Financial Management

Investor Inattention and the Underreaction to Stock Recommendations

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Investors' reaction to stock recommendations is often incomplete so that there is a predictable postrecommendation drift. I investigate investor inattention as a plausible explanation for this drift by using prior turnover as a proxy for attention. I find that low-attention stocks react less to stock recommendations than high-attention stocks around the three-day event window. Subsequently, the recommendation drift of firms with low attention is more than double in magnitude when compared to firms with high attention. Similar conclusions are reached with alternative proxies for attention. The evidence supports investor inattention as a source of the stock recommendation drift.

The existing literature finds that while security analysts' stock recommendations lead to an immediate price reaction, a drift continues in the subsequent months (Womack, 1996; Barber et al., 2001; Boni and Womack, 2006; Barber, Lehavy, and Trueman, 2010). Although it is possible that analysts possess some superior ability to predict future stock price movements, there should be no price drift if the market recognizes that analysts possess such ability.[1]

Presumably, a recommendation has an immediate impact on the stock price because it reveals information about the firm.[2] A predictable drift afterward begs the question as to why this information did not get fully incorporated in the stock price when the recommendation was released. One could potentially appeal to short sale constraints (Diether, Malloy, and Scherbina, 2002; Nagel, 2005) as an explanation as to why a negative drift follows downgrades. However, it is not as obvious why there is an underreaction to upgrades. Barber et al. (2001) suggest that markets are semistrong inefficient so that stock returns are predictable based on public information

I thank Hank Bessembinder, Tarun Chordia, Karl Diether, Rudi Fahlenbrach, Fangjian Fu, David Hirshleifer, Kewei Hou, Ravi Jagannathan, Andrew Karolyi, Mike Lemmon, Sonya Lim, Taylor Nadauld, Carrie Pan, Lin Peng, Lakshmanan Shivakumar, Avanidhar Subrahmanyam, Bhaskaran Swaminathan, Siew Hong Teoh, an anonymous referee, and especially René Stulz for their comments. I am also grateful to seminar participants at Ohio State University, Singapore Management University, and the FMA 2008 meetings in Texas for providing many useful suggestions.

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[1]There is some evidence that analysts herd (Welch, 2000; Jegadeesh and Kim, 2010), although there is also some indication that they antiherd (Bernhardt, Campello, and Kutsoati, 2006). Analysts' recommendations could also be affected by conflicts of interests (see the survey by Mehran and Stulz, 2007). Even if analyst recommendations contain some bias, this does not explain why investors systematically fail to account for such biases so that the market typically underreacts to stock recommendations.

[2]Asquith, Mikhail, and Au (2005) demonstrate that analysts sometimes produce their own interpretation of already public news about the firm. However, an interpretation of already public news may also constitute material information about the firm.

such as stock recommendations. This paper posits investor inattention as a possible avenue of this inefficiency. If investors temporarily neglect the information contained in stock recommendations, a predictable drift follows when investors gradually incorporate this information.

Theoretical models predict that investor inattention may cause underreaction to public information. Hirshleifer and Teoh (2005) present a model where a subset of investors neglect information regarding the firm's future profitability contained in an earnings surprise. Consequently, the firm's stock price underreacts to announcements of earnings surprises. Peng and Xiong (2006) indicate that investor attention constraints lead to "category learning" so that investors focus on market-wide and industry-wide information rather than on firm-specific information. This implies that investors may underreact to firm-specific information such as analysts' stock recommendations. Peng (2005) also reports that investor attention could vary across firms. For example, they may allocate more attention to large firms since these firms contribute greater fundamental uncertainty to their portfolios. It is important to note that, in general, an inattention-based explanation requires some limits to arbitrage. Otherwise, it would suffice to have one single attentive agent with no capital constraints to drive the stock price to fundamental value instantly.[3]

Empirical studies examining the impact of investor inattention on asset prices can be classified into two types. The first group of studies uncovers the predictability of returns in certain settings and posits investor inattention as an explanation. For instance, Hong, Torous, and Valkanov (2007) find that a number of industry returns can forecast the market's return by up to two months and contend that investors are inattentive to the predictive information contained in industry returns. Similarly, Cohen and Frazzini (2008) report abnormal profits while using a strategy of buying (selling) firms whose customers experience positive (negative) news and argue that investors are inattentive to customer linkages between firms. The second group in the literature defines an attention proxy and then investigates the implications of inattention on asset prices. For instance, Hou, Peng, and Xiong (2006), using share turnover as a proxy for investor attention, demonstrate that an earnings momentum strategy is more profitable when investors are inattentive. They argue that underreaction-driven anomalies should be more profitable when investors are inattentive. DellaVigna and Pollet (2009) find that the market's reaction to earnings announcements is more complete during regular weekdays than on Fridays. They attribute this to investors being distracted by the approaching weekend. Hirshleifer, Lim, and Teoh (2009) use high news days (days with numerous earnings announcements) as a proxy for investor inattention and find that reactions to earnings announcements are weaker on such days. My study fits into this second group. I define a proxy for attention and test whether the recommendation drift is more pronounced when investors are inattentive. To my knowledge, there are no studies that address whether inattention contributes to the recommendation drift. An empirical advantage of the setting of recommendations is that there are clearly defined categories of favorableness. Further, unlike seasonal earnings announcements, stock recommendations occur throughout the year.

This study also addresses the question as to whether some recommendations result in higher abnormal returns than other recommendations. Kecskes, Michaely, and Womack (2009) indicate that recommendations with concurrent same direction earnings forecast revisions are more profitable. Loh and Mian (2006) report that analysts who possess more accurate earnings forecasts at the time of the recommendation issue more profitable recommendations. Sorescu and Subrahmanyam (2006) find that low strength recommendation changes by analysts from reputable

[3] Another argument is that attention-constrained investors could specialize in a few stocks so that they are fully attentive to those stocks. However, if investors are risk averse and time and attention are costly, highly attentive investors are limited in the extent that they are willing to bear risk in order to exploit mispricing (Hirshleifer and Teoh, 2003).

brokerages are associated with more return persistence. However, none of these studies explicitly examine whether the level of investor attention surrounding a firm contributes to the profitability of stock recommendations. My findings suggest that inattention is a potential explanation for the stock recommendation drift.

I proxy for investor attention using the prior turnover in the firm's stock following Hou, Peng, and Xiong (2006). I argue that prior trading activity directly proxies for the amount of active attention investors pay to the firm. Each day, I sort firms with recommendation changes into two groups: high prior turnover and low prior turnover. I then compare the response of investors to rating changes issued for these two groups. I posit that recommendation changes on low-turnover firms will have weaker reactions, but stronger drifts. The evidence strongly supports this hypothesis. Strikingly, the drift following recommendation changes for low-turnover firms is more than double that of high-prior-turnover firms.

Trading activity around and after the recommendation event reveals patterns consistent with the inattention hypothesis. I demonstrate that the stock's average daily turnover is higher in the three-day event window when compared to the stock's average turnover in the prior three months. However, this increase in turnover is much lower in magnitude for low-prior-turnover stocks, consistent with investors failing to pay enough attention to the recommendations on these stocks. In the next three months, the pattern reverses. Turnover increases more for low-turnover stocks consistent with inattentive investors reacting with a delay to recommendations.

Trading volume can also be associated with other firm characteristics, such as liquidity and uncertainty (Chordia, Huh, and Subrahmanyam, 2007). To purge uncertainty and illiquidity from turnover, I sort stocks on their residuals from a cross-sectional regression involving the universe of stocks with turnover against the Amihud (2002) illiquidity measure and analyst forecast dispersion. With this cleaner measure of attention, I continue to find that low-attention stocks have larger stock recommendation drifts. I also use institutional ownership, analyst coverage, the number of earnings announcements, and a free float-adjusted prior turnover measure as alternative dimensions to define investor attention and find corroborating results.

The rest of the paper is organized as follows. Section I lays out the hypotheses and the proxies for investor attention. Section II describes the data. Section III presents the main results while Section IV reports additional tests. Section V presents my conclusions.

I. Hypotheses and Proxies

Investor attention can be identified based on multiple dimensions, but I focus on the attention surrounding a firm. Alternatively, one could look at the analyst dimension (do investors pay more attention to an analyst from a reputable broker?) or at the market level (does the market pay less attention on high news days?). A firm-level perspective allows for more powerful tests that exploit the cross-sectional variation in attention across firms. More importantly, this suits the express objective of stock recommendations, that is, to guide investors in stock selection.[4]

If investors are inattentive to stock recommendations on some firms, they may not react as strongly to these recommendations. As such, the corresponding drift in prices would be more pronounced. My measure of the level of attention investors are paying to a firm uses the prior

[4]Frankel, Kothari, and Weber (2006) also adopt a firm-level perspective to investigate whether some analysts are more informative based on the covered firm's characteristics such as size, analyst coverage, institutional ownership, etc. However, they look at earnings forecasts and not stock recommendations. Further, they focus on the absolute value of the reaction, while my focus is on both the magnitude and direction of the reaction. Most importantly, they consider only the event reaction while I consider both the event reaction and the subsequent drift.

amount of trading in the firm's stock. I specifically target the average daily turnover of the stock over the three months prior to the recommendation. Trading volume has been used as a proxy for attention in various other papers. Hou, Peng, and Xiong (2006) use the prior turnover of a firm's stock as a proxy for investor attention regarding a firm and examine its implications for price and earnings momentum. Lee and Swaminathan (2000) find that positive momentum stocks with low prior turnover (which they suggest is a measure of neglect) earn much higher returns over a longer period than positive momentum stocks with high turnover.[5] Chordia and Swaminathan (2000) observe that the returns of high-turnover stocks lead the returns of low-turnover stocks. They report that turnover disentangles the effect of firm size from trading volume since turnover has a low correlation with firm size. Studies that also use the volume of a stock as measures of visibility are Gervais, Kaniel, and Mingelgrin (2001) and Barber and Odean (2008).

For my purpose, a firm whose shares are actively traded is likely to have vigilant investors who are attentive to news events like analyst recommendation changes. Any underreaction following recommendation changes would be less severe with a large pool of attentive investors. Alternatively, a firm whose shares have low turnover is likely to have a smaller proportion of vigilant investors resulting in a delayed response.[6]

In robustness tests, I examine measures of attention that control for other variables that are also associated with turnover, but not directly related to investor attention. Trading volume could proxy for differences of opinion among investors (Diether, Malloy, and Scherbina, 2002) or the liquidity of a firm's stock (Amihud, 2002). For instance, low trading volume can also be associated with illiquidity. As a result, prices could take longer to adjust due to illiquidity and not because of inattention. Therefore, it is important to disentangle these effects to obtain a sharper measure for attention. Separating turnover into its various components is also similar to the approach in Chordia, Huh, and Subrahmanyam (2007) who decompose turnover into components related to visibility, uncertainty, and liquidity. To compute residual turnover that is orthogonal to illiquidity and uncertainty, I sort firms on the residual turnover from a cross-sectional regression of the universe of stocks' prior turnover against the prior Amihud (2002) illiquidity measure and the most recent analyst forecast dispersion. In additional tests, I use analyst coverage, institutional ownership, and the number of earnings announcements in a day as other proxies for attention. The following three related hypotheses summarize the implications of investor inattention on stock recommendations.

Hypothesis 1a: The magnitude of stock recommendation reaction for firms with low prior turnover is smaller than that for firms with high prior turnover.

Hypothesis 1b: The magnitude of stock recommendation drift for firms with low prior turnover is larger than that for firms with high prior turnover.

Hypothesis 1c: The proportion of return on the recommendation date as a percentage of the total recommendation return is smaller for low prior turnover firms.

[5]Empirically, the literature examines the magnitude of price and earnings momentum conditional upon turnover (Lee and Swaminathan, 2000; Hou, Peng, and Xiong, 2006). My approach is similar except that it examines the stock recommendation drift conditional on prior turnover. Another distinguishing feature is that my study is based on an event. Therefore, it can jointly examine the reaction and drift of the event. This allows for richer tests on underreaction.

[6]I check the impact of adjusting the prior turnover proxy by the stock's free float. I use data on director and officer ownership from Fahlenbrach and Stulz (2009). To the extent that insiders own their shares passively, a turnover measure based on free float would be a better measure of attention. However, Fahlenbrach and Stulz (2009) report that for a typical firm, the insider ownership fraction fluctuates significantly over time, especially in response to past stock returns. It is not clear, therefore, whether free float-adjusted turnover is superior to raw turnover as a proxy for active attention. Nevertheless, I repeat the portfolio tests with a measure of free float-adjusted turnover and find support for my conclusions. I thank Rudi Fahlenbrach for providing their data.

II. Data and Sample Statistics

A. Stock Recommendation Data

The sample of individual analyst recommendations is from Thomson Financial's I/B/E/S US Detail File from 1993 to 2006. Due to limited coverage in 1993, I focus on rating changes where the current rating is issued from 1994 forward. I/B/E/S reports ratings ranging from 1 (strong buy) to 5 (sell). I reverse the ratings (5 for strong buy and 1 for sell, etc.) so that higher ratings correspond to more favorable recommendations. I focus on rating changes and not levels since prior research confirms that changes are more informative than levels (Boni and Womack, 2006; Jegadeesh and Kim, 2010; Barber, Lehavy, and Trueman, 2010). The recommendation change, *RECCHG*, is computed as the current rating minus the prior rating by the same analyst. Anonymous analysts are removed as we cannot track their revisions. By construction, $RECCHG \in [-4, 4]$. When an analyst initiates a recommendation, I compute *RECCHG* as the new rating minus a hold rating of 3. I also screen out stale ratings by removing recommendation changes where the prior rating is more than one year old (stale definition follows Barber, Lehavy, and Trueman, 2007).

In an important paper, Ljungqvist, Malloy, and Marston (2009) examine seven downloads of I/B/E/S recommendations data from 2000 to 2007 and find inconsistencies in matched observations across downloads. In response to their paper, they report that Thomson Financial restored such alterations to the recommendation history file as of February 12, 2007. My paper uses the corrected March 15, 2007 snapshot.[7]

The chosen sample undergoes further screens. Since my objective is to investigate the recommendation drift and not the earnings announcement drift, I remove stock recommendations that are issued in the three-day window centered on the I/B/E/S quarterly earnings announcement date. Thirteen percent of all eligible recommendation changes are removed. This fraction is similar to that reported in Womack (1996) and Malmendier and Shanthikumar (2007). A portion of the sample period is affected by Rule 2711 of the National Association of Securities Dealers (NASD). Part of the rule required a broker to report the distribution of stock ratings across its coverage universe. Many brokers reissued recommendations so that their recommendation distributions looked less optimistic. This rule was approved on May 8, 2002 with an implementation period ending September 9, 2002. As a result, 2002 contains the most number of recommendations in I/B/E/S (Barber et al., 2006). Hence, I remove rating changes where the current rating is issued between May 8, 2002 and September 9, 2002 (inclusive) and where the prior rating was issued prior to May 8, 2002. Such rating changes are not likely to be motivated by stock selection.

B. Stock Return Data

The daily returns of US firms are from the Center for Research in Security Prices (CRSP). I only include stocks classified as ordinary shares (Share Codes 10 or 11). Delisting returns are added

[7]To test the sensitivity of my results to potential residual I/B/E/S problems, I also use alternative methodologies and recommendation data sets and arrive at the same conclusions. First, I redefine recommendation changes using the broker code instead of the analyst code. Using the broker code deals incorrectly with analyst job changes, but it allows me to restore anonymized analysts into the recommendation data set as I/B/E/S does not anonymize the broker code. Second, I report results from 1994 to 2000 using an I/B/E/S snapshot on January 19, 2001. Using this early snapshot intentionally avoids the time period when the I/B/E/S alterations were found to have taken place. To the extent that these alterations are a result of analysts or brokers trying to touch up their preregulation stock picking histories during the period of heightened regulatory scrutiny on analysts, the early snapshot should be closer to an "as was" tape. Finally, I switch from I/B/E/S to First Call recommendations and repeat the main tests. All these additional tests provide support that the paper's findings are not sensitive to the choice of recommendation database.

from the CRSP delisting file. In cases where the delisting return is missing, I follow Shumway (1997) by inserting a delisting return of −30% if the corresponding delisting code indicates a performance-related delisting. Firms in the sample must also have available and nonnegative book-to-market (B/M) information from the CRSP-Compustat Merged File. The B/M ratio is computed as in Fama and French (2006). As benchmarks for some tests, I compute the returns of Daniel, Grinblatt, Titman, and Wermers (1997) (hereafter DGTW) characteristic portfolios from this universe of CRSP stocks.[8]

C. Construction of Attention Proxies and Control Variables

For each trading day in the sample, firms with recommendation changes are sorted into two groups of high-turnover and low-turnover stocks based on the average prior daily turnover over [−63, −2]. Daily turnover is the CRSP-reported number of shares traded divided by the total number of shares outstanding. Following LaPlante and Muscarella (1997), I divide the volume of NASDAQ firms by two to account for the double counting of interdealer trades. For recommendations on nontrading days, Day 0 is the first trading day after the recommendation date. A three-month horizon is more suited in my setting as I want to capture the most recent attention surrounding the stock immediately prior to the recommendation event. Because periods of one week or one month may be too noisy to compute a reliable measure of attention, studies such as Gervais Kaniel, and Mingelgrin (2001) and Kaniel, Saar, and Titman (2008) rely on roughly three months of turnover when defining visibility. Lee and Swaminathan (2000) and Hou, Peng, and Xiong (2006) use up to 12 months to compute prior turnover. While using a 12-month horizon produces similar results, I stick to a three-month horizon for the baseline tests since longer horizons underweight the most recent attention accorded to the stock.

For some tests, I require additional measures of illiquidity, analyst forecast dispersion, and analyst coverage. A stock's liquidity is measured using the Amihud (2002) illiquidity measure, which is the average daily absolute return divided by the daily dollar trading volume (in millions) over the same horizon that prior turnover is measured. The two analyst variables are from the I/B/E/S Summary Unadjusted US File. Analyst coverage is the most recent number of analysts contributing to the monthly consensus FY1 earnings forecasts. Forecast dispersion is the most recent standard deviation of estimates divided by the absolute value of the mean estimate.

D. Descriptive Statistics of Sample

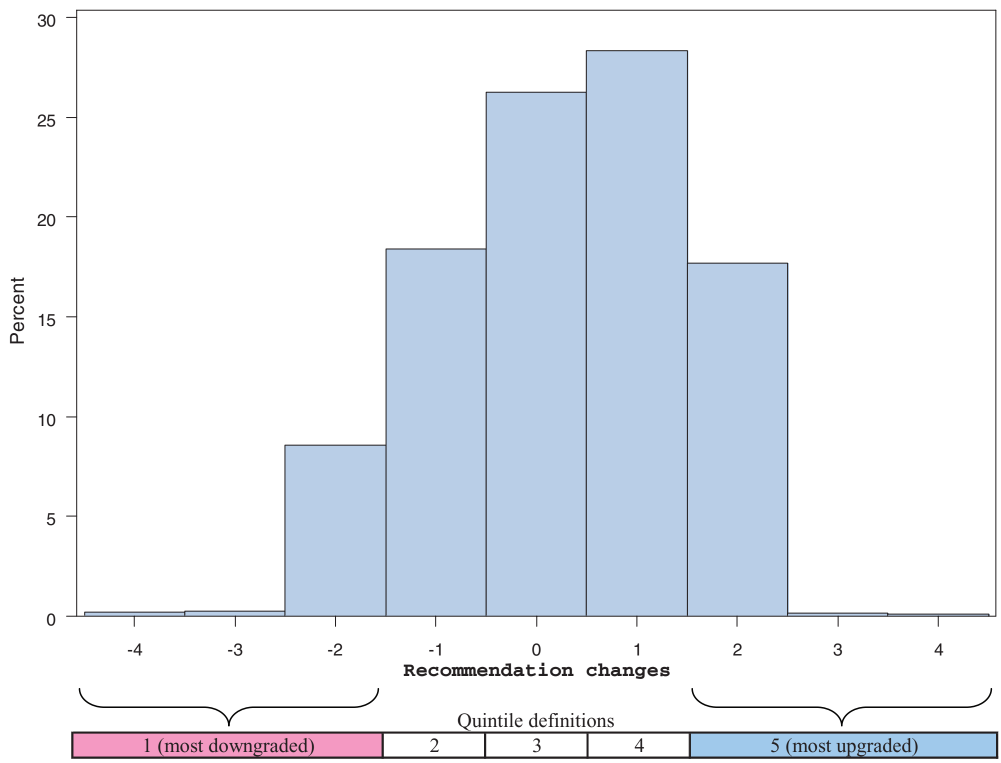
Figure 1 presents the distribution of the 218,537 recommendation changes in my sample. There are nine categories of rating changes from −4 to +4, but I note that extreme rating changes occur less frequently. To ensure that there are sufficient recommendations in the extreme rating change categories, I classify ratings changes into five groups. Rating changes in [−4, −2] are classified as the most downgraded stocks and those in [+2, +4] are the most upgraded stocks. Rating changes of −1, 0, and +1 make up the middle three groups.

Table I, Panel A reports annual descriptive statistics of the 1994-2006 sample. Overall, the assembled sample contains stock recommendations issued by 8,751 analysts from 569 brokers for 8,154 firms over a 13-year sample period. The average recommendation change across all

[8]Every July, firms are first sorted into quintiles based on their market cap on June 30 of each year using breakpoints determined from NYSE stocks. Second, firms are then sorted within each size quintile into quintiles based on their B/M ratios. Third, firms within each size-B/M group are sorted into momentum quintiles every month based on the buy-and-hold return over the prior 12 months skipping the most recent month. Therefore, the size and B/M rankings are updated every 12 months while the momentum rankings are updated monthly. Finally, the stocks within each characteristic portfolio are equally weighted at the beginning of each month and the buy-and-hold average daily returns are computed.

Figure 1. Distribution of Recommendations Changes

The distribution of the recommendation rating changes described in Table I is displayed. Data are from I/B/E/S Detail Recommendation File from 1994 to 2006. A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold).



observations is 0.275 (an upgrade). The analyst-level statistics in Panel A are computed first by averaging repeated analyst-year observations and then taking the cross-sectional average across all analysts in that year. Firm-level averages follow a similar procedure. The average number of firms covered by an analyst is 4.78 and the average number of recommendations issued by an analyst in one year is 6.53. I note that the number of analysts issuing recommendations for a firm in a typical year is 3.92 and the average market cap is slightly over $3 billion. On average, about 64 firms are recommended in a typical day in the sample. As such, there would be a sufficient number of firms each day to allow them to be sorted into high- and low-attention groups. The average daily turnover (in the three months prior to the recommendation) for a typical recommended firm is 0.4852%.

Panel B of Table I presents statistics by turnover groups. Here, the averages are computed for firm-level statistics by averaging repeated firm years within each turnover group and then taking the average across all firm year averages within each turnover group. The average prior turnover is 0.8110% for a typical high turnover firm and 0.2600% for a low turnover firm, evidence that

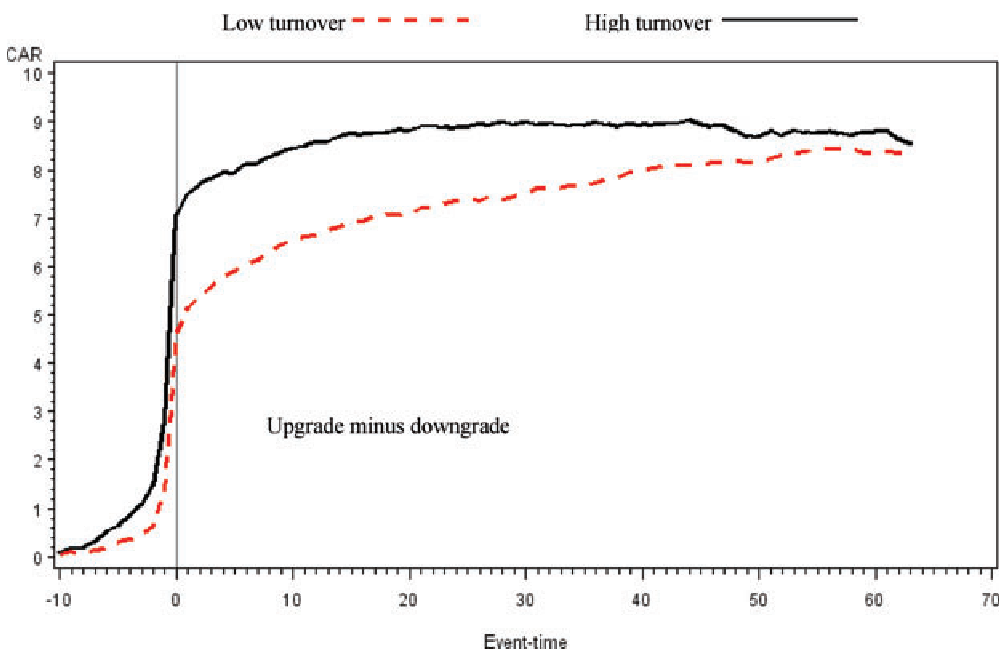
Table I. Sample of Stock Recommendation Changes

Stock recommendations are from the I/B/E/S Detail Recommendations File from 1994 to 2006 with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Firms must be matched to the CRSP universe of ordinary shares. The five-point recommendation scale ranges from 1 (sell) to 5 (strong buy). A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold). The average prior daily turnover is measured over $[-63, -2]$ days from the recommendation. Market cap is averaged over $[-63,-2]$ days. For the year 2002, rating changes motivated by National Association of Securities Dealers 2711 are excluded. For annual firm-level statistics in Panel A, repeated firm-years are averaged before the cross-sectional average across all firms is computed. For analyst-level statistics, repeated analyst-year observations are averaged before the cross-sectional average across all analysts is computed. In Panel B, the procedure is the same except that the repeated firm- and analyst-year observations are first averaged within each turnover group.

Group	No. of Recs.	Avg. Rec. Change	Analyst-Level Variables				Firm-Level Variables				
			No. of Analysts	No. of Brokers	Avg. No. of Firms Covered	Avg. No. of Recs. per Analysts	No. of Firms	No. of Analysts Per Firm	Avg. Market Cap ($m)	Avg. Prior Daily Turnover (%)	Avg. No. of Firms Recommended Per Day
Panel A. By Years											
1994	19,167	0.295	1794	143	7.36	10.68	3,039	4.35	1,350	0.3184	73.0
1995	16,757	0.250	1895	146	5.88	8.84	3,122	3.57	1,509	0.3559	64.8
1996	15,439	0.332	2134	174	5.21	7.23	3,375	3.29	1,791	0.3890	59.0
1997	15,415	0.387	2446	206	4.75	6.30	3,660	3.17	2,146	0.4114	59.4
1998	18,050	0.356	2793	230	4.77	6.46	3,758	3.54	2,644	0.4061	68.7
1999	16,741	0.431	2910	222	4.36	5.75	3,309	3.83	3,594	0.4810	62.7
2000	14,810	0.347	2852	212	3.92	5.19	3,110	3.59	4,617	0.5498	55.2
2001	15,636	0.282	2779	185	4.17	5.63	2,855	4.06	4,344	0.5396	59.1
2002	20,057	0.075	2910	194	5.00	6.89	2,916	4.99	3,609	0.5169	73.6
2003	19,779	0.152	2705	230	5.26	7.31	2,872	4.95	3,538	0.5452	73.0
2004	16,827	0.217	2738	262	4.65	6.15	2,921	4.36	4,212	0.5851	63.6
2005	14,702	0.302	2776	269	4.06	5.30	2,925	3.85	4,537	0.6042	56.0
2006	15,157	0.229	2726	250	4.18	5.56	2,965	3.85	4,837	0.6730	58.1
Overall	218,537	0.275	8751	569	4.78	6.53	8,154	3.92	3,231	0.4852	63.6
Panel B. By Turnover Groups											
High	112,276	0.255	7652	519	5.33	7.37	5,404	4.08	3,199	0.8110	N/A
Low	106,261	0.297	7645	528	5.44	7.50	7,318	2.74	3,647	0.2600	N/A

Figure 2. Cumulative Abnormal Returns (CARs) of Recommendation Changes for High-Turnover versus Low-Turnover Stocks

The abnormal return each day is the raw CRSP return less the return on a matched size-B/M-momentum characteristic portfolio. Unbroken lines (broken lines) indicate the average CAR of recommendations changes for high (low turnover stocks). Each day, stocks with recommendation changes are sorted into two groups based on the average daily turnover over the period [−63, −2] days from the rating change. A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold). The graph indicates the hedged CAR (upgrade-downgrade) where upgrades are rating changes ≥ +2 and downgrades are rating changes ≤ −2. Firm days where the lagged price is less than $1 are excluded. Recommendations are from I/B/E/S from 1994 to 2006.



I have economically meaningful differences in turnover. I note that the average market cap of low-turnover firms is $3.647 billion, slightly larger than that of high turnover firms ($3.199 billion). Thus, there is no evidence that high-turnover firms are larger firms. Low-turnover firms have 2.74 analysts issuing recommendations in a typical firm year compared to 4.08 analysts for high-turnover firms, suggestive of greater visibility for high turnover firms.

III. Results

A. Cumulative Abnormal Returns (CARs)

Figure 2 plots the average cumulative abnormal returns (CARs, in percent) of the extreme rating changes up to three months. The daily abnormal return (AR) is the raw CRSP return less the return on a matched DGTW portfolio. Using the market return as a benchmark does not affect any of the conclusions. The CAR is simply the cumulative sum of the ARs. To prevent the results from being biased by low-priced stocks, the CAR excludes observations where the lagged stock price is less than $1.

One can see that recommendation changes indeed convey steep event reactions. More importantly, I note interesting differences between high- and low-turnover stocks. According to Hypothesis 1a, the event-day reaction to rating changes will be lower for low-turnover stocks. Correspondingly, Hypothesis 1b predicts that the drift after the event date would be more pronounced for low-turnover stocks as investors slowly incorporate the information contained in these recommendations. Figure 2 demonstrates that for low-turnover stocks (dotted lines), rating changes tend to have a smaller reaction around the event date. The trend of smaller reaction and larger drift for low turnover stocks is visually evident.

Next, Table II tests whether the average recommendation change CARs are meaningfully different between low- and high-turnover stocks. Note that the standard errors in this analysis are clustered by calendar day to account for cross-correlation between firms. I first focus on the event date [−1, 1] reaction to recommendation changes. Panel A tests Hypothesis 1a to determine whether the rating change event reaction magnitudes are smaller for low turnover stocks. This is indeed the case. For the most downgraded group, high turnover stocks see an average [−1, 1] CAR of −4.137% while low turnover stocks experience an average CAR of −2.801% (a difference of 1.335% that has a t-statistic of 6.10). For the most upgraded stocks, the difference between the CAR of low and high-turnover stocks is −0.130% ($t = 1.63$). Although the support for Hypothesis 1a for upgrades is weak in this univariate setting, later multiple regression estimations will provider stronger support.[9] Next, looking at Group 5–1 (most upgraded minus most downgraded), the low turnover stocks produce event reaction CARs that are 1.465% ($t = -6.29$) less than the CARs of the high turnover stocks.

Next, I test Hypothesis 1b to ascertain whether recommendations issued for low-turnover stocks are associated with larger drifts. The evidence in Panels B-D of Table II indicates that recommendation changes associated with low turnover stocks experience larger drifts. Consider the two-month horizon. The average [2, 42] CAR of the most upgraded minus the most downgraded stocks is 1.259% for high-turnover stocks but 2.767% (more than double) for low-turnover stocks. Overall, Table II provides support for the hypotheses. That low-turnover stocks produce less reaction, and larger drifts in response to analysts' stock recommendation changes is consistent with an inattention explanation for the stock recommendation drift.

B. Underreaction Coefficients

Next, I consider the ratio of the event date reaction to the total return implication of the recommendation. This is the underreaction coefficient in Cohen and Frazzini (2008). To illustrate, suppose a recommendation produced a CAR of 5% for the period [−1, 42] and the event reaction over [−1, 1] is 3%. The underreaction coefficient is $3 \div 5 = 0.6$, meaning that 60% of the recommendation's two-month return occurred on the event date. An underreaction coefficient, $\in$

[9] When another measure of attention is used (residual turnover that controls for illiquidity and dispersion), the difference becomes statistically significant at $t = 2.45$. The results from the multiple regression in Table VI also provide support for Hypothesis 1a for upgrades. The reader may also be concerned that upgrades for low-attention stocks appear to convey more total return over the entire −1 to +63 horizon than upgrades for high-attention stocks. However, unreported tests determine that this difference disappears economically and statistically once I control for other firm variables used in Table VI.

Table II. Average Cumulative Abnormal Returns (CARs) of Stock Recommendations Changes for Turnover Groups

The average percentage CAR of stock recommendation changes are reported according to turnover groups. For each day, firms with rating changes are classified into high-turnover and low-turnover groups according to the average daily percentage of shares traded from [−63, −2] days of the recommendation. NASDAQ firms' CRSP volumes are divided by 2 to account for interdealer double counting. The five-point rating scale ranges from 1 (sell) to 5 (strong buy). A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold). Firms are then placed in five rating change groups: [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded). The abnormal return each day is the raw CRSP return less the return on a matched size-B/M-momentum characteristic portfolio. Days where the lagged stock price is less than $1 are excluded. Recommendations are from I/B/E/S from 1994 to 2006. Statistical significance is based on standard errors clustered by calendar day with the associated *t*-statistics in parentheses below the estimates.

Group	High Turnover	Low Turnover	Low–High	High Turnover	Low Turnover	Low–High
	Panel A. Event Reaction CAR [−1, 1]			*Panel B. Drift CAR [2, 21]*		
1 (Most downgraded)	−4.137***	−2.801***	1.335***	−0.509***	−0.760***	−0.250
	(−25.69)	(−18.87)	(6.10)	(−3.41)	(−5.95)	(−1.27)
2	−3.859***	−2.419***	1.440***	−0.400***	−0.487***	−0.087
	(−28.51)	(−25.70)	(8.73)	(−3.03)	(−5.25)	(−0.54)
3	−0.692***	−0.319***	0.373***	0.033	0.173**	0.139
	(−11.77)	(−8.59)	(5.37)	(0.28)	(2.51)	(1.01)
4	1.541***	1.325***	−0.217***	0.665***	0.878***	0.213*
	(27.77)	(30.50)	(−3.07)	(7.60)	(12.92)	(1.92)
5 (Most upgraded)	1.901***	1.771***	−0.130	0.737***	1.203***	0.466***
	(31.80)	(33.42)	(−1.63)	(6.98)	(14.21)	(3.45)
5–1	6.037***	4.572***	−1.465***	1.246***	1.962***	0.716***
	(35.15)	(29.00)	(−6.29)	(6.81)	(12.81)	(3.00)

(*Continued*)

Table II. Average Cumulative Abnormal Returns (CARs) of Stock Recommendations Changes for Turnover Groups (*Continued*)

Group	High Turnover	Low Turnover	Low–High	High Turnover	Low Turnover	Low–High
	Panel C. Drift CAR [2, 42]			*Panel D. Drift CAR [2,63]*		
1 (Most downgraded)	−0.472**	−1.083***	−0.611**	−0.175	−0.970***	−0.795**
	(−2.28)	(−6.24)	(−2.26)	(−0.70)	(−4.65)	(−2.44)
2	0.010	−0.594***	−0.604***	0.128	−0.604***	−0.733***
	(0.06)	(−4.57)	(−2.81)	(0.62)	(−4.02)	(−2.85)
3	0.274**	0.334***	0.060	0.231	0.521***	0.291
	(1.99)	(3.32)	(0.35)	(1.38)	(4.21)	(1.39)
4	0.812***	1.383***	0.571***	0.969***	1.683***	0.714***
	(6.32)	(14.59)	(3.57)	(5.97)	(14.71)	(3.59)
5 (Most upgraded)	0.787***	1.684***	0.897***	0.919***	1.996***	1.077***
	(5.24)	(13.99)	(4.66)	(4.97)	(13.45)	(4.54)
5–1	1.259***	2.767***	1.508***	1.095***	2.966***	1.872***
	(4.92)	(13.10)	(4.55)	(3.52)	(11.59)	(4.65)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

[0, 1), represents underreaction and any other positive number represents overreaction.[10] Among cases of underreaction, a lower number represents greater underreaction.

Figure 3 reports the underreaction coefficients. Shaded bars in Figure 3 denote the high-turnover group and striped bars denote the low-turnover group. For example, the chart for the one-month CAR demonstrates that the underreaction coefficient for the 5–1 recommendation group is 82.9% for the high-turnover group. This percentage is derived by taking 6.037/(6.037 + 1.246), where the high-turnover 5–1 group's event reaction of 6.037% is from Table II, Panel A, and 1.246% is from the corresponding cell in Panel B for the drift of the high-turnover group. The underreaction coefficient for the low turnover 5–1 group can also be computed similarly and it is 70.0%. This indicates that for the high-turnover group where investors are presumably paying attention, 82.9% of a rating's one-month return occurs during the three-day event window while only 70.0% of a rating's one-month return occurs on the event window for low-turnover stocks.

At the two-month horizon, the difference in underreaction is even starker. The proportion of the two-month most upgraded return that occurs on the event date is 82.7% for high-turnover stocks is only 62.3% for low-turnover stocks. In sum, Figure 3 provides support for Hypothesis 1c. A larger fraction of the return associated with rating changes occurs on the event date for high-turnover stocks as compared to the fraction for low-turnover stocks.

C. Calendar-Time Portfolios

To determine whether the differences in CAR hold in portfolio strategies, I form daily calendar-time portfolios. For each turnover group, five daily rebalanced portfolios buy-and-hold stocks for two months with rating changes matching the five rating change groups. I focus on the two-month holding period for the portfolio tests since we can see from Table II that the average stock recommendation drift trails off in the third month.[11] Following Barber et al. (2006) and Fang and Yasuda (2007), the return for a portfolio containing rating change i on day τ is

$$R_{p\tau} = \sum_{i=1}^{n} x_{i\tau} R_{i\tau} \Bigg/ \sum_{i=1}^{n} x_{i\tau}. \tag{1}$$

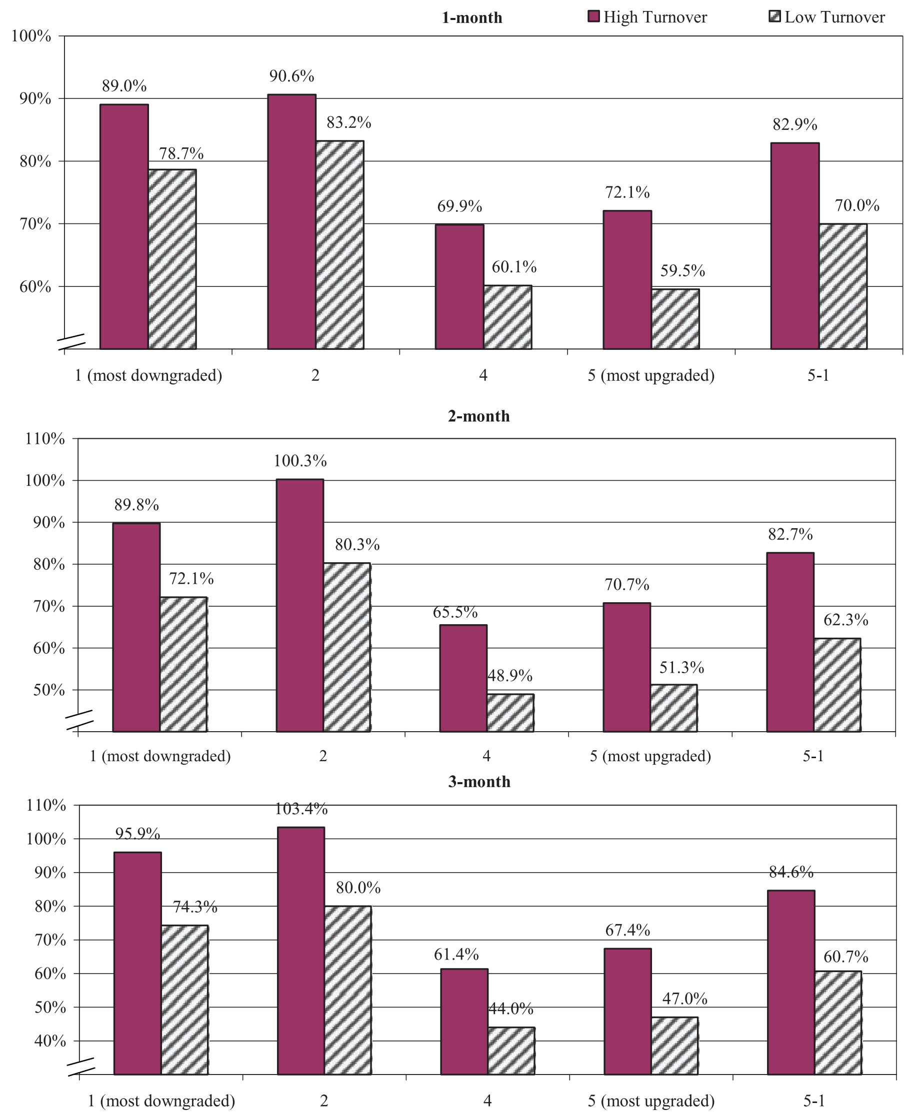
The weight $x_{i\tau}$ is the cumulative value of \$1 invested in the recommendation from the day the recommendation enters the portfolio to the close of trading on day $\tau - 1$. This buy-and-hold approach avoids the upward bias in equal weighting as describe in Canina et al. (1998). Note that if a stock is recommended multiple times, each rating is treated as a separate observation. Return days where the lagged price is less than \$1 are excluded from the portfolio. Additionally, in cases when there are no ratings in day τ for the portfolio, I assume an investment in the market portfolio. The daily time-series of portfolio returns from Equation (1) are cumulated to monthly returns and the risk-free rate is subtracted. The monthly portfolio excess returns are regressed on the Fama and French (1993) three factors plus momentum (factors from Kenneth French's website).

[10]There could also be negative numbers for this ratio (e.g., when the event day reaction is −2% and the two-month return is 10%). One could think of such cases as neither underreaction nor overreaction, but some kind of "wrong" reaction.

[11]I also verify in unreported results that the unconditional stock recommendation drift is about 2% the first month, a statistically significant 0.5% the second month, and almost 0 in the third month. Thus, it seems reasonable to exclude the third month from our baseline portfolio strategies (although the results also hold for a one- or three-month holding period).

Figure 3. Percentage of Average Cumulative Abnormal Returns (CARs) Occurring on Recommendation Date

This figure reports whether low prior turnover firms underreact more to recommendation changes. The top graph illustrates the percentage of average one-month [−1, 21] CAR that occurs on the [−1, 1] recommendation change date. The next two graphs are for the two-month [−1, 42] and three-month [−1, 63] horizons, respectively. A percentage ≥ 0, but < 100 represents underreaction and overreaction otherwise. For each day, firms with rating changes are classified into high-turnover and low-turnover groups according to the average daily percentage of shares traded from [−63, −2] days of the recommendation date. NASDAQ firms have their CRSP volume divided by two to account for interdealer double counting. Firms are then placed in five rating change groups: [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded). The abnormal return each day is the raw CRSP return less the return on a matched size-B/M-momentum characteristic portfolio. Days where the lagged stock price is less than $1 are excluded. Average CAR numbers are from Table II and recommendations are from I/B/E/S from 1994 to 2006.



The time-series average of the DGTW characteristics-adjusted returns are also reported in the tables. The daily benchmark return for a portfolio p with recommendation i is given by

$$R_{p\tau}^{DGTW} = \sum_{i=1}^{n} x_{i\tau}^{DGTW} R_{i\tau}^{DGTW} \Bigg/ \sum_{i=1}^{n} x_{i\tau}^{DGTW}. \quad (2)$$

This is the same as the previous equation except that all terms refer to the return of recommendation i's benchmark portfolio. The daily time-series of $R_{p\tau}^{DGTW}$ are then cumulated to monthly returns R_{pt}^{DGTW}, and the time-series average of $R_{pt} - R_{pt}^{DGTW}$ is reported in the tables. The characteristics-adjusted returns have the advantage of not assuming that the factor exposures are constant over the entire sample period. Finally, I compute industry-adjusted returns where the benchmark return is based on the Fama and French (1997) 49 industry groups.

We can see in Table III that for high-turnover stocks (Panel A), the abnormal return of the hedge portfolio (5–1) measured by the four-factor model is 0.802% per month ($t = 3.94$). For the low-turnover group, the abnormal return is about double in magnitude at 1.633% (consistent with earlier results in Table II). The difference between the low- and high-turnover groups is 0.831% ($t = 3.42$). Similar results are obtained when looking at excess returns, DGTW-adjusted returns, or industry-adjusted returns.

D. Calendar-Time Results with Residual Turnover

Sorting stocks on prior turnover could capture variables other than attention as turnover is constructed from volume which could also proxy for illiquidity or the differences of opinion among investors. To address these concerns, I sort stocks based on their residual turnover. For the universe of stocks, I estimate a cross-sectional regression of average prior turnover against the Amihud (2002) illiquidity measure and the dispersion of analysts' earnings forecasts. The regression residual is used to sort firms with recommendation changes into high- and low-attention firms. By construction, this residual is an attention measure orthogonal to illiquidity and dispersion. Table IV reports the results of portfolio strategies that are closely similar to those in Table III except that residual turnover is used. The results in Table IV are consistent with earlier results and support the attention hypothesis.

IV. Additional Tests

A. Change in Turnover around Recommendation Change Event

To determine if the conclusions on the inattention hypothesis are robust, Table V reports the increase in turnover, defined as average turnover in $[-1, 1]$ minus average turnover in $[-63, -2]$ to see if investors are indeed slower to trade on recommendations on low attention stocks. Note in Panel A that the change in average daily turnover is much lower in magnitude for low-turnover stocks. For the most downgraded group, a recommendation on a high-turnover (high-attention) firm leads to the average percentage daily turnover increasing by 1.107%. A similar rating on a low-turnover firm results in only an increase of 0.472% (the difference of 0.635% is significant). This trend occurs throughout all five rating change groups providing evidence that investors fail to respond sufficiently to recommendations issued on low-attention stocks. Panels B and C scale the change in turnover by firm variables. This could be important if the amount of trading required to impound a recommendation's information into prices is different across different

Table III. Calendar-Time Portfolios of Recommendation Changes Sorted by Turnover

Each day, firms that experience recommendation changes are sorted into two groups based on their average daily turnover [−63, −2] days from the recommendation date. NASDAQ firms' CRSP volume are divided by two to account for interdealer double counting. The five-point rating scale ranges from 1 (sell) to 5 (strong buy). A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold). Firms are then placed into five portfolios that contain rating changes in [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded). Firm days where the lagged price is less than $1 are excluded. The daily buy-and-hold weighted average returns (see Equation (1)) of each portfolio are computed and then cumulated to monthly portfolio returns. The portfolio returns in excess of the risk-free rate is then regressed against the monthly four factors and the coefficients reported. Also reported is the average DGTW-adjusted return, which is the portfolio return less the return on a matched size-B/M-momentum characteristic portfolio, and the Fama-French (1997) 49-industry adjusted return. Sample data are from I/B/E/S and CRSP from 1994 to 2006. The *t*-statistics are in parentheses below the estimates.

Portfolio		Four-Factor Model							DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)
	Rawret-R_f (%)	Intercept (%)	MktRF	SMB	HML	UMD	Adj R^2	No. of Unique Firms per Day		
Panel A. High Prior Turnover										
1 (Most downgraded)	0.084	−0.542**	1.379***	0.652***	−0.138	−0.413***	0.8633	111.6	−0.596***	−0.896***
	(0.13)	(−2.07)	(5.33)	(8.94)	(−1.50)	(−8.16)			(−2.98)	(−3.06)
2	0.359	−0.274	1.392***	0.640***	−0.116	−0.424***	0.9110	206.0	−0.324**	−0.643**
	(0.56)	(−1.33)	(7.02)	(11.16)	(−1.59)	(−10.65)			(−2.03)	(−2.40)
3	0.595	−0.078	1.367***	0.617***	−0.195***	−0.297***	0.9361	270.1	−0.134	−0.549**
	(0.96)	(−0.46)	(8.04)	(13.19)	(−3.28)	(−9.13)			(−0.95)	(−2.15)
4	1.001*	0.197	1.357***	0.590***	−0.195***	−0.102***	0.9269	303.5	0.234	−0.148
	(1.68)	(1.14)	(7.61)	(12.26)	(−3.20)	(−3.06)			(1.59)	(−0.58)
5 (Most upgraded)	1.008	0.261*	1.308***	0.704***	−0.267***	−0.125***	0.9436	214.1	0.230	−0.082
	(1.65)	(1.68)	(7.29)	(16.24)	(−4.85)	(−4.14)			(1.50)	(−0.33)
5–1	0.924***	0.802***	−0.071	0.052	−0.128*	0.289***	0.3206	325.7	0.825***	0.814***
	(4.00)	(3.94)	(−1.28)	(0.92)	(−1.78)	(7.32)			(4.57)	(3.79)

(*Continued*)

Table III. Calendar-Time Portfolios of Recommendation Changes Sorted by Turnover (*Continued*)

Portfolio	Four-Factor Model								DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)
	Rawret-R_f (%)	Intercept (%)	MktRF	SMB	HML	UMD	Adj R^2	No. of Unique Firms per Day		
					Panel B. Low Prior Turnover					
1 (Most downgraded)	−0.175	−0.706***	0.893***	0.436***	0.347***	−0.356***	0.8774	101.4	−0.971***	−1.042***
	(−0.46)	(−4.97)	(−2.77)	(11.01)	(6.90)	(−12.95)			(−7.09)	(−6.07)
2	0.275	−0.386***	0.964	0.339***	0.401***	−0.248***	0.9080	202.7	−0.582***	−0.773***
	(0.77)	(−3.34)	(−1.16)	(10.51)	(9.79)	(−11.07)			(−5.90)	(−4.26)
3	0.816**	0.180	0.938*	0.307***	0.449***	−0.280***	0.8944	306.5	−0.081	−0.277
	(2.32)	(1.48)	(−1.87)	(9.02)	(10.40)	(−11.87)			(−0.77)	(−1.58)
4	1.437***	0.650***	1.018	0.400***	0.489***	−0.191***	0.9069	324.7	0.504***	0.370**
	(3.96)	(5.49)	(0.57)	(12.13)	(11.68)	(−8.34)			(5.80)	(2.07)
5 (Most upgraded)	1.699***	0.927***	1.050	0.366***	0.380***	−0.165***	0.8881	215.1	0.717***	0.628***
	(4.47)	(6.82)	(1.34)	(9.67)	(7.89)	(−6.27)			(7.23)	(3.21)
5–1	1.875***	1.633***	0.157***	−0.070	0.033	0.191***	0.1879	316.6	1.688***	1.670***
	(10.76)	(9.73)	(3.43)	(−1.49)	(0.55)	(5.89)			(10.83)	(10.18)
					Panel C. Low–High Prior Turnover					
1 (Most downgraded)	−0.259	−0.164	−0.486***	−0.216***	0.485***	0.057	0.5663	213.0	−0.375	−0.146
	(−0.65)	(−0.59)	(−6.41)	(−2.77)	(4.91)	(1.06)			(−1.46)	(−0.52)
2	−0.085	−0.112	−0.429***	−0.301***	0.517***	0.176***	0.7249	408.7	−0.258	−0.131
	(−0.23)	(−0.54)	(−7.59)	(−5.20)	(7.03)	(4.38)			(−1.20)	(−0.53)
3	0.221	0.258	−0.429***	−0.310***	0.644***	0.016	0.7747	576.6	0.053	0.272
	(0.57)	(1.31)	(−8.03)	(−5.66)	(9.25)	(0.43)			(0.25)	(1.18)
4	0.435	0.453**	−0.338***	−0.190***	0.684***	−0.089**	0.7656	628.2	0.270	0.518**
	(1.24)	(2.50)	(−6.87)	(−3.75)	(10.67)	(−2.53)			(1.41)	(2.40)
5 (Most upgraded)	0.691**	0.666***	−0.258***	−0.338***	0.646***	−0.040	0.7703	429.2	0.487**	0.710***
	(1.98)	(3.72)	(−5.32)	(−6.77)	(10.21)	(−1.16)			(2.47)	(3.36)
5–1	0.950***	0.831***	0.227***	−0.122*	0.161*	−0.097**	0.1430	642.2	0.862***	0.856***
	(3.87)	(3.42)	(3.45)	(−1.80)	(1.87)	(−2.07)			(3.87)	(3.64)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table IV. Calendar-Time Portfolios of Recommendation Changes Sorted by Residual Turnover Controlling for Illiquidity and Analyst Forecast Dispersion

Each day, firms that experience recommendation changes are sorted into two groups based on their average residual daily turnover [−63, −2] days from the recommendation date. NASDAQ firms' CRSP volume are divided by two to account for interdealer double counting. Residual turnover is the residual from a cross-sectional regression of all firms in the CRSP ordinary share universe on the day of the recommendation. The average daily turnover from [−63, −2] is regressed against the average illiquidity from [−63, −2] and the most recent I/B/E/S Summary File reported monthly dispersion of analysts' FY1 earnings forecasts. Within each residual turnover group, firms are then placed into five portfolios containing rating changes in [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded), respectively. A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. Rating changes based on stale prior ratings (more than one year old) are excluded and the rating change for an initiation is computed as the initiation rating minus 3 (a hold). Firm days where the lagged price is less than $1 are excluded. The daily buy-and-hold-weighted average returns of each portfolio are then compounded to monthly returns, subtracting the risk-free rate then regressed on the monthly four factors and the coefficients reported. Also reported is the average DGTW-adjusted return, which is the portfolio return less the return on a matched size-B/M-momentum characteristic portfolio, and the industry-adjusted Fama-French (1997) 49 industries return. Sample data are from I/B/E/S and CRSP from 1994 to 2006. The *t*-statistics are in parentheses below the estimates.

Portfolio	Four-Factor Model								DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)
	Rawret-R_f (%)	Intercept (%)	MktRF	SMB	HML	UMD	Adj R^2	No. of Unique Firms per Day		
Panel A. High Prior Residual Turnover (Controls for Illiquidity and Analyst Forecast Dispersion)										
1 (Most downgraded)	0.204	−0.433	1.418***	0.672***	−0.142	−0.433***	0.8600	102.6	−0.470**	−0.779**
	(0.30)	(−1.58)	(5.62)	(8.82)	(−1.47)	(−8.19)			(−2.21)	(−2.53)
2	0.396	−0.258	1.427***	0.622***	−0.110	−0.425***	0.9048	192.4	−0.291*	−0.605**
	(0.60)	(−1.19)	(7.27)	(10.34)	(−1.43)	(−10.17)			(−1.71)	(−2.17)
3	0.597	−0.071	1.377***	0.599***	−0.190***	−0.310***	0.9304	252.2	−0.118	−0.546**
	(0.96)	(−0.40)	(7.88)	(12.20)	(−3.05)	(−9.10)			(−0.80)	(−2.08)
4	0.979	0.179	1.358***	0.579***	−0.186***	−0.112***	0.9214	280.6	0.202	−0.170
	(1.64)	(1.00)	(7.37)	(11.62)	(−2.94)	(−3.23)			(1.37)	(−0.65)
5 (Most upgraded)	0.980	0.239	1.332***	0.662***	−0.242***	−0.158***	0.9362	194.6	0.215	−0.102
	(1.60)	(1.44)	(7.38)	(14.36)	(−4.14)	(−4.94)			(1.35)	(−0.40)
5–1	0.775***	0.672***	−0.086	−0.010	−0.101	0.275***	0.2595	297.2	0.685***	0.677***
	(3.33)	(3.14)	(−1.48)	(−0.17)	(−1.33)	(6.64)			(3.70)	(3.05)

(*Continued*)

Table IV. Calendar-Time Portfolios of Recommendation Changes Sorted by Residual Turnover Controlling for Illiquidity and Analyst Forecast Dispersion (*Continued*)

Portfolio	Four-Factor Model								DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)
	Rawret-R_f (%)	Intercept (%)	MktRF	SMB	HML	UMD	Adj R^2	No. of Unique Firms per Day		
Panel B. Low Prior Residual Turnover (Controls for Illiquidity and Analyst Forecast Dispersion)										
1 (Most downgraded)	−0.188	−0.709***	0.889***	0.420***	0.379***	−0.381***	0.8627	94.7	−0.946***	−1.063***
	(−0.49)	(−4.68)	(−2.69)	(9.94)	(7.06)	(−13.00)			(−6.59)	(−5.62)
2	0.297	−0.394***	0.982	0.349***	0.449***	−0.253***	0.9115	191.8	−0.541***	−0.744***
	(0.83)	(−3.44)	(−0.58)	(10.93)	(11.08)	(−11.42)			(−5.45)	(−3.95)
3	0.762**	0.114	0.956	0.268***	0.462***	−0.277***	0.9019	283.4	−0.104	−0.329*
	(2.17)	(0.97)	(−1.39)	(8.20)	(11.11)	(−12.20)			(−0.99)	(−1.73)
4	1.289***	0.511***	1.024	0.351***	0.487***	−0.194***	0.9064	296.1	0.407***	0.237
	(3.58)	(4.33)	(0.76)	(10.68)	(11.67)	(−8.49)			(4.55)	(1.24)
5 (Most upgraded)	1.514***	0.760***	1.035	0.316***	0.389***	−0.169***	0.8794	190.2	0.605***	0.464**
	(4.08)	(5.51)	(0.93)	(8.23)	(7.98)	(−6.36)			(5.79)	(2.21)
5–1	1.702***	1.469***	0.146***	−0.104**	0.010	0.212***	0.2069	284.8	1.550***	1.527***
	(9.36)	(8.48)	(3.10)	(−2.15)	(0.16)	(6.31)			(9.49)	(9.05)
Panel C. Low–High Prior Residual Turnover (Controls for Illiquidity and Analyst Forecast Dispersion)										
1 (Most downgraded)	−0.393	−0.276	−0.528***	−0.252***	0.520***	0.052	0.5889	197.3	−0.475*	−0.284
	(−0.93)	(−0.95)	(−6.69)	(−3.11)	(5.06)	(0.93)			(−1.74)	(−0.94)
2	−0.099	−0.136	−0.445***	−0.274***	0.558***	0.172***	0.7158	384.2	−0.250	−0.139
	(−0.26)	(−0.62)	(−7.48)	(−4.49)	(7.22)	(4.07)			(−1.11)	(−0.54)
3	0.165	0.185	−0.421***	−0.331***	0.652***	0.033	0.7739	535.6	0.014	0.217
	(0.42)	(0.93)	(−7.77)	(−5.94)	(9.23)	(0.85)			(0.07)	(0.93)
4	0.310	0.332*	−0.333***	−0.228***	0.672***	−0.082**	0.7614	576.7	0.205	0.407*
	(0.88)	(1.79)	(−6.63)	(−4.42)	(10.27)	(−2.29)			(1.06)	(1.90)
5 (Most upgraded)	0.534	0.521***	−0.297***	−0.346***	0.631***	−0.012	0.7561	384.8	0.390*	0.566**
	(1.49)	(2.75)	(−5.76)	(−6.55)	(9.41)	(−0.31)			(1.87)	(2.56)
5–1	0.927***	0.797***	0.232***	−0.093	0.111	−0.064	0.0973	582.0	0.865***	0.850***
	(3.77)	(3.19)	(3.42)	(−1.34)	(1.25)	(−1.32)			(3.84)	(3.59)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table V. Change in Turnover after the Recommendation Change Event

The average change in turnover is reported for the sample of recommendation change events. In Panel A, change in % average daily turnover is the average daily turnover on the [−1, 1] event window minus the prior [−63, −2] average daily turnover for the stock. The averages are in percent (i.e., 1.000 means event turnover minus prior turnover equals 1%). Also in Panel A, is the % average daily turnover in the [2, 42] recommendation drift window minus the prior [−63, −2] average daily turnover for the stock. Panels B and C report the change in turnover numbers scaled by analyst coverage and institutional ownership, respectively. The analyst coverage scaling variable is the number of analysts covering the stock divided by 10, and the institutional ownership variable is the fraction of shares owned by 13f institutions (0.01 is added to the fraction to prevent 0 denominators). High (low) turnover indicates that the average daily turnover of the stock in [−63, −2] was in the upper (low) half of all stocks experiencing recommendation changes in Day 0. Within each turnover group, recommendations are sorted into five portfolios containing rating changes in [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded), respectively. The *t*-statistics in parentheses are reported below the averages and are based on standard errors clustered by calendar day.

Group	Change in Average % Daily Turnover in the [−1, 1] Window			Change in Average % Daily Turnover in the [2, 42] Window		
	High Turnover	Low Turnover	Low–High	High Turnover	Low Turnover	Low–High
			Panel A. Change in Turnover			
1 (Most downgraded)	1.107***	0.472***	−0.635***	−0.004	0.059***	0.063***
	(30.19)	(17.21)	(−13.87)	(−0.52)	(19.59)	(8.30)
2	0.815***	0.294***	−0.521***	−0.020***	0.047***	0.066***
	(29.19)	(24.58)	(−17.17)	(−3.99)	(26.88)	(12.70)
3	0.184***	0.085***	−0.100***	−0.038***	0.035***	0.073***
	(14.19)	(17.74)	(−7.21)	(−9.43)	(17.23)	(16.29)
4	0.302***	0.133***	−0.169***	−0.011***	0.043***	0.054***
	(31.79)	(35.15)	(−16.52)	(−2.97)	(38.15)	(14.40)
5 (Most upgraded)	0.293***	0.146***	−0.147***	−0.010**	0.053***	0.062***
	(27.63)	(31.95)	(−12.74)	(−2.42)	(34.93)	(14.60)

(*Continued*)

Table V. Change in Turnover after the Recommendation Change Event (*Continued*)

Group	Change in Average % Daily Turnover in the [−1, 1] Window			Change in Average % Daily Turnover in the [2, 42] Window		
	High Turnover	Low Turnover	Low–High	High Turnover	Low Turnover	Low–High
Panel B. Change in Turnover Scaled by Number of Analysts ÷ 10						
1 (Most downgraded)	2.528***	1.452***	−1.076***	0.023	0.159***	0.136***
	(18.09)	(15.01)	(−6.33)	(0.94)	(15.40)	(5.06)
2	1.574***	0.684***	−0.891***	−0.007	0.096***	0.103***
	(18.65)	(17.57)	(−9.58)	(−0.49)	(18.27)	(6.46)
3	0.320***	0.221***	−0.099***	−0.062***	0.086***	0.148***
	(10.50)	(11.10)	(−2.72)	(−5.86)	(9.12)	(10.44)
4	0.496***	0.287***	−0.209***	−0.028***	0.102***	0.130***
	(17.15)	(20.10)	(−6.49)	(−2.69)	(24.56)	(11.55)
5 (Most upgraded)	0.581***	0.385***	−0.195***	−0.041***	0.151***	0.193***
	(16.08)	(18.00)	(−4.66)	(−2.90)	(22.05)	(12.18)
Panel C. Change in Turnover Scaled by Fraction of Insitutional Ownership						
1 (Most downgraded)	1.858***	1.025***	−0.833***	−0.055***	0.126***	0.181***
	(24.99)	(18.88)	(−9.05)	(−3.32)	(15.74)	(9.78)
2	1.352***	0.658***	−0.693***	−0.093***	0.103***	0.196***
	(25.15)	(23.80)	(−11.47)	(−4.99)	(16.29)	(9.94)
3	0.297***	0.256***	−0.041	−0.112***	0.118***	0.230***
	(11.08)	(6.54)	(−0.86)	(−8.04)	(4.21)	(7.36)
4	0.681***	0.383***	−0.298***	−0.029*	0.129***	0.158***
	(10.64)	(8.62)	(−3.82)	(−1.66)	(15.25)	(8.11)
5 (Most upgraded)	0.724***	0.492***	−0.233***	−0.101***	0.199***	0.300***
	(10.11)	(12.39)	(−2.84)	(−3.81)	(14.65)	(10.07)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

stocks. I consider analyst coverage and institutional ownership as scaling variables. I also find that turnover increases more for high attention than low-attention stocks per unit of analyst coverage or per unit fraction of institutional ownership.[12]

This table also reports the change in turnover for the drift horizon. This is simply the average daily turnover in the drift window minus the before-event turnover. If investors are inattentive to recommendations issued on low turnover stocks, this change will be larger for low-turnover stocks. I determine that this is indeed the case and that investors react (trade) slowly to recommendations on low-attention stocks.

B. Controlling for Postearnings Announcement Drift and Other Factors

In this section, I estimate a regression of recommendation change CAR against a low prior turnover dummy and various control variables. This allows me to control for multiple potential factors that may be related to recommendation reaction and drift. To control for past earnings surprise, I include the most recent quarterly earnings surprise in the CAR regressions. Earnings surprise is defined as the most recent I/B/E/S reported actual Q1 earnings minus the final monthly consensus analysts' earnings forecast, scaled by price. I also include a Forecast Revision variable. Kecskes, Michaely, and Womack (2009) find that rating changes accompanied by earnings forecast revisions are more profitable. Forecast Revision is the most recent monthly revision in the consensus FY1 earnings forecasts from I/B/E/S, scaled by price. Next, I include a dummy variable, Small Broker, which is equal to one if the rating is not issued from a top quintile broker based on the number of recommendations issued last year. This controls for the reputation of the analyst to the extent that a reputable broker is more likely to house a star analyst. Other usual control variables such as dispersion, illiquidity, and analyst coverage are also included.

Table VI reports coefficients estimates. Since CARs are already characteristics adjusted on size, B/M, and momentum, there is no need for such factor controls in the regression. Panel A presents the event date CAR. Low Turnover indicates that the firm is in the lower half of firms sorted on their prior three-month average daily turnover. For the most downgraded stocks, a low prior turnover results in a significantly less negative reaction. This is consistent with investors reacting less to negative ratings in low-prior-turnover stocks. For the most upgraded stocks, investors react significantly less positively when stocks have low prior turnover. Turning to Panel B, the finding that low prior turnover results in a stronger recommendation drift remains intact even after adding all the control variables. Both the most downgraded stocks and the most upgraded stocks have larger drifts when prior turnover is low.

C. Alternative Measures of Attention

I also use other proxies for attention. The first measure is related to residual turnover in Table IV that controls for illiquidity and dispersion except that multiple proxies are used for both illiquidity and dispersion. Using multiple proxies reduces the number of firms with available data but provides a test for the robustness of the result to multiple proxies. To compute this measure of residual turnover, I estimate a cross-sectional regression involving the universe of stocks with prior turnover against 15 control variables. All the control variables are measured in the

[12]The caveat for this particular result is that a smaller trading reaction for low-attention stocks is not present if one uses prior turnover as the scaling variable. However, since the stocks are sorted by prior turnover, it is not surprising that the change in turnover as a percentage of already low prior turnover is large. Hence, the event reaction result here is supportive of the inattention hypothesis to the extent that analyst coverage or institutional ownership are better proxies than prior turnover for how much trading is needed for information to be impounded into prices.

Table VI. Regression of Cumulative Abnormal Returns (CARs) on Turnover with Multiple Control Variables

Characteristics-adjusted CARs are regressed on the inattention variable (low turnover) with multiple controls. Panel A is for event reaction CARs from Days −1 to +1 of the recommendation date and Panel B is for the drift from +2 to +42 trading days from the recommendation date. For each Day 0, firms that experience recommendation changes are sorted into two groups based on their average daily turnover [−63,−2] days from the recommendation date. The group with lower turnover has Low Turnover = 1. Earnings Surprise is the most recently reported actual Q1 earnings minus the I/B/E/S Summary File forecasted earnings before the earnings announcement date, scaled by last month's price. Forecast Revision is the most recent monthly revision in forecasted FY1 earnings, scaled by price. Forecast Dispersion is the most recent standard deviation of FY1 earnings forecasts, scaled by the absolute value of the mean forecast. No. of Analysts is the number of analysts issuing FY1 earnings forecasts. Illiquidity is the average daily Amihud (2002) illiquidity measure over the same horizon used to compute the average turnover. Small Broker = 1 if the broker is not in the top quintile of brokers by number of recommendations issued in the prior calendar year. The regressions are estimated for each rating change category, namely, rating changes in [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded). Sample data are from I/B/E/S and CRSP from 1994 to 2006. The regression is estimated by OLS with the standard errors clustered by calendar day. The *t*-statistics in parentheses are reported below the coefficient estimates.

Group	Intercept	Low Turnover	Current Rec.	Earnings Surprise	Forecast Revision	Illiquidity	Small Broker	Forecast Dispersion	ln (No. of Analysts)	R^2 (%)	No. of Obs. (No. of Clusters)
Panel A. Dependent Variable: Characteristic-Adjusted CAR from [−1,1]											
1 (Most downgraded)	−9.799***	1.645***	−0.334***	0.496	1.468***	0.205*	1.983***	0.178**	2.113***	2.827	16727
	(−17.84)	(8.20)	(−3.11)	(0.43)	(4.02)	(1.90)	(10.50)	(1.97)	(14.60)		(3055)
2	−8.608***	1.659***	0.139	−0.010***	−0.165	0.130**	1.810***	0.063	1.457***	1.915	35321
	(−17.65)	(12.59)	(1.49)	(−4.61)	(−0.42)	(2.24)	(11.72)	(0.93)	(14.59)		(3188)
3	−2.743***	0.412***	0.376***	−0.299	−0.305	0.069***	0.228***	0.091**	0.272***	0.354	49822
	(−12.38)	(6.16)	(8.52)	(−0.27)	(−0.25)	(3.24)	(3.13)	(2.43)	(5.43)		(3201)
4	1.762***	−0.366***	0.346***	0.106	−0.762	0.139***	−1.011***	0.176***	−0.567***	0.867	54024
	(5.36)	(−5.21)	(4.98)	(1.64)	(−0.97)	(3.19)	(−14.88)	(2.88)	(−11.27)		(3204)
5 (Most upgraded)	4.806***	−0.311***	−0.060	0.260	−1.095	−0.001	−1.100***	0.302***	−0.953***	1.689	33188
	(10.11)	(−3.93)	(−0.70)	(0.51)	(−0.61)	(−0.02)	(−14.32)	(5.10)	(−16.82)		(3190)
Panel B. Dependent Variable: Characteristic-adjusted CAR from [2, 42]											
1 (Most downgraded)	−2.497***	−0.784***	−0.083	−0.348	−1.228**	0.222	0.186	−0.556**	1.048***	0.338	16727
	(−3.30)	(−2.83)	(−0.53)	(−0.18)	(−2.46)	(1.47)	(0.66)	(−2.37)	(4.91)		(3055)
2	0.636	−0.726***	−0.235	−0.060***	−0.466	0.223*	−0.356	0.284*	0.182	0.122	35321
	(0.96)	(−3.40)	(−1.55)	(−16.95)	(−0.51)	(1.74)	(−1.61)	(1.80)	(1.04)		(3188)
3	1.051*	−0.172	−0.139	−8.023***	−2.583	0.103	−0.090	0.022	−0.039	0.084	49822
	(1.86)	(−1.02)	(−1.07)	(−2.94)	(−0.64)	(0.92)	(−0.47)	(0.26)	(−0.31)		(3201)
4	2.693***	0.182	0.046	0.493***	−4.580***	0.109	−0.017	0.118	−0.793***	0.145	54024
	(3.67)	(1.07)	(0.31)	(3.87)	(−3.73)	(0.63)	(−0.09)	(1.11)	(−6.38)		(3204)
5 (Most upgraded)	2.362**	0.397**	0.147	1.108*	−3.017	0.367***	−0.086	0.028	−0.889***	0.235	33188
	(2.38)	(2.00)	(0.82)	(1.84)	(−1.40)	(3.24)	(−0.44)	(0.22)	(−5.99)		(3190)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

[−63, −2] horizon and are as follows: 1) Amihud (2002) illiquidity measure, 2) average trading volume, 3) average dollar trading volume, 4) reciprocal of the average closing price, 5) fraction of zero volume days, 6) coefficient of variation (CV) of the Amihud (2002) measure (using CV measures of illiquidity is suggested by Chordia, Subrahmanyam, and Anshuman, 2001), 7) CV of volume, 8) CV of dollar volume, 9) CV of turnover, 10) holding-period return, 11) idiosyncratic volatility with respect to the market portfolio, 12) total volatility, 13) analyst forecast dispersion, 15) most recent earnings surprise (SUE) as in Chordia and Shivakumar (2006), and 15) standard deviation of past eight SUEs. The first 10 variables relate to illiquidity while the rest of the variables relate to the level of uncertainty surrounding the stock. Sorting stocks on residual turnover then provides a measure of turnover that is unrelated to multiple proxies for illiquidity and uncertainty. Therefore, one could say the residual proxies for attention (visibility). Abnormal returns from a calendar-time hedged portfolio of most upgraded minus most downgraded stocks are reported in Panel A of Table VII. Note that the low residual turnover stocks, as a whole, experience larger recommendation drifts than the high residual turnover stocks.

The second and third additional proxies for attention are institutional ownership and analyst coverage. The proportion of shares owned by institutions (from Thomson 13f) can proxy for the level of sophisticated investor scrutiny, and, as such, the overall level of attention on the firm. Analyst coverage is also usually related to a firm's visibility (Hong, Lim, and Stein, 2000; Kecskes and Womack, 2007). Using these two measures of attention produces similar evidence that low-attention stocks are associated with much larger stock recommendation drifts.

The fourth proxy is a time-series measure of attention employed in Hirshleifer, Lim, and Teoh (2009), that is, the number of earnings announcements in a day. Hirshleifer, Lim, and Teoh (2009) argue that investors may not react fully to information when there are many competing news events. I define high news day as days where there are more than 100 Compustat-reported quarterly earnings announcements. Choosing a numerical cutoff instead of sorting all sample trading days on the number of earnings announcements avoids a look-ahead bias. Roughly half (specifically 58.9%) of trading days have more than 100 earnings announcement events. These are defined as low attention days. In Panel D of Table VII, I demonstrate that the stock recommendation drift is more pronounced on low-attention days, providing additional support for the inattention hypothesis.

V. Conclusion

This paper examines the impact of investor inattention on the market's response to stock recommendations. If the market reacts efficiently to the information in recommendations, there should not be any predictable drift in stock prices. The extant literature, however, documents a strong drift. Barber et al. (2001) argue that this evidence is consistent with semistrong inefficient markets where public information can predict future stock returns. Using a stock's prior turnover as the main measure of investor attention, I test whether investor inattention contributes to a larger stock recommendation drift. This would be in line with inattentive investors not reacting sufficiently to stock recommendations and a subsequent predictable drift accompanies their gradual realization of the true stock price implication of the recommendation.

Consistent with this hypothesis, I determine that the reaction to recommendation changes is much smaller for low-prior-turnover stocks than it is for high-prior-turnover stocks. Consequently, the recommendation drift is more pronounced for low-turnover firms. This result is robust to controlling for other variables that could be associated with trading volume such as illiquidity and uncertainty. The results also hold for alternative proxies for attention. The implication of

Table VII. Abnormal Returns of Portfolios Sorted by Alternative Attention Proxies

Each day, firms that experience recommendation changes are sorted into two groups based on alternative attention proxies. Panels B-D proxy low attention, respectively, as low institutional ownership (the proportion held by 13f institutions), low number of analysts issuing FY1 I/B/E/S estimates in the most recent month, and > 100 earnings announcements in the market on that day. Panel A's proxy for low attention is low residual average daily turnover [−63, −2] days from the recommendation date. Residual turnover is the residual from a cross-sectional regression of all firms in the CRSP ordinary share universe on the day of the recommendation with average daily turnover regressed against 15 proxies for illiquidity and uncertainty measured in [−63, −2], namely, the Amihud (2002) illiquidity measure, average trading volume, avg $ trading volume, inverse of avg closing price, % days with zero volume, CV of Amihud (2002) measure, CV of volume, CV of $ volume, CV of turnover, holding period return, idiosyncratic volatility, total volatility, most recent dispersion of analysts' FY1 forecasts, most recent SUE, and standard deviation of past eight SUEs. Within each attention group, firms are then placed into five portfolios containing rating changes in [−4, −2] (most downgraded), −1, 0, +1, and [+2, +4] (most upgraded) with firm days where the lagged price is less than $1 excluded. A rating change is the current rating minus the prior rating for the same analyst with anonymous analysts and recommendations made in the three-day window around earnings announcements excluded. The daily buy-and-hold-weighted average returns of each portfolio are then compounded to monthly returns, subtracting the risk-free rate and regressed on the monthly four factors. Also reported is the average DGTW-adjusted return, which is the portfolio return less the return on a matched size-B/M-momentum characteristic portfolio, and the industry-adjusted (Fama-French (1997) 49 industries) return. The abnormal return of the most upgraded minus the most downgraded is reported for the high versus low attention group. Sample data are from I/B/E/S and CRSP from 1994 to 2006. The *t*-statistics in parentheses are reported below the coefficient estimates.

Most Upgraded–Most Downgraded Portfolio	Rawret-R_f (%)	DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)	4-Factor Alpha (%)	Rawret-R_f (%)	DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)	4-Factor Alpha (%)
	Panel A. Residual Turnover (Controlling for Multiple Illiquidity and Uncertainty Proxies)				*Panel B. Institutional Ownership*			
High attention	0.910***	0.931***	0.861***	0.658***	0.499**	0.465***	0.441**	0.454**
	(4.03)	(5.47)	(4.25)	(3.19)	(2.60)	(3.16)	(2.41)	(2.49)
Low attention	1.567***	1.313***	1.388***	1.379***	2.095***	1.938***	1.865***	1.746***
	(7.19)	(7.14)	(6.76)	(6.64)	(9.21)	(11.13)	(9.41)	(9.05)
Low–High	0.657**	0.381	0.527**	0.721**	1.595***	1.474***	1.424***	1.292***
	(2.49)	(1.61)	(2.13)	(2.56)	(6.81)	(7.21)	(6.52)	(5.49)

(*Continued*)

Table VII. Abnormal Returns of Portfolios Sorted by Alternative Attention Proxies (*Continued*)

Most Upgraded–Most Downgraded Portfolio	Rawret-R_f (%)	DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)	4-Factor Alpha (%)	Rawret-R_f (%)	DGTW-Adj. Ret (%)	Industry-Adj. Ret (%)	4-Factor Alpha (%)
	Panel C. Analyst Coverage				*Panel D. Distraction Proxy: No. of Earnings Announcement News in the Aggregate Market*			
High attention	0.848***	0.711***	0.739***	0.823***	1.202***	1.115***	1.083***	0.973***
	(4.84)	(4.53)	(4.27)	(4.83)	(5.29)	(6.28)	(5.11)	(4.76)
Low attention	1.830***	1.720***	1.645***	1.507***	1.953***	1.695***	1.769***	1.954***
	(8.16)	(10.18)	(8.35)	(7.83)	(8.14)	(7.87)	(8.10)	(8.01)
Low–High	0.982***	1.009***	0.906***	0.684***	0.752**	0.580**	0.686**	0.981***
	(4.70)	(5.01)	(4.44)	(3.25)	(2.58)	(2.22)	(2.41)	(3.30)

***Significant at the 0.01 level.
**Significant at the 0.05 level.

my evidence is that investor inattention is a plausible explanation for the stock recommendation drift. Also, investors would be better off mimicking the stock recommendations of firms to which the market is inattentive, so that they can profit from the drift in stock price when the market eventually corrects such underreaction. ■

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