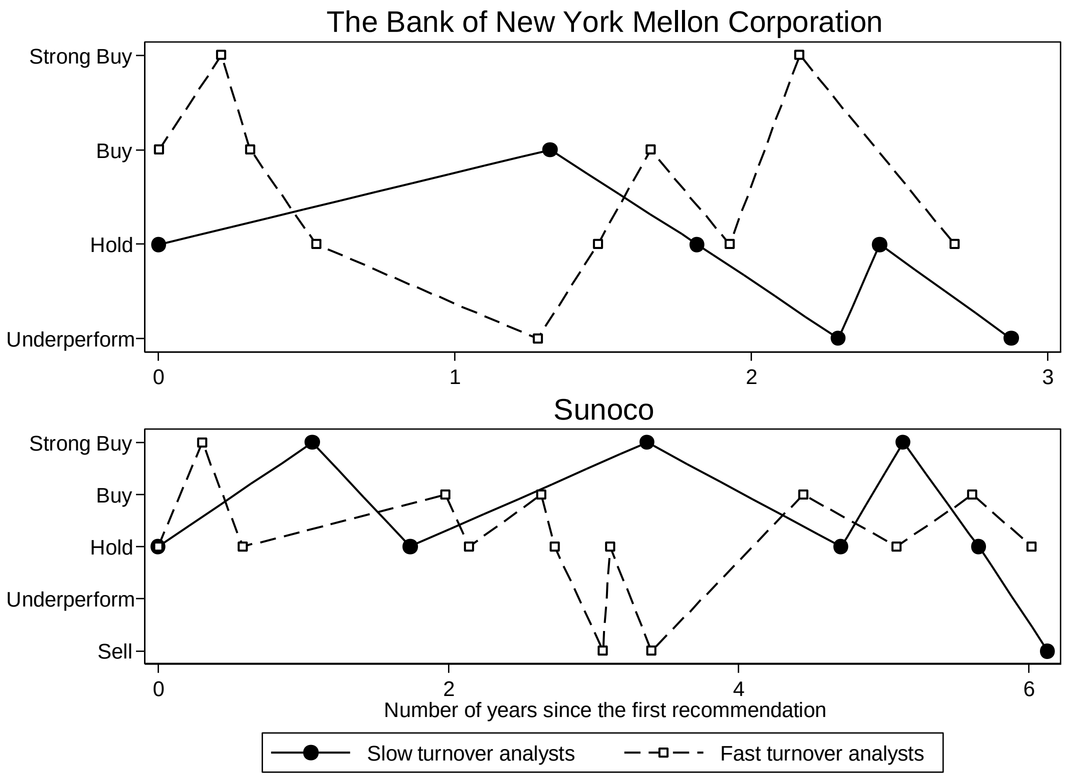
Correction for bias due to right–truncation



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 Appendix **B**, we show how to adjust for the right-truncation bias by estimating a Poisson-likelihood model.

Figure 2

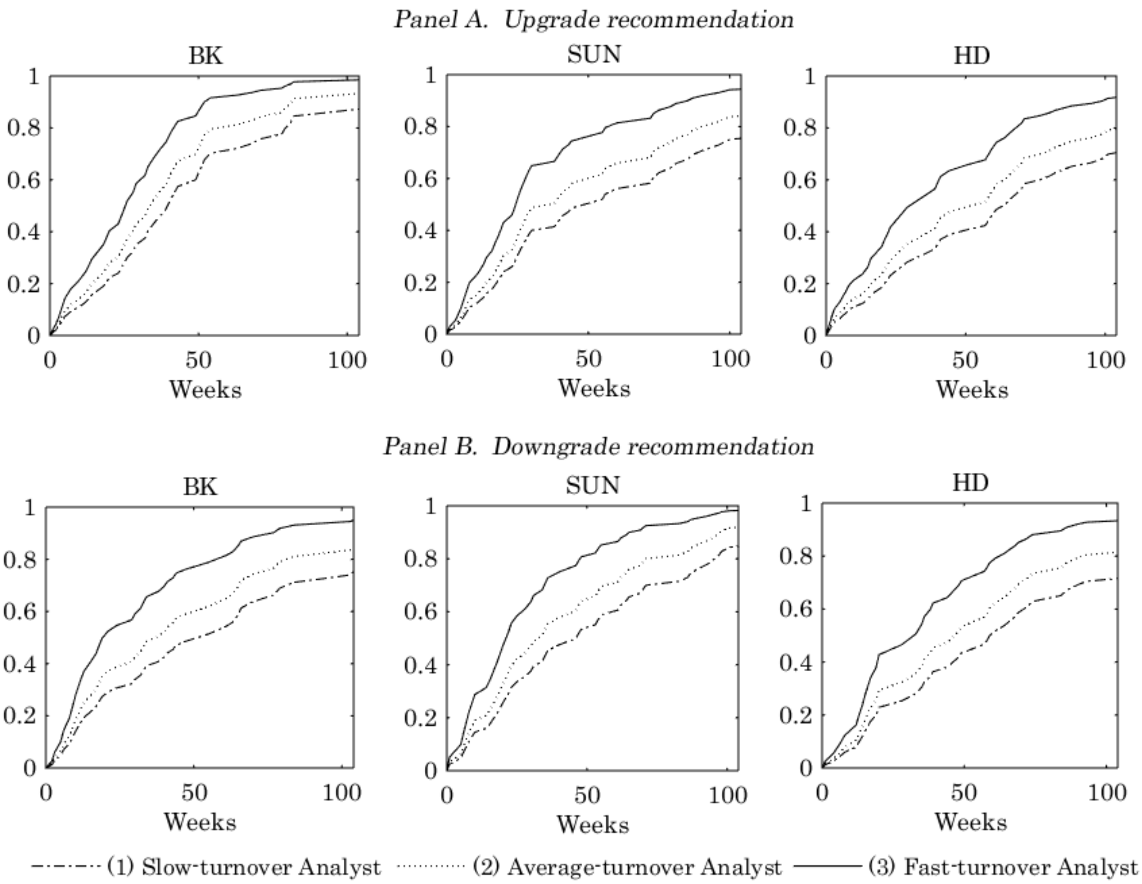
Slow vs. Fast recommendation turnover analysts: Examples



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. We classify analysts in our sample at the end of the calendar year from 1996 through 2012. See text for more details. The x-axis represents the number of years elapsed since an analyst made his first recommendation on that stock.

Figure 3

Cumulative probability of a recommendation revision and decision speed-style



This figure plots the cumulative probability that analysts with different decision speed-styles will revise their recommendations as a function of weeks since their last recommendation revision. We plot results for three sample firms: The Bank of New York Mellon (BK), Sunoco (SUN), and Home Depot (HD). The cumulative probability of a recommendation revision is calculated using estimates from the Cox proportional hazard model in Table 3. We use estimates reported in Columns (2) and (5) of Table 3 for upgrades and downgrades, respectively. For each firm, time-varying covariates in the hazard-rate model are set equal to their sample means. Fixed effects are set equal to their reference levels. Panel A (Panel B) reports results for downgrade (upgrade) revisions. The x-axis in each panel indicates the number of weeks since the analyst's last recommendation change. The y-axis indicates the probability that the analyst will have revised her recommendation after a certain number of weeks have passed. Each panel plots hazard rates across three analyst recommendation speed-styles: Slow-, Average-, and Fast-turnover. The hazard rates are calculated using results from Table 3 corresponding to estimates in Column (2) for upgrades and Column (5) for downgrades.

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 2012. 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 1996–2012, resulting in 24,042 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. *Time a recommendation is in place* is the average 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	6.57	6.00	3.80	0.00	4.00	9.00	18.00
Stock coverage	6.91	6.00	3.95	3.00	4.00	9.00	70.00
All-Star	0.16	0.00	0.37	0.00	0.00	0.00	1.00
Male	0.89	1.00	0.32	0.00	1.00	1.00	1.00
Top broker	0.41	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	0.43	0.42	0.22	0.00	0.28	0.56	1.00
EPS optimism	0.48	0.48	0.15	0.00	0.39	0.58	1.00
EPS precision	0.00	0.03	0.26	−8.08	−0.10	0.14	1.00
Forecast frequency	1.78	1.83	0.35	1.00	1.58	2.03	2.50
Leader-follower ratio (LFR)	2.01	1.00	4.20	0.01	0.50	2.00	52.00
Industry concentration (HHI)	5.10	1.88	7.31	0.22	1.00	5.06	28.44
Time a recommendation is in place (months)	12.36	11.20	5.30	0.83	7.85	14.75	46.30

Table 2

Descriptive of the 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 1996–2012. We characterize each revision as an upgrade or downgrade by comparing the revised recommendation with the previous active recommendation for the stock by the revising analyst. Revisions that are neither upgrades nor downgrades, i.e. reiterations, are excluded. We eliminate mechanical recommendation changes due to the migration of a five-tier rating system to a three-year rating system in 2002 (see Kadan et al. (2009)). We apply additional filters to remove stale recommendations; see text for further details. For each year from 1996 through 2012, 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. Section 2.2 in the main text describes the full methodology. Panel A reports the number 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. We correct for the right-truncation bias when calculating time between recommendation revisions at the analyst-stock pair level. See text for more details. Panel C reports the transition probability matrices of analysts' turnover classification from Year t to Year t+1, and from Year t to Year t+3.

Panel A. Distribution of analysts in the recommendation turnover grouping by year

Year	Total	Number of analysts in each group		
		(1) Slow turnover analyst	(2) Average turnover analyst	(3) Fast turnover analyst
1996	521	69	391	61
1997	816	138	591	87
1998	934	193	651	90
1999	1,106	241	765	100
2000	1,297	293	868	136
2001	1,327	281	909	137
2002	1,336	269	942	125
2003	1,602	285	1,104	213
2004	1,714	282	1,204	228
2005	1,692	306	1,186	200
2006	1,704	348	1,175	181
2007	1,699	365	1,184	150
2008	1,650	411	1,113	126
2009	1,638	374	1,117	147
2010	1,654	377	1,091	186
2011	1,650	390	1,094	166
2012	1,702	423	1,101	178
Overall	24,042	5,045	16,486	2,511

Table 2

Descriptive of the recommendation turnover classification (continued...)

Panel B. Bias-adjusted time between recommendation revisions (in months)

	Nobs	Mean	Median	Std. dev.	Min.	25th pct	75th pct	Max.
All analysts	24,042	13.4	12.4	6.1	1.0	9.0	16.6	56.6
Grouped by turnover classification								
(1) Slow-turnover	5,045	20.7	19.8	6.2	5.3	16.5	23.9	56.6
(2)	16,486	12.2	11.8	4.0	2.4	9.3	14.7	35.1
(3) Fast-turnover	2,511	6.4	6.2	2.4	1.0	4.7	7.8	20.8

Panel C. Transition matrix of analyst speed-style

		Turnover type: Year t+1			Turnover type: Year t+3		
		(1) Slow	(2)	(3) Fast	(1) Slow	(2)	(3) Fast
Turnover Type: Year t	(1) Slow	72.5%	27.3%	0.2%	62.4%	36.7%	0.9%
	(2)	12.0%	84.3%	3.7%	22.8%	73.7%	3.5%
	(3) Fast	0.5%	48.8%	50.7%	5.1%	70.1%	24.8%

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. Panels A and B report results for upgrade revisions and downgrade revisions, respectively. 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 $\lambda(t)$. We assume the hazard rate at which each recommendation will be revised follows a log-linear model:

$$\lambda(t\ ) = \lambda_{0,j}(t) \exp\left(\alpha_{Slow} Slow_a \ + \ \alpha_{Fast} Fast_a \ + \Sigma_i \ \beta_i X_{i,j}(t)\right).$$

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. The baseline hazard function for time to the next recommendation change is firm specific, and denoted by $\lambda_{0,j}(t)$ for firm *j*. We include firm-level, industry-level, and recommendation-level controls in the model; they are represented by $\Sigma_i \ \beta_i X_{i,j}(t)$ in the log-linear hazard rate model. Year-month 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 control variables are included as potential predictor of a recommendation change and are lagged by one period. *News intensity* is the number of firm-specific news observed in the previous week. We obtain news database from Capital IQ 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 2012. All other regression specifications are estimated using observations from 1996 through 2012. *Stock return* is the cumulative one-month buy-and-hold stock return observed in the previous week. *Industry return* is the cumulative one-month buy-and-hold return of the equally-weighted industry portfolio that stock *j* belongs to 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 stock and 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. *Breadth* is the number of firms that the analyst is actively covering. We control for previous-recommendation-level fixed effects using indicator variables *Last recom*. The estimate and the hazard ratio for each *Last recom* fixed-effect variable are reported and calculated relative to the reference "hold" recommendation level, i.e., 3 in the IBES code. *No observations* report the number of recommendation-week observations used in the estimation. *No events* report the number of recommendation revisions used in the estimation. Standard errors are reported in parentheses below each estimate. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3 (Continued…)
Hazard model for predicting time to the next recommendation change

	Panel A. Upgrade						*Panel B. Downgrade*						
	(1)		(2)		(3)		(4)		(5)		(6)		Prediction
	Estimate	HR	Estimate	HR	Estimate	HR	Estimate	HR	Estimate	HR	Estimate	HR	
Slow	**-0.273*****	**0.76**	**-0.268*****	**0.77**	**-0.324*****	**0.72**	**-0.293*****	**0.75**	**-0.286*****	**0.75**	**-0.325*****	**0.72**	**(−)**
	(0.013)		(0.014)		(0.019)		(0.011)		(0.013)		(0.018)		
Fast	**0.450*****	**1.57**	**0.446*****	**1.56**	**0.537*****	**1.71**	**0.482*****	**1.62**	**0.484*****	**1.62**	**0.584*****	**1.79**	**(+)**
	(0.012)		(0.013)		(0.018)		(0.011)		(0.013)		(0.017)		
Concurrent with earnings	1.317***	3.73	1.276***	3.58	1.184***	3.27	1.348***	3.85	1.310***	3.71	1.227***	3.41	(+)
	(0.011)		(0.012)		(0.017)		(0.010)		(0.011)		(0.015)		
News intensity					0.189***	1.21					0.211***	1.24	(+)
					(0.005)						(0.004)		
Stock return			1.093***	2.98	1.161***	3.19			-1.810***	0.16	-1.407***	0.25	(+ UPG / − DNG)
			(0.034)		(0.048)				(0.036)		(0.050)		
Industry return			-0.274***	0.76	-0.265***	0.77			0.302***	1.35	0.617***	1.85	(− UPG / + DNG)
			(0.038)		(0.050)				(0.029)		(0.041)		
Stock Volatility			-0.598***	0.55	-0.496***	0.61			-0.531***	0.59	-0.701***	0.50	(?)
			(0.044)		(0.057)				(0.033)		(0.050)		
Stock Volume (log)			0.284***	1.33	0.266***	1.30			0.286***	1.33	0.325***	1.38	(+)
			(0.008)		(0.012)				(0.007)		(0.011)		
Industry Volume (log)			-0.004	1.00	-0.001	1.00			-0.001	1.00	-0.016***	0.99	(?)
			(0.004)		(0.005)				(0.004)		(0.005)		
Price rel. to 52-week high			0.354***	1.43	0.174***	1.19			-0.753***	0.47	-0.639***	0.53	(+ UPG / − DNG)
			(0.030)		(0.040)				(0.028)		(0.039)		
# level up/down			-0.019*	0.98	-0.016	0.98			-0.073***	0.93	-0.003	1.00	(−)
			(0.010)		(0.013)				(0.010)		(0.015)		
Breadth			0.010***	1.01	0.017***	1.02			0.012***	1.01	0.018***	1.02	(+)
			(0.001)		(0.001)				(0.001)		(0.001)		
Last recom. = 1 ("Strong buy")							0.003	1.00	0.100***	1.11	-0.018	0.98	
							(0.012)		(0.014)		(0.019)		
Last recom. = 2 ("Buy")	0.116***	1.12	0.105***	1.11	0.063***	1.07	0.039***	1.04	0.062***	1.06	-0.020	0.98	
	(0.013)		(0.014)		(0.023)		(0.012)		(0.014)		(0.018)		
Last recom. = 4 ("Sell")	0.290***	1.34	0.297***	1.35	0.272***	1.31	0.401***	1.49	0.452***	1.57	0.467***	1.60	
	(0.014)		(0.015)		(0.019)		(0.052)		(0.056)		(0.068)		
Last recom. = 5 ("Strong sell")	0.478***	1.61	0.505***	1.66	0.486***	1.63							
	(0.018)		(0.020)		(0.025)								
No observations	3,514,093		3,099,084		2,657,573		4,982,312		4,377,867		2,438,053		
No of events	71,532		62,335		44,709		86,678		73,799		39,712		
Year-month fixed effects	YES		YES		YES		YES		YES		YES		

Table 4
Determinants of analysts' recommendation turnover

We report estimates from an ordered probit model on the likelihood that an analyst recommendation speed-style changes from (1) *Slow* to (2) *Average* to (3) *Fast*. The dependent variable of interest, i.e. analyst turnover, takes on an increasing integer value from 1 to 3. For each year from 1996 through 2012, we assign analysts into three groups: (1) Slow-turnover analyst, (2) Average-turnover analyst, and (3) Fast-turnover analyst. All analyst characteristics are calculated yearly for each analyst; see Appendix **A** for definitions. A positive (negative) and significant coefficient suggests the probability that an analyst is a fast (slow) recommendation changer is positively related to this variable. Year and brokerage fixed effects are included in the estimation. Robust standard error is reported in parenthesis below each estimate. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: Probability of being classified as Slow (1) to Fast (3) turnover analysts	
General experience	–0.122***
	(0.003)
Breadth	0.011***
	(0.003)
All-star	–0.118***
	(0.028)
Male	–0.009
	(0.027)
Top broker	–0.139***
	(0.024)
Recommendation boldness	–0.082**
	(0.044)
Recommendation optimism	0.050
	(0.040)
EPS optimism	0.043
	(0.058)
EPS precision	–0.010
	(0.007)
Forecast frequency	–0.049*
	(0.030)
Leader–follower ratio (LFR)	–0.023***
	(0.004)
Industry concentration (HHI)	0.001
	(0.266)
Year fixed effects	Yes
Brokerage-fixed effects	Yes
Pseudo R-square	0.677
Nobs.	22,310

Table 5
Stock price reactions to recommendation revisions

This table reports cumulative buy-and-hold abnormal returns following recommendation revisions. We characterize each revision as an upgrade or downgrade by comparing the revised recommendation with the previous active recommendation for the stock by the revising analyst. The sample consists of recommendation changes issued by the analysts in our classification sample (see Table 2) from 1996 through 2012. We compute H-day buy-and-hold abnormal returns (BHAR) from time t to time t+H as follows:

$$BHAR_i(t, t+H) = \prod_{\tau=t}^{t+H}(1 + R_{\mathrm{i},\tau}) - \prod_{\tau=t}^{t+H}(1 + R_{\mathrm{DGTW},\tau}),$$

where $R_{\mathrm{i},\tau}$ is the raw return on stock i on day τ, and $R_{\mathrm{DGTW},\tau}$ is the return of a benchmark portfolio with the same size, book-to-market (B/M), and momentum characteristics as the stock (DGTW, 1997). Panels A and B report average BHAR for upgrades and downgrades, respectively. We classify analysts by how fast they revise their recommendations relative to their peers. The classification is done at the analyst-year level and is based on analysts' past recommendation patterns. For each year from 1996 through 2012, 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. Heteroskedasticity-adjusted standard error is reported in parenthesis below each estimate. The last two rows in each panel report the difference and p–value of BHAR between slow- and fast-turnover analysts. ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Analyst classification	Nobs.	Number of trading days since recommendation revision					
		0	1	7	30	60	120
Panel A. Upgrade							
(1) Slow-turnover analyst	9,705	2.64%***	2.85%***	3.19%***	3.51%***	3.59%***	4.22%***
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
(2)	47,276	2.51%***	2.80%***	3.10%***	3.35%***	3.57%***	4.05%***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
(3) Fast-turnover analyst	11,299	1.87%***	2.18%***	2.39%***	2.41%***	2.43%***	2.29%***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Slow −Fast turnover		0.77%***	0.67%***	0.80%***	1.10%***	1.15%***	1.93%**
p-value		0.01	0.01	0.01	0.01	0.01	0.02
Panel B. Downgrade							
(1) Slow-turnover analyst	12,346	−3.13%***	−3.34%***	−3.56%***	−3.86%***	−4.35%***	−4.54%***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
(2)	57,297	−3.08%***	−3.31%***	−3.54%***	−3.75%***	−4.15%***	−4.41%***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(3) Fast-turnover analyst	12,668	−2.06%***	−2.22%***	−2.50%***	−2.55%***	−2.80%***	−3.32%***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Slow −Fast turnover		−1.07%***	−1.12%***	−1.07%***	−1.20%***	−1.55%***	−1.23%**
p-value		0.01	0.01	0.01	0.01	0.01	0.02

Table 6
Stock Price Reaction to Recommendation Changes: Regression analysis

This table presents panel regression results from examining the difference in immediate stock price reaction to recommendation changes made by *Slow-* vs. *Fast-turnover* analysts. The sample consists of recommendation changes issued by slow-turnover and fast-turnover analysts in our classification sample (see Table 2) from 1996 through 2012. The dependent variable is the buy-and-hold abnormal return (BHAR) from day −1 to day +1 centered on the date of the recommendation change. We calculate BHAR for stock i from day −1 to day 1 against the return of a benchmark portfolio with the same size, book-to-market (B/M), and momentum characteristics as the stock (DGTW, 1997). Revisions that are neither upgrades nor downgrades, i.e. reiterations, are excluded. Regression model (1) reports results for upgrades, while regression model (2) reports results for downgrades. The main independent variable of interest is *Slow vs. Fast analyst*, which is an indicator variable equal to one if the recommendation change is issued by a slow-turnover analyst, and zero otherwise. The coefficient estimate on this variable measures how the market reacts differently to a recommendation change of a slow-turnover analyst versus that of a fast-turnover analyst. We control for analyst-level characteristics, recommendation-level characteristics, and stock-level characteristics. *High EPS precision* is an indicator variable equal to one if the analyst's *EPS precision* level is ranked above the sample median in the previous year, and zero otherwise. *High EPS optimism* is an indicator variable equal to one if the analyst's *EPS optimism* level is ranked above the sample median in the previous year, and zero otherwise. All other control variables are defined in Appendix **A.** We include brokerage, industry, and year fixed-effects in the regression. Robust standard error adjusted for heteroskedasticity and clustered at the firm level is reported in parenthesis below each coefficient estimates. $*$, $**$, and$***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6 *(continued…)*

	Dependent Variable: BHAR(-1,+1)	
	(1) Upgrade	(2) Downgrade
Recommendation turnover		
Slow vs. Fast turnover analyst	0.519**	−0.764***
	(0.232)	(0.206)
Stock-level characteristics		
Size	−0.818***	0.430***
	(0.098)	(0.068)
Volatility	0.240***	−0.237***
	(0.068)	(0.060)
Institutional investor (quartiles)	−0.488***	−0.551**
	(0.141)	(0.224)
Analyst characteristics		
General experience	−0.078	0.101***
	(0.066)	(0.032)
All-star	0.570	0.004
	(0.555)	(0.258)
Male	0.191	0.350
	(0.221)	(0.296)
Breadth	−0.010	0.015
	(0.012)	(0.015)
High EPS precision	0.299**	−0.235*
	(0.179)	(0.169)
High EPS optimism	−0.172	0.277
	(0.207)	(0.175)
Recommendation-level characteristics		
# level up/down	1.118***	−1.203***
	(0.193)	(0.232)
Initial level	−0.333***	0.196
	(0.123)	(0.157)
Concurrent with earnings announ.	0.942***	−2.585***
	(0.284)	(0.309)
Earnings-related revision	−0.841***	0.687**
	(0.252)	(0.298)
Pre-earnings revision	0.547	0.743
	(0.387)	(0.606)
Away from consensus	0.499***	−1.098***
	(0.191)	(0.235)
Brokerage, Industry & Year fixed effects	Yes	Yes
Firm-level clustering	Yes	Yes
Nobs.	15328	17657
Adj. R^2	13.4%	13.8%

Table 7

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 2012. Portfolios are formed over the 1996–2012 period and their returns are calculated daily. Panels A, B, and C report annualized alphas of long-short portfolio returns with holding period of 30, 60, and 120 trading days, respectively. Within each panel, 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. In the last column, we report *p*–values associated with the test for the difference in portfolio alphas earned by investing following recommendation changes of slow-turnover analysts versus fast-turnover analysts.

	Slow-turnover analyst		Fast-turnover analyst		Slow vs. Fast
	Alpha	*t*-stat	*Alpha*	*t*-stat	(*p*-value)
Panel A. 30-day holding period					
Market-adjusted	29.2%	9.95	19.30%	7.48	0.006
Fama French three-factor	29.0%	9.89	19.38%	7.51	0.007
Carhart four-factor	27.1%	9.53	18.13%	7.14	0.010
Panel B. 60-day holding period					
Market-adjusted	23.1%	10.45	13.76%	7.15	0.001
Fama French three-factor	23.0%	10.39	13.76%	7.14	0.001
Carhart four-factor	21.1%	10.09	12.43%	6.68	0.001
Panel C. 120-day holding period					
Market-adjusted	15.4%	9.47	10.27%	7.25	0.009
Fama French three-factor	15.4%	9.50	10.22%	7.21	0.008
Carhart four-factor	13.9%	9.19	9.08%	6.73	0.009

Table 8
Timing of recommendation changes

This table reports results examining the timing of analyst recommendation changes relative to news arrival using the Probit model. We define news as a visibly large stock price change, i.e., "jump", that cannot be explained by the firm's current volatility level. The method that we use follows that of Loh and Stulz (2011). On each day, buy-and-hold adjusted stock return is scaled by its recent volatility estimate. A daily scaled return that exceeds the 5% rejection criterion is considered to be visibly large and corresponds to a price-relevant news arrival, i.e., there is a jump in the stock price. The dependent variables in the regression specifications below are an indicator variable that is equal to one when a recommendation change is: (1) Leading news, (2) Influencing news, (3) Following news. A recommendation change is *leading news* if we observe news arrival in the (+2, +7) days after the recommendation date. A recommendation change is *influencing news* if we observe news arrival contemporaneously with the recommendation date, i.e., (0, +1) days. A recommendation change is *following news* if we observe news arrival in the (+7, +2) days before the recommendation date. The main variable of interest is the *Recommendation Speed-style*, which classifies each analyst annually from 1996–2012 as either a (1) Slow-turnover analyst, (2) Average-turnover analyst, or (3) Fast-turnover analyst. *Downgrade* is a dummy variable equal to one if the recommendation change is a downgrade, and zero otherwise. All other variables are defined in Appendix **A**. *No. Of events* refers to the number of news arrival observed in each probit model, i.e., when the dependent variable is equal to one. Year, industry, and brokerage-fixed effects are included in the estimation. Robust standard error is reported in parenthesis below each estimate. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Probit model for the likelihood that a recommendation is:		
	(1) Leading news	(2) Influencing news	(3) Following news
Recommendation Speed-style	−0.250***	−0.076***	−0.004
{ (1) Slow, (2), (3) Fast }	(0.017)	(0.014)	(0.016)
All-star	−0.007	0.028**	0.017
	(0.029)	(0.012)	(0.027)
General experience	−0.004	0.009	0.017***
	(0.003)	(0.006)	(0.003)
Breadth	−0.009***	0.001	−0.001
	(0.002)	(0.002)	(0.002)
Downgrade	−0.047***	0.057***	−0.064***
	(0.017)	(0.013)	(0.015)
Year and Ind fixed effects	Yes	Yes	Yes
Brokerage fixed effects	Yes	Yes	Yes
Pseudo R-square	50.6%	36.4%	46.4%
No of events	17037	30306	20708
Nobs.	145,252	145,252	145,252

Table 9

Analysts' experience and decision-speed style

This table examines the impact of analysts' experience on their decision-speed style through time. First, we show that analysts with less (greater) career experience are likely to be fast (slow) recommendation changers, and that this relationship holds throughout the sample period (Panel A). Second, we show that analysts, on average, become slower recommendation changers as their career tenure increases (Panel B). We consider analysts that are in the classification sample (see Table 2) from 1996 through 2012. In Panel A, we report the distribution of analysts' recommendation turnover type (i.e., fast, average, or slow) grouped by career experience ("Young" or "Old") at four different time points: 1996, 2000, 2005, and 2010. We label analysts as "Young" (or "Old") if their general experience is ranked in the lowest (highest) tercile of the analyst population in a given year. In Panel B, we consider a balanced panel of 189 analysts who were ranked in the lowest experience tercile in 1996 and consecutively appear in our classification until 2005. We label these 189 analysts as "Then-young", in the year 1996. We report their distribution grouped by recommendation turnover type (i.e., fast, average, or slow). We follow these analysts over the next ten years and report their distribution again in year 2000 during their "Mid-career", and again in year 2005 when they are "Now-old". We label these analysts as "Now-old" after ten additional years of experience. Overall, using a control sample of analysts that consecutively appear in the data, Panel B shows a tendency for analysts to become slower recommendation changers as their career tenure increases.

Panel A. Cross-sectional snapshots of the full sample: 1996, 2000, 2005, 2010

	1996		2000		2005		2010	
Analyst classification	Young	Old	Young	Old	Young	Old	Young	Old
(1) Slow-turnover	7.9%	21.3%	3.3%	32.9%	4.4%	36.7%	8.0%	34.8%
(2)	70.0%	73.3%	73.0%	62.9%	69.9%	59.3%	68.4%	61.6%
(3) Fast-turnover	22.1%	5.4%	23.7%	4.2%	25.7%	4.0%	23.7%	3.6%

Panel B. Cross section of analysts that consecutively appear in the sample between 1996 and 2005

Analyst classification	1996	2000	2005
	"Then-Young""	"Mid-career"	"Now-old"
(1) Slow-turnover	15.3%	25.7%	37.2%
(2)	72.7%	69.9%	59.6%
(3) Fast-turnover	12.0%	4.4%	3.3%