Fisher College of Business Working Paper Series

Investor Inattention and the Underreaction to Stock Recommendations

Roger Loh, Department of Finance, The Ohio State University and Singapore Management University

Dice Center WP 2008-2
Fisher College of Business WP 2008-03-002

February 2008

Investor inattention and the underreaction to stock recommendations

Roger K. Loh*

February 2008

Abstract

Investors' reaction to stock recommendations is often incomplete so that there is a predictable post-recommendation drift. I investigate whether investor inattention contributes to this drift by using turnover as a proxy for investor attention. I find that the recommendation drift of firms with low prior turnover is more than double in magnitude compared to that of firms with high prior turnover. Additional proxies for attention, such as analyst coverage, institutional ownership, days with few distracting news events, or a measure of residual turnover that controls for liquidity and uncertainty, produce similar results. Volume reactions around the recommendation event show that investors fail to react promptly to recommendations on low attention stocks. Together, the evidence suggests that investor inattention is a plausible explanation for investors' underreaction to stock recommendations.

Keywords: Underreaction; Investor Attention; Security Analysts; Stock Recommendations

JEL Classification Codes: G12; G14

---

* I thank Tarun Chordia, Karl Diether, Rudi Fahlenbrach, Kewei Hou, Andrew Karolyi, Taylor Nadauld, Carrie Pan, Avanidhar Subrahmanyam, Siew Hong Teoh, seminar participants at Ohio State University, and especially René Stulz for their comments.

Address correspondence: Department of Finance, Fisher College of Business, Ohio State University, 606 Fisher Hall, 2100 Neil Ave, Columbus, OH 43210, U.S.A. Telephone: 614-292-7562, Fax: 614-292-2418. Email: loh.26@osu.edu.

1. Introduction

Existing literature finds that while security analysts' stock recommendations lead to an immediate price reaction, a drift in the stock price continues for one to six months (see, for example, Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), and Boni and Womack (2006)). 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 is fully cognizant about analysts possessing such ability.

Presumably, a recommendation has an immediate impact on a firm's stock price because it reveals information about the firm.[1] A predictable drift afterwards 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 (for example, Diether, Malloy, and Scherbina (2002), and Nagel (2005)) as an explanation of why a negative drift follows downgrades, but it is not so obvious why one should observe an underreaction to upgrades. Barber et al. (2001) offer the explanation that markets are semi-strong inefficient so that stock returns are predictable based on public information like stock recommendations.[2] This paper posits investor inattention as a possible avenue of inefficiency in the market's response to stock recommendations. If investors temporarily neglect the

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

[2] The sample period considered in this paper (1994-2006) is associated with the instant public dissemination of stock recommendations through the Internet (example, Yahoo! Finance). Therefore it is reasonable that stock recommendations are not simply privy to some institutional clients but public information for *both* retail and institutional investors.

information contained in stock recommendations, a predictable drift follows when investors gradually incorporate this information.[3]

Theoretical models predict that investor inattention can cause underreaction to public information. Hirshleifer and Teoh (2005) present a model where a subset of investors neglects the information about 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) develop a model where investor attention constraints lead to "category learning" so that investors focus more on market-wide and industry-wide information rather than on firm-specific information. This implies that investors could underreact to firm-specific information such as analysts' firm-specific stock recommendations. It is important to note that in general, an inattention-based explanation for underreaction requires some limits to arbitrage. Otherwise, it suffices to have one single attentive agent with no capital constraints to drive the stock price to its fundamental value instantly.[4]

Empirical studies examining the impact of investor inattention on asset prices can be classified into two types. The first group of studies uncovers predictability of returns in a certain setting 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

[3] There is some evidence that analysts herd (example, Welch (2000) and Jegadeesh and Kim (2006)), although there is also some evidence that they anti-herd (example, Bernhardt, Campello, and Kutsoati (2006)). Analysts' recommendations could also be affected by conflicts of interests (see for example, the survey by Mehran and Stulz (2007)). Regardless, even if analyst recommendations contain some bias, this cannot be an explanation for why investors systematically fail to account for such biases so that the market on average underreacts to stock recommendations.

[4] 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 to which they are willing to bear risk in order to exploit mispricing (Hirshleifer and Teoh (2003)).

by up to two months and contend that investors are inattentive to the predictive information contained in industry returns. Similarly, Cohen and Frazzini (2007) report abnormal profits to 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 of studies defines an attention proxy and then investigate the implications of inattention on asset prices. For instance, Hou, Peng, and Xiong (2006), using share turnover as a proxy for investor attention, show that an earnings momentum strategy is more profitable when investors are inattentive and argue that underreaction-driven anomalies should be more profitable when investors are inattentive. DellaVigna and Pollet (2008) find that the market's reaction to earnings announcements is more complete during regular weekdays than on Fridays and attribute this to investors being distracted by the approaching weekend. Hirshleifer, Lim, and Teoh (2006) 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 of studies where I define a proxy for attention and test whether the stock recommendation drift is more pronounced when investors are inattentive. To my knowledge, there are no studies on whether investor inattention contributes to the stock recommendation drift.[5]

This study also contributes to the question of whether some recommendations earn higher abnormal returns than other recommendations. Michaely and Womack (2006), for instance, show that stock recommendations with concurrent same-direction earnings forecast revisions are more profitable. Loh and Mian (2006) report that analysts who possess more

[5] An empirical advantage of the setting of stock recommendations (rather than the setting of earnings announcements) is that there are clearly defined categories of favorableness. Further, unlike earnings announcements that occur seasonally, stock recommendations in general can be issued at any time.

accurate earnings forecasts at the time of the recommendation issue more profitable stock recommendations. Sorescu and Subrahmanyam (2006) find that low strength recommendation changes by analysts from reputable 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. Our 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 et al. (2006). I argue that prior trading activity directly proxies for the amount of active attention investors are paying 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 recommendation changes issued for these two groups of firms. If investor inattention is a potential explanation for the stock recommendation drift, rating 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* in magnitude compared to the drift for high prior turnover firms.

Further tests consider alternative interpretations of turnover, because trading volume can also be associated with other firm characteristics. Specifically, turnover can be associated with liquidity (for example, Amihud (2002)) so that the low turnover stocks could simply be illiquid stocks that require a longer time to incorporate public information. Volume can also proxy for the differences of opinion among investors (for example, as in Diether et al. (2002)). Higher dispersion of opinion could proxy for mispricing (for example, see Sadka and Scherbina (2007)) so that the mispricing is corrected slowly after a recommendation and hence results in a larger drift. That turnover can be decomposed into components of visibility, uncertainty, and liquidity is in line with 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 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. This result holds even when a battery of proxies for illiquidity and uncertainty are included to compute residual turnover.

Trading activity around and after the recommendation event shows patterns consistent with the investor inattention hypothesis. First, I show that the average daily turnover increases in the three-day recommendation event window compared to the 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 these stocks when the recommendation was issued. In the subsequent three months following the event, the pattern reverses—turnover increases more for the low prior turnover stocks than it does for the high prior turnover stocks—consistent with investors reacting with a delay to the recommendations on low turnover stocks.

Finally, separate tests consider other proxies for investor attention. I use the percentage of institutional ownership and the number of analysts covering the stock as other proxies for attention. These two variables have been regularly used as investor attention proxies since they reflect the number of sophisticated investors who pay attention to the firm. I also use the number of earnings announcements in the aggregate market as a proxy for how distracted investors are. Hirshleifer et al. (2006) contend investors could be slow to react to every piece of information when they have to process a large number of competing news events on a single day. All these three proxies for attention support the conclusion that low investor attention results in a larger stock recommendation drift.

The recommendations used in this paper are from I/B/E/S. Therefore, I investigate the potential impact of the I/B/E/S recommendation history file problem reported in Ljungqvist, Malloy, and Marston (2006). The authors examine two snapshots of 1993-2002 recommendations data, one snapshot in 2002 and the other in 2004, and find that some analysts were anonymized, records were deleted, added, or altered between these two snapshots. I perform the three tests to determine whether my results, which are for the period 1994 to 2006, are sensitive to such changes in the database. First, I redefine recommendation changes using the broker code instead of the analyst code. This restores anonymizations because although an analyst code can be anonymized, I/B/E/S does not anonymize the broker code. Second, I redo my results for a sub-period 1994-2000 from an I/B/E/S snapshot in January 2001—avoiding the 2002-2004 period when such alterations occurred. To the extent that these alterations are a result of analysts trying to touch up their stock-picking histories during the period of heightened regulatory scrutiny on analysts, the pre-2001 period should be less tainted by such alterations. Third and lastly, I replicate the main results of the paper using First Call recommendations. All three tests provide support for the main result of the paper.

The rest of the paper is organized as follows. Section 2 lays out the hypotheses and the proxies for investor attention surrounding a firm. Section 3 describes the data used and reports some summary statistics. Section 4 presents the main results of the analysis, Section 5 reports some further tests, and Section 6 concludes.

2. Hypotheses and proxies

Investor attention can be specified based on multiple dimensions. The paper's focus is to examine the attention surrounding a *firm*. Alternatively, one could look at the analyst level (for example, do investors pay more attention to an analyst from a reputable broker?) or at the entire stock market level (for example, does the market pay less attention on high news days?). The main tests in this paper examine attention from a firm's perspective since this allows for more powerful tests that exploit the cross-sectional variation in attention across firms. More importantly, a firm-level perspective suits the express objective of stock recommendations—to guide investors in stock selection.[6]

If investors are inattentive to some stock recommendations, they may not react as strongly to these recommendations and hence the corresponding drift in prices would be more pronounced. My measure of how much attention investors are paying to a firm employs the prior amount of trading in the firm's stock. Trading volume has been used as a proxy for investor attention in various other papers. Hou et al. (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. Chordia and Swaminathan (2000) find that the returns of high turnover stocks leads the returns of low turnover stocks. They report that turnover disentangles the effect of firm size from trading volume since turnover has low correlation

[6] Frankel, Kothari, and Weber (2006) also adopt a firm-level perspective in investigating 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. Finally, and more importantly, they consider only the event reaction while I consider both the event reaction and the subsequent drift.

with firm size.[7] Some other studies use the volume of a stock as a measure of visibility of a stock (for example, Gervais, Kaniel, and Mingelgrin (2001) and Barber and Odean (2007)).

For my purpose, it can be argued that trading activity proxies for the amount of active attention that investors are paying to the firm. A firm whose shares have a lot of trading activity likely has vigilant investors who are attentive to news events like analyst recommendation changes. Any underreaction following recommendation changes would be less severe with such a large pool of attentive investors. Alternatively, a firm whose shares have low turnover likely has a smaller proportion of vigilant investors and this could result in a delay in the price response to rating changes. The main measure of attention I employ is the average daily turnover of the stock over the three months before the rating change (specifically, [-63,-2] trading days from the recommendation date). Turnover, the average number of shares traded divided by the number of shares outstanding, is more attractive as a measure of attention than raw trading volume or dollar trading volume because turnover controls for firm size better.

In robustness tests, I examine measures of attention that control for other variables that are also associated with trading volume but not directly related to investor attention. Trading volume could proxy for differences of opinion among investors (Diether et al. (2002)) or the liquidity of a firm's stock (Amihud (2002)). For instance, low trading volume can also be associated with illiquidity and as a result prices could take a longer time to adjust due to illiquidity and not due to inattention. It is therefore important to disentangle these effects to obtain a sharper measure for attention. Separating turnover into its various components is also

[7] I verify that in my sample, there is no evidence that high turnover firms are larger than low turnover firms.

similar to the approach in Chordia et al. (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' turnover against the Amihud illiquidity measure and the most recent analyst forecast dispersion. I also consider multiple proxies for illiquidity and uncertainty in additional tests. Further tests also use analyst coverage, institutional ownership, and the number of earnings announcements in a day as other proxies of investor attention.

The following three related hypotheses summarize the implications of investor inattention (as proxied by low turnover or residual turnover) 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 that occurs on the recommendation date as a percentage of longer-horizon return is smaller for low turnover firms than it is for high turnover firms. This is consistent with more underreaction to stock recommendations for low turnover firms.

3. Data and sample statistics

3.1. Stock recommendation data

The stock recommendations sample is from Thomson Financial's I/B/E/S U.S. Detail File, which contains stock recommendation ratings issued by individual analysts from 1993-2006. Because 1993 only contains 3 months of data, my sample focuses on rating changes where the current rating is issued from 1994 onwards. I/B/E/S reports ratings ranging from 1 (strong buy) to 5 (sell). To make the ratings more intuitive, 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 recommendation revisions and not levels since prior research confirms that recommendations changes are more informative than mere levels (for example, Boni and Womack (2006) and Jegadeesh and Kim (2006)). The recommendation change *RECCHG* is computed as the current rating minus the prior rating by the same analyst. By construction, $RECCHG \in [-4,4]$. When an analyst initiates a recommendation or when the prior recommendation is stale (issued more than 365 days ago), I compute *RECCHG* as the new rating minus a hold rating of 3. I also remove analysts coded as anonymous by I/B/E/S since it is not possible to track their recommendation revisions.

Ljungqvist et al. (2006) report that some records in the I/B/E/S recommendations data for the period 1994-2002 underwent alteration between 2002 and 2004. They also document that Thomson Financial, in response to their paper, has recently reinstated the missing analyst names in the recommendation history file as of February 12, 2007. The dataset I employ is dated March 15, 2007 and likely reflects these recent corrections by Thomson. To address concerns about the impact of the remaining uncorrected alterations on my results, a subsequent subsection (page 24) considers a snapshot (January 2001) of I/B/E/S prior to the time when such alterations occurred. I also test the robustness of my results using First Call recommendations.

The chosen recommendation sample must then undergo further screens. Of particular importance is that recommendations are sometimes made on the same day as earnings announcements. Consequently, the market's response to these recommendations would be commingled with the reaction to earnings announcements. Because my objective is to investigate the stock recommendation drift and not the earnings announcement drift, I remove stock recommendations that are issued in the three-day window centered around the I/B/E/S quarterly earnings announcement date. 13% of all eligible recommendation changes are removed—this percentage is similar to that reported in Womack (1996) and Malmendier and Shanthikumar (2007).[8] A portion of the sample period is affected by the introduction of Rule 2711 by the National Association of Securities Dealers (NASD). Part of the NASD 2711 rule required brokerages to report the distribution of stock ratings across its coverage universe. This rule was approved on May 8, 2002 with an implementation period ending September 9, 2002. Many brokers reissued stock recommendations in the implementation period so that their recommendation distributions looked less optimistic. As a result, 2002 contains the most number of recommendations in I/B/E/S compared to any other sample year (see Barber, Lehavy, McNichols, and Trueman (2006)). To account for this structural break, I remove recommendation changes where the current recommendation is issued between May 8, 2002 and September 9, 2002 (inclusive) *and* the prior recommendation was issued before May 8,

[8] A previous version of the paper does not exclude recommendations made together with earnings announcements and arrives at the same conclusions.

2002. Such recommendations changes are likely to be motivated by adherence to the NASD 2711 rule rather than by stock selection.[9]

3.2. Stock return data

The daily returns of U.S. firms are from the Center for Research in Security Prices (CRSP), where I only include stocks classified as ordinary shares (share codes 10 or 11). Delisting returns are added from the CRSP delisting file. For 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. Performance-related delistings are defined as codes 500, and 505 to 588, as in Shumway and Warther (1999). Firms in the sample must also have available and non-negative book-to-market (B/M) information from the CRSP-Compustat Merged File. Book equity is calculated following Fama and French (2006)[10] and the B/M value for a firm is updated every 12 months beginning July 1. B is book equity for the fiscal year ending in the preceding calendar year, and M is the December-end market cap from the preceding calendar year.

As benchmarks for some return tests, I also compute the returns of Daniel, Grinblatt, Titman, and Wermers (1997) (thereafter DGTW) characteristic portfolios from this universe of CRSP stocks. Every July, firms are first sorted into quintiles based on their market cap on June 30 of each year using break-points determined from NYSE stocks. Second, firms are then sorted within each size quintile into quintiles based on their B/M ratios. Third, firms

---

[9] Another time period that could be special is the year 2000. Barber, Lehavy, McNichols, and Trueman (2003) report that the year 2000 was the worst stock-picking year for analysts. I check that the main results are robust to removing the year 2000.

[10] Specifically, book equity is total assets (Compustat data item #6), minus liabilities (#181), plus balance sheet deferred taxes and investment tax credit (#35) if available, minus (as available) either liquidation (#10), redemption (#56), or carrying value (#130) of preferred stock.

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.

3.3. Construction of attention proxies and control variables

The amount of attention surrounding a stock prior to a recommendation change is proxied by the average daily turnover in the stock in the period [-63,-2] trading days from the recommendation date. Day 0 of a recommendation is the I/B/E/S reported recommendation date. For recommendations issued on non-trading days (for example Saturdays, or September 11, 2001), day 0 is the first trading day after the recommendation date. Daily turnover is the CRSP reported number of shares traded divided by the total number of shares outstanding. I divide the volume of NASDAQ firms by two to account for the double counting of inter-dealer trades (see for example, LaPlante and Muscarella (1997)).[11] Hou et al. (2006) who also use prior turnover to proxy for attention, employ a 12-month horizon instead of a three-month horizon. A three-month horizon is more suited in my setting since I want to capture the most recent attention surrounding the stock immediately prior to the recommendation. I verify that my results are similar with a prior 12-month horizon.

For some tests, I require additional measures of illiquidity, analyst forecast dispersion, analyst coverage, and size. A stock's liquidity is measured using the Amihud (2002) illiquidity measure, which is the average daily absolute return divided by the daily dollar

[11] An earlier version of the paper uses only NYSE stocks and arrives at similar conclusions.

trading volume (in millions) over the same horizon that prior turnover is measured. These two analyst variables are from the I/B/E/S Summary Unadjusted U.S. File. Analyst coverage is the most recent number of analysts contributing to the monthly consensus FY1 earnings forecasts. Defining analyst coverage using the earnings forecasts file yields a more accurate number of total analysts covering the firm compared to just using the recommendations file. Forecast dispersion is the most recent standard deviation of estimates divided by the absolute value of the mean estimate. Using the unadjusted file instead of the standard I/B/E/S file ensures that the rounding problem associated with firms that undergo stock splits does not affect my findings (Diether et al. (2002) document this issue).

3.4. Descriptive statistics of sample

[Figure 1 here]

Figure 1 presents the distribution of the 263,716 recommendation changes in my sample. We see that extreme rating changes greater than +2 or less than -2 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. Figure 1 shows that upgrades are more numerous than downgrades and this could be due to the fact that analysts often initiate coverage of firms with a buy recommendation and this will show up in the sample as a rating change of +1.

Panel A of Table 1 reports annual descriptive statistics of the 1994-2006 sample. Overall, the assembled sample contains stock recommendations issued by 8,759 analysts from

569 brokers for 8,285 firms over a 13-year sample period. The average recommendation change across all observations is 0.341 (an upgrade). The analyst-level statistics in Panel A are computed by first 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 5.61 and the average number of recommendations issued by an analyst in one year is 7.59. We see that the number of analysts issuing recommendations for a firm in a typical year is 4.53 and the average market cap is slightly over $3 billion. On average, about 76 firms are recommended in a typical day in the sample. Hence, there would be sufficient firms each day to allow firms 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 0.4745%.

[Table 1 here]

Panel B of Table 1 shows the statistics by turnover groups. Here the averages are computed, for example in 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 0.824% for a typical high turnover firm and 0.2579% for a low turnover firm, evidence that we have economically meaningful differences in turnover. Here we see that the average market cap of low turnover firms is $3.458b, slightly larger than that of high turnover firms ($3.154b). Low turnover firms have 3.15 analysts issuing recommendations in a typical firm-year compared to 4.65 analysts for high turnover firms, suggestive of higher visibility for high turnover firms.

4. Results

4.1. Cumulative abnormal returns (CARs)

We first report CAR plots of the recommendation changes. Note that in all our analysis, each observation is a recommendation change and it is possible that a firm-day is represented more than once (i.e., when multiple analysts issue recommendations for a firm in a single day). The daily abnormal return (AR) is the raw CRSP return less the return on a matched size-B/M-momentum DGTW characteristics portfolio.[12] The CAR is simply the cumulative sum of the ARs. To prevent the results from being biased by very low priced stocks and microstructure noise, the CAR excludes days where the lagged stock price is less than one dollar.

Figure 2 plots the average CAR (in percent) of the extreme rating changes (i.e., $|RECCHG| \geq 2$) beginning the event day -10 to 63 trading days (3 months) after the recommendation. For each trading day in the sample, firms with recommendation changes are sorted into two groups—high turnover and low turnover stocks based on the average prior daily turnover over [-63,-2]. The average CAR of upgrades and downgrades are tracked for these two groups in the top graph.

[Figure 2 here]

One can see that recommendation changes indeed convey important information about the firm. Stock price reactions are steep on the day of the recommendation for both high and

[12] One could also specify AR more simply as the raw return minus the market return. Although the results of the paper are stronger when using a simpler version of AR, I prefer the characteristics-adjusted AR so that I can be sure that the recommendation drift that I detect is not related to known factor characteristics.

low turnover stocks. The average reaction magnitudes in the figure are comparable to similar strength rating changes reported in Boni and Womack (2006). Not surprisingly, reactions to downgrades are larger in magnitude than reactions to upgrades. More importantly, the figure reveals 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 because investors slowly incorporate the information contained in these recommendations. Figure 2 shows that for low turnover stocks (represented by dotted lines), rating changes tend to have a smaller reaction around the event date (especially so for downgrades). This is consistent with the hypothesis 1a that investors are inattentive to stock recommendations and so react less when their attention level to the stock is low. The drift of low turnover upgraded stocks also appears more pronounced compared to the drift of high turnover stocks. Observing the gradient of the downgrade drift, the drift for downgrades of low turnover stocks also appears steeper than that of the drift of high turnover stocks. The bottom graph in Figure 2 shows the average upgrade-downgrade CAR. The stark trend of smaller reaction and larger drift for low turnover stocks becomes even more evident.

[Table 2 here]

Next, Table 2 tests whether the average recommendation change CARs are meaningfully different between low and high turnover stocks. I first focus on the event date [-1,1] reaction to recommendation changes. It is notable that for both high and low turnover groups, favorable rating changes produce significantly positive average event date CARs and unfavorable rating changes produce negative reactions. Panel A of Table 2 tests hypothesis 1a, whether the rating change event reaction magnitudes are smaller for low turnover stocks than for high turnover stocks. We see that this is indeed the case. For the most downgraded group, high turnover stocks see an average [-1,1] CAR of -4.107% while low turnover stocks experience an average CAR of -2.715%. This difference is statistically significant with an associated t-statistic of 6.55. Note that the standard errors in this analysis are clustered by calendar day to account for cross-correlation between firms. For the most upgraded stocks, the difference between the CAR of low and high turnover stocks is -0.098% but this is not statistically significant. However, for the group 5-1 (most upgraded minus most downgraded), the low turnover stocks produce event reaction CARs that are 1.490% less than the CARs of the high turnover stocks (significant with t-statistic of -6.62).

Next, I test hypothesis 1b, whether stock recommendations issued for low turnover stocks are indeed associated with larger drifts. The horizons examined are from one to three months from day 0 of the recommendation (using 21 trading days to represent a month). The evidence in Panels B to D of Table 2 is unequivocal—stock recommendation changes associated with low turnover stocks experience a statistically larger drift than those associated with high turnover stocks. To get a sense of the economic magnitude of this difference, consider Panel C, the two-month horizon. The average [2,42] CAR of the most upgraded minus the most downgraded stocks is 1.184% for high turnover firms but 2.678% for low turnover stocks. In other words, the average two-month CAR following rating changes for low turnover stocks is more than double in magnitude of the CAR following rating changes for high turnover stocks.

In sum, Table 2 provides support for hypotheses 1a and 1b. That low turnover stocks (i.e. low attention firms) produce less reaction and larger drifts in response to analysts' stock recommendation changes is consistent with an inattention explanation for the stock recommendation drift.

4.2. Underreaction coefficients

Next, we consider the ratio of the recommendation event date reaction to the total return implication of the recommendation. This is termed the underreaction coefficient and can be used to determine the amount of underreaction surrounding an event (see, for example Cohen and Frazzini (2007)). To illustrate, suppose a stock recommendation produced a CAR of 5% for the period [-1,42] and the event date reaction over [-1,1] is 3%. The underreaction coefficient here will be $3 \div 5 = 0.6$, meaning that 60% of the recommendation's two-month return occurred on the recommendation date. One can see that an underreaction coefficient $\in [0,1)$ represents underreaction and any other positive number represents overreaction.[13] Among cases of underreaction, a lower number represents more severe underreaction. I hypothesize in hypothesis 1c that low attention stocks (proxied by low prior turnover) would be associated with more severe underreaction to stock recommendation changes.

[Figure 3 here]

Figure 3 reports the underreaction coefficients. The numbers that go into the computation of the underreaction coefficients are taken from Table 2 (Quintile 3 is excluded from Figure 3 since it represents a rating change of zero). Shaded bars in Figure 3 denote the high turnover group and striped bars denote the low turnover group. For instance, the chart for

[13] There could also be negative numbers for this ratio, for example, 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.

the 1-month CAR shows that the underreaction coefficient for the 5-1 recommendation group is 83.8% for the high turnover group. 83.8% comes from taking 5.974/(5.974+1.155), where the 5-1 group's event reaction of 5.974% is from Panel A of Table 2 for the high turnover group, and 1.155% is from 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 69.5%. This indicates that for the high turnover group where investors are presumably paying attention, 83.8% of a recommendation's 1-month return occurs on the three-day event window while only 69.5% of a recommendation's 1-month return occurs on the event window for low turnover stocks.

At the 2-month and 3-month horizons, the differences in underreaction are even starker. The proportion of 2-month return that occurs after the event date is 83.5% for high turnover stocks but it is only 62.6% for low turnover stocks. Altogether, Figure 3 provides support for hypothesis 1c—that a larger fraction of the return associated with stock recommendation changes occurs on the event date for high turnover stocks compared to the fraction for low turnover stocks.

4.3. Calendar-time portfolios

To determine if the differences in CAR translate to differences in the performance of portfolio strategies, I form calendar-time portfolios based on recommendation changes for high turnover and low turnover stocks. For each turnover group, five daily rebalanced portfolios buy and hold stocks for two months with rating changes matching the five rating change categories. Holding stocks for one or three months produce similar findings and the results are hence unreported. Following Barber et al. (2006) and Fang and Yasuda (2007), the return for a portfolio containing recommendation change *i* on day τ is:

$$R_{p\tau} = \frac{\sum_{i=1}^{n} x_{i\tau} R_{i\tau}}{\sum_{i=1}^{n} x_{i\tau}}. \qquad (1)$$

The weight $x_{i\tau}$ is equal to the cumulative value of one dollar invested in the recommendation from the day the recommendation enters the portfolio to the close of trading on day $\tau - 1$. Computing average returns in such a buy-and-hold manner avoids the upward bias in equal-weighting documented by Canina, Michaely, Thaler, and Womack (1998). Note that if a stock is recommended multiple times in the portfolio, each recommendation is treated as a separate observation. Return-days where the lagged price is less than one dollar are excluded from the portfolio and in cases when there are no qualifying recommendations in day τ, the portfolio assumes an investment in the market portfolio. Next, the daily time-series of portfolio returns from equation (1) are cumulated to monthly returns from which the risk-free rate is subtracted. The monthly portfolio excess returns are then regressed on the Fama and French (1993) three factors plus a momentum factor.[14] The time-series data for the four-factors and the risk-free rate are taken from Kenneth French's website.

[14] Some studies estimate the factor regression with daily portfolio returns on the daily time-series of the four-factors (example, Barber et al. (2006) and Fang and Yasuda (2007). Although my results are stronger with a daily four-factor time-series estimation, I prefer the monthly approach so that the number of observations in the time-series regression is not artificially inflated by a factor of 21. Most t-statistics in the calendar-time tables would become larger with daily time-series regressions.

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:

$$R_{p\tau}^{DGTW} = \frac{\sum_{i=1}^{n} x_{i\tau}^{DGTW} R_{i\tau}^{DGTW}}{\sum_{i=1}^{n} x_{i\tau}^{DGTW}} \qquad (2)$$

This is exactly 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 instead the average return of stocks in the same Fama and French (1997) industry group, using the updated 49-industry groupings from Kenneth French's website.

[Table 3 here]

The results show that following recommendation changes issued on low attention stocks is a better strategy than following recommendations issued for high attention stocks. We can see that for high prior turnover stocks (Panel A), the abnormal return of the hedge portfolio (5-1) measured by the four-factor model is 0.788% per month (t=3.85). This means that recommendation changes are also profitable for the high prior turnover group. For the low prior turnover group, the abnormal return is about double in magnitude at 1.636%

(consistent with earlier results in Table 2). The difference between the low and high turnover groups is 0.847% (t=3.66). Similar results are obtained when looking at excess returns, DGTW-adjusted returns, or industry-adjusted returns. We also note that factor loadings show that high turnover stocks are smaller growth stocks. However, the statistically significant differences in the factor-adjusted returns show that controlling for such differences in characteristics cannot explain the differences in recommendation returns between high and low turnover stocks. That the drift of stock recommendations is larger for low attention stocks is consistent with an attention-based explanation for the stock recommendation drift.

4.4. Calendar time results with residual turnover

Sorting stocks on turnover could capture variables other than attention. In particular, turnover is constructed from trading volume, which could also proxy for illiquidity or the differences of opinion among investors. When a stock is illiquid, it could take a longer time for new information to get incorporated so that it becomes important that the low turnover stocks that I label as low attention stocks are not simply illiquid stocks. Higher dispersion could proxy for mispricing (for example, Sadka and Scherbina (2007)) so that the mispricing is slowly corrected following recommendations resulting in a larger drift. To address these concerns, instead of sorting stocks into high and low attention groups based on prior turnover, I sort stocks based on their residual turnover. To obtain the residual turnover, for the universe of stocks, I estimate a cross-sectional regression of average prior turnover against the average illiquidity and the dispersion of analysts' earnings forecasts. The turnover and Amihud (2002) illiquidity measures are computed for the three months immediately prior to the recommendation (i.e., [-63,-2] days). The Amihud illiquidity measure is the average daily absolute return divided by the daily dollar trading volume (in millions) and forecast dispersion is the most recently monthly standard deviation of analysts' consensus FY1 earnings forecasts. The residual from this cross-sectional regression is used to sort firms with recommendation changes into high residual turnover and low residual turnover firms. By construction, this residual is a measure of attention that is orthogonal to illiquidity and dispersion.

[Table 4 here]

Table 4 reports the results of calendar-time strategies that are exactly similar to those in Table 3 except that residual turnover instead of raw turnover is used to sort firms into high and low attention groups. The results in Table 4 are consistent with the earlier conclusions. The additional DGTW-adjusted return (see Panel C) from following rating changes for low turnover stocks is 0.891% (t=4.17) higher than that from following rating changes for high turnover stocks.

4.5. Using alternative recommendation databases

I now examine the usage of different recommendation databases. Ljungqvist et al. (2006) compare two snapshots of 1993-2002 I/B/E/S recommendations data, one snapshot in 2002 and the other in 2004, and find that some records were anonymized, deleted, added, or altered. They also find that these changes collectively made the distribution of recommendations appear more conservative and improved the track record of some analysts. In response to their paper, Ljungqvist et al. report that Thomson Financial reinstated the missing analyst names in the recommendation history file as of February 12, 2007. My paper uses the March 15, 2007 snapshot and hence includes these recent corrections by Thomson. To check that uncorrected alterations do not sway my findings, I perform some further tests. I redo the calendar time strategies in Table 3 (sorting on raw prior turnover) and Table 4 (residual prior turnover which controls for illiquidity and dispersion) on alternative datasets and report the DGTW-adjusted returns in Table 5.

[Table 5 here]

First, I redefine recommendation changes using the broker code instead of the analyst code. This restores anonymized analysts into the recommendation dataset because although an analyst code can be anonymized, I/B/E/S does not anonymize the broker code. The drawback to the method of using broker-defined recommendation changes is that it does not deal correctly with analysts moving across brokers. The sample 2 row of Table 5 shows that broker-defined recommendation changes produces the same result—that recommendations on low attention firms have abnormal returns that are twice that on high attention firms.

Next, I focus on the sub-period 1994-2000. Sample 3 reports the coefficients using the original sample 1 but for the time period 1994-2000. Sample 4 and 5 also report results for 1994-2000 but using an I/B/E/S snapshot on January 19, 2001. Using this early snapshot intentionally avoids the 2002-2004 period when the I/B/E/S alterations were documented. To the extent that these alterations are a result of analysts or brokers trying to touch up their stock-picking histories during the period of heightened regulatory scrutiny on analysts, the pre-2001 snapshot should be less tainted by such alterations. Sample 4 in Table 5 reports portfolio returns from this snapshot based on analyst-defined recommendation changes and sample 5 reports returns based on broker-defined recommendation changes. Finally, I replicate the main results of the paper using First Call recommendations. Because coverage in

First Call is sparse in the early years, this sample excludes 1994 and 1995 and is for 1996-2006 only. All these robustness tests provide support for our main result.

5. Additional tests

5.1. Change in turnover and dispersion around recommendation change event

Table 6 reports the increase in turnover, defined as average turnover in [-1,1] minus average turnover in [-63,-2]. We see in Panel A that the change in average daily turnover is much lower in magnitude for low prior turnover stocks than it is for high prior turnover groups. For the most downgraded group, a recommendation on a high prior turnover (high attention) firm leads to the average percentage daily turnover increasing by 1.041%. A similar recommendation on a low prior turnover firm results only in an increase of 0.390%. The difference of 0.651% is statistically 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. Panel B then reports the change in turnover for the period over which drift is measured. This is simply the average daily turnover in [2,63] minus the average daily turnover [-63,-2]. If investors are inattentive to recommendations issue on low prior turnover stocks, this change in turnover will be larger for the low prior turnover stocks. Panel B reports that this change in turnover is significantly larger for low prior turnover stocks than it is for high prior turnover stocks.

[Table 6 here]

The next test in Panel C explores an alternative explanation for this paper's findings—that uncertainty increases more around a low attention firm recommendation than it does for a high attention firm recommendation. Consequently, the resulting larger drift for a low attention firm recommendation is not underreaction, but is a manifestation of this larger increase in uncertainty. To investigate this, I compute the change in dispersion of analysts FY1 earnings forecasts around the recommendation date. Dispersion is the standard deviation of forecasts divided by the absolute value of the mean estimate, multiplied by 100. I look back for the most recent dispersion one month before the recommendation and look forward for the most recent dispersion one month after to proxy for the change in uncertainty. Table 6 shows that, in general, dispersion increases across most of the recommendation change groups for both high and low prior turnover stocks, although the increase is not always statistically significant. However, there is no evidence that dispersion increases more for low prior turnover stocks than it does for high prior turnover stocks. Hence, the larger drift documented for low prior turnover stocks is unlikely to be due to a larger increase in uncertainty.

5.2. Controlling for post-earnings 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 one to control for multiple potential factors that may be related to recommendation reaction and drift.

One key issue is that recommendation drift could be commingled with the post-earnings announcement drift (PEAD). Although I already removed recommendations issued within the three-day window around earnings announcement dates, it is still possible that recommendations issued afterward continue to repeat the information contained in earnings announcements. To further control for PEAD, I include the most recent quarterly earnings surprise as an explanatory variable in the CAR regressions. Earnings surprise is defined as the most recent (before the recommendation date) I/B/E/S reported actual Q1 earnings minus the final monthly consensus analysts' earnings forecast, scaled by the lagged-month CRSP price.

I also include another control variable, Forecast Revision, which could proxy for the amount of earnings support surrounding the stock recommendation change. This is motivated by Michaely and Womack (2006) who 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. Forecast Revision, defined in this manner also proxies for earnings momentum as in Chan, Jegadeesh, and Lakonishok (1996). Note both the earnings surprise and forecast revision variables are constructed from the I/B/E/S Unadjusted Summary File so that we obtain the precise measures and not excessively rounded values (Diether et al. (2002)).[15] Next, I include a dummy variable, Small Broker, which equals one if the rating was not issued from a reputable broker. This controls for the reputation of the analyst, to the extent that a reputable broker is more likely to house a star analyst. Each year, I define reputable brokers as those in the highest quintile of the total number of recommendations issued in the prior calendar year. In my sample, brokers in the top quintile are responsible for more than two-thirds of all issued recommendations, making us reasonable confident that truly reputable brokers are identified. Other control variables include the most recent dispersion of analysts' earnings forecasts, the average illiquidity over the period where prior turnover was measured, the log number of

[15] Specifically, I obtain earnings forecasts and actual earnings data from the Unadjusted File. Then I adjust these stock-split unadjusted values using the I/B/E/S the Split Adjustments File. Adjusting the unadjusted estimates is important since to ensure that the differences in forecasts or differences between the forecasted and the actual earnings are not due to stock splits.

analysts covering the firm, and the level of the recommendation after the recommendation change.

The OLS regressions of CARs against these variables for each recommendation change group are reported in Table 7. Note that the CARs are already characteristics-adjusted (DGTW size-B/M-momentum adjustments) so that there is no need for such factor controls on the RHS of the regression. The standard errors of the regression coefficient estimates are clustered by calendar day.

[Table 7 here]

Panel A of Table 7 shows the CAR around the event date [-1,1]. We focus on the dummy variable Low Turnover, which indicates that the firm is in the lower half of firms sorted on their average daily turnover in [-63,-2]. For the group of most downgraded stocks, a low prior turnover results in a significantly less negative reaction. This is consistent with investors reacting less to negative recommendations in low prior turnover stocks. The same result is true for the most upgraded stocks—investors react significantly less to upgraded stocks that have low prior turnover.

Turning to Panel B, I first discuss the signs of a few of the control variables. The positive and significant coefficients for earnings surprise in the most upgraded and most downgraded groups reveals that the recommendation drift is indeed stronger when the most recent earnings surprise is in the same direction as the recommendation change. This reinforces the need to control for PEAD. Also, the coefficient for illiquidity is positive for the most upgraded stocks, supporting the earlier conjecture that more illiquid stocks are associated with larger recommendation drifts. However, the coefficient for illiquidity is insignificant for the most downgraded stocks. Finally, the coefficient for analyst forecast dispersion is negative for the most downgraded stocks but almost zero for the most upgraded stocks. The negative coefficient reveals that the negative drift to downgrades is stronger when dispersion is high. That the coefficient is negative for the most downgraded stocks supports the Diether et al. (2002) view that dispersion is a proxy for differences in opinion and short-sale constraints prevent prices from reflecting negative information immediately. Importantly for Panel B, the finding that low prior turnover results in a stronger recommendation drift remains intact even after adding all the above control variables. Both the most downgraded stocks and the most upgraded stocks have larger drifts when the prior turnover is low.

5.3. Alternative measures of attention

I also use other proxies for attention. The first measure is related to residual turnover in Table 4 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, we 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 [-63,-2] horizon and are as follows:

1. Amihud illiquidity measure
2. Average trading volume measured by the number of shares traded
3. Average dollar trading volume
4. Reciprocal of the average closing price
5. Proportion of days with zero volume
6. Coefficient of variation (CV) of the Amihud 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. Most recent dispersion of analysts' FY1 forecasts
14. Most recent earnings surprise (SUE) as in Chordia and Shivakumar (2006)
15. Standard deviation of past eight SUEs.

The first ten variables relate to illiquidity and the rest of the variables generally relate to the level of uncertainty surrounding the stock. Sorting stocks on residual turnover then provides us with turnover that is unrelated to multiple proxies for illiquidity and uncertainly and hence we can say that the residual proxies for attention (visibility). Adding SUE in the mix also controls for PEAD as an alternative explanation for our results. Abnormal returns from a calendar-time hedged portfolio of most upgraded minus most downgraded are reported in Panel A of Table 8 and we see that the low residual turnover stocks experience larger recommendation drifts than the high residual turnover stocks.

[Table 8 here]

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

Finally, we use a time-series measure of attention employed in Hirshleifer et al. (2006): the number of earnings announcement news events in a day. Hirshleifer et al. argue that investors may not react fully to information on days where there are many competing news events. In support, they find that post-earnings announcement drift is significantly stronger on high news days. I define a 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 and these are defined as low attention days. In Panel D of Table 8, I show that the stock recommendation drift is more pronounced on low attention days than it is on high attention days, providing additional support that the stock recommendation drift could be driven by investor inattention.

5.4. Are results driven by analysts' issuing recommendations in reaction to news?

A potential concern is that the high turnover stocks are cases where the analyst issues a recommendation in response to a big piece of news that hits the firm. This news event would presumably cause a volume surge just prior to the recommendation—making the firm more likely to be classified as high turnover (high attention). Consequently, by the time the analyst issues the recommendation that repeats the news, the firm's stock price would have already adjusted to the earlier news, hence explaining why recommendations on high turnover stocks exhibit less drift. A very related concern is that some stock recommendations are leaked to institutional investors before they are issued to the investing public. Irvine, Lipson, and Puckett (2007) report such tipping activity in the five days prior to a recommendation. In this case, leaked recommendations will have more prior trading activity than non-leaked recommendations.

I argue that these are unlikely explanations for the results for at least three reasons. First, the recommendation event reactions for high turnover stocks are higher than those of low turnover stocks. This is inconsistent with recommendations on high turnover stocks merely repeating stale news for which the market had already reacted to. Second, the measure of attention does not focus on the prior week, but the prior three months. Further, the results are also similar when using a prior 12-month window to determine high and low turnover. This suggests that news-related (or leakage-related) episodic bursts in turnover say one week before the recommendation have minimal impact on the study's conclusions. Third and finally, in unreported results, I modify the measure of attention by moving the window for measuring prior turnover back by one week. This potentially limits the influence of recent news-related high turnover from influencing a stock's classification into high or low attention. My results are insensitive to this reclassification.

6. 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 contained in stock recommendations, there should not be any predictable post-recommendation drift in stock prices. Extant literature, however, documents a strong post-recommendation drift. Barber et al. (2001) contend that this evidence is consistent with semi-strong 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 show 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 than it is for high turnover firms. This result is robust to controlling for other variables that could be associated with trading volume, for instance, illiquidity and uncertainly. I also rule out the alternative explanation that the post-earnings announcement drift can explain the result. The direct implication of my evidence is that 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.

While I emphasize the robustness of my results, I note that there is still a drift following recommendation changes for high prior turnover firms. This suggests that my evidence should be viewed alongside the caveat that investor attention may not completely explain the stock recommendation drift. However, it is still the case that investing in recommendations issued on identified low attention firms on average earns twice the abnormal returns of recommendations issued on high attention firms.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Asquith, Paul, Michael B. Mikhail, and Andrea Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245-282.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analysts' recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2003, Reassessing the returns to analysts' stock recommendations, *Financial Analysts Journal* 59, 88-96.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2006, Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations, *Journal of Accounting & Economics* 41, 87-117.

Barber, Brad M., and Terrance Odean, 2007, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies*, forthcoming.

Bernhardt, Dan, Murillo Campello, and Edward Kutsoati, 2006, Who herds?, *Journal of Financial Economics* 80, 657-675.

Boni, Leslie, and Kent L. Womack, 2006, Analysts, industries, and price momentum, *Journal of Financial & Quantitative Analysis* 41, 85-109.

Canina, Linda, Roni Michaely, Richard Thaler, and Kent Womack, 1998, Caveat compounder: A warning about using the daily CRSP equal-weighted index to compute long-run excess returns, *Journal of Finance* 53, 403-416.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam, 2007, The cross-section of expected trading activity, *Review of Financial Studies* 20, 709-740.

Chordia, Tarun, and Lakshmanan Shivakumar, 2006, Earnings and price momentum, *Journal of Financial Economics* 80, 627-656.

Chordia, Tarun, Avanidhar Subrahmanyam, and V. Ravi Anshuman, 2001, Trading activity and expected stock returns, 59, 3-32.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, *Journal of Finance* 55, 913-935.

Cohen, Lauren, and Andrea Frazzini, 2007, Economic links and predictable returns, *Journal of Finance*, forthcoming.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

DellaVigna, Stefano, and Joshua Pollet, 2008, Investor inattention and Friday earnings announcements, *Journal of Finance*, forthcoming.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross-section of stock returns, *Journal of Finance* 57, 2113-2141.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fama, Eugene F., and Kenneth R. French, 2006, The value premium and the CAPM, *Journal of Finance* 61, 2163-2185.

Fang, Lily, and Ayako Yasuda, 2007, Are stars' opinions worth more? The relation between analyst reputation and recommendation values, Working paper, University of Pennsylvania.

Frankel, Richard, S.P. Kothari, and Joseph Weber, 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics* 41, 29-54.

Gervais, Simon, Ron Kaniel, and Dan Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877-919.

Hirshleifer, David, Sonya Lim, and Siew Hong Teoh, 2006, Driven to distraction: Extraneous events and underreaction to earnings news, Working paper, University of California, Irvine.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.

Hirshleifer, David, and Siew Hong Teoh, 2005, Limited investor attention and stock market misreactions to accounting information, Working paper, University of California, Irvine.

Hong, Harrison, Terrence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Hong, Harrison, Walter Torous, and Rossen Valkanov, 2007, Do industries lead stock markets?, *Journal of Financial Economics* 83, 367-396.

Hou, Kewei, Lin Peng, and Wei Xiong, 2006, A tale of two anomalies: The implication of investor attention for price and earnings momentum, Working paper, Ohio State University.

Irvine, Paul, Marc Lipson, and Andy Puckett, 2007, Tipping, *Review of Financial Studies* 20, 741-768.

Jegadeesh, Narasimhan, and Woojin Kim, 2006, Imitation or information-driven herding? An analysis of analysts' recommendations and market reactions, Working paper, Emory University.

Kecskés, Ambrus, and Kent L. Womack, 2007, Adds and drops of analyst coverage: Does the stock market overreact?, Working paper, Dartmouth College.

LaPlante, Michele, and Chris J. Muscarella, 1997, Do institutions receive comparable execution in the NYSE and Nasdaq markets? A transaction study of block trades, *Journal of Financial Economics* 45, 97-134.

Ljungqvist, Alexander, Christopher J. Malloy, and Felicia C. Marston, 2006, Rewriting history, Working paper, New York University.

Loh, Roger K., and G. Mujtaba Mian, 2006, Do accurate earnings forecasts facilitate superior investment recommendations?, *Journal of Financial Economics* 80, 455-483.

Malmendier, Ulrike, and Devin Shanthikumar, 2007, Are investors naïve about incentives?, *Journal of Financial Economics* 85, 457-489.

Mehran, Hamid, and René M. Stulz, 2007, The economics of conflicts of interest in financial institutions, *Journal of Financial Economics* 85, 267-296.

Michaely, Roni, and Kent L. Womack, 2006, What are analysts really good at?, Working paper, Darthmouth College.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 77, 277-309.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence, and category learning, *Journal of Financial Economics* 80, 563-602.

Sadka, Ronnie, and Anna Scherbina, 2007, Analyst disagreement, mispricing, and liquidity, *Journal of Finance* 62, 2367-2403.

Shumway, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327-340.

Shumway, Tyler, and Vincent A. Warther, 1999, The delisting bias in CRSP's Nasdaq data and its implications for the size effect, *Journal of Finance* 54, 2361-2379.

Sorescu, Sorin, and Avanidhar Subrahmanyam, 2006, The cross section of analyst recommendations, *Journal of Financial & Quantitative Analysis* 41, 139-168.

Welch, Ivo, 2000, Herding among security analysts, *Journal of Financial Economics* 58, 369-396.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

Table 1

Sample of stock recommendation changes

Stock recommendations are from the I/B/E/S Detail Recommendations File from 1994-2006 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) and a recommendation change is the analyst's current rating minus her prior rating. When the prior rating is stale (i.e. issued more than 365 days ago) or when there is no prior rating, the rating change is computed as the current 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 NASD 2711 are excluded—i.e., where the current recommendation is issued between May 8, 2002 and September 9, 2002 (inclusive) *and* the prior recommendation was issued before May 8, 2002.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.

			Analyst-level variables				Firm-level statistics				
Group	# Recommend-ations	Avg rec-change	# Analysts	# Brokers	Avg # firms covered	Avg # recs per analyst	# Firms	# Analysts per firm	Avg market cap ($m)	Avg prior daily turnover (%)	Avg # firms recommended per day
Panel A: By Years											
1994	19,378	0.301	1,795	143	7.47	10.80	3,051	4.40	1,346	0.3181	73.8
1995	20,502	0.319	1,945	147	7.12	10.54	3,308	4.19	1,445	0.3500	78.7
1996	18,593	0.410	2,179	174	6.20	8.53	3,563	3.79	1,714	0.3871	70.6
1997	19,207	0.467	2,524	207	5.77	7.61	3,881	3.75	2,065	0.4025	73.3
1998	22,251	0.437	2,891	230	5.73	7.70	3,970	4.17	2,529	0.3987	83.8
1999	20,736	0.518	3,029	223	5.24	6.85	3,579	4.44	3,353	0.4643	76.5
2000	18,605	0.454	3,006	214	4.73	6.19	3,363	4.23	4,329	0.5300	68.4
2001	19,480	0.385	2,952	189	4.84	6.60	3,057	4.67	4,123	0.5190	71.7
2002	22,992	0.135	2,981	198	5.60	7.71	3,023	5.52	3,512	0.5056	84.0
2003	22,940	0.195	2,762	239	6.05	8.31	2,986	5.59	3,424	0.5312	83.8
2004	20,539	0.256	2,859	267	5.47	7.18	3,037	5.15	4,062	0.5739	76.7
2005	18,570	0.340	2,908	273	4.93	6.39	3,046	4.70	4,401	0.5944	69.6
2006	19,923	0.269	2,897	257	5.21	6.88	3,124	4.83	4,629	0.6557	75.2
Overall	263,716	0.341	8,759	569	5.61	7.59	8,285	4.53	3,100	0.4745	75.9
Panel B: By Turnover Groups											
High	133,183	0.320	7,676	520	6.21	8.49	5,529	4.65	3,154	0.8024	NA
Low	130,533	0.362	7,678	530	6.31	8.60	7,480	3.15	3,458	0.2579	NA

Table 2
Average CAR 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 two to account for inter-dealer double-counting. The five-point rating scale ranges from from 1 (sell) to 5 (strong buy). 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 one dollar are excluded. Recommendations are from I/B/E/S from 1994-2006. *, **, and *** respectively denote statistical significance (based on standard errors clustered by calendar day) at the 10%, 5%, or 1% levels 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)	-4.107***	-2.715***	1.392***	-0.447***	-0.743***	-0.296
	(-25.98)	(-19.09)	(6.55)	(-3.00)	(-5.98)	(-1.53)
2	-3.815***	-2.381***	1.434***	-0.335***	-0.421***	-0.085
	(-28.59)	(-25.16)	(8.77)	(-2.60)	(-4.71)	(-0.54)
3	-1.201***	-0.638***	0.563***	0.006	0.051	0.045
	(-17.73)	(-15.13)	(7.06)	(0.06)	(0.83)	(0.37)
4	1.172***	1.129***	-0.044	0.627***	0.774***	0.147
	(22.24)	(28.12)	(-0.66)	(7.71)	(12.35)	(1.43)
5 (most upgraded)	1.868***	1.770***	-0.098	0.708***	1.224***	0.516***
	(33.44)	(37.05)	(-1.33)	(7.54)	(16.29)	(4.30)
5-1	5.974***	4.484***	-1.490***	1.155***	1.966***	0.812***
	(35.64)	(29.89)	(-6.62)	(6.56)	(13.56)	(3.56)
	Panel C: Drift CAR [2,42]			Panel D: Drift CAR [2,63]		
1 (most downgraded)	-0.332	-1.017***	-0.684**	0.359	-0.778***	-1.136***
	(-1.59)	(-5.96)	(-2.54)	(1.44)	(-3.76)	(-3.51)
2	0.132	-0.488***	-0.619***	0.424**	-0.391***	-0.816***
	(0.78)	(-3.92)	(-2.94)	(2.07)	(-2.71)	(-3.26)
3	0.237*	0.311***	0.074	0.430***	0.613***	0.182
	(1.86)	(3.39)	(0.47)	(2.83)	(5.44)	(0.96)
4	0.797***	1.280***	0.483***	1.031***	1.677***	0.646***
	(6.70)	(14.78)	(3.28)	(6.85)	(15.90)	(3.52)
5 (most upgraded)	0.852***	1.661***	0.809***	1.107***	1.966***	0.858***
	(6.20)	(15.71)	(4.67)	(6.50)	(15.07)	(4.00)
5-1	1.184***	2.678***	1.494***	0.748**	2.743***	1.995***
	(4.74)	(13.34)	(4.66)	(2.48)	(11.21)	(5.14)

Table 3

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 inter-dealer double-counting. The five-point rating scale ranges from from 1 (sell) to 5 (strong buy). 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 one dollar are excluded. The daily buy-and-hold weighted average returns (see Eq. 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 49-industry adjusted return. Sample data are from I/B/E/S and CRSP from 1994-2006. *, **, and *** respectively denote statistical significance at the 10%, 5%, or 1% levels with the associated t-statistics in parentheses below the estimates.

	Four-Factor Model									
Portfolio	Rawret-R_f (%)	Intercept (%)	MktRF	SMB	HML	UMD	Adj R-Sq	# Unique Firms Per Day	DGTW-adj ret (%)	Industry-adj ret (%)
Panel A: High Prior Turnover										
1 (most downgraded)	0.107	-0.475*	1.357***	0.649***	-0.161*	-0.439***	0.8637	116.1	-0.585***	-0.883***
	(0.16)	(-1.82)	(5.02)	(8.91)	(-1.74)	(-8.68)			(-2.94)	(-3.04)
2	0.373	-0.261	1.399***	0.636***	-0.113	-0.429***	0.9113	213.3	-0.309*	-0.632**
	(0.58)	(-1.27)	(7.14)	(11.07)	(-1.55)	(-10.78)			(-1.94)	(-2.36)
3	0.561	-0.084	1.328***	0.599***	-0.147**	-0.325***	0.9377	329.6	-0.187	-0.569**
	(0.93)	(-0.53)	(7.55)	(13.43)	(-2.60)	(-10.49)			(-1.41)	(-2.35)
4	0.999*	0.211	1.343***	0.589***	-0.161***	-0.132***	0.9315	350.2	0.210	-0.164
	(1.70)	(1.29)	(7.69)	(12.88)	(-2.78)	(-4.17)			(1.54)	(-0.67)
5 (most upgraded)	1.073*	0.313**	1.302***	0.656***	-0.218***	-0.119***	0.9433	255.1	0.252*	-0.043
	(1.81)	(2.08)	(7.37)	(15.63)	(-4.09)	(-4.08)			(1.72)	(-0.18)
5-1	0.966***	0.788***	-0.055	0.007	-0.057	0.320***	0.3289	371.2	0.837***	0.839***
	(4.13)	(3.85)	(-0.99)	(0.12)	(-0.78)	(8.08)			(4.70)	(3.94)
Panel B: Low Prior Turnover										
1 (most downgraded)	-0.221	-0.735***	0.888***	0.423***	0.331***	-0.362***	0.8819	106.8	-1.002***	-1.085***
	(-0.58)	(-5.28)	(-2.96)	(10.90)	(6.72)	(-13.44)			(-7.40)	(-6.48)
2	0.275	-0.359***	0.951	0.344***	0.384***	-0.265***	0.9109	212.8	-0.574***	-0.760***
	(0.77)	(-3.14)	(-1.58)	(10.80)	(9.50)	(-12.01)			(-5.88)	(-4.27)
3	0.803**	0.173	0.915***	0.318***	0.458***	-0.277***	0.9061	394.8	-0.116	-0.285*
	(2.36)	(1.55)	(-2.81)	(10.21)	(11.60)	(-12.80)			(-1.16)	(-1.67)
4	1.380***	0.609***	0.996	0.387***	0.492***	-0.191***	0.9087	389.2	0.444***	0.299*
	(3.91)	(5.34)	(-0.14)	(12.16)	(12.19)	(-8.66)			(5.44)	(1.69)
5 (most upgraded)	1.675***	0.901***	1.022	0.355***	0.411***	-0.155***	0.8927	267.0	0.684***	0.599***
	(4.61)	(7.07)	(0.64)	(10.01)	(9.11)	(-6.27)			(7.87)	(3.11)
5-1	1.896***	1.636***	0.134***	-0.067	0.080	0.207***	0.2333	373.8	1.686***	1.683***
	(11.58)	(10.67)	(3.22)	(-1.57)	(1.48)	(6.98)			(11.76)	(10.86)
Panel C: Low-High Prior Turnover										
1 (most downgraded)	-0.327	-0.260	-0.469***	-0.227***	0.492***	0.078	0.5641	222.8	-0.417	-0.202
	(-0.82)	(-0.93)	(-6.16)	(-2.90)	(4.96)	(1.43)			(-1.63)	(-0.72)
2	-0.098	-0.097	-0.448***	-0.292***	0.496***	0.164***	0.7238	426.1	-0.265	-0.129
	(-0.27)	(-0.47)	(-7.97)	(-5.06)	(6.79)	(4.10)			(-1.24)	(-0.53)
3	0.242	0.258	-0.414***	-0.281***	0.606***	0.048	0.7828	724.4	0.071	0.284
	(0.67)	(1.42)	(-8.39)	(-5.56)	(9.44)	(1.37)			(0.36)	(1.31)
4	0.381	0.398**	-0.347***	-0.202***	0.653***	-0.059*	0.7684	739.4	0.234	0.464**
	(1.11)	(2.25)	(-7.21)	(-4.09)	(10.43)	(-1.72)			(1.27)	(2.23)
5 (most upgraded)	0.602*	0.588***	-0.279***	-0.301***	0.629***	-0.036	0.7778	522.1	0.432**	0.642***
	(1.78)	(3.45)	(-6.03)	(-6.32)	(10.43)	(-1.08)			(2.30)	(3.20)
5-1	0.929***	0.847***	0.190***	-0.074	0.137*	-0.113**	0.1237	744.9	0.849***	0.844***
	(4.02)	(3.66)	(3.02)	(-1.15)	(1.67)	(-2.53)			(4.01)	(3.81)

Table 4
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 inter-dealer 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 quintile, firms are then placed into five portfolios containing rating changes in [-4,-2] (most downgraded), -1, 0, +1, and [+2,+4] (most upgraded), respectively. Firm-days where the lagged price is less than one dollar 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 and 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 49 industries) return. Sample data are from I/B/E/S and CRSP from 1994-2006. *, **, and *** respectively denote statistical significance at the 10%, 5%, or 1% levels with the associated t-statistics 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-Sq	# Unique Firms Per Day		
Panel A: High Prior Residual Turnover (Controls for illiquidity and analyst forecast dispersion)										
1 (most downgraded)	0.241	-0.363	1.399***	0.676***	-0.157	-0.455***	0.8642	106.8	-0.440**	-0.748**
	(0.35)	(-1.35)	(5.47)	(9.01)	(-1.65)	(-8.74)			(-2.09)	(-2.46)
2	0.412	-0.246	1.433***	0.626***	-0.100	-0.430***	0.9059	199.1	-0.273	-0.592**
	(0.63)	(-1.14)	(7.40)	(10.43)	(-1.32)	(-10.33)			(-1.60)	(-2.12)
3	0.558	-0.089	1.346***	0.584***	-0.137**	-0.339***	0.9314	306.7	-0.175	-0.572**
	(0.92)	(-0.52)	(7.51)	(12.36)	(-2.29)	(-10.34)			(-1.27)	(-2.28)
4	0.984*	0.201	1.342***	0.580***	-0.151**	-0.144***	0.9260	324.4	0.188	-0.184
	(1.68)	(1.18)	(7.40)	(12.23)	(-2.51)	(-4.36)			(1.38)	(-0.74)
5 (most upgraded)	1.033*	0.276*	1.325***	0.619***	-0.189***	-0.151***	0.9378	233.1	0.227	-0.074
	(1.75)	(1.75)	(7.59)	(14.11)	(-3.39)	(-4.97)			(1.52)	(-0.30)
5-1	0.792***	0.639***	-0.075	-0.056	-0.032	0.304***	0.2883	339.9	0.666***	0.674***
	(3.36)	(3.01)	(-1.30)	(-0.95)	(-0.42)	(7.39)			(3.69)	(3.08)
Panel B: Low Prior Residual Turnover (Controls for illiquidity and analyst forecast dispersion)										
1 (most downgraded)	-0.232	-0.739***	0.882***	0.421***	0.367***	-0.387***	0.8690	99.4	-0.984***	-1.107***
	(-0.61)	(-5.01)	(-2.95)	(10.24)	(7.03)	(-13.54)			(-6.94)	(-5.99)
2	0.294	-0.375***	0.972	0.352***	0.436***	-0.267***	0.9125	200.8	-0.537***	-0.736***
	(0.82)	(-3.29)	(-0.92)	(11.09)	(10.82)	(-12.10)			(-5.44)	(-3.94)
3	0.750**	0.109	0.931**	0.280***	0.472***	-0.274***	0.9122	364.8	-0.140	-0.335*
	(2.20)	(1.01)	(-2.37)	(9.32)	(12.37)	(-13.11)			(-1.41)	(-1.83)
4	1.229***	0.461***	1.008	0.333***	0.494***	-0.194***	0.9065	356.0	0.339***	0.162
	(3.49)	(4.00)	(0.25)	(10.37)	(12.12)	(-8.68)			(3.98)	(0.85)
5 (most upgraded)	1.504***	0.742***	1.012	0.309***	0.419***	-0.155***	0.8865	238.8	0.573***	0.444**
	(4.23)	(5.78)	(0.34)	(8.66)	(9.24)	(-6.26)			(6.29)	(2.17)
5-1	1.736***	1.481***	0.130***	-0.112**	0.052	0.231***	0.2740	338.2	1.557***	1.551***
	(10.17)	(9.52)	(3.09)	(-2.59)	(0.95)	(7.69)			(10.45)	(9.81)
Panel C: Low-High Prior Residual Turnover (Controls for illiquidity and analyst forecast dispersion)										
1 (most downgraded)	-0.473	-0.376	-0.518***	-0.254***	0.524***	0.068	0.5977	206.2	-0.545**	-0.359
	(-1.13)	(-1.32)	(-6.69)	(-3.20)	(5.20)	(1.24)			(-2.03)	(-1.20)
2	-0.118	-0.129	-0.462***	-0.274***	0.537***	0.164***	0.7185	399.9	-0.264	-0.145
	(-0.31)	(-0.59)	(-7.85)	(-4.54)	(7.01)	(3.91)			(-1.17)	(-0.57)
3	0.192	0.198	-0.415***	-0.304***	0.609***	0.065*	0.7838	671.5	0.035	0.237
	(0.52)	(1.07)	(-8.29)	(-5.91)	(9.34)	(1.83)			(0.17)	(1.08)
4	0.246	0.260	-0.334***	-0.247***	0.646***	-0.050	0.7630	680.4	0.151	0.346*
	(0.70)	(1.43)	(-6.77)	(-4.88)	(10.04)	(-1.42)			(0.81)	(1.67)
5 (most upgraded)	0.471	0.466***	-0.313***	-0.310***	0.608***	-0.004	0.7681	471.8	0.346*	0.518**
	(1.37)	(2.62)	(-6.49)	(-6.27)	(9.68)	(-0.11)			(1.76)	(2.50)
5-1	0.944***	0.842***	0.205***	-0.056	0.084	-0.072	0.0897	678.1	0.891***	0.876***
	(4.14)	(3.62)	(3.25)	(-0.86)	(1.02)	(-1.61)			(4.17)	(3.97)

Table 5

Sensitivity of calendar time portfolio results to different recommendation databases

To address concerns about the impact of I/B/E/S recommendation database problems documented in Ljungqvist et al. (2006), I redo the results in Table 3 and 4 with other samples. The reported numbers are four-factor monthly regression intercepts computed with the methods in Table 3 (raw turnover) and Table 4 (residual turnover which controls for illiquidity and dispersion). Sample 1 is the original result. Sample 2 uses the I/B/E/S broker code to define recommendation changes instead of the I/B/E/S analyst code. Because the broker code is usually unchanged, this restores anonymized analysts into the sample. Sample 4 and 5 use a shorter time period 1994-2000 from an I/B/E/S snapshot as at Jan 19, 2001. Since the documented changes to the I/B/E/S file occurred between 2002 and 2004, the Jan 2001 snapshot likely contains the I/B/E/S recommendations before alteration. For comparison, sample 3 is repeats sample 1 for the period 1994-2000. Sample 4 uses the analyst code to define recommendation changes and sample 5 uses the broker code. Finally, sample 6 uses First Call recommendations are used from 1996 to 2006. 1994 and 1995 are excluded for the First Call sample because coverage is sparse in those years.

Sample	DGTW-adjusted return of most upgraded minus most downgraded quintile					
	Raw turnover			Residual turnover		
	High prior turnover	Low prior turnover	High-low	High prior turnover	Low prior turnover	High-low
1. Original results in Table 3 and 4. 1994-2006 I/B/E/S recommendations file as at Mar 15, 2007.	0.837***	1.686***	0.849***	0.666***	1.557***	0.891***
	(4.70)	(11.76)	(4.01)	(3.69)	(10.45)	(4.17)
2. Sample (1), except recommendations changes are defined by broker code instead of analyst code. Fixes anonymization problem reported in Ljunqqvist et al. (2006)	0.820***	1.631***	0.811***	0.695***	1.457***	0.762***
	(5.20)	(11.60)	(4.32)	(4.23)	(9.90)	(3.93)
3. Sample (1), except for the period 1994-2000	0.994***	1.874***	0.880***	0.925***	1.793***	0.868***
	(3.86)	(9.49)	(2.88)	(3.44)	(8.22)	(2.76)
4. 1994-2000 I/B/E/S recommendation file as at Jan 19, 2001. This does not contain the deletions, alterations, anonymizations, and additions to the 1994-2002 period that Ljungqvist et al. (2006) report occurred between the 2002 and 2004 snapshots.	1.080***	1.933***	0.853***	0.974***	1.882***	0.908***
	(4.41)	(9.32)	(2.90)	(3.89)	(8.26)	(3.10)
5. Sample (4), except that recommendations changes are defined by broker code	1.099***	1.893***	0.794***	1.000***	1.814***	0.814***
	(4.71)	(8.67)	(2.80)	(4.17)	(7.61)	(2.79)
6. 1996-2006 First Call recommendations.	1.035***	1.587***	0.552**	0.843***	1.493***	0.649**
	(4.33)	(8.87)	(2.26)	(3.40)	(8.29)	(2.48)

Table 6
Change in turnover and dispersion after the recommendation change event

The average change in dispersion and 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 in Panel B are in percent, i.e. 1.000 means event turnover minus prior turnover equals one percent. Panel B reports the % average daily turnover in the [2,63] recommendation drift window minus the prior [-63,-2] average daily turnover for the stock. Change in Dispersion, Panel C, is the dispersion of analysts' FY1 earnings forecasts one-month after the recommendation change minus the dispersion one month before the recommendation change. Dispersion is the I/B/E/S Unadjusted Summary File reported standard deviation of FY1 forecasts, scaled by the absolute value of the mean forecast, multiplied by 100. 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. T-statistics in parentheses are reported below the averages and are based on standard errors clustered by calendar day with *, **, and *** respectively indicating statistical significance at the 10%, 5%, or 1% levels.

Group	Panel A: Change in average % daily turnover in the (-1,1) window			Panel B: Change in average % daily turnover in the (2,63) window			Panel C: Change in dispersion of analysts' forecasts		
	High Turnover	Low Turnover	Low-High	High Turnover	Low Turnover	Low-High	High Turnover	Low Turnover	Low-High
1 (most downgraded)	1.041***	0.390***	-0.651***	0.046***	0.064***	0.018***	2.625**	1.347	-1.278
	(28.10)	(19.49)	(-15.46)	(7.80)	(26.17)	(2.73)	(2.17)	(1.63)	(-0.87)
2	0.778***	0.269***	-0.509***	0.020***	0.052***	0.032***	1.583*	2.240***	0.657
	(27.76)	(26.44)	(-17.06)	(4.45)	(30.23)	(6.82)	(1.83)	(2.60)	(0.54)
3	0.329***	0.128***	-0.201***	-0.005	0.039***	0.044***	1.721***	0.286	-1.435*
	(19.35)	(23.76)	(-11.28)	(-1.61)	(27.60)	(12.10)	(2.61)	(0.58)	(-1.74)
4	0.324***	0.138***	-0.186***	0.014***	0.046***	0.031***	0.886	0.217	-0.669
	(34.03)	(38.75)	(-18.32)	(4.85)	(47.36)	(10.19)	(1.33)	(0.47)	(-0.83)
5 (most upgraded)	0.292***	0.149***	-0.143***	0.016***	0.055***	0.039***	0.942	-0.509	-1.451*
	(30.23)	(36.06)	(-13.63)	(4.98)	(42.98)	(11.11)	(1.57)	(-1.07)	(-1.89)

Table 7
Regression of CAR on turnover with multiple control variables

Characteristics-adjusted CARs are regressed on the inattention variable (low turnover) with mltuple controls. 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 forecasts, scaled by the absolute value of the mean forecast. # Analysts is the number of analysts issuing FY1 forecasts and is assumed to be zero when missing. 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 1994-2006. The regression is estimated by OLS with the standard errors clustered by calendar day. *, **, and *** respectively denote statistical significance at the 10%, 5%, or 1% levels with the associated t-statistics in parentheses below the estimates.

Group	Intercept	Low Turnover	Current Rec	Earnings Surprise	Forecast Revision	Illiquidity	Small Broker	Forecast Dispersion	ln (#Analysts)	R-sq (%)	#Obs (#Clusters)
Dependent Variable: Characteristic-adjusted CAR from [-1,1]											
1 (most downgraded)	-14.693***	1.367***	-0.395***	-0.668*	0.691*	0.277***	2.038***	0.187**	0.972***	3.039	17903
	(-14.01)	(6.63)	(-3.79)	(-1.82)	(1.88)	(2.65)	(10.78)	(2.20)	(4.14)		(3092)
2	-11.706***	1.469***	0.053	-0.011***	0.054	0.190***	1.825***	0.059	0.630***	1.875	37472
	(-14.10)	(11.11)	(0.56)	(-4.70)	(0.23)	(3.15)	(11.61)	(0.89)	(3.82)		(3211)
3	-6.003***	0.584***	0.664***	-0.025	-0.305**	0.092***	0.596***	0.147***	0.156*	0.764	66908
	(-13.76)	(8.13)	(14.09)	(-0.25)	(-2.46)	(3.78)	(7.46)	(3.51)	(1.86)		(3229)
4	3.029***	-0.080	0.487***	0.011	0.440	0.064	-0.861***	0.130*	0.080	0.737	66682
	(6.71)	(-1.21)	(6.98)	(0.26)	(1.02)	(1.50)	(-13.10)	(1.92)	(1.01)		(3230)
5 (most upgraded)	7.743***	-0.133*	-0.016	-0.224**	0.639**	-0.038	-1.256***	0.209***	-0.250***	1.975	42462
	(13.69)	(-1.81)	(-0.19)	(-2.40)	(2.02)	(-0.88)	(-17.24)	(4.06)	(-2.98)		(3215)
Dependent Variable: Characteristic-adjusted CAR from [2,42]											
1 (most downgraded)	-3.886***	-0.598**	0.024	2.486**	-1.563***	0.147	0.224	-0.412*	1.006***	0.383	17903
	(-2.81)	(-2.12)	(0.16)	(2.57)	(-4.32)	(0.98)	(0.81)	(-1.84)	(2.99)		(3092)
2	2.003*	-0.577***	-0.246*	-0.061***	-0.259	0.089	-0.365*	0.271*	0.476	0.107	37472
	(1.76)	(-2.67)	(-1.70)	(-17.75)	(-0.57)	(0.68)	(-1.65)	(1.79)	(1.56)		(3211)
3	2.499***	-0.027	-0.060	-0.588	-1.342***	0.073	-0.069	0.044	0.297	0.055	66908
	(2.70)	(-0.18)	(-0.47)	(-1.47)	(-6.18)	(0.76)	(-0.40)	(0.53)	(1.58)		(3229)
4	5.621***	0.251	0.072	0.283***	-1.826***	0.095	-0.114	0.148	-0.054	0.173	66682
	(5.77)	(1.58)	(0.48)	(3.08)	(-2.85)	(0.74)	(-0.65)	(1.46)	(-0.29)		(3230)
5 (most upgraded)	3.955***	0.461**	0.256	0.762***	-1.786***	0.289***	-0.328*	0.037	-0.358*	0.238	42462
	(3.36)	(2.52)	(1.44)	(9.39)	(-6.69)	(2.65)	(-1.85)	(0.35)	(-1.69)		(3215)

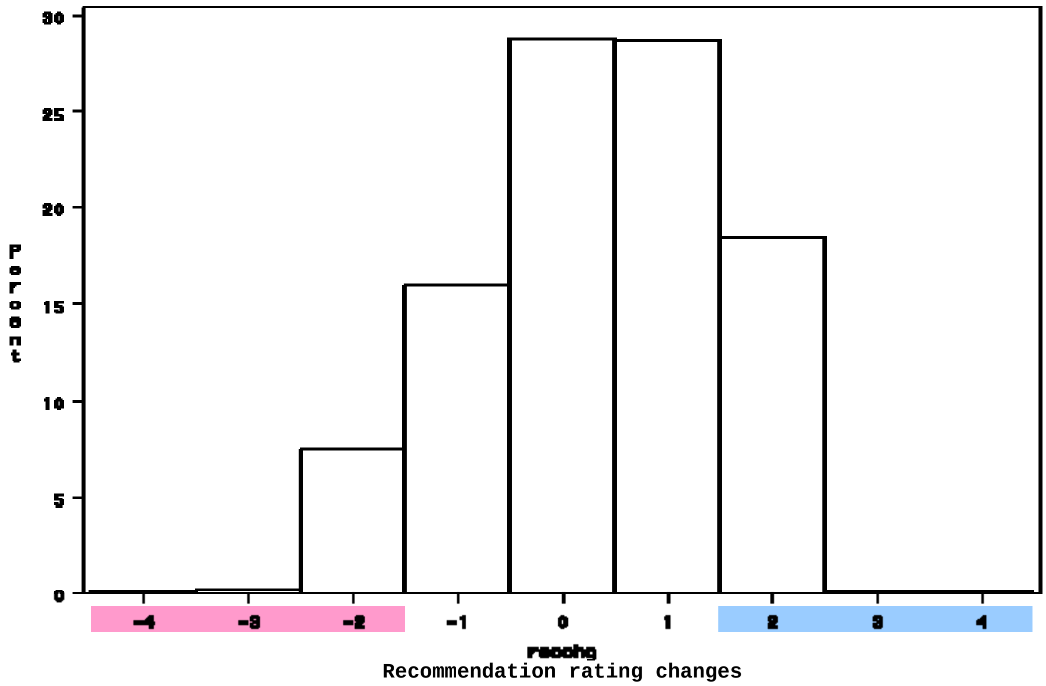
Table 8
Abnormal returns of portfolios sorted by alternative attention proxies

Each day, firms that experience recommendation changes are sorted into two groups based on alternative attention proxies. Panels B to D proxies 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 illiquidity measure, average trading volume, avg $ trading volume, inverse of avg closing price, % days with zero volume, CV of Amihud 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 stdev of past eight SUEs. Within 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), respectively, with firm-days where the lagged price is less than one dollar excluded. The daily buy-and-hold-weighted average returns of each portfolio are then compounded to monthly returns, subtracting the risk-free rate then 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 49 industries) return. The abnormal return of quintile 5 minus 1 is reported for the high versus low attention group. Sample data are from I/B/E/S and CRSP from 1994-2006. *, **, and *** respectively denote statistical significance at the 10%, 5%, or 1% levels with the associated t-statistics in parentheses below the estimates.

Most upgraded minus 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	0.918***	0.905***	0.864***	0.647***	0.558***	0.491***	0.475***	0.485***
	(4.13)	(5.61)	(4.43)	(3.29)	(3.00)	(3.45)	(2.73)	(2.89)
Low Attention	1.594***	1.317***	1.395***	1.381***	2.146***	1.957***	1.922***	1.750***
	(7.71)	(7.71)	(7.13)	(7.13)	(9.38)	(11.17)	(9.62)	(9.16)
Low-High	0.676***	0.412*	0.530**	0.734***	1.588***	1.466***	1.447***	1.265***
	(2.80)	(1.88)	(2.33)	(2.85)	(7.05)	(7.08)	(6.86)	(5.74)
	Panel C: Analyst Coverage				Panel D: Distraction proxy: # of earnings announcement news in the aggregate market			
High Attention	0.855***	0.692***	0.727***	0.844***	1.272***	1.171***	1.154***	1.028***
	(5.05)	(4.62)	(4.33)	(5.10)	(5.76)	(7.01)	(5.71)	(5.26)
Low Attention	1.883***	1.751***	1.700***	1.495***	1.937***	1.604***	1.730***	1.839***
	(8.26)	(10.60)	(8.53)	(7.94)	(8.91)	(8.32)	(8.61)	(8.21)
Low-High	1.028***	1.059***	0.973***	0.652***	0.665**	0.433*	0.576**	0.811***
	(4.84)	(5.40)	(4.76)	(3.16)	(2.51)	(1.85)	(2.24)	(2.95)

Figure 1
Distribution of recommendations changes

The distribution of 263,716 recommendation rating changes is displayed. Data are from I/B/E/S Detail Recommendation File from 1994-2006. 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. When the prior rating is stale (i.e. issued more than 365 days ago) or when there is no prior rating (i.e. initiation), the rating change is the current rating minus 3 (a hold).



Quintile definitions

1 (most downgraded)	2	3	4	5 (most upgraded)

Figure 2

CAR 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. Black unbroken lines (red 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. The first graph shows the average CAR of upgrades (rating changes ≥+2) and downgrades (rating changes ≤-2) and the second graph shows the hedged CAR (upgrade-downgrade). Firm days where the lagged price is less than one dollar are excluded. Recommendations are from I/B/E/S from 1994-2006.

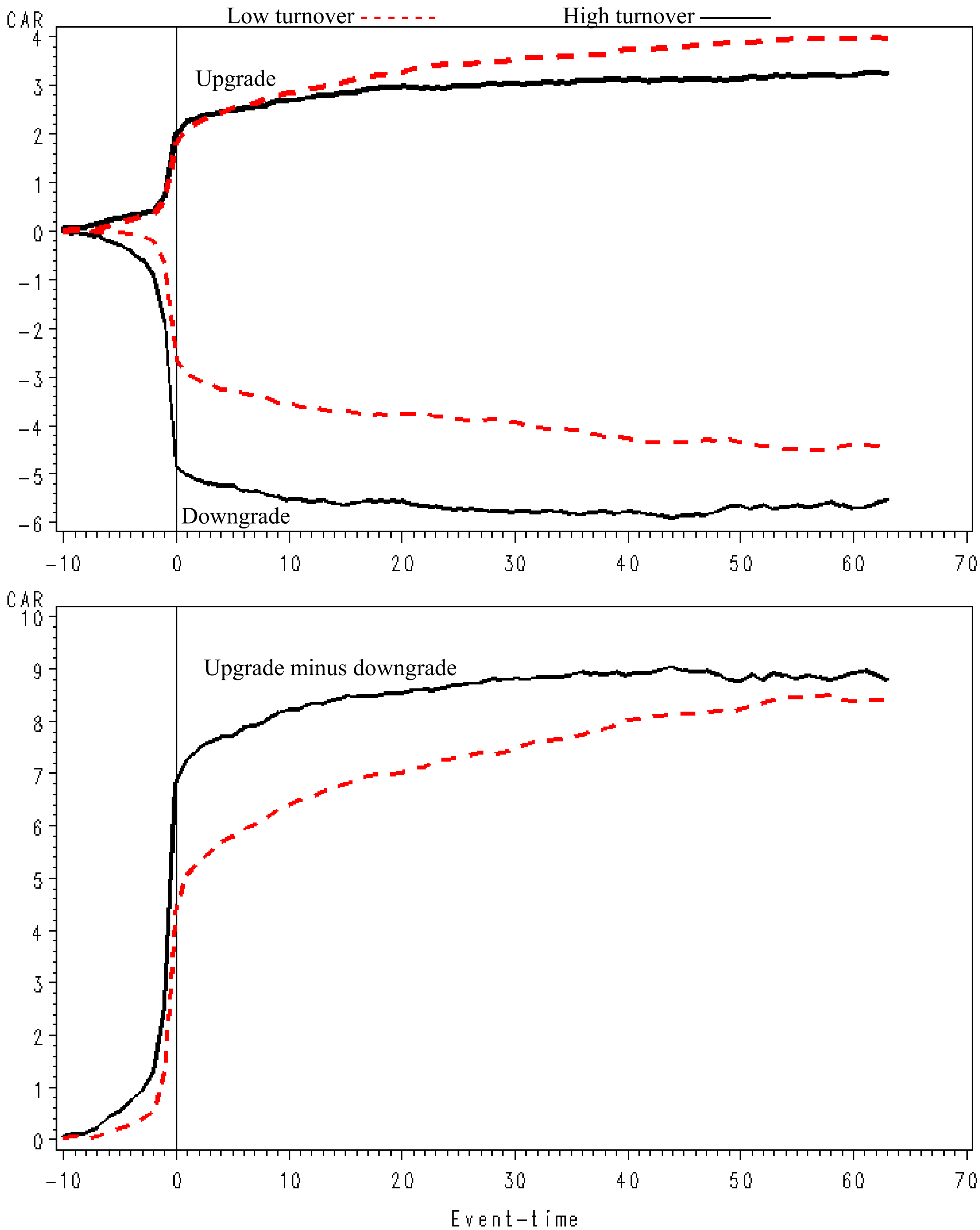


Figure 3
Percentage of average CAR occurring on recommendation date

This table reports whether low prior turnover firms underreact more to recommendation changes. The top graph shows the percentage of average 1-month [-1,21] CAR that occurs on the [-1,1] recommendation change date. The next two graphs are for the 2-month [-1,42] and 3-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 inter-dealer 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 one dollar are excluded. Average CAR numbers are from Table 2 and recommendations are from I/B/E/S from 1994-2006.