A Tale of Two Anomalies: The Implication of Investor Attention for Price and Earnings Momentum[*]

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Abstract

We examine the profitability of price and earnings momentum strategies. We find that price momentum profits are higher among high volume stocks and in up markets, while earnings momentum profits are higher among low volume stocks and in down markets. In the long run, price momentum profits are reversed, while earnings momentum profits are not. The dichotomy between price and earnings momentum is more pronounced when we orthogonalize one with respect to the other. To the extent that trading volume increases with investor attention and that investors tend to pay more attention to stocks in up markets, our results suggest a dual role for investor attention: while price underreaction to earnings news declines with investor attention, price continuation caused by investors' overreaction rises 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 exists 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. There is now a growing literature analyzing the economic consequences of agents' attention. Sims (2003) models agents' attention constraints to explain consumption and price stickiness. Hirshleifer and Teoh (2003, 2005) analyze firms' accounting disclosure policy and the resulting price dynamics in the presence of inattentive investors. Gabaix, et al (2005) study agents' directed attention in response to economic incentives. Barber and Odean (2005) study how salient events can capture investors' attention and affect their stock buying and selling decisions. Peng (2005) and Peng and Xiong (2006) analyze the effects of limited attention on investors' learning behavior and equilibrium price dynamics.

Attention is a crucial factor in investors' reaction to information. In this paper, we examine how attention affects asset price dynamics through investors' under- and overreactions to information, two basic mechanisms developed in the finance literature to explain a large body of empirical anomalies in asset return predictability.[2] Specifically, we analyze the role of investor attention in two widely documented anomalies – price momentum and earnings momentum (also known as post-earnings announcement drift).

We hypothesize that investor attention has a dual role– on the one hand, inadequate attention directly causes ignorance of useful information and therefore stock price underreaction; on the other, attention can interact with investors' behavioral biases, such as extrapolative expectations and overconfidence, to generate price overreaction. When investors pay less attention to a company's stock, they are more likely to ignore the company's earnings announcements and, therefore, they are unable to

[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 these empirical anomalies and the related behavioral theories.

fully incorporate the information into the stock prices. Consequently, there is a more pronounced post-announcement drift as this information later becomes reflected in the prices. Post-earnings announcement drift has been documented by a large number of empirical studies, e.g., Ball and Brown (1968) and Bernard and Thomas (1989). They find that buying stocks with recent good earnings news, while simultaneously shorting stocks with recent bad earnings news, can generate positive profits that are unrelated to risk.

Attention is also a necessary condition for investors to overreact to any information. The existing models typically attribute overreaction to behavioral biases. For example, De Long, et al (1990) associate investors' overreaction to assets' past returns with their extrapolative expectations. Daniel, Hirshleifer and Subrahmanyam (1998) use overconfidence and self attribution bias as a source of investors' overreaction to their private information. Both of these overreaction mechanisms can explain price momentum. This is a phenomenon, as documented by Jegadeesh and Titman (1993), wherein buying stocks with recent superior returns while simultaneously shorting stocks with recent inferior returns can provide excess profits. While these behavioral biases have received considerable thought in the literature, a crucial ingredient in these mechanisms – investor attention – is often ignored. We introduce attention into these mechanisms and hypothesize that overreaction-driven price momentum is more pronounced among those stocks that attract more investor attention.

In this paper, we perform both cross-sectional and time-series tests of our hypothesis using proxies associated with investor attention. For the cross-sectional analysis, we use trading volume as a proxy. Trading often involves investors' attention in analyzing their portfolios and asset fundamentals. On the one hand, when investors pay less attention to a stock, they are less likely to trade it; on the other, when they pay more attention to a stock, behavioral biases such as overconfidence can give rise to heterogeneous opinions among investors about asset fundamentals, thus generating more trading (Odean, 1998 and Scheinkman and Xiong, 2003). In consideration of both effects, the hypothesis for the cross-sectional analysis is that *low* volume stocks tend to exhibit stronger price underreaction to earnings news; in contrast, *high* volume stocks tend to 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 volume and prior stock returns. We measure price momentum profit as the average return difference between past winners and losers. Similarly, we construct portfolios sorted by volume and standardized unexpected earnings (SUE). We measure earnings momentum profits by the return difference between stocks having the highest and the lowest unexpected earnings. We also consider the possibility that investors' under- and overreactions could operate together in generating both price and earnings momentum profits. To focus on the part of price momentum profits caused by investors' overreaction to past returns, we regress the prior one-year return onto SUE and use the regression residual as the sorting variable to form price momentum portfolios. Likewise, to focus on the part of earnings momentum profits caused by investors' underreaction to earnings news, we regress unexpected earnings onto the prior 12-month stock return and use the regression residual as the sorting variable to form earnings momentum portfolios. To account for the return premia associated with size and book-to-market equity, we adjust stock returns by employing 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 profits, in both raw and adjusted returns, monotonically increase with trading volume. The difference in characteristic-adjusted price momentum profits between the highest and lowest volume quintiles is both statistically and economically significant with a value of 83 basis points per month. Controlling for earnings momentum causes the price momentum profits to drop across volume quintiles, but does not change the monotonically increasing relationship between price momentum profits and volume. We also find evidence of reversal – the long-run returns of the price momentum portfolios for months 13-60 after portfolio formation are negative for all volume quintiles with or without controlling for earnings momentum. Overall, these results suggest that there is a significant overreaction-driven component in price momentum and this component monotonically increases with trading volume, consistent with our hypothesis that over-reaction driven price momentum increases with investor attention.

We find that earnings momentum profits decrease with trading volume, with a difference in characteristic-adjusted profits between the two extreme volume quintiles of 64 basis points per month. The difference becomes even larger after controlling for price momentum. The characteristic-adjusted profit in the lowest volume quintile is 94 basis points per month higher than that in the highest quintile, and this difference is significant with a p-value of 0.01%. Controlling for price momentum also causes a sizable drop in earnings momentum profits among high volume stocks, suggesting that earnings momentum profits are partially related to price momentum. Finally, the long-run returns of the earnings momentum portfolios in years 2-5 show no sign of reversal. These results support our hypothesis that investors' underreaction to earnings news contributes to earnings momentum and the degree of underreaction is decreasing 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 investors' underreaction to earnings news is *stronger* in down markets than in up markets, but overreaction-driven price momentum is *weaker* in down markets.

We define a month as an "UP" or "DOWN" market depending on whether the market return for the prior 36 or 24 months is above or below zero. We then analyze the patterns in price and earnings momentum profits across the UP and DOWN months. We find that price momentum profits barely exist in DOWN months, but are significantly positive in UP months. The difference, more than 1 percent per month, is statistically significant. By contrast, the earnings momentum profits, after controlling for price momentum, are significantly higher in DOWN months than in UP months with a difference of 42 basis points per month. We also employ an alternative definition of market states based on the business cycles classified by the National Bureau of Economic Research (NBER) and find similar results. The opposing patterns in price and earnings momentum profits across UP and DOWN months directly support our attention-based hypothesis.

Our study contributes to the literature on price and earnings momentum anomalies by demonstrating that the analysis of investor attention can sharpen our understanding of the two phenomena. Existing theories in behavioral finance adopt mechanisms based on either investors' under- or overreaction to explain these two phenomena. Although there is evidence supporting both types of mechanisms, the literature remains largely inconclusive on which mechanism is the main driver. This is because competing theories often make similar predictions regarding each phenomenon, lacking distinct implications to differentiate their sources. Incorporating investor attention allows us to generate contrasting predictions for under- and overreaction-based mechanisms, which we test empirically.

Our study also contributes to the growing empirical literature analyzing the effects of investor inattention on stock price dynamics, e.g., Huberman and Regev (2001), Hirshleifer, et al (2004), Hou and Moskowitz (2005), Hong, Torous and Valkanov (2005), Della Vigna and Pollet (2005a, b), Cohen and Frazzini (2006), and Hirshleifer, Lim and Teoh (2006). 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 results emphasize the dual role of investor attention: investor attention not only affects stock price underreaction, but also interacts with price overreaction. This dual role sharpens our understanding of earnings and price momentum, two pervasive patterns in stock price dynamics.

Finally, our study adds to the findings of Lee and Swaminathan (2000) and Cooper, Gutierrez, and Hameed (2004). Lee and Swaminathan find that price momentum is more pronounced among high volume stocks, while Cooper, Gutierrez, and Hameed show that price momentum is stronger in up markets. Motivated by the attention-based hypothesis, we extend these studies by analyzing the joint properties of price and earnings momentum for stocks with different levels of trading volume and across up and down markets.

The paper is organized as follows. Section 2 reviews the related empirical and theoretical literature on price and earnings momentum. Section 3 develops attention-based hypotheses for these two anomalies. Section 4 describes the data used in our empirical analysis. In Sections 5, we test our cross-sectional hypothesis using trading volume as a proxy of investor attention. In Section 6, we analyze the price and earnings momentum profits across up and down markets. We conclude in Section 7.

2 Related literature on price and earnings momentum

There is a large body of literature studying the price and earnings momentum anomalies. In this section, we review several closely related empirical studies and explanations based on investors' under- and overreactions to information.

Jegadeesh and Titman (1993) demonstrate that a trading strategy based on buying recent winners over the past 3-12 months and simultaneously shorting recent losers can generate a significant profit. 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 (2006).

Several studies, e.g., Ball and Brown (1968) and Bernard and Thomas (1989) find that for a period of 60 days after earnings announcements, returns of NYSE/AMEX stocks continue to drift up for "good news" firms and down for "bad news" firms. This phenomenon is often referred to as post-earnings announcement drift or earnings momentum. Chan, Jegadeesh and Lakonishok (1996) show that earnings momentum strategies are profitable even among larger stocks and cannot be explained by the Fama-French three-factor model. Furthermore, they show that although price and earnings momentum are related, one effect cannot be subsumed by the other.

Since there is not enough evidence to justify rational factor risk models as the sole explanation of price and earnings momentum effects, the finance literature has explored frictions and biases in investors' information processing for alternative explanations. Several papers model investors' underreaction to information, e.g., Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999). In these models, investors underreact to news about firm fundamentals, resulting in insufficient initial price reaction to the news. As the news gradually gets incorporated into prices, this process generates both price and earnings momentum. These models differ in the specific mechanism that leads to investor underreaction. Barberis, Shleifer and Vishny (1998) assume that investors are subject to conservatism, the tendency to underweight new information and overweight their priors. Hong and Stein (1999) assume that private information diffuses slowly among a population of "newswatchers", who makes forecasts based only on their private information. More recently, Hirshleifer and Teoh (2005), Peng (2005), and Peng and Xiong (2006) show that investor inattention can lead to ignorance of useful information and therefore price underreaction. This inattention-based underreaction reflects investors' attention constraints in information processing, it is not a behavioral bias in itself. Inattention is also a potential explanation for the slow-information-diffusion mechanism proposed by Hong and Stein (1999). Our hypotheses build on the inattention-based underreaction mechanism.

De Long et al (1990) and Daniel, Hirshleifer and Subrahmanyam (1998) focus on investors' overreactions. De Long et al model positive feedback traders, who buy more of an asset that has recently gone up in value. This type of positive feedback trading can be driven by extrapolative expectations, where investors extrapolate past returns into their expectation of future returns (a form of overreaction). If a company's stock price goes up this period, positive feedback traders buy the stock in the following period, causing a further price increase, which in turn can generate both earnings and price momentum. Daniel, Hirshleifer and Subrahmanyam focus on investors' overconfidence, a tendency to overestimate the precision of their private information, and self attribution bias, a tendency to attribute success to themselves but failure to external reasons. They show that 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 initial overconfidence is, on average, followed by even greater overconfidence. This mechanism generates momentum. We extend these overreaction-driven mechanisms by analyzing their interaction with investor attention.

Investors' under- and overreaction to information can work together or independently to generate earnings and price momentum. Both explanations command some support from the data. Hong, Lim and Stein (2000) find that price momentum is more pronounced among smaller firms and firms with lower levels of analyst coverage. Since information tends to diffuse slowly for these firms, their findings support the slow information diffusion hypothesis as a potential explanation of price momentum. Lee and Swaminathan (2000) and Cooper, Gutierrez, and Hameed (2004) show that price momentum profits tend to reverse after two years, suggesting that at least part of the observed price momentum profits is driven by investors' overreaction. The existing studies do not find any evidence of long run reversion in earnings momentum (Chan, Jegadeesh and Lakonishok, 1996), suggesting that earnings momentum is largely driven by investors' underreaction. Our attention-based hypotheses relate to both investor under- and overreactions by drawing contrasting predictions for price and earnings momentum.

3 Hypothesis development

Due to limited attention, investors can only attend to a subset of all available information. Investor attention could have a dual role on stock prices. On the one hand, inadequate attention directly leads to ignorance of certain information and consequently stock price underreaction; on the other, investors' behavioral biases, such as extrapolative expectations and overconfidence, could lead to price overreaction to information to which investors attend. In this section, we develop this notion and form empirical hypotheses for price and earnings momentum.

Investor attention affects asset prices when the marginal investor is attention constrained. This view is supported by the growing evidence that useful public information is ignored or only gradually incorporated in stock prices. Huberman and Regev (2001) provide a vivid example: the initial news about a new cancer curing drug from EntreMed was ignored by investors and did not cause much stock price reaction; but when the same news appeared several months later on the front page of *New York Times*, the price jumped up for more than 300%. Hou and Moskowitz (2005) demonstrate delays in the incorporation of information into the prices of individual stocks, especially for smaller and less visible stocks. Hong, Torous, and Valkanov (2005) find that the returns of several industry portfolios are able to predict the movement of market indices in U.S. and eight other developed countries. Della Vigna and Pollet (2005a) show that publicly available demographic information is not fully incorporated into the stock prices of age-sensitive industries, such as toys, vehicles, beer, life insurance, and nursing homes. Cohen and Frazzini (2006) find that stock prices do not promptly incorporate public news about economically related firms, such as customers and suppliers. The recent accounting literature, e.g., Sloan (1996) and Hirshleifer, et al (2004), find that a firm' accruals, a component in reported earnings that adjusts cash flows, have negative predictive power for stock returns, suggesting that investors ignore the differences in different earnings components. Della Vigna and Pollet (2005b) find that earnings announcements made on Friday, during which market participants are usually less attentive to business activities, generate significantly lower price reactions and trading volume than non-Friday announcements and experience 60 percent greater delayed responses in the long run. Hirshleifer, Lim and Teoh (2006) study the competition for investor attention of earnings announcements. They find that the immediate stock price and volume reaction to a firm's earnings surprise is weaker, and post-earnings announcement drift is stronger, when a greater number of earnings announcements by other firms are made on the same day.

The marginal investor represents an aggregation of individual and institutional investors in the market. There is evidence suggesting that both individual investors and professionals have limited attention.[3] Barber and Odean (2005) find that individual in-

[3]Many standard asset pricing theories require the existence of perfectly efficient arbitrageurs, who distill new information with lightning speed and seamless precision. However, such efficiency is unreal-

vestors' stock buying and selling decisions are influenced by salient, attention-grabbing events. Corwin and Coughenour (2005) show that NYSE specialists' attention constraints affect execution quality (price improvement and transaction cost) in securities that they are responsible for making markets. In addition, Hirst and Hopkins (1998) provide experimental evidence that professional analysts often fail to recall and respond appropriately to information in complex financial disclosures.

Limited attention imposes a constraint on the amount of information that investors can process and react to. Consequently, investors could ignore useful public information. Hirshleifer and Teoh (2005), Peng (2005), and Peng and Xiong (2006) develop theoretical models to analyze this effect. Hirshleifer and Teoh analyze a setting in which only a fraction of investors attend to a firm, while Peng and Xiong study models in which the marginal investor allocates attention across firms. These models 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, the price continues to drift in the direction of the earnings surprises, as the information eventually gets incorporated. Thus, investor inattention gives rise to earnings momentum. Furthermore, the magnitude of the earnings momentum decreases with the level of investor attention.

Limited attention is not a behavioral bias, but it could interact with biases in the way investors react to information. Extrapolative expectations and overconfidence are two types of behavioral biases that have been used to explain price momentum based on investor overreaction, e.g., De Long, et al (1990) and Daniel, Hirshleifer and Subrahmanyam (1998). In particular, extrapolative expectations cause investors to overly extrapolate stocks' past returns into their expectations of future returns, while overconfidence causes investors to overweight their private information and therefore overreact to this information. Both mechanisms can generate price momentum, with investor attention being a necessary ingredient. If investors do not pay attention to a stock, they can neither overly extrapolate the stock's past returns, nor overreact

istic. 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 arbitrageurs.

to their private information. 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 summary, investor attention has a dual role in stock price under- and overreaction: while inadequate attention directly generates price underreaction to earnings news and earnings momentum, the interaction between attention and investors' learning biases (extrapolative expectations or overconfidence), leads to overreaction-driven price momentum. Cross-sectionally, we expect stocks that receive *more* investor attention to display *stronger* overreaction-driven price momentum, but *weaker* earnings momentum.

It is difficult to directly measure investor attention. The economics and psychology literature still do not fully comprehend the determinants of investor attention.[4] We use trading volume as a proxy of investor attention in our cross-sectional analysis. On the one hand, investors cannot actively trade a stock if they do not pay attention to it; on the other, when investors do pay attention, behavioral biases such as overconfidence can give rise to heterogeneous opinions among investors about asset fundamentals, thus generating more trading (Odean, 1998 and Scheinkman and Xiong, 2003).

There is evidence supporting the link between trading volume and investor attention. Lo and Wang (2000) show that trading volume tends to be higher among large stocks, consistent with the fact that large stocks attract more investor attention. Chordia and Swaminathan (2000) find that, controlling for firm size, returns of high volume portfolios lead returns of low volume portfolios, suggesting that low volume stocks receive less investor attention and that trading volume is a better measure of investor attention than firm size. Gervais, Kaniel and Mingelgrin (2001) find that prices of stocks that experience unusually high volume appreciate more in the following month.

[4]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 (2005), 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 (2005) examine stock trading generated by investor attention that is driven by salient events.

They argue that the increase in volume raises a stock's visibility and attracts more investor attention. Finally, a stock's abnormal daily trading volume has also been used by Barber and Odean (2005) as an attention proxy.

Using trading volume as a proxy for investor attention, we obtain the following testable hypothesis:

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

We further expect that the overreaction-driven price momentum would reverse in the long run, as price overreaction is eventually corrected. In contrast, if earnings momentum is caused by investor inattention, then the price drift 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 activity in three Scandinavian data sets: the daily number of investor account look-ups at a large Norwegian financial service company, the daily number of online logins of a major Swedish bank, and the daily number of pension account look-ups by investors of the Swedish Pension Authority. In their study, 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.[5]

The increased attention in up markets can cause investors to overreact more to their private information or to past returns, generating a more pronounced pattern of overreaction-driven price momentum. The increased attention also means that firms' earnings announcements are less likely to be ignored by investors, causing weaker earnings momentum in up markets. We summarize the time-series predictions of price and earnings momentum in the following hypothesis:

[5]Karlsson, Loewenstein and Seppi explain this finding with a model, in which allocating attention to one's portfolio not only provides additional information, but also increases the psychological impact of information on utility.

Hypothesis II. Price momentum is *stronger* in *up* markets than in down markets, while earnings momentum is *weaker* in up markets than in down markets.

4 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. excluding ADRs, closed-end funds, 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 make the volume incomparable with NYSE/AMEX volume.[6]

We measure trading volume using the average monthly turnover during 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 is 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, a firm has to have the most recent earnings announcement within four months prior to the portfolio formation month. Following Chan, Jegadeesh and Lakonishok (1996), we measure earnings surprise using the standardized unexpected earnings (SUE).[7] The SUE for stock i in month t is defined as

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

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.

[6]We obtain very similar results when we include NASDAQ stocks by following the literature, e.g., LaPlante and Muscarella (1997) and Hou (2006), to divide the NASDAQ volume by a factor of two. For brevity, they are not reported but can be made available upon request.

[7]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 obtain results that are very similar to those using the SUE measure.

In addition, size is CRSP market capitalization at the end of June of year t. Book equity is COMPUSTAT stockholder's equity plus balance sheet deferred tax and investment tax credit minus the book value of preferred stock. Book-to-market equity is then calculated by dividing book equity from the fiscal year end in year $t-1$ by CRSP market capitalization at the end of December of year $t-1$. Size and book-to-market equity are matched with monthly returns from July of year t to June of year $t+1$, following Fama and French (1992). For some of our tests, we obtain analyst coverage and institutional ownership data from the Institutional Brokers Estimate System (IBES) and the Standard & Poors, respectively. The data on analyst coverage are available from 1976, and the data on institutional ownership are available from 1981. The availability of these two variables are generally biased towards larger firms. Analyst coverage is defined as the monthly number of analysts providing current fiscal year earnings estimates, averaged over the previous year. We also compute analyst dispersion, which is the monthly standard deviation of analysts' annual earnings forecasts divided by the absolute value of the mean forecast, averaged over the previous year, as in Diether, Malloy, and Scherbina (2002). The calculation of analyst dispersion further restricts our sample to firms covered by at least two analysts. Institutional ownership is measured in December of the year t-1. Finally, we measure a stock's liquidity using Amihud's (2002) illiquidity measure, which is the average daily absolute return divided by daily dollar trading volume over the previous year.

5 Cross-sectional analysis

In this section, we examine Hypothesis I, which posits that price momentum is stronger among high volume stocks, whereas earnings momentum is stronger among low volume stocks.

5.1 Empirical methodologies

To examine the relationship 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 stocks into quintiles based on their cumulative return over the past twelve months (skipping the most recent month to avoid market microstructure effects).[8] 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.

Part of the price momentum profits could be caused by investors' underreaction to the earnings news. This would be the case if past return winners recently had positive earnings surprises, and past return losers recently had negative earnings surprises. To control for this possibility, we estimate cross-sectional regressions of the past 12-month stock returns on the most recent unexpected earnings (SUE) and use the residual returns as the sorting variable to form price momentum portfolios.[9]

To analyze the relationship between trading volume and earnings momentum, we form portfolios double-sorted by turnover and unexpected earnings (SUE). 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. An earnings momentum strategy is to buy stocks in the highest SUE quintile and simultaneously short stocks in the lowest SUE quintile. The profit of this strategy is the return spread between the highest and the lowest SUE quintiles.

The observed earnings momentum profits can be partially driven by investors' overreaction to the prior return, independent of their response to the unexpected earnings. This would be the case when a prior positive (negative) earnings surprise coincided with

[8]Earlier studies, e.g., Jegadessh and Titman (1993), find that alternative strategies with portfolio formation periods ranging from 1 to 4 quarters and holding periods from 1 to 12 months provide similar trading profits.

[9]We have also used a two-way sorting procedure to purge the effect of past unexpected earnings from past returns, and obtained very similar results. Specifically, within each turnover quintile, we first sort stocks into five SUE groups based on their most recent unexpected earnings. Stocks within each SUE group are then sorted into five portfolios based on their past twelve month returns. Finally, 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 unexpected earnings relatively constant.

a positive (negative) stock return. The existence of this overreaction-driven component in earnings momentum could confound our inferences of investors' underreaction to earnings news. To control for this effect, we estimate cross-sectional regressions of SUE on the past one-year return, and then use the regression residuals to form earnings momentum portfolios.

We also analyze the long-run performance of price and earnings momentum strategies. We compute profits for four additional holding periods, months 1-3, 1-6, 1-12, and 13-60 after the portfolio formation month.

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

$$R_{jt} = \alpha_j^{FF} + \beta_j^M R_{Mt} + \beta_j^{HML} R_{HML,t} + \beta_t^{SMB} R_{SMB,t} + \epsilon_{jt}, \tag{1}$$

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 captured to the book-to-market effect in average returns, $R_{SMB,t}$ is the return spread between portfolios of small and large stocks, designed to captured 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} measures the average momentum profit unexplained by the Fama-French three-factor model. The factor returns are downloaded from Ken French's website.

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 analyze the characteristic-adjusted returns of the turnover and past-return/earnings surprise double-sorted portfolios, as well as the momentum profits computed from the characteristics-adjusted returns. We follow the characteristics-matching procedure in Daniel, Grinblatt, Titman, and Wermers (1997) to account for the return premia associated with size and book-to-market equity. In particular, we sort stocks first into size deciles, and then within each size decile further into book-to-market deciles. Stocks are equal-weighted within each of these 100 portfolios to form a set of 100 benchmark portfolios. To calculate the size and

BE/ME-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 BE/ME completely describe the cross-section of expected returns.

Previous literature has documented 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 stocks' average monthly 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 turnover-sorted momentum portfolios.

5.2 Results on price momentum

Table 1 reports average monthly raw and characteristic-adjusted returns of portfolios sorted by turnover and past one year return, as well as the return spread between past winners and past losers within each turnover group. For all turnover quintiles, the average monthly price momentum profit is statistically significant. Consistent with our hypothesis, the raw profit increases monotonically from 49 basis points per month for the lowest turnover quintile to 138 basis points for the highest turnover quintile. The difference in profits between the two extreme turnover quintiles is 89 basis points and is statistically significant.

After controlling for the Fama-French factor returns and/or characteristic-based benchmark portfolio returns, the price momentum profit continues to increase monotonically with turnover. For example, the characteristic-adjusted momentum profit increases from 40 basis points per month for the lowest turnover quintile to 123 basis points for the highest turnover quintile, a difference of 83 basis points per month that is highly significant (p-value=0.0060). Additionally, adjusting for the Fama-French factor returns further increases the difference in momentum profit to 98 basis points per month between the two extreme turnover quintiles.[10]

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).[11] The monotonically increasing relationship between turnover and price momentum profit remains robust. The average characteristic-adjusted profit increases from 7 basis points per month for the lowest turnover quintile to 104 basis points per month for the highest turnover quintile. The difference between the two extreme quintiles is significant at the one percent level (p-value=0.0036). When compared to Table 1, the average price momentum profit in Table 2 drops by approximately 20-30 basis points per month and is insignificant in the lowest turnover quintile, suggesting that underreaction to earnings news partially contributes to the price momentum profits observed in Table 1.[12]

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+59. We report the characteristic-adjusted profits for all holding periods, and in addition, the raw profits for month t+12 to t+59.[13] Panel A presents the results without controlling for earnings momentum, while Panel B presents the results after controlling for earnings momentum by orthogonalizing past returns with respect to past earnings surprises.

[10]Table 1 also shows that almost the entire differences in price momentum profit across turnover quintiles come from loser portfolios. The high turnover losers under-perform low turnover losers by 81 basis points per month after characteristic adjustment, whereas the difference is only 1 basis point per month for winner portfolios. This finding suggests that when investors pay attention, they overreact much more to negative past returns than to positive ones.

[11]Due to the availability of quarterly earnings data, the analysis in this table is performed over the October 1971 to December 2005 period.

[12]We have verified that the reductions in price momentum profit is not due to the difference in sample between Tables 1 and 2. For example, the characteristic-adjusted price momentum profit (not controlling for earnings momentum) is 45, 66, 77, 102, 129 basis points per month for turnover quintile 1 through 5 when we restrict our analysis to the October 1971 to December 2005 period and to firms with non-missing quarterly earnings data.

[13]We report raw profits for the longer holding period because past research (e.g. Fama and French (1996)) has shown 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 of DeBondt and Thaler (1985), which could in turn limit our ability to identify potential reversal of price momentum profits.

As the holding period increases from one month to 12 months after portfolio formation, the average monthly price momentum profit (with or without controlling for earnings momentum) drops across the five turnover quintiles, although most of them still remain significantly positive. The decrease in profits suggests that price momentum gradually weakens during the first year after portfolio formation. More importantly, price momentum profit continues to increase monotonically with turnover. The difference in profit between the two extreme turnover quintiles decreases as holding period increases, but remains significant for six months after portfolio formation.

Between years two and five, the raw price momentum profit is negative for all five turnover quintiles, and is significant in most cases. After adjusting for size and book-to-market characteristics and the Fama-French three-factor model, the negative profits fall substantially and most of them also lose their statistical significance. Nevertheless, Table 3 shows that price momentum profit reverses two to five years after portfolio formation, confirming that a significant part of the observed price momentum is driven by investor overreaction.[14]

Taken together, Tables 1-3 demonstrate that an important part of the observed price momentum profit is related to investor overreaction and this overreaction-driven price momentum effect is more pronounced among high turnover stocks, supporting the hypothesis that overreaction-driven price momentum increases with investor attention.[15]

5.3 Results on earnings momentum

Table 4 reports the average monthly raw and characteristic-adjusted returns of portfolios sorted by turnover and standardized unexpected earnings (SUE), as well as the

[14]One might argue that since investor overreaction is stronger among high turnover stocks, we should expect more pronounced reversals in years 2-5 from these stocks as well. However, the difference in raw momentum profit between turnover quintiles 5 and 1 for this holding period is insignificant, largely reflecting noise in long-run returns.

[15]Our results are also consistent with the finding of Lee and Swaminathan (2000), who document a monotonically increasing relationship between price momentum profit and trading volume. Motivated by our attention-based hypothesis, we extend their study by analyzing the joint patterns of price and earnings momentum. Our hypothesis also motivates us to control for the effect of earnings momentum in studying price momentum.

return spread between the highest and lowest SUE portfolios within each turnover quintile. The earnings momentum profit is highly significant for all five turnover quintiles. The average raw profit is 181 basis points per month for the lowest turnover quintile and 107 basis points for the highest turnover quintile. The difference of 74 basis points per month is highly significant at the one percent level. The magnitude and statistical significance of the difference in profit remain similar after controlling for the Fama-French three-factor model or the characteristic-based benchmark portfolios. Finally, the profit pattern is somewhat flat across turnover quintiles 3-5.

Table 5 reports the earnings momentum profits after controlling for the price momentum effect, using the residual SUE with respect to past one year return as the sorting variable. The earnings momentum profit now decreases monotonically with turnover, consistent with our attention-based hypothesis. For example, the characteristic-adjusted profit drops from 151 basis points per month in turnover quintile 1 to 57 basis points in quintile 5. The spread of 94 basis points is statistically significant with a p-value of 0.01%, and is much bigger than the corresponding spread of 64 basis points in Table 5. After controlling for price momentum, the analysis reveals a clear and negative relationship between trading volume and earnings momentum profit. The table also shows that after controlling for price momentum, the earnings momentum profit drops by roughly 30-40% for high turnover stocks, which suggests that price momentum contributes significantly to the observed earnings momentum profits for these stocks.[16]

Table 6 examines the long run performance of earnings momentum strategies for various holding periods. Panel A provides the results without controlling for price

[16]Table 5 also reveals 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 advocated by Barber and Odean (2005). 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. This asymmetry makes attention more important to buying decisions than to selling decisions. Empirically, Barber and Odean 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. Extending this argument, when there is good earnings news to a low attention stock, it takes longer for potential buyers to recognize the news and therefore longer for the stock price to fully incorporate the news, 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 the current owners who are already paying attention to the stock.

momentum, while Panel B controls for price momentum. Both panels show that during the first year earnings momentum profit decreases with holding horizon, but remains positive and significant. In addition, it continues to decrease with increasing turnover for holding periods up to six months after portfolio formation. The raw profits during years 2-5 are small in magnitude and are statistically indistinguishable from zero. There is no evidence of reversal in the long run, suggesting that earnings momentum is largely driven by investors' underreaction to earnings news.

In summary, Tables 4-6 show that the earnings momentum effect is more pronounced among low turnover stocks, and this negative relationship becomes even stronger after controlling for price momentum. Furthermore, the earnings momentum profits do not reverse in the long run. These results support our hypothesis that earnings momentum is mainly caused by investors' underreaction to earnings surprises and this underreaction effect is more severe among stocks receiving the least amount of investor attention.

5.4 Discussion

Our cross-sectional analysis demonstrates that a significant part of the observed price momentum effect is related to investor overreaction, and this overreaction-driven price momentum is more pronounced among high volume stocks. By contrast, we find that a significant part of the observed earnings momentum effect is caused by investors' underreaction to earnings news, and this effect is stronger among low volume stocks. To the extent that trading volume increases with investor attention, these results support our hypothesis that overreaction-driven price momentum strengthens with investor attention, while investors' underreaction to earnings news weakens with investor attention. In this subsection, we analyze the robustness of our findings and several alternative mechanisms.

Could the opposite patterns of price- and earnings-momentum profits across different turnover quintiles be caused by the correlations between turnover and variables such as size and analyst coverage that are known to generate variations in momentum profits? To address this question, we control for these variables and report the characteristic-adjusted price- and earnings-momentum profits across different residual turnover quintiles in Table 7. The residual turnover is estimated from a cross-sectional regression of average monthly turnover on size, analyst coverage, institutional ownership, analyst dispersion, and Amihud's (2002) illiquidity measure. Due to the shorter sample of our analyst coverage and institutional ownership data, the residual turnover results are calculated for the July 1981 to December 2005 period. In addition, the sample is biased toward larger and more visible stocks especially because the construction of analyst dispersion requires at least two analysts covering a stock. For a typical year, the residual turnover measure is available for about 60% of the NYSE/AMEX stocks.

Despite the shorter period and the bias towards larger stocks, Panel A of Table 7 shows that there is still a monotonically increasing pattern in the price-momentum profit across the residual turnover quintiles: The price-momentum profit after controlling for earnings momentum increases from 31 basis points per month for residual turnover quintile 1 to 167 basis points for residual turnover quintile 5. Panel B shows that the earnings-momentum profit after controlling for price momentum decreases monotonically from 64 basis points per month for residual turnover quintile 1 to 7 basis points for residual turnover quintile 5.[17] These patterns confirm that the opposite patterns of price- and earnings-momentum profits across different turnover quintiles are not driven by the control variables.

One might argue for firm size and analyst coverage as alternative proxies of investor attention, because larger stocks and stocks with higher levels of analyst coverage may attract more investor attention. However, two recent studies by Jiang, Lee and Zhang (2005) and Zhang (2005) find that both price- and earnings-momentum profits decrease with size and analyst coverage. These results differ from the opposite patterns that we find in price and earnings momentum profits with respect to trading volume. How to explain the differences in these findings? We attribute the differences to trading

[17]Panel B also shows that without controlling for price momentum, the earnings-momentum profit exhibits a U-shaped pattern across the residual turnover quintiles within a tight range of 57-81 basis points per month. However, 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 pattern between raw turnover and earnings momentum profit (without controlling for price momentum) among stocks with non-missing residual turnover.

volume being a more direct measure of investor attention. Size and analyst coverage proxy for the amount of information available in the public domain. How investors attend to this information may be a different issue. As argued by Barber and Odean (2005), people's attention is often captured by salient events. Relative to size and analyst coverage, trading volume is more directly related to actual attention, since it is a direct outcome of investor attention. In fact, Chordia and Swaminathan (2000) show that, even after controlling for firm size, high volume stocks tend to respond more quickly to information in market returns than low volume stocks. Their results suggest that trading volume captures investor attention better than firm size.

One might also argue that trading volume could pick up the cross-sectional variation in the degree of investors' overreaction to information. However, overreaction by itself cannot generate the opposite patterns in price and earnings momentum profits that we find. In particular, pure overreaction stories cannot explain why earnings momentum profit decreases with volume 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 trading volume come at least in part from the cross-sectional variation in investor attention. Nevertheless, it would be a worthwhile exercise to disentangle the effects of attention and overreaction, which we leave for future research.

Lo and Wang (2000) show that there is a significant market component in trading volume that is caused by investors' portfolio rebalancing activities. However, portfolio rebalancing due to systematic factors could not generate contrasting patterns of price and earnings momentum profits. Furthermore, since our results hold after controlling for market and other common risk factors, these results cannot be driven by common components in volume. Finally, Sadkar (2006) shows that a systematic liquidity risk factor can contribute to both price and earnings momentum. But this systematic factor would not generate the contrasting patterns we find.

6 Time-series analysis

Investor attention also varies with the state of the stock markets. As discussed earlier, Karlsson, Loewenstein and Seppi (2005) find that investors pay more attention to stocks in up markets, but "put their heads in the sand" in down markets. In this section, we test the hypothesis that price momentum is more pronounced in up markets, while earnings momentum is stronger in down markets.

Following Cooper, Gutierrez and Hameed (2004), we define market state based on the recent performance of the value-weighted CRSP index (including dividends) over the most recent 36 months or 24 months. We label a month as an "UP" market month if the recent CRSP index return is nonnegative, and as a "DOWN" market month if the recent CRSP index return is negative. There are 498 (411) months in the July 1964 to December 2005 period (or the October 1971 to December 2005 subperiod, for which we have quarterly earnings data). With the 36-month market state definition, there are 434 (355) UP months and 64 (56) DOWN months. With the 24-month market state definition, there are 428 (354) UP months and 70 (57) DOWN months.

We compute the characteristic-adjusted price and earnings momentum profits and compare the average profits across UP and DOWN months. We also use two time-series regression models to control for factor risk premia. The first regression specification uses the CAPM model:

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

R_t is the month t profit of either the price or earnings momentum strategy. α^M is the regression intercept. R_{Mt} is the excess return of the market portfolio, and β^M is the market beta of the momentum profit. $I_t(UP)$ is an indicator variable, which takes a value of 1 if month t is in an UP month and zero otherwise. k^M is the regression coefficient of the market state indicator variable. ϵ_t is random noise. The regression intercept α^M measures the average momentum profit in DOWN months, while the coefficient k^M captures the incremental average profit in UP months relative to DOWN months.

The second regression specification uses the Fama-French three factor model:

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

This specification adds two more factor-mimicking returns, $R_{HML,t}$ and $R_{SMB,t}$. α^{FF} and k^{FF} bear similar interpretations as in Equation (3).

To demonstrate that our results are robust to alternative market state specifications, we replace the market-state dummies in regressions (2) and (3) with lagged market returns over the previous 36 or 24 months. The coefficients on the lagged market returns provide further evidence on how market states affects the price- and earnings-momentum profits.

We also employ an alternative definition of market state based on the NBER business cycles. More specifically, we define the months during a recession and those within two years following the recession as "DOWN" cycle months and other months as "UP" cycle months. We extend the DOWN cycles to two years after a recession is over because it usually takes a long period of time for investors to rekindle their interest in stock markets after a recession. There are 296 months in UP cycles and 202 months in DOWN cycles for the July 1964 to December 2005 period (or 230 months in UP cycles and 181 months in DOWN cycles for the October 1971 to December 2005 subperiod, for which we have quarterly earnings data).

Table 8 reports the results on price momentum profits across the UP and DOWN market states. Panel A presents the unconditional momentum profits: The average price momentum profit before controlling for earnings momentum is 83 basis points per month, while it becomes 62 basis points per month after. Panel B compares the price momentum profits across the UP and DOWN states. The left-hand-side panel reports results based on the 36-month market state definition. In UP months, the average price momentum profit is 100 basis points per month before controlling for earnings momentum and is 83 basis points after. Both of these values are highly significant with t-statistics of 5.98 and 4.50, respectively. By contrast, the average price momentum profit in DOWN months is negative – -33 basis points per month before controlling for earnings momentum and -68 basis points after. Neither of the two values is statistically significant. The difference in price momentum profits across the UP and DOWN months is large – 133 basis points before controlling for earnings momentum and 151 basis points after. Both values are statistically significant. The right-hand-side panel reports similar results using the 24-month market state definition.

Panel C of Table 8 reports results from regressions (2) and (3). We use 8 different regression specifications by combining two alternative measures of price momentum profits (before and after controlling for earnings momentum), two alternative market-state definitions (36 and 24 months) and two different risk controls (CAPM and Fama-French factors). Across all specifications, the regression intercepts, which correspond to momentum profits in DOWN months, are always statistically insignificant. By contrast, the market-state dummy coefficients, which correspond to the difference in momentum profits across UP and DOWN months, range from 98 to 148 basis points per month and are significant across all of these regression specifications. These regression coefficients confirm that the price momentum profit is significantly higher in UP months than in DOWN months. Panel D repeats those regressions in Panel C, except replacing the discrete UP-DOWN state dummies with the corresponding continuous lagged market returns. The coefficients of the lagged market returns are all positive and significant. These regression coefficients again confirm 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 profit barely exists in DOWN markets, but is significantly positive in UP markets.

Table 9 reports the results on the earnings momentum profits across UP and DOWN market states. Panel A shows that the average earnings momentum profit before controlling for price momentum is 114 basis point per month, while it drops to 84 basis points per month after controlling for price momentum. Panel B compares the earnings momentum profits across UP and DOWN months. In UP months defined by the prior 36-month market return, the average characteristic-adjusted earnings momentum profit before controlling for price momentum is 111 basis points per month. In DOWN months, the average profit is 128 basis points, 17 basis points higher than that in UP months. The direction of this difference is consistent with our attention-based hypothesis; its t-statistic is, however, not significant. The lack of a significant difference in earnings momentum profits across DOWN and UP markets may be caused by price continuation that is unrelated to earnings news. After we control for the prior one-year return in SUE, Table 9 shows that the difference in earnings momentum profits across the DOWN and UP months now increases to 42 basis points per month, and is statistically significant with a t-statistic of 2.46. We obtain similar results, albeit with a smaller magnitude and lower significance using the alternative 24-month definition of market state.

Panels C and D report the results from regressing earnings momentum profits on market-state dummies and on lagged market returns. The basic results are similar to those shown in Panel B. After controlling for price momentum, the regression coefficients of the market state dummies and lagged market returns are negative and statistically significant. For example, the coefficient on the dummy variable has a value of -46 basis points per month and a t-statistic of -2.67, using the 36-month market state definition and Fama-French factors as risk controls. Overall, Table 9 shows that earnings momentum profit exists in both UP and DOWN markets, but is significantly stronger in DOWN markets after controlling for price momentum.

Table 10 compares the momentum profits across the UP and DOWN business cycles. Panel A shows that the average price momentum profit before controlling for earnings momentum is 113 basis points per month in UP cycles and 42 basis points in DOWN cycles. The difference is 71 basis points per month with a significant t-statistic of 1.96. After controlling for earnings momentum, the difference becomes even larger and more significant. Panel B reports coefficients from regressing price momentum profits on the business-cycle dummy, which takes a value of zero in DOWN-cycle months and one in UP-cycle months. The regression coefficients again confirm that price momentum profit, especially after controlling for earnings momentum, is larger in UP cycles than in DOWN cycles.

Panel C of Table 10 shows that the average earnings momentum profit before controlling for price momentum is 114 basis points per month in UP cycles and is 117 basis points per month in DOWN cycles, almost identical to each other. However, after controlling for price momentum, the average monthly earnings momentum profit becomes 77 basis points in UP cycles and 102 basis points in DOWN cycles. The difference across the UP and DOWN cycles is -25 basis points and is statistically significant. The regression analysis in Panel D also confirms that after controlling for price momentum, earnings momentum profit is significantly higher in DOWN cycles.

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

It is worth noting that our time-series findings cannot be explained by fluctuations in the degree of investor overconfidence over time. As analyzed in Daniel, Hirshleifer and Subrahmanyam (1998) and Gervais and Odean (2001), self-attribution bias can lead investors to become more overconfident about the precision of their private information in up markets than in down markets, and subsequently to overreact more to their private information in up markets. This mechanism can lead to stronger overreaction-driven price momentum in up 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. This, however, is not what we observe.

7 Conclusion

In this paper, we examine the hypothesis that investor attention has a dual role in stock price dynamics: While inadequate attention causes the stock prices to underreact to earnings news, which causes earnings momentum, attention can interact with investors' learning biases such as extrapolative expectations and overconfidence to generate overreaction-driven price momentum. The hypothesis predicts that earnings momentum decreases with investor attention, while price momentum increases.

We perform cross-sectional and time-series tests of this hypothesis. In the cross-sectional analysis, we use trading volume as an attention proxy and find that while the earnings momentum effect is more pronounced among low volume stocks, the price momentum effect is stronger among high volume stocks. Motivated by evidence that investors tend to pay more attention to stocks in up markets, we also examine the momentum profits across up and down markets. We find that while the earnings momentum effect is more pronounced in down markets, the price momentum effect is stronger in up markets. Furthermore, we find that price momentum profits reverse in the long run, while earnings momentum profits do not. The opposite patterns of earnings and price momentum effects in both the cross-section and time-series not only support the attention-based hypothesis, but also confirm the relevance of both under- and overreaction in driving these two momentum anomalies.

Reference

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

Ball, R. and P. Brown 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-177.

Barber, B., T. Odean (2003), All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors, Working paper. University of California at Davis and University of California at Berkeley.

Barberis, Nicholas, Andrei Shleifer and Robert Vishny (1998), A model of investor sentiment, *Journal of Financial Economics* 48, 307-343.

Barberis, Nicholas and Richard Thaler (2003), A survey of behavioral finance, in George Constantinides, Milton Harris and Rene Stulz (ed.), *Handbook of the Economics of Finance*, North-Holland.

Bernard, V. L. and J. K. Thomas 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting Research, Supplement* 27, 1-48.

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

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 (2006), Economic links and predictable returns, Working paper, Yale University.

Cooper, Michael, Roberto C. Gutierrez, and Allaudeen Hameed (2004), Market states and momentum, *Journal of Finance* 59, 1345-1365.

Corwin, S. and J. Coughenour (2005), Limited attention and the allocation of effort in securities trading, Unpublished working paper, University of Notre Dame.

DeBondt, W. and R. Thaler (1985), Does the stock market overreact?, *Journal of Finance* 40, 793-805.

Daniel, Kent, and Sheridan Titman (1997), Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 52, 1-33.

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

Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam (1998), Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839-1885.

Della Vigna, Stefano and Joshua Pollett (2005a), Attention, demographics, and the stock market, Working paper, University of California at Berkeley.

Della Vigna, Stefano and Joshua Pollett (2005b), Investor inattention, firm reaction, and friday earnings announcements, Working paper, University of California at Berkeley.

De Long, Bradford J., Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldman (1990), Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

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 (1996), Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

Francis, J., D. Pagach, and J. Stephan (1992), The stock market response to earnings announcements released during trading versus nontrading periods, *Journal of Accounting Research* 30, 165-184.

Gabaix, Xavier, David Laibson, Guillermo Moloche and Stephen Weinberg (2005), Costly information acquisition: Experimental analysis of a boundedly rational model, *American Economic Review*, forthcoming.

Gervais, Simon and Terrance Odean (2001), Learning to be overconfident, *Review of Financial Studies* 14, 1-27.

Gervais, Simon, Ron Kaniel and Dan Mingelgrin (2001), The high-volume return premium, *Journal of Finance* 56, 877-920.

Griffin, John M., Xiuqing Ji, and J. Spencer Martin (2003), Momentum investing and business cycle risk: Evidence from pole to pole, *Journal of Finance* 58, 2515-2547.

Grundy, Bruce D., and J. Spencer Martin (2001), Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.

Hirshleifer, David (2001), Investor psychology and asset pricing, *Journal of Finance* 56, 1533-1597.

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

Hirshleifer, David and Siew Hong Teoh (2005), Limited investor attention and earnings-related under- and over-reactions, Working paper, Ohio State University.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh and Yinglei Zhang (2004), Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38, 297-331.

Hirshleifer, David, Seongyeon Lim and Siew Hong Teoh (2006), Driven to distraction: extraneous events and underreaction to earnings news, Working paper, Ohio State University.

Hirst, D. E. and P. E. Hopkins (1998), Comprehensive income reporting and analysts' valuation judgements, *Journal of Accounting Research* 36, 47-75.

Hong, Harrison, and Jeremy Stein (1999), A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, Terence Lim, and Jeremy 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 Ross Valkanov (2005), Do industries lead the stock market? *Journal of Financial Economics*, forthcoming.

Hou, Kewei (2006), Industry information diffusion and the lead-lag effct in stock returns, *Review of Financial Studies*, forthcoming.

Hou, Kewei, G. Andrew Karolyi, and Bong-Chan Kho (2006), What factors drive global stock returns?, Working paper, Ohio State University.

Hou, Kewei and Tobias Moskowitz (2005), Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981-1020.

Huberman, Gur and Tomer Regev (2001), Contagious speculation and a cure for cancer: a non-event that made stock prices soar, *Journal of Finance* 56, 387-396.

Jegadeesh, Narasimhan, and Sheridan Titman (1993), Returns to buying winners and selling losers: Implication for stock market efficiency, *Journal of Finance* 48, 65-91.

Jiang, Guohua, Charles Lee, and Grace Zhang (2005), Information uncertainty and expected returns, *Review of Accounting Studies* 10, 185-221.

Kahneman, Daniel (1973), *Attention and Effort*, Prentice Hall, New Jersey.

Karlsson, Niklas, George Loewenstein, and Duane Seppi (2005), The 'ostrich effect': selective attention to information about investments, Working paper, Carnegie Mellon University.

LaPlante, M. and C.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.

Lee, Charles, and Bhaskaran Swaminathan (2000), Price momentum and trading volume, *Journal of Finance* 55, 2017-2069.

Lo, Andrew and Jiang Wang (2000), Trading volume: Definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 13, 257-300.

Odean, Terrance (1998), Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887-1934.

Pashler, H. and J. Johnston (1998), Attentional limitations in dual-task performance, In: Pashler, H., (Ed.), Attention, Psychology Press.

Peng, Lin (2005), Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307-329.

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

Rouwenhorst, K. Geert (1998), International momentum strategies, *Journal of Finance* 53, 267-284.

Sadka, Ronnie (2006), Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309-349.

Scheinkman, Jose and Wei Xiong (2003), Overconfidence and speculative bubbles, *Journal of Political Economy* 111, 1183-1219.

Shleifer, Andrei and Robert Vishny (1997), The limits of arbitrage, *Journal of Finance* 52, 35-55.

Sims, Chris (2003), Implications of rational inattention, *Journal of Monetary Economics,* 50, 665-690.

Sloan, Richard (1996), Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review* 71, 289-315.

Yantis, S. (1998), Control of visual attention, In: Pashler, H., (Ed.), Attention, Psychology Press.

Zhang, Frank (2006), Information uncertainty and stock returns, *Journal of Finance* 61, 105-137.

Table 1. Turnover and Price-Momentum Profits

Average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past one year return are reported over the period from July 1964 to December 2005. At the beginning of each month, all stocks on NYSE/AMEX are ranked 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 placed into quintiles. Within each turnover quintile, stocks are further sorted into quintiles based on return over the past twelve months (skipping the most recent month). Reported are the equal-weighted raw and adjusted returns and t-statistics (in *italics*) of the turnover and past return sorted portfolios, the spreads in returns between past return quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the price momentum profit on the Fama-French three-factor model. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the *T* (*F*) statistics for the hypothesis that the average price momentum profits (α) are identical across turnover quintiles 5 and 1.

	Raw Returns							Characteristic-Adjusted Returns							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0137	0.0126	0.0136	0.0158	0.0186	**0.0049**	**0.0067**	Turnover1	-0.0007	-0.0010	0.0000	0.0020	0.0034	**0.0040**	**0.0059**
	4.51	*6.10*	*7.17*	*8.20*	*8.12*	*2.32*	*3.18*		*-0.59*	*-1.00*	*0.02*	*2.22*	*3.36*	*2.43*	*3.56*
2	0.0110	0.0120	0.0119	0.0145	0.0186	**0.0076**	**0.0097**	2	-0.0024	-0.0007	-0.0007	0.0012	0.0042	**0.0066**	**0.0085**
	3.59	*5.29*	*5.83*	*7.09*	*7.72*	*3.51*	*4.47*		*-2.21*	*-0.91*	*-1.12*	*1.66*	*4.79*	*3.89*	*5.04*
3	0.0083	0.0132	0.0124	0.0149	0.0182	**0.0099**	**0.0121**	3	-0.0037	0.0006	-0.0004	0.0017	0.0042	**0.0079**	**0.0099**
	2.73	*5.39*	*5.45*	*6.43*	*6.87*	*4.67*	*5.67*		*-3.80*	*0.92*	*-0.68*	*2.70*	*4.37*	*4.66*	*5.78*
4	0.0068	0.0115	0.0131	0.0146	0.0191	**0.0123**	**0.0151**	4	-0.0051	-0.0010	0.0005	0.0015	0.0052	**0.0103**	**0.0132**
	1.96	*4.08*	*4.91*	*5.61*	*6.77*	*5.21*	*6.42*		*-3.93*	*-1.43*	*0.94*	*2.36*	*5.03*	*5.10*	*6.53*
Turnover5	0.0023	0.0093	0.0113	0.0142	0.0160	**0.0138**	**0.0176**	Turnover5	-0.0088	-0.0027	-0.0008	0.0015	0.0035	**0.0123**	**0.0157**
	0.55	*2.74*	*3.58*	*4.58*	*4.84*	*4.81*	*6.20*		*-4.62*	*-2.46*	*-0.94*	*1.61*	*2.54*	*4.93*	*6.29*
Test (turnover1=turnover5)						2.50	9.60							2.75	10.56
P-value						0.0125	0.0020							0.0060	0.0012

Table 2. Turnover and Price-Momentum Profits, Controlling for Earnings Momentum

Average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and the component of past one year return not associated with past earnings surprises are reported over the period from October 1971 to December 2005. At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked 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 placed into quintiles. Within each turnover quintile, stocks are further sorted into quintiles based on the orthogonalized return over the past twelve months (skipping the most recent month) with respect to past earnings surprises. The orthogonalized return component is estimated using the residuals from first-stage cross-sectional regressions of past one-year return on the most recent earnings surprises. Reported are the equal-weighted raw and adjusted returns and t-statistics (in *italics*) of the turnover and past return sorted portfolios, the spreads in returns between past return quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the price momentum profit on the Fama-French three-factor model. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the *T* (*F*) statistics for the hypothesis that the average price momentum profits (α) are identical across turnover quintiles 5 and 1.

	Raw Returns							Characteristic-Adjusted Returns							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0167	0.0137	0.0147	0.0171	0.0180	**0.0014**	**0.0035**	Turnover1	0.0015	-0.0006	0.0003	0.0023	0.0022	**0.0007**	**0.0031**
	4.69	*5.74*	*6.52*	*7.59*	*7.01*	*0.58*	*1.46*		*1.11*	*-0.61*	*0.31*	*2.30*	*1.92*	*0.38*	*1.60*
2	0.0125	0.0121	0.0130	0.0147	0.0176	**0.0051**	**0.0071**	2	-0.0010	-0.0007	-0.0002	0.0010	0.0031	**0.0041**	**0.0064**
	3.68	*4.78*	*5.58*	*6.38*	*6.51*	*2.14*	*2.93*		*-0.84*	*-0.89*	*-0.31*	*1.32*	*3.17*	*2.19*	*3.35*
3	0.0090	0.0131	0.0130	0.0142	0.0174	**0.0084**	**0.0100**	3	-0.0026	0.0007	0.0003	0.0013	0.0036	**0.0063**	**0.0082**
	2.76	*4.86*	*5.19*	*5.72*	*6.05*	*3.74*	*4.40*		*-2.44*	*0.99*	*0.41*	*1.90*	*3.49*	*3.38*	*4.35*
4	0.0067	0.0111	0.0125	0.0138	0.0180	**0.0113**	**0.0138**	4	-0.0048	-0.0010	0.0002	0.0007	0.0044	**0.0092**	**0.0121**
	1.80	*3.76*	*4.44*	*4.91*	*6.03*	*4.45*	*5.42*		*-3.31*	*-1.47*	*0.28*	*0.92*	*4.08*	*4.22*	*5.54*
Turnover5	0.0031	0.0093	0.0107	0.0134	0.0155	**0.0124**	**0.0161**	Turnover5	-0.0074	-0.0025	-0.0012	0.0008	0.0030	**0.0104**	**0.0139**
	0.69	*2.55*	*3.21*	*4.08*	*4.40*	*4.12*	*5.35*		*-3.56*	*-2.03*	*-1.29*	*0.80*	*2.05*	*3.91*	*5.24*
Test (turnover1=turnover5)						2.87	10.88							2.92	10.81
P-value						0.0042	0.0010							0.0036	0.0010

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

Average monthly characteristic-adjusted returns on portfolios sorted by turnover and past one year return are reported over the period from July 1964 to December 2005 (Panel A) and from October 1971 to December 2005 (Panel B) for various holding periods. At the beginning of each month, stocks are ranked by turnover and placed into quintiles. Within each turnover quintile, stocks are then sorted into quintiles based on return over the past twelve months (skipping the most recent month). The equal-weighted adjusted returns on these double-sorted portfolios are computed for four holding periods: month t, months t to t+5, months t to t+11, months t+12 to t+59. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panel A reports average monthly adjusted-return spreads and t-statistics (in *italics*) between past return quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the average return spreads on the Fama-French three-factor model, respectively. For holding period t+12 to t+59, we report the raw profit constructed using the raw return spreads between quintiles 5 and 1. Also reported are the *T* (*F*) statistics for the hypothesis that the average return spreads (α) are identical across turnover quintiles 5 and 1. Panel B repeats the analysis in A, but instead of using raw returns over the past twelve months to measure price momentum, employs returns orthogonalized with respect to past earnings surprises which are calculated from first-stage cross-sectional regressions of past one year returns on past earnings surprises.

Panel A: Not controlling for earnings momentum

	t		*t : t+2*		*t : t+5*		*t : t+11*		*t+12 : t+59*		
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Raw Profit	Profit	F-F α
Turnover1	0.0040	0.0059	0.0040	0.0061	0.0029	0.0049	0.0012	0.0030	-0.0033	-0.0008	-0.0004
	2.43	*3.56*	*2.57*	*3.88*	*2.05*	*3.42*	*1.01*	*2.51*	*-3.23*	*-1.43*	*-0.66*
2	0.0066	0.0085	0.0060	0.0079	0.0048	0.0065	0.0019	0.0035	-0.0026	-0.0007	-0.0003
	3.89	*5.04*	*3.94*	*5.18*	*3.50*	*4.77*	*1.66*	*3.12*	*-2.90*	*-1.41*	*-0.66*
3	0.0079	0.0099	0.0067	0.0086	0.0055	0.0075	0.0032	0.0050	-0.0020	0.0000	0.0005
	4.66	*5.78*	*4.23*	*5.47*	*3.81*	*5.21*	*2.75*	*4.31*	*-2.14*	*0.03*	*1.17*
4	0.0103	0.0132	0.0095	0.0122	0.0077	0.0104	0.0046	0.0070	-0.0029	-0.0011	-0.0003
	5.10	*6.53*	*5.11*	*6.67*	*4.63*	*6.34*	*3.36*	*5.24*	*-3.00*	*-2.00*	*-0.61*
Turnover5	0.0123	0.0157	0.0110	0.0143	0.0083	0.0115	0.0044	0.0074	-0.0029	-0.0011	-0.0007
	4.93	*6.29*	*4.81*	*6.24*	*3.89*	*5.45*	*2.51*	*4.30*	*-3.10*	*-1.92*	*-1.27*
Test (1=5)	2.75	10.56	2.52	8.80	2.07	6.69	1.50	4.42	0.28	0.44	0.23
P-value	0.0060	0.0012	0.0119	0.0030	0.0384	0.0097	0.1349	0.0357	0.7759	0.6622	0.6338

Panel B: Controlling for earnings momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+59***		
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Raw Profit	Profit	F-F α
Turnover1	0.0007	0.0031	0.0013	0.0035	0.0010	0.0030	-0.0005	0.0014	-0.0050	-0.0021	-0.0015
	0.38	*1.60*	*0.75*	*1.97*	*0.60*	*1.88*	*-0.33*	*1.00*	*-4.01*	*-3.23*	*-2.26*
2	0.0041	0.0064	0.0043	0.0064	0.0039	0.0057	0.0009	0.0025	-0.0027	-0.0013	-0.0009
	2.19	*3.35*	*2.50*	*3.77*	*2.51*	*3.67*	*0.67*	*1.93*	*-2.53*	*-2.14*	*-1.42*
3	0.0063	0.0082	0.0058	0.0076	0.0052	0.0071	0.0030	0.0047	-0.0019	0.0000	0.0004
	3.38	*4.35*	*3.38*	*4.37*	*3.31*	*4.46*	*2.28*	*3.61*	*-1.65*	*0.04*	*0.63*
4	0.0092	0.0121	0.0079	0.0109	0.0062	0.0092	0.0039	0.0066	-0.0022	-0.0007	0.0001
	4.22	*5.54*	*3.94*	*5.49*	*3.48*	*5.21*	*2.62*	*4.54*	*-1.78*	*-0.85*	*0.15*
Turnover5	0.0104	0.0139	0.0093	0.0126	0.0068	0.0101	0.0032	0.0064	-0.0027	-0.0010	-0.0005
	3.91	*5.24*	*3.81*	*5.15*	*2.98*	*4.44*	*1.69*	*3.43*	*-2.42*	*-1.46*	*-0.71*
Test (1=5)	2.92	10.81	2.63	9.05	2.08	6.46	1.56	4.76	1.43	1.15	1.05
P-value	0.0036	0.0010	0.0086	0.0027	0.0379	0.0111	0.1191	0.0293	0.1531	0.2493	0.3049

Table 4. Turnover and Earnings-Momentum Profits

Average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past earnings surprises are reported over the period from October 1971 to December 2005. At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked 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 placed into quintiles. Within each turnover quintile, stocks are further sorted into quintiles based on their most recent earnings surprises. Earnings news is measured by standardized unexpected earnings (SUE), which is the difference between the most recent quarter's earnings and earnings four quarters ago divided by the standard deviation of the earnings changes over the last eight quarters. Reported are the equal-weighted raw and adjusted returns and t-statistics (in *italics*) of the turnover and past earnings surprise-sorted portfolios, the spreads in returns between earnings surprise quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the earnings momentum profit on the Fama-French three-factor model. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the *T* (*F*) statistics for the hypothesis that the average earnings momentum profits (α) are identical across turnover quintiles 5 and 1.

	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	0.0123	0.0159	0.0207	0.0252	**0.0181**	**0.0181**	Turnover1	-0.0068	-0.0025	0.0009	0.0053	0.0092	**0.0160**	**0.0161**
	2.81	*4.75*	*6.14*	*8.38*	*9.97*	*14.30*	*13.99*		*-6.65*	*-2.53*	*0.95*	*5.76*	*9.44*	*13.34*	*13.14*
2	0.0079	0.0113	0.0153	0.0168	0.0205	**0.0126**	**0.0134**	2	-0.0054	-0.0021	0.0010	0.0032	0.0064	**0.0119**	**0.0126**
	2.93	*4.16*	*5.79*	*6.77*	*8.36*	*9.58*	*10.18*		*-6.65*	*-2.69*	*1.42*	*4.08*	*7.86*	*9.91*	*10.32*
3	0.0078	0.0112	0.0140	0.0165	0.0182	**0.0104**	**0.0115**	3	-0.0044	-0.0017	0.0011	0.0035	0.0051	**0.0095**	**0.0101**
	2.84	*3.90*	*5.11*	*6.26*	*6.82*	*7.98*	*8.90*		*-5.88*	*-2.38*	*1.59*	*5.24*	*6.71*	*8.30*	*8.67*
4	0.0074	0.0100	0.0133	0.0150	0.0173	**0.0098**	**0.0114**	4	-0.0045	-0.0025	0.0003	0.0022	0.0046	**0.0092**	**0.0105**
	2.38	*3.24*	*4.39*	*5.14*	*5.95*	*7.11*	*8.25*		*-5.28*	*-3.41*	*0.50*	*3.02*	*5.93*	*7.32*	*8.31*
Turnover5	0.0055	0.0072	0.0105	0.0137	0.0162	**0.0107**	**0.0123**	Turnover5	-0.0058	-0.0045	-0.0015	0.0015	0.0038	**0.0096**	**0.0109**
	1.43	*1.96*	*2.98*	*3.93*	*4.66*	*5.90*	*6.75*		*-4.03*	*-3.77*	*-1.46*	*1.35*	*3.26*	*5.89*	*6.61*
Test (turnover1=turnover5)						3.33	6.69							3.17	6.44
P-value						0.0009	0.0098							0.0016	0.0112

Table 5. Turnover and Earnings-Momentum Profits, Controlling for Price Momentum

Average monthly raw and characteristic-adjusted returns on portfolios sorted by turnover and past earnings surprises are reported over the period from October 1971 to December 2005. At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked 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 placed into quintiles. Within each turnover quintile, stocks are further sorted into quintiles based on the orthogonalized earnings surprises with respect to returns over the prior year. The orthogonalized earnings surprise variable is estimated using the residuals from first-stage cross-sectional regressions of past earnings surprises on past one year returns. Reported are the equal-weighted raw and adjusted returns and t-statistics (in *italics*) of the turnover and past earnings surprise-sorted portfolios, the spreads in returns between earnings surprise quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the earnings momentum profit on the Fama-French three-factor model. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the *T* (*F*) statistics for the hypothesis that the average earnings momentum profits (α) are identical across turnover quintiles 5 and 1.

	Raw Returns							Characteristic-Adjusted Returns							
	Mom1	2	3	4	Mom5	5-1	FF α		Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	0.0082	0.0124	0.0160	0.0195	0.0250	**0.0167**	**0.0162**	Turnover1	-0.0061	-0.0026	0.0013	0.0041	0.0090	**0.0151**	**0.0144**
	3.38	*5.06*	*6.39*	*7.51*	*9.45*	*13.54*	*12.87*		*-6.16*	*-2.50*	*1.41*	*4.42*	*9.65*	*13.26*	*12.44*
2	0.0092	0.0119	0.0150	0.0163	0.0194	**0.0102**	**0.0106**	2	-0.0043	-0.0020	0.0009	0.0029	0.0056	**0.0099**	**0.0100**
	3.58	*4.52*	*5.84*	*6.14*	*7.85*	*8.81*	*9.05*		*-5.68*	*-2.70*	*1.22*	*3.80*	*7.05*	*9.38*	*9.21*
3	0.0097	0.0119	0.0137	0.0154	0.0170	**0.0073**	**0.0079**	3	-0.0029	-0.0013	0.0007	0.0029	0.0042	**0.0071**	**0.0070**
	3.64	*4.32*	*5.02*	*5.60*	*6.32*	*6.60*	*7.05*		*-4.24*	*-1.79*	*1.06*	*4.01*	*5.82*	*7.04*	*6.74*
4	0.0089	0.0131	0.0125	0.0136	0.0154	**0.0065**	**0.0072**	4	-0.0036	0.0004	-0.0006	0.0011	0.0031	**0.0066**	**0.0069**
	2.91	*4.41*	*4.21*	*4.45*	*5.14*	*5.37*	*5.86*		*-4.70*	*0.52*	*-0.89*	*1.47*	*3.93*	*6.42*	*6.42*
Turnover5	0.0079	0.0101	0.0102	0.0120	0.0137	**0.0059**	**0.0060**	Turnover5	-0.0039	-0.0018	-0.0022	0.0001	0.0018	**0.0057**	**0.0057**
	2.18	*2.88*	*2.92*	*3.28*	*3.81*	*4.06*	*4.03*		*-3.18*	*-1.68*	*-2.13*	*0.08*	*1.46*	*4.24*	*4.15*
Test (turnover1=turnover5)						5.74	27.43							5.37	23.14
P-value						0.0001	0.0001							0.0001	0.0001

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

Average monthly characteristic-adjusted returns on portfolios sorted by turnover and past earnings surprises are reported over the period from October 1971 to December 2005 for various holding periods. At the beginning of each month, stocks are ranked by turnover and placed into quintiles. Within each turnover quintile, stocks are then sorted into quintiles based on their most recent earnings surprises. The equal-weighted adjusted returns on these double-sorted portfolios are computed for four holding periods: month t, months t to t+5, months t to t+11, months t+12 to t+59. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panel A reports the average monthly adjusted-return spreads and t-statistics (in *italics*) between earnings surprises quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the average return spreads on the Fama-French three-factor model. For holding period t+12 to t+59, we report the raw profit constructed using the raw return spreads between quintiles 5 and 1. Also reported are the *T* (*F*) statistics for the hypothesis that the average return spreads (α) are identical across turnover quintiles 5 and 1. Panel B repeats the analysis in A, but instead of using raw SUE to measure earnings news, employs SUE orthogonalized with respect to past returns which are calculated from a first stage cross-sectional regression of SUE on past returns.

Panel A: Not controlling for price momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+59***		
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Raw Profit	Profit	F-F α
Turnover1	0.0160	0.0161	0.0122	0.0124	0.0089	0.0092	0.0049	0.0055	-0.0003	0.0008	0.0009
	13.34	*13.14*	*12.09*	*11.97*	*10.30*	*10.32*	*6.22*	*6.83*	*-0.54*	*1.58*	*1.80*
2	0.0119	0.0126	0.0086	0.0096	0.0059	0.0067	0.0036	0.0044	0.0002	0.0011	0.0012
	9.91	*10.32*	*7.49*	*8.17*	*5.86*	*6.53*	*4.23*	*5.17*	*0.40*	*2.48*	*2.58*
3	0.0095	0.0101	0.0063	0.0069	0.0043	0.0051	0.0026	0.0033	-0.0004	0.0004	0.0004
	8.30	*8.67*	*5.77*	*6.15*	*4.54*	*5.22*	*3.11*	*3.98*	*-0.84*	*1.04*	*1.08*
4	0.0092	0.0105	0.0073	0.0084	0.0064	0.0074	0.0043	0.0051	-0.0003	0.0003	0.0002
	7.32	*8.31*	*6.23*	*7.17*	*6.27*	*7.24*	*4.97*	*5.76*	*-0.56*	*0.64*	*0.37*
Turnover5	0.0096	0.0109	0.0071	0.0085	0.0060	0.0076	0.0041	0.0056	-0.0007	0.0001	0.0002
	5.89	*6.61*	*4.84*	*5.71*	*4.44*	*5.69*	*3.50*	*4.84*	*-0.94*	*0.14*	*0.34*
Test (1=5)	3.17	6.44	2.86	4.72	1.86	0.96	0.57	0.01	0.38	0.92	0.87
P-value	0.0016	0.0112	0.0043	0.0299	0.0633	0.3282	0.5668	0.9124	0.7058	0.3565	0.3522

Panel B: Controlling for price momentum

	t		***t : t+2***		***t : t+5***		***t : t+11***		***t+12 : t+59***		
	Profit	F-F α	Profit	F-F α	Profit	F-F α	Profit	F-F α	Raw Profit	Profit	F-F α
Turnover1	0.0151	0.0144	0.0116	0.0111	0.0084	0.0081	0.0047	0.0046	0.0009	0.0014	0.0014
	13.26	*12.44*	*12.42*	*11.68*	*10.67*	*9.97*	*7.03*	*6.73*	*1.92*	*3.47*	*3.50*
2	0.0099	0.0100	0.0071	0.0074	0.0047	0.0049	0.0031	0.0034	0.0009	0.0013	0.0013
	9.38	*9.21*	*7.28*	*7.38*	*5.52*	*5.57*	*4.34*	*4.55*	*2.00*	*3.09*	*2.84*
3	0.0071	0.0070	0.0043	0.0040	0.0028	0.0028	0.0018	0.0019	0.0000	0.0003	0.0001
	7.04	*6.74*	*4.77*	*4.31*	*3.77*	*3.60*	*2.67*	*2.74*	*0.08*	*0.81*	*0.37*
4	0.0066	0.0069	0.0048	0.0049	0.0045	0.0046	0.0031	0.0030	0.0010	0.0011	0.0007
	6.42	*6.42*	*5.17*	*5.10*	*5.65*	*5.47*	*4.97*	*4.61*	*1.98*	*2.24*	*1.31*
Turnover5	0.0057	0.0057	0.0040	0.0042	0.0039	0.0041	0.0032	0.0035	0.0008	0.0008	0.0008
	4.24	*4.15*	*3.39*	*3.44*	*3.60*	*3.79*	*3.67*	*3.82*	*1.36*	*1.53*	*1.48*
Test (1=5)	5.37	23.14	5.08	20.17	3.44	8.48	1.28	0.95	0.14	0.92	1.13
P-value	0.0001	0.0001	0.0001	0.0001	0.0006	0.0036	0.2022	0.3292	0.8901	0.3565	0.2888

Table 7. Residual Turnover and Momentum Profits

Average monthly characteristic-adjusted returns on portfolios, which are first sorted by residual turnover and then by past one year return or by past earnings surprises, are reported over the period from July 1981 to December 2005. At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked by their residual turnover (estimated from a first stage cross-sectional regression of average monthly turnover on size, analyst coverage, institutional ownership, analyst dispersion, and Amihud (2002)'s illiquidity measure) and placed into quintiles. Panel A further sort stocks within each turnover quintile into quintiles based on the return (or orthogonalized return with respect to past earnings surprises) over the past twelve months (skipping the most recent month). The orthogonalized return component is estimated using the residuals from first-stage cross-sectional regressions of past one-year return on the most recent earnings surprises. Panel B further sort stocks in each turnover quintile into quintiles based on the earnings surprises (or the orthogonalized earnings surprises with respect to returns over the prior year). The orthogonalized earnings surprise variable is estimated using the residuals from first-stage cross-sectional regressions of past earnings surprises on past one year returns. Reported are the equal-weighted adjusted returns and t-statistics (in *italics*) of the turnover and past return sorted portfolios, the spreads in returns between past return quintiles 5 and 1 within each turnover group, as well as the intercepts, α, from time series regressions of the price momentum profit on the Fama-French three-factor model. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Also reported are the *T* (*F*) statistics for the hypothesis that the average price momentum profits (α) are identical across turnover quintiles 5 and 1.

Panel A: Price Momentum Profits

	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	-0.0008	0.0009	0.0018	0.0023	**0.0047**	**0.0069**	Turnover1	-0.0017	-0.0002	0.0009	0.0015	0.0013	**0.0031**	**0.0051**
	-1.37	*-0.62*	*0.71*	*1.32*	*1.62*	*1.85*	*2.72*		*-1.03*	*-0.19*	*0.72*	*1.08*	*0.97*	*1.25*	*2.04*
2	-0.0040	0.0006	0.0008	0.0017	0.0033	**0.0073**	**0.0087**	2	-0.0029	0.0011	0.0002	0.0007	0.0035	**0.0063**	**0.0079**
	-2.59	*0.61*	*1.10*	*1.82*	*3.07*	*3.26*	*3.79*		*-1.91*	*1.13*	*0.30*	*0.80*	*3.34*	*2.94*	*3.57*
3	-0.0051	-0.0015	-0.0004	0.0013	0.0042	**0.0093**	**0.0113**	3	-0.0039	-0.0014	0.0000	-0.0001	0.0036	**0.0074**	**0.0093**
	-2.95	*-1.45*	*-0.60*	*1.75*	*4.00*	*3.91*	*4.70*		*-2.35*	*-1.35*	*0.05*	*-0.12*	*3.27*	*3.17*	*3.92*
4	-0.0042	-0.0020	-0.0010	0.0016	0.0062	**0.0104**	**0.0125**	4	-0.0038	-0.0019	-0.0001	0.0011	0.0058	**0.0095**	**0.0113**
	-2.32	*-1.81*	*-1.24*	*1.76*	*4.41*	*4.03*	*4.85*		*-2.12*	*-1.87*	*-0.17*	*1.17*	*4.19*	*3.84*	*4.49*
Turnover5	-0.0090	-0.0020	0.0011	0.0038	0.0085	**0.0175**	**0.0193**	Turnover5	-0.0082	-0.0017	0.0009	0.0029	0.0084	**0.0167**	**0.0183**
	-4.00	*-1.53*	*0.87*	*2.40*	*4.02*	*5.52*	*5.93*		*-3.81*	*-1.26*	*0.72*	*1.79*	*4.02*	*5.46*	*5.85*
Test (turnover1=turnover5)						3.16	8.95							3.47	10.89
P-value						0.0017	0.0028							0.0006	0.0010

Panel B: Earnings Momentum Profits

Not Controlling for Price Momentum							
	Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	-0.0024	-0.0028	0.0015	0.0023	0.0052	**0.0075**	**0.0090**
	-2.12	*-2.30*	*1.25*	*2.11*	*4.44*	*5.61*	*6.74*
2	-0.0021	-0.0024	0.0009	0.0027	0.0042	**0.0063**	**0.0066**
	-2.11	*-2.30*	*0.91*	*2.62*	*4.64*	*4.77*	*4.80*
3	-0.0025	-0.0017	-0.0004	0.0025	0.0032	**0.0057**	**0.0050**
	-2.19	*-1.41*	*-0.35*	*2.80*	*3.19*	*3.52*	*2.98*
4	-0.0022	-0.0002	0.0007	0.0014	0.0059	**0.0081**	**0.0080**
	-1.78	*-0.15*	*0.61*	*1.19*	*4.81*	*4.66*	*4.54*
Turnover5	-0.0024	-0.0005	0.0019	0.0038	0.0055	**0.0079**	**0.0082**
	-1.26	*-0.28*	*1.24*	*2.24*	*3.40*	*3.70*	*3.72*
Test (turnover1=turnover5)						0.14	0.09
P-value						0.8922	0.7682

Controlling for Price Momentum							
	Mom1	2	3	4	Mom5	5-1	FF α
Turnover1	-0.0017	-0.0018	-0.0003	0.0024	0.0047	**0.0064**	**0.0072**
	-1.59	*-1.49*	*-0.29*	*2.11*	*4.05*	*5.31*	*5.82*
2	-0.0016	-0.0012	-0.0010	0.0040	0.0032	**0.0048**	**0.0049**
	-1.67	*-1.19*	*-1.05*	*3.94*	*3.13*	*3.52*	*3.42*
3	-0.0020	-0.0018	0.0000	0.0023	0.0027	**0.0047**	**0.0035**
	-1.89	*-1.64*	*-0.01*	*2.13*	*2.47*	*3.06*	*2.24*
4	-0.0004	0.0009	0.0006	0.0002	0.0042	**0.0046**	**0.0040**
	-0.31	*0.77*	*0.54*	*0.14*	*3.34*	*2.75*	*2.38*
Turnover5	0.0016	0.0025	0.0014	0.0019	0.0022	**0.0007**	**0.0007**
	0.86	*1.43*	*0.93*	*1.18*	*1.50*	*0.37*	*0.36*
						2.64	8.52
						0.0086	0.0036

Table 8. Market States and Price-Momentum Profits

This table reports average monthly characteristic-adjusted returns on portfolios sorted by past one year return from July 1964 to December 2005 (498 monthly observations) or portfolios sorted by past one year return orthogonalized with respect to past earnings surprises from October 1971 to December 2005 (411 monthly observations). At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked by their return over the past twelve months (skipping the most recent month) and placed into quintiles. The equal-weighted adjusted returns on these portfolios are computed over the following month. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panel A reports the average return spreads and t-statistics (in *italics*) between past return quintiles 5 and 1 for the entire sample. Panel B reports the average return spreads and t-statistics and for up and down market states, which are defined using returns on the value-weighted CRSP index over the previous 36 or 24 months. The t-statistics for the hypothesis that the price momentum profits are identical across up and down market states are also reported. Panel C reports the intercepts, α, and regression coefficients on a dummy variable for market state, from time series regressions of the price momentum profit on the CAPM and the Fama-French three-factor model. Panel D reports the intercepts, α, and regression coefficients on lagged 36-month (24-month) market return, from time series regressions of the price momentum profit on the CAPM and the Fama-French three-factor model.

Panel A: Average monthly profits for the entire sample

N	Price momentum	Price momentum, controlling for earnings momentum
498 (411)	0.0083	0.0062
	4.80	*3.33*

Panel B: Average monthly profits following Up/Down markets

	Previous 36-months			Previous 24-months		
	N	Price momentum	Price momentum, controlling for earnings momentum	N	Price momentum	Price momentum, controlling for earnings momentum
Up market	434 (355)	0.0100	0.0083	428 (354)	0.0101	0.0083
		5.98	*4.50*		*6.10*	*4.63*
Down market	64 (56)	-0.0033	-0.0068	70 (57)	-0.0023	-0.0068
		-0.46	*-0.96*		*-0.33*	*-0.91*
Up-Down	*t (Mean)*	2.58	2.78		2.49	2.81

Panel C: Profits regressed on Up/Down market dummy

		Previous 36-months		Previous 24-months	
		Price momentum	Price momentum, controlling for earnings momentum	Price momentum	Price momentum, controlling for earnings momentum
CAPM regression coefficients	CAPM α	-0.0024	-0.0061	-0.0020	-0.0068
	t(α)	*-0.51*	*-1.22*	*-0.44*	*-1.38*
	Dummy(up market)	0.0128	0.0148	0.0125	0.0158
	t(Dummy)	*2.49*	*2.76*	*2.53*	*2.95*
FF regression coefficients	F-F α	0.0022	-0.0014	0.0015	-0.0030
	t(α)	*0.46*	*-0.27*	*0.34*	*-0.62*
	Dummy(up market)	0.0098	0.0117	0.0108	0.0138
	t(Dummy)	*1.95*	*2.22*	*2.23*	*2.64*

Panel D: Profits regressed on past market returns

		Previous 36-months		Previous 24-months	
		Price momentum	Price momentum, controlling for earnings momentum	Price momentum	Price momentum, controlling for earnings momentum
CAPM regression coefficients	CAPM α	0.0042	0.0012	0.0050	0.0022
	t(α)	*1.56*	*0.42*	*2.06*	*0.81*
	Lagmarket	0.0121	0.0140	0.0154	0.0179
	t(Lagmarket)	*2.21*	*2.51*	*2.16*	*2.40*
FF regression coefficients	F-F α	0.0072	0.0045	0.0078	0.0052
	t(α)	*2.72*	*1.58*	*3.21*	*1.97*
	Lagmarket	0.0094	0.0109	0.0125	0.0142
	t(Lagmarket)	*1.75*	*2.00*	*1.79*	*1.94*

Table 9. Market States and Earnings-Momentum Profits

This table reports average monthly characteristic-adjusted returns on portfolios sorted by past earnings surprises or past earnings surprise orthogonalized with respect to past returns from October 1971 to December 2005 (411 monthly observations). At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked by their most recent earnings surprises and placed into quintiles. The equal-weighted adjusted returns on these portfolios are computed over the following month. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panel A reports the average return spreads and t-statistics (in *italics*) between earnings surprise quintiles 5 and 1 for the entire sample. Panel B reports the average return spreads and t-statistics and for up and down market states, which are defined using returns on the value-weighted CRSP index over the previous 36 or 24 months. The t-statistics for the hypothesis that the earnings momentum profits are identical across up and down market states are also reported. Panel C reports the intercepts, α, and regression coefficients on a dummy variable for market state, from time series regressions of the earnings momentum profit on the CAPM and the Fama-French three-factor model. Panel D reports the intercepts, α, and regression coefficients on lagged 36-month (24-month) market return, from time series regressions of the earnings momentum profit on the CAPM and the Fama-French three-factor model.

Panel A: Average monthly profits for the entire sample

N	Earnings momentum	Earnings momentum, controlling for price momentum
411	0.0114	0.0084
	12.92	*14.15*

Panel B: Average monthly profits following Up/Down markets

	Previous 36-months			Previous 24-months		
	N	Earnings momentum	Earnings momentum, controlling for price momentum	N	Earnings momentum	Earnings momentum, controlling for price momentum
Up market	355	0.0111	0.0079	354	0.0114	0.0081
		12.64	*12.58*		*13.62*	*13.46*
Down market	56	0.0128	0.0121	57	0.0110	0.0107
		3.88	*6.76*		*2.93*	*4.93*
Up-Down *t (Mean)*		0.65	2.46		0.16	1.58

Panel C: Profits regressed on Up/Down market dummy

		Previous 36-months		Previous 24-months	
		Earnings momentum	Earnings momentum, controlling for price momentum	Earnings momentum	Earnings momentum, controlling for price momentum
CAPM regression coefficients	CAPM α	0.0128	0.0121	0.0110	0.0106
	t(α)	*5.31*	*7.43*	*4.55*	*6.53*
	Dummy(up market)	-0.0017	-0.0043	0.0004	-0.0027
	t(Dummy)	*-0.65*	*-2.46*	*0.16*	*-1.61*
FF regression coefficients	F-F α	0.0147	0.0126	0.0129	0.0112
	t(α)	*6.18*	*7.69*	*5.43*	*6.82*
	Dummy(up market)	-0.0028	-0.0046	-0.0008	-0.0031
	t(Dummy)	*-1.13*	*-2.67*	*-0.31*	*-1.83*

Panel D: Profits regressed on past market returns

		Previous 36-months		Previous 24-months	
		Earnings momentum	Earnings momentum, controlling for price momentum	Earnings momentum	Earnings momentum, controlling for price momentum
CAPM regression coefficients	CAPM α	0.0121	0.0095	0.0122	0.0095
	t(α)	*8.84*	*10.35*	*9.56*	*11.06*
	Lagmarket	-0.0018	-0.0030	-0.0032	-0.0044
	t(Lagmarket)	*-0.70*	*-1.71*	*-0.92*	*-1.89*
FF regression coefficients	F-F α	0.0134	0.0099	0.0135	0.0099
	t(α)	*9.90*	*10.54*	*10.68*	*11.30*
	Lagmarket	-0.0029	-0.0033	-0.0048	-0.0050
	t(Lagmarket)	*-1.18*	*-1.91*	*-1.43*	*-2.16*

Table 10. Business Cycles and Price-Momentum and Earnings-Momentum Profits

At the beginning of each month, all stocks on NYSE/AMEX with non-missing earnings announcement data within the last four months are ranked by their return over the past twelve months (for price momentum portfolios) or their most recent earnings surprises (for earnings momentum portfolios) and placed into quintiles. The equal-weighted adjusted returns on these portfolios are computed over the following month. The adjusted returns employ a characteristic-based matching procedure which accounts for the return premia associated with size and BE/ME following Daniel, Grinblatt, Titman, and Wermers (1997). Panels A and B report average monthly characteristic-adjusted returns on portfolios sorted by past one year return from July 1964 to December 2005 (498 monthly observations) or portfolios sorted by past one year return orthogonalized with respect to past earnings surprises from October 1971 to December 2005 (411 monthly observations). Panel A reports the average return spreads and t-statistics (in *italics*) between past return quintiles 5 and 1 for up and down business cycles, where a down cycle includes a recession and the following two years. Also reported are the t-statistics for the hypothesis that the price momentum profits are identical across up and down business cycles. Panel B reports the intercepts, α, and regression coefficients on a dummy variable for business cycle, from time series regressions of the price momentum profit on the CAPM and the Fama-French three-factor model. Panels C and D report average monthly characteristic-adjusted returns on portfolios sorted by past earnings surprises or past earnings surprise orthogonalized with respect to past returns from October 1971 to December 2005 (411 monthly observations). Panel C reports the average return spreads and t-statistics (in *italics*) between past return quintiles 5 and 1 for up and down business cycles, as well as the t-statistics for the hypothesis that the earnings momentum profits are identical across up and down business cycles. Panel D reports the intercepts, α, and regression coefficients on a dummy variable for business cycle, from time series regressions of the earnings momentum profit on the CAPM and the Fama-French three-factor model.

Panel A: Average monthly price-momentum profits following Up/Down business cycle

	N	Price momentum	Price momentum, controlling for earnings momentum
Up cycle	296 (230)	0.0113	0.0101
		5.58	*4.46*
Down cycle	202 (181)	0.0042	0.0013
		1.36	*0.42*
Up-Down *t (Mean)*	*t (Mean)*	1.96	2.35

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	0.0045	0.0017
	t(α)	*1.68*	*0.59*
	Dummy(up cycle)	0.0071	0.0091
	t(Dummy)	*2.02*	*2.44*
FF regression coefficients	F-F α	0.0077	0.0050
	t(α)	*2.84*	*1.78*
	Dummy(up cycle)	0.0052	0.0068
	t(Dummy)	*1.52*	*1.87*

Panel C: Average monthly earnings-momentum profits following Up/Down business cycle

	N	Earnings momentum	Earnings momentum, controlling for price momentum
Up cycles	230	0.0114	0.0077
		11.41	*11.53*
Down cycles	181	0.0117	0.0102
		7.38	*8.31*
Up-Down *t (Mean)*		0.00	1.96

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	0.0114	0.0102
	t(α)	*8.60*	*9.38*
	Dummy(up cycle)	0.0000	-0.0026
	t(Dummy)	*0.01*	*-2.03*
FF regression coefficients	F-F α	0.0128	0.0106
	t(α)	*9.70*	*9.63*
	Dummy(up cycle)	-0.0011	-0.0029
	t(Dummy)	*-0.62*	*-2.27*