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

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Abstract

There are significant differences among sell-side analysts in how frequently they revise recommendations. We show that much of this variation is an analyst-individual trait. Analysts who change recommendations more slowly make recommendations that are more influential and generate better portfolio returns. Slower-revising analysts tend to change recommendations following corporate news that are harder to interpret by nonstock experts, and our evidence suggests that their investment value derives from their ability to better interpret hard-to-assess information. On average, analysts change recommendations less frequently as their career progresses; however, recommendation speed-style is the dominant predictor of their recommendation value.

I. Introduction

> "All of us would be better investors if we just made fewer decisions."
> – Daniel Kahneman[1]

Professor Kent L. Womack passed away unexpectedly in 2015. This article is his last work, and he is greatly missed. He was at the Rotman School of Management, University of Toronto.

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[1]Nobel Laureate in Economics, in Zweig, J. "Do You Sabotage Yourself?" Money Magazine, May (2001), 78.

This study examines speed as an important decision-making-process choice of individual analysts. All else equal, one might hypothesize that reputation would be enhanced by "getting there first" (i.e., beating industry competitors by reacting quickly to new information). But there is another side to the speed story. Warren Buffet's famous line, "Wait for the fat pitch," is a decision maxim urging investors *not* to be in a hurry because there are many investment opportunities, but not many good ones. There may be other cogent reasons for slower decision-making. If an analyst is truly talented, her previous recommendations will remain accurate longer, and thus, she should have less need to change them frequently.

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

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

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

We introduce a methodology to identify an analyst's propensity to update her recommendations on the spectrum of fast to slow, relative to her competitors covering a similar portfolio of firms. We denote this speed-style as the "recommendation turnover," representing how often the analyst overturns her recommendation opinions. The method builds on a simple Binomial test. It accounts for time-varying characteristics that may influence the revision frequency at the firm level and the number of stocks that the analyst covers. In each calendar year, we use all recommendation history to classify analysts into three recommendation turnover groups: i) slow, ii) average, and iii) fast. We repeat this process yearly from 1996 to 2013. As a result, our method provides an *out-of-sample* estimate of analysts' recommendation decision-speed types from 1996 to 2013. On average, we find that *fast-turnover* analysts change their recommendations every 6 months, whereas *slow-turnover* analysts typically change their recommendations every 20 months.

We find strong evidence that much of the variation in the speed at which analysts revise their recommendations is an inherent-individual trait. We estimate a version of the Cox hazard model to identify factors influencing the speed at which an analysts' future recommendations will be revised. We find that analysts' future recommendation speed strongly depends on how fast or slow they have been revising recommendations in the past (an individual trait). We control for a host of observable signals that may trigger or delay recommendation revisions. Our modeling approach allows for unobserved heterogeneity across analysts (i.e., private information), and it controls for analysts' broker switches and Broker × Year fixed effects. The economic impact of analysts' individual speed-style is large. The model estimates imply that on any given week, fast-turnover analysts are about 2 times more likely to revise their recommendations relative to slow-turnover analysts.

We next examine the *value* of recommendations made by analysts with different decision-speed styles using investable real-calendar-time portfolios in the style of Barber, Lehavy, McNichols, and Trueman (2001). The portfolio invests (and sells) $1 on the upgraded (downgraded) stock at the closing-day price after the recommendation change. We find portfolios that follow recommendation changes of slow-turnover analysts yield annualized alpha that is 5%–10% larger, and statistically significant, than that of portfolios that follow recommendation changes of fast-turnover analysts. On the other hand, the difference in alphas between portfolios that follow recommendation changes of analysts sorted by other ex ante characteristics (i.e., All-star status, brokerage size, earnings forecast precision, and career tenure) is not significant statistically and economically.

We examine analyst characteristics that are associated with different recommendation speed-styles. An important aspect we observe is that during the career, there is a tendency for all surviving analysts to change their recommendations less frequently. In fact, analysts' career tenure (i.e., experience) is a significant determinant of their decision-speed style (Prendergast and Stole (1996)). Other aspects that are associated with slower-revising analysts include their likelihood of being awarded the All-star status by the *Institutional Investor* magazine and the size of their brokerage house. These characteristics, however, do not explain the difference in investment values of slow versus fast decision-speed style.

The higher likelihood of finding slow-turnover analysts working at large and reputable brokers raises an important question. Is speed-style a characteristic associated with where analysts work rather than an individual trait? We examine this alternative explanation by looking at analysts' job switches.[2] Our evidence suggests that slower-style analysts tend to migrate to brokers that cater primarily to institutional and investment banking clientele, perhaps because these employers

[2]We thank the editor and the referee for encouraging us to look at analysts' brokerage migration.

value their slower decision-speed traits.[3] The migration of slower-style analysts toward certain employer types explains why they are more likely found working at large and reputable brokers.

The above results beg the following important questions: Why are analysts who make less-frequent recommendations better stock pickers? What cues do they use? Livnat and Zhang (2012) and Rubin, Segal, and Segal (2017), among others, find that analysts' recommendations are valuable because they help investors interpret the contents of corporate disclosures. Motivated by these studies, we examine the value of fast- versus slow-turnover analysts in facilitating the price discovery of corporate disclosures. Using a comprehensive news database from Capital IQ Key Developments, we find that fast-revising analysts tend to update their recommendations following verifiable and less ambiguous corporate disclosures such as earnings announcements, or security issuances.

On the other hand, slower-revising analysts tend to revise recommendations following news with potentially ambiguous price impact (i.e., "soft" information), such as news about the product market competition, operation strategy, and legal issues. These news announcements are mostly unscheduled and tend to carry forward-looking information about their underlying firm value, which, we believe are harder to interpret by nonstock experts.[4] We find support for this conclusion by comparing real-calendar time portfolio performance of slow- versus fast-turnover analysts across firm characteristics. We find that the investment value of slower speed-style analysts concentrates among firms, which are harder to value, and firms that have a relatively high number of news classified as "soft" information.

This article contributes to the sell-side analyst literature which supports the view that analysts play an important role in collecting, digesting, and disseminating value-relevant market knowledge to investors.[5] As information processing agents who are monitored by their own firms and their clients, analysts' attention to their own reputations affect their decisions (Hong and Kubik (2003), Clement and Tse (2005), and Hilary and Hsu (2013)). We add to this literature by identifying the decision speed-style of stock experts based on their recommendation changes, and by considering the differing investment value implications thereof. Our work relates to studies that estimate models for how analysts make recommendation changes. For instance, Conrad, Cornell, Landsman, and Rountree (2006) models how analysts change recommendations after large stock movements and find that they are "sticky" in one direction, with analysts more reluctant to downgrade.

A study by Bernhardt, Wan and Xiao (2016) which estimates a model examining how analysts revise recommendations is perhaps the closest to ours. Their

[3]Harford, Jiang, Wang, and Xie (2019) find that analysts allocate greater effort on firms within their portfolio that are ranked higher in importance to institutional investors. Birru, Gokkaya, Liu, and Stulz (2020) find that despite the potential conflict of interests associated with analysts' greater effort on firms that are more important to institutional investors, their recommendations on these firms have greater investment value.

[4]We corroborate this finding by reading 2,052 recommendation reports downloaded from Investext and find that slower speed-style analysts tend to reference company-specific news that carry "soft" information.

[5]For instance, see Womack (1996), Clement (1999), Barber et al. (2001), Frankel, Kothari, and Weber (2006), Fang and Yasuda (2009), Loh and Stulz (2018), and Crane and Crotty (2020).

study finds that analysts strategically introduce frictions when updating their recommendations to avoid frequent revisions, and as argued by the authors, this is because customers would question the ability of an analyst who repeatedly revises recommendations. Our study differs from Bernhardt, Wan and Xiao (2016) on several aspects. Their study documents frictions in the recommendation decision of a *representative* analyst in the sell-side industry. We show that there are significant differences among analysts in the degree of frictions they apply to their recommendations and that this variation is an analyst characteristic. Importantly, our method is designed to identify analysts who are predictably quicker (or slower) to revise their recommendations in an *out-of-sample* fashion. This enables us to study their differing investment-value implications.[6]

This article is organized as follows: Section II describes the data and the methodology we use to identify analysts' decision-speed style. Section III provides evidence that the decision-speed style is an analyst individual trait. Section IV discusses the investment value of differing decision-speed styles. Section V examines the sources behind superior value of slower recommendation-speed style. Finally, Section VI concludes.

II. Data and Methodology

A. Data and Filters

We obtain analyst recommendations and earnings forecast data from IBES. We restrict our attention to equity analysts that appear in both the detailed recommendation and forecast IBES files from 1993 to 2013. This initial sample contains 629,400 recommendations made by 14,242 unique analysts. Security returns data and firm-level information are obtained from CRSP and COMPUSTAT, respectively. We identify "star analysts" based on *Institutional Investor*'s annual ranking of All-American team (see Fang and Yasuda (2009), (2014)). The gender of analysts is identified using their full names collected from the *Institutional Investor* magazine and verified against multiple sources (see Kumar (2010), Law (2013)).

We apply various filters to the IBES recommendation data file. We require that firms in our sample have records on the CRSP daily database and have CRSP share code of 10 or 11. We remove 19,809 anonymous recommendations in IBES since it is not possible to track which analysts issue these recommendations. We require that analysts issue 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 IBES database is coded with a rating scale between 1 and 5, ranging from "strong buy" to "strong sell," respectively. We characterize each revision as an upgrade or a downgrade. We do not consider initiations and reiterations in our empirical analysis.

[6]Hobbs, Kovacs, and Sharma (2012) find superior portfolio performance formed following recommendations of faster-revising analysts, suggesting that quantity trumps quality; a conclusion that differs from ours. However, their study measures analysts' recommendation frequency using only recommendations that are revised within 12 months. This approach would eliminate about half of recommendation changes from the sample because the median time between revisions is 11.2 months. We reconcile the difference between our finding and their study in the Supplementary Material.

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

We define a recommendation as outstanding according to Ljungqvist, Malloy, and Marston (2009). We remove recommendations that have been dropped by each broker using IBES Stopped File. We further remove stale recommendations that have been neglected by analysts without being officially dropped by their broker. If an analyst's recommendation has been outstanding for more than 1 year without a reiteration and if this analyst also makes less than one earnings forecast per year on the stock, we consider her outstanding recommendation to be stale. We find 54,226 recommendations to have been outstanding for more than 1 year, and we classify 3,533 of them as stale.

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

B. Sample Descriptive

We focus on analysts who actively issue recommendations during the period 1996–2013. Although IBES recommendation file begins in 1993, we start our analysis in 1996 to allow analysts' recommendation history file to sufficiently develop. In each year from 1996 to 2013, we calculate various characteristics for each analyst. The number of analysts in our sample is updated yearly. We require that an analyst provides active recommendation coverage on at least three stocks. We consider that an analyst has initiated an active coverage of a stock if she has issued at least two recommendation changes on the firm. The final sample consists of 4,563 unique analysts who provide active recommendation coverage during 1996–2013, resulting in 25,678 analyst-year observations.

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

The average RECOM_INPLACE is 11.92 months, with a median of 11.19 months. This key variable reflects the time that a recommendation by an analyst remains outstanding. Importantly, we find that the standard deviation and the percentile distribution of this key variable show significant variations.

TABLE 1

Analyst Characteristics

Table 1 reports a sample descriptive of analyst characteristics. The sample consists of analysts that provide active recommendations coverage between 1996 and 2013. Recommendations and earnings forecast data are obtained from IBES. We require that an analyst provides active recommendation coverage on at least three stocks to remain the sample each year. Details of filters used to construct the sample can be found in the main text. The sample consists of 4,563 unique analysts providing active recommendation coverage in 1996–2013, resulting in 25,678 analyst-year observations. We summarize analyst characteristics calculated at the analyst-year level. All variables are defined in the Appendix. EXPERIENCE is the number of years since the analyst's first recommendation appears in the IBES database. BREADTH is the number of stocks for which an analyst provides active recommendation coverage. ALLSTAR is the indicator variable equal to 1 if analyst is elected to the *Institutional Investor*'s annual All-American team (Fang and Yasuda (2014)). MALE is the indicator variable equal to 1 if the analyst is a male. TOP_BROKER is the indicator variable equal to 1 if analysts are working for the largest brokerage house defined as those in the top tenth size decile measured by the number of analysts employed each year. RECOM_BOLDNESS is the indicator variable equal to 1 if an analyst's recommendation revision is away from the consensus as defined by Jegadeesh and Kim (2010). RECOM_OPTIMISM is the indicator variable equal to 1 if an analyst's recommendation is more optimistic than the prevailing consensus (Clement (1999)). EPS_OPTIMISM is the indicator variable equal to 1 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)). EPS_FREQUENCY is the average number of earnings forecasts made per quarter by an analyst on all the stocks that she actively covers. LFR is the lead-follower ratio which measures the timeliness of an analyst recommendation revision relative to other analysts (Cooper, Day, and Lewis (2001)). A higher LFR ratio implies that an analyst issues more timely recommendation. IND_HHI is the measure of the industry concentration of an analyst's portfolio based on the Herfindahl–Hirschman index (HHI). RECOM_INPLACE is the number of months between recommendation revisions.

Variable	Mean	Median	Std. Dev.	Min.	25th Pct	75th Pct	Max.
EXPERIENCE	6.78	6.00	3.99	0.00	4.00	9.00	19.00
BREADTH	6.93	6.00	3.94	3.00	4.00	9.00	40.00
ALLSTAR	0.16	0.00	0.36	0.00	0.00	0.00	1.00
MALE	0.89	1.00	0.31	0.00	1.00	1.00	1.00
TOP_BROKER	0.40	0.00	0.49	0.00	0.00	1.00	1.00
RECOM_BOLDNESS	0.51	0.50	0.20	0.00	0.39	0.63	1.00
RECOM_OPTIMISM	0.42	0.42	0.22	0.00	0.28	0.56	1.00
EPS_OPTIMISM	0.49	0.49	0.15	0.00	0.39	0.58	1.00
EPS_PRECISION	0.00	0.03	0.26	−9.08	−0.10	0.14	1.00
EPS_FREQUENCY	1.79	1.84	0.36	1.00	1.60	2.05	2.50
LFR	2.18	1.07	2.55	0.04	0.51	2.50	8.00
IND_HHI	6.45	1.88	13.07	0.22	1.00	5.06	85.00
RECOM_INPLACE	11.92	11.19	5.38	0.83	7.94	14.97	46.30

C. Methodology for Identifying Analysts' Recommendation Speed-Style

We classify analysts into different recommendation speed-style groups on a yearly basis from 1996 to 2013. The method is an *out-of-sample* classification. For instance, when classifying the speed of analysts in the year 2000, we use IBES recommendations history only up until Dec. 1999. As for the year 2001, we extend the history file to include an additional year of recommendation-change records.[7] The methodology for classifying analysts into different speed-style groups consists of the following three steps, which we discuss next.

1. Estimating the Time Between Revisions for Each Analyst-Stock Pair: Step 1

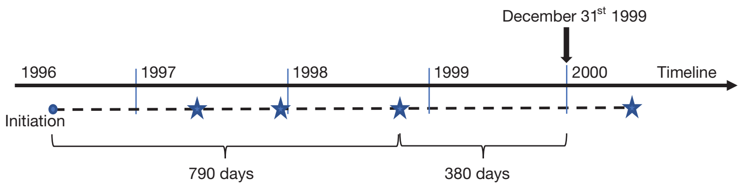
At the end of each calendar year starting in 1995, we calculate the average number of days between recommendation revisions for each *analyst-stock* pair. One concern associated with the annual updating is the right-truncation bias, which we illustrate in Figure 1. In this example, we want to calculate the average time between recommendation revisions for an analyst-stock pair at the end of 1999. This analyst initiates the coverage in 1996. Based on Dec. 31, 1999, she has revised

[7]Our main conclusions are unaffected when using a 7-year, 5-year, or 3-year rolling window of recommendation history, instead of all history, to classify our analysts. Section E in the Supplementary Material reports robustness-check results using different rolling windows of recommendation history.

FIGURE 1

Correction for the Right-Truncation Bias

Figure 1 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 her recommendation on a stock as viewed on Dec. 31, 1999. Stock coverage is initiated in 1996, and we observe three revisions by the end of 1999. However, this figure shows that on Dec. 31, 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 Section B of the Supplementary Material, we show how to adjust for the right-truncation bias by estimating a Poisson-likelihood model.



the recommendation three times with the last revision in 1998. This is 790 days since her coverage initiation. A naïve calculation would suggest that she revises her recommendation on this stock approximately every 263 (~790/3) days. However, there is a 380-day gap between her 1998 revision and when we truncate the sample on Dec. 31, 1999. Therefore, an exclusion of this 380-day truncation gap will result in an underestimation of the time between recommendation revisions. We adjust for this right-truncation bias when we calculate the average number of days between recommendation revisions for each analyst-stock pair. We discuss the procedure in Section B of the Supplementary Material.

2. Ranking Analysts' Revision Times Stock by Stock: Step 2

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

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

3. Identifying the Speed-Style of Each Analyst: Step 3

Using the revision-speed ranking results from Step 2, we statistically test, for each analyst, whether she exhibits a distinct recommendation-speed pattern

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(i.e., fast or slow) *across* all the stocks that she covers. The logic of our test is as follows: If an analyst does not exhibit a distinct recommendation-revision speed, she should be equally represented in all four speed quartiles. In other words, the likelihood that her revision speed on any stock falls in the first (or the fourth) speed quartile should be one-fourth. This is the null hypothesis.

For instance, consider an analyst who covers 8 stocks and does not have an extreme speed-style preference, we expect probabilistically that $1/4 \times 8 = 2$ of her stock-revision speeds are equally observed in one of the four quartiles from the first (fastest) to the fourth (slowest). However, if we find that 7 out of 8 stocks in her portfolio are ranked in the fastest revisions quartile, it is likely that this analyst has a revision speed that is faster than the average analyst. But, according to this example, is 7 out of 8 a sufficient cut-off to confidently classify that this analyst is "fast"? Importantly, analysts do not usually cover the same number of stocks. What if this analyst covers 12 stocks instead of 8? What should the cut-off for the minimum number of stocks that are in the fastest quartile be before we can decidedly classify her as a "fast" analyst? We address this using the standard Binomial test. This method helps us define the cut-offs that we can use to conclusively classify an analyst as being distinctly "fast" or "slow" based on the same statistical criteria (0.05 p-value) regardless of the number of stocks that she covers. 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 revision-speed quartile is not greater than 25%.

H_0 (SLOW). The probability that stocks in an analyst's portfolio are ranked in the slowest revision-speed quartile is not greater than 25%.

A rejection of the above hypothesis H_0 (FAST) at the 5% significant level allows us to confidently classify an analyst to be faster at revising recommendations relative to her peers.[8] Similarly, a rejection of H_0 (SLOW) at the 5% significant level would lead us to conclude that the analyst is slower at revising recommendations relative to her peers. Finally, we assign analysts into three groups: i) Slow-turnover analyst, ii) Average-turnover analyst, and iii) Fast-turnover analyst. Analysts for whom we can reject neither of the two null hypotheses are classified as average-turnover analysts. Figure 2 illustrates examples of slow- versus fast-turnover analysts' recommendation patterns on Bank of New York Mellon Corporation (Graph A) and Sunoco (Graph B). Here, we pick two analysts with different recommendation turnover groups who revise their recommendations on the same stock over a similar period.

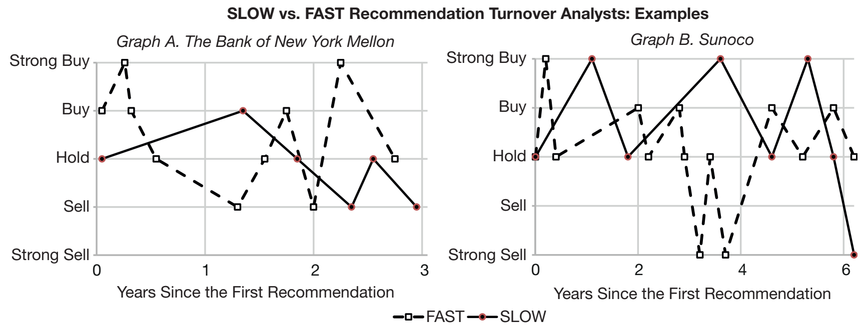
Panel A of Table 2 reports the number of analysts in each recommendation turnover group from 1996 through 2013. There are 521 distinct analysts in the sample in 1996, which is due to the relatively short recommendation history available in IBES for identifying eligible analysts. However, the number of analysts that enter the sample increases steadily each year to 1,714 in the year 2004. Panel B

[8]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.

FIGURE 2

SLOW Versus FAST Recommendation Turnover Analysts: Examples

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



of Table 2 reports summary statistics for the bias-adjusted time between recommendations. There is a clear difference in the time between recommendation revisions between the slow-turnover group (median of 19.4 months) and the fast-turnover group (median of 6.0 months). About 68% of analysts in the sample are classified in the average-turnover group.

III. Is Recommendation Speed-Style an Analyst's Individual Trait?

We provide evidence that much of the variations in the speed at which analysts revise their recommendations is an analyst-level characteristic.

A. Cox Model for Predicting Time to the Next Recommendation Change

We estimate the Cox Proportional Hazard (Cox PH) model for the hazard rate at which an analyst will revise her future recommendations in any given week. The Cox PH model is commonly used in survival analysis, and we prefer it over the logistic model because it can handle censored outcome variables.

Let $\lambda(t)$ denote the hazard rate that an outstanding recommendation on stock j by an analyst a will be revised in week t, we assume that $\lambda(t)$ follows a log-linear model:

$$\lambda(t) = \lambda_{0,j}(t)\exp\left(\alpha_{\text{SLOW}}\text{SLOW}_a + \alpha_{\text{FAST}}\text{FAST}_a + \Sigma_i \beta_i X_{i,j}(t) + \eta_a\right). \quad (1)$$

We estimate the Cox PH model at the recommendation-week level, and separately for upgrades and downgrades. For each recommendation, we create a weekly panel where each observation corresponds to a distinct week t, starting from when this recommendation became outstanding until when it is revised. The weekly (rather than daily) frequency choice is motivated by computational practicality and

TABLE 2

Descriptive of Recommendation Turnover Classification

Table 2 summarizes the distribution of analysts after their speed-style classification. We classify analysts by how fast they revise their recommendations relative to their peers. The classification is done at the analyst-year level. The sample consists of analysts that provide active recommendations coverage in 1996–2013. For each year from 1996 through 2013, we assign analysts into three groups: i) Slow-turnover analyst (SLOW), ii) Average-turnover analyst (AVERAGE), and iii) Fast-turnover analyst (FAST). We use analysts' past recommendation patterns up to the previous year to identify their current-year recommendation speed-style. Panel A reports the number (and percentage) of analysts in each recommendation turnover group. Panel B reports summary statistics for the time between recommendations revisions for the overall sample, as well as for each analyst turnover group. We express time between revisions in unit months corrected for the right-truncation bias. See text for more details.

Panel A. Distribution of Analysts Across Three Recommendation-Turnover Groups

		1. SLOW		2. AVERAGE		3. FAST	
Year	Total	#	%	#	%	#	%
1996	521	69	13	391	75	61	12
1997	816	138	17	591	72	87	11
1998	934	193	21	651	70	90	10
1999	1,106	241	22	765	69	100	9
2000	1,297	293	23	868	67	136	10
2001	1,327	281	21	909	69	137	10
2002	1,336	269	20	942	71	125	9
2003	1,602	285	18	1,104	69	213	13
2004	1,714	282	16	1,204	70	228	13
2005	1,692	306	18	1,186	70	200	12
2006	1,704	348	20	1,175	69	181	11
2007	1,699	365	21	1,184	70	150	9
2008	1,650	411	25	1,113	67	126	8
2009	1,638	374	23	1,117	68	147	9
2010	1,654	377	23	1,091	66	186	11
2011	1,650	390	24	1,094	66	166	10
2012	1,702	423	25	1,101	65	178	10
2013	1,636	417	25	1,044	64	175	11
Overall	25,678	5,462	21	17,530	68	2,686	10

Panel B. Bias-Adjusted Time Between Recommendation Revisions (in Months)

	Nobs	Mean	Median	Std. Dev.	Min.	25th Pct	75th Pct	Max.
All analysts	25,678	13.1	12.2	6.0	1.0	8.8	16.3	55.9
Grouped by Turnover Classification								
SLOW	5,462	20.2	19.4	6.0	5.1	16.2	23.4	55.9
AVERAGE	17,530	11.9	11.5	3.9	2.3	9.1	14.4	34.0
FAST	2,686	6.2	6.0	2.3	1.0	4.5	7.5	20.1

because a recommendation change that occurs within 1 week is extremely rare (i.e., 0.06% of all revisions). There are about 8.5 million weekly panel observations created from 158,210 recommendation revisions over the 1996–2013 period, where approximately 3.5 million of them are upgrades.[9]

Our independent variables of interests are the two dummy variables SLOW and FAST. SLOW(FAST) is equal to 1 if the analyst was classified as the slow-turnover (fast-turnover) type in the previous year, and 0 otherwise. We include a series of firm-level, industry-level, and recommendation-level controls in the Cox PH model. They are represented by $\Sigma_i \beta_i X_{i,j}(t)$ in equation (1). The baseline hazard rate function in equation (1) is assumed to be firm specific and denoted by $\lambda_{0,j}(t)$ for firm j.

Table 3 reports the estimation results. Panels A and B of Table 3 report results for upgrades and downgrades, respectively. A positive value on the

[9]For certain specifications, it can take about 12–24 hours to estimate each Cox PH model specification on the SAS WRDS-Cloud server with this weekly panel data over the 1996–2013 period.

TABLE 3

Hazard Model for Predicting Time to the Next Recommendation Change

Table 3 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 upgrades and downgrades 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:

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

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; they are written in bold. We let the baseline hazard be firm specific, and denoted by $\lambda_{0,j}(t)$ for firm *j*. In columns 1 and 2, we allow for unobserved heterogeneity in the hazard-rate model at the analyst level by including analyst-random effects. This is represented by η_a, which is normally distributed. In column 3, we control for Broker × Year fixed effects. CONCURRENT_EARNINGS is an indicator variable equal to 1 if there is an earnings announcement in the current week t, and 0 otherwise. All other independent variables are lagged by one period. NEWS_INTENSITY is the number of firm-specific news observed in the previous week. We obtain news releases data from the Capital IQ Key developments database and the sample period begins in 2003. Therefore, regression specifications with NEWS_INTENSITY (i.e., columns 2 and 3) are estimated using observations from 2003 through 2013. Regression specification in column 1 is estimated using observations from 1996 through 2013. All other variables are defined in the Appendix. Standard error is reported in parentheses below each estimate. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

	1996–2013		2003–2013		2003–2013		
	Estimate	HR	Estimate	HR	Estimate	HR	Prediction
	1		2		3		
Panel A. Hazard Model for Time to an Upgrade Revision							
Previous Year Speed-Style							
SLOW	**−0.210*****	**0.81**	**−0.251*****	**0.78**	**−0.213*****	**0.81**	**(−)**
	(0.018)		(0.024)		(0.022)		
FAST	**0.259*****	**1.30**	**0.360*****	**1.43**	**0.344*****	**1.41**	**(+)**
	(0.019)		(0.025)		(0.024)		
Control Variables							
CONCURRENT_EARNINGS	1.308***	3.70	1.184***	3.27	1.589***	4.90	(+)
	(0.013)		(0.017)		(0.018)		
NEWS_INTENSITY			0.193***	1.21	0.215***	1.24	(+)
			(0.005)		(0.005)		
POSITIVE_JUMP	−0.142***	0.87	−0.273***	0.76	−0.271***	0.76	(?)
	(0.017)		(0.025)		(0.025)		
NEGATIVE_JUMP	0.019	1.02	−0.063**	0.94	−0.067**	0.94	(?)
	(0.019)		(0.027)		(0.028)		
MKT_ADJRET	0.949***	2.58	1.088***	2.97	1.125***	3.08	(+)
	(0.052)		(0.072)		(0.075)		
IND_ADJRET	0.167***	1.18	0.118**	1.13	0.140**	1.15	(+)
	(0.039)		(0.053)		(0.055)		
VOLATILITY	−0.256***	0.77	−0.325***	0.72	−0.226***	0.80	(−)
	(0.048)		(0.065)		(0.068)		
log(STOCK_VOLUME)	0.320***	1.38	0.300***	1.35	0.259***	1.30	(+)
	(0.009)		(0.013)		(0.014)		
log(IND_VOLUME)	0.003	1.00	−0.001	1.00	0.001	1.00	(+)
	(0.003)		(0.004)		(0.005)		
REL_52WEEKHIGH	0.343***	1.41	0.190***	1.21	0.148***	1.16	(+)
	(0.026)		(0.036)		(0.039)		
LEVEL_CHANGE	−0.065***	0.94	−0.063***	0.94	−0.107***	0.90	(−)
	(0.013)		(0.017)		(0.023)		
BREADTH	−0.018***	0.98	−0.006***	0.99	0.001	1.00	(?)
	(0.001)		(0.002)		(0.002)		
Previous Recommendation Level							
LAST_RECOM = 2 ("Buy")	0.122***	1.13	0.046*	1.05	−0.015	0.99	(+)
	(0.017)		(0.027)		(0.031)		
LAST_RECOM. = 4 ("Sell")	0.372***	1.45	0.344***	1.41	0.302***	1.35	(+)
	(0.018)		(0.022)		(0.023)		
LAST RECOM = 5 ("Strong sell")	0.544***	1.72	0.546***	1.73	0.524***	1.69	(+)
	(0.023)		(0.028)		(0.029)		
Brokerage Turnover History							
BROKER_SWITCHER	−0.046***	0.96	−0.014	0.99	0.029	1.03	(−)
	(0.014)		(0.018)		(0.018)		
RECENT_SWITCH	0.237***	1.27	0.265***	1.30	0.301***	1.35	(?)
	(0.025)		(0.034)		(0.036)		

(continued on next page)

TABLE 3 (continued)

Hazard Model for Predicting Time to the Next Recommendation Change

	1996–2013		2003–2013		2003–2013		
	Estimate	HR	Estimate	HR	Estimate	HR	Prediction
	1		2		3		
Panel A. Hazard Model for Time to an Upgrade Revision (continued)							
Year fixed effects	Yes		Yes		Yes		
Analyst random effects	Yes		Yes		No		
Broker × year fixed effects	No		No		Yes		
N	2,738,023		1,646,558		1,646,558		
NUM_RECOM	62,327		36,011		36,011		
Panel B. Hazard Model for Time to a Downgrade Revision							
Previous Year Speed-Style							
SLOW	**−0.203***** (0.017)	**0.82**	**−0.288***** (0.023)	**0.75**	**−0.229***** (0.021)	**0.80**	**(−)**
FAST	**0.328***** (0.018)	**1.39**	**0.454***** (0.024)	**1.57**	**0.396***** (0.024)	**1.49**	**(+)**
Control Variables							
CONCURRENT_EARNINGS	1.289*** (0.012)	3.63	1.206*** (0.017)	3.34	1.622*** (0.017)	5.06	(+)
NEWS_INTENSITY			0.217*** (0.005)	1.24	0.242*** (0.005)	1.27	(+)
POSITIVE_JUMP	0.038** (0.016)	1.04	−0.039* (0.023)	0.96	−0.043* (0.024)	0.96	(?)
NEGATIVE_JUMP	−0.219*** (0.017)	0.80	−0.292*** (0.025)	0.75	−0.300*** (0.026)	0.74	(?)
MKT_ADJRET	−1.852*** (0.050)	0.16	−1.601*** (0.076)	0.20	−1.481*** (0.080)	0.23	(−)
IND_ADJRET	−0.233*** (0.031)	0.79	−0.359*** (0.047)	0.70	−0.386*** (0.051)	0.68	(−)
VOLATILITY	−0.366*** (0.038)	0.69	−0.426*** (0.058)	0.65	−0.340*** (0.060)	0.71	(−)
log(STOCK_VOLUME)	0.334*** (0.008)	1.40	0.366*** (0.013)	1.44	0.330*** (0.013)	1.39	(+)
log(IND_VOLUME)	0.003 (0.003)	1.00	0.008* (0.004)	1.01	0.002 (0.005)	1.00	(+)
REL_52WEEKHIGH	−0.463*** (0.028)	0.63	−0.276*** (0.040)	0.76	−0.276*** (0.042)	0.76	(−)
LEVEL_CHANGE	−0.088*** (0.012)	0.92	−0.001 (0.018)	1.00	0.008 (0.021)	1.01	(−)
BREADTH	−0.013*** (0.001)	0.99	−0.001 (0.002)	1.00	0.001 (0.002)	1.00	(?)
Previous Recommendation Level							
LAST_RECOM = 2 (“Buy”)	0.107*** (0.017)	1.11	−0.006 (0.022)	0.99	0.028 (0.023)	1.03	(+)
LAST_RECOM. = 4 (“Sell”)	0.106*** (0.016)	1.11	0.016 (0.021)	1.02	0.023 (0.022)	1.02	(+)
LAST RECOM = 5 (“Strong sell”)	0.400*** (0.066)	1.49	0.427*** (0.079)	1.53	0.371*** (0.082)	1.45	(+)
Brokerage Turnover History							
BROKER_SWITCHER	−0.055*** (0.013)	0.95	−0.038** (0.017)	0.96	−0.028 (0.017)	0.97	(−)
RECENT_SWITCH	0.343*** (0.025) (0.017)	1.41	0.389*** (0.034) (0.023)	1.48	0.441*** (0.037) (0.020)	1.55	(?)
Year fixed effects	Yes	Yes	Yes				
Analyst random effects	Yes	Yes	No				
Broker × year fixed effects	No	No	Yes				
N	3,741,758		2,123,157		2,123,157		
NUM_RECOM	73,793		39,706		39,706		

coefficient estimate indicates that an increase in the independent variable will increase the rate at which a recommendation will be revised, and vice versa.

We allow for unobserved heterogeneity across analysts through analyst-random effects. This is represented by the term η_a in equation (1). This modeling approach is known as the frailty model in survival analysis. It controls for unobserved analyst characteristics or new information that analysts uncover which are unobservable to econometricians.

We allow for various fixed effects. They include year, previous-recommendation level, Broker × Year, and brokerage-turnover fixed effects. For brokerage turnover, we track changes in analysts' brokerage affiliation annually. Table A1 summarizes the frequency of analysts' brokerage switches. An analyst is a BROKER_SWITCHER if she has switched brokerage affiliation at least once during her career. This corresponds to about 54.7% of analysts in our sample. We also consider the impact of recent brokerage switches. We define RECENT_SWITCH as a dummy variable equal to 1 if the analyst has switched brokerage within the past year. We find that each year, on average, 9.1% of analysts have recently switched their brokerage affiliation. In our analysis, BROKER_SWITCHER controls for fixed effects associated with job switchers versus nonjob switchers, whereas RECENT_SWITCH controls for effects associated with recent changes in analysts' job functions due to the brokerage switch.

1. Speed-Style as a Predictable Analyst-Level Characteristic

Column 1 in each Panel of Table 3 reports the baseline estimates. We find that the coefficient estimates on SLOW are negative, while that on FAST is positive. This finding indicates that an analyst with a history of slow (fast) recommendation-revising pattern is likely to revise her next recommendation more slowly (quickly) than an average-turnover analyst, which is the reference group. We can interpret the economic magnitude of each coefficient estimate by looking at its corresponding hazard ratio, which is calculated as the exponent of each coefficient estimate. The hazard ratios are reported under the column titled "HR" next to each estimate. Hazard ratio represents the relative increase (or decrease) in the likelihood that a recommendation will be revised for a 1-unit change in the independent variable.

Column 1 in Panel A of Table 3 shows the hazard ratio for FAST is 1.30, and for SLOW is 0.81. This implies that relative to an average-turnover analyst on any given week, a fast-turnover analyst is 1.30 times more likely to upgrade a stock while for a slower-turnover analyst, the likelihood is 0.81 times lower. We can compare the speed of recommendation changes between slow- versus fast-turnover analysts using their hazard ratios (i.e., 1.30/0.81 ≈ 1.60). This suggests that on any given week, a fast-turnover analyst is 1.60 times more likely to upgrade her recommendation relative to that of a slow-turnover analyst. We find a similar economic magnitude for downgrades. Column 1 in Panel B of Table 3 suggests that a fast-turnover analyst is 1.39/0.82 ≈ 1.70 times more likely than a slow-turnover analyst to downgrade a stock on any given week.

Columns 2 and 3 report results with NEWS_INTENSITY included as a control variable. This is the number of firm-specific news observed in the previous week. We obtain news releases data from the Capital IQ Key Development database (Capital IQ), a comprehensive database of company-specific news collected from public news sources.[10] They include firm- and nonfirm-initiated news found in newswire services, third-party sources (e.g., newspaper articles), investor transcripts, or disclosure wires. News coverage in Capital IQ was relatively thin until the end of 2002. Therefore, the estimation sample used in columns 2 and 3 is from 2003 to 2013.

Column 3 reports results with Broker × Year fixed effects. Analysts' speed-style may be influenced by the incentives given on the job due to the clientele that their employer serves, which could be time varying in nature. We control for this time-varying unobserved variable at the broker-year level in column 3. This is our most conservative specification.

Table 3 shows that the coefficient estimates on SLOW and FAST remain strongly significant and are similar in magnitude across all specifications. This conclusion applies to both upgrades and downgrades in Panels A and B, respectively. Overall, we find that analysts' past revision-speed pattern is a robust predictor of their future recommendation speed-style after controlling for various potential recommendation triggers.

2. Controls for Other Recommendation Triggers

Intuitively, an analyst would revise a recommendation when the ratio of her stock valuation to price (*V/P*) exceeds or falls below a certain threshold. Under this framework, several factors could affect when analysts revise their recommendations. We discuss how we control for various recommendation triggers below.

We use CONCURRENT_EARNINGS and NEWS_INTENSITY as proxies for the arrival of new information that affects an analyst's stock valuation (*V*). The variable CONCURRENT_EARNINGS controls for the well-known fact that analysts often revise their recommendations around earnings announcements. As expected, estimates on CONCURRENT_EARNINGS and NEWS_INTENSITY are positive and statistically significant.

We include a large set of controls for changes in the publicly traded share prices (*P*). This includes an upward or a downward stock price momentum relative to the aggregate market (i.e., MKT_ADJRET) or to an industry benchmark (i.e., IND_ADJRET). Large changes in share price can also occur abruptly, and they are often referred to as jumps, which we control for using two indicator variables POSITIVE_JUMP and NEGATIVE_JUMP.[11] We also include VOLATILITY as a control because high volatility may lower analysts' ability to precisely estimate their stock valuation-to-price ratio (*V/P*). Finally, we include the stock price ratio relative to its 52-week high because previous research has shown that the 52-week high price serves as a reference point for the decisions of traders (e.g., George and Huang (2004)). This control is represented by REL_52WEEKHIGH. Where applicable, all control variables are lagged by 1 week.

[10]Capital IQ prefilters the data to eliminate duplicates and extraneous information (e.g., when a firm-initiated news is disseminated through two different wire services). This leads to a cleaner data set that consolidates a particular news item from different sources into a single record (see Edmans, Goncalves-Pinto, Wang, and Xu (2018)).

[11]We apply the method of Loh and Stulz (2011) to detect daily stock returns that are outliers, in a sense that they cannot be explained by the firm's current volatility level.

We control for previous-recommendation-level fixed effects using LAST_RECOM and the magnitude of recommendation change using LEVEL_CHANGE. The reference level for the previous-recommendation fixed effects is "hold." Panel A of Table 3 shows the coefficients on LAST_RECOM for upgrades are mostly positive. This suggests that upgrades out of a "hold" recommendation are stickier than upgrades out of a "strong sell" or a "sell." We find a similar pattern for downgrades in Panel B. That is, downgrades out of a "hold" recommendation are stickiest.

Table 3 shows that all coefficient estimates on RECENT_SWITCH are positive and statistically significant. This suggests that analysts tend to revise stock recommendations more quickly after they recently switched employer. This effect is temporary. We believe this temporary recommendation-speed increase is associated with career concerns. Analysts who recently switched brokerage may feel pressured to quickly revise their existing recommendations to signal their greater effort to the new employer.

We find that the coefficient estimates on BROKER_SWITCHER are negative, which is expected. Analysts with better career longevity are more likely to have switched brokerage at least once during their career and these analysts, which we later show in Table 4, are more likely to have a slower speed-style. Nevertheless, column 3 shows that coefficient estimates on BROKER_SWITCHER are no longer significant once Broker × Year fixed effects are included. We discuss, in greater details, how these control variables are related to analysts' speed-style in Section D of the Supplementary Material.

B. Recommendation Speed-Style and Analyst Characteristics

We examine analyst characteristics that are associated with different recommendation speed-styles. Table 4 reports the results. We estimate three logit models. In the first model, the dependent variable is an indicator function that is equal to 1 if the analyst in year t belongs to the slow-turnover group, and 0 otherwise. Similarly, in the second and third specifications, the dependent variable is an indicator function that is equal to 1 if the analyst on year t belongs to the average-turnover and fast-turnover group, respectively.

All independent variables in Table 4 are analyst-level characteristics and are defined in the Appendix. We first examine the set of variables that are related to analysts' career outcomes. Looking at column 1, we find that EXPERIENCE, ALLSTAR, TOP_BROKER are positively and significantly associated with the probability that an analyst is identified with the slow-turnover group. This finding indicates that slow-turnover analysts tend to have better career outcomes in the sense that they have better career longevity, are more likely to attain the All-star status, and work for a top brokerage firm. Among these three career-outcome variables, EXPERIENCE has the strongest association with slow-turnover analysts with a t-statistic of 27. Looking at columns 2 and 3 for the average- and fast-turnover group, we find the coefficients on these three variables EXPERIENCE, ALL_STAR, and TOP_BROKER are negative. Put together, we find that a slower decision-speed style is associated with analysts' better career outcomes.

TABLE 4

Analyst Characteristics and Recommendation Speed-Style

Table 4 reports estimation results from a logistic model examining characteristics that are associated with an analyst being classified into each of the three speed-style groups i) SLOW, ii) AVERAGE, and iii) FAST. The logit model is estimated at the analyst-year level. The dependent indicator variables in columns 1–3) are equal to 1 if the analyst is identified with the slow-, average-, and fast-turnover group, respectively, in that year. All analyst characteristics are calculated yearly for each analyst; see the Appendix for definitions. *N* reports the number of observations. Year-fixed effects are included in the estimation. Robust standard error clustered at the brokerage-year level is reported in parenthesis below each estimate. Each regression model contains 25,678 analyst-year observations. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Likelihood That the Analyst Is Associated With a Recommendation Speed-Style		
	SLOW	AVERAGE	FAST
	1	2	3
EXPERIENCE	0.188***	−0.035***	−0.304***
	(0.007)	(0.006)	(0.013)
ALLSTAR	0.506***	−0.204***	−0.858***
	(0.056)	(0.050)	(0.107)
TOP_BROKER	0.265***	−0.017	−0.388***
	(0.052)	(0.038)	(0.058)
BREADTH	−0.031***	0.007	0.060***
	(0.005)	(0.005)	(0.007)
RECOM_OPTIMISIM	−0.154*	0.044	0.243**
	(0.093)	(0.073)	(0.104)
RECOM_BOLDNESS	0.002	0.130	−0.417***
	(0.108)	(0.084)	(0.108)
EPS_OPTIMISM	0.012	0.015	−0.068
	(0.123)	(0.102)	(0.146)
EPS_PRECISION	0.045	0.046	−0.178**
	(0.077)	(0.056)	(0.074)
LFR	0.026***	0.006	−0.064***
	(0.007)	(0.006)	(0.011)
EPS_FREQUENCY	0.102	0.086	−0.383***
	(0.067)	(0.056)	(0.086)
MALE	0.023	−0.019	0.009
	(0.055)	(0.046)	(0.072)
IND_HHI	−0.001	0.000	0.000
	(0.001)	(0.001)	(0.002)
N	25,678	25,678	25,678

We next turn to characteristics of stock recommendations that analysts with different recommendation-speed styles make. Columns 1 and 3 of Table 4 show the LFR, which measures the average timeliness of an analyst's recommendation change, to be positively associated with slow-turnover analysts, but negatively with fast-turnover analysts. This implies that recommendation changes of slower-revising analysts tend to "lead the pack," in the sense that they often front-run recommendation changes of faster-revising analysts. Relatedly, we find that recommendations of fast-turnover analysts tend to be less bold (i.e., they herd more toward the consensus).

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

C. Analysts' Place of Employment as the Driver of Speed-Style

Results in Table 4 show that slow-turnover analysts are more likely to work at a large broker (i.e., a top broker or an All-star research team). Therefore, to what extent is the speed of recommendation changes a persistent, individual trait, rather than a function of the job associated with where analysts work? Slow-turnover analysts may primarily serve institutional investors who already possess in-house capacity to process hard information, and thus, have less incentives to revise their recommendation quickly. This hypothesis would imply that the speed of recommendation changes largely depends on where analysts work rather than being an analyst-individual trait. We address this question next.

First, we recall that the Cox PH model in column 3 of Table 3 is estimated with Broker × Year fixed effects. Therefore, we have already controlled for the time-varying unobserved impacts associated with analysts' job functions at the broker-year level.

Second, we examine analysts' job migrations as their career progresses and find that slow-turnover analysts tend to migrate to brokers that cater to investment banking and institutional clientele. This finding explains why slower speed-style analysts are more likely found working at a certain brokerage type. We illustrate this finding in Table 5. Here, we estimate a linear probability model examining the type of broker that slow- versus fast-turnover analysts are likely found working at using three distinct samples as described in Table A1. In column 1, we consider all analyst-year observations; it is the baseline specification. In column 2, the sample BROKER_SWITCHER considers only analysts that have switched their broker at least once during their career. Finally, in column 3, the sample RECENT_SWITCH considers only analysts who have switched brokers within the past year.

We examine the likelihood of finding analysts working at two brokerage types. In Panel A, the dependent variable is 1 (and 0 otherwise) if the analyst is working at a Top-League Table broker. League Table ranking measures the importance of each investment bank based on the dollar volume of security issuance (IPO, SEO, and public debt). We label a sell-side broker as a TOP_LT broker if it is associated with an investment bank that is ranked in the top 20th of the League Table (see Section C in the Supplementary Material for details about the data collection). In Panel B, we report results where the dependent variable is 1 (and 0 otherwise) if the analyst is working at an All-star-concentrated broker (ALLSTAR_BROKER). All-star status is annually awarded to sell-side research teams by institutional investors. We use the concentration of All-star analysts to identify brokers that are more likely to provide valuable research to institutional investors. We calculate the fraction of All-star analysts working at each broker yearly. We label brokers with the fraction of All-star analysts above the cross-sectional median as ALLSTAR_BROKER.

In all specifications, the coefficient estimates on SLOW and FAST are positive and negative, respectively. Looking at all analysts in columns 1, slow-turnover analysts

TABLE 5

Brokerage Migration and Recommendation Speed-Style

Table 5 reports OLS regression results examining the probability that the analyst is working at a certain type of brokerage house. The regression is done at the analyst-year level. In each panel, the dependent variable is a dummy variable that is equal to 1 (and 0 otherwise) if the analyst currently works at a certain type of brokerage house. Panel A shows results for Top League-Table brokers (TOP_LT = 1). Panel B reports results for All-star-concentrated brokers (ALLSTAR_BROKER = 1). See Section III.C for how these variables are defined. Each panel reports three regression results that are estimated using three distinct samples. Column 1 reports results estimated using all analysts in the sample. Column 2 reports results estimated using analysts who have switched brokerage house at least once during their career (i.e., BROKER_SWITCHER = 1). Column 3 reports results estimated using analyst who have recently switched brokerage house within the past year (i.e., RECENT_SWITCH = 1). Year fixed effects are included. Standard errors clustered at the year level are reported in parentheses below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Panel A. Probability of Working at a Top-League Table Broker			*Panel B. Probability of Working at an All-Star-Concentrated Broker*		
	All Analysts	Brokerage Switchers	Recent Switches	All Analysts	Brokerage Switchers	Recent Switches
	1	2	3	1	2	3
Recommendation speed-style						
SLOW	0.0788***	0.0971***	0.0569**	0.0850***	0.0802***	0.0602**
	(0.0109)	(0.0111)	(0.0259)	(0.0157)	(0.0185)	(0.0265)
FAST	−0.0801***	−0.0963***	−0.0510*	−0.0621***	−0.0773***	−0.0258
	(0.0111)	(0.0150)	(0.0243)	(0.0103)	(0.0144)	(0.0196)
Analyst characteristics						
BREADTH	0.0139***	0.0146***	0.00810***	0.00768***	0.00958***	0.00554*
	(0.00116)	(0.00130)	(0.00269)	(0.00109)	(0.00140)	(0.00274)
EPS_OPTIMISM	0.112***	0.124***	0.108**	0.0831***	0.0864***	0.0825**
	(0.0148)	(0.0134)	(0.0375)	(0.0154)	(0.0133)	(0.0320)
EPS_PRECISION	−0.132***	−0.146***	−0.163**	−0.0470**	−0.0575**	−0.0986*
	(0.0221)	(0.0265)	(0.0608)	(0.0192)	(0.0272)	(0.0563)
	0.276***	0.285***	0.245***	0.156***	0.136***	0.157***
	(0.0102)	(0.0147)	(0.0391)	(0.0119)	(0.0129)	(0.0316)
N	25,678	14,046	2,349	25,678	14,046	2,349
Adj. R^2	0.076	0.069	0.074	0.057	0.069	0.075

are 8%–9% more likely found working at a TOP_LT or an ALLSTAR_BROKER. On the other hand, fast-turnover analysts are 6%–8% less likely to be found working at these brokerage types. This finding confirms that slower (faster) speed-style is more (less) common among analysts working at TOP_LT or an ALLSTAR_BROKER. However, columns 2 and 3 show that this finding could be explained by the endogenous migration of slower speed-style analysts to a TOP_LT or an ALLSTAR_BROKER. For instance, columns 3 report results estimated using analysts that have recently switched brokerage within the past year. They suggest that when analysts switch brokers, slow-turnover analysts are more likely to move to a TOP_LT or an ALLSTAR_BROKER. The economic magnitude is comparable to what we obtain for the cross-sectional estimate based on all analysts. Put together, these results suggest that slow-revising analysts tend to migrate toward brokers that cater primarily to investment banking and institutional investors, potentially because these brokers value their slow-style trait.

IV. Investment Value Implications

A. Real-Calendar-Time Portfolio Strategy

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

We assume that the stock is transacted at the closing-day price *after* the recommendation change. This ensures that the strategy is implementable by *ordinary investors* without private access to analysts' recommendations (i.e., before recommendation changes are made public). We carefully adjust for after-trading-hour recommendation releases using their timestamps recorded in the IBES 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 minutes of the current trading day (after 3:45PM ET), it is pushed to the next trading day. This is because IBES recommendation timestamps are often delayed (Bradley, Clarke, Lee, and Ornthanalai (2014)), and such consideration helps make the strategy more implementable for ordinary investors.

We create a daily portfolio that invests \$1 in each upgraded stock and sells \$1 in each downgraded stock. Once added to the portfolio, the stock is held for a fixed number of trading days: 30, 60, and 120. Two distinct long-short portfolios are formed separately for the strategy that follows fast- and slow-turnover analysts. For each portfolio, we compute the value-weighted portfolio return following Barber, Lehavy, and Trueman (2007). We calculate the risk-adjusted returns using the CAPM, the Fama–French 3-factor model, and the Carhart 4-factor model.

Table 6 presents our results with annualized alphas. Panel A reports the performance of the strategy that follows recommendations issued by fast-turnover analysts against that of slow-turnover analysts. For the 30-day holding period, the difference in alphas is between 8.5% and 9.5% per year, and statistically significant at the 1% level. This confirms that analysts in the slow-turnover group generate a greater investment value despite issuing fewer recommendations. The difference in alphas remains stable for the 60-trading day holding period and decreases to about 5% for the 120-trading day holding period. Nevertheless, they remain statistically significant at the 1% level. Supplementary Material Table IA4 provides detailed results on the long ("buy") and short ("sell") sides of the portfolio strategy at the daily level which shows that the strategy based on slow-turnover analysts dominates on both the long and short sides. In the Supplementary Material Table IA5, we compare our real-calendar time portfolio alphas against prior studies. We find that our strategy yields excess returns with the magnitude that are comparable with those previously documented. For instance, Barber, Lehavy, McNichols, and Trueman (2006) find annualized alpha from a 4-factor model in the [4.03; 10.08] range for the long side and [−11.09; −5.54] for the short side.

We examine how the investment value of differing recommendation speed-style stacks up against other analyst characteristics. Panels B–E of Table 6 report portfolio performance from the following recommendation changes of analysts sorted by other analyst-level or brokerage-level traits. We consider the strategy that follows recommendation changes of analysts ranked based on their earnings forecast precision in Panel B, career tenure length in the sell-side industry in Panel C, ranking in the *Institutional Investor*'s All-star status in Panel D, and brokerage-house status in Panel E. The Appendix provides definitions of variables that we use

TABLE 6
Real-Calendar Time Portfolio Results

Table 6 reports annualized alphas (in percentage terms) for the 30, 60, and 120-day holding period returns earned by investing $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. Portfolios are formed over the 1996–2013 period and their returns are calculated daily. Panel A reports portfolio alphas from the trading strategy that follows slow- versus fast-turnover analysts. Panel B reports results from a trading strategy that follows recommendation changes of analysts ranked in the top- versus bottom-quartile of earnings forecast precision (EPS_PRECISION). Panel C reports results based on recommendation changes of analysts from the top- versus bottom-quartile of general experience (EXPERIENCE). Panel D reports results based on recommendation changes of top-ranked All-star analysts (TOP_ALLSTAR = 1) versus non-All-star analysts (ALLSTAR = 0). Panel E reports results based on recommendation changes of analysts from high-status brokers (HIGH_BROKER = 1) versus low-status brokers (LOW_BROKER = 1). See the Appendix for definitions. Abnormal returns are calculated using three benchmarks: CAPM, the Fama–French 3-factor model, and the Carhart 4-factor model. The rows with bolded fonts indicate the difference between two groups of analysts (e.g., SLOW vs. FAST).

		Annualized Portfolio Alpha (%)					
	Holding Period (Trading Days)	CAPM	*t*-Stat	Fama–French 3-Factor	*t*-Stat	Carhart 4-Factor	*t*-Stat
Panel A. Performance Based on Analysts' Speed-Style							
Speed-style							
SLOW	30	27.9	9.95	27.7	7.32	25.8	7.57
FAST	30	18.4	7.48	18.5	7.51	17.3	7.14
Difference	**30**	**9.5**	**2.54**	**9.2**	**2.47**	**8.5**	**2.35**
SLOW	60	22.0	10.45	21.9	10.39	20.1	10.09
FAST	60	9.9	7.15	13.1	7.14	11.9	6.68
Difference	**60**	**12.2**	**4.35**	**8.8**	**3.14**	**8.3**	**3.09**
SLOW	120	14.7	9.47	14.7	9.50	13.2	9.19
FAST	120	9.9	7.25	9.8	7.21	8.7	6.73
Difference	**120**	**4.8**	**2.35**	**5.0**	**2.42**	**4.6**	**2.36**
Panel B. Performance Based on Analysts' Earnings Forecast Precision							
EPS_PRECISION							
Top quartile	30	24.74	11.68	24.73	11.66	23.26	11.37
Bottom quartile	30	21.79	8.48	21.78	8.48	20.17	8.08
Difference	**30**	**2.95**	**0.89**	**2.95**	**0.89**	**3.09**	**0.96**
Top quartile	60	19.44	12.42	19.48	12.44	18.15	12.24
Bottom quartile	60	18.47	9.66	18.44	9.64	16.76	9.31
Difference	**30**	**0.97**	**0.39**	**1.04**	**0.42**	**1.39**	**0.60**
Top quartile	120	14.19	12.31	14.28	12.39	13.12	12.32
Bottom quartile	120	13.61	9.60	13.62	9.61	12.24	9.31
Difference	**120**	**0.58**	**0.32**	**0.66**	**0.36**	**0.89**	**0.52**
Panel C. Performance Based on Analysts' General Experience							
EXPERIENCE							
Top quartile	30	26.20	9.73	26.24	9.74	24.64	9.38
Bottom quartile	30	24.25	10.75	24.24	10.75	22.63	10.43
Difference	**30**	**1.95**	**0.56**	**2.00**	**0.57**	**2.00**	**0.59**
Top quartile	60	21.19	10.41	21.26	10.44	19.63	10.12
Bottom quartile	60	18.54	10.94	18.68	11.04	17.20	10.79
Difference	**60**	**2.65**	**1.00**	**2.59**	**0.98**	**2.43**	**1.40**
Top quartile	120	16.33	10.27	16.41	10.32	14.81	10.08
Bottom quartile	120	13.71	11.05	13.85	11.17	12.59	11.03
Difference	**120**	**2.61**	**1.30**	**2.56**	**1.27**	**2.22**	**1.19**
Panel D. Performance Based on Analysts' All-Star Ranking Status							
All-star ranking status							
TOP_ALLSTAR	30	23.70	8.39	23.80	8.39	22.16	8.00
NON_ALLSTAR	30	21.79	7.16	21.66	7.16	20.08	6.77
Difference	**30**	**1.91**	**0.46**	**2.14**	**0.52**	**2.08**	**0.51**
TOP_ALLSTAR	60	15.42	7.13	15.49	7.16	13.68	6.67
NON_ALLSTAR	60	13.08	5.89	13.01	5.85	11.49	5.35
Difference	**60**	**2.34**	**0.75**	**2.48**	**0.80**	**2.19**	**0.74**
TOP_ALLSTAR	120	11.38	6.77	11.49	6.84	9.77	6.32
NON_ALLSTAR	120	9.48	5.99	9.41	5.96	8.13	5.40
Difference	**120**	**1.90**	**0.82**	**2.08**	**0.90**	**1.64**	**0.76**
Panel E. Performance Based on Analysts' Brokerage Status							
Brokerage status							
HIGH_BROKER	30	25.00	15.63	24.91	15.58	23.47	15.64
LOW_BROKER	30	25.53	14.21	25.49	14.19	23.83	14.18
Difference	**30**	**−0.53**	**−0.22**	**−0.58**	**−0.24**	**−0.36**	**−0.16**
HIGH_BROKER	60	20.62	16.36	20.59	16.34	19.12	16.98
LOW_BROKER	60	19.72	14.15	19.70	14.17	18.09	14.53
Difference	**60**	**0.90**	**0.48**	**0.89**	**0.47**	**1.03**	**0.61**
HIGH_BROKER	120	14.85	14.91	14.85	14.92	13.58	15.67
LOW_BROKER	120	13.99	12.84	13.99	12.88	12.51	13.53
Difference	**120**	**0.86**	**0.58**	**0.86**	**0.58**	**1.07**	**0.84**

to group analysts. In each panel, we compare the investment value of analysts from the top-ranked category against the bottom-ranked category; the middle category is omitted.

Overall, Panels B to E show that the difference in portfolio alphas sorted based on analyst-level traits other than the decision speed-style is not significant statistically and economically. This finding holds at all holding horizons. Some of these findings have been documented in prior literature. For instance, Barber et al. (2006) do not find that the strategy formed following recommendations of analysts from high-rating brokers outperforms that of analysts from low-rating brokers. Similarly, Fang and Yasuda (2014) use a real-calendar time portfolio analysis like ours to examine the difference in recommendation values of TOP_ALLSTAR versus NON_ ALLSTAR analysts and do not find that they significantly differ.

B. Stock Price Reaction to Recommendation Revision

We examine the difference in immediate market reactions to recommendation changes made by slow- versus fast-turnover analysts. Using regression analysis, we examine how the buy-and-hold adjusted return (BHAR) from days $t-1$ to day $t+1$ relative to the recommendation date t differs between slow- versus fast-turnover analysts. We control for various characteristics of the stocks on which the recommendations are issued, as well as analyst-level characteristics. Table IA3 in the Supplementary Material reports the results which we summarize here. Overall, we find the market reacts significantly more to recommendation changes issued by slow- relative to fast-turnover analysts. On average, an upgrade (downgrade) made by a slow-turnover analyst generates a 45 (76) basis points larger immediate market reaction than that of a fast-turnover analyst.

V. Understanding the Source of Differing Investment Values

We examine the type of corporate news fast- versus slow-turnover analysts react to when they make recommendations. After, we examine firm characteristics that are associated with the differing investment value of slow- versus fast-turnover analysts.

A. Reaction to News and Recommendation Speed-Style

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

Given that most recommendations are made after corporate news releases (Li et al. (2015)), the value of a recommendation revision depends on its incremental information beyond what market participants could learn from the preceding disclosure. News that are not based on hard figures or those containing forward-looking information about a company (e.g., merger and acquisitions, corporate strategy, and management forecasts) are harder to interpret by investors who do not follow the firm professionally. Thus, recommendations that follow these new releases are likely more valuable to investors because they significantly facilitate price discovery.

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

We use the Capital IQ data set. Importantly for our purpose, and in contrast to other news data sets, the CIQ data set provides a very fine news classification.[12] We supplement the Capital IQ data set with earnings announcements and management forecasts from IBES and eliminate duplicate events found among these three databases. The merged Capital IQ–IBES database contains 98 distinct news items from 1.14 million news.[13] To facilitate the interpretation, we aggregate these items into 14 broader topics. Appendix A.2 shows the mapping of news items into the 14 news topics. About a third of the news corresponds to Agenda Communication which are the date of forthcoming corporate events (e.g., investor day and annual meetings). These press releases typically inform the public about the date and the organization of the events which are unlikely to contain meaningful information; we remove them from our analysis. We further remove topics that make up less than 1% of the data set, there are 9 news topics that we consider: Earnings; Product Market & Operation; Management forecasts; Executive Turnover; M&A; Payout Policy; Security Trading; Securities Issuance; and Legal Issues.

We denote a recommendation change as being related to a specific news if it occurs within a [0; +15] day-window after the news release. We choose the 15-day window because some news may take analysts longer to distill their contents as well as channel checking their sources. Our conclusions are qualitatively unaffected when using a shorter 1-week window or a longer 4-week window. We estimate the probability of observing recommendation changes made by slow- or fast-turnover analysts in relation to news flows. For slow-turnover analysts, we estimate the following logit model:

$$\begin{aligned} (2)\qquad \Pr(\text{SLOW}_i = 1) = \alpha &+ \beta_1.\text{EARNINGS}_i \\ &+ \beta_2.\text{MANAGEMENT\_FORECASTS}_i \\ &+ \beta_3.\text{M\&A}_i + \cdots + \varepsilon_i, \end{aligned}$$

where the dependent variable in the logit function is equal to 1 if the recommendation change is made by a slow-turnover analyst, and 0 otherwise. We include 9 dummy variables each indicating whether the recommendation change is preceded by 1 of the 9 news topics that we consider. For fast-turnover analysts, we estimate a logit model similar to that in equation (2), but with FAST as the

[12]Studies that take advantage of this feature in Capital IQ key development database include Livnat and Zhang (2012), Cohn, Gurun, and Moussawi (2014), and Edmans et al. (2018).

[13]Section G in the Supplementary Material describes the database construction.

dependent logit variable. Year and industry-fixed effects are included in the model. Table 7 reports the results. Columns 1 and 2 report results for slow- and fast-turnover analysts, respectively.

We observe a distinct pattern in the type of corporate news that fast- versus slow-turnover analysts follow. We find that fast-turnover analysts tend to revise recommendations following earnings announcements, which are prescheduled and contain quantitatively verifiable information about the firm's past performance, while slow-turnover analysts do not. On the other hand, slow-turnover analysts are more likely to revise recommendations following news about Product Market & Operation, Management Forecasts, M&A, and Legal Issues, while fast-turnover analysts do not. These four categories are often unscheduled and tend to convey information about the firm's future performance.

Further, we believe that the contents of news that tend to precede recommendations of slow-turnover analysts are not as easily interpretable by nonstock experts. For instance, the change in product market strategy (e.g., new product launch and new corporate alliance) can affect the firm's value in different ways over the long run. Similarly, certain companies issue management forecasts. While these forecasts help guide investors about the firm's future earnings or

TABLE 7

Analyst Reaction to News

Table 7 reports estimation results from a logistic model for the probability that a recommendation change is issued by a slow-turnover analyst (column 1) or a fast-turnover analyst (column 2). The sample consists of recommendation changes from 2003 to 2013. The dependent variable is equal to 1 when the recommendation change is from a slow-turnover analyst (or fast-turnover analyst). All independent variables are indicator functions for various news type. Each independent variable is equal to 1 if its corresponding news was issued in the [−15, 0] calendar-day window before the recommendation change, and 0 otherwise. We consider 9 different types of news leading to a recommendation change. Earnings announcements and earnings guidance are from the IBES actual and guidance files, respectively. All other news events are from the Capital IQ "key development" data set. See Appendix A.2 for classification of news. Industry and Year-fixed effects are included in the estimation. Robust standard error clustered at the firm level is reported in parenthesis below each estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Probability That the Recommendation Change is From:	
News Leading Recommendation	SLOW	FAST
	1	2
EARNINGS	−0.079***	0.045**
	(0.027)	(0.022)
PRODUCT_MARKET&OPERATION	0.097***	−0.065**
	(0.025)	(0.033)
MANAGEMENT_FORECASTS	0.067**	−0.124***
	(0.028)	(0.034)
M&A	0.046*	−0.084**
	(0.028)	(0.035)
LEGAL_ISSUES	0.122***	−0.116**
	(0.044)	(0.057)
EXECUTIVE_TURNOVER	0.057*	−0.002
	(0.031)	(0.036)
PAYOUT_POLICY	−0.095***	0.028
	(0.031)	(0.034)
SECURITY_ISSUANCE	0.025	0.201***
	(0.049)	(0.051)
SECURITY_TRADING	−0.016	0.072
	(0.063)	(0.069)
N	76,229	76,229
No. of dependent var. = 1	11,650	10,499
Pseudo-R^2	2.02%	4.54%

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sales, they are estimates and made at the discretion of the management team. On the contrary, the contents of earnings announcements (i.e., EPS), which fast-turnover analysts tend to follow, can be easily compared against analysts' prior consensus, making their impact on stock valuation easier to quantify.

B. Rationales Behind Stock Recommendations: Evidence From Investext

We provide further evidence to support the conclusion in Table 7 by analyzing the contents in analysts' recommendation reports downloaded from Thomson One's Investext. We employ a labor-intensive approach of reading analysts' reports and identifying rationales and information sources behind each report. All reports are cross read by three researchers. We find that faster-revising analysts are more likely to use earnings-based valuation to make their recommendations. On the other hand, slower-revising analysts are more likely to base their recommendations on news that reflect changes in the firm's operating strategy, and product market competition. Additionally, we examine whether the superior recommendation value of slower-turnover analysts derive from their better access to management and do not find strong evidence in support of this hypothesis. We describe the methodology and further discuss results from reading analysts' recommendation reports in Section H of the Supplementary Material.

C. Firm Characteristics and the Investment Value of Slow Versus Fast Speed-Style

Finally, we examine firm characteristics that are associated with the superior investment value of slow- versus fast-turnover analysts using the real-calendar-time portfolio method described in Section IV.A. We compare the performance of the strategy that follows recommendation changes of slow- versus fast-turnover analysts for different groups of firms sorted by SIZE and VOLATILITY. We define SIZE as the firms' market capitalization and VOLATILITY as the idiosyncratic volatility calculated using the Carhart 4-factor model with 252 past trading days. We double-sort firms into 3×3 groups based on SIZE and VOLATILITY terciles annually at the end of June.

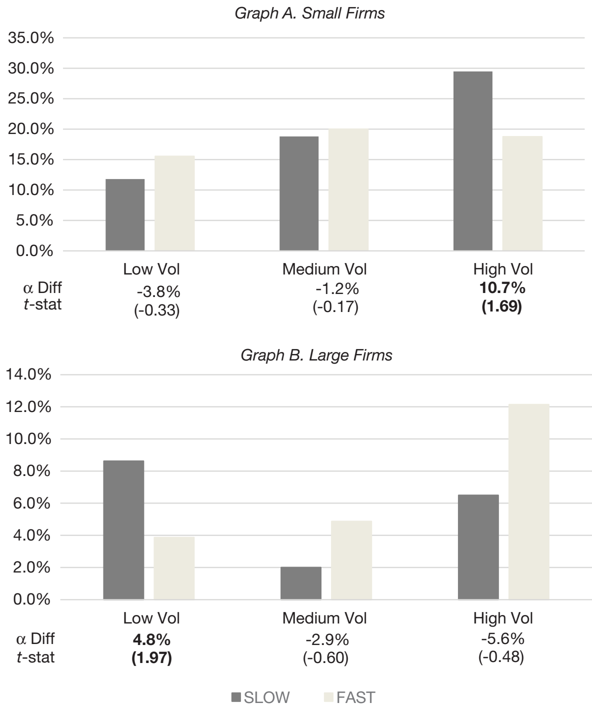
We find an interesting pattern in the superior investment value of slower recommendation speed-style, which we illustrate in Figure 3. Here, we plot portfolio alphas calculated from the Carhart 4-factor model with 120-day holding period for firms in the smallest and largest SIZE terciles. The superior investment value of slow- versus fast-turnover analysts emerges from the following two groups of firms. The first refers to small-cap stocks with high idiosyncratic volatility (see Panel A). These firms are usually less transparent and thus more difficult to value, which possibly makes the skill differential between slow- versus fast-turnover analysts matter more.

The second group of firms refers to large-cap stocks with low idiosyncratic volatility (see Panel B). In fact, slow-turnover analysts do not provide better investment value as the volatility level increases. We further examine why this is the case. We are motivated by one of our key findings in Table 7 that slow-revising

FIGURE 3

Real-Calendar Time Portfolio Alphas by SIZE × VOLATILITY Double-Sorted Terciles

In Figure 3, we double sort firms into 3 × 3 groups based on SIZE and VOLATILITY. For each group, we calculate real-calendar time portfolio results earned by investing $1 on a stock at the closing-day price *after* recommendation changes of slow- versus fast-turnover analysts. Graph A plots real-calendar time portfolio alphas (in annualized terms) with 120-day holding period returns for firms in the smallest-sized tercile. Similarly, Graph B reports results for firms in the largest-sized tercile. The difference in portfolio alphas between slow- versus fast-turnover analysts and its corresponding *t*-statistic are shown at the bottom of each panel. We define SIZE as the stock market capitalization, and VOLATILITY as the firm's idiosyncratic volatility calculated using the Carhart 4-factor model over 252 trading days. Firms are double sorted into 3 × 3 groups based on SIZE and VOLATILITY terciles annually.



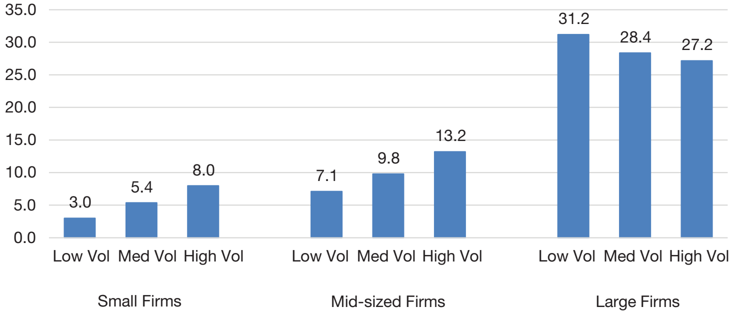
analysts tend to make recommendation changes following news containing "soft" information, which are harder to assess by nonstock experts. Figure 4 plots the annual average number of news that can be classified as "soft" information per firm. Motivated by our prior analysis, we classify news as containing soft information if it falls under one of these categories: Product Market & Operation; Executive Turnover; M&A; and Legal Issues.

Figure 4 plots the results separately for each group of firms double-sorted by their SIZE and VOLATILITY terciles. It shows that the average firm-level of soft information is increasing with volatility except for the largest tercile. In other words, the amount of "soft" information produced on large-cap firms is greatest among those with low volatility. This finding is consistent with our results in Table 7 which shows that slow-turnover analysts often revise recommendations following news with soft information. These news arrivals are harder to interpret, which explain the skill differential between slow- versus fast-turnover analysts.

FIGURE 4

Average Soft Information by SIZE × VOLATILITY Terciles

Figure 4 reports the average number of firm-specific news in the Capital IQ–IBES merged database that are classified as soft information at the stock-year level. We report results grouped by firms' SIZE and VOLATILITY double-sorted terciles. Appendix A.2 provides a mapping of news in the database into 14 topics. We classify news as containing soft information if it falls under one of these categories: Product Market & Operation; Executive Turnover; M&A; and Legal Issues. We define SIZE as the stock market capitalization, and VOLATILITY as the firm's idiosyncratic volatility calculated using the Carhart 4-factor model over 252 trading days. Firms are double sorted into 3 × 3 groups based on SIZE and VOLATILITY terciles annually.



VI. Concluding Remarks

We document significant variation in how frequently sell-side security analysts change their recommendation opinions. We develop a simple method for identifying analysts who revise their recommendation distinctly more frequently (vs. 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.

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

Appendix

A.1. List of Variables

Analyst-Level Variables

EXPERIENCE: Number of years since an analyst's first recommendation in the database to the current recommendation. Source: IBES.

RECOM_OPTIMISM: Average annual number of an analyst's new recommendation changes that are above (i.e., more optimistic than) the consensus. See Clement

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(1999) and Hong and Kubik (2003). For more details, see Section A of the Supplementary Material. Source: IBES.

RECOM_BOLDNESS: 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 Section A of the Supplementary Material. Source: IBES.

ALLSTAR: Dummy variable equal to 1 if an analyst is currently elected to the *Institutional Investor*'s All-American team annual ranking. The All-star title is awarded to top four analysts in each industry sector: first place, second place, third place, and runner-up. Source: Fang and Yasuda (2014).

TOP_ALLSTAR: Dummy variable equal to 1 if an analyst is currently elected to the *Institutional Investor*'s All-American team first and second places in the annual rankings. Source: Fang and Yasuda (2014).

MALE: Dummy variable equal to 1 if the analyst is a male and 0 otherwise. Source: Kumar (2010) and Law (2013).

EPS_FREQUENCY: Number of earnings forecasts made by an analyst per stock per quarter, averaged across all stocks an analyst covers each year. See Clement and Tse (2005). Source: IBES.

BREADTH: Number of stocks an analyst provides active recommendation coverage each year. Source: IBES.

LFR: Lead-follower ratio. The ratio of expected arrival times of other analysts' recommendations during the pre and postrecommendation 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 Section A of the Supplementary Material for further details. Source: IBES.

EPS_OPTIMISM: Average number of quarterly earnings forecasts that is above the consensus, excluding the analyst's own previous forecast level. See Section A of the Supplementary Material for further details. Source: IBES.

EPS_PRECISION: 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 each year. A higher value indicates a higher precision of an analyst's forecasts. See Clement and Tse (2005) and Bae, Stulz and Tan (2008). For more details, see Section A of the Supplementary Material. Source: IBES.

IND_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 (2009)). See Section A of the Supplementary Material for further details. Source: CRSP.

BROKER_SWITCHER: Dummy variable equal to 1, and 0 otherwise, if the analyst has switched her brokerage affiliation at least once during her tenure. Source: IBES.

RECENT_SWITCH: Dummy variable equal to 1, and 0 otherwise, if the analyst has switched her brokerage affiliation within the past year. Source: IBES.

Brokerage-Level Variables

TOP_BROKER: Dummy variable equal to 1 if the sell-side broker is in the top tenth size-percentile measured by the number of analysts employed each year. See Clement (1999). Source: IBES.

TOP_LT: Dummy variable equal to 1 if the sell-side broker is associated with a top 20th investment bank ranked in the League Tables based on the dollar volume of security issuance (IPO, SEO, and public debt). Source: Bloomberg.

ALLSTAR_BROKER: Dummy variable equal to 1 if the sell-side broker employs a relatively high percentage (above cross-sectional median) of All-star analysts in proportion of its analyst workforce. Source: Fang and Yasuda (2014).

HIGH_BROKER: Dummy variable equal to 1 if the sell-side broker is among the top 10 biggest brokerages each year based on number of analysts; see also Hong and Kubik (2003). Source: IBES.

LOW_BROKER: Dummy variable equal to 1 if the sell-side broker is in the bottom 90th size-percentile measured by the number of analysts employed each year. Source: IBES.

Stock-Level and Industry-Level Variables

SIZE: Logarithm of market capitalization. Source: CRSP.

VOLATILITY: Standard deviation of residuals from the Carhart 4-factor model estimated using daily returns. Source: CRSP.

POSITIVE_JUMP/NEGATIVE_JUMP: For each day t, we flag the security as experiencing a positive (or negative) jump if its 1-day buy-and-hold adjusted return exceeds $1.96 \times \sigma_\varepsilon$ (or falls below $-1.96 \times \sigma_\varepsilon$), where σ_ε is the idiosyncratic volatility calculated using the Carhart 4-factor model over the $[-60, -5]$ days relative to day t. Source: Loh and Stulz (2011).

MKT_ADJRET: Cumulative 1-month buy-and-hold stock return relative to that of the CRSP value-weighted index return. Source: CRSP.

IND_ADJRET: Cumulative 1-month buy-and-hold stock return relative to that of the industry portfolio return. Source: CRSP.

STOCK_VOLUME: Total trading volumes on the stock. Source: CRSP.

IND_VOLUME: Total trading volume on the industry classified based on 3-digit GICs. Source: CRSP.

REL_52WEEKHIGH: Ratio of the stock price to its 52-week high price. Source: CRSP.

Recommendation-Level Variables

RECOM_INPLACE: Number of days (or months) between the current recommendation revision and when it was last revised. Source: IBES.

LAST_RECOM: Level of the recommendation before the revision (i.e., “Strong Buy,” “Buy,” “Hold,” “Sell,” and “Strong Sell”). Source: IBES.

LEVEL_CHANGE: Difference between the final and the initial recommendation level. Source: IBES.

TABLE A1

Distribution of Brokerage Changes by Sell-Side Analysts

Table A1 summarizes the number of analysts' brokerage-house switches from 1996 to 2013. We keep track of brokerage house that employs each analyst on a yearly basis. Column 1 reports the total number of analysts each year in our sample with successfully matched brokerage-history records. Column 2 reports the number of analysts who have switched their brokerage house during their career (i.e., BROKER_SWITCHER = 1). Column 3 reports the number of analysts that recently changed their brokerage house within that calendar year (i.e., RECENT_SWITCH = 1).

Year	Total	Brokerage Switchers		Recent Brokerage Switch	
	1	2		3	
1996	521	122	23.4	48	9.2
1997	816	247	30.3	92	11.3
1998	934	334	35.8	105	11.2
1999	1,106	474	42.9	122	11.0
2000	1,297	642	49.5	172	13.3
2001	1,327	685	51.6	109	8.2
2002	1,336	709	53.1	93	7.0
2003	1,602	836	52.2	131	8.2
2004	1,714	913	53.3	136	7.9
2005	1,692	921	54.4	129	7.6
2006	1,704	969	56.9	141	8.3
2007	1,699	976	57.4	116	6.8
2008	1,650	991	60.1	173	10.5
2009	1,638	1,020	62.3	190	11.6
2010	1,654	1,030	62.3	185	11.2
2011	1,650	1,048	63.5	149	9.0
2012	1,702	1,091	64.1	137	8.0
2013	1,636	1,038	63.4	121	7.4
	25,678	14,046	54.7	2,349	9.1

A.2. Capital IQ–IBES News Dictionary

Appendix A.2 provides the mapping between the Capital IQ Key Development items and IBES news to our 14 news categories. The Capital IQ data set classifies news into various items with a label and numeric code. We supplement the Capital IQ database with IBES earnings announcements and management forecasts data. We group various news items into 14 categories listed below. Sources: IBES Data Sets and Capital IQ Key Development Labels.

EARNINGS: IBES actual file ANNDATS_ACT variable Announcements of Earnings (28).

MANAGEMENT FORECASTS: IBES global estimates file ANNOUNCE_DT variable Corporate Guidance – Lowered (26), Corporate Guidance – Raised (27), Corporate Guidance – New/Confirmed (29).

PRODUCT MARKET & OPERATION: Discontinued Operations/Downsizings (21), Strategic Alliances (22), Client Announcements (23), Business Expansions (31), Business Reorganizations (32), Product-Related Announcements (41), Labor-related Announcements (44), Considering Multiple Strategic Alternatives (63), Announcements of Sales/Trading Statement (138).

PAYOUT POLICY: Buybacks (36), Dividend Affirmations (45), Dividend Increases (46), Dividend Decreases (47), Special Dividend Announced (94), Dividend Cancelation (213), Dividend Initiation (214), Preferred Dividend (215), Buyback Update (151), Potential Buyback (152).

EXECUTIVE TURNOVER: Executive/Board Changes – Other (16), Executive Changes – CEO (101), Executive Changes – CFO (102).

SECURITIES ISSUANCE: Debt Financing Related (42), Private Placements (83), IPOs (85), Follow-on Equity Offerings (86), Fixed Income Offerings (87), Derivative/Other Instrument Offerings (88), Structured Products Offerings (135), Public Offering Lead Underwriter Change (136).

M&A: Seeking to Sell/Divest (1), Seeking Acquisitions/Investments (3), M&A Calls (52), M&A Rumors and Discussions (65), M&A Transaction Announcements (80), M&A Transaction Closings (81), M&A Transaction Cancelations (82), Spin-Off/Split-Off (137).

RESTATEMENT & AUDITING: Restatements of Operating Results (43), Impairments/Write Offs (73), Auditor Going Concern Doubts (59), Auditor Changes (150).

AGENDA COMMUNICATION: Notification of Earnings Calls (48), Notification of Guidance/Update Calls (49), Notification of Shareholder/Analyst Calls (50), Notification of Company Conference Presentations (51), Notification of Earnings Release Date (55), Notification of Delayed Earnings Announcements (61), Notification of Special/Extraordinary Shareholders Meeting (97), Notification of Sales/Trading Statement Calls (139), Notification of Sales/Trading Statement Release Date (140), Announcements of Conferences (149), Announcements of Analyst/Investor Day (192), Announcements of Special Calls (194), Notification of Annual General Meeting (62), Notification of Board Meeting (78).

LEGAL ISSUES: Regulatory Agency Inquiries (24), Lawsuits & Legal Issues (25), Legal Structure Changes (76), Changes in Company Bylaws/Rules (77), Regulatory Authority – Regulations (205), Regulatory Authority – Compliance (206), Regulatory Authority – Enforcement Actions (207).

SHAREHOLDER ACTIVISM: Investor Activism – Proposal Related (156), Investor Activism – Activist Communication (157), Investor Activism – Target Communication (160), Investor Activism – Proxy/Voting Related (163), Investor Activism – Agreement Related (164), Investor Activism – Nomination Related (172), Investor Activism – Financing Option from Activist (177), Investor Activism – Supporting Statements (187).

BANKRUPTCY: Bankruptcy – Filing (89), Bankruptcy – Conclusion (90), Bankruptcy – Emergence/Exit (91), Bankruptcy – Asset Sale/Liquidation (153), Bankruptcy – Financing (154), Bankruptcy – Reorganization (155), Bankruptcy – Other (7), Debt Defaults (74).

SECURITY TRADING: Delayed SEC Filings (11), Delistings (12), Exchange Changes (57), Ticker Changes (58), Index Constituent Drops (75), Index Constituent Adds (95), End of Lock-Up Period (92), Shelf Registration Filings (93).

OTHERS: Seeking Financing/Partners (5), Name Changes (56), Address Changes (60), Fiscal Year End Changes (79), Potential Privatization of Government Entities (99), Composite Units Offerings (134).

Supplementary Material

To view supplementary material for this article, please visit https://doi.org/10.1017/S0022109022000199.

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