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Consistent winners and losers

Abdulaziz M. Alwathainani *

York University, 4700 Keele Street, TEL Bldg. 2044, Toronto ON, Canada M3J 1P3

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ABSTRACT

This paper investigates two related questions. First, I examine whether a string of relatively high (low) stock return performance that is measured over short periods ranging from the past two to four months triggers a market overreaction that gradually reverts to fundamentals. Second, I assess whether these two mispricing patterns, i.e., the momentum and reversal effects, are empirically linked. Results reported in this paper show that a zero-investment strategy that is long on consistent winners and short on consistent losers earns substantial average monthly abnormal returns that continue to be economically and statistically significant over the next twelve months. Subsequently, however, the return for the zero-investment portfolio in Years 2 to 5 is negative, resulting in a reversal of the bulk of the initial momentum profit. This evidence suggests that the return momentum and the price reversal anomalies are likely to be driven by the same investor psychology. This finding remains robust to the four-factor regression (the Fama-French three-factor model extended by the momentum factor) and various sensitivity tests. My evidence is consistent with the spirit of the psychology-based models.

1. Introduction

Over the last three decades, empirical research in the finance literature has documented two major findings that seem to be diametrically opposed; the price run or momentum over the next three-to-nine months (e.g., Jegadeesh & Titman, 1993) and reversals at long horizons (e.g., DeBondt & Thaler, 1985). The momentum effect is interpreted as a market failure to adequately respond to a fundamental signal. As a consequence, information contained in this signal is slowly reflected in share prices over time, resulting in a return autocorrelation. On the other hand, the long-run price reversal is believed to be due to a market overreaction to a firm's past performance (e.g., past returns and accounting data) that is subsequently corrected when the market discovers its erroneous expectations.

The reconciliation of these two mispricing effects presents serious challenges to both financial scholars and investment managers. If these market anomalies are caused by cognitive biases on the part of investors, how can investors underreact to one set of market signals and overreact to another? Can these two phenomena be a manifestation of an investor overreaction to a particular information signal as suggested by recent behavioral models (e.g., Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998)? As well, is it possible that a short-run price drift, i.e., underreaction can result in a market overreaction? If this is true, what is the tipping point at which an investor underreaction switches to an overreaction?

In this paper, I am interested in two related questions. First, I test whether a string in a firm's past monthly return that is measured over short horizons varying from two to four month intervals is likely to trigger a market overreaction that is gradually corrected when market participants discover that their prior expectations are not warranted by future performance, resulting in a short-run return continuation and a long-term price reversal. According to Daniel et al. (1998) and Barberis et al. (1998),

* Tel.: +1 4167362100x30596; fax: +1 4167365963.
E-mail address: wathnani@yoruk.ca.

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consistency in good (bad) news signals leads to an investor overreaction, pushing market prices away from expected values. Eventually, this error in valuation gradually recovers as future performance brings share prices back to their fair values. Evidence from the experimental research (e.g., Bloomfield & Hales, 2002; Kahneman & Tversky, 1973; Tversky & Kahneman, 1974) indicates that investors are likely to overweight patterns of past performance data when forecasting future outcomes even if these patterns have no predictive values.

Second, I examine whether the short-term return continuation (e.g., Jegadeesh & Titman, 1993) and the long-run price reversal (e.g., DeBondt & Thaler, 1985) represent two stages of a market reaction: a market overreaction followed by a correction. There are, at least, two reasons to believe that the market under-and-overreaction phenomena are caused by the same investor sentiments. First, empirical studies (e.g., Jegadeesh & Titman, 1993, 2001; Lee & Swaminathan, 2000) find the momentum gain to reverse over the following 2 to 5 years. Lee and Swaminathan (2000) provide empirical evidence indicating that the bulk of the price momentum is offset by subsequent price reversal in the following two to five years. They argue that their finding casts doubt on the notion that a short-term price continuation is evidence of a market failure to incorporate new information signals into asset prices quickly and without bias. Instead, they suggest that a significant part of the price momentum should be viewed as a market overreaction that is eventually corrected, resulting in a price reversal at the long horizon.

However, the finding of Grinblatt and Moskowitz (2004) shows no association between the momentum and reversal effects. They argue that the momentum and reversal anomalies seem to be driven by different forces. Further, they argue that if there is a link between these two empirical regularities, it must be weak. Given these mixed results, I believe return consistency should provide a sharper and more powerful test for the relationship between these two mispricing patterns than the magnitude of past returns used by Lee and Swaminathan (2000) and Grinblatt and Moskowitz (2004). Second, recent theoretical models (e.g., Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999) show that the intermediate-term price run and long-run reversal can be two components of a market overreaction in which security prices systematically diverge from their fair values. Eventually, this mispricing is corrected as the market gradually discovers that its prior expectations are unwarranted.

The bulk of the existing momentum and reversal literature has mainly focused on the connection between the magnitude of past returns and the future price movements. Watkins (2006, page 436) argues that "even when there is not a strong past return, consistency leads to extremely strong, reliable price predictability." He views the predictive power of return consistency for future price movements as distinct from that of past return magnitudes. He argues that unlike a return magnitude, consistency is informative about how path dependent stock prices are.

There are a few empirical studies (e.g., Grinblatt & Moskowitz, 2004; Gutierrez & Kelley, 2008; Watkins, 2003, 2006) that have explored the price impact of past return consistency on future price movements. All these studies use a loose definition of consistency where a stock is classified as a consistent winner or loser if the stock has consistently positive or negative past returns. However, Alwathainani (2010) finds that a relative measure of a firm's past return consistency can forecast the firm's future price path. Similar to Alwathainani (2010), in this study past price performance consistency is defined in a relative term rather than the positive/negative dichotomy used in Grinblatt and Moskowitz (2004), Watkins (2003, 2006) and Gutierrez and Kelley (2008). The present study considers a firm to be a consistent winner (loser) if it achieves a stock return string that places it in the top (bottom) 30% relative to other firms in all months comprising each estimation period varying from the past two to four months.

Using past return data from 1964 to 2008, I show that a string of a firm's monthly stock returns over the last two to four months generates strong return momentum that continues to be statistically and economically significant throughout the following twelve months to the ranking period. In the first year, a zero-investment portfolio that is long on consistent winners (CW) and short on consistent losers (CL), i.e., the CW–CL portfolio, earns average monthly abnormal returns varying from 0.68% for the two-month formation period to 1.37% for the four-month ranking interval.

However, over the long horizon, that is, Year 2 through Year 5 both the CW and CL portfolios experience price reversals. The average abnormal monthly return for the CW–CL portfolio in Years 2 to 5 is negative, leading to a loss that offsets the bulk of the momentum profit of Year 1. Both the momentum and subsequent reversal increase monotonically as more months of past return data are included in the formation interval. My finding is robust to the four-factor regression (the Fama-French three-factor model extended by the momentum factor) and several robustness tests.

Evidence reported in this paper extends the existing literature in three ways. First, I contribute to the momentum literature (e.g., Jegadeesh & Titman, 1993) by showing that a consistent return trend that is measured over short horizons ranging from the past two to four months has incremental predictive power for future price movements above and beyond that of the return magnitude used in the momentum literature. My finding shows that return consistency has a strong impact on expected returns even if the consistent patterns exist only for a short horizon. Second, I extend the growing literature on the relationship between investor cognitive biases and asset prices (e.g., Barberis et al., 1998; Daniel et al., 1998). The finding is of significant importance to academic researchers and investment managers alike because it shows how past return patterns can sway investor beliefs and expectations and how this perceptual change on the part of investors affects asset prices and the allocation of wealth and resources in the economy.

Finally, I contribute to the recent empirical and theoretical work (i.e., Daniel et al., 1998; Lee & Swaminathan, 2000) that views market momentum and long-term reversals in market prices as two integrated components of a market overreaction to information signals (e.g., performance consistency) driving market stock prices away from their underlying values. Eventually, this mispricing pattern is corrected over the long horizon as investors come to realize that their expectations about future performance are not fully warranted.

Studying the interaction between the trading volume and momentum return, Lee and Swaminathan (2000) document a momentum profit that persists over the next twelve months following their portfolio formation period, but the bulk of this momentum return is offset by subsequent return reversals in Years 2 through 5. They argue that their finding casts great doubt on the view that the momentum evidence is a product of an inadequate market response to new information signals, causing stock prices to continue to move in the same trajectory of good (bad) information for a period of time. Instead, they contend that their evidence suggests an investor overreaction that pushes market prices too high (low) compared to their fundamentals and it takes a long period for this mispricing to dissipate.

The rest of this paper is organized as follows. Section 2 reviews related literature and Section 3 discusses data sources, consistent return trend, and descriptive statistics of sample firms. Empirical tests, test results and robustness check analyses are described in Section 4. My concluding remarks are summarized in Section 5.

2. Literature review

The last three decades have seen a growing body of empirical evidence indicating that expected returns are predictable. However, two findings of this research stream seem to be moving in the opposite directions. These are the short-term positive autocorrelation in stock returns, i.e., price momentum (e.g., Jegadeesh & Titman, 1993) and the long-run share price reversal (e.g., DeBondt & Thaler, 1985). The price run is referred to as the well-researched anomaly in which market prices of stocks with high (low) past returns experience a price increase (decline) in the next twelve-month period. This empirical evidence is commonly interpreted as evidence of a market failure to adequately respond to a new information signal. Consequently, it takes this information up to twelve months to be completely reflected in market stock prices. As well, the momentum profitability is documented in the international equity markets (e.g., Cheng & Wub, 2010; Rouwenhorst, 1998).

The long-term price reversal is believed to be a manifestation of a market extrapolation of exceptionally high (low) past returns too much into the future that it is not justified by fundamentals. Once future performance is revealed, market prices revert to their fair values, creating the well-documented return reversal patterns over the long horizon, i.e., three to five years (e.g., DeBondt & Thaler, 1985, 1987). Although the psychology link has gained momentum in the literature (e.g., Shleifer, 2000), it is not universal. Some studies (e.g., Conrad & Kaul, 1998; Fama, 1998) argue that the evidence of these anomalous returns is either due to random occurrences that are expected under market models or due to risk exposures. However, empirical evidence (e.g., DeBondt & Thaler, 1987; Grundy & Martin, 2001; Jegadeesh & Titman, 2001) shows that neither risk exposure nor variations in cross-sectional stock returns is likely to explain the impact of past returns on future price behavior.

These two major market regularities present serious challenges not only to the market models that are built on the assumption that future price movements cannot be forecasted based on publicly available data but also to academic researchers and investment managers. If these two mispricing patterns are created by investor biases as suggested by the momentum and reversal literature, how does the market appear to fail to adequately react to one type of market data and overreact to another? In recent years, some authors (e.g., Barberis et al., 1998; Daniel et al., 1998) have drawn on evidence from the cognitive psychology literature in an attempt to reconcile these two empirical anomalies in terms of investor behavior.

Although these analytical models differ in terms of their underlying assumptions about the nature and driving forces behind the price momentum, they theorize that a price performance string (i.e., consistency) is likely to create excessive optimism (pessimism) about good (bad) performing stocks in the past. This investor bias will cause market prices of these stocks to move away from their fair values for a temporary period of time. This misvaluation will be eventually brought back to fundamentals when market participants realize that the stock prices of these firms are not warranted by their future performance.

The predictions of these models are supported by evidence of experimental studies (e.g., Bloomfield & Hales, 2002; Tversky & Kahneman, 1974). In a market experimental study, Bloomfield and Hales (2002) test the prediction of Barberis et al.'s (1998) theory and report evidence indicating that historical data patterns play a significant role in the decisions of their experimental participants. As well, the experimental finding of Tversky and Kahneman (1974) and Kahneman and Tversky (1973) shows that people have a tendency to extrapolate past data patterns even if the trend in this data is too short to justify overweighting it in predicting the future outcomes.

My objectives in this paper are twofold. First, I investigate the impact of a string of relatively high (low) past monthly share price performance on subsequent stock returns. Specifically, I examine whether an unbroken pattern of a firm's monthly return that is measured over short periods varying from the past two to four months leads the market to conclude that the trend in the firm's recent price performance is a strong predictor of its future return potential. If this is the case, the firm's recent price trend will be weighted heavily in setting its current stock prices. This will cause share prices to overshoot their underlying values, creating a temporary mispricing that will eventually revert back to fair values.

Second, I am interested in testing whether the short-term momentum profit (e.g., Jegadeesh & Titman, 1993) and the long-term negative autocorrelation in stock returns (e.g., DeBondt & Thaler, 1985) are a product of an investor overreaction to a recent trend in a firm's past performance as predicted by a group of recent models (e.g., Barberis et al., 1998; Daniel et al., 1998). There are, at least, two reasons to believe that the evidence of price momentum and reversal represents two stages in a market cycle of constant overreaction followed by a period of correction. First, empirical studies (e.g., Jegadeesh & Titman, 1993, 2001; Lee & Swaminathan, 2000) find that prior winners and losers experience a return reversal in years 2 through 5 subsequent to their ranking period. For example, Lee and Swaminathan (2000) show that the bulk of their first-year momentum gain is wiped out by price reversals of past winners and losers over the next 2 to 5 years of their holding horizon. They argue that their evidence casts a serious doubt on the view that characterizes price continuation as evidence of a market underreaction. Further, they argue that a significant portion of the momentum gain should be viewed as a market overreaction to past performance.

However, the finding of Grinblatt and Moskowitz (2004) shows no association between the momentum and reversal effects. They argue that the market under-and-overreaction effects appear to be driven by different forces and if there is a link between these two mispricing patterns, it is a weak connection at best. Second, recent theories (e.g., Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999) show that the momentum and reversal anomalies can be characterized as two stages in a market overreaction in which security prices systematically deviate from their fair values. Eventually, this mispricing is corrected as the market gradually discovers that its prior expectations are not justified by future performance.

The bulk of the price drift and reversal literature has mainly focused on the magnitude of past returns as a predictor of future price behavior. Watkins (2006) argues that the ability of return consistency to forecast subsequent price movements is distinct from that of the past return magnitude. Further, he argues that unlike return magnitude, consistency is path dependent (i.e., directional relation) and its ability to predict expected returns remains strong even when the magnitude of past returns is tenuous.

There are a few empirical studies in the finance literature that examine the impact of return consistency on future price movements (e.g., Grinblatt & Moskowitz, 2004; Gutierrez & Kelley, 2008; Watkins, 2003, 2006). Their findings show that a past trend in market stock prices is a useful predictor of subsequent returns. In these studies, consistency is defined as a positive or negative past return. However, Alwathainani (2010), who uses a relative measure of return consistency, shows that a firm's past return patterns can forecast its future price path.

Similar to Alwathainani (2010), the present study defines return consistency in a relative term rather than the positive/negative dichotomy used in Grinblatt and Moskowitz (2004), Watkins (2003, 2006) and Gutierrez and Kelley (2008). In this study a firm is deemed to be a consistent winner (loser) if the firm achieves a stock return string that places it in the top (bottom) 30% relative to other firms in all months comprising each estimation period ranging from the past two to four months.

The models of Daniel et al. (1998) and Barberis et al. (1998) predict that consistent patterns of a firm's past performance are likely to create an environment that is conducive for a market overreaction. However, neither Daniel et al. (1998) nor Barberis et al. (1998) have specified a particular consistency measure nor identified the length of a time horizon over which consistency should be measured.

In this study, performance consistency is measured as a string of relatively high (low) firm's past return performance over short horizons, ranging from two to four consecutive months. This is tighter and sharper definition of consistency than that used in previous studies (.e.g., Alwathainani, 2010; Grinblatt & Moskowitz, 2004; Gutierrez & Kelley, 2008; Watkins, 2003, 2006). It can be argued that the definition of consistency that I use in this study provides a powerful test for the predictions of the behavioral models. As well, measuring consistency as a string of relatively strong (weak) stock return over short periods, ranging from the past two to four months allows me to assess the predictive power of return consistency over that of the return magnitude used in the momentum literature (e.g., Jegadeesh & Titman, 1993).

3. Sample, return consistency and descriptive statistics

3.1. Data sources

Monthly returns data for 1964–2008 are from the Center for Research in Security and Prices (CRSP).[1] Book values are taken from the Compustat database. Because my portfolio tests require past return data, January 1965 was the first month in which portfolio return performance was measured. As well, since my empirical tests require tracking the price impact of past return consistency for the next five years, December 2003 was the final month in which portfolios were formed.

3.2. Consistent return trend

Each month from the beginning of January 1965 to the end of December 2003, all stocks with required data are sorted by their monthly returns over the past two to four months into three groups: winners, moderates, and losers.[2] Winners include firms in the top 30% in terms of their past stock returns while losers contain stocks in the bottom 30% and the balance is placed in the moderate category.[3] Firms with a return string that places them in the top group, i.e., the winner category in all months comprising each estimating interval that ranges from the past two to four months are defined as "*consistent winners*" and firms with return performance that consistently rank in the loser group (i.e., the bottom 30%), are labeled as "*consistent losers*".[4]

3.3. Descriptive statistics

Summary statistics of stocks with required past return data is reported in Table 1. The time-series average of cross-sectional correlations among past returns (RET), firm market betas (Beta), book-to-market ratios (B/M), and market values (Size) is reported in Panel A. Both Beta and B/M are negatively related to firm size, but none of them is statistically significant.

In Panel B, I provide the average counts of firms with required return data for two, three, and four month formation intervals over eight sub-sample periods of five years each. As expected, the number of firms decreases slightly as more months of past returns are included in the formation periods. The time-series averages of the proportion of stocks that are classified as consistent

[1] If a firm is delisted after the ranking period, its delisting return from the CRSP delisting return file is used if it is available for the month in which it was delisted. I eliminate real estate investment trusts (REIT), closed-end funds, foreign firms, and American Depository Receipts (ADR).

[2] Firms with stock price less than $5 are deleted at the ranking period to avoid the influence of small illiquid stocks or market microstructures.

[3] I am interested in whether consistent high (low) past returns produce price momentum and reversals. Thus, in this paper I do not report return performance for moderate firms.

[4] In an unreported analysis, I sort my sample firms into top (bottom) 10 and 20% instead of highest (lowest) 30% and this does not change my findings. As well, I use a five-month formation period and the result is similar to that of the four-month ranking horizon. I decided not to use the five-month formation period because it included a smaller number of firms.

Table 1
Sample Descriptive Statistics.

Panel A: Spearman (Pearson) correlations are in the upper-right (lower-left) side[a]

Variables	Variables			
	RET	BETA	B/M	SIZE
RET		0.05	−0.08	−0.04
BETA	0.05		0.56	−0.65
B/M	−0.18	0.46		−0.55
SIZE	−0.06	−0.62	−0.50	

Panel B: Firms with required data for the past two to four months

Average Firms for Each Five Years	Formation Periods		
	Past Two Months	Past Three Months	Past Four Months
1965–1969	1876	1809	1757
1970–1974	1998	1872	1812
1975–1969	1826	1753	1642
1980–1984	2124	2059	1998
1985–1989	3522	3360	3189
1990–1994	4002	3811	3642
1995–1999	5932	5642	5457
2000–2004	4983	4743	4574

Panel C: Consistent winners and losers as percentages of the total sample firms

Formation Periods	CW and CL Portfolios	
	CW	CL
Past Two Months	12.2%	12.3%
Past Three Months	7.8%	7.7%
Past Four Months	3.7%	3.5%

Panel D: Firm characteristics

Formation Periods	Statistics	Sample Firms		
		CW	CL	ALL
Past Two Months	Ret	0.15	−0.11	0.02
	Beta	1.12	1.14	1.01
	B/M	0.66	0.82	0.76
	Size	895	733	1029
Past Three Months	Ret	0.15	−0.11	0.02
	Beta	1.15	1.13	1.02
	B/M	0.58	0.84	0.76
	Size	930	628	1084
Past Four Months	Ret	0.16	−0.13	0.02
	Beta	1.18	1.16	1.01
	B/M	0.56	0.88	0.76
	Size	873	564	1290

At the end of each month from December 1964 to December 2003, stocks are sorted by their monthly returns over the past two to four months into three groups: winners, moderates, and losers. Winners include stocks in the top 30% in terms of their past returns while losers contain firms in the lowest 30%. Firms consistently ranking in the winner group over all months comprising the ranking interval, i.e., past two, three, or four months are classified as "consistent winners" while stocks consistently ranking in the lowest return group, i.e., the loser category is defined as "consistent losers." These portfolios are held without rebalancing for the next five years.

Variable Definitions:

Firms	Number of firms in each portfolio.
RET	The average past stock returns.
BM	The book-to-market ratios at the end of the fiscal quarter immediately preceding the ranking month.
Beta	A firm's market beta. It is computed from monthly returns over the prior 60 months, with a minimum of 36 months, prior to the ranking month.
Size	Market value of equity capital (in $million) at the end of the fiscal quarter immediately prior the ranking month. It is calculated as the number of shares outstanding multiplied by the stock price.
CL	Consistent Losers.
CW	Consistent Winners.

[a] The correlation matrix is based on stocks with four months of consistent past returns.

winners (CW) or consistent losers (CL) appear in Panel C. The total number firms that fall into CW and CL categories are approximately equal across all formation periods (see Panel C). However, the proportion of CW and CL as percentages of the total sample of firms decreases as the formation intervals increase.

Panel D reports time-series averages of RET, Beta, B/M and size for CW and CL firms as well as those of the overall sample firms. As expected, the average past return for CW stocks is positive while that of the CL firms is negative. As shown in Panel D, firms in the CW and CL portfolios have slightly higher betas and smaller market capitalizations relative to the average sample firms although CL stocks tend be smaller in terms of market values compared to their CW cohorts. This dispersion in firm size becomes noticeable as the formation interval increases. Further, CW stocks have low B/M ratios while CL firms are associated with higher B/M ratios as compared to the average sample stocks.

4. Empirical tests and results

4.1. Portfolio formation

To examine the price impact of return consistency on future returns, I form two equally weighted portfolios, i.e., consistent winners (CW) and consistent losers (CL).[5] The CW portfolio includes stocks that rank in the top 30% in terms of their returns over the past two to four months while the CL portfolio contains firms consistently ranking in the lowest quartile for the same intervals. The return for a portfolio that buys CW firms and sells their CL counterparts is referred to as "CW–CL." The positions in these portfolios are held for the next five years and the price performance is measured as average monthly returns for each year (Years 1 through 5) independently.

4.2. Portfolio returns

In this section, I report the return results for the CW and CL portfolios as well as for their differential stock returns, i.e., the CW–CL returns for each year of the holding period (Years 1 through 5). The return performance for these portfolios is presented in Table 2, which is divided into three parts. Results for portfolios based on return consistency over the last two months are displayed in the top portion of Table 2 while returns for stocks sorted by their return patterns over the last three and four months are presented in the middle and last parts of Table 2, respectively.

As shown in Table 2 under the Year 1/R1 column, the average monthly returns for the CW portfolio increase uniformly from 1.31% for stocks with a two-month consistent past return to 1.52% for their counterparts with a three-month ranking period to 1.63% for a portfolio formed based on a four-month past return. On the other hand, the average monthly returns for the CL portfolio decrease monotonically from 0.65% to 0.42% to 0.27% for portfolios based on return consistency for the past two, three, and four months, respectively.

The difference in returns between the CW and CL portfolios, that is, the CW–CL is economically and statistically significant ranging from 0.68% (t = 7.81) a month for the two-month ranking period to 1.10% (t = 8.90) per month for firms with three-month consistent stock

Table 2
Return Performance for Consistent Winner and Loser Portfolios.

Formation Periods	Portfolios	Year 1	Year 2	Year 3	Year 4	Year 5
		R1	R2	R3	R4	R5
Past Two Months	**CW**	1.31	1.04	1.11	1.19	1.23
		5.71***	**4.41****	**5.00****	**5.40*****	**5.56*****
	CL	0.65	1.16	1.31	1.28	1.30
		2.73**	**5.01****	**5.43*****	**5.48*****	**6.21*****
	CW–CL	*0.68*	*−0.13*	*−0.20*	*−0.09*	*−0.07*
		7.81***	**−1.91***	**−2.04****	**−1.30**	**−1.43**
Past Three Months	**CW**	1.52	1.02	1.06	1.17	1.21
		6.11***	**3.88****	**4.56****	**5.12****	**5.03****
	CL	0.42	1.20	1.34	1.30	1.31
		1.65	**4.87*****	**5.38*****	**5.16*****	**6.21*****
	CW–CL	*1.10*	*−0.18*	*−0.28*	*−0.13*	*−0.10*
		8.90***	**−2.16****	**−2.41****	**−1.15**	**-1.65**
Past Four Months	**CW**	1.63	1.04	1.10	1.14	1.17
		6.61***	**3.84****	**4.35****	**4.80****	**4.93****
	CL	0.27	1.25	1.40	1.32	1.29
		1.03	**4.72****	**4.98****	**5.08****	**5.74*****
	CW–CL	*1.36*	*−0.21*	*−0.30*	*−0.18*	*−0.12*
		9.31***	**−2.21****	**−2.37****	**−1.46**	**−1.55**

In this table, I report the average buy-and-hold monthly returns for the CW and CL portfolios as well as for their return differential, i.e., CW–CL for each year (Years 1 through 5). The CW–CL is a portfolio that goes long on CW and short on CL. At the end of each month from December 1964 to December 2003, stocks are sorted by their monthly returns over the past two to four months into three groups: winners, moderates, and losers. Winners include stocks in the top 30% in terms of their past returns while losers contain firms in the lowest 30%. Firms consistently ranking in the winner group over all months comprising the ranking interval, i.e., past two, three, or four months are classified as "consistent winners" while stocks consistently ranking in the lowest return group, i.e., the loser category is defined as "consistent losers." These portfolios are held without rebalancing for the next five years and their return is measured as the average buy-and-hold monthly returns for each year. The Newey-West *t*-statistics are reported in **bold** below the portfolio returns. ****, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[5] In an unreported robustness test, I use value-weighted returns and my results remain the same.

returns to 1.36% (t = 9.31) per month for the four-month formation horizon. Results reported in Table 2 under the Year 1/R1 column show that the CW–CL return is strengthened as an additional month of past return consistency is included in the ranking interval.[6]

Now, I turn to the long-term returns (Years 1 through 5) for the CW and CL portfolios. As shown under the last four columns, i.e., the Year 2/R2 to Year 5/R5 columns, past consistent losers beat their past consistent winner counterparts in Years 2 through 5 across all ranking intervals. The price reversals of past CW and CL stocks increase monotonically as the ranking interval (i.e., the formation period) is extended. However, the premium return earned by CL portfolios above that of their CW counterparts is only statistically significant in Years 2 and 3 (see Table 2, under the Year 2/R2 to Year 5/R5 columns). This evidence of price reversals is consistent with Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) who find that the return of past winners and losers exhibit reversal patterns over the long horizons.

Evidence reported in Table 2 shows that consistent patterns of past monthly returns lead to price momentum over the next twelve months following the formation period. Eventually, this price continuation is reversed in the long run, that is, Year 2 to Year 5. Further, the momentum and subsequent reversal in returns is strengthened as more monthly return data are included in the ranking interval.

4.3. Regression results

Table 3 reports the average monthly four-factor regression intercepts (alphas) from the three-factor Fama-French model (Market–RF, size, and book) and the momentum factor (UMD). The momentum return is provided under the Year 1/R1 column while the long-term price reversal is presented under the Year 2/R2 through Year 5/R5 columns.

As shown in Table 3 under the Year 1/R1 column, the average monthly alpha for the CW portfolio increases monotonically from 0.81% a month for stocks with a two-month formation period, to 1.00% per month for a three-month ranking horizon, to 1.11% per month for firms with a four-month history of consistent past returns.

In comparison, the average monthly returns for the CL portfolio tell a similar story but in the opposite direction. For example, the returns for CL stocks decrease from 0.14% a month for a two-month ranking period to −0.26% for stocks with a four-month formation horizon. The return differential between the CW and CL portfolios, that is, the CW–CL return increases uniformly from 0.68% (t = 7.51) per month to 1.37% (t = 8.91) a month for two and four month formation horizons, respectively (see Table 3 under the Year 1/R1 column).

Over the long run (Years 2 to 5), however, both CW and CL exhibit a reversal in stock prices. For instance, the CW–CL returns in Year 2 through 5 are negative although not statistically significant except in Years 2 and 3 for the three-and-four-month ranking periods. Similar to evidence reported in Table 2, the regression results presented in Table 3 indicate that the return continuation and subsequent reversal become stronger as an additional month of past return data is added to the ranking horizon.

Table 3
The average monthly four-factor alphas for consistent winner and loser portfolios for years 1 through 5.

Formation Periods	Portfolios	Year 1	Year 2	Year 3	Year 4	Year 5
		R1	R2	R3	R4	R5
Past Two Months	**CW**	0.81	0.53	0.61	0.69	0.72
		3.52**	**2.22****	**2.70****	**2.98****	**3.21****
	CL	0.14	0.66	0.78	0.77	0.85
		0.56	**2.73****	**3.07****	**3.18****	**3.90****
	CW–CL	*0.68*	*−0.13*	*−0.17*	*−0.08*	*−0.13*
		7.51***	**−1.86***	**−1.08**	**−1.12**	**−1.62**
Past Three Months	**CW**	1.00	0.51	0.56	0.67	0.70
		4.03**	**1.82***	**2.26****	**2.76****	**2.80****
	CL	−0.10	0.74	0.81	0.78	0.86
		−0.39	**2.85****	**3.10****	**2.99****	**3.63****
	CW–CL	*1.10*	*−0.23*	*−0.25*	*−0.11*	*−0.15*
		8.75***	**−2.44****	**−2.38****	**−1.02**	**−1.76***
Past Four Months	**CW**	1.11	0.49	0.55	0.64	0.68
		4.16**	**1.84***	**1.83***	**2.55****	**2.76****
	CL	−0.26	0.76	0.87	0.79	0.82
		−0.93	**2.90****	**2.96****	**2.84****	**3.54****
	CW–CL	*1.37*	*−0.27*	*−0.32*	*−0.15*	*−0.14*
		8.91***	**−2.13****	**−2.56****	**−1.37**	**−1.53**

Table 3 presents the average monthly four-factor regression alphas from the Fama-French three-factor model (Market–RF, size, and book) and the momentum factor for the CW and CL portfolios as well as for their return differential, i.e., CW–CL for each year (Years 1 through 5). The CW–CL is a portfolio that goes long on CW and short on CL. At the end of each month from December 1964 to December 2003, stocks are sorted by their monthly returns in the past two to four months into three groups: winners, moderates, and losers. Winners include stocks in the top 30% in terms of their past returns while losers contain firms in the lowest 30%. Firms consistently ranking in the winner group over all months comprising the ranking interval, i.e., past two, three, or four months, are classified as “consistent winners” while stocks consistently ranking in the lowest return group, i.e., the loser category is defined as “consistent losers.” These portfolios are held without rebalancing for the next five years. The dependent variables in these cross-sectional monthly regressions are the monthly return for each portfolio less the risk-free rate except for the return differentials, i.e., the CW–CL. The Newey-West *t*-statistics are reported in **bold** below the portfolio returns. ****, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[6] In unreported results, I extend the ranking period to five months and find that the marginal impact of past return consistency on future price movements to diminish significantly after the four month interval.

Evidence reported in Table 3 shows that return consistency driven momentum remains economically and statistically significant after controlling for the Fama-French three factors (Market–RF, size, and book) as well as the momentum factor (UMD). This suggests that return consistency has incremental predictive power for expected returns above that of the past return magnitude used in the momentum literature (e.g., Jegadeesh & Titman, 1993).

4.4. Relation to the psychology-based models

Evidence reported in Tables 2 and 3 indicates firms with consistent stock return patterns over the past two to four months experience strong price momentum over the next twelve months. Eventually, this market momentum reverses over the long horizon, i.e., Years 2 through 5. The ability of consistent past returns to forecast price momentum and reversals is robust to the Fama-French three factor model (Market–RF, size, and book) and the momentum factor.

In recent years, a group of financial scholars (i.e., Barberis et al., 1998; Daniel et al., 1998) have proposed behavioral models in an attempt to explain the two persistent market regularities, i.e., the price momentum and long-term reversal in stock returns. In Barberis et al.'s (1998) model, the conservatism bias leads investors to dismiss a firm's recent performance (i.e., earnings or price change) because they believe the firm's recent performance will reverse. As a result, investors fail to adequately update their prior beliefs. This causes the initial positive correlation in market stock prices. On the other hand, the representativeness bias may cause investors to become overly optimistic about a firm with a string of good (bad) recent performance driving its shares' prices too high (low) relative to their underlying values.

Daniel et al. (1998) argue that well-informed investors are likely to be overly confident in their private information signals and their trading activities create an initial market overreaction. Further, they argue that subsequent public performance news that confirms investors' private information signals results in additional market overreactions. Although Daniel et al. (1998) and Barberis et al. (1998) have different views on the nature and cause underlying the market underreaction, both of their models are predicated on the assumption that an unbroken series of a firm's relatively strong (weak) performance creates a conducive setting for a market overreaction. This market overreaction will gradually revert to fundamentals as firms' future performance of past winners and losers fails to meet (exceeds) investor expectations.

Results reported in Tables 2 and 3 are consistent with the spirit of Barberis et al.'s (1998) and Daniel et al.'s (1998) models suggesting that consistent patterns of historical performance are likely to sway investor expectations, causing market prices to diverge frequently and significantly from their underlying values. My evidence shows that a portfolio that takes a long position in CW firms and a short position in their CL counterparts generates substantial momentum profits that increase monotonically from 0.68% ($t=7.51$) a month for firms with a two-month formation period to 1.37% ($t=8.91$) per month for four-month ranking horizon stocks. This price momentum continues to be statistically and economically significant for the next twelve months following the formation month even after controlling for the three-factor Fama-French model (Market–RF, size, and book) and the momentum factor (see Table 3 under the Year 1/R1 column).

As shown in both Tables 2 and 3 under columns Year 2/R2 through Year 5/R5, the return momentum in Year 1 reverses itself in Year 2 through Year 5. In other words, both CW and CL firms experience price reversals over the long horizon. For example, the return in Year 2 to Year 5 for a portfolio that buys stocks with consistent strong returns over the last four months and sells their CL cohorts with consistent weak returns over the same period is negative as shown under Year 2/R2 through Year 5/R5 columns of Table 3. The price reversal for the CW–CL portfolios based on the two and three month horizons exhibit similar patterns.

Empirical evidence documented in this study contradicts the finding of Grinblatt and Moskowitz (2004) indicating that the price momentum of Jegadeesh and Titman (1993) and the return reversal effect of DeBondt and Thaler (1985) are not linked. On the contrary this evidence shows that these two mispricing patterns are likely to be empirically related. My finding extends that of Lee and Swaminathan (2000) who report negative return performance for a portfolio that goes long in past winners and short in their past loser counterparts. They argue that their evidence indicates that price momentum should be viewed as an investor overreaction not an underreaction as it is commonly interpreted.

4.4. Robustness tests

4.4.1. Consistency of momentum return

In this section, I assess the consistency of the CW–CL return in Year 1, i.e., the momentum return to show how often the CW portfolio underperforms its CL counterpart. If CW stocks are more fundamentally riskier than the CL firms and this risk exposure is not accounted for by the four-factor regression of the Fama-French three-factor model extended by the momentum effect, then the CW stocks should earn lower returns than the CL portfolio in bear markets. Because investors have less appetite for risk during bad states of the economy, they will sell firms in the CW portfolio and buy the less risky CL firms. As a result, the CW stocks should underperform their CL firms during market downturns.

In Fig. 1, I graphically present the average monthly four-factor regression alphas derived from the Fama-French three-factor regression (Market–RF, size, and book) and the momentum factor for the momentum returns in each years from 1965 to 2004 for the CW–CL portfolio that is formed based on a four-month ranking period.[7] As displayed in Fig. 1, the return performance for the CW–CL portfolio is positive in 38 years out of 40 over the sample period. This evidence does not indicate that the CW stocks are

[7] In unreported results, I perform the same test for the CW–CL portfolios based on two-and-three-month horizons and the results are similar to those illustrated in Fig. 1.

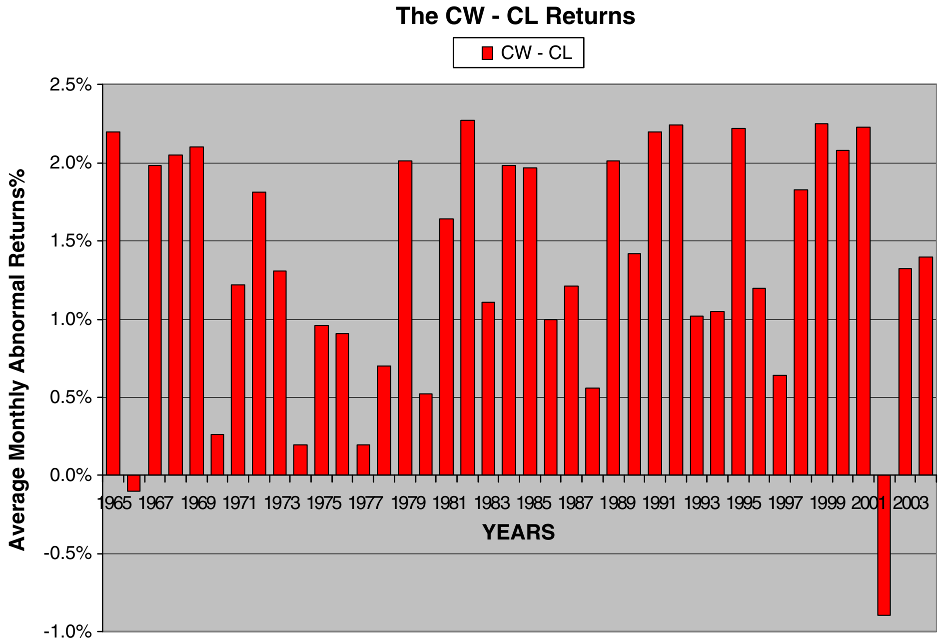

Fig. 1. This figure presents the average monthly alphas from the Fama-French three-factor regression (Market–RF, size and book) and the momentum factor (UMD) for the CW–CL portfolio, which is based on a four-month formation interval, in the first year subsequent to the ranking interval for each year from 1965 to 2004. The CW–CL is a portfolio that goes long on CW stocks and short on consistent loser stocks. At the end of each month from December 1964 to December 2003, stocks are sorted by their monthly returns into three groups: winners, moderates, and losers. Winners include stocks in the top 30% in terms of their past returns while losers contain firms in the lowest 30%. Firms consistently maintaining their ranks in the winner group over in all four months comprising the ranking interval are classified as "consistent winners" while stocks consistently ranking in the lowest return group, i.e., the loser category are defined as "consistent losers." The CW–CL is the return differential between CW and CL portfolios. The dependent variable in this cross-sectional regression is the return differential between the CW and CL portfolio, that is, the CW–CL return.

likely to be riskier than their CL cohorts. If the superior stock return for the CW portfolio is compensation for risk factors, the CW stocks should report negative market return more often (see Fama & MacBeth, 1973 for a review).

4.4.2. Sub-sample periods

I conduct a four sub-sample period analysis for January 1965–December 1974, January 1975–December 1984, January 1985–December 1994, and January 1995–December 2004. In each of these sub-sample periods, Table 4 reports the average monthly four-factor regression intercepts (alphas) from the three-factor Fama-French model and the momentum factor for the CW–CL portfolio in Year 1 (i.e., the momentum return) for all three formation horizons. As shown in Table 4, the momentum profit is economically and statistically significant across all sub-sample periods.

Table 4
The average monthly four-factor alphas for the CW–CL portfolio in Year 1 (the momentum returns) for four sub-sample periods.

Formation Periods	Portfolios	Sub-Sample Periods			
		1965–1974	1975–1984	1985–1994	1995–2004
Past Two Months	**CW–CL**	*0.52*	*0.62*	*0.79*	*0.80*
		3.11**	**4.76****	**8.10*****	**6.08****
Past Three Months	**CW–CL**	*0.91*	*1.02*	*1.23*	*1.22*
		3.98**	**6.07****	**9.74*****	**7.86****
Past Four Months	**CW–CL**	*1.13*	*1.31*	*1.56*	*1.54*
		4.34**	**6.09****	**10.15*****	**8.03****

Table 4 presents the average monthly four-factor regression alphas from the Fama-French three-factor model (Market–RF, size, and book) and the momentum factor for the CW–CL portfolios for four sub-sample periods. The first sub-period covers from 1965 to 1974, the second sub-period spans from 1975 to 1984, the third sub-sample period runs from 1985 to 1994, and the final sub-period covers from 1995 to 2004. The CW–CL is a portfolio that goes long on CW and short on CL. At the end of each month from December 1964 to December 2003, stocks are sorted by their monthly returns in the past two to four months into three groups: winners, moderates, and losers. Winners include stocks in the top 30% in terms of their past returns while losers contain firms in the lowest 30%. Firms consistently ranking in the winner group over all months comprising the ranking interval, i.e., past two, three, or four months, are classified as "consistent winners" while stocks consistently ranking in the lowest return group, i.e., the loser category is defined as "consistent losers." These portfolios are held without rebalancing for the next five years. The dependent variables in these cross-sectional monthly regressions are the monthly differentials for the CW–CL portfolios. The Newey-West *t*-statistics are reported in **bold** below the portfolio returns. **** and ** indicate statistical significance at the 5% and 10% levels, respectively.

5. Conclusions

In this paper, I empirically investigated two related questions. First, I test whether a relatively high (low) return string that is measured over short periods varying from the past two to four month intervals triggers a market overreaction that gradually reverts to underlying values over the long horizon, resulting in a return continuation and long-term price reversal. Second, I examine whether the short-term momentum profit (e.g., Jegadeesh & Titman, 1993) and negative autocorrelation in stock returns at the long horizon (e.g., DeBondt & Thaler, 1985) are a product of an investor overreaction to a recent trend in a firm's past performance as predicted by a group of recent models (e.g., Barberis et al., 1998; Daniel et al., 1998).

My finding shows that stock return consistency over the last two to four months produces strong price momentum over the next twelve months and price reversal in the long run, i.e., Years 2 through 5 For example, a zero-investment strategy that goes long on the CW stocks and short on their CL cohorts, that is, the CW–CL portfolio generates strong price momentum in the first twelve months after the ranking period.

Subsequently, however, both groups experience return reversals in Years 2 to 5. Over this extended horizon, the return for the CW–CL portfolio is negative. The momentum return earned by the CW–CL strategy is almost wiped out by the total price reversal in Years 2 to Year 5. This finding is robust to the four-factor regression analysis of the Fama-French three-factor model (Market – RF, size, B/M) and the momentum factor as well as to various sensitivity tests.

Evidence reported in this paper extends the existing literature in three ways. First, my finding contributes to the return momentum literature (e.g., Jegadeesh & Titman, 1993) by showing that consistent patterns of past monthly returns have incremental predictive power for expected returns above and beyond that of the return magnitude used in the momentum literature. Evidence documented in this study indicates that consistency of monthly returns leads to a strong price continuation and reversal in returns over the long run and this finding remains robust after controlling for the Fama-French three factors (Market–RF, size, and book) and the momentum factor as well as several sensitivity tests.

Second, I add to the growing literature on the relationship between investor psychology and asset prices (e.g., Barberis et al., 1998; Daniel et al., 1998). Results reported in this study shed light on how investors process and evaluate past return consistency and how this mechanism affects the formation of market prices. This finding is of significant importance for academic scholars and investment managers alike because it shows how patterns of a firm's historical price performance sway investor beliefs and expectations. Consequently, this perceptual change on the investors' part has very important implications for market prices and wealth allocation in the economy.

Finally, my evidence extends the recent empirical and theoretical models suggesting that market momentum and long-term return reversals can be viewed as two components of a price formation process in which stock prices overreact to new information signals (e.g., Daniel et al., 1998; Lee & Swaminathan, 2000). Eventually, this market overreaction is gradually pushed back to fundamentals once the market comes to realize its biased expectations. Examining the interaction between trading volume and a price momentum strategy, Lee and Swaminathan (2000) document a momentum profit in the first year following their formation period, but they find the bulk of this momentum gain to be offset by subsequent price reversals in Year 2 through Year 5. They argue that their finding suggests that, at least, a significant part of the return momentum should be viewed as a stock price overreaction rather than an underreaction as it is widely believed.

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