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Patterns of past monthly return performance and future price movements

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In this study, I show that consistency of past price performance is useful in predicting expected stock returns. Prior winners (consistent and inconsistent firms) have higher rates of returns in the first year following portfolio formation than past losers (consistent and inconsistent firms). However, over the long run, i.e., years 2 through 5, past losers outperform their prior winner counterparts. The impact of consistency on price momentum is more pronounced for consistent winners and losers relative to inconsistent winners and losers. Consistent losers exhibit the strongest and the most persistent return reversals. The results of multiple regressions indicate that return consistency is related to future returns. However, the effect of consistency is stronger for prior consistent losers compared to other firms (consistent winners as well as inconsistent winners and losers). This evidence is robust for the inclusion of beta, book-to-market ratios, firm size and momentum effect.

Key words: Asset pricing; Past monthly return patterns; Investors' psychology

JEL classification: G11; G14

1. Introduction

The conventional economic models are predicated on the assumption that markets are populated by rational and wealth maximizing individuals. It follows that available information is believed to be reflected in market prices instantly without bias (Fama, 1970, 1991). However, empirical research over the last three decades has found market prices exhibit a positive association over the intermediate horizon (3-12 months) and a reversal at long intervals (3-5 years). The finding of this literature is linked to investors' psychology (e.g., DeBondt and Thaler, 1985; Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998). This link has gained prominence in the literature (e.g., Shleifer, 2000).

In recent years, a number of authors (e.g., Barberis et al., 1998; Daniel et al., 1998) have proposed models based on behavioural decision theory that attempt to explain these two major empirical phenomena. Although these models differ in their characterization of the medium-horizon momentum, they agree that consistency in a firm's prior performance should lead to a market overreaction and subsequently this firm will experience a price reversal at the long period.

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The momentum literature has been almost exclusively focused on the ability of the magnitude of past returns to predict the future price movement. However, little attention was given to the relationship between the consistency of past price performance and expected returns. All psychology-based theories are built on the assumption that a string of performance drifting in the same direction over a sufficient time period should trigger a market overreaction. Therefore, consistency of a firm's past return performance should provide a sharper test to the predictions of behavioural models than the return magnitude. Watkins (2006) argues that the effect of performance consistency is significantly different from that of the magnitude of change in past prices. Further, he argues that even in some cases when there is no strong past return, consistency results in exceptionally strong price predictability over the short horizon.

In this paper, I examine whether investors overreact to consistency of a firm's monthly price performance. If investors overweight patterns of a firm's monthly returns when forecasting the firms' future prospects, return consistency will lead to a medium-term price momentum followed by a reversal in stock returns at the long horizon as suggested by behavioural models (e.g., Daniel et al., 1998).

Using past stock return data from 1963 to 2007, I contribute to the price momentum and reversal literatures in several ways. First, I extend the work of Jegadeesh and Titman (1993) by showing that consistency in a firm's past price performance generates an intermediate price drift over the following year. Prior winner stock categories (consistent and inconsistent winners) have higher rates of returns than loser firms (consistent and inconsistent losers) in the first year following portfolio formation. This momentum is very pronounced for consistent winners and losers. In Year 1, for example, firms consistently ranking in the highest 40 percent of past price performance earn statistically and economically significant greater returns relative to their inconsistent winner firm counterparts. Similarly, consistent losers (i.e., stocks consistently ranking in the bottom 40 percent) substantially underperform inconsistent losers in the same period.

Second, like Jegadeesh and Titman (2001) and Lee and Swaminathan (2000), I show that the price momentum of Year 1 reverses over Years 2 through 5 in which loser groups outperform their winner counterparts. This price reversal is more pronounced and persistent for prior consistently losing firms relative to other firm categories (consistent and inconsistent winners as well as inconsistent losers). The reversal of the momentum effect at the long horizon is consistent with the notion that the intermediate price drift is a manifestation of investor overreaction that corrects itself over the long run (e.g., Daniel et al., 1998; and Lee and Swaminathan, 2000).

Third, the results of multiple regressions indicate that consistency of a firm's past price behaviour is useful in predicting expected returns. However, the impact of past return consistency on future price movements is greater for past consistent losers relative to prior winners and inconsistent losers as well. Finally, regression analysis shows that my findings are robust for the inclusion of beta, book-to-market ratios, firm size, and momentum effect.

Overall, the findings documented in this study are broadly consistent with the predictions of psychology-based theories (e.g., Barbris et al., 1998; Daniel et al., 1998) suggesting that investors are likely to overreact to firms with a string of past performance metrics moving in the same direction for a sufficient period of time. Daniel et al., (1998) argue that overly confident investors heavily weight firms' recent financial performance when projecting the future outlooks of these firms. Further, they argue that consistency in prior performance measures confirming investors' prior behavioural biases lead to additional mispricing. Consequently, stocks of these firms will generate price reversals when it becomes clear to investors that their prior anticipations were not completely warranted.

Most of the empirical studies examining the relationship between a firm's expected stock returns and its historical price performance have almost exclusively focused on the ability of the past price change to predict the price movement in the future. However, little is known about whether and how the consistency of past price performance, affects future returns. Grinblatt and Moskowitz (2004) and Watkins (2003) explore return consistency over the intermediate and long horizon and they show that positive consistency in past stock returns have predictive power with respect to future returns, but they provide mixed results on whether consistency of prior negative returns results in lower returns. Further, Watkins (2006) focuses on short-term consistency and finds firms with a positive (negative) seven trading day returns in the last two weeks earn lower (higher) returns over the next few weeks. As in Grinblatt and Moskowitz (2004) and Watkins (2003, 2006), I focus on the ability of consistency in a firm's past price movements to predict future returns. However, this study differs from Grinblatt and Moskowitz (2004) and Watkins (2003, 2006) in three ways.

First, I define consistency of a firm's return performance in the past as the number of months in which a firm maintains stock returns that place it in the highest or lowest 40 percent of all firms, based on its monthly return over the previous twelve months. On the other hand, Grinblatt and Moskowitz (2004) and Watkins (2003) classify a firm as a consistent winner or loser if the firm has positive (negative) monthly returns out of the number of months included in the ranking period.[1] Analogously, Watkins (2006) considers a firm to be consistent if the firm experiences a seven-day positive (negative) return out of the prior two weeks.[2] Thus, my definition of consistency is much tighter (ranking in the top or bottom 40% of returns) than those of Grinblatt and Moskowitz (2004) and Watkins (2003, 2006) who only define consistency in terms of positive or negative past returns.

Second, systematically classifying firms by their past price performance into the highest and lowest performers allows me to capture the full dynamics of whether and how consistency of firms' prior performance measures change investors' expectations. This methodology enables me to test the underlying assumptions of psychology-based models suggesting that exceptionally high (low) past performance facilitates a market overreaction and the consistency of such performance that confirms investor prior perceptions should trigger an additional overreaction (e.g., Daniel et al., 1998).

Finally, I use a five-year holding period following the ranking date to assess whether return consistency generates intermediate price momentum and reversals at the long horizon as predicted by behavioural models (e.g., Barberis et al., 1998; Daniel et al., 1998). If it takes a long period for investors to correct their prior expectations as suggested by behavioural models (e.g., Daniel et al., 1998), it is reasonable to assume that extending the holding horizon will capture the full mechanism by which investors change their prior perceptions about the future outlooks of consistent winners and losers. Lee and Swaminathan (2000) argue that studies that employ holding periods of less than five years were unsuccessful in capturing the extent of the relationship between momentum and the subsequent price reversal.

The rest of this paper is organised as follows: Section 2 presents my research hypotheses. Section 3 defines consistency in past stock returns and discusses my empirical tests. The empirical results are presented and discussed in Section 4. Finally, the findings of the study are summarised in Section 5.

2. Research hypotheses

The conventional economic model is predicated on the assumption that markets are populated with rational, careful, and wealth maximizing individuals. It follows that new information is reflected in market prices instantly and without bias (e.g., Fama, 1991). Even in some cases where market participants make mistakes, these errors are assumed to be uncorrelated and therefore they should cancel out in market equilibrium (e.g., Fama, 1965).

However, an ample amount of evidence from the judgment and decision-making literature points to a flaw in the conventional economic model (e.g., Tversky and Kahneman, 1974). The representativeness heuristic holds that people are inclined to think in complete and discrete categories, leading to overweighting as the most likely scenario while ignoring the possible alternative (Tversky and Kahneman, 1974). Barberis et al. (1998) argue that observing a string of past firms' performance, investors expect the future performance of these firms to be no different than the recent past. Accordingly, market prices of firms consistently performing well (poorly) in the past will be pushed significantly above (below) their fair values. Subsequently, these firms should suffer high return reversals at the long horizon when it becomes clear to investors that their prior projections are not fully justified. In an experimental setting, Bloomfield and Hales (2002) report that experimental subjects are inclined to believe that a firm's future earnings are not expected to be different from the current earnings change unless the change-in-earnings follows a string of reversals.

Empirical evidence from the experimental psychology literature suggests individuals are likely to overweight attention-grabbing information signals. This claim is supported by evidence from the cognitive psychology literature indicating that people do not understand the full dynamics of the relationship among competing cues (e.g., Kruschke and Johanson, 1999). As a consequence, the effects of salient cues dominate the effects of other cues.

Grinblatt and Moskowitz (2004) find consistency of past returns to be a determining factor of momentum profitability. Watkins (2006) shows that a consistently positive or negative short-term return is useful in predicting expected returns over the next few weeks. Alwathainani (2009) shows that consistency of a firm's accounting performance variables in the past is useful in predicting its future stock price movements. These findings are supported by evidence from the work of Tversky and Kahneman (1974), who in an experiment ask subjects to form categories based on historical data. They find experimental subjects heavily weight patterns of this historical data even if such data exists only for a brief time period.

Daniel et al. (1998) argue that overly exuberant investors are likely to overestimate the future prospects of firms with exceptionally high or low performance in the recent past, sending stock prices of these firms away from their fair values. Further, they argue that this mispricing will deepen as consistency in such performance measures confirms investors' prior misperceptions. However, over the long term, stock prices will recover to their fundamentals as investors' expectations are proven unwarranted. This prediction is supported by evidence from experimental psychology.

To summarise, although behavioural models differ in their characterizations of the medium-term price momentum, they all agree that consistency of a firm's historical performance facilitates a market overreaction. Accordingly, firms with consistently high (low) price performance in the past should exhibit great price momentum at the intermediate period. Eventually, this mispricing will revert to fundamentals, resulting in price reversals at the long horizon. These predictions are presented in the following testable alternative hypotheses:

Hypothesis 1: *If investors overreact to consistency in firms' past price performance, firms with consistently high past returns will generate stronger intermediate price momentum and reversals at the long horizon relative to firms with inconsistent high past returns.*

Hypothesis 2: *If investors overreact to consistency in firms' past price performance, firms with consistently low past returns will generate stronger intermediate price momentum and reversals at the long horizon relative to firms with inconsistent low past returns*

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3. Sample, measurement, and empirical tests

3.1 Data sources

Monthly returns data (including the delisting returns) for the period 1963-2007 are taken from the Center for Research in Security and Prices (CRSP).[3] Book values are extracted from the Compustat database. Because we need 12-month returns to sort stock into portfolios considered in this study, December 1963 was the first formation period. Further, our empirical tests require stock returns for the next five years following portfolio formation data. Thus, December 2002 is the last formation period for all portfolios considered in this paper.

3.2 Consistency in Past Returns

Consistency in a firm's price performance in the past is defined as the number of months in which the firm maintains monthly equity returns that put it in the highest, or lowest 40 percent compared to other firms in each respective month. At the end of December of each year, stocks are sorted by their monthly returns over the last twelve months prior to the ranking date. Based on this ranking, stocks are grouped into one of 3 categories: top 40 percent, middle 20 percent, and bottom 40 percent. Stocks consistently ranking in the highest 40 percent for at least 6 months out of the last twelve months included in the ranking period are defined as *"consistent winners."* Analogously, firms consistently ranking in the lowest 40 percent in at least 6 months during the past twelve months are labeled *"consistent losers."*

Firms are classified as *"inconsistent winners"* if they achieve past returns that place them in the top 40 percent for no more than three months during the last twelve months.[4] Similarly, firms are identified as *"inconsistent losers"* if they experience low price performance in the past that put them in the bottom 40 percent for three months, but no less than one month of the prior twelve months.

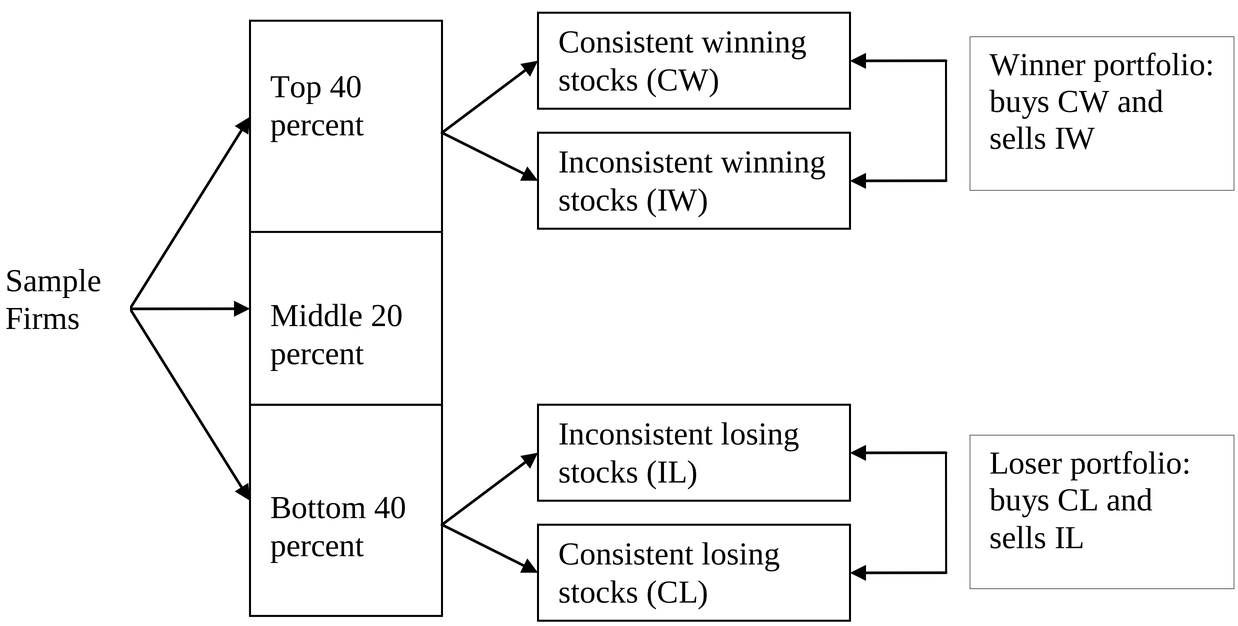
3.3 Empirical tests

3.3.1 Portfolio tests

To test hypotheses 1 (H1) and 2 (H2), I form two portfolios. The procedures used to construct these two portfolios are illustrated in Figure 1. The first portfolio buys consistent winners (CW) and sells inconsistent winners (IW). This strategy is labeled as a *"winner portfolio"* and its returns are referred to as "CW – IW." H2 is supported if the CW – IW is significantly greater than zero in the first year after the ranking period and less than zero in Years 2 through 5. The second portfolio involves taking a long position in consistent loser stocks (CL) and short position in inconsistent loser firms (IL). This hedge portfolio is defined as a "*loser portfolio*" and its returns are called to "CL – IL." H2 is supported if the CL – IL is significantly less than zero in the first post-formation year and greater than zero in Years 2 through 5 of the subsequent holding period.

All portfolios reported in this study are held without rebalancing for the next five years following the formation date.[5] As in Alwathainani (2009), raw buy-and-hold annual returns and the size-and-book adjusted abnormal returns (SAR) are calculated for each year of the investment period (Year 1 through Year 5) to avoid potential serial correlations in stock returns caused by overlapping holding horizons. SAR is calculated as the annual raw return for firm j minus the average annual return for the size-and-book portfolio to which the firm j belongs at the beginning of each period. The mean returns and mean-size-and-book adjusted abnormal returns for each portfolio are averaged over the sample period and t-tests are calculated as in Fama-MacBeth (1973).

Figure 1: Method used to calculate portfolio performance shown in Table 2.



Predictions:

(1) Winner portfolio (top 40 percent): Returns, i.e., CW – IW < 0

(2) Loser portfolio (bottom 40 percent): Returns, i.e., CL – IL > 0

3.3.2 Regression tests

To test whether investors overreact to consistency in a firm's past price performance, we run three separate regressions (models 1 through 3; see under Table 3). The size-and-book adjusted abnormal returns (SAR) are the dependent variables in these regressions. Models 1 and 2 are run each year (Year 1 through Year 5) while model 3 is estimated annually for Year 2 to Year 5. Model 1 includes past stock returns (PRET) as the only independent variable while model 2 included Beta, CW, CL, IW, and IL, where Beta is the market beta for firm j computed using monthly returns for the last 60 months, with a minimum of 36 months, prior to the portfolio formation date. CW and CL are dummy variables that take the value of 1 if the firm j is consistent winner or loser and 0 if they are not. IW and IL are indicator variables taking the value of 1 if a firm j is an inconsistent winner or loser and 0 otherwise.

If consistency in a firm's monthly returns leads investors to form unwarranted expectations about the firms' future performance, the regression slopes for CW variable are expected to be positive and statistically different from zero in the first post-ranking year, but significantly less than zero in subsequent years, particularly for Years 3 through 5. Similarly, the regression estimates for CL variable will be significantly less than zero for the first year and positive and significantly different from zero in the remaining years of the holding period, particularly for Year 3 through Year 5.

Model 2 includes PRET, Beta, and SARj1, the first year returns after portfolio was formed for firm j (the momentum return). Model 4 includes Beta, CW, CL, IW, IL, and SARj1, the first year returns after portfolio (the momentum return). SARj1 is included in the regression to control for the momentum effect. The slope coefficients from these regressions are averaged over the sample period and t-statistics are computed as in Fama-MacBeth (1973).

4. Empirical results

4.1 Descriptive statistics

Summary statistics of firms' ranked by their consistency in past monthly returns (PRET) and correlations between PRET and market betas (Betas), book-to-market ratios (B/M), and equity market capitalization (Size) are reported in Table 1. Panel A, Table 1 illustrates the average correlation coefficients between PRET, Beta, B/M, and Size, where Spearman (Pearson) correlations are displayed in the upper (lower) diagonal. As shown in Panel A, PRET is negatively correlated with Beta and B/M ratio, but positively correlated with Size, though none is statistically significant. Beta has a positive association with B/M (Spearman coefficients = 0.55, $p < 0.003$), indicating that firms with higher B/M ratios tend to have large Beta. Further, Beta is negatively correlated with Size

(Pearson correlations = -0.86, $p < 0.0001$). This suggests that large firms are likely to have lower Beta relative to their small firm counterparts.

Summary statistics of firms sorted by their consistency in their past monthly returns are presented in Panel B. Loser firms tend to be smaller firms, particularly consistent losers (in terms of their equity market capitalizations) with slightly greater Betas and B/M ratios compared to winner firms. Further, as shown in Panel B, consistent winners (CW) and consistent losers (CL) have approximately equal number of firms. CW firms have slightly larger market values and lower B/M ratios relative to their inconsistent winner cohorts.

Table 1: Summary/Descriptive Statistics and Correlations

Panel A: Spearman (Pearson) Correlations are in the Upper (Lower) Side

Variables	**Variables**			
	PRET	**BETA**	**B/M**	**SIZE**
PRET		-0.02	-0.25	0.16
BETA	-0.08		0.55	-0.83
B/M	-0.31	0.45		-0.50
SIZE	0.12	-0.86	-0.45	

Panel B: Firms Sorted by Return Consistency for the Prior 2-5 Years

Portfolios	**Statistics**			
	FIRMS	**BETA**	**B/M**	**SIZE**
CL	128	1.18	1.01	336
IL	803	1.13	0.85	676
CW	132	1.10	0.54	1361
IW	828	1.08	0.72	1016

Each year at the end of December from 1963 to 2002, all firms with past return data are sorted by their monthly returns over the last twelve months and assigned to one of three categories: top 40 percent, middle 20 percent, and bottom 40 percent. Firms with monthly returns that consistently place them in the highest (bottom) 40 percent for at least six months out of the last twelve months are classified as "*consistent winners (losers)*". Firms ranking in the top (bottom) 40 percent for at least one month, but no more than three months out of the last 12-months are defined as *"inconsistent winners (losers).*

Variable Definitions:

PRET = The mean of stock market returns over the past 12-months before portfolio formation date.
BM = The book-to-market ratios at the end of the fiscal year prior to portfolio formation date.
Beta = A firm's market beta. It is calculated using monthly returns over the prior 60 months, with a minimum of 36 months, prior to portfolio formation date.
Size = Market value of equity capital (in $million) at the portfolio formation date t. It is calculated as the number of shares outstanding multiplied by the stock price.
Firms = Number of firms in each portfolio
CL = Consistent Losers
IL = Inconsistent losers
CW = Consistent Winners
IW = Inconsistent winners

4.2 Portfolio test results

The return performance for winners and losers is presented in Table 2. Panel A includes returns for consistent and inconsistent winner portfolios while returns for consistent and inconsistent loser firms are reported in Panel B. In Panels A and B, annual raw returns (R1 through R5) as well as size-and-book adjusted abnormal returns (SAR1 through SAR5) are provided for each post-formation year (Years 1 through 5). Further, I calculated the average annual returns (AR) and average size-and-book adjusted abnormal returns (ASAR) over the investment period (Years 1 through 5). The last row of Panel A shows the difference in returns between the return of the consistent winner (CW) portfolio and that of inconsistent winner (IW) firms, i.e., the CW – IW return. Similarly, the return gap between the return for consistent loser (CL) firms and that of inconsistent loser (IL) firms is displayed in the last row of Panel B.

As shown under the Average/AR column of Panel A, consistent winners (CW) generate a five-year average return of 11.13 percent while their inconsistent winner (IW) counterparts have an average return of 12.67 percent with a return gap, i.e., the CW – IW return, of -1.54 percent (t = -1.94). As well, Panel A indicates that consistently winning firms underperform their inconsistent winner cohorts across the investment horizon except in the first year after the ranking date. In Year 1, the CW portfolio earns 2.55 percent (t = 2.87) and 4.31 percent (t = 3.80) for raw returns and SAR, respectively (see under Year 1/R1 and SAR1 columns in Panel A).

Panel B, Table 2 indicates that consistent losers (CL) have a mean return over the five-year investment period of 15.57 percent. On the other hand, inconsistent losers (IL) earn an average annual return of 13.08 percent as shown under the Average/AR column of Panel B. The difference in returns between these two portfolios (CL and IL), that is, the CL – IL return, is 2.49 percent (t = 3.74). Further, CL firms earn substantially superior returns than IL portfolios across the holding periods except in Year 1. In this particular year, the CL portfolio underperforms its IL portfolio counterpart by -4.45 percent (t = -2.74) and -4.41 percent (t = -3.02) for raw return and SAR, respectively (see under Year 1/R1 and SAR1 columns in Panel B).

A close look at Table 2 reveals that prior loser categories i.e., consistent and inconsistent losers, underperform their past winner counterparts (consistent and inconsistent winner firms) in the first year after portfolios are formed. However, losers earn substantially superior share returns compared to winners in the subsequent periods (Years 2 through 5). Similarly, past winners, i.e., consistent and inconsistent winners, generate higher returns than prior losers (consistent and inconsistent losers) in the first post-ranking year. However, over the remainder of the investment horizon (Years 2 through), winners have lower rates of return relative to their loser cohorts.

Results reported in Table 2 suggest that consistency of a firm's past price performance predicts momentum returns at the intermediate period and reversals in prices at the long horizon. However, there is a significant asymmetry in investor reactions to good and bad news contained in the consistency of firms' past price performance of winners and losers. This is evident from the stronger price reversal of consistent losers in Years 2 through 5 relative to that of their consistent winner counterparts.

4.3 Regression test results

Table 3 reports the results for the regression analysis (models 1 through 4). The time-series averages of the regression estimates are calculated from annual regressions, and the t-statistics are computed from the time-series variation of these regression coefficients as in Fama and MacBeth (1973).[6]

The regression estimates for PRET variables are positive and significantly different from zero for Year 1 and negative for the subsequent horizons (Years 2 through 5), but it is only statistically significant for Year 2. As shown in model 1, the slope coefficients for PRET fall between 0.047 (t = 3.41) for Year 1 (see Panel A) and -0.020 (t = -1.90) for Year 5 (see Panel C). This evidence indicates that PRET is a predictor for both price momentum and reversals in stock returns. However, as shown in Panel B and C, the power of PRET to predict future reversals in stock prices dissipates after Year 2.

The estimated coefficients for CW variable are positive and significant for Year 1 and negative for Years 2 through 5, but it is not statistically distinguished from zero after Year 3. The estimated regression slopes corresponding to Years 1 and 3 are 0.048 (t = 3.67) and -0.023 (t = -2.13), respectively as displayed in model 3. Similarly, the slope regressions for IW are positive for the first post-formation year (Year 1), but negative for subsequent years (Year 2 to year 5). Although the regression estimates for IW variable have the right signs, none is statistically significant.

Model 2, Panel A shows that the regression coefficients on CL variable is negative and statistically significant with an estimated slope of -0.039 (t = -3.13) indicating a positive price drift for Year 1. However, the slope coefficients for Years 2 through 5 are uniformly positive and statistically and economically significant varying from 0.036 (t = 2.23) to 0.045 (t = 3.30) as shown in Panels C and B of model 2, respectively.

Model 2 in Panels A through C shows that the regression slopes for IL are negative and significant for Year 1 and positive for Years 2 through 5, but only significantly different from zero in Years 2 and 3 with regression slope estimates varying from - 0.016 (t = - 2.86) to 0.010 (t = 2.42), for Years 1 and 3, respectively. This evidence shows that consistency of low past performance predicts both momentum effect and long-run price reversals. Model 3 indicates that the ability of return consistency to predict future return is robust after controlling for the price momentum effect.[7]

Overall, the results of the regression analysis reported in Table 3 reveal that consistency of a firm's past returns generates a medium-term autocorrelation in stock returns and reversals in stock prices at the long horizons (Years 2 through 5). However, the effect of past low returns on future price reversals is stronger for prior losing firms and for consistent losers in particular relative to prior winners. For example, price reversals for winners and losers begin in Year 2 and persist though Year 5. However, only the CL variable continues to predict future return reversals until the end of Year 5 while the power of CW and IL to predict long run reversals in returns dissipated after Year 3.

Evidence reported in Tables 2 and 3 are consistent with predictions of the behavioural models (e.g., Barberis et al., 1998; Daniel et al. (1998) suggesting that a string of a firm's prior performance measure moving in the same direction for a sufficient time period triggers a market overreaction that should revert to the fair value over the long run.

According to these models, the market momentum (overreaction) and subsequent price reversals (correction) are assumed to be equal for both prior winners and losers. However, results reported in Tables 2 and 3 indicate that the past consistent losers exhibit greater return reversals compared to the other firms (i.e., CW, IW, and IL groups) for Years 2 through 5. In particular, consistently losing firms generate substantial price reversals at the long horizon, i.e. Years 2 though 5, relative to their winner firm counterparts.

The results presented in Tables 2 and 3 extend two streams of research. First, I extend the momentum literature (e.g., Jegadeesh and Titman, 1993) by showing that consistency in a firm's past price performance predicts a continuation of a share price drift over the next twelve months. Second, my findings extend the evidence of the link between the intermediate-term price drift and long run price reversals (Lee and Swaminathan, 2000; Jegadeesh and Titman, 2001) by showing that the momentum profit following a string of consistent past returns reverses itself in the long horizon.

Table 2: Returns for Prior Loser and Winner Portfolios

Panel A: Loser Portfolios Ranked by Their Consistency in Past Monthly Returns

Portfolio	Year 1		Year 2		Year 3		Year 4		Year 5		Average	
	R1	SAR1	R2	SAR2	R3	SAR3	R4	SAR4	R5	SAR5	AR	ASAR
CW	15.48	5.36	9.39	-1.35	9.99	-1.06	10.37	-0.73	10.43	0.18	11.13	0.47
	4.44	**3.91**	**2.41**	**-0.90**	**2.82**	**-0.92**	**3.42**	**-0.55**	**3.06**	**0.11**	**7.35**	**0.72**
IW	12.92	1.05	12.75	0.32	12.53	0.31	12.52	0.32	12.64	0.43	12.67	0.48
	4.13	**1.51**	**3.77**	**0.34**	**4.21**	**0.31**	**4.36**	**0.36**	**4.39**	**0.46**	**10.15**	**1.09**
CW–IW	*2.55*	*4.31*	*-3.36*	*-1.67*	*-2.54*	*-1.38*	*-2.15*	*-1.05*	*-2.20*	*-0.25*	*-1.54*	*-0.01*
	2.87	**3.80**	**-2.24**	**-1.47**	**-1.57**	**-1.09**	**-1.91**	**-0.89**	**-1.72**	**-0.17**	**-1.94**	**-0.01**

Panel B: Loser Portfolios Ranked by Their Consistency in Past Monthly Returns

Portfolio	Year 1		Year 2		Year 3		Year 4		Year 5		Average	
	R1	SAR1	R2	SAR2	R3	SAR3	R4	SAR4	R5	SAR5	AR	ASAR
CL	6.75	-6.80	18.86	5.54	19.40	5.69	19.57	5.26	18.25	3.91	15.57	2.72
	1.42	**-3.50**	**3.43**	**2.40**	**4.28**	**2.63**	**5.14**	**3.58**	**4.95**	**3.03**	**9.10**	**2.93**
IL	11.21	-2.39	13.64	1.67	13.67	1.85	13.52	1.72	13.38	1.61	13.08	0.89
	-3.06	**-2.10**	**4.14**	**1.95**	**4.36**	**2.68**	**4.55**	**2.39**	**4.83**	**2.11**	**9.87**	**2.09**
CL–IL	*-4.45*	*-4.41*	*5.22*	*3.87*	*5.73*	*3.84*	*6.05*	*3.54*	*4.87*	*2.30*	*2.49*	*1.83*
	-2.74	**-3.02**	**2.88**	**2.24**	**2.90**	**2.07**	**2.58**	**2.71**	**2.90**	**2.11**	**3.74**	**2.29**

Returns presented in Panel A, Table 2 are for a portfolio that takes a long position in consistent losers and short position in firms with inconsistent past low returns while Panel B, Table 2 reports returns performance for portfolio that buys consistent losers and sells firms with inconsistent past low returns (See Table 1, Panel B for a portfolio construction procedures). Portfolios considered in this table are held without rebalancing for the five years following the portfolio formation date. Buy-and-hold annual raw returns (R1 through R5) and size-and-book adjusted abnormal returns (SAR1 through SAR5) are calculated for each post-formation year (years 1 through 5). SAR is defined as the annual raw returns for firm j less the average size-and-book returns for a portfolio to which a firm belongs. The mean annual returns (AR) and mean size-and-book adjusted abnormal returns (ASAR) are computed over the test period (years 1 through 5). The CW– IW in the last row of Panel A refers to the difference in returns between CW and IW portfolios. Similarly, the CL– IL in the last row of Panel B refers to the difference in returns between CL and IL portfolios. Returns are computed each year and averaged over the sample period and the t-tests are computed as in Fama-MacBeth (1973). The t-statistics are reported in **bold**.

Table 3: Regression Results for Portfolios Based on Consistency in Past Monthly Stock Returns (PRET)

Panel A: Parameter Estimates for First Year after Portfolio Formation

Regression Models	Parameter Estimates						
	Int.	**PRET**	**Beta**	**CW**	**CL**	**IW**	**IL**
Model 1	-0.005	0.047					
	-0.59	**3.41**					
Model 2	0.001		0.008	0.048	-0.039	0.006	-0.016
	0.06		**0.42**	**3.67**	**-3.13**	**1.08**	**-2.86**

Panel B: Parameter Estimates for Third Year after Portfolio Formation

Regression Models	Parameter Estimates							
	Int.	**PRET**	**Beta**	**CW**	**CL**	**IW**	**IL**	**SAR1**
Model 1	0.024	-0.025						
	3.38	**-1.88**						
Model 2	-0.010		0.035	-0.023	0.045	-0.006	0.010	
	-0.59		**1.96**	**-2.13**	**3.30**	**-0.94**	**2.42**	
Model 3	-0.012		0.031	-0.017	0.047	-0.005	0.009	-0.068
	-0.69		**1.74**	**-1.60**	**3.38**	**-0.88**	**2.18**	**-4.85**

Panel C: Parameter Estimates Five Years after Portfolio Formation

Regression Models	Parameter Estimates							
	Int.	**PRET**	**Beta**	**CW**	**CL**	**IW**	**IL**	**SAR1**
Model 1	0.031	-0.020						
	5.52	**-1.90**						
Model 2	-0.019		0.025	-0.016	0.036	-0.007	**0.001**	
	-1.04		**1.81**	**-1.23**	**2.23**	**-1.57**	**0.18**	
Model 3	-0.021		0.024	-0.012	0.034	-0.006	0.001	-0.037
	-1.17		**1.74**	**-0.93**	**2.14**	**-1.35**	**0.26**	**-2.91**

At the end of each year after portfolio formation, I run the first and third regressions (models 1 and 2) while model 3 is estimated annually for years 2 through 5. The size-and-book adjusted abnormal returns (SAR1 through SAR5) are the dependent variables in all these regressions.

Model 1: $SAR_{j\tau} = \beta_0 + \beta_1 PRET_{jt} + \mu_{j\tau}$ (1)

Model 2: $SAR_{j\tau} = \beta_0 + \beta_2 Beta_{j\tau-1} + \beta_7 SAR_{j1} + \mu_{j\tau}$ (2)

Model 3 $SAR_{j\tau} = \beta_0 + \beta_2 Beta_{j\tau-1} + \beta_3 CW + \beta_4 CL + \beta_5 IW + \beta_6 IL + \beta_7 SAR_{j1} + \mu_{j\tau}$ (3)

$SAR_{j\tau}$ = the size-and-book adjusted abnormal return for firm j in each post-formation year, where τ varies from one to five years after the portfolio is formed.; $PRET_{jt}$ = the average stock returns for firm j over the last 12-months prior to portfolio formation date t.; $Beta_{j\tau-1}$= market beta for firm j, calculated using monthly stock returns over the prior 60 months (with a minimum of 36 months); CW= an indicator variable that takes the value of one if a firm is consistent winner, or zero otherwise; CL= an indicator variable that takes the value of one if a firm is a consistent loser, or zero otherwise; IW= an indicator variable that takes the value of one if a firm is an inconsistent winner, or zero otherwise; IL= an indicator variable that takes the value of one if a firm is an inconsistent loser, or zero otherwise; SAR_{j1} = the size-and-book adjusted abnormal return for firm j in the first post-formation year. The average coefficients and t-statistics (in **bold**) reported in this table are based on annual regressions for the third post-formation year over the sample period using the Fama-MacBeth (1973) procedures. The parameter estimates reported in this table are for three-years subsequent to the portfolio formation date.

5. Conclusions

In this study, I show that consistency in a firm's past price performance predicts future price movements. However, the effect of consistency on future returns (both in magnitude and duration) is stronger for consistent losers than for consistent winners. More specifically, portfolio and regression tests reveal a number of interesting findings. First, my analyses show prior loser categories (consistent and inconsistent loser firms) outperform winner stock groups (consistent and inconsistent winners) in all investment horizons, except in the first year (Year 1) after the portfolio formation. In Year 1, winner categories have higher returns than loser groups. The momentum and reversal effect is stronger for the two extreme categories, i.e., consistent winners and losers relative to that for inconsistent winners and losers.

Second, I find that consistent losers, i.e., firms consistently ranking in the bottom 40 percent of past returns, earn substantially superior future stock returns than their inconsistent loser counterparts over the holding periods, except in the first year (Year 1) following the portfolio formation. In Year 1, inconsistent losing firms outperform consistent losers by a significant margin. Third, consistent winners, i.e., firms consistently ranking in the highest 40 percent, underperform their inconsistent firm cohorts across the investment horizons, except in the first post-formation year, that is, Year 1. In Year 1 in particular, consistently winning firms beat inconsistent winner stocks by a significant return.

Fourth, multiple regression results indicate that consistency of a firm's past stock returns leads to initial market momentum at an intermediate horizon and reversals over the long period. The regression analysis shows that the price reversal is stronger for prior consistent losers compared to that of other categories, i.e., consistent winners and inconsistent winners and losers. Finally, the regression results indicate that the ability of return consistency to predict future price movement is robust after controlling for the price momentum effect.

My findings have very important implications for capital market research, particularly for the momentum and reversal literatures. I extend the price momentum literature (e.g., Jegadeesh and Titman, 1993) by showing that consistency of firms' price performance in the past generates medium-term return momentum. As well, I extend the work of Jegadeesh and Titman (2001) and Lee and Swaminathan (2000) by providing evidence that the price momentum reverses over the long run. My results show that the reversal for past consistent losers in Years 2 through 5 far exceeds the momentum effect in Year 1 suggesting that the reversal is not only a response to a market overreaction in Year 1, but it appears to be a correction to an overreaction that occurred before the portfolio formation date.

Overall, my findings are consistent with the predictions of behavioural-based theories (e.g., Barberis et al., 1998; Daniel et al., 1998) that suggest that consistency of a firm's prior performance measures should lead to a market overreaction. Daniel et al. (1998) argue that overly optimistic investors overreact to exceptionally strong (weak) past performance and consistency of such performance confirming investors past perceptions will invite even an additional overreaction. Eventually, however, stock market prices will reverse to their fair values when investors realise that their past expectations were not fully justified by future performance of these stocks.

End Notes

[1] See Grinblatt and Moskowitz (2004) and Watkins (2003) for more details.
[2] See Watkins (2006) for more details.
[3] If a firm is delisted after the ranking period, its delisting return from the CRSP delisting return file is used if it is available. This approach is consistent with that of Chan (2003). As well, firms whose share prices are below one dollar are excluded.
[4] A firm cannot be included in more than one group.
[5] I repeated my analysis using value-weighted returns and my findings remain qualitatively the same.
[6] The results for 2nd and 4th year regressions are similar as those reported and are available upon request.
[7] In untabulated results, I used the largest 50 percent of stocks in terms of their market value and my key findings remain unchanged.
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