A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum*

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Abstract

We examine the role of investor attention in explaining the profitability of price and earnings momentum strategies. Using trading volume and market state to measure cross-sectional and time-series variations of investor attention, we find that price momentum profits are higher among high volume stocks and in up markets, but that earnings momentum profits are higher among low volume stocks and in down markets. In the long run, price momentum profits reverse but earnings momentum profits do not. These results suggest that price underreaction to earnings news weakens with investor attention, but price continuation caused by investors' overreaction strengthens with attention.

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1. Introduction

Attention is a scarce cognitive resource (Kahneman, 1973). A large body of psychological research shows that there is a limit to the central cognitive-processing capacity of the human brain.[1] The inevitability of limited attention in relation to the vast amount of information available makes attention an important factor in agents' learning and decision-making processes.

In this paper, we examine how attention affects asset price dynamics through investors' under- and overreactions to information, two mechanisms that have been proposed to explain a large body of empirical anomalies in asset return predictability.[2] Specifically, we study the implications of investor attention for the price and earnings momentum effects.

We hypothesize that investor attention plays a dual role. On the one hand, limited attention can cause investors to ignore useful information, which leads to stock price underreaction. When investors pay less attention to a company's stock, they are more likely to ignore the company's earnings announcements, and therefore are unable to instantaneously incorporate the earnings news into prices. Consequently, prices continue to drift in the same direction of the earnings news after the announcements as the information gradually gets impounded into prices. Limited investor attention thus provides an explanation for the post-earnings announcement drift (also known as earnings momentum) effect.[3] Our hypothesis suggests that the underreaction-driven earnings momentum should be more pronounced among stocks that receive less investor attention.

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[1] See Pashler and Johnston (1998) for a recent review of these studies.

[2] See Hirshleifer (2001) and Barberis and Thaler (2003) for recent reviews of the empirical anomalies and the related behavioral theories.

[3] For example, Ball and Brown (1968) and Bernard and Thomas (1989) find that buying NYSE/AMEX stocks with recent good earnings news, while simultaneously shorting stocks with bad earnings news, can generate positive profits for a holding period of 60 days after earnings announcements. Chan, Jegadeesh and Lakonishok (1996) show that the earnings momentum strategies are profitable even among larger stocks and that the profitability cannot be explained by the Fama-French three-factor model.

On the other hand, investor attention can also interact with behavioral biases to generate price overreaction, which can explain the price momentum effect.[4] The existing behavioral theories typically attribute overreaction to biases in the way investors process information, such as extrapolative expectations and overconfidence.[5] However, attention is a necessary condition for overreaction, since investors can only overreact to information when they pay attention to a stock. Therefore, we expect the overreaction-driven price momentum to be more pronounced among stocks that attract more investor attention.

We perform both cross-sectional and time-series tests of our hypothesis using variables associated with investor attention. For our cross-sectional analysis, we use trading volume as a proxy since active trading involves investors' attention in analyzing their portfolios and asset fundamentals. When they pay less attention to a stock, they are less likely to trade it; and when they pay more attention to a stock, behavioral biases such as overconfidence can give rise to heterogeneous opinions among investors about the stock, thus generating more trading (Odean, 1998, and Scheinkman and Xiong, 2003). Hence, the hypothesis for our cross-sectional analysis is that *low* volume stocks should exhibit stronger underreaction-driven earnings momentum; in contrast, *high* volume stocks should display stronger overreaction-driven price momentum.

We test this hypothesis by analyzing the profitability of price and earnings momentum strategies for stocks with different levels of trading volume. We construct two-way sorted portfolios of NYSE/AMEX stocks using turnover (as a measure of trading volume) and prior stock returns. We measure price momentum profit as the average return difference between past return winners and losers within each turnover group. Similarly, we construct portfolios sorted by turnover and standardized unexpected

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[4] Jegadeesh and Titman (1993) are the first to document the phenomenon of price momentum. They find that buying recent winners over the past three to 12 months while simultaneously shorting recent losers can provide excess profits unrelated to systematic risk. Fama and French (1996) and Grundy and Martin (2001) show that the Fama-French three-factor model cannot explain this price momentum effect. Price momentum strategies are not only profitable in the U.S., but also in other developed and emerging markets, as shown by Rouwenhorst (1998), Griffin, Ji, and Martin (2003), and Hou, Karolyi, and Kho (2007).

[5] De Long, et al (1990) attribute overreaction to investors' extrapolative expectations. Daniel, Hirshleifer and Subrahmanyam (1998) model overconfidence and self attribution bias as a source

earnings (SUE). We measure earnings momentum profit by the average return difference between stocks with the highest and the lowest levels of earnings surprises within each turnover group. We also consider the possibility that under- and overreactions could operate together in generating both price and earnings momentum effects and control for each other in the analysis. To account for the return premia associated with size and book-to-market equity, we adjust stock returns using the Fama and French (1993) three-factor model at the portfolio level and a characteristic-based matching procedure as in Daniel, Grinblatt, Titman, and Wermers (1997) at the individual stock level.

We find that price momentum profit increases monotonically with turnover. The difference in raw (characteristic-adjusted) price momentum profits between the highest and lowest turnover quintiles is both statistically and economically significant with a value of 100 (94) basis points per month. We also find evidence of reversal: the long-run returns of the price momentum portfolios for months 13-36 after portfolio formation are negative for all turnover quintiles. Our results suggest that there is a significant overreaction-driven component in price momentum profits and that this component increases with trading volume, consistent with our attention-based hypothesis.

We find that earnings momentum profit decreases with turnover. The difference of 76 (68) basis points per month in raw (characteristic-adjusted) profits between the two extreme turnover quintiles is highly significant. We also find that the long-run returns of the earnings momentum portfolios for months 13-36 after portfolio formation show no sign of reversal. These results support our hypothesis that investors' underreaction to earnings news drives the earnings momentum effect and that the degree of underreaction weakens with investor attention.

We also analyze the time-series implications of investor attention for price and earnings momentum. A recent study by Karlsson, Loewenstein and Seppi (2005) documents an “ostrich effect” − investors pay more attention to stocks in rising markets, but “put their heads in the sand” in flat or falling markets. The ostrich effect motivates us to hypothesize that the underreaction-driven earnings momentum should be stronger in down markets than in up markets, but the overreaction-driven price momentum should be weaker in down markets.

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of investors’ overreaction to their private information.

We define a month as an “up” or “down” market month depending on whether the market return for the prior 36 months is above or below zero. We then analyze the differences in price and earnings momentum profits between the up and down months. We find that price momentum strategies are not profitable in down months, but return significant profits in up months. The difference, 134 basis points per month in characteristic-adjusted returns, is statistically significant. By contrast, the earnings momentum profits, after we control for price momentum, are significantly higher in down months than in up months with a difference of 47 basis points per month. We also use an alternative definition of market states based on the the National Bureau of Economic Research (NBER) business cycles and find similar results. The opposing patterns of price and earnings momentum profits across up and down markets is again consistent with our attention-based hypothesis.

Our study contributes to the growing literature on the effects of investor inattention on stock price dynamics, e.g., Huberman and Regev (2001), Hirshleifer, et al (2004), Hou and Moskowitz (2005), Hirshleifer, Lim and Teoh (2009), Hong, Torous and Valkanov (2007), Della Vigna and Pollet (2007, 2009), and Cohen and Frazzini (2008). These studies provide evidence that stock prices underreact to public information about firm fundamentals, such as new products, earnings news, demographic information, or information about related firms. Our findings broaden this literature by examining the implications of investor attention for both underreaction and overreation. Our analysis also contributes to the literature on price and earnings momentum anomalies by demonstrating that analyzing the role of investor attention can sharpen our understanding of these two phenomena.

The paper is organized as follows. In Section 2, we develop attention-based hypotheses for price and earnings momentum. In Section 3, we describe the data used in the empirical analyses. In Section 4, we test the cross-sectional hypothesis using trading volume as a proxy of investor attention. In Section 5, we analyze the price and earnings momentum profits across up and down markets. Section 6 concludes.

2 Hypothesis development

There is ample evidence suggesting that both individual investors and professionals have limited attention. For example, Barber and Odean (2008) find that individual investors' stock buying and selling decisions are influenced by salient, attention-grabbing events. Corwin and Coughenour (2008) show that NYSE specialists' attention constraints affect execution quality in terms of price improvement and transaction costs for securities for which they are market makers. Hirst and Hopkins (1998) provide experimental evidence that professional analysts often fail to recall, and to respond appropriately to, information in complex financial disclosures.

We hypothesize that investor attention plays a dual role in stock prices' reaction to information. On the one hand, limited attention can lead to ignorance of certain information and, consequently, to stock price underreaction. On the other hand, attention can interact with investors' behavioral biases, such as extrapolative expectations and overconfidence, to generate price overreaction to the information that investors do attend to.

Limited attention causes price underreaction because it imposes a constraint on the amount of information that investors can process and react to.[6] Theoretical models by Hirshleifer and Teoh (2005), Peng (2005), and Peng and Xiong (2006) suggest that, when investors' attention to a firm is inadequate, they may ignore its earnings announcements, resulting in stock price underreaction to the earnings news. After the announcements, prices continues to drift in the direction of the earnings news as the information gradually gets incorporated. Thus, limited investor attention can give rise to earnings momentum. Furthermore, the magnitude of the earnings momentum should decrease with the level of investor attention. This hypothesis is supported by Della Vigna and Pollet (2009) and Hirshleifer, Lim and Teoh (2009), who find that stock prices show weaker immediate reaction but stronger post-announcement drift to earnings announcements made on Friday, during which market participants are usually less attentive to business activities, or on days when a greater number of firms announce their earnings.

It is worth emphasizing that limited attention is not a behavioral bias in itself: it

[6] Traditional asset pricing theories assume that there exist perfectly efficient arbitrageurs, who distill new information with lightning speed and seamless precision. However, such efficiency is unrealistic. In addition, as argued by Shleifer and Vishny (1997) and others, short-term price risk and agency problems between professional arbitrageurs and their investors could further limit the effectiveness of arbitrage.

reflects constraints in investors' information processing. Thus, the inattention-driven underreaction is different from the bias-driven underreaction mechanism in Barberis, Shleifer and Vishny (1998), which assumes that investors are subject to conservatism bias. It also provides a potential explanation for the slow-information-diffusion mechanism proposed by Hong and Stein (1999).

Investor attention can also interact with behavioral biases such as extrapolative expectations and overconfidence to generate overreaction-driven price momentum. Investors with extrapolative expectations tend to extrapolate past returns into their expectation of future returns (a form of overreaction). De Long, et al. (1990) show that these investors buy more shares of a stock that has recently gone up in value, causing the price to increase further, which generates price momentum. Daniel, Hirshleifer, and Subrahmanyam (1998) focus on investors' overconfidence bias, which is a tendency to overestimate the precision of their private information; and self-attribution bias, which is a tendency to attribute success to themselves but failure to external reasons. Overconfidence causes investors to overreact to their private information. Self-attribution bias causes investors' confidence level to go up further after public news confirms their private information, but to remain unchanged after disconfirming public news. This asymmetric response implies that, on average, initial price reactions are followed by further price movements along the same direction, thus generates price momentum.

A necessary ingredient in these overreaction-driven price momentum mechanisms is investor attention. If investors do not pay attention to a stock, they can neither over-extrapolate the stock's past returns, nor can they overreact to their private information on that stock. Consequently, there will be no overreaction-driven price momentum. Conversely, when investors pay more attention to a stock, these biases can generate stronger price momentum.

In sum, we expect that more investor attention leads to weaker underreaction-driven earnings momentum, but stonger overreaction-driven price momentum.

It is often difficult to directly measure investor attention, as the economics and psychology literature still do not fully comprehend the determinants of investor attention.[7] We use trading volume as our proxy of investor attention in the cross-sectional analysis. Trading volume should be highly correlated with attention because investors cannot actively trade a stock if they do not pay attention to it, and when they do pay attention, heterogeneous opinions generated by biases in investors' information processing can lead to more trading (Odean, 1998, and Scheinkman and Xiong, 2003).

The link between trading volume and investor attention is supported by empirical evidence. Lo and Wang (2000) show that trading volume tends to be higher among large stocks which tend to attract more investor attention. Several authors argue that volume is a better measure of investor attention than variables such as size and analyst coverage. Although size and analyst coverage roughly proxy for the amount of information available in the public domain, how closely investors attend to this information is a different issue. Chordia and Swaminathan (2000) show that even after controlling for size, high volume stocks tend to respond more quickly to information in market returns than do low volume stocks. Their results suggest that trading volume contains information about investor attention that is not captured by size. Gervais, Kaniel and Mingelgrin (2001) suggest that the increase in volume raises a stock's visibility and attracts more investor attention. Barber and Odean (2008) argue that volume is more directly related to actual attention, since it is a direct outcome of investor attention, and use a stock's abnormal daily trading volume to capture the change in investor attention to the stock.

We develop the following testable hypothesis using trading volume as the proxy for investor attention:

Hypothesis *I*. In a cross-section of stocks, those with higher trading volume should display stronger price momentum, but weaker earnings momentum.

[7] Psychological studies, as reviewed by Yantis (1998), suggest that attention can not only be directed by people's deliberate strategies and intentions, but also be captured by an abrupt onset of stimulus and other salient events. Economic studies have utilized both channels of directing attention. Sims (2003), Gabaix, et al (2007), Peng (2005), and Peng and Xiong (2006) provide models to analyze agents' actively controlled attention in response to economic incentives. In particular, Peng (2005) shows that stocks with greater contribution to the fundamental uncertainty of investors' portfolios tend to receive more attention allocation. On the other hand, Barber and Odean (2008) examine the trading behavior generated by investors' attention to salient events.

We also expect that the overreaction-driven price momentum will reverse in the long run as price overreaction is eventually corrected. In contrast, if earnings momentum is caused by inattention-driven underreaction, then the effect will not reverse in the long run.

The attention that investors allocate to stocks not only varies in the cross-section, but also over time. Karlsson, Loewenstein, and Seppi (2005) analyze account activities in three Scandinavian data sets: the daily numbers of investor account look-ups at a large Norwegian financial service company, online logins of a major Swedish bank, and pension account look-ups by investors of the Swedish Pension Authority. They find that investors are more likely to look up their portfolios in up markets than in down markets. This "ostrich effect" suggests that investors pay more attention to stocks in rising markets, but "put their heads in the sand" in flat or falling markets.

The higher levels of attention in up markets can cause investors to overreact more to their private information or to past returns, thus generating more pronounced overreaction-driven price momentum. The increased attention also means that firms' earnings announcements are less likely to be ignored by investors, which should weaken the underreaction-driven earnings momentum. We summarize the time series prediction of price and earnings momentum in the following hypothesis:

Hypothesis *II.* Price momentum should be stronger in up markets than in down markets, but earnings momentum should be weaker in up markets than in down markets.

3. Data description

To test our hypotheses, we examine all NYSE/AMEX listed securities on the Center for Research in Security Prices (CRSP) monthly data files with sharecodes 10 or 11 (e.g. we exclude ADRs, closed-end funds, and REITs) from July 1964 to December 2005. We exclude Nasdaq firms from our sample because the volume information is not available for Nasdaq firms on the CRSP tapes until after 1981. Furthermore, the reported volume for Nasdaq firms includes inter-dealer trades, which means that the volume is not comparable to the NYSE/AMEX volume.[8]

We measure trading volume using the average monthly turnover over the prior year. The monthly turnover is the number of shares traded during a month divided by the number of shares outstanding at the end of the month. We obtain quarterly earnings data from Compustat. Since the earnings data are only available from 1971, our tests on earnings momentum are restricted to the subperiod from October 1971 to December 2005. To avoid using stale earnings, we require that a firm must have the most recent earnings announcement within four months prior to the portfolio formation month to enter the earning momentum tests. Following Chan, Jegadeesh, and Lakonishok (1996), we measure earnings surprise using the standardized unexpected earnings (SUE).[9] Specifically, the SUE for stock i in month t is

$$SUE_{i,t} = \frac{e_{i,t} - e_{i,t-4}}{\sigma_{i,t}}$$

where $e_{i,t}$ is earnings as of the most recent quarter, $e_{i,t-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ is the standard deviation of earnings changes over the last eight quarters.

We define size as the CRSP market capitalization at the end of June of year t. Book equity is the Compustat stockholder's equity plus balance sheet deferred tax and investment tax credit minus the book value of preferred stock. We calculate the book-to-market equity by dividing the book equity from the fiscal year end in year $t-1$ by the CRSP market capitalization at the end of December of year $t-1$. We follow Fama and French (1992) and match the size and book-to-market equity with monthly returns from July of year t to June of year $t+1$. For some of our tests, we also obtain analyst coverage data from the Institutional Brokers Estimate System (IBES) and institutional ownership data from Standard & Poors. The data on analyst coverage are available from 1976, and the data on institutional ownership are available from 1981.

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[8] We obtain very similar results when we include Nasdaq stocks and follow the literature, e.g., LaPlante and Muscarella (1997) and Hou (2007), by dividing the Nasdaq volume by a factor of two. For brevity, they are not reported but are available upon request.

[9] Chan, Jegadeesh and Lakonishok (1996) examined two other measures of earnings surprise − the cumulative abnormal stock return around the earnings announcement and the change in analysts' earnings forecast. They obtained results that are very similar to those using the SUE

They are generally biased towards larger firms. We measure institutional ownership in December of the prior year. We calculate analyst coverage as the average monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous year. Following Diether, Malloy, and Scherbina (2002), we also compute analyst dispersion as the monthly standard deviation of analysts' annual earnings forecasts divided by the absolute value of the mean forecast, averaged over the previous year. Calculating analyst dispersion further restricts our sample to firms covered by at least two analysts. We measure a stock's liquidity using Amihud's (2002) illiquidity measure, which is the daily absolute return divided by daily dollar trading volume averaged over the previous year.

4. Cross-sectional analysis

4.1. Empirical methods

To examine the relation between trading volume and price momentum, we form portfolios double-sorted by turnover and past returns. At the beginning of each month, we sort all NYSE/AMEX stocks in our sample into quintiles based on their average monthly turnover over the previous year. Within each turnover quintile, we then sort the stocks into quintiles based on their cumulative return over the past 12 months. We skip the most recent month to avoid market microstructure effects. We then compute equal-weighted returns of these portfolios over the following month. The return spread between the winner and loser portfolios (past-return quintiles 5 and 1 within each turnover quintile) constitutes the profit from the price momentum strategy.[10]

Part of the price momentum profits could be attributed to investors' underreaction to the earnings news. This is the case when past-return winners (losers) had positive (negative) earnings surprises recently. To control for this possibility, we estimate a cross-sectional regression of the past 12-month's stock return on the most recent unexpected earnings (SUE) and use the residual return as the sorting variable to form

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measure.

[10] Earlier studies, e.g., Jegadessh and Titman (1993), find that alternative strategies with portfolio formation periods ranging from 3 to 12 months and holding periods from 1 to 12 months provide similar trading profits.

price momentum portfolios.[11]

To analyze the relation between trading volume and earnings momentum, we form portfolios double-sorted by turnover and unexpected earnings. Each month, we first sort stocks into quintiles based on their turnover. Within each turnover quintile, we then group stocks into quintiles based on their most recent SUE. The profit of the earnings momentum strategy is the return spread between the highest and the lowest SUE quintiles within each turnover group.

The earnings momentum profits can be partially driven by investors' overreaction to past returns, independent of their response to past earnings news. This is the case when a prior positive (negative) earnings surprise coincides with a positive (negative) stock return. The existence of this overreaction-driven component in earnings momentum profits could confound our inferences on investors' underreaction to earnings news. To control for this effect, we estimate a cross-sectional regression of SUE on the past one-year return, and then use the regression residual to form earnings momentum portfolios.

We use the Fama-French three-factor model to account for factor risk premia in momentum profits:

$$R_{jt} = \alpha_j^{FF} + \beta_j^M R_{Mt} + \beta_j^{HML} R_{HML,t} + \beta_t^{SMB} R_{SMB,t} + \varepsilon_{jt}, \quad (1)$$

where R_{jt} is the momentum profit in turnover quintile j in month t; R_{Mt} is the excess return of the market portfolio; $R_{HML,t}$ is the return spread between high and low book-to-market portfolios, designed to capture the book-to-market effect in average returns; $R_{SMB,t}$ is the return spread between portfolios of small and large stocks, designed to capture the size effect in average returns; and β_j^M, β_j^{HML}, and β_j^{SMB} are the corresponding risk loadings on the three factors. The regression intercept α_j^{FF}

[11] We have also used a two-way sorting procedure to purge the effect of past earnings surprises from past returns, and obtained very similar results. Specifically, within each turnover quintile, we first sort stocks into five SUE groups. Stocks within each SUE group are further sorted into five portfolios based on their past twelve month returns. Then, stocks with the same past return rankings from each of the five SUE groups are placed into one portfolio. This procedure creates, within each turnover quintile, five past return portfolios while holding past earnings surprises relatively constant.

measures the average momentum profit unexplained by the Fama-French three-factor model.

Motivated by the finding in Daniel and Titman (1997) that characteristics, rather than estimated covariances, seem to do a better job explaining the cross-section of average returns in the post-1963 era, we also calculate the characteristic-adjusted returns of the price and earnings momentum portfolios. We follow the characteristic-matching procedure in Daniel, Grinblatt, Titman, and Wermers (1997) to account for the return premia associated with size and book-to-market equity. Specifically, we sort stocks first into size deciles, and then within each size decile into book-to-market deciles. We equal-weight stocks within each of these 100 portfolios to form a set of 100 benchmark portfolios. To calculate the size and book-to-market-hedged return for an individual stock, we subtract the return of the equal-weighted benchmark portfolio to which that stock belongs from the return of that stock. The expected value of this excess return is zero if size and book-to-market completely describe the cross-section of expected returns.

Previous studies show that momentum profits vary with stock characteristics, such as size, analyst coverage, institutional ownership, analyst dispersion, and liquidity. To demonstrate that the links between turnover and price and earnings momentum profits are not driven by these known effects, we estimate a first-stage cross-sectional regression of turnover on size, analyst coverage, institutional ownership, analyst dispersion, and Amihud's (2002) illiquidity measure. We then use the residual turnover as the sorting variable to verify the robustness of our results based on the raw turnover variable.

4.2. Results on price momentum

Table 1 reports the average monthly raw and characteristic-adjusted returns of portfolios sorted by turnover and past one-year returns, and the return spread between past return winners and losers within each turnover group. For all turnover quintiles, the average price momentum profits are statistically significant. More importantly, consistent with our hypothesis, the raw profit increases monotonically from 45 basis points per month for the lowest turnover quintile to 145 basis points for the highest turnover quintile. The difference in profit between the two extreme turnover quintiles is 100 basis points and is statistically significant (p -value=0.0053).

When we control for either the Fama-French factor returns or characteristic-based benchmark portfolio returns or both, the price momentum profit continues to increase monotonically with turnover. For example, the characteristic-adjusted profit increases from 36 basis points per month for the lowest turnover quintile to 130 basis points for the highest turnover quintile, with a highly significant difference of 94 basis points per month (p-value=0.002). Additionally adjusting for the Fama-French factor returns further increases the difference to 109 basis points per month (p-value=0.0003) between the two extreme turnover quintiles.[12]

Table 2 reports the average returns of portfolios sorted by turnover and past one-year return, orthogonalized with respect to past earnings surprises (to control for the earnings momentum effect).[13] The monotonically increasing relation between turnover and price momentum profit remains robust. The average characteristic-adjusted profit increases from eight basis points per month for the lowest turnover quintile to 108 basis points per month for the highest turnover quintile. The difference between the two extreme quintiles is highly significant (p-value=0.0031). Compared to Table 1, the average profit in Table 2 drops by approximately 20 to 30 basis points per month and is not significant in the lowest turnover quintile.[14] This result suggests that underreaction to earnings news partially contributes to the price momentum profits.

Table 3 studies the long-run performance of price momentum strategies and reports the average monthly profits for five different holding periods: month t, month t to t+2, month t to t+5, month t to t+11, and month t+12 to t+35. We report the

[12] Table 1 also shows that almost the entire differences in price momentum profit between the two extreme turnover quintiles come from past return losers. The high turnover losers under-perform low turnover losers by 86 basis points per month after characteristic adjustment, whereas the difference is only seven basis point per month for winners. This finding suggests that when investors pay attention, they overreact much more to negative past returns than to positive ones.

[13] Due to the availability of quarterly earnings data, the analysis in this table covers the October 1971 to December 2005 period.

[14] This reduction in profit is not due to the difference in sample between Tables 1 and 2. For example, when we restrict our analysis to the October 1971 to December 2005 period and to firms with non-missing quarterly earnings data, the characteristic-adjusted price momentum profits (not controlling for earnings momentum) are 43, 68, 82, 102, and 131 basis points per month for turnover quintiles 1 through 5, and are all statistically significant.

both the raw and the Fama-French factor-adjusted profits for all holding periods. Panel A presents the results when we do not control for earnings momentum, and Panel B presents the results when we control for earnings momentum by orthogonalizing past returns with respect to past earnings surprises.

When the holding period increases from one month to 12 months after portfolio formation, the average price momentum profits (before or after we control for earnings momentum) drops across the five turnover quintiles, although most of them still remain significantly positive. The decrease in profit suggests that price momentum gradually weakens during the first year after portfolio formation. More importantly, price momentum profit continues to increase monotonically with turnover, and the difference in profit between the two extreme turnover quintiles remains significant for holding periods up to twelve months after portfolio formation.

For months $t+12$ to $t+35$, the price momentum profits are significantly negative for all turnover quintiles. This result suggests that price momentum profits reverse two to five years after portfolio formation, which is consistent with the hypothesis that price momentum is driven by a significant overreaction component.[15] One might argue that if investor overreaction is more prevalent among high turnover stocks, we should expect to see stronger reversals in years 2-3 from these stocks as well. However, the difference in momentum profit between turnover quintiles 5 and 1 for this holding period is insignificant, which is likely due to noise in long-run returns.

Tables 1-3 demonstrate that an important part of price momentum profits is related to investor overreaction, and that this overreaction-driven component is more pronounced among high turnover stocks. This finding supports our hypothesis that overreaction-driven price momentum strengthens with investor attention.

4.3. Results on earnings momentum

Table 4 reports the average monthly raw and characteristic-adjusted returns of

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[15] After adjusting for the Fama-French three-factor model, the negative long-run profits fall substantially and most of them also lose their statistical significance. This is consistent with past research (e.g., Fama and French, 1996), which shows that controlling for the size and book-to-market effects using either the Fama-French three-factor model or characteristic-based benchmark portfolios substantially weakens the long run reversal effect.

portfolios sorted by turnover and standardized unexpected earnings, and the return spread between the highest and lowest SUE portfolios within each turnover group. The earnings momentum profits are highly significant for all five turnover quintiles. The average raw profit is 184 basis points per month for the lowest turnover quintile and 108 basis points for the highest turnover quintile. The difference of 76 basis points per month is highly significant (p -value=0.0007), consistent with our attention-based hypothesis. The magnitude and statistical significance of the difference in profit remain largely unchanged after we control for the Fama-French three-factor model or the characteristic-based benchmark portfolios. The profit pattern is somewhat flat across turnover quintiles 3-5.

Table 5 reports the average returns of portfolios sorted by turnover and residual SUE (SUE orthogonalized with respect to past returns to control for the price momentum effect). The earnings momentum profit now decreases monotonically with turnover. For example, the raw profit drops from 164 basis points per month for the lowest turnover quintile to 58 basis points for the highest turnover quintile. The difference of 106 basis points is highly significant with a p -value of 0.0001, and is bigger than the corresponding difference of 76 basis points in Table 4. The table also shows that after we control for price momentum, the earnings momentum profit drops by roughly 30% to 40% for high turnover stocks. This result suggests that price momentum contributes partially to the earnings momentum profits for these stocks.[16]

Table 6 examines the long-run performance of earnings momentum strategies for various holding periods. Panel A reports the results when we do not control for price

[16] Tables 4 and 5 also reveal that after bad earnings news, the price drifts of low turnover and high turnover stocks are similar in magnitude, but after good earnings news the price drift of low turnover stocks is much stronger than that of high turnover stocks. This pattern is consistent with the asymmetry in attention-based buying and selling behavior documented by Barber and Odean (2008). They find that investors are more likely to buy stocks that attract their attention, but their selling decisions are not as sensitive to stocks' attention characteristics. They argue that when buying a stock, investors have to choose from thousands of individual stocks; but when selling a stock, they only need to sell among those they already own. Extending this argument, when there is good earnings news to a low attention stock, it takes a long time for potential buyers to recognize the news and to incorporate the news into prices, resulting in a more pronounced price drift. In contrast, the process of incorporating bad earnings news is not sensitive to investor attention − selling after bad news is mostly done by current owners of the stock who are already paying attention to it.

momentum, and Panel B reports the results after controlling for price momentum. Both panels show that during the first year after portfolio formation, earnings momentum profits for all turnover quintiles decrease with holding horizon, but remain positive and significant. The profit continues to decrease with turnover for holding periods up to six months after portfolio formation. The raw profits for years 2-3 are small and statistically indistinguishable from zero. Therefore, there is no evidence of long-run reversal.

Taken together, Tables 4-6 suggest that earnings momentum is largely driven by investors' underreaction to earnings news, and this underreaction effect is stronger among low turnover stocks. These results are consistent with our hypothesis that investors' underreaction to earnings news weakens with investor attention.

4.4. Robustness

In this section, we examine whether the opposite patterns of price and earnings momentum profits across different turnover quintiles could be explained by the correlations between turnover and other variables, such as size and analyst coverage, which have been shown to generate variations in momentum profits. To address this question, in Table 7 we control for those known momentum determinants and report the raw and characteristic-adjusted price and earnings momentum profits for different residual turnover quintiles. We estimate the residual turnover from a cross-sectional regression of turnover on size, analyst coverage, institutional ownership, analyst dispersion, and Amihud's (2002) illiquidity measure. Due to data availability of analyst coverage and institutional ownership, we calculate the residual-turnover results for the shorter July 1981 to December 2005 period. In addition, the sample is biased toward larger and more visible stocks because the calculation of analyst dispersion requires a stock to be covered by at least two analysts.[17] On avegarge these control variables explain 60% of the variation in turnover across firms.

Despite the shorter period and the bias toward larger stocks, Panel A of Table 7 shows that price momentum profit continues to increase monotonically with residual turnover: after we control for earnings momentum, the raw price momentum profit

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[17] For a typical year, the residual-turnover measure can be estimated for about 60% of the NYSE/AMEX stocks.

increases from 36 basis points per month for the lowest residual-turnover quintile to 166 basis points for the highest residual-turnover quintile.

Panel C shows that after we control for price momentum, the earnings momentum profit decreases monotonically from 87 basis points per month for the lowest residual turnover quintile to 29 basis points for the highest residual turnover quintile.[18] These results confirm that the opposite patterns of price and earnings momentum profits across different turnover quintiles are not driven by the control variables we use to estimate residual turnover.

One might argue that turnover is simply picking up the cross-sectional variation in the degree of investors' overreaction to information. However, overreaction in and of itself cannot generate the opposite patterns in price and earnings momentum profits that we find: pure overreaction stories cannot explain why earnings momentum profit decreases with turnover or why it does not reverse in the long run. Thus, the joint dynamics of price and earnings momentum across stocks of different levels of turnover come at least in part from the cross-sectional variation in investor attention.

Lo and Wang (2000) show that there is a significant market component in trading volume that is caused by investors' portfolio rebalancing activities. Sadkar (2006) also finds that a systematic liquidity risk factor can contribute to both price and earnings momentum. However, portfolio rebalancing due to systematic factors or any systematic liquidity factor cannot generate the contrasting patterns of price and earnings momentum profits. Furthermore, our results based on residual volume measures show that these contrasting patterns are robust after controlling for these risk factors.

Our cross-sectional results on price momentum are also consistent with Lee and Swaminathan (2000), who find that price momentum is more pronounced among high volume stocks. We go beyond their study by investigating the joint dynamics of price and earnings momentum. Our attention-based hypothesis also motivates us to control for the effect of earnings momentum when studying price momentum.

[18] Panel C also shows that if we do not control for price momentum, the earnings momentum profit exhibits a U-shaped pattern across the residual turnover quintiles within a range of 60-101 basis points per month. This result is largely caused by the reduction in sample size, not by using residual turnover in place of raw turnover. In unreported analysis, we find a similar relation between raw turnover and earnings momentum profit (without controlling for price momentum)

5 Time-series analysis

Investor attention also varies with the state of the stock markets: they tend to pay more attention to stocks in up markets than in down markets. In this section, we test the hypothesis that price momentum should be more pronounced in up markets and earnings momentum should be more pronounced in down markets.

We follow Cooper, Gutierrez, and Hameed (2004) and define market state using the cumulative return of the value-weighted CRSP market index (including dividends) over the most recent 36 months.[19] We label a month as an up market month if the CRSP index return is positive, and as a down market month if the CRSP index return is negative. There are 434 up months and 64 down months for the July 1964 to December 2005 sample period, and 355 up months and 56 down months for the October 1971 to December 2005 subperiod, for which we have quarterly earnings data.

We compute the characteristic-adjusted price and earnings momentum profits and compare the average profits between up and down market months. We also use two time-series regression models to test for the difference in profits. The first regression is based on the CAPM model:

$$R_t = \alpha^M + k^M I_t(UP) + \beta^M R_{Mt} + \varepsilon_t, \tag{2}$$

where R_t is the month t profit of either the price or earnings momentum strategy, R_{Mt} is the excess return of the CRSP market portfolio, and $I_t(UP)$ is a dummy variable that takes the value of one if month t is in an up month, and zero otherwise. The regression intercept α^M measures the average momentum profit in down market months, and the coefficient k^M captures the incremental average profit in up market months relative to down months.

The second regression adds the two Fama-French factor mimicking returns ($R_{HML,t}$ and $R_{SMB,t}$) to control for the premia associated with the size and book-to-market effects:

$$R_t = \alpha^{FF} + k^{FF} I_t(UP) + \beta^M R_{Mt} + \beta^{HML} R_{HML,t} + \beta^{SMB} R_{SMB,j} + \varepsilon_t, \tag{3}$$

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among stocks with non-missing residual turnover.

[19] The results are similar if we use an alternative 24 month market state definition.

where α^{FF} and k^{FF} have interpretations similar to those in Equation (2).

To ensure the robustness of our regression results, we also replace the market state dummy in Equations (2) and (3) with lagged market return over the previous 36 months. The coefficients on the lagged market return provide further evidence on how market state affect the price and earnings momentum profits.

We also use an alternative definition of market state, based on the NBER business cycles. We define the months during a period that starts six months following the beginning of a recession and ends two years following a recession as down cycle months and other months as up cycle months. We start the down cycle six months after the beginning of a recession because it takes a while for the investors to realize that the economy is in a recession (the NBER officially announces a recession with a minimum six month lag). We extend the down cycles to two years after the recessions are over because it usually takes longer time for investors to rekindle their interest in stock markets after a recession. There are 331 up cycle months and 167 down cycle months for the July 1964 to December 2005 sample period, and 259 up cycle months and 152 down cycle months for the October 1971 to December 2005 subperiod, for which we have quarterly earnings data.

Table 8 presents the results on price momentum. Panel A reports the unconditional profits. The average price momentum profit before we control for earnings momentum is 87 basis points per month, and becomes 64 basis points per month after. Panel B compares the price momentum profits between up and down market states. In up market months, the average price momentum profits are 104 basis points per month before we control for earnings momentum, and 84 basis points after. Both of these values are highly significant with t-statistics of 6.08 and 4.45, respectively. In contrast, the average price momentum profits in down market months are negative -30 basis points per month before we control for earnings momentum and -64 basis points after. Neither of these two values is statistically significant. The differences between the up and down months are large in magnitude (134 basis points before we control for earnings momentum and 148 basis points after) and statistically highly significant (t-statistics of 2.56 and 2.68, respectively).

Panel C of Table 8 reports the results from estimating Regressions (2) and (3). We consider four specifications by combining the two regressions with two alternative measures of price momentum profits (before and after we control for earnings momentum). For all specifications, the regression intercepts, which correspond to momentum profits in down market months, are not statistically significant. By contrast, the coefficients on the market state dummy, which correspond to the difference in momentum profits between up and down market months are always significant, ranging from 99 to 146 basis points per month. These regressions confirm the result in Panel B that price momentum profit is significantly higher in up market months than in down months.

Panel D repeats the regressions in Panel C, except that we replace the discrete market state dummy with the corresponding lagged market returns. The coefficients on the lagged market return are all positive and in almost all cases highly significant, again suggesting that price momentum profit tends to be higher in booming markets when investors pay more attention to stocks. Overall, Table 8 shows that price momentum is not profitable in down markets, but generates significant profits in up markets. These results are also consistent with the findings of Cooper, Gutierrez, and Hameed (2004)..

Table 9 reports the results on the earnings momentum. Panel A shows that before we control for price momentum, the average unconditional earnings momentum profit is 114 basis point per month, and that it drops to 82 basis points per month after we control for price momentum. Panel B compares the earnings momentum profits between up and down market states. In up months, the average earnings momentum profit before we control for price momentum is 113 basis points per month. In down months, the average profit is 122 basis points, which is nine basis points higher than that in up months, but the difference is insignificant. The lack of a significant difference may be caused by price momentum that is unrelated to earnings news. Indeed, after we control for price momentum, the difference in profit between down and up months now increases to 47 basis points per month, and is statistically significant with a t-statistic of 2.75.

Panels C and D report the results from regressing earnings momentum profits on the market state dummy or lagged market return, controlling for additional factor mimicking returns. The results are consistent with the findings in Panel B. After we control for price momentum, the regression coefficients on the market state dummy and lagged market return are negative and statistically significant in most cases. For example, the coefficient on the market state dummy is -51 basis points per month with a *t*-statistic of -2.97, when we use Fama-French factors as controls.

Overall, Table 9 shows that earnings momentum is profitable in both up and down markets, and that the profits are significantly higher in down markets after we control for price momentum.

Table 10 compares the momentum profits between up and down business cycles. Panel A shows that before we control for earnings momentum, the average price momentum profit is 109 basis points per month in up cycles and 42 basis points in down cycles. The difference is 67 basis points per month with a *t*-statistic of 1.82. After we control for earnings momentum, the difference increases to 84 basis points per month with a *t*-statistic of 2.14.

Panel B reports the results from regressing price momentum profits on factor mimicking returns and a business-cycle dummy variable, which takes a value of zero in down cycle months and one in up cycle months. The coefficients on the dummy variable confirm that price momentum profits, especially after we control for earnings momentum, are higher in up cycles than in down cycles.

Panel C of Table 10 shows that before we control for price momentum, the average earnings momentum profit is 109 basis points per month in up cycles and 124 basis points per month in down cycles. The differnce of 15 basis points per month is statitically insignificant (*t*-statistic = 0.84). However, after we control for price momentum, the average profits become 70 basis points in up cycles and 102 basis points in down cycles. The difference in profit is 32 basis points and is statistically significant (*t*-statistic = 2.68). The regression results in Panel D also confirms that after we control for price momentum, earnings momentum profits are significantly higher in down cycles than in up cycles.

Taken together, Tables 8-10 show opposite patterns of price and earnings momentum profits across up and down markets (or business cycles). Price momentum is stronger in up markets, and earnings momentum is stronger in down markets. These results are consistent with the fluctuation in investor attention across market states.

Our time-series findings cannot be simply explained by fluctuations in the degree of investor overconfidence. As implied by Daniel, Hirshleifer and Subrahmanyam (1998) and Gervais and Odean (2001), self-attribution bias could cause investors to become more overconfident about the precision of their private information in up markets, and subsequently to overreact more to their private information. This results in a stronger overreaction-driven price momentum in up markets than in down markets. However, more overconfidence in up markets also implies that investors will underweight public information such as earnings announcements, resulting in a stronger earnings momentum in up markets, which is the opposite of what we find.

6. Conclusion

In this paper, we examine the hypothesis that investor attention plays a dual role in stock price dynamics: on the one hand, limited investor attention causes stock prices to underreact to earnings news and leads to earnings momentum; on the other hand, investor attention can interact with investors' learning biases, such as extrapolative expectations and overconfidence, to generate price momentum. The hypothesis predicts that earnings momentum weakens with investor attention, and that price momentum strengthens with investor attention.

We perform cross-sectional and time-series tests of this hypothesis. In the cross-sectional analysis, we use trading volume as a proxy for attention. We find that price momentum profits are higher among high volume stocks, but earnings momentum profits are higher among low volume stocks. We also use market state to measure time series variation in investor attention, and find that price momentum profits are higher in up markets, but earnings momentum profits are higher in down markets. Furthermore, we find that price momentum profits reverse in the long run, but earnings momentum profits do not. The opposite patterns of earnings and price momentum in both the cross section and time series support our attention-based hypothesis and offer a new insight on the importance of investor attention in understanding price under- and overreaction.

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Table 1. Trading Volume and Price Momentum

The table reports the average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past one year return for the period from July 1964 to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX by their average monthly turnover (the number of shares traded in a month divided by the number of shares outstanding at the end of the month) over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their return over the past 12 months (skipping the most recent month). We report the average equal-weighted raw and adjusted returns and *t*-statistics (in *italics*) of these double-sorted portfolios, the average return spreads between past return quintiles 5 and 1 within each turnover group, and the intercepts from time series regressions of the 5-1 return spreads on the Fama-French factors. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. The table also reports the *t* and *F* statistics for the hypotheses that the average price momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively.

	Raw Returns								Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0139	0.0123	0.0138	0.0161	0.0184	0.0045	0.0062	Turnover1	-0.0005	-0.0013	0.0003	0.0022	0.0032	0.0036	0.0054
	4.49	*5.85*	*7.27*	*8.32*	*8.00*	*2.11*	*2.91*		*-0.40*	*-1.36*	*0.34*	*2.36*	*3.13*	*2.15*	*3.23*
2	0.0105	0.0120	0.0123	0.0142	0.0185	0.0080	0.0103	2	-0.0028	-0.0006	-0.0004	0.0009	0.0041	0.0068	0.0090
	3.35	*5.30*	*5.91*	*6.85*	*7.69*	*3.59*	*4.60*		*-2.43*	*-0.88*	*-0.59*	*1.25*	*4.68*	*3.93*	*5.19*
3	0.0078	0.0128	0.0124	0.0150	0.0188	0.0109	0.0128	3	-0.0041	0.0003	-0.0004	0.0017	0.0047	0.0088	0.0106
	2.57	*5.20*	*5.41*	*6.42*	*7.01*	*5.17*	*6.02*		*-4.20*	*0.45*	*-0.64*	*2.81*	*4.87*	*5.21*	*6.21*
4	0.0064	0.0113	0.0130	0.0146	0.0193	0.0129	0.0157	4	-0.0054	-0.0011	0.0004	0.0016	0.0054	0.0108	0.0137
	1.81	*3.97*	*4.84*	*5.58*	*6.78*	*5.28*	*6.45*		*-4.00*	*-1.66*	*0.66*	*2.62*	*5.19*	*5.17*	*6.59*
Turnover5	0.0018	0.0089	0.0113	0.0138	0.0163	0.0145	0.0183	Turnover5	-0.0091	-0.0031	-0.0008	0.0012	0.0039	0.0130	0.0163
	0.43	*2.63*	*3.56*	*4.43*	*4.90*	*5.05*	*6.42*		*-4.80*	*-2.85*	*-0.91*	*1.29*	*2.77*	*5.18*	*6.53*
Test (turnover1=turnover5)						2.80	11.57							3.10	13.13
P-value						0.0053	0.0007							0.0020	0.0003

Table 2. Trading Volume and Price Momentum, Controlling for Earnings Momentum

The table reports the average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past one-year return orthogonalized with respect to past earnings surprises. The sample period is October 1971 to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX with non-missing quarterly earnings data by their average monthly turnover over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their return over the past year orthogonalized with respect to past earnings surprises. We estimate the orthogonalized return by running a cross-sectional regression of past one-year return on the most recent earnings surprise. The table reports the average equal-weighted raw and adjusted returns and *t*-statistics (in *italics*) of these double-sorted portfolios, the average return spreads between past return quintiles 5 and 1 within each turnover group, and the intercepts from time series regressions of the 5-1 return spreads on the Fama-French factors. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. The table also reports the *t* and *F* statistics for the hypotheses that the average price momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively.

	Raw Returns							Characteristic-Adjusted Returns							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0168	0.0139	0.0148	0.0170	0.0182	0.0014	0.0034	Turnover1	0.0016	-0.0005	0.0003	0.0022	0.0025	0.0008	0.0031
	4.68	*5.76*	*6.52*	*7.60*	*7.03*	*0.60*	*1.43*		*1.22*	*-0.51*	*0.32*	*2.17*	*2.14*	*0.42*	*1.58*
2	0.0124	0.0125	0.0130	0.0144	0.0176	0.0053	0.0073	2	-0.0012	-0.0003	-0.0002	0.0009	0.0030	0.0042	0.0065
	3.59	*4.97*	*5.56*	*6.26*	*6.51*	*2.18*	*3.00*		*-0.98*	*-0.43*	*-0.33*	*1.16*	*3.03*	*2.21*	*3.39*
3	0.0091	0.0129	0.0129	0.0143	0.0177	0.0086	0.0102	3	-0.0025	0.0005	0.0001	0.0013	0.0040	0.0064	0.0083
	2.79	*4.80*	*5.15*	*5.75*	*6.18*	*3.78*	*4.37*		*-2.28*	*0.75*	*0.13*	*1.85*	*3.77*	*3.41*	*4.32*
4	0.0064	0.0113	0.0122	0.0141	0.0176	0.0112	0.0137	4	-0.0049	-0.0009	-0.0001	0.0010	0.0041	0.0090	0.0118
	1.71	*3.82*	*4.32*	*5.00*	*5.88*	*4.35*	*5.24*		*-3.28*	*-1.29*	*-0.10*	*1.27*	*3.79*	*4.04*	*5.30*
Turnover5	0.0024	0.0091	0.0106	0.0136	0.0153	0.0129	0.0166	Turnover5	-0.0079	-0.0026	-0.0013	0.0010	0.0029	0.0108	0.0144
	0.54	*2.50*	*3.18*	*4.11*	*4.36*	*4.18*	*5.38*		*-3.70*	*-2.19*	*-1.47*	*0.99*	*1.99*	*3.97*	*5.27*
Test (turnover1=turnover5)						2.93	11.35							2.96	11.30
P-value						0.0035	0.0008							0.0031	0.0008

Table 3. Long-Run Performance of Volume-Based Price Momentum

The table reports the average monthly price momentum profits for different turnover groups and various holding periods from July 1964 to December 2005 (Panel A) or from October 1971 to December 2005 (Panel B). At the beginning of each month, we rank all stocks on NYSE/AMEX by their average monthly turnover over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their return over the past year. We compute the equal-weighted raw returns of these double-sorted portfolios for four holding periods: month t, months t to t+5, months t to t+11, and months t+12 to t+35. Panel A reports the average return spreads between past return quintiles 5 and 1 within each turnover group and their associated *t*-statistics (in *italics*), as well as the intercepts from time series regressions of the return spreads on the Fama-French factors. Also reported are the *t* and *F* statistics for the hypotheses that the average price momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively. In Panel B, we repeat the analysis in A, but use past one-year return orthogonalized with respect to past earnings surprises to measure price momentum.

Panel A: Not Controlling for Earnings Momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+35***	
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α
Turnover1	0.0045	0.0062	0.0041	0.0063	0.0019	0.0046	-0.0009	0.0023	-0.0039	-0.0008
	2.11	*2.91*	*1.96*	*3.08*	*0.92*	*2.29*	*-0.47*	*1.25*	*-2.50*	*-0.59*
2	0.0080	0.0103	0.0070	0.0095	0.0050	0.0077	0.0009	0.0040	-0.0035	-0.0007
	3.59	*4.60*	*3.35*	*4.57*	*2.54*	*3.99*	*0.47*	*2.31*	*-2.55*	*-0.58*
3	0.0109	0.0128	0.0093	0.0114	0.0070	0.0096	0.0032	0.0063	-0.0025	0.0004
	5.17	*6.02*	*4.60*	*5.69*	*3.68*	*5.13*	*1.85*	*3.87*	*-1.99*	*0.33*
4	0.0129	0.0157	0.0113	0.0144	0.0092	0.0126	0.0048	0.0085	-0.0028	0.0003
	5.28	*6.45*	*4.97*	*6.35*	*4.34*	*6.12*	*2.55*	*4.83*	*-2.05*	*0.23*
Turnover5	0.0145	0.0183	0.0126	0.0165	0.0095	0.0138	0.0042	0.0088	-0.0033	-0.0003
	5.05	*6.42*	*4.71*	*6.30*	*3.82*	*5.71*	*1.88*	*4.28*	*-2.41*	*0.26*
Test (1=5)	2.80	11.57	2.51	9.41	2.37	8.61	1.73	5.69	0.30	0.09
P-value	0.0053	0.0007	0.0121	0.0022	0.0180	0.0034	0.0835	0.0171	0.7675	0.7677

Panel B: Controlling for Earnings Momentum

	t		*t : t+2*		*t : t+5*		*t : t+11*		*t+12 : t+35*	
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α
Turnover1	0.0014	0.0034	0.0019	0.0041	0.0004	0.0030	-0.0022	0.0009	-0.0053	-0.0021
	0.60	*1.43*	*0.83*	*1.81*	*0.17*	*1.37*	*-1.06*	*0.44*	*-2.98*	*-1.30*
2	0.0053	0.0073	0.0053	0.0076	0.0043	0.0066	0.0001	0.0028	-0.0038	-0.0014
	2.18	*3.00*	*2.35*	*3.33*	*1.97*	*3.08*	*0.05*	*1.49*	*-2.42*	*-0.95*
3	0.0086	0.0102	0.0085	0.0100	0.0072	0.0091	0.0036	0.0061	-0.0021	0.0003
	3.78	*4.37*	*3.98*	*4.64*	*3.57*	*4.51*	*1.94*	*3.44*	*-1.47*	*0.26*
4	0.0112	0.0137	0.0096	0.0126	0.0076	0.0110	0.0042	0.0078	-0.0017	0.0013
	4.35	*5.24*	*4.04*	*5.22*	*3.44*	*5.07*	*2.15*	*4.22*	*-1.09*	*0.94*
Turnover5	0.0129	0.0166	0.0112	0.0149	0.0081	0.0122	0.0031	0.0076	-0.0028	0.0001
	4.18	*5.38*	*3.94*	*5.26*	*3.04*	*4.65*	*1.32*	*3.45*	*-1.92*	*0.04*
Test (1=5)	2.93	11.35	2.55	8.92	2.21	7.28	1.69	5.14	1.10	1.10
P-value	0.0035	0.0008	0.0109	0.0029	0.0271	0.0070	0.0912	0.0235	0.2725	0.2940

Table 4. Trading Volume and Earnings Momentum

The table reports the average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past earnings surprise for the period from October 1971 to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX with non-missing quarterly earnings data by their average monthly turnover over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their most recent earnings surprise, measured by standardized unexpected earnings (SUE). The table reports the average equal-weighted raw and adjusted returns and *t*-statistics (in *italics*) of these double-sorted portfolios, the average return spreads between earnings surprise quintiles 5 and 1 within each turnover group, and the intercepts from time series regressions of the 5-1 return spreads on the Fama-French factors. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. The table also reports the *t* and *F* statistics for the hypotheses that the average earnings momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively.

	Raw Returns							Characteristic-Adjusted Returns							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0071	0.0122	0.0163	0.0208	0.0255	0.0184	0.0183	Turnover1	-0.0069	-0.0025	0.0012	0.0054	0.0094	0.0164	0.0165
	2.81	*4.68*	*6.29*	*8.42*	*10.08*	*14.31*	*13.89*		*-6.58*	*-2.51*	*1.31*	*5.67*	*9.62*	*13.53*	*13.24*
2	0.0082	0.0114	0.0145	0.0175	0.0200	0.0118	0.0126	2	-0.0053	-0.0019	0.0005	0.0037	0.0059	0.0112	0.0119
	3.05	*4.21*	*5.46*	*7.06*	*8.13*	*9.08*	*9.66*		*-6.49*	*-2.32*	*0.77*	*4.68*	*7.28*	*9.57*	*9.96*
3	0.0078	0.0109	0.0142	0.0166	0.0185	0.0107	0.0118	3	-0.0044	-0.0020	0.0013	0.0035	0.0054	0.0098	0.0104
	2.86	*3.80*	*5.23*	*6.27*	*7.00*	*8.17*	*9.09*		*-5.91*	*-2.84*	*1.93*	*5.09*	*7.03*	*8.30*	*8.67*
4	0.0074	0.0099	0.0133	0.0149	0.0171	0.0097	0.0114	4	-0.0045	-0.0026	0.0003	0.0021	0.0044	0.0089	0.0103
	2.36	*3.21*	*4.39*	*5.09*	*5.90*	*7.01*	*8.29*		*-5.31*	*-3.47*	*0.41*	*2.90*	*5.59*	*7.19*	*8.25*
Turnover5	0.0054	0.0073	0.0105	0.0139	0.0162	0.0108	0.0123	Turnover5	-0.0059	-0.0044	-0.0015	0.0017	0.0037	0.0096	0.0109
	1.40	*2.00*	*2.98*	*4.00*	*4.65*	*5.90*	*6.70*		*-4.06*	*-3.66*	*-1.40*	*1.55*	*3.26*	*5.88*	*6.55*
Test (turnover1=turnover5)						3.42	7.14							3.31	7.16
P-value						0.0007	0.0076							0.0010	0.0075

Table 5. Trading Volume and Earnings Momentum, Controlling for Price Momentum

The table reports the average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past earnings surprise orthogonalized with respect to past one-year return, for the period from October 1971 to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX with non-missing quarterly earnings data by their average monthly turnover over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their most recent earnings surprise orthogonalized with respect to return over the prior year. We estimate the orthogonalized earnings surprise by running a cross-sectional regression of past earnings surprise on past one-year return. The table reports the average equal-weighted raw and adjusted returns and *t*-statistics (in *italics)* of these double-sorted portfolios, the average return spreads between earnings surprise quintiles 5 and 1 within each turnover group, and the intercepts from time series regressions of the 5-1 return spreads on the Fama-French factors. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. The table also reports the *t* and *F* statistics for the hypotheses that the average earnings momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively.

	Raw Returns						
	Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0085	0.0124	0.0158	0.0204	0.0249	0.0164	0.0158
	3.46	*5.00*	*6.22*	*7.89*	*9.43*	*13.63*	*12.81*
2	0.0093	0.0122	0.0141	0.0169	0.0191	0.0098	0.0103
	3.53	*4.68*	*5.42*	*6.46*	*7.59*	*8.27*	*8.55*
3	0.0098	0.0119	0.0139	0.0151	0.0172	0.0075	0.0079
	3.68	*4.33*	*5.14*	*5.50*	*6.44*	*6.51*	*6.92*
4	0.0087	0.0125	0.0126	0.0134	0.0153	0.0066	0.0074
	2.88	*4.19*	*4.26*	*4.40*	*5.08*	*5.20*	*5.69*
Turnover5	0.0078	0.0092	0.0105	0.0122	0.0136	0.0058	0.0060
	2.15	*2.62*	*2.95*	*3.34*	*3.78*	*3.95*	*3.99*
Test (turnover1=turnover5)						5.62	25.18
P-value						0.0001	0.0001

	Characteristic-Adjusted Returns						
	Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	-0.0060	-0.0026	0.0015	0.0048	0.0090	0.0150	0.0142
	-5.84	*-2.56*	*1.54*	*4.92*	*9.93*	*13.45*	*12.56*
2	-0.0044	-0.0015	0.0001	0.0034	0.0053	0.0097	0.0098
	-5.97	*-2.06*	*0.08*	*4.44*	*6.59*	*9.16*	*8.99*
3	-0.0030	-0.0010	0.0006	0.0028	0.0044	0.0073	0.0072
	-4.37	*-1.46*	*1.01*	*4.11*	*5.98*	*7.18*	*6.85*
4	-0.0037	-0.0002	-0.0005	0.0010	0.0030	0.0068	0.0070
	-4.91	*-0.24*	*-0.79*	*1.33*	*3.82*	*6.26*	*6.26*
Turnover5	-0.0038	-0.0026	-0.0018	0.0002	0.0017	0.0055	0.0056
	-3.09	*-2.46*	*-1.68*	*0.20*	*1.38*	*4.05*	*3.99*
Test (turnover1=turnover5)						5.42	22.93
P-value						0.0001	0.0001

Table 6. Long-Run Performance of Volume-Based Earnings Momentum

The table reports the average monthly earnings momentum profits for different turnover groups and various holding periods from October 1971to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX by their average monthly turnover over the previous year and place them into quintiles. Within each turnover quintile, we further sort stocks into quintiles based on their most recent earnings surprise. We compute the equal-weighted raw returns of these double-sorted portfolios for four holding periods: month t, months t to t+5, months t to t+11, and months t+12 to t+35. Panel A reports the average return spreads between earnings surprises quintiles 5 and 1 within each turnover group and their associated *t*-statistics (in *italics*), as well as the intercepts from time series regressions of the return spreads on the Fama-French factors. Also reported are the *t* and *F* statistics for the hypotheses that the average price momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively. In Panel B, we repeat the analysis in A, but use earnings surprise orthogonalized with respect to past one-year return to measure earnings momentum.,

Panel A: Not Controlling for Price Momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+35***	
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α
Turnover1	0.0184	0.0183	0.0142	0.0144	0.0098	0.0103	0.0050	0.0060	0.0000	0.0014
	14.31	*13.89*	*12.65*	*12.49*	*9.63*	*9.84*	*5.43*	*6.49*	*0.07*	*2.00*
2	0.0118	0.0126	0.0088	0.0100	0.0062	0.0073	0.0035	0.0046	0.0007	0.0021
	9.08	*9.66*	*7.30*	*8.25*	*5.61*	*6.56*	*3.69*	*4.98*	*0.99*	*3.02*
3	0.0107	0.0118	0.0079	0.0090	0.0060	0.0074	0.0033	0.0049	-0.0003	0.0006
	8.17	*9.09*	*6.32*	*7.27*	*5.39*	*6.71*	*3.39*	*5.10*	*-0.54*	*0.97*
4	0.0097	0.0114	0.0074	0.0090	0.0063	0.0076	0.0039	0.0053	0.0004	0.0013
	7.01	*8.29*	*5.71*	*7.07*	*5.51*	*6.88*	*3.86*	*5.35*	*0.45*	*1.65*
Turnover5	0.0108	0.0123	0.0084	0.0101	0.0069	0.0089	0.0047	0.0069	-0.0007	0.0005
	5.90	*6.70*	*5.01*	*5.98*	*4.39*	*5.80*	*3.38*	*5.10*	*-0.78*	*0.53*
Test (1=5)	3.42	7.14	2.82	4.37	1.58	0.54	0.18	0.29	0.66	0.60
P-value	0.0007	0.0076	0.0049	0.0368	0.1149	0.4632	0.8600	0.5894	0.5110	0.4402

Panel B: Controlling for Price Momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+35***	
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α
Turnover1	0.0164	0.0158	0.0132	0.0127	0.0095	0.0091	0.0054	0.0053	0.0014	0.0019
	13.63	*12.81*	*12.61*	*11.83*	*10.05*	*9.34*	*6.50*	*6.15*	*2.29*	*3.00*
2	0.0098	0.0103	0.0067	0.0072	0.0046	0.0049	0.0033	0.0036	0.0013	0.0020
	8.27	*8.55*	*6.10*	*6.38*	*4.63*	*4.83*	*4.15*	*4.40*	*2.30*	*3.49*
3	0.0075	0.0079	0.0047	0.0051	0.0034	0.0040	0.0020	0.0026	0.0004	0.0007
	6.51	*6.92*	*4.60*	*4.95*	*3.78*	*4.43*	*2.61*	*3.37*	*0.76*	*1.30*
4	0.0066	0.0074	0.0046	0.0052	0.0041	0.0043	0.0028	0.0030	0.0008	0.0010
	5.20	*5.69*	*4.20*	*4.68*	*4.47*	*4.64*	*3.82*	*3.98*	*1.39*	*1.65*
Turnover5	0.0058	0.0060	0.0049	0.0051	0.0045	0.0048	0.0039	0.0042	0.0009	0.0011
	3.95	*3.99*	*3.79*	*3.85*	*3.94*	*4.11*	*3.89*	*4.13*	*1.26*	*1.61*
Test (1=5)	5.62	25.18	4.99	19.41	3.36	7.82	1.21	0.70	0.59	0.63
P-value	0.0001	0.0001	0.0001	0.0001	0.0008	0.0052	0.2256	0.4042	0.5585	0.4268

Table 7. Residual Volume and Price and Earnings Momentum

The table reports the average monthly raw and characteristic-adjusted returns on portfolios sorted by residual turnover and past one-year return (Panels A and B) or past earnings surprise (Panels C and D). The sample period is from July 1981 to December 2005. At the beginning of each month, we rank all stocks on NYSE/AMEX with non-missing quarterly earnings data by their residual turnover and placed into quintiles. We estimate residual turnover from a cross-sectional regression of turnover on size, analyst coverage, institutional ownership, analyst dispersion, and Amihud (2002)'s illiquidity measure. In Panels A and B, we further sort stocks within each residual turnover quintile into quintiles based on either the past one-year return or past return orthogonalized with respect to past earnings surprises. We estimate the orthogonalized return by running a cross-sectional regression of past one-year return on the most recent earnings surprises. In Panels C and D, we further sort stocks in each residual turnover quintile into quintiles based on either the most recent earnings surprise or earnings surprise orthogonalized with respect to past one-year return. We estimate the orthogonalized earnings surprise by running a cross-sectional regressions of past earnings surprise on past one-year return. Panels A and C (B and D) report the average equal-weighted raw (characteristic-adjusted) returns and *t*-statistics (in *italics*) of the double-sorted portfolios, the average return spreads between past return quintiles 5 and 1 within each turnover group, and the intercepts from time series regressions of the 5-1 spreads on the Fama-French factors. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. The table also reports the *t* and *F* statistics for the hypotheses that the average momentum profits and Fama-French three-factor model intercepts for turnover quintiles 5 and 1 are equal, respectively.

Panel A: Price Momentum Profits, Raw Returns

	Not Controlling for Earnings Momentum								Controlling for Earnings Momentum						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0092	0.0122	0.0136	0.0148	0.0149	0.0057	0.0076	Turnover1	0.0101	0.0133	0.0138	0.0138	0.0137	0.0036	0.0054
	2.57	*4.68*	*5.51*	*6.06*	*5.86*	*2.04*	*2.72*		*2.86*	*5.17*	*5.49*	*5.80*	*5.39*	*1.31*	*1.97*
2	0.0061	0.0122	0.0133	0.0142	0.0160	0.0100	0.0114	2	0.0072	0.0128	0.0135	0.0129	0.0156	0.0084	0.0101
	1.63	*3.90*	*4.58*	*4.99*	*5.57*	*3.73*	*4.27*		*1.95*	*4.17*	*4.63*	*4.53*	*5.49*	*3.21*	*3.87*
3	0.0057	0.0094	0.0112	0.0143	0.0162	0.0106	0.0128	3	0.0067	0.0097	0.0121	0.0131	0.0157	0.0090	0.0111
	1.35	*2.67*	*3.43*	*4.61*	*4.96*	*4.00*	*4.97*		*1.63*	*2.76*	*3.62*	*4.20*	*4.83*	*3.47*	*4.33*
4	0.0054	0.0090	0.0115	0.0140	0.0195	0.0141	0.0162	4	0.0059	0.0095	0.0119	0.0135	0.0193	0.0134	0.0150
	1.20	*2.43*	*3.32*	*4.07*	*5.40*	*4.79*	*5.53*		*1.32*	*2.58*	*3.40*	*3.97*	*5.23*	*4.48*	*5.02*
Turnover5	0.0011	0.0080	0.0120	0.0157	0.0193	0.0182	0.0197	Turnover5	0.0023	0.0087	0.0122	0.0154	0.0188	0.0166	0.0179
	0.22	*2.00*	*3.09*	*3.86*	*4.24*	*5.62*	*5.93*		*0.47*	*2.12*	*3.09*	*3.73*	*4.14*	*5.12*	*5.40*
Test (turnover1=turnover5)						2.93	7.80							3.06	8.37
P-value						0.0036	0.0053							0.0023	0.0039

Panel B: Price Momentum Profits, Characteristic-Adjusted Returns

	Not Controlling for Earnings Momentum								Controlling for Earnings Momentum						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	-0.0024	-0.0003	0.0008	0.0021	0.0027	0.0051	0.0072	Turnover1	-0.0013	0.0004	0.0008	0.0015	0.0014	0.0027	0.0047
	-1.39	*-0.25*	*0.61*	*1.50*	*1.91*	*2.03*	*2.84*		*-0.77*	*0.33*	*0.64*	*1.07*	*1.05*	*1.12*	*1.90*
2	-0.0048	0.0007	0.0010	0.0016	0.0037	0.0085	0.0102	2	-0.0036	0.0011	0.0011	0.0002	0.0035	0.0072	0.0090
	-3.14	*0.72*	*1.24*	*1.75*	*3.43*	*3.83*	*4.49*		*-2.45*	*1.22*	*1.43*	*0.26*	*3.31*	*3.30*	*4.10*
3	-0.0045	-0.0024	-0.0009	0.0014	0.0036	0.0081	0.0102	3	-0.0034	-0.0023	0.0000	0.0004	0.0029	0.0063	0.0081
	-2.64	*-2.31*	*-1.22*	*1.99*	*3.44*	*3.53*	*4.40*		*-2.06*	*-2.23*	*-0.05*	*0.64*	*2.75*	*2.80*	*3.55*
4	-0.0051	-0.0025	-0.0005	0.0014	0.0066	0.0117	0.0138	4	-0.0046	-0.0021	-0.0001	0.0009	0.0063	0.0109	0.0125
	-2.68	*-2.31*	*-0.60*	*1.50*	*4.83*	*4.52*	*5.26*		*-2.40*	*-1.92*	*-0.15*	*1.02*	*4.54*	*4.19*	*4.73*
Turnover5	-0.0088	-0.0025	0.0009	0.0042	0.0084	0.0171	0.0189	Turnover5	-0.0079	-0.0020	0.0009	0.0039	0.0079	0.0158	0.0173
	-4.06	*-1.99*	*0.66*	*2.58*	*3.90*	*5.58*	*6.03*		*-3.61*	*-1.48*	*0.63*	*2.23*	*3.68*	*5.19*	*5.57*
Test (turnover1=turnover5)						3.05	8.47							3.34	10.01
P-value						0.0024	0.0037							0.0009	0.0016

Panel C: Earnings Momentum Profits, Raw Returns

	Not Controlling for Price Momentum								Controlling for Price Momentum						
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0083	0.0101	0.0132	0.0150	0.0182	0.0099	0.0111	Turnover1	0.0087	0.0109	0.0128	0.0150	0.0174	0.0087	0.0092
	2.98	*3.87*	*5.27*	*5.86*	*7.61*	*7.30*	*8.13*		*3.21*	*4.46*	*5.08*	*5.74*	*6.83*	*7.59*	*7.78*
2	0.0092	0.0090	0.0124	0.0153	0.0168	0.0076	0.0076	2	0.0105	0.0098	0.0119	0.0154	0.0152	0.0047	0.0044
	3.06	*2.86*	*4.28*	*5.31*	*5.64*	*5.46*	*5.35*		*3.47*	*3.30*	*4.06*	*5.24*	*4.89*	*3.56*	*3.23*
3	0.0091	0.0096	0.0112	0.0131	0.0151	0.0060	0.0051	3	0.0099	0.0101	0.0117	0.0128	0.0137	0.0038	0.0026
	2.66	*2.67*	*3.34*	*3.94*	*4.48*	*3.61*	*3.10*		*2.95*	*2.97*	*3.51*	*3.66*	*3.97*	*2.42*	*1.66*
4	0.0081	0.0104	0.0127	0.0132	0.0164	0.0082	0.0088	4	0.0105	0.0127	0.0127	0.0105	0.0145	0.0041	0.0041
	2.12	*2.83*	*3.57*	*3.69*	*4.47*	*5.05*	*5.21*		*2.81*	*3.48*	*3.63*	*2.88*	*3.89*	*2.66*	*2.61*
Turnover5	0.0063	0.0089	0.0127	0.0139	0.0165	0.0101	0.0100	Turnover5	0.0106	0.0113	0.0114	0.0116	0.0135	0.0029	0.0024
	1.42	*2.07*	*3.16*	*3.31*	*3.91*	*4.52*	*4.38*		*2.44*	*2.63*	*2.84*	*2.76*	*3.18*	*1.52*	*1.23*
Test (turnover1=turnover5)						0.09	0.17							2.65	9.33
P-value						0.9252	0.6788							0.0083	0.0023

Panel D: Earnings Momentum Profits, Characteristic-Adjusted Returns

Not Controlling for Price Momentum								Controlling for Price Momentum							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	-0.0034	-0.0022	0.0006	0.0025	0.0052	0.0085	0.0097	Turnover1	-0.0029	-0.0016	0.0000	0.0025	0.0049	0.0077	0.0082
	-2.99	*-1.90*	*0.58*	*2.25*	*4.28*	*6.73*	*7.72*		*-2.63*	*-1.46*	*-0.04*	*2.18*	*4.40*	*7.26*	*7.54*
2	-0.0022	-0.0022	0.0002	0.0030	0.0043	0.0065	0.0069	2	-0.0014	-0.0018	-0.0001	0.0033	0.0030	0.0043	0.0043
	-2.43	*-2.58*	*0.23*	*3.59*	*4.47*	*5.01*	*5.14*		*-1.47*	*-2.02*	*-0.12*	*3.47*	*3.18*	*3.50*	*3.38*
3	-0.0028	-0.0022	-0.0004	0.0009	0.0028	0.0055	0.0049	3	-0.0022	-0.0023	-0.0005	0.0013	0.0020	0.0042	0.0033
	-2.45	*-2.02*	*-0.42*	*1.13*	*3.24*	*3.68*	*3.21*		*-2.15*	*-2.47*	*-0.55*	*1.29*	*2.16*	*2.96*	*2.30*
4	-0.0032	-0.0011	0.0006	0.0008	0.0041	0.0073	0.0080	4	-0.0013	0.0006	0.0004	-0.0009	0.0025	0.0038	0.0041
	-2.52	*-0.94*	*0.54*	*0.77*	*3.81*	*4.59*	*4.91*		*-1.13*	*0.59*	*0.37*	*-0.84*	*2.30*	*2.66*	*2.75*
Turnover5	-0.0042	-0.0019	0.0015	0.0032	0.0051	0.0093	0.0094	Turnover5	0.0000	0.0005	0.0002	0.0008	0.0023	0.0023	0.0020
	-2.29	*-1.24*	*0.97*	*1.98*	*3.11*	*4.42*	*4.35*		*-0.03*	*0.30*	*0.11*	*0.53*	*1.48*	*1.36*	*1.15*
Test (turnover1=turnover5)						0.31	0.02							2.66	8.77
P-value						0.7583	0.8905							0.0082	0.0031

Table 8. Market State and Price Momentum

The table reports the average monthly characteristic-adjusted price momentum profits from July 1964 to December 2005 (498 monthly observations), and price momentum profits after controlling for earnings momentum from October 1971 to December 2005 (411 monthly observations). At the beginning of each month, we rank all stocks on NYSE/AMEX by their return over the past year (skipping the most recent month) or past one-year return orthogonalized with respect to past earnings surprises and placed into quintiles. We estimate the orthogonalized return by running a cross-sectional regression of past one-year return on the most recent earnings surprise. We compute equal-weighted characteristic-adjusted returns on the quintile portfolios over the following month. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. Panel A reports the average return spreads between past return quintiles 5 and 1 for the entire sample period and their associated *t*-statistics (in *italics*). Panel B reports the average return spreads and *t*-statistics for up and down market states separately. We define market state using returns on the value-weighted CRSP market index over the previous 36 months. Panel B also reports the *t*-statistics for the hypothesis that the price momentum profits for up and down market states are equal. Panel C reports the intercepts and coefficients on a dummy variable for market state, from time series regressions based on the CAPM and the Fama-French three-factor model. Panel D reports the intercepts and regression coefficients on lagged 36-month market return, from time series regressions based on the CAPM and the Fama-French three-factor model.

Panel A: Average Unconditional Profits

N	Price Momentum	Price Momentum, Controlling for Earnings Momentum
498 (411)	0.0087	0.0064
	4.93	*3.35*

Panel B: Average Profits Following Up/Down Markets

	N	Price Momentum	Price Momentum, Controlling for Earnings Momentum
Up Market	434 (355)	0.0104	0.0084
		6.08	*4.45*
Down Market	64 (56)	-0.0030	-0.0064
		-0.42	*-0.90*
Up-Down	*t (Mean)*	2.56	2.68

Panel C: Profits Regressed on Up/Down Market State Dummy

		Price Momentum	Price Momentum, Controlling for Earnings Momentum
CAPM Regression Coefficients	CAPM α	-0.0022	-0.0057
	t(α)	*-0.45*	*-1.12*
	Dummy(Up Market)	0.0129	0.0146
	t(Dummy)	*2.47*	*2.66*
FF Regression Coefficients	F-F α	0.0025	-0.0010
	t(α)	*0.52*	*-0.19*
	Dummy(Up Market)	0.0099	0.0114
	t(Dummy)	*1.93*	*2.12*

Panel D: Profits Regressed on Lagged Market Returns

		Price Momentum	Price Momentum, Controlling for Earnings Momentum
CAPM Regression Coefficients	CAPM α	0.0043	0.0013
	t(α)	*1.57*	*0.44*
	Lagmarket	0.0128	0.0142
	t(Lagmarket)	*2.30*	*2.50*
FF Regression Coefficients	F-F α	0.0074	0.0046
	t(α)	*2.72*	*1.57*
	Lagmarket	0.0100	0.0110
	t(Lagmarket)	*1.84*	*1.99*

Table 9. Market State and Earnings Momentum

The table reports the average monthly characteristic-adjusted earnings momentum profits (before and after controlling for price momentum) from October 1971 to December 2005 (411 monthly observations). At the beginning of each month, we rank all stocks on NYSE/AMEX with non-missing quarterly earnings data by their most recent earnings surprise, or earnings surprise orthogonalized with respect to past one-year return and place them into quintiles. We estimate the orthogonalized earnings surprise by running a cross-sectional regression of past earnings surprise on past one-year return. We compute equal-weighted characteristic-adjusted returns on these quintile portfolios over the following month. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. Panel A reports the average return spreads between earnings surprise quintiles 5 and 1 for the entire sample period and their associated *t*-statistics (in *italics*). Panel B reports the average return spreads and *t*-statistics for up and down market states separately. We define market state using returns on the value-weighted CRSP market index over the previous 36 months. Panel B also reports the *t*-statistics for the hypothesis that the earnings momentum profits for up and down market states are equal. Panel C reports the intercepts and coefficients on a dummy variable for market state, from time series regressions based on the CAPM and the Fama-French three-factor model. Panel D reports the intercepts and regression coefficients on lagged 36-month market return, from time series regressions based on the CAPM and the Fama-French three-factor model.

Panel A: Average Unconditional Profits

N	Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
411	0.0114	0.0082
	12.98	*13.78*

Panel B: Average Profits Following Up/Down Markets

	N	Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
Up Market	355	0.0113	0.0076
		12.80	*11.96*
Down Market	56	0.0122	0.0123
		3.78	*7.41*
Up-Down	*t (Mean)*	0.34	2.75

Panel C: Profits Regressed on Up/Down Market State Dummy

		Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
CAPM Regression Coefficients	CAPM α	0.0122	0.0122
	t(α)	*5.13*	*7.63*
	Dummy(Up Market)	-0.0009	-0.0047
	t(Dummy)	*-0.34*	*-2.73*
FF Regression Coefficients	F-F α	0.0144	0.0126
	t(α)	*6.15*	*7.82*
	Dummy(Up Market)	-0.0025	-0.0051
	t(Dummy)	*-1.00*	*-2.97*

Panel D: Profits Regressed on Lagged Market Returns

		Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
CAPM Regression Coefficients	CAPM α	0.0116	0.0094
	t(α)	*8.52*	*10.22*
	Lagmarket	-0.0005	-0.0032
	t(Lagmarket)	*-0.18*	*-1.81*
FF Regression Coefficients	F-F α	0.0131	0.0096
	t(α)	*9.67*	*10.29*
	Lagmarket	-0.0021	-0.0037
	t(Lagmarket)	*-0.83*	*-2.06*

Table 10. Business Cycles and Price and Earnings Momentum

The table reports the average monthly characteristic-adjusted price and earnings momentum profits. At the beginning of each month, we rank all stocks on NYSE/AMEX by their return over the past year or their most recent earnings surprise and place them into quintiles. We compute equal-weighted characteristic-adjusted returns on the quintile portfolios over the following month. To calculate the characteristic-adjusted returns, we follow Daniel, Grinblatt, Titman, and Wermers (1997) and use a characteristic-based matching procedure to account for the return premia associated with size and book-to-market. Panel A report the average price momentum profits and *t*-statistics (in *italics*) for up and down business cycles separately. A down cycle starts six months following the beginning of a recession (as defined by NBER) and ends two years after the recession is over. We also report the *t*-statistics for the hypothesis that the price momentum profits for up and down business cycles are equal. Panel B reports the intercepts and coefficients on a dummy variable for business cycle, from time series regressions based on the CAPM and the Fama-French three-factor model. Panels C and D repeat the analyses in Panels A and B for earnings momentum.

Panel A: Average Price Momentum Profits Following Up/Down Business Cycle

	N	Price Momentum	Price Momentum, Controlling for Earnings Momentum
Up Cycle	331 (259)	0.0109	0.0095
		5.43	*4.09*
Down Cycle	167 (152)	0.0042	0.0011
		1.24	*0.33*
Up-Down	*t (Mean)*	1.82	2.14

Panel B: Price Momentum Profits Regressed on Up/Down Business Cycle Dummy

		Price Momentum	Price Momentum, Controlling for Earnings Momentum
CAPM Regression Coefficients	CAPM α	0.0048	0.0016
	t(α)	*1.57*	*0.52*
	Dummy(Up Cycle)	0.0065	0.0083
	t(Dummy)	*1.74*	*2.13*
FF Regression Coefficients	F-F α	0.0084	0.0055
	t(α)	*2.77*	*1.75*
	Dummy(Up Cycle)	0.0041	0.0055
	t(Dummy)	*1.13*	*1.42*

Panel C: Average Earnings Momentum Profits Following Up/Down Business Cycle

	N	Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
Up Cycles	259	0.0109	0.0070
		10.58	*9.05*
Down Cycles	152	0.0124	0.0102
		7.69	*11.28*
Up-Down	*t (Mean)*	0.84	2.68

Panel D: Earnings Momentum Profits Regressed on Up/Down Business Cycle Dummy

		Earnings Momentum	Earnings Momentum, Controlling for Price Momentum
CAPM Regression Coefficients	CAPM α	0.0124	0.0101
	t(α)	*8.58*	*10.44*
	Dummy(Up Cycle)	-0.0015	-0.0032
	t(Dummy)	*-0.84*	*-2.61*
FF Regression Coefficients	F-F α	0.0141	0.0104
	t(α)	*9.80*	*10.48*
	Dummy(Up Cycle)	-0.0029	-0.0035
	t(Dummy)	*-1.65*	*-2.86*