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Does bad economic news play a greater role in shaping investors' expectations than good news?

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Using consistency in monthly returns as a proxy for good and bad economic news, I show that investors overreact to a series of favourable and unfavourable news. However, bad economic news plays a greater role in shaping investors' expectations than good news. Consistent losers exhibit stronger price momentum in Year 1 followed by a more pronounced and persistent price reversal in Years 2 through 5 relative to their consistent winner counterparts. This evidence is robust to the three-factor Fama-French model and momentum factor. Results reported in this study provide general support to the psychology-based theories, but none of the existing models fully captures the weighting differential that negative and positive information signals play in shaping investors' expectations.

Field of Research: Behavioural Finance, Asset pricing, Investors' Psychology

1. Introduction

A large body of empirical research over the last three decades shows that a firm's expected returns can be discernable from its stock price performance in the past. This body of research has been attributed to investors' sentiments (e.g., DeBondt and Thaler, 1985; Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998). In recent years, a number of analytical studies (e.g., Barberis et al., 1998; Daniel et al., 1998) have drawn on evidence from the psychology literature to develop models that address a growing list of market anomalies, particularly medium horizon price momentum and reversals in returns at the long run. Despite their differences about the characterisation of the intermediate period autocorrelation in stock returns, these theories agree that a string of firms' performance drifting in the same direction for a sufficient time period would facilitate a market overreaction. Eventually, the share prices of these firms will return to their fundamentals, resulting in a long run price reversal.
Almost all psychology-based models (e.g., Daniel et al., 1998; Barberis et al., 1998) are implicitly or explicitly built on the assumption that good and bad economic news have the same effect on investors' expectations. However, significant evidence from the psychology literature suggests that negative information has a greater effect on people's judgments and decisions than positive information (e.g., Ronis and Lipiniski, 1985; Singh and Teoh, 2000). According to the prospect theory, investors assign heavier weight to losses than that given to gains (Kahneman and Tversky, 1979, 1984).

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Despite the recent analytical studies that attempt to provide explanations for the market under-and-overreaction phenomena in an investors' behavioural context, little is known about whether bad news has a greater effect in investors' decision-making processes than good news. In this study I use consistency in firms' monthly price performance in the recent past as a proxy for good and bad news to investigate whether information contained in return consistency of prior losers is weighted heavier in market expectations than that of their past winner counterparts. If bad news plays a greater role in shaping investors' expectations, consistent losers will experience stronger intermediate price momentum and a long horizon reversal in stock returns relative to their consistent winner counterparts.

Using past return data of a sample of publicly traded firms from January 1963 to December 2007 on their future price performance, I divide my sample firms into three groups: top 30 percent, middle 40 percent, and bottom 30 percent based on consistency of their price performance in the past twelve months prior to the ranking period. Firms consistently ranking in the highest 30 percent are defined as consistent winners while firms in the bottom 30 are classified as consistent losers. Firms ranking in the middle 40 percent are called consistent moderates.
Firms in the consistent moderate category are assumed to be fairly priced for three reasons. First, firms in this group are likely to be large firms with stable financial performance measures, i.e., earnings and their future cash flow is much easier to estimate relative to that of firms at both ends of the performance matrix (i.e., consistent winners and losers). Second, in general these firms are unlikely to attract favourable or unfavourable media coverage that may influence investors' perceptions about these firms. Finally, past price performance of firms in this category is unlikely to exhibit extreme patterns that may lead to a market reaction as do those of consistent winners or losers. Therefore, firms in this group are used as a benchmark (reference) portfolio against which the return performance of consistent winners and losers are measured. Remarkably, the alphas of the Fama-French three-factor regression for these firms in each year of the holding period (Year 1 to Year 5 subsequent to the ranking date) are virtually zero.[1]

During the sample period, the consistent loser portfolio (CL) underperforms the benchmark portfolio (CM) by about 69 basis points per month in Year 1 after the portfolio formation date while the consistent winner portfolio (CW) outperforms the benchmark portfolio by about 47 basis points per month for the same period. In Years 2 through 5, the CL portfolio earns substantially greater returns than both the CW and CM portfolios while the CW portfolio underperforms the CM portfolio by marginal returns. The return differentials between the CL and CM portfolios range from 28 basis points per month in Year 2 to 49 basis points per month in Year 5. On the other hand, the difference in returns between the CW and CM portfolios falls between -23 basis points per month in Year 2 and -4 basis points per month in Year 5. This evidence indicates that the return reversal at the long horizon is greater and more persistent for consistent losers compared to their consistent winner cohorts.

Taken together, the evidence of the intermediate horizon price momentum in Year 1 and subsequent reversals in returns in Years 2 through 5 as well as the relationship between these two phenomena has three significant implications on our understanding of how investors respond to good and bad economic news and how their reactions affect the price formation mechanism in the securities markets. First, results reported in this study suggest a price formation process in which the market overreacts to past performance of consistent winners and losers and subsequently corrects itself. However, this correction may take a long horizon.

Second, investors' responses to consistency in good and bad news are asymmetric. Bad economic news is likely to play a more significant role in shaping investors' expectations than good economic news. Results reported in this study indicate that investors tend to believe that the losing path of past losers is expected to continue moving in the same trajectory for a longer period than that of their consistent winner cohorts (e.g., Balsara, Zheng, Vidozzi, and Vidozzi, 2006; Alwathainani, 2009). These findings are robust to the four-factor Fama-French model (market, size, book, and momentum factors). This asymmetry in perceptions about consistent losers and winners leads investors to overreact to past performance of these firms, driving market prices of losers way below their fair values relative to the degree the prices of winners is pushed above their fundamentals. As a result, consistent losers exhibit a stronger positive autocorrelation in stock returns at the intermediate period (Year 1) followed by more persistent and pronounced price reversals at the long horizon (Year 2 to Year 5) compared to consistent winners.

Finally, my findings provide support to the hypothesis that the intermediate positive and long-run negative autocorrelations in stock returns should be viewed as two components of a price formation process. In this price formation mechanism, a market overreacts to favourable and unfavourable information news (although its reaction is asymmetric) in the medium period and corrects itself at a long horizon (e.g., Daniel et al., 1998; Lee and Swaminathan, 2000). This is contrary to the prevailing notion that investors respond to new information with a time lag. Overall my findings provide general support for theories proposed by Daniel et al. (1998) and Barberis et al. (1998). However, neither of these models explains the asymmetry of investors' responses to good and bad economic news documented in this study. Both Daniel et al., (1998) and Barberis et al. (1998) assume that investors' reaction to good and bad news is symmetric while results reported in this study indicate that investors are likely to put more weight on past performance of losers than that of winners when predicting the future performance of these firms. This is evident from a more pronounced drift in prices in Year 1 followed by a more robust and persistent negative correlations in stock returns in the long horizon (Years 2 to 5) for prior consistent losers relative to their consistent winner counterparts. The magnitude of the price momentum in

Year 1 and the persistence of the long-term price reversals in Years 2 through 5 of consistent losers compared to their consistent winner cohorts suggest that investors process past performance of losers and winners differently.

Veronesi (1999) proposes a theoretical model based on a regime shift in dividends and attempts to explain whether this shift influences volatility in market prices. He graphically presents side-by-side a time series of dividend and return data. Based on the patterns of these data, he concludes that market prices overreact to bad news (a negative shift in dividends) in good times. However, Veronesi (1999) does not empirically examine subsequent price performance to determine whether a negative shift in dividends sways market expectations. Other authors have studied the relationship between past returns consistency and expected returns (Watkins, 2003, 2006; Grinblatt and Moskowitz, 2004; Gutierrez and Kelley, 2008). However, none of these papers examines whether bad economic news plays a more significant role in shaping investors' expectations than good economic news. The rest of the paper is organised as follows: Hypothesis development is presented in Section 2. Sample and variable measurements are discussed in Section 3. Section 4 presents empirical tests and discusses empirical results. Finally, my results are summarised in Section 5.

2. Hypothesis development

The conventional market paradigm assumes that the majority of market participants are rational and wealth maximizing individuals. It follows that new information is instantly captured into assets market prices in unbiased fashion (e.g., Fama, 1991). However, evidence from the psychology literature suggests that individuals' judgments depart from Bayesian rationality in many ways (e.g., Tversky and Kahneman, 1974). Because of our tendency to think in complete and independent categories, the most representative scenarios receive more weight relative to other plausible alternatives (Tversky and Kahneman, 1974). According to Barberis et al. (1998), a string of positive *or* negative changes in a firm's past performance measures (e.g., earnings) causes investors to believe that the future earnings of the firms is unlikely to be different from its recent past. Accordingly, share prices of firms achieving consistent high (low) price performance in the past are likely to be pushed away from their fair values. Eventually, this mispricing will be corrected as investors realise that their past expectations are not fully warranted. The prediction of Barberis et al. (1998) is confirmed by the experimental results of Bloomfield and Hales (2002). Their findings show that their experimental participants tend to believe a firm's past earnings resemble its recent past unless past results display a significant reversal.

Daniel et al. (1998) argue that overly confident investors are likely to push market prices of firms with relatively high (low) return performance in the past above (below) their fair values. As well, they argue that consistent performance that affirms investors' prior false expectations will deepen this mispricing even further.

However, as future performance of these firms becomes known share prices will regress toward to their fundamentals, causing a long term reversal in returns. Almost all psychology-based models including those of Daniel et al. (1998) and Barberis et al. (1998) are predicated on the assumption that investors' response to favourable and unfavourable signals is symmetric. However, the psychology literature suggests that negative signals have a greater impact on individuals' judgments and decisions than positive cues (e.g., Ronis and Lipiniski, 1985; Singh and Teoh, 2000). The experimental psychology literature indicates that the asymmetry in people's responses to information is the product of cognitive weighting, where more weight is assigned to unique or attention-grabbing cues (e.g., Fiske, 1980). According to the prospect theory of Kahneman and Tversky (1979, 1984), investors assign heavier weight to losses than that given to gains.
Balsara et al, (2006) argue that news about losers carries a heavier weight compared to that about winners because investors expect the declining performance path of losers to continue much longer than the gain streak of winners. Consequently, the reversal in future prices of past consistent losers should be greater and more persistent relative to that of prior winners. If performance consistency of past losers is weighted more than that of winners in shaping investors' perceptions about the future firm outlooks, the mispricing of losing firms is expected to be more pronounced relative to that of their winner counterparts. Consequently, consistent losers in the past will experience greater price reversals over the long horizons than their consistent winner cohorts. This prediction is presented in the following testable alternative hypothesis:

If bad economic news plays a greater role in shaping investors' expectations relative to good economic news, consistent losers will experience stronger price momentum and subsequent return reversal than their consistent winner counterparts.

3. Sample, variable measurements, and descriptive statistics

3.1 Data sources

My sample firms include all stocks with available monthly return data including delisting returns and shares outstanding from the Center for Research in Security and Prices (CRSP) for the period 1963-2007.[2] Because I require stock returns for the last twelve months, January 1964 is the first formation period for all portfolios. As well, empirical tests require five-year monthly returns. Thus, December 2002 is the last formation interval for all portfolios. Stocks priced less than $5 at the beginning of the holding period are eliminated to avoid the influence of illiquid and small firms or market microstructures.

3.2 Consistent in monthly return performance

Consistency in monthly return performance is defined as the number of months in which a stock ranks in the top 30 percent, middle 40 percent, and bottom 30 percent of all stocks based on its monthly returns over the last twelve months prior to the ranking period. Each month from January 1963 to December 2002, stocks are sorted by their monthly returns and assigned to three categories: top 30 percent, middle 40 percent, and bottom 30 percent. Firms achieving monthly returns that place them in the highest 30 percent for at least 6 months out of the last twelve months are classified as "*consistent winners.*" Similarly, firms with monthly returns the put them in the lowest 30 percent in at least six of the prior twelve months are defined as *"consistent losers."* Firms consistently ranking in the middle 40 percent in at least six out of the last twelve months are labeled as *"consistent moderate firms."*[3] Firms in the later category are used as a benchmark portfolio.

3.3 Descriptive statistics

Table 1 provides descriptive statistics for firms with required data. Summary statistics for firms ranked by consistency in their past monthly stock returns (PRET) is reported in Panel A. The number of firms in CL, CM, and CW portfolios is approximately equal. The average past monthly returns (PRET) is -0.06, 0.02, and 0.10 for CL, CM, and CW portfolios, respectively compared to 0.02 for the average stocks in the sample. CL firms tend to be slightly smaller with greater B/M ratios relative to the average firms in the sample. Firms in the CM portfolio are much larger than CW, CL, and the average sample firms. Both CL and CW portfolios have greater market betas than the stocks in the sample although the CL firms have slightly larger betas relative to their CW counterparts. Panel B presents the means, medians, and standard deviations of past stock returns (PRET), year-to-year changes in operating earnings (OEG), earnings before extraordinary items and discontinued operations (EBG), and cash flow (CFG). [4] The means (medians) of OEG, EBG, and CFG fall between 0.08 (0.06) and 0.06 (0.05) and their standard deviations range from 0.61 to 0.68.

Performance measure characteristics of firms sorted by their return consistency in the past twelve months are reported in Panel C. A closer look at Panel C reveals that the standard deviations (STD) for OEG, EBG, and CFG for both CW and CL stocks are almost identical, ranging from 0.64 for OEG as shown under the OEG column to 0.76 for EBG (see under the EBG column). However, the STD of the CM firms is 0.32, 0.35, and 0.36 for OEG, CFG, and EBG, respectively. As shown in Panel C, the STD of growth rates in earnings and cash flow (i.e., OEG, EBG, and CFG) for CW and CL portfolios is twice as much as that of the CM firms. Further, the STD of PRET for CW and CL is almost six times greater than that of CM stocks. These statistics indicate that earnings and cash flow of CM firms are more stable and more predictable relative to those of their CW and CL counterparts.

Table 1: Summary/Descriptive Statistics

Panel A: Firms with sufficient data

Statistics	Portfolios			
	CL	CM	CW	ALL
Firms	46	54	48	2012
PRET	-0.06	0.02	0.10	0.02
Beta	1.23	0.88	1.17	1.01
B/M	1.02	0.72	0.51	0.75
Size	652	1918	1274	1208

Panel B: Descriptive statistics

Variables	Mean	Median	Std. dev.	Max	Min
PRET	0.02	0.01	0.10	0.85	-0.43
OEG	0.08	0.06	0.61	4.02	-2.84
EBG	0.06	0.05	0.68	4.54	-6.56
CFG	0.08	0.06	0.64	4.03	-4.63
BETA	1.01	0.96	0.34	1.42	-0.46
B/M	0.75	0.65	0.72	5.04	-2.38

Panel C: Performance measure characteristics of consistent portfolios

Portfolios	Statistics	Performance Measures			
		PRET	OEG	EBG	CFG
CW	Mean	0.09	0.31	0.38	0.36
	Median	0.08	0.16	0.21	0.18
	STD	0.11	0.65	0.74	0.71
CM	Mean	0.02	0.08	0.07	0.09
	Median	0.02	0.06	0.06	0.07
	STD	0.02	0.32	0.36	0.35
CL	Mean	-0.06	-0.24	-0.31	-0.28
	Median	-0.05	-0.14	-0.22	-0.16
	STD	0.11	0.64	0.76	0.67

At the end of each month from January from 1963 to December 2002, all firms with data on past returns are ranked by their monthly stock returns and assigned to one of three groups: top (bottom) 30 percent and middle 40 percent. Firms consistently ranking in the highest (bottom) 30 percent for the entire estimation interval are classified as "*consistent winners (losers)".* Similarly, firms with past returns that consistently place them in the middle 40 percent are defined as "*consistent moderate firms*" and used as a benchmark portfolio.

Variable Definitions:

Firms = number of firms in each portfolio.
PRET = the average monthly stock returns over the prior twelve months before portfolio formation.
OEG = a year-to-year change in operating earnings over the sample period.
EBG = a year-to-year change in earnings before extraordinary items and discontinued operations over the sample period. .
CFG = a year-to-year change in cash flow. It is calculated as earnings before extraordinary items and discontinued operation plus depreciation and amortization expense over the sample period.
Beta = a firm's market beta. It is calculated using monthly returns over the past 60 months, with a minimum of 36 months, prior to portfolio formation date.
BM = the book-to-market ratios at the fiscal year-end 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.
CW = consistent winners, CL= consistent losers, CM = consistent moderate firms, and ALL= all firms with available data.

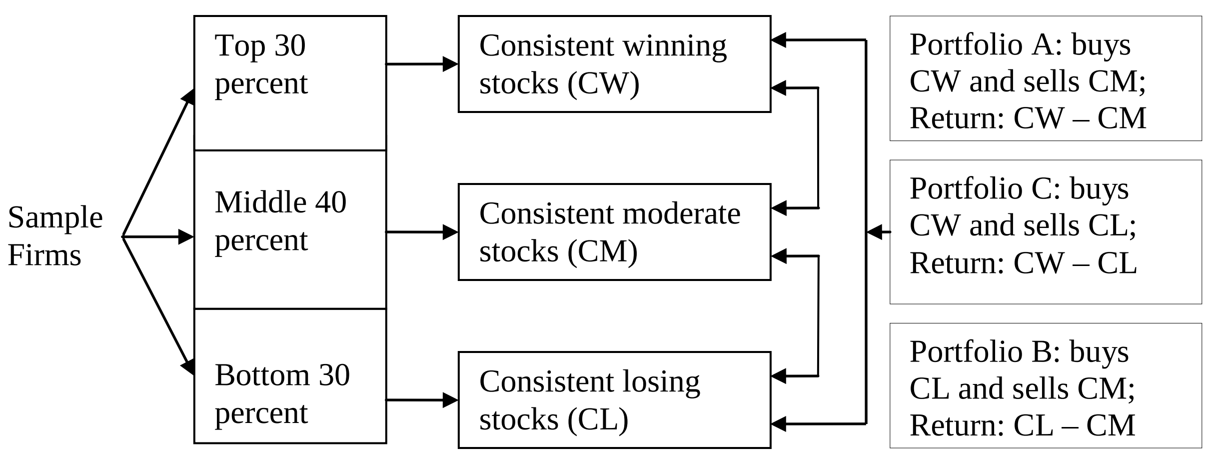
4. Empirical tests

4.1 Portfolio formation

To test my hypothesis, the equally weighted three consistent portfolios: consistent winners (CW), consistent losers (CL), and consistent moderates or the benchmark portfolio (CM) are held for the next five years and their returns are measured.[5] The return on a portfolio (portfolio A, illustrated in Figure 1) buying stocks in the CW portfolio and selling short stocks in the CM portfolios is referred to as "CW – CM." Similarly, the return on a portfolio (portfolio B, shown in Figure 1) going long in the CL stocks and short in the CM stocks are labeled as "CL – CM." The return for a portfolio (portfolio C, displayed in Figure 1) taking a long position in CW and a short position in CL is dubbed as "CW – CL."

I expect CW – CM, that is, the return for portfolio A, to be positive and statistically significant in the first-post formation year (Year 1) and negative in the remaining years (Years 2 through 5) of the holding period. On the other hand, the return differential between CL and CM portfolios, i.e., CL – CM (the payoff for portfolio B), is expected to be significantly less than zero, in Year 1 and positive and statistically different from zero for Years 2 through 5. The payoff for portfolio C, i.e., CW – CL, is expected to be positive and statistically and economically greater than zero in Year 1 and negative and significantly distinguishable from zero in Years 2 through 5.

Figure 1: Method used to compute portfolio return performance reported in Table 2



Predictions:
(1) Portfolio A: CW – CM > 0 for Year 1 and CW – CM < 0 for Years 2 through 5
(2) Portfolio B: CL – CM < 0 for Year 1 and CL – CM > 0 for Years 2 through 5
(3) Portfolio C: CW – CL > 0 for Year 1 and CW – CL < 0 for Years 2 through 5

4.2 Portfolio returns

The average monthly returns for consistent winner (CW), consistent loser (CL), and consistent moderate (CM) portfolios are presented in Table 2. For each year of the holding period (Years 1 through 5), I provide the average monthly returns (R1 through R5). The return differentials between CW and CM portfolios (the return for portfolio A), i.e., the CW – CM returns, for years 1 through 5 are reported in the third last row of Table 2. The return gap between the CL and CM portfolios, that is, the CL – CM returns, is presented in the second last row of Table 2. Further, the difference in returns between the CW and CL portfolios, i.e., the as CW – CL return (the payoff for portfolio C) is provided in the last row.

Table 2 indicates that the average monthly holding-period returns for Year 1 (the momentum returns) increase monotonically from 0.45 percent (t = 1.94) for the CL portfolio to 1.61 percent (t = 6.91) for the CW portfolio over the sample period. The return differential between the CW and CM portfolios, that is, CW – CM, is a positive and significantly different from zero at 0.47 percent (t = 2.84) per month. Similarly, the difference in returns between the CL and CM portfolios, i.e., CL – CM, is a negative and statistically and economically significant at -0.69 percent (t = -4.87) per month. In other words, the CW portfolio outperforms the CM portfolio by 0.47 percent per month while the CL stocks underperform its CM stock counterparts by 0.69 percent per month in Year 1. Further, the Year 1 return differential between the CW and CL portfolios, that is, the CW – CL return is positive and economically and statistically different from zero at 1.16 percent per month with a t-statistic of 5.65. Now, I turn to the analysis of long-term returns (Years 2 through 5) of these portfolios.

The average monthly returns for each year after Year 1 tell a different story. In Years 2 through 5, the CL portfolio outperforms both the CW and CM portfolios by a significant margin. As shown under R2 through R5 columns, the return differential between CL and CM portfolios, i.e., CL – CM, ranges from 0.28 (t = 1.60) for Year 2 to 0.49 percent (t = 3.23) for Year 5. The CW earns lower average monthly returns relative to the CL and CM portfolios. However, the return gap between the CW and CM portfolios, that is, the CW – CM, is not distinguishable from zero varying from -0.04 percent (t = -0.28) to -0.23 percent (t = -1.39) for the same period. Further, the return differential between the CW and CL portfolios, i.e., the CW – CL, falls between -0.47 percent (t = -2.19) and -0.53 percent (t = -2.88).

It is evident from the results reported in Table 2 that consistent losers (CL) have stronger price momentum (see Year 1 returns) and greater return reversals (see returns for Years 2 through 5) relative to consistent winners (CW). This evidence suggests that investors respond differently to good and bad economic news. According to the psychology-based theories (e.g., Daniel et al., 1998; Barberis et al., 1998), investors are likely to overreact to consistency of past performance drifting in the same direction for a sufficient period of time. This overreaction should manifest itself in intermediate price momentum followed by a long-term price reversal as investors realise that their prior expectations are not fully warranted. My findings provide general support to this prediction. However, neither of these models captures the asymmetric in investors' responses to a string of good and bad news reported in this paper. The theories of Daniel et al. (1998) and Barberis et al. (1998) assume implicitly or explicitly that investors' reactions to good and bad news is symmetric. However, a closer look at Table 2 reveals that the CL portfolio exhibits stronger momentum in Year 1 and return reversals in Years 2-5 relative to its CW and CM cohorts. This evidence suggests that bad economic news plays a significant role in determining investors' expectations than good economic news. It is indicative from the results reported in Table 2 that investors tend to have different perceptions of the impact and persistency of firms' past good and bad performance on the future prospects of these firms. These results suggest that investors expect the price decline of losers to continue in the same trajectory much longer than the price gain of winners. As a result, investors give a heavier weight to information about prior losers than information signals about past winners when predicting the future performance of these firms.

This asymmetric reaction to firms' past good and bad price performance should lead to a strong price drift over the short horizon and a long run price reversal for consistent losers compared to their consistent winner cohorts. This prediction is consistent with the findings reported in Table 2. These results indicate that investors are inclined to give a heavier weight to information about prior losers than information about past winners. This causes the mispricing of consistently losing firms to become substantially stronger than that of the consistent winners. Consequently, consistent losers will experience a greater price reversal compared to consistent winning stocks.

4.3 Regression results

The results from the Fama and French three-factor regression are presented in Table 3. The return for each portfolio (CL, CM, and CW as well their return differentials, i.e., CW – CM, CL – CM, and CW – CL) in Year 1 (the momentum return) is regressed on the three-factor Fama-French model. As shown in Panel A, the intercepts (FF-factor alphas) increases uniformly from -1.01 percent per month (t = -7.38) for the CL portfolio to 0.67 percent per month (t = 6.54) for the CW portfolio. The payoff for the CL – CM portfolio that buys CL and sells CM, is -1.02 percent per month (t = -7.69) while the return on the CW – CM portfolio that is long the CW and short the CM is 0.65 percent per month (t = 5.42). The return gap between the CW – CM and CL – CM, that is, the CW – CL return is 1.68 percent per month with t-statistic of 8.48. The risk-adjusted payoffs for the CL – CM, CW – CM, and CW – CL portfolios are slightly higher than those reported in Table 2 even after accounting for the Fama-French factors. This is due to the slightly higher sensitivity of the CL firms to the Fama-French three factors as shown in Table 1, Panel A.

In Panel B of Table 3, I provide the results from the three Fama-French factor model for Years 2 through 5. The monthly returns for each portfolio in Years 2 through 5 are regressed on the Fama-French three-factor model. The regression results indicate that the intercepts (FF-factor alphas) increase monotonically from -0.13 percent per month (t = -2.33) for the CW portfolio to 0.20 percent per month (t = 2.68) for the CL portfolio as shown in Panel B, Table 3. The return for the CL – CM is 0.25 percent per month (t = 2.91) and the return for the CW – CM is -0.08 percent per month (t = - 1.18). Moreover, the return differential between the CW and CL portfolios, i.e., the CW – CL returns, is -0.32 percent per month with t-statistic of -3.45.

A closer look at Panels A and B of Table 3 reveals that consistent losers have stronger price momentum in Year 1 and experience higher price reversals in Years 2 through 5 compared to their consistent winner counterparts. This evidence implies that information contained in the past performance of consistent losers is given a greater weighting than information about prior consistent winners. Remarkably, the risk-adjusted return for the CM portfolio in Year 1 is 0.01 percent per month (t = 0.39) and its excess return on the three-factor Fama-French model in Years 2 through 5 is -0.05 percent per month (t = -1.38). In both cases, the risk-adjusted abnormal return for the CM portfolio after controlling for the Fama-French three factors is virtually zero. This provides a strong support for my rationale to use the CM firms as a benchmark portfolio against which the return for both CL and CW portfolios are measured. Taken together, evidence reported in Tables 2 and 3 supports my hypothesis.

Table 2: Returns for Portfolios Ranked by Consistency in PRET

Portfolios	Year 1	Year 2	Year 3	Year 4	Year 5
	R1	**R2**	**R3**	**R4**	**R5**
CL	0.45	1.40	1.46	1.52	1.61
	1.94	**5.80**	**5.89**	**6.43**	**7.12**
CM	1.14	1.12	1.06	1.06	1.12
	6.68	**6.89**	**6.56**	**6.67**	**6.98**
CW	1.61	0.89	0.99	1.01	1.08
	6.91	**3.47**	**4.21**	**4.85**	**4.46**
CW – CM	*0.47*	*-0.23*	*-0.07*	*-0.05*	*-0.04*
	2.84	**-1.39**	**-0.47**	**-0.31**	**-0.28**
CL – CM	*-0.69*	*0.28*	*0.40*	*0.46*	*0.49*
	-4.87	**1.60**	**2.09**	**2.59**	**3.23**
CW – CL	*1.16*	*-0.51*	*-0.47*	*-0.51*	*-0.53*
	5.65	**-2.50**	**-2.19**	**-2.21**	**-2.88**

This table provides average monthly return performance for equally weighted portfolios formed based on consistency in past stock returns (PRET). Each month from January 1963 to December 2002, all stocks in CRSP monthly file with available data are sorted by their monthly returns and assigned to three groups: top 30 percent, middle 40 percent, and bottom 30 percent. Stocks ranking in the highest 30 percent for at least six-months out of the last twelve months are defined as "*consistent winners*" while stocks with past returns that place them in the lowest 30 percent for at least six out of the last twelve months are classified as "*consistent losers.*" Similarly, firms ranking in the middle 40 percent for at least six out of the prior twelve months are labels as "*consistent moderate*" and used as a benchmark portfolio. All portfolios: consistent winners (CW), consistent losers (CL), and consistent moderates (CM) are held without rebalancing for the ensuing five years. Stocks priced less than $5 at the beginning of the holding period are excluded to ensure that my results are not driven by illiquid and small stocks or by bid-ask bounce. The CW– CM in the third last row refers to the return gap between CW and CM portfolios. The CL– CM in the second last row refers to the differential return between CL and CM stocks. The CW – CL in the last row is the difference in returns between the CW – CM and the CL – CM. Newey West t-statistics are shown in **bold**.

Table 3

Panel A: Average monthly regression estimates for Year 1 after portfolio formation date for portfolios based on consistency of PRET

Portfolios	Fama-French Three Factors			
	FF Alphas	**Market**	**SMB**	**HML**
CL	-1.01	1.31	0.92	0.45
	-7.38	**53.46**	**20.67**	**9.55**
CM	0.01	0.89	0.33	0.43
	0.39	**42.45**	**19.68**	**19.75**
CW	0.67	1.14	0.58	-0.35
	6.54	**47.66**	**23.55**	**-13.40**
CW – CM	0.65	0.25	0.27	-0.79
	5.42	**11.67**	**8.57**	**-22.30**
CL – CM	-1.02	0.42	0.66	0.02
	-7.69	**15.89**	**17.43**	**0.49**
CW – CL	*1.68*	-0.17	-0.40	-0.81
	8.48	**-5.54**	**-6.86**	**-13.72**

Panel B: Average monthly regression estimates for Years 2 through 5 after portfolio formation date for portfolios based on consistency of PRET.

Portfolios	Fama-French Factors			
	FF Alphas	**Market**	**SMB**	**HML**
CL	0.20	1.07	0.86	0.36
	2.68	**37.89**	**24.06**	**9.08**
CM	-0.05	0.91	0.38	0.47
	-1.38	**32.95**	**16.98**	**23.34**
CW	-0.13	1.21	0.60	0.08
	-2.33	**42.72**	**18.41**	**2.61**
CW – CM	-0.08	0.30	0.32	-0.38
	-1.18	**12.88**	**9.35**	**-11.95**
CL – CM	0.25	0.16	0.67	-0.10
	2.91	**5.32**	**18.97**	**-2.36**
CW– CL	-0.32	0.14	-0.35	-0.28
	-3.45	**4.43**	**-7.28**	**-5.49**

Table 3 presents the average monthly regression estimates of excess portfolio returns on the three Fama-French factor model. Panel A includes the average monthly regression parameters for Year 1 after the ranking period while Panel B includes the pooled average monthly regression estimates for Years 2 through 5 of the holding period. The sample includes all stocks on the CRSP monthly file with available data from January 1963 to December 2002. Stocks with market prices less than $5 are excluded at the beginning of the holding horizon. CL is the equal-weighted portfolio of stocks consistently ranking in the bottom 30 percent for at least six out of the last twelve months while CW is the equal-weighted stocks with past stock returns that place them in the top 30 percent of at least six out of the prior twelve months. The CM includes firms maintaining stock returns that put them in the middle 40 percent for at least six out of the past twelve months. This group is used as a benchmark portfolio. FF-factor alphas are the intercepts from the Fama-French three-factor regression. Market is the market factor (market beat), SMB is the size factor (small minus big), and HML is the book-market factor (the high minus low). Newey West t-statistics are reported in **bold.**

4.4 Robustness Checks

To test whether the impact of return consistency on subsequent returns is distinguishable from the momentum effect (Jegadeesh and Titman, 1993), I repeat the three Fama-French factor regression reported in Panel A of Table 3 after adding the momentum factor (UMD) to it.[6] As shown in Panel A, Table 4, the estimated intercepts for CL and CW portfolios remain statistically significant after controlling for the momentum factor with FF alphas of -0.41 percent (t = -2.68) and 0.24 percent (t = 2.34) per month for CL and CW stocks, respectively. Further, the return gap between these portfolios (i.e., CL and CW) and CM portfolio are both statistically different from zero. Interestingly, the return differential between CW and CL stocks is 0.65 percent (t = 3.18) a month. This evidence indicates that the ability of return consistency to predict future return is not subsumed by the momentum factor. [7]

Table 4

Panel A: Average monthly regression estimates for Year 1 after portfolio formation date for portfolios based on consistency of PRET

Portfolios	Fama-French Three Factors + Momentum Factor				
	FF Alphas	**Market**	**SMB**	**HML**	**UMD**
CL	-0.41	1.19	0.84	0.16	-0.64
	-2.68	**23.61**	**11.83**	**2.23**	**-10.16**
CM	0.01	0.89	0.34	0.43	-0.05
	1.14	**24.38**	**7.22**	**6.83**	**-1.51**
CW	0.24	1.21	0.66	-0.08	0.39
	2.34	**26.32**	**8.56**	**-0.93**	**5.80**
CW – CM	0.23	0.31	0.32	-0.52	0.44
	2.12	**4.90**	**4.10**	**-6.15**	**8.54**
CL – CM	-0.42	0.30	0.51	-0.27	-0.60
	-2.84	**4.57**	**8.43**	**-4.18**	**-6.84**
CW – CL	*0.65*	0.02	-0.18	-0.24	1.04
	3.18	**0.24**	**-2.10**	**-2.34**	**10.89**

Table 4, reports the four-factor alphas (intercepts) from the Fama-French factor regressions after including the momentum factor (UMD), the return in the first post-formation year (Year 1). The sample includes all stocks on the CRSP monthly file with available data from January 1963 to December 2002. Stocks with market prices less than $5 are excluded at the beginning of the holding horizon. CL is the equal-weighted portfolio of stocks consistently ranking in the bottom 30 percent for at least six out of the last twelve months while CW is the equal-weighted stocks with past stock returns that place them in the top 30 percent of at least six out of the prior twelve months. The CM includes firms maintaining stock returns that put them in the middle 40 percent for at least six out of the past twelve months. This group is used as a benchmark portfolio. FF-factor alphas are the intercepts from the Fama-French three-factor regression. Market is the market factor (market beat), SMB is the size factor (small minus big), HML is the book-market factor (the high minus low) and UDM is the momentum returns (winners minus losers). Newey West t-statistics are shown in **bold**.

5. Conclusions

Almost all psychology-based theories (e.g., Daniel et al., 1998; Barberis et al., 1998) as well as empirical economic studies assume implicitly if not explicitly that investors' reactions to good and bad economic news are symmetric. However, evidence from the psychology literature indicates that there is a positive-negative asymmetry in individuals' responses to favourable and unfavourable information signals. Negative information has a greater impact on people judgments and decisions than positive information (e.g., Ronis and Lipiniski, 1985; Singh and Teoh, 2000). In this study, I use consistency in past monthly return performance for consistent winners and losers as a proxy for bad and good economic news to examine whether bad news plays a greater role in shaping investors' expectations relative to good news about the future prospects of these firms. My findings show that investors' overreact to favourable and unfavourable information, but their reaction to bad news is a stronger and more persistent than their response to good news. This evidence is robust to the three-factor Fama-French model extended by the momentum return effect.

Results reported in this study about the short-term drift in returns, long-term returns reversals, and the relationship between these two market regularities have significant implications for our understanding of how investors react to good and bad economic news and how their reactions influence the price formation mechanism in the securities markets. Evidence provided in this paper indicates that stock markets are likely to overreact to information contained in past performance consistency of losers and winners. However, there is a significant asymmetry in investors' responses to good and bad news. Unfavourable information signals tend to play a greater role in influencing investors' expectations than favourable information cues. This asymmetry leads to a stronger investors' overreaction to past performance of consistent losers relative to that of their consistent winner counterparts, leading to more pronounced price momentum in Year 1 followed by a strong and more persistent price reversal in Year 2 through Year 5 for consistent losers than consistent winners.

The evidence of a strong price drift in Year 1 and subsequent persistent reversals in returns in Years 2 though 5 supports the assumption that the market underreaction and the negative returns in the long run should be viewed as two components of a single price formation mechanism (Daniel et al., 1998; Lee and Swaminathan, 2000). In this price formation process, a market overreacts to both favourable and unfavourable information signals (although its reaction is asymmetric) in the intermediate period and corrects itself over the long run. This is inconsistent with the hypothesis that investors' response to new information is inadequate resulting in information being impounded into market prices with a time lag. If new information is reflected in assets prices in a gradual basis due to investors' cognitive biases or transaction costs, the long horizon price reversal will not be observed.

Results reported in this study are consistent with the overall prediction of Barberis et al. (1998) and Daniel et al. (1998). However, neither of these theories captures the asymmetry in investors' reactions to consistency of good and bad news documented in this study. The models of both Daniel et al. (1998) and Barberis et al., (1998) are built on the assumptions that investor overreactions to good and bad news are equal in magnitude, but different in direction. However, my findings indicate that investors are inclined to place heavier weight on past performance of consistent losers when projecting the future prospects of these firms than that of prior consistent winner firms. This asymmetry in investors' responses to good and bad news is not captured by these models.

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End Notes

[1] This evidence coupled with the descriptive characteristics of CM firms relative to those of CW and CL firms summarized in Panel C of Table 1, provides strong support for my rationale for using these firms as a benchmark against which the performance of consistent winners and losers are measured.

[2] In case a stock disappears after the ranking period, I use its delisting returns if available. This method is similar to that of Chan (2003).

[3] A firm cannot be included in more than one group.

[4] Cash flow is defined as earnings before extraordinary items and discontinued operations plus depreciation and amortization expense.

[5] I repeat my analysis using value-weighted returns and I obtain similar results as those of equally weighted returns.

[6] I have conducted sub-periods analysis in which I divide my sample period into three roughly equal sub-periods and the results of this analysis show that the key findings of this study remain unchanged.

As well, as a robustness check, I repeat my analyses reported in Tables 2 and 4 using only the largest 50 percent of stocks in terms of market values of equity and I obtain similar results. Further, in unreported results, I include share turnover ratios and industrial dummies in the regression as robustness checks for transactions costs and industry effects and my findings remain qualitatively the same.

[7] I repeat my analysis in January and outside of January and the results show that my key findings are unchanged although the return performance exhibits some seasonality.

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