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

Internet Appendix

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This document contains discussions and additional results that we left out of the main paper due to space considerations.

Section I. Reconciliation with Hobbs et al. (2012)

Section A

Variable constructions for selected analyst characteristics

- RECOM_BOLDNESS measures the fraction of recommendation changes that move away from the consensus in the spirit of Jegadeesh and Kim (2010). A recommendation is away from the consensus if its rating scale changes in the direction away from the recommendation consensus. We calculate recommendation consensus as the mean of outstanding recommendations issued on each stock, excluding an analyst's own recommendation level. We calculate the boldness of an analyst using all recommendation changes from January to December of each year. In few situations when an analyst makes less than four recommendation changes in the year, we extend the sample back by one year to increase the sample size.
- RECOM_OPTIMISM is the average number of an analyst's new recommendation changes in each calendar year that are above the consensus. Following prior literature such as Hong and Kubik (2003), and Malmendier and Shanthikumar (2014), we consider a recommendation that is above the consensus to be optimistic. We exclude an analyst's own recommendation level on a stock when calculating her recommendation consensus. To calculate Optimism at the analyst-year level, we assign a dummy variable equal to one to each new recommendation that is optimistic, and zero otherwise. We then calculate the average value of all recommendation-level optimism dummies associated for each analyst during the calendar year.
- EPS_PRECISION is defined following Clement and Tse (2005), and Bae, Stulz and Tan (2008). It measures the accuracy of an analyst's earnings forecasts relative to other analysts providing forecasts on the same firm-quarter. EPS Precision of an analyst i on firm j for the fiscal quarter Q is calculated as

$$\text{EPS Precision}_{\text{i,j,Q}} = -1 \times \frac{\text{AFE}_{\text{i,j,Q}} - \overline{\text{AFE}_{\text{j,Q}}}}{\overline{\text{AFE}_{\text{j,Q}}}},$$

  where $\text{AFE}_{\text{i,j,Q}}$ is the absolute forecast error of analyst i forecasting firm j's fiscal quarter Q earnings, and $\overline{\text{AFE}_{\text{j,Q}}}$ is the average absolute forecast error across all analyst forecasts of firm j's fiscal quarter Q earnings. As explained in Clement (1999), we subtract $\text{AFE}_{\text{i,j,Q}}$ by $\overline{\text{AFE}_{\text{j,Q}}}$ to adjust for the firm–year effect. The difference is then deflated by $\overline{\text{AFE}_{\text{j,Q}}}$ to correct for heteroskedasticity in forecast error distribution. After, we multiply this figure by (-1) so that a higher value of this variable indicates higher precision of an analyst's forecasts.
- EPS_OPTIMISM is the average number of quarterly earnings forecasts of an analyst that are above the consensus, excluding the analysts' own previous forecast level (Malmendier and Shanthikumar, 2014). We assign a dummy variable equal to one to each forecast made by an analyst that is optimistic, and zero otherwise. We first calculate EPS optimism at the analyst–stock–year level using all her quarterly

forecasts in a given year. After, we average the results across all stocks that analyst i covers to produce EPS optimism at the analyst–year level.

- LFR is the leader–follower ratio. It measures the average timeliness of an analyst's recommendation change in the spirit of Cooper, Day and Lewis (2001) who developed the LFR to quantify the timeliness of an analyst's forecasts. We apply the method that they developed to analysts' recommendation revisions. LFR is calculated as the ratio of the cumulative lead-time, T_0, over the cumulative follow-time, T_1, for the *K* recommendation changes made by a given analyst. The cumulative lead-time and the cumulative follow-time for *K* recommendation changes are calculated as:

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

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

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

Section B

Bias correction for the time between recommendation revisions

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

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

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

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

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

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

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

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

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

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

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

Section C

Brokerage classification based on primary clientele: Institutional vs. Retail?

We classify sell-side research brokerages based on the importance of their functions toward institutional clientele versus retail investors. We consider two approaches:

1. **Top League-Table broker**. We manually collect *historical* league table of Investment banks based on the dollar volume of security issuance in the US (IPO, SEO, and public debt issuance) and match it with broker name in IBES. We use Bloomberg as our data source because unlike Reuter's Thomson Eikon, it provides historical data (e.g., Lehman Brother does not appear in Reuter's league table). The data is available from 1999 onwards. We hypothesize that sell-side research firms that are affiliated with Top-League table investment banks are more likely to produce research that cater to the large investment-banking clientele. We classify a broker that is ranked in the top 20 of the league table as the Top-League table broker (TOP_LT)
2. **All-star concentrated broker**. Each year, we calculate the fraction of all-star analysts that work at each sell-brokerage. This is the proportion of all-star analysts over all analysts working for the broker. All-star status is awarded to sell-side research teams each year based on the voting of institutional investors (i.e., analysts' clients). We believe that this variable measures how well each equity research firm is recognized by institutional investors. We consider a broker with the fraction of all-star analysts above the cross-sectional median as an All-star concentrated broker (ALLSTAR_BROKER).

Section D

Effects of other control variable as potential recommendation triggers

This section describes the list of control variables that we apply to the Cox Proportional Hazard (Cox PH) model estimation in Table 3 of the main text. We discuss how these control variables impact the hazard rate of a recommendation revision in relation to the framework of potential recommendation triggers that we outlined earlier in Section III.A of the main text.

The first variable that substantially influences the speed at which analysts revise their recommendations is the arrival of public news, which we control for using NEWS_INTENSITY. We find the coefficient estimates on NEWS_INTENSITY in Columns (3) of Table 3 are positive and strongly significant. The economic impact of news arrival is large. The hazard ratios on NEWS_INTENSITY are 1.24 and 1.27 for upgrade and downgrade revisions, respectively. This implies that an increase of one news article reported in the previous week is likely to increase the probability that an analyst will revise her recommendation by about 1.2–1.3 times.

The next set of control variables that we include is related to changes in the publicly traded share prices. This includes an upward or downward stock price momentum relative to the aggregate market. We include MKT_ADJRET, which is the cumulative one-month buy-and-hold stock return in excess of the CRSP value-weighted index return. This variable captures the firm's equity performance relative to the stock market. A strong positive price momentum should lower the analyst's valuation-to-price ratio (*V/P)*, thereby triggering a downgrade revision. The opposite argument would hold for a strong negative price momentum, where we expect it to trigger an upgrade recommendation. Thus, we expect MKT_ADJRET to positively (negatively) affect the hazard rate of a recommendation upgrade (downgrade). This is exactly what we find in Table 3. A positive (negative) stock price momentum subsequently induces an analyst to upgrade (downgrade) the stock. The effect of MKT_ADJRET is much stronger for downgrades than upgrades, suggesting that an analyst is quicker to respond to a persistent stock price decline than a persistent stock price increase. For instance, Column (3) of Panel A shows the hazard ratio on MKT_ADJRET is 3.08, suggesting that one unit (i.e., 100%) increase in stock price relative to the market index over the last month increases the probability of an upgrade revision by about 3.1 times. As for downgrades, Column (3) of Panel B shows the hazard ratio on this variable is 0.23, indicating that a 100% decrease in stock price relative to the market index over the last month increases the probability of a downgrade revision by about 1/0.23= 4.35 times.

As discussed in Kadan et al. (2012), industry expertise is an important aspect of sell-side research. Analysts might change their recommendation at different time, depending on the industry benchmark they use for stock recommendations. We include IND_ADJRET, which is the cumulative one-month buy-and-hold stock return relative to the return of the benchmark industry. We follow Kadan et al. (2012) and group firms into 68 industries using the Global Industry Classification Standard (GICS), which is widely adopted by investment banks as the industry classification system. The industry benchmark return is calculated as the equally weighted portfolio of stocks in the industry. We expect IND_ADJRET to positively (negatively) affect the rate of an upgrade (downgrade) revision, in a similar way that MKT_ADJRET does. Table 3 shows the coefficient estimates on IND_ADJRET are strongly significant. The sign of these estimates is consistent with our expectation. The economic impact of IND_ADJRET on the hazard rate is significant, and smaller in magnitude than that of the MKT_ADJRET variable.

Changes in share price can occur abruptly, rather than gradually as in the case of stock price momentum. Such large price changes are often referred to as jumps and we include them in our list of potential recommendation triggers. 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.[1] When a jump is detected, we further classify it into a positive jump or a negative jump depending on its direction. We use two indicator variables: POSITIVE_JUMP and NEGATIVE_JUMP. These two variables are equal to 1 if we observe a positive (or negative) jump in the firm stock price in the previous week, and 0 otherwise. Our prior on the impact of stock price jumps is mixed. A visibly large increase in stock return may convey a favorable information about the firm, which could trigger an analyst to upgrade the stock. However, this sudden price change could contain stale information, which analysts have already uncovered, but was later picked up by the market with a delayed price adjustment.

We find an interesting pattern on the effect of stock price jumps in Table 3. Panel A shows the coefficients on POSITIVE_JUMP are negative and strongly significant, suggesting that an analyst is less likely to upgrade her recommendation following a positive stock price jump. In other words, analysts do not generally upgrade their recommendations by chasing large positive price change (i.e., "piggybacking") as argued by Altinkilic and Hansen (2009). As for the estimates on NEGATIVE_JUMP, we also find that they are negative, but the economic magnitude is smaller relative to POSITIVE_JUMP.

In Panel B, we find a consistent pattern that analysts do not downgrade a stock by simply chasing sudden large price decline. We see this from the negative and strong significant estimates on NEGATIVE_JUMP. Besides the recent stock price momentum and sudden stock price jumps, we include other security-trading signals that are informative about the share price. They include the stock trading volume, the stock return volatility, and the stock price value relative to its 52-week high. We expect the hazard rate that a recommendation will be revised is increasing with the stock trading volume since it signals an increasing investors' attention to trade on

[1] For each day t, we flag the security as experiencing a positive jump if its 1-day buy-and-hold adjusted return exceeds $1.96 \times \sigma_\varepsilon$, and flat it as experiencing a negative jump if its 1-day buy-and-hold adjusted returns dips below $-1.96 \times \sigma_\varepsilon$, where σ_ε is the idiosyncratic volatility. Following Loh and Stulz (2011), we calculate the buy-and-hold adjusted stock return following Daniel, Grinblatt, Titmans, and Wermers (1997), i.e., DGTW-adjusted return, while the idiosyncratic volatility is calculated using the Carhart 4−factor model over the [−60, −5] days relative to day t. We use 1.96 as the cut-off value in detecting return outliers which corresponds to the 5 percent detection rate for a standard normal distribution. We repeat this procedure for all stocks in our sample and for all trading days between 1996−2013.

the security. Consistent with our prediction, Table 3 shows that an increase in trading volume raises the probability of a recommendation for both upgrades and downgrades.

Our prior on the effect of stock return volatility is that it negatively affects the hazard rate of a recommendation revision. High volatility raises the level of uncertainty in analysts' ability to distill information, resulting in lower precision on their estimate of the stock valuation-to-price ratio (*V/P*). Therefore, we expect that an increase in stock volatility would delay the recommendation revision. The coefficient estimates of the variable VOLATILITY in Table 3 are consistent with our prediction; they are negative and strongly significant across all columns.

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 is represented by REL_52WEEKHIGH. Table 3 shows the coefficient estimates on this variable is positive for upgrades (Panel A), but negative for downgrades (Panel B). This finding suggests that analysts are more likely to upgrade their recommendations when the stock price increases relative to its 52-week high, while downgrading them when the stock price continually falls further below its 52-week high.

The time it takes an analyst to revise her recommendation can depend on the magnitude of the recommendation change that she is evaluating. We control for this effect in Table 3 using LEVEL_CHANGE We define LEVEL_CHANGE as the absolute value of the difference between the new and previous recommendation levels. This variable captures the empirical fact that an upgrade revision by 2 notches from "hold" to "strong buy" occurs less often than a 1-notch upgrade from "hold" to "buy." We define LEVEL_CHANGE as the absolute value of the difference between the new and previous recommendation levels. We find that the magnitude of the recommendation change, i.e., LEVEL_CHANGE, is negatively related to the speed of a recommendation revision. This is consistent with Loh and Stulz (2011), which shows that multiple-level recommendation changes occur less frequently than one-level recommendation changes

Section E

Alternative window lengths for identifying recommendation speed-style

The empirical results shown in the main text assume that investors update their belief about each analyst's recommendation speed-style using all her past recommendation history and those of her peers. For instance, when classifying the speed of analysts in the year 2000, we use *all* recommendations history up until December 1999. For the year 2001, we extend the recommendation history window by one year, i.e., up until December 2000. We provide results in this Internet Appendix showing that our main conclusions are qualitatively unaffected when using shorter periods of recommendation history to identify analysts' recommendation speed-style.

We use three alternative rolling windows of recommendation history as our robustness checks: 7, 5, and 3 years. Besides the difference in the rolling-window length, the method used to identify analysts' recommendation speed-style is identical to that described in the main text. Figure IA1 in this Internet Appendix plots the frequency of fast-, average-, and slow-turnover analysts identified each year using different windows of recommendation history. The sample period is 1996–2013. Panel A plots the baseline results used in the main text. Panels B, C, and D plot results for the other recommendation windows. We find that the number of analyst-year observations slightly decline as we shorten the windows of recommendation history. This is because we require analysts in the sample to have active recommendation-change history on at least three stocks, and importantly for each stock that an analyst covers, she must have made at least two recommendation changes on it. Consequently, analysts that have relatively short records in I/B/E/S are more likely dropped from the sample as we shorten the length of the recommendation-window history.

Although the number of observations slightly drops as we shorten the window length, Figure IA1 shows that the yearly distributions of analysts' speed-style are similar across the four panels. This finding suggests that the method we use provides a stable classification of analysts' speed-style within a finite sample. That is, on any given year, we find that the proportion of analysts in the three turnover groups are highly similar across the four panels.

Table IA1 in this Internet Appendix reports the Pearson correlation of analyst turnover groups identified using the four different recommendation windows. Panel A reports results for the slow-turnover analysts. Panels B and C report results for the average- and fast-turnover groups, respectively. On average, we find the correlations are high, i.e., about 60–90%. As expected, we find the correlation values decrease as the difference in recommendation window lengths increases. For instance, Panel A shows the correlation of slow-turnover analysts identified using all recommendation history and those identified using a 7-year rolling window is 87%. This value drops to 87%, 75% and 58% when comparing the results using all recommendation history against those obtained using 7-year, 5-year and 3-year rolling windows, respectively. Overall, we find that decreasing the window length affects the classification of analyst recommendation speed-style. Nevertheless, the results obtained using different windows are within reasonable ranges.

We examine whether analysts' speed-style identified using shorter recommendation windows can robustly predict the speed at which analysts will revise their future recommendations. We follow the same methodology outlined in Section III.B of the main text. We apply the Cox Proportional Hazard (Cox PH) model to estimate analysts' time to the next recommendation revision, controlling for various recommendation triggers. We denote $\lambda(t)$ as the hazard rate at which an outstanding recommendation on stock *j* by an analyst *a* will be revised in week *t*. We estimate the hazard rate that a recommendation will be revised following a log-linear model:

$$\lambda(t) = \lambda_{0,j}(t) \exp\left(\alpha_{Slow} SLOW_a + \alpha_{Fast} FAST_a + \Sigma_i \beta_i X_{i,j}(t) + \eta_a\right). \quad (1)$$

We estimate the above hazard-rate model at the recommendation-week level, and separately for upgrades and downgrades. The model that we estimate is identical to the regression models in columns (3) and (6) in Table 3 of the main text, for which we include the control variable NEWS_INTENSITY that measures the number of firm-specific news per week. The sample period is 2003–2013. Table IA2 in the Internet Appendix reports the estimation results. Panels A and B report results for upgrades and downgrades, respectively. In each panel, results obtained using four different recommendation windows are reported. Column (1) reports the results obtained using all recommendation history, which are the results that we report in the main text. The main variable of interests are indicator variables SLOW and FAST, indicating the recommendation speed-style of the analyst obtained from the previous year. To save space, we only report coefficient estimates on two control variables CONCURRENT_EARNINGS and NEWS_INTENSITY.

Table IA2 shows that the coefficient estimates on SLOW are negative and highly significant in all columns. This suggests that analysts whom we identify as a slow-turnover type based on their past recommendation patterns tend to revise their future recommendations more slowly. Importantly, the magnitude of coefficients on SLOW are very similar across all columns. This finding indicates that the speed-style classification method that we use is highly robust to the choice of recommendation windows.

Table IA2 shows that coefficient estimates on FAST are positive and highly significant across all columns. This finding suggests that fast-turnover analysts are likely to revise their future recommendations more quickly than their peers are, and importantly, this conclusion is unaffected by the length of past recommendation windows. However, we find that the magnitude of coefficients on FAST decreases as the recommendation window used shortens. This suggests that the identification of fast recommendation-revising analysts become more difficult when we use shorter recommendation-change history to infer about their recommendation speed-style. This finding is expected because when we shorten the recommendation window, analysts with shorter records in I/B/E/S are more likely to be eliminated from the sample. These eliminated analysts are likely to be in their early career stage, and as shown in Table 4 in the main paper, they are usually classified as a fast-turnover type.

Overall, we find that our main conclusions are qualitatively robust to the choice of recommendation windows used for the speed-style classification. The use of a shorter recommendation window affects the identification of fast-revising analysts more than the identification of slow-revising analysts.

Section F

Investment value implications of differing decision speed-style

F1. Stock price reaction to recommendation revision

We examine the difference in immediate market reactions to recommendation changes made by slow- versus fast-turnover analysts. We estimate the following regression model:

$$\text{(2)} \qquad \mathrm{BHAR}[-1;+1]_{\mathrm{s,i,t}} = \mathrm{SLOW_i} + \beta \mathrm{A}\textsc{nalyst\_}\mathrm{C}\textsc{ontrols}_{\mathrm{I,T}} + \gamma \mathrm{R}\textsc{evision\_}\mathrm{C}\textsc{ontrols}_{\mathrm{S,T}}$$
$$+ \delta \mathrm{S}\textsc{tock\_}\mathrm{C}\textsc{ontrols}_{\mathrm{S,T}} + \varepsilon_{s,i,t},$$

where $\mathrm{BHAR}[-1;+1]_{\mathrm{s,i,t}}$ is the buy-and-hold abnormal return (BHAR) centered on the recommendation revision made by analyst *i* on stock *s* at time *t*. The BHAR from days $t-1$ to day $t+1$ relative to the recommendation date *t* is calculated as follows:

$$\mathrm{BHAR}[-1,+1] = \prod_{\tau=t-1}^{t+1}(1+R_{\mathrm{s},\tau}) - \prod_{\tau=t-1}^{t+1}(1+R_{\mathrm{DGTW},\tau}),$$

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

Table IA3 reports the results. For this analysis, we include only recommendation changes that are made by slow- and fast-turnover analysts. Our variable of interest here is $\mathrm{SLOW_i}$, which is an indicator variable equal to 1 if analyst i is a slow-turnover type, and 0 if she is a fast-turnover type. Therefore, $\mathrm{SLOW_i}$ measures the difference in market reaction to recommendation changes of slow- versus fast-turnover. We include various characteristics of the stocks on which the recommendations are issued, as well as analyst-level characteristics (ALLSTAR, MALE, and BREADTH). We also include firm brokerage, industry and year-fixed effects in the regression, and cluster standard errors at the firm level.

Columns (1) and (2) present results for upgrades and downgrades, respectively. We find that, on average, an upgrade made by a slow-turnover analyst generates a 45 basis points higher immediate market reaction than that of a fast-turnover analyst. Similarly, we find the market reacts significantly more to a downgrade made by a slow revising analyst; the difference in magnitude is about 76 basis points. Interestingly, we find that EXPERIENCE dampens the market reaction to downgrades but not upgrades. Therefore, all else equal, the market does not react more strongly to recommendation changes by a more experienced analyst.

We define HIGH_EPS_OPTIMISM and HIGH_EPS_PRECISION as dummy variables that are equal to one if the analyst's EPS_OPTIMISM and EPS_PRECISION, respectively, are above the sample median. Among other analyst-level characteristics, we find the coefficient estimate on HIGH_EPS_PRECISION is significant for upgrades but not for downgrades. Nevertheless, the estimate on HIGH_EPS_PRECISION is smaller in magnitude relative to that on SLOW_i.

We emphasize that the results in Table IA3 are estimated with various controls for characteristics that are specific to each recommendation revision. We include dummies for recommendation revisions that occur one week before (EARNINGS_LEADING), one week after (EARNINGS_FOLLOWING), and around the day of an earnings announcement (CONCURRENT_EARNINGS) because the timing of the recommendation revision relative to earnings news conveys information (Ivkovic and Jegadeesh, 2004). PRE_EARNINGS, EARNINGS_RELATED, and CONCURRENT_EARNINGS, are equal to 1 if the recommendation occurs on the [-7,-2]. We include a dummy variable for revisions that do not herd toward the consensus (AWAY_CONSENSUS) as defined in Jegadeesh and Kim (2010). Recommendation consensus is the mean of outstanding recommendations issued on each stock, excluding the analysts' own recommendation level. We also control for the magnitude of the recommendation change (LEVEL_CHANGE), and the recommendation level before it is revised (LAST_RECOM).

Overall, we find the market reaction to recommendation changes issued by slow- versus fast-turnover analysts is economically large and statistically significant.

F2. Real-calendar Time Portfolio Results: Comparison with existing literature

Table IA5 provides a detailed comparison of the alpha generated by our trading strategy with those reported in the literature. Panel A summarizes the sample source, data source, and methodology used by each study (Barber et al. (2001, 2006, 2007); Fang and Yasuda (2014)). In Panel B, we show the alpha as reported in each paper along with the frequency used to compute the alphas. In Panel C, to allow a common ground for comparison, we compute yearly alpha based on a four-factor model by adjusting the reported estimates (i.e. multiplying daily return by 252 and monthly return by 12). We also compute a pseudo long/short portfolio by adding the alpha from the long and short portfolios together. We find our estimates to be in line with previous studies. For instance, for the long/short portfolio, we report alpha estimates in the [8.67; 25.82] range, while Barber et al. (2001) reports a single 9.04 estimate, Barber et al. (2006) reports estimate in the [9.58; 21.17] range and Barber et al. (2007) in the [2.02;14.36] range.

F3. Real-calendar Time Portfolio Results across Firm Volatility and Size

We compare real-calendar time portfolio alphas between the strategy that follows slow- vs. fast-turnover analysts separately for firms sorted by their *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. Firms are sorted into SIZE and VOLATILITY quintiles annually at the end of June.

Tables IA6 and IA7 report real-calendar time portfolio results for firms sorted into SIZE and VOLATILITY quintiles, respectively. The last two columns in each table report the number of stocks that are held in each portfolio on any given day. These numbers represent the average number of unique stocks that appear in the portfolio each day as securities are added or dropped in accordance with the trading strategy.

We focus our discussion on the 120-day holding period as this strategy allows for the greatest number of firms present in the real-calendar-time portfolio. Tables IA5 and IA6 show that alphas from the portfolio that follows slow-turnover analysts are higher than those from the portfolio that follows fast-turnover analysts. This finding holds across all SIZE and VOLATILITY quintiles. For a visual comparison, Figures IA2 and IA3 plot portfolio alphas earned from following recommendation changes of slow- vs. fast-turnover analysts across SIZE and VOLATILITY quintiles.

Looking across SIZE quintiles in Figure IA2, we find that the difference in alphas between SLOW minus FAST analysts (a Diff) is largest among small firms, and statistically significant (t-stat of 1.95) for the smallest SIZE quintile.

Looking across VOLATILITY quintiles, we find a U-shaped pattern for the difference in alphas. Figure IA3 shows that the superior investment value of slow- vs. fast-turnover analysts (i.e., a Diff) concentrates in the least-volatile quantile (6.9% with 2.02 t-stat) and the most-volatile quintile (12.3% with 1.51 t-stat). Although the difference in alphas is largest in the most-volatile quintile, its statistical significance is weak. The weaker statistical significance found in the most-volatile quintile is expected as firm volatility in this quintile is, on average, 3 times higher than those in the least-volatile quintile.

To better understand the investment value of SLOW vs. FAST analysts along the volatility dimension, we double-sort firms by their SIZE and VOLATILITY. We use tercile sorting along each characteristic to ensure enough firms in each double-sorted (3-by-3) portfolio. Table IA8 summarizes the results. For brevity, we report the portfolio alphas calculated from the Carhart Four-factor model with 120-day holding period. For a visual comparison, we plot these portfolio alphas in Figure IA4.

Looking at the SIZE × VOLATILITY sorted portfolios, the superior investment value of slow- vs. fast-turnover analysts clearly emerges for the following two groups of firms:

(i) **Small firms with high idiosyncratic volatility**. Small firms, on average, are opaquer and have lower news coverage. Further, those with high idiosyncratic volatility would be even harder to value, and thus, the skill difference between Slow vs Fast analysts matters more.

(ii) **Large firms with low idiosyncratic volatility**. The difference in alphas between Slow vs. Fast analysts for this group is 4.8% (with t-stat of 1.97). In fact, we do not find that slow-turnover analysts 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 that slow-revising analysts tend to make recommendation changes following news classified as "soft" information, which are harder to assess by non-stock experts. This evidence is shown in Table 8 of the main manuscript provides results on how SLOW vs. FAST analysts react to different news releases. We also find support for this conclusion when manually reading analysts' recommendation reports downloaded from Thomson One's Investext.[2]

Figure IA5 plots the average firm-level of soft information per year. We plot the results for firms double-sorted by SIZE and VOLATILITY. The data for firm-specific news is from the Capital IQ Key Development database. Consistent with our prior analysis, we classify news as containing soft information if it falls under one of these categories PRODUCT MARKET & OPERATIONS; M&A; EXECUTIVE TURNOVER; LEGAL ISSUES

Figure IA5 shows an interesting pattern. The average firm-level of soft information is increasing with volatility except for the largest tercile. This finding suggests that news coverage on large-and-low-volatility firms tend to carry more soft information, which are harder to interpret and thus the skill difference between Slow vs Fast analysts matters more.

[2] See Internet Appendix Section H.

Section G

News Database for the Analyses on Analysts' Reaction to News

Our main source for news flows is the Capital IQ's Key Development database (Capital IQ). This is a comprehensive database of company-specific news collected from over 20,000 public news sources. They include firm- and non-firm-initiated news found in newswire services (e.g., Business Wire, PR Newswire), third-party sources (e.g., newspaper articles), investor transcript or disclosure wires. Importantly for our purpose, the advantage of the CIQ dataset is that it eliminates duplicates and provides a very fine classification of news categories. This allows us to distinguish news that contain "soft" information (e.g., change in the firm strategy or the introduction of a new product) versus those containing primarily "hard" information such as earnings announcements. Another attractive feature of the Capital IQ database is that it pre-filters 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 dataset that consolidates a particular news item from different sources into a single record (see Edmans et al (2018)).

For comprehensiveness, we supplement the Capital IQ dataset with two well-known corporate news databases: (i) Earnings announcements from the I/B/E/S actual file; and (ii) Management forecasts from the I/B/E/S guidance estimate file. The I/B/E/S guidance file provides forward-looking statement issued by the company along several metrics. The following three primary metrics account for 80% of the observations: EPS (37%), sales (31%), capital expenditures (12.3%). The dataset contains both annual forecasts (62% of observations) and quarterly forecasts (38%). For each forecast, the management provides either one single value (25% of observations) or a range of values (75%). In our analysis, we use all observations from the guidance estimate file and set the MANAGEMENT_FORECAST dummy to one if there is a management forecast issued on a particular day.

The CIQ dataset also contains news about earnings announcements and management forecasts about earnings and sales. Therefore, we eliminate any duplicate events found among these three databases.[3] We find that the universe of firms covered in Capital IQ is slightly smaller than that in I/B/E/S. We are able to map 88% of firms in I/B/E/S to the Capital IQ database. As a result, we lose about 10% of I/B/E/S firms that were in our initial sample when we conduct empirical tests using the Capital IQ–I/B/E/S dataset. The Capital IQ dataset starts in mid-2002. We exclude the year 2002 because news coverage was less comprehensive at the start of the sample. Therefore, empirical results in this paper that use the Capital IQ–I/B/E/S news flows are limited to the 2003–

[3] The timing of earnings announcements may be inaccurately recorded in I/B/E/S, sometimes by +/- 1 trading day (see Bradley et al. (2014)). This potential error could lead to duplicate observations when earnings announcements are correctly recorded in Capital IQ while they are not in I/B/E/S. We carefully correct for these duplicates by searching for identical earnings announcements between the two databases over two-overlapping days.

2013 period. The final Capital IQ–I/B/E/S news dataset contains 1.14 million news on 19,831 firm-year observations with 3,848 distinct firms.

Capital IQ classifies news into more than 100 different items. To facilitate interpretations, we aggregate news items in the joint Capital IQ–I/B/E/S dataset into 14 main categories. Appendix Table A3 in the main text provides the mapping of the original Capital IQ's Key development label to the 14 news categories. EARNINGS ANNOUNCEMENT; MANAGEMENT FORECASTS; PRODUCT MARKET & OPERATIONS; PAYOUT POLICY; EXECUTIVE TURNOVER; SECURITIES ISSUANCE; M&A; RESTATEMENT AND AUDITING; AGENDA COMMUNICATION; LEGAL ISSUES; SHAREHOLDER ACTIVISM; BANKRUPTCY; SECURITY TRADING; AND OTHER.

About one third of the news corresponds to communications about the date of forthcoming corporate events (e.g., investor day, annual meetings, etc.). These press releases typically inform the public about the date and the organization of the events and are unlikely to contain meaningful information. For our empirical tests, we remove news classified as AGENDA COMMUNICATION from the analysis.

Section H

Analyst Investext Report: Empirical method and findings

Empirical results on the timing of analyst recommendations in relation to news flows suggest that slow- and fast-turnover analysts react to different news types. Table 8 in the main text reports these results. We find that fast-turnover analysts tend to make recommendation changes following "hard" and verifiable information such as scheduled earnings announcements. On the other hand, slow-turnover analysts are more likely to revise their recommendations following news with forward-looking and more ambiguous contents. These news types include changes in the product market line, firm operating strategy, management earnings forecasts, and mergers and acquisitions. As a result, slow-turnover analysts play a greater information-intermediary role by distilling the information embedded in "soft" news contents into an unambiguous stock recommendation. In this Internet Appendix section, we provide further evidence on the contents and information sources that an analyst uses when making stock recommendations from reading over 2,000 analyst-recommendation reports obtained from Thomson One's Investext.

Recent studies that use Investext to analyze the contents in analyst reports include Huang et al. (2014), and De Franco et al. (2015). For instance, De Franco et al. (2015) employ textual analysis to examine the readability of analyst reports and examine whether such characteristic affects the stock market reaction. We depart from the existing literature that uses a quantitative—algorithmic approach to quantify the contents and tone in analyst reports. For our study, we manually read analyst recommendation reports from Investext and identify the rationales and information sources that analysts use to support their recommendation decisions.

H1. Data and the Matched Sample Construction

Our data source for analyst recommendation reports are from Thomson One's Investext over the 2002–2012 period. Investext organizes data at the report level, while I/B/E/S recommendation detail file organizes data at the recommendation level. We take a special care when merging the two databases. We ensure that each report from Investext is from the corresponding analyst and her brokerage house.

Coverage of analyst recommendation reports in the Investext universe is smaller than that in I/B/E/S. Investext collects analyst reports for companies and industries from more than 600 leading investment banks, brokerage houses and consulting firms worldwide. For our analysis, we construct a matched sample of fast-turnover and slow-turnover analysts and study their recommendation reports downloaded from Investext. The main objective for constructing the matched sample is to mitigate potential biases that could arise due to coverage choice of analysts and brokerage houses in Investext. Our findings in Table 4 in the main paper indicate that slow-turnover analysts are likely to work at top brokerage house and attain the All-star status. Therefore, we match fast- and slow-turnover analysts based on key observable characteristics to ensure that our sample contains analysts from a similar experience, brokerage size, and All-star status. Additionally, the use of a matched sample helps reduce the number of recommendation reports. This is advantageous because we employ a highly labor-intensive approach of reading analysts' reports, which requires identifying rationales and information sources behind each report. In particular, all reports are cross-read by three research assistants in order to mitigate errors from misreading their contents.

We next describe how we construct the matched sample. We start by retaining analysts that are in our baseline sample as shown in Table 2 over the 2002–2012 period. We keep analysts that were identified as either a fast- or slow-turnover type for at least three consecutive years and do not change their brokerage house. This filter removes analysts who do not stay in a specific speed-style category for a sufficiently long period, and ensure that we are focusing on analysts with a relatively persistent speed-style decision. There are 457 distinct analysts that meet this requirement, for which 349 are slow-turnover analysts.[4] We estimate a logistic model on these 457 analysts for the likelihood that they are a fast-turnover type. More specifically, the dependent variable in the logistic model is equal to 1 if the analyst is a fast-turnover analyst, and 0 otherwise. We use four observable characteristics in the model: EXPERIENCE, ALLSTAR, TOP_BROKER, and BREADTH. These variables are motivated by our results in Table 4. We eliminate from the sample analysts whose propensity score is below 15% and higher than 85%. These cutoffs eliminate extreme observations, particularly, analysts whose characteristics strongly associate them with a slow- or a fast-turnover type. This filter reduces the sample to 175 distinct analysts, 79 of which are slow-turnover analysts. We match a slow-turnover analyst with a fast-turnover analyst based on their propensity scores using a one-to-one matching without replacement. We use the caliper clipping approach by requiring the maximum permitted difference in the propensity scores between the matched pair to be +/-10%. Sixty-eight matched pairs meet this caliper-clipping requirement.

We further eliminate analysts whose recommendation reports are not sufficiently covered in Thomson One's Investext database. We require that over the period that an analyst is consecutively identified as a fast- or slow-turnover type, at least two consecutive years of her recommendation reports on at least two companies that she actively covers are available in Investext. We retain the best 50 matched pairs based on the propensity score and use them as our matched sample. Table IA8 in this Internet Appendix reports the selection-test results for the matched sample using a logistic model. Here, the dependent variable is equal to 1 if the analyst is a fast-turnover analyst, and 0 otherwise. We find that none of the coefficient estimates on EXPERIENCE, ALLSTAR, TOP_BROKER, and BREADTH are statistically significant. This indicates that fast- and slow-turnover analysts in the matched sample do not significantly differ in these four dimensions.

[4] There are disproportionately more slow-turnover analysts after this filter. We expect this finding because analysts, on average, tend to become slower at revising their recommendations as their career tenure increases. As a result, it is less likely to observe an analyst who consecutively remains a fast-turnover type.

We download all recommendation reports issued by the 100 analysts in the matched sample. We keep only the reports that coincide with the period that these analysts were consecutively classified as a fast- or slow-turnover type. We keep reports on stocks that the analysts are actively covering. We consider only reports written on large-sized firms (S&P500 constituents), and medium-sized firms (S&P400 Midcap constituents). This filter excludes small companies with low media coverage and sparse coverage in Investext. If the analyst has more than three consecutive years of reports available in Investext, we remove reports found in the first year. This filter ensures that we are not reading reports when analysts have recently switched their recommendation speed-style, or have just joined the sell-side industry. The final sample consists of 2,052 reports, of which 846 are recommendation revisions while the remaining are reiterations. These reports cover 310 distinct firms. We keep reiterating-recommendation reports for this analysis. Nevertheless, we verify that our results are qualitatively the same when we analyze only recommendation-change reports.

H2. Methodology for Reading Analyst Reports

We assign each analyst recommendation report to three research assistants for cross reading. We hired four research assistants.[5] We provide all research assistants with two weeks of training before randomly assigning them recommendation reports to read. Figure IA6 in this Internet Appendix shows the instruction sheet that we send to each research assistant. For each analyst-report reading, we ask the research assistant to identify a minimum of three and up to five main reasons (i.e., rationales) that an analyst uses to support her recommendation following the themes shown in Figure IA7. These reasons are then ranked in order that they appear in the report. We ask the readers to record the coding symbol associated with each rationale that they identified, as well as write down an excerpt from the report that corresponds to it. There are 17 rationales shown in Figure IA7, grouped into 5 main themes: *Valuation, Operation & Strategy, Macro economy, Industry, and Finance*. Additionally, we ask the readers to identify the information source that the analyst uses to support each of her rationales following the coding shown in Figure IA8. The analysts' information sources can be broken down into three main groups: *Management-related source*, *Non-management source*, or from an analyst's own *Interpretation* of public information. Additional notes and clarifications that we hand out to the research assistants are included in Figure IA9.

Each recommendation report is cross-read by three research assistants. This procedure helps reduce human errors and noises in the reports' contents. We combine results from these readings and determine the three leading consensus reasons in each report. We keep only rationales that two or more readers can identically identify; the

[5] We thank Valerie Zhang, Ching Tse Chen, Talha Irshad, and Yang (Karl) Qu for their excellent research assistance.

supporting excerpts from the report must also match. We retain the three most agreed upon reasons. For tie breakings, we use the average ranking of each rationale that readers have recorded.

The column labeled *Pct. Reports found* in Figure IA7 reports the percentage of analyst reports that are associated with each of the 17 rationales. We find that *Operating fundamentals* (OFL) is the most common reason; it appears in about 46% of the reports. This is followed by *Short-term valuation* (VES) in about 19.4% of the reports, and *Merger and Acquisition* (FMA) in about 11.4% of the reports. Similarly, Figure IA8 shows the percentage of analyst reports that are associated with different information sources. Clearly, *Interpretation* (IN) is the most common source that an analyst uses when making stock recommendations; it is found in all reports. We find that in about 7% of the reports, analysts cite a management-related source as the channel of information discovery.

H3. Rationales behind Stock Recommendations

We examine how fast- and slow-turnover analysts differ in the rationales that they use when making stock recommendations. Our assumption is that the contents of analysts' reports are reflective of their recommendation decisions. We are motivated by the empirical results in Table 8, which show that fast-turnover analysts are more likely to revise their recommendations following earnings announcements. On the other hand, slow-turnover analysts are more likely to revise recommendations after news about the companies' product market and operations. We test whether these tendencies of fast- vs. slow-turnover analysts to react to different news are also visible in their recommendation reports.

We estimate a logistic model for the probability that fast- and slow-turnover analysts will include these two reasoning themes in their reports: (1) Valuation based on earnings and sales (VES/VEL), (2) Operation and Strategy (OFL/OCP/OMS /OST). See Figure IA7 for definitions of each reasoning code. Table IA9 in this Internet Appendix reports the results. Columns (1) and (2) report results for the likelihood that a recommendation includes *Valuation –earnings/sales (VES/VEL)* as the reason in the report. Columns (3) and (4) report results for the likelihood that a recommendation includes *Operation & Strategy (OFL/OCP/OMS/OST)* in the report. The main variable of interests in all columns is FAST*,* which is equal to 1 if the report is issued by a fast-turnover analyst, and 0 otherwise.

The first hypothesis tests whether a fast-turnover analyst is more likely to include valuation based on earnings or sales as a reason in their report. This hypothesis is motivated by the finding that fast-turnover analysts tend to revise their recommendations after scheduled earnings announcements; see Table 8. We find evidence consistent with this hypothesis in Columns (1) and (2) of Table IA9. Only recommendation-change reports are used for the model in Column (1), while both reiteration and recommendation-change reports are included for the model in Column (2). We include analyst-level control variables in the logistic model. These control variables are identical to those used to construct the matched sample of fast- and slow-turnover analysts. Results in both Columns (1) and (2) show that coefficients on FAST variable are positive and significant. This suggests that fast-turnover analysts are more likely than slow-turnover analysts to use valuations based on earnings and sales as one of their recommendation rationales. The economic magnitude is large. Column (1) shows the coefficient estimate on FAST is 0.81, which implies an odd ratio of $\exp(0.81) \approx 2.25$. This estimate indicates that recommendation-change reports of fast-turnover analysts are 2.25 times more likely to include *Valuation–earnings/sales* as one of its reason relative to those of slow-turnover analysts. Similarly, the estimate in Column (2) shows that for both reiteration and recommendation-change reports, the odd ratio is $\exp(0.50) \approx 1.65$.

The second hypothesis we test is motivated by the finding that slow-turnover analysts tend to revise their recommendations following news about the firm operating strategy and/or its product market. This finding is shown in Table 8 of the main text. We hypothesize that slow-turnover analysts are more likely to include *Operation & Strategy* as a reason in their report than fast-turnover analysts are. Columns (3) and (4) report results supporting this hypothesis. The coefficients on FAST are negative and significant in both columns. In term of economic magnitude, Column (3) implies that a slow-turnover analyst is $1/\exp(-0.34) \approx 1.4$ times more likely than a fast-turnover analyst to include firm operation and strategy as a reason in her recommendation-change decisions. We find a slightly weaker magnitude of $1/\exp(-0.25) \approx 1.2$ when looking at both reiteration and recommendation-change reports in Column (4).

We do not find that fast- versus slow-turnover analysts differ in how likely they are to include these three rationale themes in their reports: *Macro economy, Industry,* and *Finance.* To save space, we do not tabulate the results in this document. To conclude, results from reading analyst recommendation reports support our findings in Table 8, which suggest that fast- versus slow-turnover analysts tend to follow different public signals when making their recommendations. That is, fast-revising analysts are more likely to use earnings-based valuation to make their recommendation decisions, while slow-revising analysts are more likely to use firm operation and strategy to make their recommendation decisions. The conclusions are unchanged when we include reiteration reports in the analysis. However, the economic magnitude is stronger when we focus only on recommendation-change reports.

H4. Information Sources for Stock Recommendations

Analysts draw their conclusion on stock recommendations from various sources. For instance, an analyst may have better access to the management team of the firm that she covers (see Green et al. (2014)). This comparative advantage could arise from analysts' frequent interactions with top executives at personal meetings, or earnings conference calls. On the other hand, analysts with limited access to management-related sources may have to rely more on public signals. This difference in how analysts acquire information could affect the speed at which they revise their recommendations, and more importantly, the investment value of their recommendation changes. Our results in the main paper strongly indicate that slow-turnover analysts produce more influential recommendation changes than those of fast-turnover analysts. Thus, we test whether the difference in recommendation values of fast- versus slow-turnover analysts is due to their differential access to management-related information sources. This is the objective of this section.

We test whether fast- or slow-turnover analysts are more likely to quote a management-related source in their stock recommendation reports. Similar to the empirical test in the previous subsection, we estimate a logistic model on recommendation reports issued by fast- and slow-turnover analysts in the matched sample. Figure IA8 in this Internet Appendix shows the information sources (and their labels) that we identify from reading analyst reports. We consider that an analyst has discovered an information from a management-related source if the report includes any of the following evidence to support her recommendation rationale: a personal meeting with top executives (PM), an interaction with the management team at the investor/analyst day (IM), an attendance of earnings conference calls (CC).

Table IA10 in this Internet Appendix reports the results. The dependent variable here is equal to 1 if the analyst report quotes a management-related source (PM/ IM/ CC) as supporting evidence for its recommendation rationale, and 0 otherwise. Column (1) reports results for recommendation-change reports only, while Column (2) reports results where reiteration reports are included. The main independent variable of interest is FAST, which is a dummy variable indicating whether the report is issued by a fast-turnover analyst, and 0 otherwise. In both columns, the coefficients on FAST are negative but not significant. Overall, we do not find evidence that fast- and slow-turnover analysts have different access to management-related sources when making their stock recommendations.

Additionally, we examine the likelihood that a fast- versus slow-turnover analysts reference an information they discovered from a non-management source in their recommendation reports. This can be performed through conducting an independent survey of the firm's products and services (SY), channel-checking the information from a third party (e.g., suppliers of the firm) (CH), or communicating with analysts' own industry contacts (IS). Using a logistic model, we test whether the use of non-management sources is more prevalent in the reports of slow-turnover analysts than those of fast-turnover analysts. We find no evidence supporting this conjecture; results are not tabulated.

Section I

Reconciliation with Hobbs et. al (2012)

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

Our method for classifying analysts' decision speed-style differs from Hobbs et al. (2012) in two important aspects. First, their study measures analysts' decision-speed using only recommendations that are revised within 12 months. This filter eliminates about half of valid recommendation observations from the sample because the median recommendation, on average, remains in place for 11.92 months (see Table 1 in the main text). This practice narrows down the sample to analysts who already revise their recommendations faster than the average population, or on stocks requiring frequent recommendation revisions. In fact, the average recommendation revision time in their sample is about five months, which is shorter than the 6.4 months revision time of fast-turnover analysts that we find in Table 2. Second, they identify recommendation speed-type of each analyst by averaging the time between her recommendation revisions *across all* the covered stocks. This simple averaging does not account for firm-level differences that may require analysts, in general, to revise their recommendation on each stock more quickly (or less often) than the other stocks. In contrast, our method sorts the time between recommendation revisions at the stock level before aggregating the results to compute the decision-speed style of each analyst.

We replicate the methodology in Hobbs et al. (2012) and find about 10% correlation between our speed-style measure and theirs. We also calculate the transition probability matrix of being classified to their (1) Slowest, (2) Average, and (3) Fastest recommendation-speed groups. Table IA12 in this Internet Appendix reports the results. We find the speed-type classification of Hobbs et al. (2012) is significantly less persistent than ours. For instance, looking at the 3-year transition probability, a slow-revising analyst in Year *t* can turn into a fast-revising analyst after 3 years with a probability of 24%—the same chance of being reclassified to the fast-revising speed group (23.9%). We further analyze the determinants of their recommendation speed-type using the binary logit model. We do not find a consistent pattern that characteristics of fast-recommendation changers are related to analysts' ex-ante measure of ability such as ALLSTAR, TOP_BROKER, EPS_PRECISION. Panel B of Table IA12 reports these results.

Using the classification method in Hobbs et al. (2012), we replicate the real-calendar time portfolio strategy over their sample period 1997–2007 and obtain a similar conclusion as theirs. That is, the portfolio formed following fastest-revising analysts' recommendations outperforms the portfolio formed following recommendations of slower-revising analysts by about 50 bps in risk-adjusted returns per month. Hobbs et al. (2012) explain why they find analysts who frequently revise their stock recommendations outperform those who do not. They show that much of their advantage derives from reacting quickly to abnormal trading activity.[6] In other words, analysts in the fastest group identified by their methodology are those who are quickest to piggyback on abnormal trading news, suggesting that their recommendations generate value from the subsequent price drifts. In an additional test, we confirm that faster-revising analysts are more likely to make recommendations following a jump in stock prices, i.e., news arrival.

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

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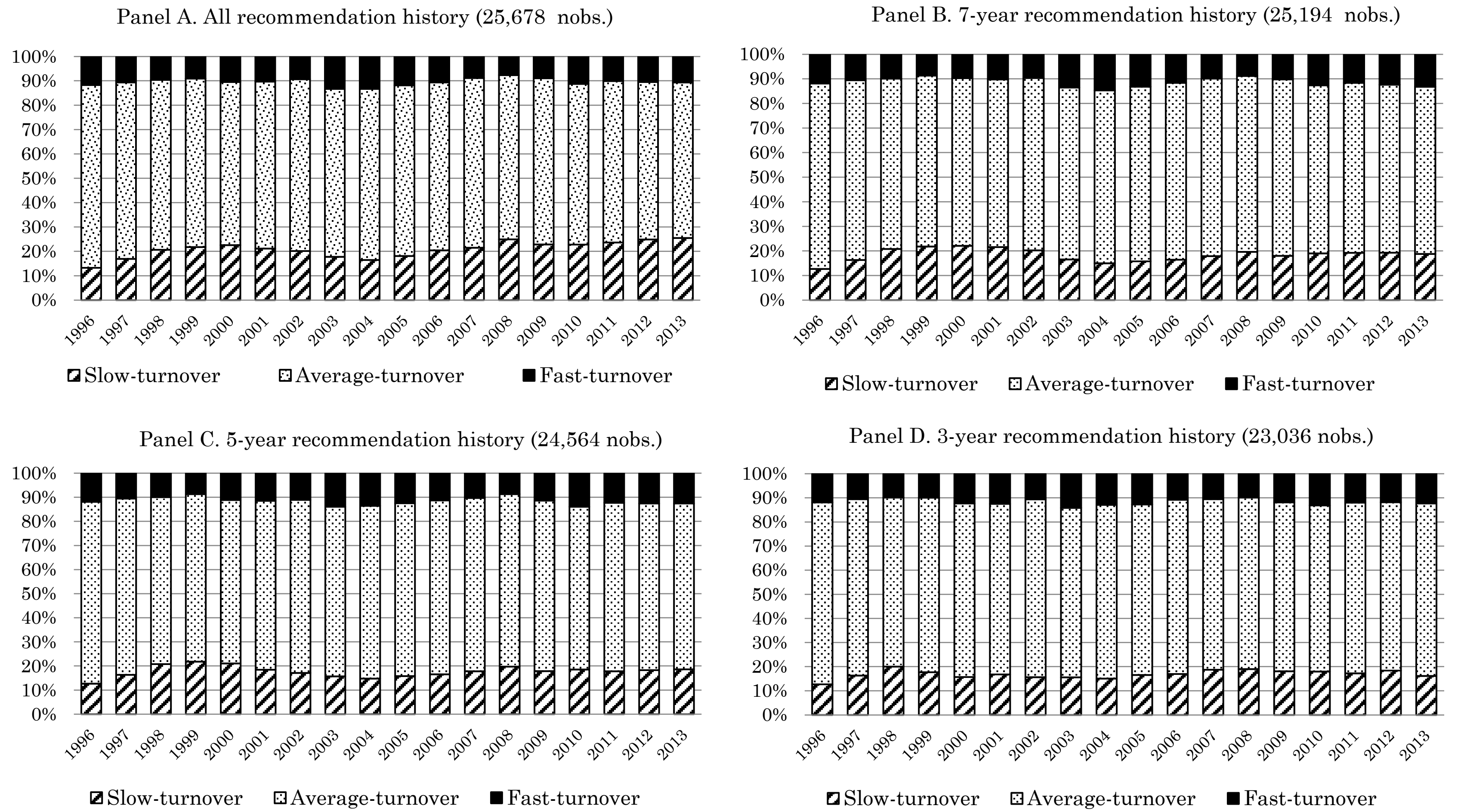
Figure IA1

Frequency of Analyst Speed-style Classified using Different Windows of Recommendation History



This figure plots the frequency of analysts' speed-style classified using different windows of recommendation-change history. The classification is done at the analyst-year level from 1996–2013. Panel A plots the results obtained using all past recommendation history, which is the main method used in the paper. Panels B, C, and D plot the results obtained using a fixed rolling-window of recommendation history with the window length of 7, 5, and 3 years, respectively. The number of observations for each method is shown in the title of each panel.

Figure IA2

Real-calendar time Portfolio Alphas by Size-sorted Quintiles

We plot real-calendar time portfolio alphas (in annualized terms) with 120-day holding period returns earned by investing $1 following recommendation changes of *slow*- versus *fast*-turnover analysts. Portfolio alphas are calculated using the Carhart four-factor model. We report results for 5 subsets of stocks sorted by their market capitalization (SIZE). The difference in portfolio alphas between slow- versus fast-turnover analysts. analysts and its corresponding t-statistic are shown at the bottom of the plot.

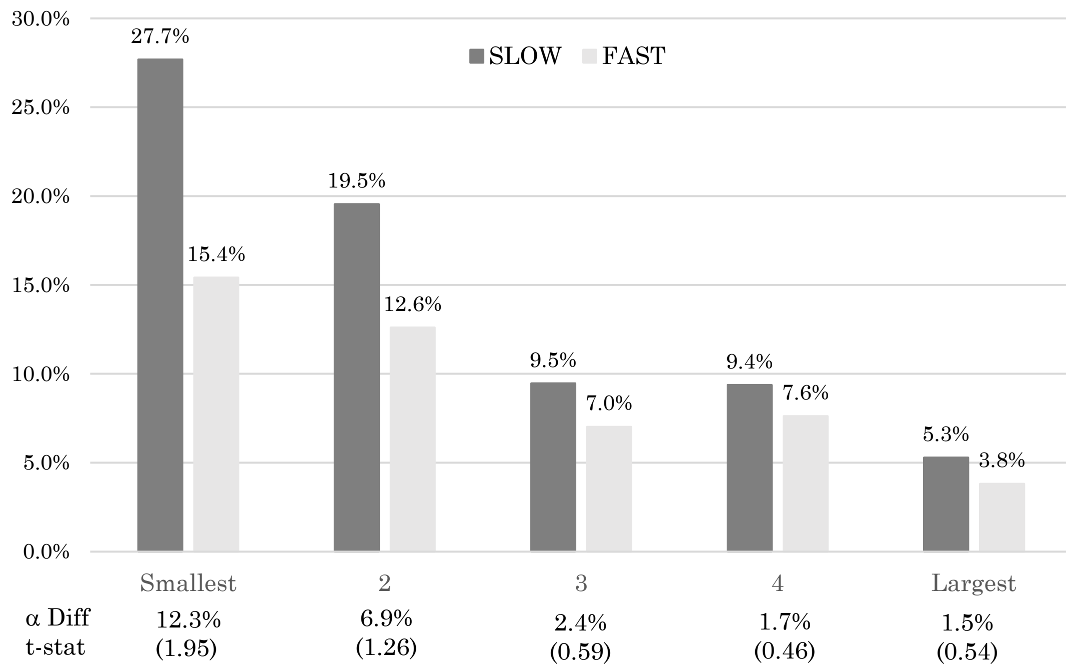


Figure IA3

Real-calendar time Portfolio Alphas by Volatility-sorted Quintiles

We plot real-calendar time portfolio alphas (in annualized terms) with 120-day holding period returns earned by investing $1 following recommendation changes of *slow*- versus *fast*-turnover analysts. Portfolio alphas are calculated using the Carhart four-factor model. We report results for 5 subsets of stocks sorted by their idiosyncratic volatility (VOLATILITY) calculated from the Carhart four-factor model over 252 trading days. The difference in portfolio alphas between *slow*- versus *fast*-turnover analysts and its corresponding t-statistic are shown at the bottom of the plot.

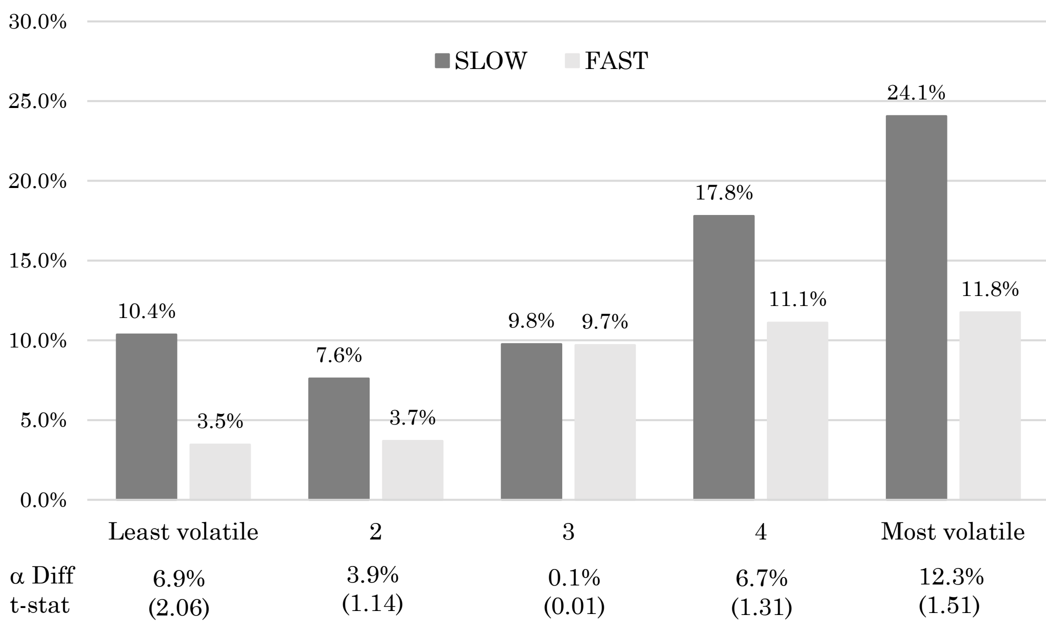


Figure IA4

Real-calendar time Portfolio Alphas by Size × Volatility double-sorted terciles

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. Panel A plots real-calendar time portfolio alphas (in annualized terms) with 120-day holding period returns for firms in the smallest-size and across volatility terciles. Similarly, Panel B reports results for the largest size 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. SIZE is calculated as the stock market capitalization. VOLATILITY is the firm's idiosyncratic volatility calculated using the Carhart four-factor model over 252 trading days.

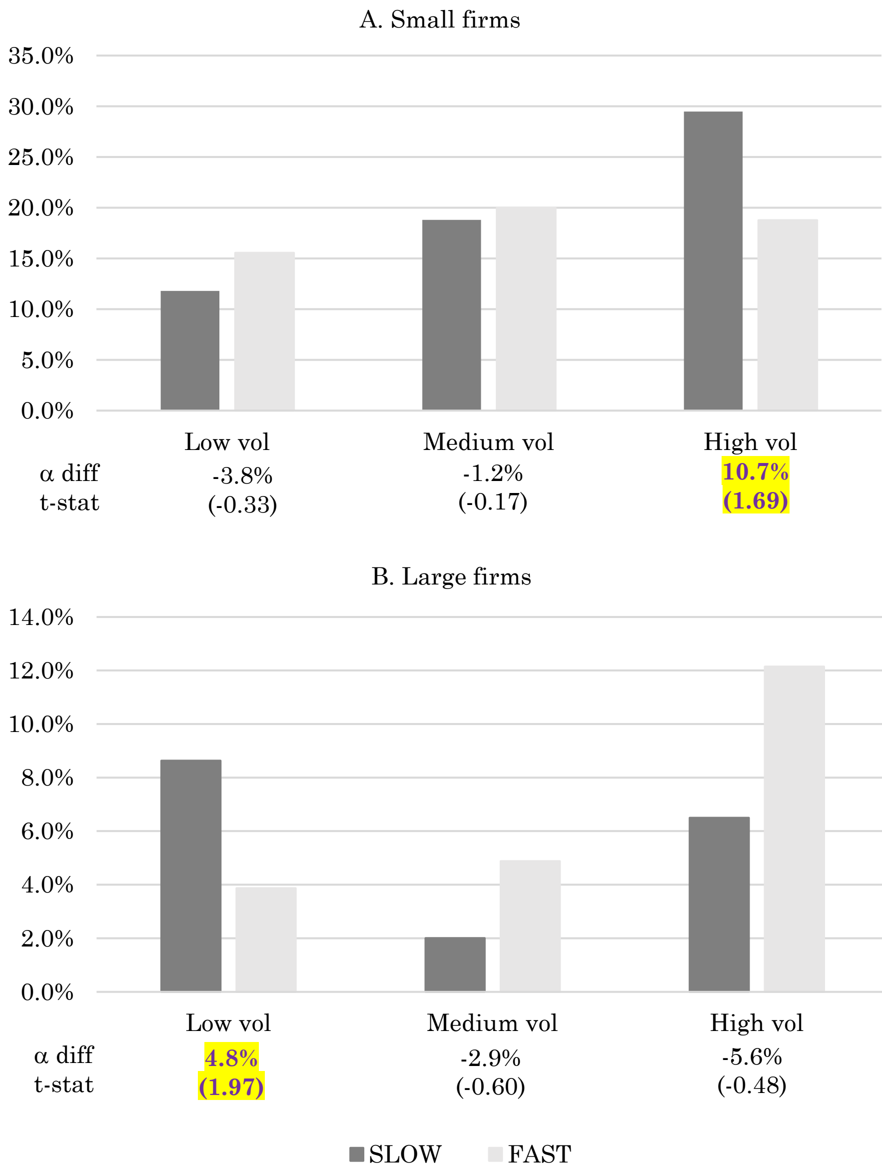


Figure IA5

Average Firm-level of Soft information by Size × Volatility terciles

We report the average number of firm-specific news in the Capital IQ Key Development 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 Table A3 in the main paper provides a mapping of news in the Capital IQ Key Development database into 14 categories. We classify news as containing soft information if it falls under one of these categories: PRODUCT MARKET & OPERATIONS; M&A; EXECUTIVE TURNOVER; LEGAL ISSUES. SIZE is calculated as the stock market capitalization. VOLATILITY is the firm's idiosyncratic volatility calculated using the Carhart four-factor model over 252 trading days.

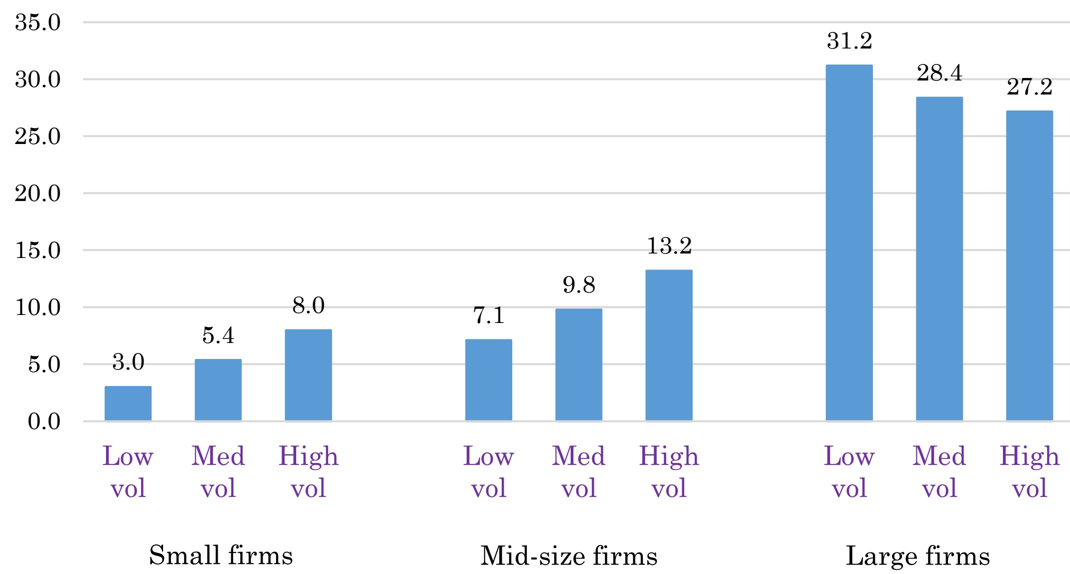


Figure IA6

Instructions to Research Assistants for reading Analysts Reports

Instructions

1. Please read recommendation reports assigned to you in our Dropbox folder. Focus on the first two to three pages of each report; in most cases, the other pages simply reiterate earlier information. You will be filling out cells in the prepared Excel spreadsheet, which is also located in this folder.

2. Write down up to five ***main reasons*** (VES, VEL, etc.) that support analysts' recommendation, in the order presented in the reports. You are expected to identify a ***minimum of three main*** reasons per report. For a rationale is considered to be a main reason if it is explained with several sentences. (See Clarification 3 for more information)

3. For each reason, copy and paste (no need to paraphrase, it will be easier to compare answers that way) the sentences in the actual report that lead you to the conclusion in step 2. Put them under "support".

4. For each reason, code it according to the themes outlined in the *Rationales for Analyst Recommendation* sheet. This sheet is located in your dropbox folder.

5. For each reason, code the information source that the analyst uses/quotes according to the themes outlined in the Information sources for Analyst Recommendation sheet. This sheet is located in your dropbox folder.

Clarifications

1. When Reason 1 causes Reason 2 to happen:

Example: "the company's expanding market share (OMS) causes its sales to grow in the short run (VES)"

Reason 1 is OMS while Reason 2 is VES. Here, we should write down Reason 1 as the dominant reason. The analysts identify OMS as the main event that will occur, while other factors may influence sales in the future, and cause it to increase/decrease.

2. If reports have several bullet points, it is normally the case that we should summarize them. One summarized bullet point may lead to the identification of one reason.

3. EPS, price targets, or EBITDA alone are not sufficient to be a reason. This is because, in most of the reports, analysts provide readers with these valuations. Unless analysts explain these valuations in detail or there are no other substantial reasons, one should refrain from writing down VES, VEL, or VIN.

4. You may not need to report a third reason, if you do not find it in the first two pages; unless the author explains it in detail in other pages.

5. Take notes on any confusion that you have during the readings; we shall discuss them in the debriefing sessions. If you have pressing questions, please feel free to email me.

Figure IA7

Rationales for Analyst recommendation: Investext Report

Symbol	Theme	Comments	Pct. of reports found
Valuation			
VES	Short term valuation	Refers to current earnings/sales or projected earnings/ sales within the next two quarters	19.4%
VEL	Long term valuation	Refers to projected earnings/ sales beyond the next two quarters	5.2%
VIN	Valuation relative to the industry	Compares the company's current valuation multiple to current industry performance	1.6%
VOR	Market mispricing	Indicate market short-term mispricing, usually due to overreaction to news	0.1%
Operation & Strategy			
OFL	Operating fundamentals	Refers to company's profitability, gross margin, operating functions, taxation, or anything that relate to fundamentals not listed below.	46%
OCP	Cash Position	Refers to the company's cash position, cash-flow risk, or information related to cash holding.	2.8%
OMS	Changes in market share	Refers to improvement or deterioration in market position	3.2%
OST	Operating strategy	Refers to changes in the firm's internal strategy. This may include: management restructuring, changes in governance, changes in firm's policy/vision, or internal strategy	2.5%
Macro economy			
ECY	Economic cycle	Refers to macroeconomic shock that is not related to the industry-wide nor company-specific events	5.6%
EPO	Economic policy	Refers to change in the economic policy by various government units, such as federal reserve board, the SEC, the senate, the house of representative, or the current presidential administration	0.4%
Industry			
IGR	Industry growth	Refers to changes in consumer taste and/or industry outlooks, often related to non-cyclical demand	10.2%
ICY	Industry cyclical upturn	Refers to industry-wide price or volume change or changes and emergence from (or entrance to) cyclical highs and lows	1.2%

IRR	Industry regulation	Refers to industry-wide legislation and legal settlements	1.4%
Finance			
FMA	Merger and Acquisition	Refers to the company's potential Merger and acquisition, and Spinoff	11.4%
FDV	Dividend and SEO	Refers to changes in the company's dividend policy, seasoned equity offering, or shares repurchased policy	5.2%
FLR	Leverage	Refers to changes in risks related to the company's leverage, capital structure, default risk, or credit rating	2.6%
FRM	Financial risk management	Refers to changes in the company's financial or operating risk management practice.	0.1%

Figure IA8

Information sources for Analyst Recommendation: Investext Report

Symbol	Theme	Examples	Pct. of reports found
Discovery- management sources			
PM	Personal Meeting	- "We recently met with top management of XYZ." - "In meeting with senior management, 1Q03 trends appear to be tracking in-line with our expectations."	1.2%
IM	Investor/ Analyst Meetings	- "Today we are attending Motorola Analyst Day…" - "Liberty Media's analyst day reinforced our belief that over the next 6-12 months, Liberty will transform itself from a holing to an operating company." - "We attended Progressive's Investor Day in Cleveland yesterday."	1.9%
CC	Conference Calls	- "In a recent conference call with investors and analysts, Aracruz management announced…" - "During the conference call, CMS indicated…" - "Post earnings, Motorola held a conference call to discuss its 1Q/03 results."	4.2%
Discovery- non-management sources			
SY	Survey	- "Based on our internal room rate surveys, we believe that upside in the first quarter can exceed $0.30." - "Based on results of our 2004 Health Benefit Survey, customers do not perceive CIGNA as bad…" - "Our recent survey confirmed the view the service levels have improved."	1.1%
CH	Channel Checks	- "Our channel checks indicate that unit demand remains strong and customer inventories are low." - "Based on our channel checks, we believe that recent demand trends have been solid." - "Channel checks at Sprint PCS stores in three major metropolitan revealed a slightly different launch strategy than that employed just four months ago."	2.2%
IS	Industry Contacts/Sources	- "Our industry sources indicate that used aircraft values may have stabilized somewhat after large declines." - "Several manufactures we've talked to recently have noted that business picked up significantly in March." - "This is inconsistent with feedbacks from brokers and consultants. "	1.6%
Interpretation			
IN	Interpretation	- "Mid-day 11/19 AMC and Loews Cineplex confirmed they are in talks about a potential merger." - "The recently released annual AF&PA capacity survey points to a solid outlook for uncoated free sheet in the U.S."	100%

Figure IA9

Definitions and Clarifications for Reading Analysts Reports

Valuation multiple: A valuation multiple is simply an expression of market value of an asset relative to a key statistic that is assumed to relate to that value. In stock trading, one of the most widely used multiples is the price-earnings ratio (P/E ratio or PER) which is popular in part due to its wide availability and to the importance ascribed to earnings per share as a value driver. Other commonly used multiples are based on the enterprise value of a company, such as (EV/EBITDA, EV/EBIT, EV/NOPAT). These multiples reveal the rating of a business independently of its capital structure, and are of particular interest in mergers, acquisitions and transactions on private companies.

Gross margin: Gross margin is a company's total sales revenue minus its cost of goods sold, divided by the total sales revenue, expressed as a percentage. The gross margin represents the percent of total sales revenue that the company retains after incurring the direct costs associated with producing the goods and services sold by a company. The higher the percentage, the more the company retains on each dollar of sales to service its other costs and obligations.

Fundamentals: Company fundamentals include the qualitative and quantitative information that contributes to the economic well-being and the subsequent financial valuation of a company, security or currency. Analysts and investors analyze these fundamentals to develop an estimate as to whether the underlying asset is considered a worthwhile investment. For businesses, information such as revenue, earnings, assets, liabilities and growth are considered some of the fundamentals.

Cash position: A cash position is the amount of cash that a company, investment fund or bank has on its books at a specific point in time. The cash position is a sign of financial strength and liquidity. In addition to cash itself, it will often take into consideration highly liquid assets such as certificates of deposit, short-term government debt and other cash equivalents.

Market position: An effort to influence consumer perception of a brand or product relative to the perception of competing brands or products. Its objective is to occupy a clear, unique, and advantageous position in the consumer's mind.

Management restructuring: Restructuring is a significant modification made to the debt, operations or structure of a company. This type of corporate action is usually made when there are significant problems in a company, which are causing some form of financial harm and putting the overall business in jeopardy. The hope is that through restructuring, a company can eliminate financial harm and improve the business. When a company is having trouble making payments on its debt, it will often consolidate and adjust the terms of the debt in a debt restructuring. After a debt restructuring, the payments on debt are more manageable for the company and the likelihood of payment to bondholders increases. A company restructures its operations or structure by cutting costs, such as payroll, or reducing its size through the sale of assets. This is often seen as necessary when the current situation at a company is one that may lead to its collapse.

Governance: Corporate governance is the system of rules, practices and processes by which a company is directed and controlled. Corporate governance essentially involves balancing the interests of the many stakeholders in a company - these include its shareholders, management, customers, suppliers, financiers, government and the community. Since corporate governance also provides the framework for attaining a company's objectives, it encompasses practically every sphere of management, from action plans and internal controls to performance measurement and corporate disclosure.

Merger and acquisition: Strong companies will act to buy other companies to create a more competitive, cost-efficient company. The companies will come together hoping to gain a greater market share or to achieve greater efficiency. Because of these potential benefits, target companies will often agree to be purchased when they know they cannot survive alone.

Seasoned equity offering: it is an issue of additional securities from an established company whose securities already trade in the secondary market. New shares issued by blue-chip companies are considered seasoned issues. Outstanding bonds trading in secondary markets are also called seasoned issues.

Shares repurchase: A program by which a company buys back its own shares from the marketplace, reducing the number of outstanding shares. Share repurchase is usually an indication that the company's management thinks the shares are undervalued. The company can buy shares directly from the market or offer its shareholder the option to tender their shares directly to the company at a fixed price.

Leverage: Leverage is the use of various financial instruments or borrowed capital, such as margin, to increase the potential return of an investment.

Capital structure: A capital structure is a mix of a company's long-term debt, specific short-term debt, common equity and preferred equity. The capital structure is how a firm finances its overall operations and growth by using different sources of funds.Debt comes in the form of bond issues or long-term notes payable, while equity is classified as common stock, preferred stock or retained earnings. Short-term debt such as working capital requirements is also considered to be part of the capital structure.

Default risk: Default risk is the event in which companies or individuals will be unable to make the required payments on their debt obligations. Lenders and investors are exposed to default risk in virtually all forms of credit extensions. To mitigate the impact of default risk, lenders often charge rates of return that correspond the debtor's level of default risk. The higher the risk, the higher the required return, and vice versa.

Credit rating: An assessment of the creditworthiness of a borrower in general terms or with respect to a particular debt or financial obligation. A credit rating can be assigned to any entity that seeks to borrow money – an individual, corporation, state or provincial authority, or sovereign government. Credit assessment and evaluation for companies and governments is generally done by a credit rating agency such as Standard & Poor's, Moody's or Fitch. These rating agencies are paid by the entity that is seeking a credit rating for itself or for one of its debt issues.

Table IA1
Correlation of Analyst Speed-style Classified using Different Windows of Recommendation History

This table reports the Pearson correlation of analyst recommendation speed-style identified using different lengths of recommendation history. The classification is done at the analyst-year level. For each year from 1996 through 2013, we assign analysts into three groups: (1) Slow-turnover analyst, (2) Average-turnover analyst, and (3) Fast-turnover analyst. Slow (fast) turnover analysts are those that revise their recommendations distinctly slower (faster) than their comparable peers. Average-turnover analysts are those that cannot be distinctly classified as either a fast- or slow-turnover type. *All history* refers to the method where we use all analysts' past recommendation-change history up to the previous year to identify their current-year recommendation speed-style; the main method used in the paper. *7-year history* refers to the method where we use a 7-year rolling-window of analysts' past recommendation history to identify their current-year recommendation speed-style. Similarly, *5-year history* (*3-year history*) refers to the methods where we use a 5-year (3-year) rolling-window of analysts' past recommendation history to identify their current-year recommendation speed-style. Panel A reports Pearson correlations for the slow-turnover analyst classification. Similarly, Panels B and C report Pearson correlations for the average-turnover analyst classification and the fast-turnover analyst classification, respectively.

Panel A. Pearson Correlations for Slow-turnover Analyst Classifications

	All history	7-year history	5-year history	3-year history
All history	1.00			
7-year history	0.87	1.00		
5-year history	0.75	0.79	1.00	
3-year history	0.58	0.60	0.65	1.00

Panel B. Pearson Correlations for Average-turnover Analyst Classifications

	All history	7-year history	5-year history	3-year history
All history	1.00			
7-year history	0.87	1.00		
5-year history	0.76	0.79	1.00	
3-year history	0.59	0.61	0.65	1.00

Panel C. Pearson Correlations for Fast-turnover Analyst Classifications

	All history	7-year history	5-year history	3-year history
All history	1.00			
7-year history	0.91	1.00		
5-year history	0.84	0.86	1.00	
3-year history	0.73	0.74	0.77	1.00

Table IA2
Hazard Model for Time to the Next Recommendation Change: Robustness Check using Different Windows of Recommendation History

We report selected estimates from the Cox proportional hazard model for predicting time to the next recommendation change. The model that we estimate is identical to that in Columns (3) and (6) of Table 3. The sample period is from 2003–2013. See descriptions in Table 3 for more details. To save space, we only report estimates for the four selected variables: FAST, SLOW, CONCURRENT_EARNINGS, and NEWS_INTENSITY. Panel A reports results for upgrade revisions, while Panel B reports results for downgrade revisions. The main variable of interests are indicator variables SLOW and FAST*,* indicating the recommendation speed-style of the analyst obtained from the previous year. Recommendation speed-style is identified using different lengths of recommendation history. *All history* refers to the method where we use all analysts' past recommendation-change history up to the previous year to identify their current-year recommendation speed-style; the main method used in the paper. *7-year history*, *5-year history*, and *3-year history* refer to the method where we use 7-year, 5-year, and 3-year rolling-windows of analysts' past recommendation history to identify their current-year recommendation speed-style. We report the hazard ratio next to each estimated under the column labeled "HR". Standard errors are reported in parentheses below each estimate. ***, **, and * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Estimates from the hazard model for time to ***an upgrade*** revision

	All history		7-year history		5-year history		3-year history	
	1		2		3		4	
	Estimate	HR	Estimate	HR	Estimate	HR	Estimate	HR
SLOW	**-0.261*****	**0.77**	**-0.253*****	**0.78**	**-0.201****	**0.82**	**-0.219*****	**0.80**
	(0.024)	0.00	(0.028)		(0.028)		(0.027)	
FAST	**0.385*****	**1.47**	**0.120*****	**1.13**	**0.109****	**1.12**	**0.084*****	**1.09**
	(0.025)	0.00	(0.025)		(0.025)		(0.025)	
CONCURRENT_EARNINGS	1.181***	3.26	1.182***	3.26	1.181**	3.26	1.181***	3.26
	(0.017)	0.00	(0.017)		(0.017)		(0.017)	
NEWS_INTENSITY	0.194***	1.21	0.193***	1.21	0.193***	1.21	0.193***	1.21
	(0.005)	0.00	(0.005)		(0.005)		(0.005)	
No observations	1,669,989		1,669,989		1,669,989		1,669,989	
Time-varying controls	Yes		Yes		Yes		Yes	
Prev. recomm-fixed effects	Yes		Yes		Yes		Yes	
Analyst-random effects	Yes		Yes		Yes		Yes	

Panel B. Estimates from the hazard model for time to ***a downgrade*** revision

	All history		7-year history		5-year history		3-year history	
	1		2		3		4	
	Estimate	HR	Estimate	HR	Estimate	HR	Estimate	HR
SLOW	**-0.285*****	**0.75**	**-0.256*****	**0.77**	**-0.249*****	**0.78**	**-0.225*****	**0.80**
	(0.023)		(0.027)		(0.027)		(0.026)	
FAST	**0.484*****	**1.62**	**0.116*****	**1.12**	**0.113*****	**1.12**	**0.112*****	**1.12**
	(0.024)		(0.024)		(0.024)		(0.024)	
CONCURRENT_EARNINGS	1.212***	3.36	1.213***	3.36	1.213***	3.36	1.213***	3.36
	(0.017)		(0.017)		(0.017)		(0.017)	
NEWS_INTENSITY	0.214***	1.24	0.214***	1.24	0.214***	1.24	0.214***	1.24
	(0.005)		(0.005)		(0.005)		(0.005)	
No observations	2,154,161		2,154,161		2,154,161		2,154,161	
Time-varying controls	Yes		Yes		Yes		Yes	
Prev. recomm-fixed effects	Yes		Yes		Yes		Yes	
Analyst-random effects	Yes		Yes		Yes		Yes	

Table IA3

Stock Price Reaction to Recommendation Changes: Slow vs. Fast-turnover Analysts

The sample consists of recommendation changes issued by slow-turnover and fast-turnover analysts from 1996 through 2013. Respectively, CONCURRENT_EARNINGS, EARNINGS_FOLLOWING, EARNINGS_LEADING are dummies equal to one for a recommendation that occurs on days [−1,+1], [+2 ,+7] and [−7, −2] relative to earnings announcement. AWAY_CONSENSUS is a dummy equal to one for recommendation change that move away from the consensus. Standard errors are clustered at the firm level. ∗, ∗∗, and∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: BHAR(−1,+1)	
	1. Upgrade	2. Downgrade
Recommendation turnover		
SLOW	**0.464****	**−0.758*****
	(0.218)	(0.205)
Stock-level characteristics		
SIZE	−0.799***	0.454***
	(0.093)	(0.065)
VOLATILITY	0.250***	−0.239***
	(0.071)	(0.060)
PCT_INSTITUTIONAL_HOLDINGS	−0.591***	−0.547***
	(0.222)	(0.145)
STOCK_RETURN	−2.021**	0.999***
	(0.999)	(−2.020)
MAKRET_RETURN	6.356***	2.062***
	(2.062)	(3.080)
Analyst characteristic		
EXPERIENCE	0.003	0.100***
	(0.025)	(0.032)
ALLSTAR	0.551	−0.012
	(0.556)	(0.258)
MALE	0.154	0.297
	(0.223)	(0.293)
BREADTH	−0.009	0.015
	(0.012)	(0.014)
HIGH_EPS_PRECISION	0.396**	−0.269
	(0.179)	(0.177)
HIGH_EPS_OPTIMISM	−0.162	0.219
	(0.207)	(0.174)
Recommendation-level characteristic		
LEVEL_CHANGE	1.124***	−1.226***
	(0.195)	(0.231)
LAST_RECOM	−0.372***	0.168
	(0.122)	(0.156)
CONCURRENT_EARNINGS	0.987***	−2.491***
	(0.281)	(0.308)
EARNINGS_FOLLOWING	−0.830***	0.694**
	(0.251)	(0.297)
EARNINGS_LEADING	0.584	0.773
	(0.382)	(0.605)
AWAY_CONSENSUS	0.462**	−1.279***
	(0.186)	(0.234)
Industry, Year, and Broker-fixed effects	Yes	Yes
Firm-level clustering	Yes	Yes
Nobs	15,328	17,657
Adjusted R-squared	13.6%	14.5%

Table IA4.
Real-calendar time Portfolio Strategy: Detailed Results

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

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

Table IA5
Real-calendar time Portfolio Strategy: Comparison with prior literature

We compare our results on the real-calendar time portfolio strategy with those reported in the literature. We consider four studies that examine real-calendar time portfolio performance from investing following analyst recommendations: Barber et al. (2001, 2006, 2007), and Fang and Yasuda (2014). Panel A summarizes the sample period, data source, and methodology used by each study. Panel B summarizes the range of portfolio alphas as reported by each study in their respective "reporting frequency" for the long and short strategy, separately. Panel C reports the range portfolio four-factor-adjusted alphas from the long-short portfolio strategy from each study in annualized term.

Panel A. Referenced studies

Study	Reference pages	Period	Data source	Methodology
Barber et al. (2001)	548-549	1985-1996	*Zacks*	Analysts' consensus recommendations
Barber et al. (2006)	108	1996-2003	*First Call*	Broker level: Brokers' favorableness for positive ratings from least to most favorable
Barber et al. (2007)	503-506	1996-2003	*First Call*	Broker level: Investment Banks vs. Independent research firms
Fang and Yasuda (2014)	38	1994-2009	*I/B/E/S*	Analyst level: All-star vs. Non all-star (30-day holding period)
Our study		1996-2013	*I/B/E/S*	Analyst level: Slow-turnover vs. Fast-turnover (30-, 60-, 120-day holding period)

Panel B. Portfolio excess returns *as reported* in existing literature

Study	Reporting Frequency	Alpha on a *long* portfolio as reported (%)			Alpha on a *short* portfolio as reported (%)		
		CAPM	Three-factor	Four-factor	CAPM	Three-factor	Four-factor
Barber et al. (2001)	Monthly	0.20	0.35	0.34	−0.60	−0.64	−0.41
Barber et al. (2006)	Daily			[0.016, 0.04]			[−0.044, −0.022]
Barber et al. (2007)	Daily			[0.007, 0.038]			[−0.019, −0.001]
Fang and Yasuda (2014)	Yearly	[13.9, 18.1]	[12.5, 16.1]	[13.1, 17.2]	[−9.8, −8.5]	[−12.3, −10.8]	[−9.9, −8.2]
Our study (Table IA3)	Daily	[−0.002, 0.047]	[−0.011, 0.040]	[−0.008, 0.044]	[−0.067,0.041]	[−0.074,−0.049]	[−0.064,−0.0040]

Panel C. Summary of Carhart four-factor adjusted returns in annualized term

Study	Reporting Frequency	Annualized alpha based on four-factor-adjusted portfolio (%)		
		Long	Short	Long/Short
Barber et al. (2001)	Annual	4.13	−4.91	9.04
Barber et al. (2006)	Annual	[4.03, 10.08]	[−11.09, −5.54]	[9.58, 21.17]
Barber et al. (2007)	Annual	[1.764, 9.576]	[−4.79, −0.252]	[2.02, 14.36]
Fang and Yasuda (2014)	Annual	[13.1, 17.2]	[−8.2, −9.9]	[21.2, 27.1]
Our study (Tables 6 and A4)	Annual	[−2.09, 10.97]	[−16.17,−10.12]	[8.13, 25.82]

Table IA6
Real-calendar time Portfolio Results: Size-sorted quintiles

We report real-calendar time portfolio results with 30, 60, and 120-day holding period returns earned by investing $1 on a stock at the closing-day price *after* recommendation changes of SLOW versus FAST turnover analysts. We report results for 5 subsets of stocks sorted by their market capitalization (SIZE). Last two columns report the average number of stocks in each portfolio daily.

SIZE quintile	Model	Holding period	SLOW		FAST		SLOW vs. FAST		Average daily #stocks	
			Alpha	*t-stat*	Alpha	*t-stat*	Alpha Diff	*t-stat*	Slow	Fast
1 Small	CAPM	30	50.8%	5.38	47.3%	4.67	3.5%	0.25	20	19
	Fama-French	30	50.9%	5.39	47.0%	4.63	3.9%	0.28	20	19
	Four-factor	30	49.3%	5.23	45.8%	4.52	3.6%	0.26	20	19
	CAPM	**60**	**47.1%**	**7.05**	**28.3%**	**3.61**	**18.9%**	**1.83**	**39**	**38**
	Fama-French	**60**	**46.8%**	**7.01**	**27.6%**	**3.52**	**19.2%**	**1.87**	**39**	**38**
	Four-factor	**60**	**44.4%**	**6.72**	**26.6%**	**3.40**	**17.8%**	**1.74**	**39**	**38**
	CAPM	**120**	**29.9%**	**6.34**	**16.4%**	**3.12**	**13.5%**	**1.91**	**75**	**74**
	Fama-French	**120**	**29.8%**	**6.31**	**16.0%**	**3.03**	**13.8%**	**1.95**	**75**	**74**
	Four-factor	**120**	**27.7%**	**5.97**	**15.4%**	**2.93**	**12.3%**	**1.95**	**75**	**74**
2	CAPM	30	40.6%	5.98	20.4%	2.71	20.3%	2.00	26	28
	Fama-French	30	40.4%	5.95	20.0%	2.67	20.4%	2.01	26	28
	Four-factor	30	37.1%	5.57	18.4%	2.46	18.7%	1.86	26	28
	CAPM	60	33.5%	6.74	20.0%	3.88	13.5%	1.89	51	55
	Fama-French	60	33.3%	6.70	19.8%	3.85	13.5%	1.89	51	55
	Four-factor	60	30.5%	6.31	18.3%	3.58	12.3%	1.84	51	55
	CAPM	120	21.7%	5.69	14.1%	3.42	7.6%	1.35	100	108
	Fama-French	120	21.6%	5.68	14.0%	3.42	7.6%	1.35	100	108
	Four-factor	120	19.5%	5.26	12.6%	3.10	6.9%	1.26	100	108
3	CAPM	30	29.6%	5.01	17.0%	2.85	12.6%	1.50	29	34
	Fama-French	30	29.5%	4.99	17.7%	2.97	11.8%	1.40	29	34
	Four-factor	30	28.4%	4.81	15.8%	2.67	12.6%	1.50	29	34
	CAPM	60	16.4%	3.78	9.8%	2.30	6.6%	1.09	57	68
	Fama-French	60	16.3%	3.74	10.2%	2.40	6.1%	1.00	57	68
	Four-factor	60	14.8%	3.43	8.6%	2.05	6.2%	1.02	57	68
	CAPM	120	10.5%	3.39	8.3%	2.92	2.2%	0.53	112	133
	Fama-French	120	10.7%	3.44	8.5%	2.99	2.2%	0.52	112	133
	Four-factor	120	9.5%	3.08	7.0%	2.53	2.4%	0.59	112	133
4	CAPM	30	12.3%	2.37	15.0%	3.16	-2.7%	-0.38	32	34
	Fama-French	30	11.6%	2.24	15.4%	3.26	-3.8%	-0.54	32	34
	Four-factor	30	9.0%	1.78	14.4%	3.06	-5.4%	-0.78	32	34
	CAPM	60	14.4%	3.68	12.8%	3.89	1.7%	0.32	63	67
	Fama-French	60	13.9%	3.55	12.9%	3.92	1.0%	0.20	63	67
	Four-factor	60	11.8%	3.08	11.5%	3.55	0.3%	0.06	63	67
	CAPM	120	11.6%	3.71	8.8%	3.82	2.7%	0.71	123	133
	Fama-French	120	11.2%	3.59	8.8%	3.80	2.4%	0.62	123	133
	Four-factor	120	9.4%	3.10	7.6%	3.37	1.7%	0.46	123	133
5 Large	CAPM	30	10.0%	2.50	8.3%	2.15	1.7%	0.30	35	36
	Fama-French	30	9.9%	2.48	7.9%	2.04	2.0%	0.36	35	36
	Four-factor	30	8.7%	2.19	6.7%	1.74	2.0%	0.36	35	36
	CAPM	60	7.5%	2.62	3.9%	1.45	3.7%	0.94	68	72
	Fama-French	60	7.7%	2.68	3.7%	1.40	4.0%	1.02	68	72
	Four-factor	60	6.7%	2.35	2.5%	0.96	4.2%	1.08	68	72
	CAPM	120	5.9%	2.88	4.9%	2.56	1.0%	0.37	133	143
	Fama-French	120	6.2%	3.03	4.7%	2.48	1.5%	0.54	133	143
	Four-factor	120	5.3%	2.63	3.8%	2.05	1.5%	0.54	133	143

Table IA7
Real-calendar time Portfolio Results: Volatility-sorted quintiles

We report real-calendar time portfolio results with 30, 60, and 120-day holding period returns earned by investing $1 on a stock at the closing-day price *after* recommendation changes of SLOW versus FAST turnover analysts. We report results for 5 subsets of stocks sorted by their idiosyncratic volatility (VOLATILITY). Idiosyncratic volatility is calculated using the Four-factor model over the past year.

VOLATILITY quintile	Model	Holding period	Slow		Fast		SLOW vs. FAST		Average daily #stocks	
			Alpha	*t-stat*	Alpha	*t-stat*	Alpha Diff	*t-stat*	Slow	Fast
1 Least volatile	CAPM	30	20.4%	3.89	13.5%	4.16	6.8%	1.11	31	34
	Fama-French	30	20.4%	3.89	13.7%	4.20	6.7%	1.09	31	34
	Four-factor	30	19.3%	3.69	13.6%	4.20	5.6%	0.91	31	34
	CAPM	**60**	**16.9%**	**4.02**	**6.8%**	**2.93**	**10.1%**	**2.11**	**60**	**67**
	Fama-French	**60**	**17.2%**	**4.09**	**6.9%**	**2.96**	**10.3%**	**2.15**	**60**	**67**
	Four-factor	**60**	**16.4%**	**3.91**	**6.7%**	**2.90**	**9.7%**	**2.02**	**60**	**67**
	CAPM	**120**	**10.8%**	**3.62**	**3.8%**	**2.45**	**7.0%**	**2.07**	**118**	**133**
	Fama-French	**120**	**11.2%**	**3.75**	**3.7%**	**2.35**	**7.5%**	**2.24**	**118**	**133**
	Four-factor	**120**	**10.4%**	**3.49**	**3.5%**	**2.23**	**6.9%**	**2.06**	**118**	**133**
2	CAPM	30	21.4%	5.03	15.8%	3.39	5.7%	0.90	29	33
	Fama-French	30	21.6%	5.06	16.1%	3.45	5.5%	0.87	29	33
	Four-factor	30	20.2%	4.78	15.3%	3.30	4.9%	0.78	29	33
	CAPM	60	14.7%	4.75	8.7%	2.70	6.0%	1.34	58	66
	Fama-French	60	14.9%	4.80	8.9%	2.75	6.0%	1.34	58	66
	Four-factor	60	13.6%	4.44	7.9%	2.47	5.7%	1.28	58	66
	CAPM	120	8.4%	3.35	4.3%	1.79	4.2%	1.20	113	131
	Fama-French	120	8.7%	3.44	4.4%	1.84	4.3%	1.23	113	131
	Four-factor	120	7.6%	3.07	3.7%	1.55	3.9%	1.14	113	131
3	CAPM	30	25.7%	4.36	16.6%	3.03	9.1%	1.13	30	31
	Fama-French	30	25.3%	4.29	16.5%	3.01	8.8%	1.10	30	31
	Four-factor	30	22.9%	3.93	15.9%	2.90	7.0%	0.87	30	31
	CAPM	60	18.3%	4.25	12.8%	3.16	5.4%	0.92	59	62
	Fama-French	60	18.1%	4.20	12.5%	3.09	5.5%	0.94	59	62
	Four-factor	60	15.5%	3.70	11.5%	2.86	3.9%	0.67	59	62
	CAPM	120	12.1%	3.81	11.1%	3.99	1.0%	0.24	116	121
	Fama-French	120	12.0%	3.76	10.8%	3.89	1.2%	0.27	116	121
	Four-factor	120	9.8%	3.20	9.7%	3.54	0.1%	0.01	116	121
4	CAPM	30	26.1%	3.47	15.9%	2.15	10.2%	0.97	27	29
	Fama-French	30	25.9%	3.45	16.0%	2.16	9.9%	0.94	27	29
	Four-factor	30	24.1%	3.22	13.8%	1.87	10.3%	0.99	27	29
	CAPM	60	26.0%	4.89	11.3%	2.18	14.6%	1.97	53	57
	Fama-French	60	25.8%	4.86	11.7%	2.25	14.1%	1.90	53	57
	Four-factor	60	24.0%	4.55	9.4%	1.84	14.6%	1.98	53	57
	CAPM	120	19.7%	5.46	12.9%	3.43	6.7%	1.29	104	112
	Fama-French	120	19.6%	5.43	13.2%	3.50	6.4%	1.22	104	112
	Four-factor	120	17.8%	5.04	11.1%	3.03	6.7%	1.31	104	112
5 Most volatile	CAPM	30	55.8%	5.07	38.8%	2.92	17.0%	0.98	22	22
	Fama-French	30	55.5%	5.05	39.0%	2.93	16.5%	0.95	22	22
	Four-factor	30	54.7%	4.97	36.5%	2.74	18.2%	1.05	22	22
	CAPM	**60**	**42.0%**	**5.42**	**23.5%**	**2.59**	**18.4%**	**1.54**	**42**	**42**
	Fama-French	**60**	**41.9%**	**5.41**	**23.6%**	**2.60**	**18.3%**	**1.53**	**42**	**42**
	Four-factor	**60**	**40.8%**	**5.27**	**21.8%**	**2.41**	**18.9%**	**1.59**	**42**	**42**
	CAPM	**120**	**24.6%**	**4.58**	**12.8%**	**2.05**	**11.8%**	**1.44**	**82**	**83**
	Fama-French	**120**	**24.9%**	**4.64**	**13.0%**	**2.09**	**11.9%**	**1.44**	**82**	**83**
	Four-factor	**120**	**24.1%**	**4.48**	**11.8%**	**1.89**	**12.3%**	**1.51**	**82**	**83**

Table IA8
Real-calendar time Portfolio Results: Size × Volatility terciles

We examine the value of recommendation changes made by SLOW versus FAST turnover analysts in subsets of stocks sorted by SIZE and VOLATILITY. We double sort firms into 3×3 groups based on SIZE and VOLATILITY. For each group, we report 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. For brevity, we report results with 120-day holding period returns and with the alphas calculated based on the Carhart four-factor model. SIZE is calculated as the stock market capitalization. VOLATILITY is the firm's idiosyncratic volatility calculated using the Carhart four-factor model over 252 trading days. We sort stocks into different SIZE and VOLATILITY terciles annually using their end-of-month values from the most recent June.

SIZE tercile	VOLATILITY tercile	Holding period (days)	SLOW		FAST		SLOW vs. FAST		Average daily #stocks	
			Alpha	*t-stat*	Alpha	*t-stat*	Alpha Diff	*t-stat*	Slow	Fast
Small size	Low vol	120	11.8%	1.60	15.5%	1.78	-3.8%	-0.33	13	20
Small size	Medium vol	120	18.8%	3.65	20.0%	3.87	-1.2%	-0.17	46	44
Small size	**High vol**	**120**	**29.5%**	**5.87**	**18.8%**	**3.22**	**10.7%**	**1.69**	**78**	**80**
Mid-size	Low vol	120	10.0%	1.99	3.3%	1.10	6.7%	1.14	52	69
Mid-size	Medium vol	120	11.0%	3.10	4.0%	1.19	7.0%	1.44	75	85
Mid-size	High vol	120	14.6%	2.57	10.5%	1.63	4.1%	0.48	52	55
Large size	**Low vol**	**120**	**8.6%**	**4.46**	**3.9%**	**2.43**	**4.8%**	**1.97**	**127**	**136**
Large size	Medium vol	120	2.0%	0.62	4.9%	1.39	-2.9%	-0.60	70	71
Large size	High vol	120	6.5%	0.78	12.1%	1.45	-5.6%	-0.48	23	24

Table IA9
Selection Test of the Matched-sample: Analyst Investext Reports

We report selection test results from a logistic model on a matched sample of fast- and slow-turnover analysts. The matched sample consists of 50 slow-turnover analysts and 50 fast-turnover analysts that have been matched using their propensity score based on four characteristics: EXPERIENCE, ALLSTAR, TOP_BROKER, and BREADTH. The dependent variable is equal to 1 if the analyst in the sample is a fast-turnover analyst, and 0 otherwise. The procedure for constructing the matched sample is as follows. We retain analysts from the baseline sample (see Table 2) that were identified as either a fast- or slow-turnover type for at least three consecutive years over the period 2002–2012. We eliminate analysts whose recommendation reports are not sufficiently covered in the Thomson One's Investext database. We require that over the period that an analyst is consecutively identified as a fast- or slow-turnover type, at least two consecutive years of her recommendation reports on at least two companies that she actively covers are available on Investext. We match a slow-turnover analyst with a fast-turnover analyst based on their propensity scores using a one-to-one matching without replacement. We use the caliper clipping approach by requiring the maximum permitted difference in the propensity scores between the matched pair is +/- 10%. There were 68 matched pairs that meet this caliper-clipping requirement. We retain the best 50 matched pairs and use them as our matched sample. The table below reports the logistic coefficient estimates from the selection test on the matched sample. Standard error is reported in parentheses below each estimate.

	Likelihood of observing a fast-turnover analyst in the matched sample
EXPERIENCE	−0.06
	(0.069)
ALLSTAR	0.80
	(0.547)
TOP_BROKER	−0.73
	(−1.610)
BREADTH	0.10
	(0.076)
Year-fixed effects	Yes
Nobs.	100
No of dep. var = 1	50
Pseudo R-squared	23%

Table IA10
Rationales behind Issuing Recommendations: Fast- vs. Slow-turnover analysts

We estimate the logistic model examining characteristics of analyst recommendation reports that are supported by the two reasoning themes: *Valuation – earnings/sales*, and *Operation & Strategy*. Figure IA2 in this Internet Appendix provide definitions for various rationales and their symbol coding that we identify from reading analysts' recommendation reports. The data source is Thomson One's Investext. Columns (1) and (2) report results for the likelihood that an analyst's report references valuation based on earnings or sales as one of its main rationales. Here, the dependent variable is equal to 1 if either VES or VEL is cited among the top three rationales in the report, and 0 otherwise. Columns (3) and (4) report results for the likelihood that an analyst report references the firm's operation & strategy as one of its top three rationales. Here, the dependent variable is equal to 1 if any of these specific reasons OFL, OCP, OMS, or OST is cited among the top three rationales in the report, and 0 otherwise. The sample consists of recommendation reports written by 50 slow-turnover analysts and 50 fast-turnover analysts from the matched sample. The main independent variable of interest is FAST, which is equal to 1 if the recommendation report is from a fast-turnover analyst, and 0 otherwise. Only recommendation-change reports (i.e., upgrade or downgrade) are included in the sample used in Columns (1) and (3), while results in Columns (2) and (4) also include reiterations. Analysts are matched using their propensity score based on four characteristics: EXPERIENCE, ALLSTAR, TOP_BROKER, and BREADTH; see Appendix Table A1 for definitions. DOWNGRADE is equal to 1 if the report is a downgrade revision, and 0 otherwise. REITERATION is equal to 1 if the report is a reiteration, and 0 otherwise. Robust standard errors clustered at the firm level is reported in parentheses below each estimate.

	Probability that the recommendation report is supported by the following reasons			
	Valuation – earnings/sales VES/VEL		Operation & Strategy (OFL / OCP / OMS / OST)	
	(1)	(2)	(3)	(4)
FAST	**0.81****	**0.50*****	**−0.34***	**−0.25****
	(0.351)	(0.146)	(0.183)	(0.109)
EXPERIENCE	0.01	0.03	−0.02	−0.02
	(0.051)	(0.020)	(0.029)	(0.018)
ALLSTAR	0.30	0.13	−0.30	−0.22
	(0.318)	(0.157)	(0.216)	(0.139)
TOP_BROKER	−0.43	0.00	−0.04	−0.17
	(0.325)	(0.138)	(0.193)	(0.113)
BREADTH	0.01	0.02	−0.01	−0.02
	(0.041)	(0.018)	(0.025)	(0.016)
DOWNGRADE	0.28*	0.23	−0.47***	−0.45***
	(0.142)	(0.157)	(0.158)	(0.156)
REITERATION		−0.46***		0.13
		(0.136)		(0.127)
Year-fixed effects	Yes	Yes	Yes	Yes
Including reiterations	No	Yes	No	Yes
Clustering	Firm	Firm	Firm	Firm
Nobs.	846	2052	846	2052
No. of dependent var. = 1	225	432	421	1100
Pseudo R-squared	6.94%	4.12%	5.02%	4.85%

Table IA11

Probability of Acquiring Information through Management-related source: Fast- vs. Slow-turnover analysts

We estimate the logistic model examining characteristics of analyst recommendation reports that reference management-related sources in support of their recommendation rationales. Figure IA3 in this Internet Appendix provide definitions for information sources and their symbol coding that we identify from reading analysts' recommendation reports. The data source is Thomson One's Investext. The dependent variable is equal to 1 (and 0 otherwise) if the report cites any of the following information sources in support of their recommendation rationales: Personal meeting with a senior manager (PM), Interaction with a senior manager at an investor meeting (IM), and Communication with a senior manager at a conference call (CC). Columns (1) reports results based on reports with recommendation revisions only, while Column (2) further include reports with reiterations. The sample consists of recommendation reports written by 50 slow-turnover analysts and 50 fast-turnover analysts from the matched sample. The main independent variable of interest is FAST, which is equal to 1 if the recommendation report is from a fast-turnover analyst, and 0 otherwise. Analysts are matched using their propensity score based on four characteristics: EXPERIENCE, ALLSTAR, TOP_BROKER, and BREADTH; see Appendix Table A1 for definitions. DOWNGRADE is equal to 1 if the report is a downgrade revision, and 0 otherwise. REITERATION is equal to 1 if the report is a reiteration, and 0 otherwise. Robust standard errors clustered at the firm level is reported in parentheses below each estimate.

	Probability of quoting a management-related source in the analyst's recommendation report (PM/ IM/ CC)	
	(1)	(2)
FAST	**-0.35**	**-0.07**
	(0.242)	(0.051)
EXPERIENCE	0.09	0.01
	(0.057)	(0.034)
ALLSTAR	0.13	0.04
	(0.512)	(0.263)
TOP_BROKER	-0.02	-0.10
	(0.405)	(0.220)
BREADTH	-0.03	-0.02
	(0.058)	(0.031)
DOWNGRADE	-0.45	-0.45
	(0.314)	(0.309)
REITERATION		0.13
		(0.227)
Year-fixed effects	Yes	Yes
Including reiterations	No	Yes
Clustering	Firm	Firm
Nobs.	846	2052
No. of dependent var. =1	50	130
Pseudo R-squared	2.24%	0.60%

Table IA12

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

We replicate the method of classifying analysts' recommendation frequency following Hobbs et al. (2012). The two panels below summarize analysts. Groups (1) and (3) refer to analysts ranked in the slowest and fastest quintiles. Group (2) refers to analysts ranked in the second, third and fourth quintiles based on recommendation frequency. Panel A reports probability transition matrices of the analysts' recommendation-speed type. Panel B reports estimates from binary logit model for the determinants of analysts' recommendation-speed type based on Hobbs et al. (2012). All independent variables in Panel B are defined in Appendix Table A1.

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

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

Panel B. Logit model for the speed of recommendation changers; see Hobbs et al. (2012)

	Logit model for the determinants of recommendation speed as in Hobbs et al. (2012)		
	1 SLOW	2 AVERAGE	3 FAST
EXPERIENCE	0.036***	-0.042***	0.028***
	(0.006)	(0.005)	(0.006)
ALLSTAR	0.333***	-0.242***	0.033
	(0.060)	(0.050)	(0.068)
TOP_BROKER	0.244***	-0.065*	-0.160***
	(0.049)	(0.037)	(0.049)
BREADTH	-0.076***	0.080***	-0.050***
	(0.006)	(0.005)	(0.007)
RECOM_OPTIMISM	-0.088	-0.036	0.154
	(0.106)	(0.081)	(0.101)
RECOM_PRECISION	0.019	0.111	-0.198*
	(0.112)	(0.090)	(0.111)
EPS_OPTIMISM	0.052	-0.207*	0.261*
	(0.135)	(0.111)	(0.140)
EPS_PRECISION	-0.002	0.083	-0.178**
	(0.085)	(0.068)	(0.074)
LFR	0.028***	-0.021***	-0.117
	(0.008)	(0.007)	(0.080)
EPS_FREQUENCY	0.054	0.201***	-0.371***
	(0.071)	(0.055)	(0.080)
MALE	-0.060	0.078	-0.059
	(0.062)	(0.050)	(0.063)
IND_HHI	0.002	0.001	-0.004**
	(0.001)	(0.001)	(0.002)
Year-fixed effects	Yes	Yes	Yes
Broker-year clustering	Yes	Yes	Yes
Nobs.	19,408	19,408	19,408