Momentum

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Abstract

There is substantial evidence that indicates that stocks that perform the best (worst) over a three- to 12-month period tend to continue to perform well (poorly) over the subsequent three to 12 months. Until recently, trading strategies that exploit this phenomenon were consistently profitable in the United States and in most developed markets. Similarly, stocks with high earnings momentum outperform stocks with low earnings momentum. This article reviews the momentum literature and discusses some of the explanations for this phenomenon.

A growing body of literature documents evidence of stock return predictability based on a variety of firm-specific variables. Among these anomalies, the price momentum effect is probably the most difficult to explain within the context of the traditional risk-based asset pricing paradigm. Jegadeesh and Titman (JT) document that U.S. stocks that perform the best (worst) over a three- to 12-month period tend to continue to perform well (poorly) over the subsequent three to 12 months (Jegadeesh & Titman 1993). In a follow-up study, JT show that momentum strategies remained profitable in the nineties (Jegadeesh & Titman 2001); a period subsequent to the sample period in Jegadeesh & Titman (1993).

As shown in **Figure 1**, the returns of a zero cost portfolio that consists of a long position in past winners and a short position in past losers made money in every five-year period starting in 1965 to 2004. In our opinion, the magnitude and persistence of these returns are too strong to be explained by risk, so the focus of this review is on the literature that provides behavioral explanations for this phenomenon. As we discuss below, this literature considers both the time-series and cross-sectional determinants of momentum profits.

Figure 1 also reveals that momentum profits in the five-year period starting in 2004 were negative. As we later discuss, the negative returns in this last period were driven mainly by extremely negative returns in 2009. We discuss the 2009 performance in detail in Section 9, where we examine the extent to which these returns can be explained by variables that were previously introduced in the time-series momentum literature.

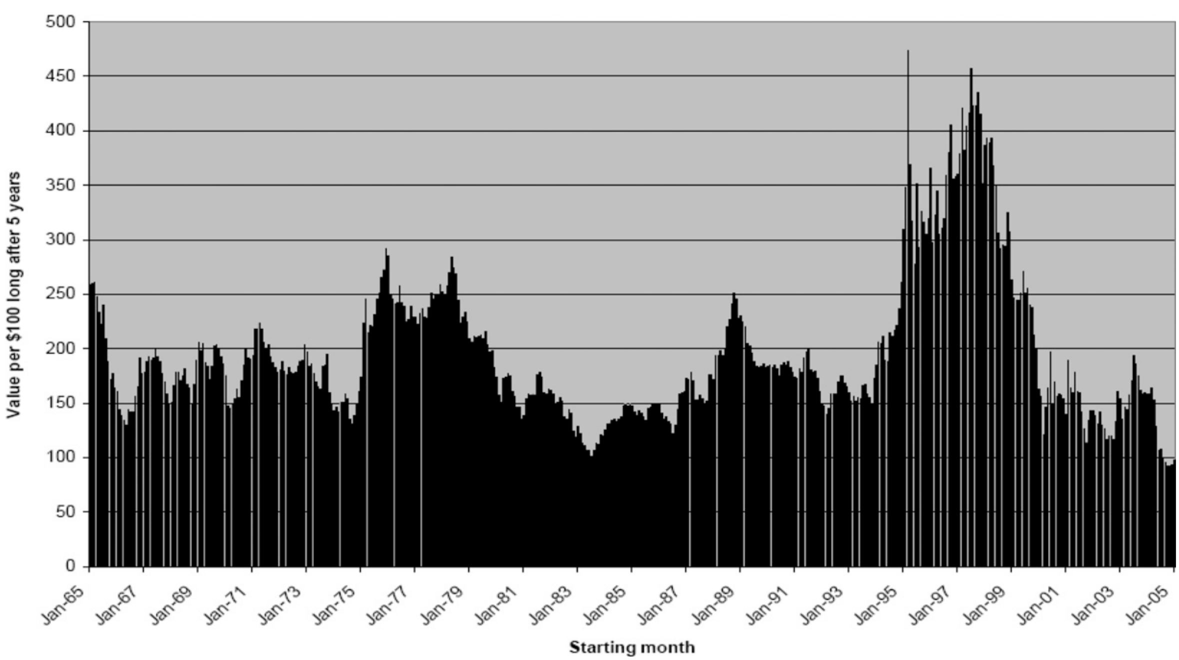

Figure 1

This figure presents the rolling five-year cumulative returns for a momentum strategy that buys winners and sells losers based on returns in month t-7 through t-2 and holds the portfolio for six months.

1. THE MOMENTUM EVIDENCE

If stock prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist. In an influential paper, DeBondt & Thaler (1985) document that past losers over three- to five-year periods outperform past winners over the subsequent three to five years. Jegadeesh (1990) and Lehmann (1990) find that losers over the past one week to one month outperform winners over the next one week to one month. These studies of very long-term and very short-term returns find profitable contrarian strategies and generally led to the conclusion that stock prices overreact to information.[1]

In contrast to these studies, JT focus on the performance of trading strategies with formation and holding periods between three and 12 months (Jegadeesh & Titman 1993). Their strategy selects stocks on the basis of returns over the past J months and holds them for K months. This J-month/K-month strategy is constructed as follows: At the beginning of each month t, securities are ranked in ascending order on the basis of their returns in the past J months. On the basis of these rankings, JT form 10 equally weighted decile portfolios. The portfolio with the highest return is called the winners decile and the portfolio with the lowest return is called the losers decile. As they show, each of these strategies earns positive returns. Moreover, when the strategies skip a week between the portfolio formation period and holding period to avoid the short-term reversals documented in Jegadeesh (1990) and Lehmann (1990), they generate higher and more significant returns.

1.1. Evidence Around the World

Momentum strategies are profitable in most major markets throughout the world. Rouwenhorst (1998) replicates JT for 12 European countries and finds profits that are very close to those in the United States. More recent papers by Griffin et al. (2003) and Chui et al. (2010) examine momentum profits around the world and find that the momentum strategy yields positive profits in most large markets, with notable exceptions in Asia (e.g., Japan).

1.2. Seasonality

Momentum strategies exhibit a unique pattern of seasonality in January. Many of the well-known strategies such as long-horizon and short-horizon return reversals, the size effect, and the book-to-market effect are significantly stronger in January than in any other calendar month. In contrast, JT find that the momentum strategy earns negative returns in January, but earns significantly positive returns in every calendar month outside of January.

2. POTENTIAL SOURCES OF MOMENTUM PROFITS

A natural interpretation of momentum profits is that there is a delayed reaction to information. For example, if stock prices only react partially to good news, then buying

[1]As pointed out in a recent paper by Asness et al. (2009), the profitability of momentum or trend-following strategies exists in several markets. For example, Chan et al. (2000) show that a momentum strategy is profitable when applied to portfolios of country stock indexes; Shen et al. (2007) show that momentum strategies generate profits in commodity futures markets; and Sweeney (1986), Taylor & Allen (1992) and Okunev & White (2003) show that momentum strategies work in currency markets. Although these papers illustrate the robustness of the momentum strategy, our review considers only the literature on equity markets.

stocks after the initial release of the news will exploit the delayed reaction and generate profits. However, such underreaction is not the only possible source of momentum profits, and JT show that there are several other factors that can also contribute to momentum profits.

One other potential source of momentum profits is cross-sectional dispersion in expected returns. Intuitively, given that realized returns contain a component related to expected returns, securities that experience relatively high returns in one period can be expected to have higher than average returns in the following period. Momentum strategies can also benefit from positive serial correlation in factor returns. With positive serial correlation, large factor realizations in one period will be followed by higher than average factor realizations in the next period. The momentum strategy will tilt toward high beta stocks following periods of large factor realizations, and hence it will benefit from the higher expected future factor realizations.

To assess whether the existence of momentum profits implies market inefficiency, it is important to identify which of these sources contribute to momentum profits. If the profits are due to either the second or the third component, they may be attributed to compensation for bearing systematic risk and need not be an indication of market inefficiency. However, if the superior performance of momentum were due to the first component, then the results would suggest market inefficiency.

To examine whether cross-sectional differences in risk explain momentum profits, several studies examine risk-adjusted returns under specific asset pricing models. In Jegadeesh & Titman (1993), JT adjust for risk using the capital asset pricing model (CAPM) benchmark, and in Jegadeesh & Titman (2001), they adjust for risk using the Fama-Franch three-factor model benchmark, as do Fama & French (1996) and Grundy & Martin (2001). In each of these cases, the alphas of the momentum strategy are significantly positive, suggesting that cross-sectional differences in risk do not explain momentum profits.

If the serial covariance of factor related returns were to contribute to momentum profits, then the factor realizations should be positively serially correlated. JT examine this implication in the context of a single-factor model and find that the serial covariance of six-month returns of the equally weighted index is negative (-0.0028), indicating that the serial correlation of factor returns is unlikely to have a positive effect on momentum profits.

Momentum profits can also potentially arise if stock prices react to common factors with some delay. Intuitively, if stock prices react with a delay to common information, investors will be able to anticipate future price movements based on current factor realizations and devise profitable trading strategies. JT show that in some situations such delayed reactions will result in profitable contrarian strategies, but in other situations it will result in profitable momentum strategies (Jegadeesh & Titman 1995).

The contribution of this lead-lag effect to momentum profits depends on the relation between contemporaneous betas and lagged betas. Specifically, lead-lag contributes to momentum if firms with large contemporaneous betas also tend to exhibit large lagged betas. For example, one can imagine small stocks that have high betas, but actually underreact to market returns, and hence have large lagged betas as well. Therefore, during market increases, these firms will tend to outperform, and because of their lagged beta, they will outperform in the following period as well. Put somewhat differently, the contemporaneous betas are less dispersed than they should be given fundamentals, causing stock prices to move together too closely with one another. In other words, if the market moves up, high beta stocks will increase more than low beta stocks, but not by as much as they should. It is possible that delayed reactions of this nature may be due to the tendency of investors to buy and sell stocks in baskets rather than individually. With such delayed reactions, a momentum strategy will buy high beta stocks following a market increase, and will profit from the delayed response in the following period.

If lead-lag effects do contribute to momentum profits then we expect the magnitude of momentum profits to depend on the magnitude of past market returns. To investigate the importance of this source, JT regress momentum profits on the squared return of the value-weighted market during the six-month formation period. Over the 1965 to 1989 sample period the coefficient on the squared market return is negative, suggesting that the lead-lag effect does not contribute to momentum profits in this time period.

In summary, the evidence suggests that momentum profits arise because of a delayed reaction to firm-specific information. One interpretation of this evidence is that investors tend to underreact to firm-specific information. An alternative interpretation is that the delayed reaction is actually an overreaction, by investors who either react to the information with a delay or who like to chase past winners. As we discuss below, the latter interpretation suggests that the momentum portfolio excess returns are eventually reversed.

3. INDUSTRY MOMENTUM

The results discussed in the last section clearly indicate that the common factor in a single-factor model cannot explain momentum profits. JT therefore conclude that the momentum profits are due to the nonmarket component of returns. Although the nonmarket component is the idiosyncratic component of returns in a single-factor model, it is possible that momentum is related to other factors in a more general multifactor setting. For example, if we introduce industry factors, serial covariance in industry returns, rather than the serial covariance of firm-specific components of returns, may account for the momentum profits.

Moskowitz & Grinblatt (1999) evaluate industry momentum. They form value-weighted industry portfolios and rank stocks based on past industry returns. They find that high momentum industries outperform low momentum industries in the six months after portfolio formation. To assess the extent to which the industry return contributes to momentum profits, they examine the performance of a random industry strategy. Specifically, they replace each firm in the winner and loser industries with other firms that are not in these industries, but have the same ranking period returns as the firms that they replace. The random industry portfolios have similar levels of past returns as the winner and loser industry portfolio. However, Moskowitz & Grinblatt find that the profit for the momentum strategy with the random industry earns close to zero returns. On the basis of this test they conclude that the momentum strategy profits from industry momentum and not from momentum in the firm-specific component of returns.

Grundy & Martin (2001) reexamine the extent to which industry momentum contributes to momentum profits. Grundy & Martin find that for a six-month ranking period and a contiguous six-month holding period, the actual industry strategy earns a significantly positive return of .78%, whereas the simulated industry strategy earns zero returns. Additionally, Grundy & Martin consider a strategy that skips a month between the ranking period and holding period to avoid the potential biases due to bid-ask spreads. When industry portfolios are formed in this manner, a momentum strategy does not yield significant profits either for the actual industry strategy or for the simulated industry strategy. In comparison, the momentum strategy with individual stocks earns a significantly positive profit of .79% during the 1966 to 1995 period.

As JT show, the momentum strategy with individual stocks is more profitable when the ranking period and holding period are not contiguous than when they are contiguous. When the holding period and the ranking period are contiguous, the profits to the momentum strategy are attenuated by the negative serial correlation in returns induced by the bid-ask spreads, and by the short-horizon return reversals. In contrast, industry momentum profits entirely disappear for the six-month ranking period when the ranking period and the holding period are not contiguous. The industry momentum seems to benefit from the positive first-order serial correlation in portfolio returns, whereas the individual stock momentum is reduced by short-horizon return reversals.

4. BEHAVIORAL EXPLANATIONS

As we mentioned in the introduction, it is very difficult to explain the observed momentum profits with a risk-based model. Therefore, researchers have turned to behavioral models to explain this phenomenon. Most of the models assume that the momentum effect is caused by the serial correlation of individual stock returns, which, as we discussed above, appears to be consistent with the evidence. However, they differ as to whether the serial correlation is caused by underreaction or delayed overreaction. If the serial correlation is caused by underreaction, then we expect to see the positive abnormal returns during the holding period followed by normal returns in the subsequent period. However, if the abnormal returns are caused by delayed overreaction, then we expect that the abnormal momentum returns in the holding period will be followed by negative returns given that the delayed overreaction must be subsequently reversed. Hence, these behavioral models motivate tests of the long-term profitability of momentum strategies that we discuss below. In addition, the behavioral models have implications about the cross-sectional determinants of momentum, which are also discussed below.

Barberis et al. (1998) discuss how a conservatism bias might lead investors to underreact to information, giving rise to momentum profits. The conservatism bias, identified in experiments by Edwards (1968), suggests that investors tend to underweight new information when they update their priors. If investors act in this way, prices will slowly adjust to information, but once the information is fully incorporated in prices there is no further predictability about stock returns.

More recent explanations that are consistent with underreaction include what is referred to as the disposition effect, which suggests that loss-averse investors tend to hold on to their past losers and sell their past winners, and the tendency to anchor on past prices. Grinblatt & Han (2005) provide evidence that is consistent with the disposition effect, and George & Hwang (2004), who show that stocks perform well after hitting their 52-week highs, provide evidence of anchoring.

The idea of delayed overreaction was originally introduced by Delong et al. (1990), who show that positive feedback trading strategies (investment strategies that buy past winners and sell past losers) cause market prices to deviate from fundamental values. To a large extent, the subsequent literature presents behavioral models that formalize how various behavioral biases can lead investors to follow such positive feedback strategies.

For example, Barberis et al. (1998) hypothesize that investors identify patterns based on what Tversky & Kahneman (1974) refer to as a "representative heuristic," which is the tendency of individuals to identify "an uncertain event, or a sample, by the degree to which it is similar to the parent population." In the context of stock prices, Barberis et al. argue that the representative heuristic may lead investors to mistakenly conclude that firms realizing consistent extraordinary earnings growths will continue to experience similar extraordinary growth in the future. They argue that although the conservatism bias in isolation leads to underreaction, this behavioral tendency in conjunction with the representative heuristic can lead to prices overshooting their fundamental value and, eventually, long-horizon negative returns for stocks with consistently high returns in the past.[2]

Daniel et al. (1998) and Hong & Stein (1999) propose alternative models that are also consistent with short-term momentum and long-term reversals. Daniel et al. argue that the behavior of informed traders can be characterized by a self-attribution bias. In their model, investors observe positive signals about a set of stocks, some of which perform well after the signal is received. Because of their cognitive biases, the informed traders attribute the performance of ex-post winners to their stock selection skills and that of the ex-post losers to bad luck. As a result, these investors become overconfident about their ability to pick winners and thereby overestimate the precision of their signals for these stocks. Based on their increased confidence in their signals, they push up the prices of the winners above their fundamental values. The delayed overreaction in this model leads to momentum profits that are eventually reversed as prices revert to their fundamentals.

Hong & Stein (1999) do not directly appeal to any behavioral biases on the part of investors but they consider two groups of investors who trade based on different sets of information. The informed investors or the news watchers in their model obtain signals about future cash flows but ignore information in the past history of prices. The other investors in their model trade based on a limited history of prices and, in addition, do not observe fundamental information. The information obtained by the informed investors is transmitted with a delay and hence is only partially incorporated in the prices when first revealed to the market. This part of the model contributes to underreaction, resulting in momentum profits. The technical traders extrapolate based on past prices and tend to push prices of past winners above their fundamental values. Return reversals obtain when prices eventually revert to their fundamentals. Both groups of investors in this model act rationally in updating their expectations conditional on their information sets but return predictability obtains due to the fact that each group uses only partial information in updating their expectations.

5. LONG-HORIZON RETURNS OF MOMENTUM PORTFOLIOS

As we discussed earlier, the momentum-effect is consistent with both investors underreacting to information, as well as with investors overreacting to past information

[2]The time horizon over which various biases come into play in the Barberis et al. model (and in other behavioral models) is unspecified. One could argue that the six-month ranking period used in Jegadeesh & Titman (1993) and others may not be long enough for delayed overreaction due to the representative heuristic effect. In such an event we would only observe underreaction due to the conservatism bias.

with a delay, perhaps due to positive feedback trading. The positive feedback effect, which is consistent with some of the behavioral models described in Section 3, implies that the momentum portfolio should generate negative returns in the periods following the holding periods considered in previous sections.

JT examine the long-horizon performance of momentum strategies to examine whether the evidence suggests returns reversals in the postholding periods (Jegadeesh & Titman 1993, 2001). Over the 1965 to 1998 sample period, the results reveal a dramatic reversal of returns in the second through fifth years. Cumulative momentum profit increases monotonically until it reaches 12.17% at the end of Month 12. From Month 13 to Month 60 the momentum profits are on average negative. By the end of Month 60 the cumulative momentum profit declines to −.44%.

The robustness of long-horizon return reversals can be evaluated by examining the performance of momentum portfolios in two separate time periods, the 1965 to 1981 and 1982 to 1998 subperiods. In addition to being the halfway point, 1981 represents somewhat of a break point for the Fama and French factor returns. The Fama-French size (SMB) and value (HML) factors have higher returns in the pre-1981 period (the monthly returns of the SMB and HML factors average .53% and .48%, respectively) than in the post-1981 period (the monthly returns of the SMB and HML factors average −.18% and .33%, respectively).

The evidence indicates that the momentum strategy is significantly profitable, and quite similar in both subperiods, in the first 12 months following the formation date. The returns in the postholding periods, however, are quite different in the two subperiods. In the 1965 to 1981 subperiod, the cumulative momentum profit declines from 12.10% at the end of Month 12 to 5.25% at the end of Month 36 and then declines further to –6.29% at the end of Month 60. Hence, the evidence in this subperiod supports the behavioral models that suggest that positive feedback traders generate momentum. In the 1982 to 1998 subperiod the cumulative profit decreases insignificantly from 12.24% at the end of Month 12 to 6.68% at the end of Month 36 and then stays at approximately the same level for the next 24 months. Hence, the evidence in the second subperiod does not support the behavioral models.

6. CROSS-SECTIONAL DETERMINANTS OF MOMENTUM

The insights provided by the behavioral models also suggest that stocks with different characteristics should exhibit different degrees of momentum. For example, given that the momentum effect is due to inefficient stock price reaction to firm-specific information, it is likely to be related to various proxies for the quality and type of information that is generated about the firm, the relative amounts of information disclosed publicly and generated privately, and to the cost associated with arbitraging away the momentum profits.

Hong et al. (2000) find that even after controlling for size, firms that are followed by fewer stock analysts exhibit greater momentum. This finding is consistent with the Hong & Stein (1999) prediction that slow dissemination of public information increases momentum profits. Because there is less public information about stocks with low analyst coverage, information about the companies may be incorporated into their stock prices more slowly. In addition, given that there is less public information available about these stocks, one might expect relatively more private information to be produced, which Daniel et al. (1998) suggest will increase price momentum.

Daniel & Titman (1999) find that momentum profits are significantly higher when the strategy is implemented on growth (low book-to-market) stocks rather than value (high book-to-market) stocks. They suggest that this result may be due to the fact that it is harder to evaluate growth stocks than to evaluate value stocks. Psychologists report that individuals tend to be more overconfident about their ability to do more ambiguous tasks. So, the overconfidence hypothesis suggests that momentum is likely to be greater for growth stocks.

Zhang (2006) examines this issue more broadly and finds that higher information uncertainty, as measured by dispersion in analyst forecasts,[3] return volatility, and cash flow volatility predict higher momentum profits. Sagi & Seasholes (2007) empirically document similar results: Momentum is stronger in stocks with higher revenue volatility and lower costs of goods sold, and these results suggest that momentum profits arise from the fact that firms that performed well in the recent past have new growth options to exploit.

Lee & Swaminathan (2000) examine the relation between momentum profits and turnover, and find that momentum is higher for stocks with greater turnover. This finding is somewhat surprising when viewed from the transaction cost perspective. Stocks with higher turnover can be traded more easily, and generally, there is more public information generated for high turnover stocks than for low turnover stocks. One potential explanation for their findings may be that there are larger differences in opinion about higher turnover, and larger differences of opinion may arise from difficulties in evaluating the fundamental values of these stocks. Hence, the Daniel & Titman explanation for why growth stocks exhibit greater momentum may also apply to high turnover stocks. Another explanation is that turnover is related to the amount of attention that a stock attracts. Hence, high turnover stocks may be more exposed to positive feedback trading strategies proposed by Delong et al. (1990).

Avramov et al. (2007) find that momentum is profitable only among firms with low credit ratings. Extreme winner and loser portfolios are comprised of high credit risk stocks. For stocks with a credit rating between AAA and BB, momentum profits are insignificant. These stocks account for 96.6% of the market capitalization and 78.8% of the total number of rated firms. Several other papers, however, find that the momentum effect is far more pervasive. For example, JT find momentum effect for small, medium, and large stocks (Jegadeesh & Titman 1993). Also, Fama & French (2008) find that "the relation between momentum (the center-stage anomaly of recent years) and average returns is similar for small and big stocks."

Finally, Chui et al. (2010) examine the determinants of the profitability of momentum strategies across countries. They hypothesize that cultural differences may be related to behavioral biases, and hence, cross-country cultural differences may explain cross-country differences in the profitability of momentum strategies. To measure cross-country differences in culture they use the individualism index developed by Hofstede (2001), which they argue is related to overconfidence and self-attribution biases, and find that it is positively correlated with momentum profits.

[3]Verardo (2009) finds similar results with dispersion in analyst forecasts but interprets her evidence to signify differences of opinion.

7. TIME-SERIES DETERMINANTS OF MOMENTUM PROFITS

To test whether momentum profits are dependent on the state of the economy, several conditioning variables have been proposed to predict time-series variations in momentum profits. These studies estimate monthly time-series regressions of the momentum profits (MOMπ) on a conditioning state variable (STATE) of the following form.

$$MOM\pi_t = \gamma_0 + \beta_1{}^{*}STATE_{t-1} + \varepsilon_{t.}$$

Chordia & Shivakumar (2002), using standard macro variables, find that the momentum strategy is only profitable during times of economic expansion. However, Griffin et al. (2003) find that macroeconomic variables cannot predict momentum profits in international markets. Cooper et al. (2004) also find that macroeconomic multifactor models that Chordia & Shivakumar use are not robust to standard price screens and skip-a-month returns. However, they find that the lagged three-year market return does predict momentum profits. Specifically, the momentum strategy generates significantly positive returns (0.93% average monthly returns) following positive market returns, but insignificantly negative returns (−0.37% average monthly returns) following negative market returns.

Stivers & Sun (2010) find that higher return dispersion predicts lower future momentum profits. Return dispersion is measured as the standard deviation of 100 size and book-to-market monthly portfolio returns over the prior three months. They suggest that return dispersion may act as a state variable that has information about subsequent market volatility. Their regression results indicate that the inclusion of return dispersion subsumes the predictive power of the market state in Cooper et al. (2004) and macro factors in Chordia & Shivakumar (2002).

Wang & Xu (2010) find that recent market volatility in combination with market state (Cooper et al. 2004) predicts momentum profits. Momentum profits tend to be higher following periods of low market volatility. In particular, the momentum strategy generates especially low average monthly returns (−3.01%, *t*-stat −1.94) during down market/high volatility states.

Antoniou et al. (2010) find that investor sentiment predicts momentum profits. Investor sentiment is estimated by taking the residual of a regression of the Conference Board Consumer Confidence Index on a set of macroeconomic variables following the approach used in Baker & Wurgler (2006, 2007). During optimistic states, momentum strategies generate significant average monthly profits of 1.64%, but during pessimistic states yield insignificant average monthly profits of 0.56%. Their results remain with the inclusion of market state variables. Momentum profits are particularly high in up/optimistic states generating 1.8% average monthly profits but only averaging 0.8% for up/pessimistic states. Unlike the previous studies, Antoniou et al. (2010) explicitly test the subsequent long-run reversal effect to momentum strategies and find that momentum profits reverse only after optimist periods.

8. EARNINGS MOMENTUM

The results so far have focused on the profitability of momentum strategies based on past returns. Naturally, returns are driven by changes in underlying fundamentals. Stock returns tend to be high, for example, when earnings growth exceeds expectations or when consensus forecasts of future earnings are revised upward. An extensive literature examines return predictability based on momentum in past earnings and momentum in expectations of future earnings as proxied by revisions in analyst forecasts. This section reviews the evidence from the earnings momentum literature and presents the interaction between earnings momentum and return momentum.

A partial list of papers that investigate the relation between past earnings momentum and futures returns includes Jones & Litzenberger (1970), Latane & Jones (1979), Foster et al. (1984), Bernard & Thomas (1989), and Chan et al. (1996). These papers typically measure earnings momentum using a measure of standardized unexpected earnings (*SUE*). *SUE* is defined as: $SUE = \frac{\text{Quarterly earnings} - \text{Expected quarterly earnings}}{\text{Standard deviation of quarterly earnings}}$.

These papers use variations of time-series models to determine earnings expectations. Typically, the papers either assume that quarterly earnings follow a seasonal random walk with drift or use changes in analyst earnings forecast to measure earnings momentum. A study by Givoly & Lakonishok (1979), which examines a sample of 67 firms from 1967 to 1974 using earnings forecast data from Standard and Poors Earnings forecaster, finds that stocks with upward revisions outperform stocks with downward revisions by approximately 5%. Stickel (1991) finds similar results using the Zacks Investment Research database over the 1981 to 1984 sample period. Chan et al. (1996) use IBES, the earnings forecast database, over the 1977 to 1993 sample period and find that Up revision portfolios earn 7.7% higher return than the Down revision portfolios over the six months after portfolio formation.

The collective evidence in the literature indicates that the analyst forecast revision strategy is remarkably robust. The profitability of this strategy is not sensitive to the specific definition of forecast revisions, nor is it sensitive to the data source for analysts' forecasts. Also, both the *SUE* strategy and the forecast revision strategy persisted for a fairly long period of time after the initial publication of the evidence.

8.1. Relation Between Earnings and Return Momentum Strategies

Chan et al. (1996) present a detailed analysis of the interactions among various momentum strategies and this subsection closely follows that paper. Not surprisingly, the price momentum and earnings momentum measures are positively correlated with one another.

8.2. Two-Way Analysis

Earnings and return momentum strategies are individually useful for predicting stock returns six to 12 months in the future. Because these variables tend to move together, it is possible that the findings may reflect not separate effects but different manifestations of a single effect.

Chan et al. (1996, 2000) examine this issue with predictability tests based on two-way classifications. At the beginning of each month, they sort the stocks in their sample on the basis of their past six-month returns and assign them to one of three equal-sized portfolios. Independently, they sort stocks into three equal-sized portfolios on the basis of *SUE* and analyst forecast revisions. Each stock, therefore, falls into one of nine portfolios for each two-way sort.

Their evidence indicates that past six-month returns and *SUE* each independently predict returns in the subsequent period. In particular, the two-way sort generated large differences in returns between stocks that were jointly ranked highest and stocks jointly ranked lowest. For example, the highest ranked portfolio outperformed the lowest ranked portfolio by 8.1% in the first six months and 11.5% in the first year. Chan et al. also find similar results using two-way analysis based on price momentum and earnings forecast revisions, and based on price momentum and past earnings announcement window returns. Overall, none of the momentum variables considered here subsumes any of the others. Instead, they each exploit underreaction to different pieces of information.

9. RECENT PERFORMANCE AND DETERMINANTS OF MOMENTUM PROFITS

This section examines the performance of the momentum strategy over the past 20 years (1990–2009). This period starts after the end of the sample period in Jegadeesh & Titman (1993), and hence provides a perspective on the performance of the strategy after the original published period. As in Jegadeesh & Titman (2001), we find evidence that the momentum effect continued after the publication of the earlier paper, but has diminished over time and did extremely poorly in the most recent period.

The particular strategy that we examine is the six-month ranking period/six-month holding period momentum strategy where we skip a month between the ranking period and the holding period to avoid the effect of one-month return reversals that Jegadeesh (1990) reports. We follow the approach in Jegadeesh & Titman (1993), and in each month construct six sets of equally weighed extreme decile portfolios based on returns in the period t-7 to t-2, t-8 to t-3, etc. The winner (loser) portfolio return in month t is the average return of the six winner (loser) portfolios based on these ranking periods. The momentum strategy return is the difference between the winner and loser portfolio returns. Our sample excludes all stocks that would be ranked among the smallest New York Stock Exchange market cap decile and stocks priced less than $5 at the end of the month prior to the holding period.

Table 1, which presents the annual momentum profits from 1990 to 2009, reveals that the momentum strategy is profitable in 16 out of the 20 years. The average annual profit is 13.5% with a t-statistic of 2.9. Although the profits are significant over the entire period, the strategy experiences a severe loss of 36.5% in 2009. The poor performance in 2009 in particular, and the overall variation in momentum profits over the more recent period in general, offer an opportunity to examine the extent to which the various sources of momentum suggested in the literature explain variation in the profitability of momentum strategies.

For example, the third term of the decomposition described earlier suggests that momentum is expected to generate negative returns in periods where the market returns exhibit negative serial correlation. This is because winners tend to have low betas and losers tend to have high betas following periods when the market does especially poorly. Hence, if the negative market returns are followed by very strong positive returns, the momentum portfolio will do poorly. As discussed in Jegadeesh & Titman (1993), this is exactly what happened in the 1930s, which was the only decade in which the momentum portfolio exhibited negative returns.

The performance of the market in 2009 is somewhat similar to what was observed in 1933. The strong market recovery in 2009 followed severe market declines in late

Table 1 Momentum strategy—annual returns[a]

	Raw return	Alpha	Beta
1990	21.61	19.96	−0.01
1991	22.44	12.15	0.36
1992	1.42	−1.06	0.53
1993	22.17	11.56	1.13
1994	−0.32	0.96	0.24
1995	15.08	6.93	0.31
1996	4.16	3.46	0.09
1997	9.05	3.18	0.27
1998	41.50	34.94	0.09
1999	67.26	36.25	1.02
2000	36.01	69.70	1.40
2001	2.56	−8.63	−1.27
2002	16.93	−6.94	−1.15
2003	−3.50	12.27	−0.54
2004	3.63	−1.54	0.50
2005	16.18	13.90	0.36
2006	5.44	−7.57	1.29
2007	25.45	23.31	−0.02
2008	−0.32	−0.14	−0.06
2009	−36.50	−18.84	−0.79
Average	13.51	10.19	
t-statistics	(2.90)	(2.30)	

[a]This table presents the annual raw returns and annualized CAPM alpha and beta for the momentum strategy that buys winners and sells losers based on returns in months *t*-7 through *t*-2 and holds the portfolio for six months. We estimate CAPM parameters by fitting the market model within each calendar year. The sample period is from January 1990 to December 2009.

2008 and early 2009, which is similar to the strong market recovery in 1933 following market declines during the Great Depression. As JT discuss, winners tend to be low beta stocks and losers tend to be high beta stocks following market declines, and hence any sharp market reversals will result in significant losses for momentum strategies. Indeed, although the beta of the momentum portfolio is close to zero on average over the entire 1990 to 2009 sample period, the beta in 2009 is −.79. When we account for the negative beta in 2009, the momentum portfolio return is −1.56% per month, compared with a raw monthly return of −3.4% per month. Therefore, more than half the losses in 2009 are explained by the beta of the momentum portfolio.[4]

Next, we examine the extent to which the variables in the literature that predict time-series variations in momentum profits anticipated the sharp loss in 2009. We consider the past three-year returns suggested by Cooper et al. (2004); the negative momentum profits in 2009 are consistent with this evidence given that 2009 was preceded by strongly negative market returns in the previous three years. We also consider RD, the cross-sectional dispersion in stock returns signal of Stivers & Sun (2010). Average RD in 2009 was 4.84%, which exceeds 3.20%, the measure in the rest of the sample period. The result that RD in 2009 was bigger than that in the rest of the sample period is directionally consistent with the low momentum profits in 2009.

We fit the following multivariate regression over the January 1990 to December 2009 period to examine the out-of-sample performance of these signals and the extent to which they anticipated the poor performance of momentum strategies in 2009:

$$\mathrm{MOM}_t = 1.12 - \underset{(-1.03)}{.42} \times RD_{t-1} + \underset{(2.21)}{.90} \times \mathrm{MktRet}_{t-36,\,t-1}.$$

In this regression, MOM_t is the return on the momentum portfolio in month t, RD_{t-1} is Stivers & Sun's (2010) *RD* variable, and $\mathrm{MktRet}_{t-36,t-1}$ is the return on the value-weighted index over the previous 36 months. We standardize the independent variables by subtracting the mean and dividing this difference by the standard deviation of the corresponding variables. The equation reports the parameter estimates and the t-statistics.

The regression estimates indicate that although the sign of RD is consistent with the results in Stivers & Sun (2010), the slope coefficient is not statistically significant. The slope coefficient on $\mathrm{MktRet}_{t-36,\,t-1}$, however, is statistically significant over the recent 20-year period as well. To examine the extent to which these two variables explained momentum profits in 2009, we computed adjusted momentum profits as follows:

$$adj\_\mathrm{MOM}_t = \mathrm{MOM}_t - \left(-.42 \times RD_{t-1} + .90 \times \mathrm{MktRet}_{t-36,\,t-1}\right).$$

The average adjusted momentum profit for 2009 was −1.5%, which is smaller in magnitude than the raw profit of −3.4%. Therefore, these signals and momentum portfolio betas explain a large part of the 2009 losses.

To examine the extent to which these variables, along with differences in beta, account for the negative momentum portfolio returns in 2009, we regress the beta-adjusted momentum profits against these independent variables. Specifically, we fit the following regression:

$$\mathrm{MOM}_t^{beta-adjusted} \equiv \mathrm{MOM}_t - \beta_t \times \mathrm{MktRet}_t = .85 - \underset{(-.85)}{.30} \times RD_{t-1} + \underset{(2.16)}{.76} \times \mathrm{MktRet}_{t-36,\,t-1},.$$

where β_t is the momentum beta fit within each calendar year. The momentum residual after we account for both CAPM beta and the other signals for 2009 is .19% per month, so most of the negative momentum returns in 2009 can in fact be explained.

[4]Daniel (2011) also examines the relation between portfolio betas and momentum profits in 2009 and in the 1930s. Similar to our findings, Daniel also reports that the beta effect provides a partial but not a complete explanation for the negative momentum returns in 2009.

Of course, there is considerable estimation error in these regressions, and hence one should not put too much weight on one observation. Nevertheless, the evidence indicates that investors who use momentum signals should pay attention to the market exposure of the portfolio and they should heed signals that are related to the strategy's performance.

10. CONCLUSION

Underlying the efficient market hypothesis is the notion that if any predictable patterns exist in returns, investors will quickly act to exploit them, until the source of predictability is eliminated. However, this does not seem to be the case for either stock return or earnings based momentum strategies. Both strategies have been well known and were well publicized by at least the early 1990s, but both continued to generate excess profits in the subsequent years.

We would argue that the momentum effect represents perhaps the strongest evidence against the efficient markets hypothesis. For this reason it has attracted substantial research, which documents more details about the anomaly, for example, the extent to which momentum profits are correlated with stock characteristics, as well as attempts to provide behavioral explanations for the phenomena. At this point, we have several interesting facts to explain as well as possible theoretical explanations. However, financial economists are far from reaching a consensus on what generates momentum profits, making this an interesting area for future research.

DISCLOSURE STATEMENT

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Contents

Errata

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