Factor Model Tests of Long-Run Price Reversals in the U.S. Stock Market

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Abstract

This paper investigates whether long-run price reversals persist in stocks that have significantly outperformed or underperformed the market. Consistent with previous studies, the results show that there are sizeable positive abnormal returns to a long-term contrarian strategy of investing in stocks with significant prior underperformance. However, these positive abnormal returns are driven by low-priced stocks, and stocks with very low market capitalizations. When the investment universe is narrowed to remove very small companies and low-priced stocks, there is no longer a statistically significant return difference between portfolios of stocks with significant prior outperformance and significant prior underperformance.

JEL Codes: G11, G12, G40

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1 Introduction

Many in the literature have debated the degree to which capital markets are efficient, and whether investment returns are at all predictable. Studies of stock market autocorrelation, for example, have shed light on whether short-run and long-run historical returns are predictive of future returns. Many studies contend that short-run positive autocorrelation of returns or "momentum" persists, but some have also argued that long-run negative autocorrelation of returns may follow.

Multi-factor asset pricing models help explain a large share of the variation in expected excess stock returns. These models use metrics including size and valuation to explain cross-sectional differences in excess returns. However, some have questioned whether these variables are sufficient to explain expected excess stock returns. Some argue that behavioral issues including investor overconfidence and overreaction are also explanatory of returns.

This study examines whether prior abnormal returns are indicative of future abnormal returns for stocks that have experienced significant outperformance or underperformance. This paper tests portfolios of prior "winning" and "losing" stocks over several many time periods to see whether there are statistically significant return differences in the months that follow.

This study was guided by three primary research objectives. First, this study uses updated monthly return data from the Center for Research in Security Prices to see whether older patterns explained in the literature still persist today. Second, it uses two multi-factor asset pricing models to control for factors that were not included in the older literature. Last, it adds additional robustness checks to determine whether these results persist when the universe of investable securities is narrowed.

Section 2 of this paper offers a brief literature review. Section 3 outlines the data and empirical model. Finally, section 4 presents and discusses the empirical results, followed by a brief conclusion is included in section 5.

2 Literature Review

Fama (1970) summarizes arguments supporting *weak form*, *semi-strong form* and *strong form* efficient views of capital markets. These views concern whether prices fully reflect various subsets of available information. In *weak form* efficient markets, prices fully reflect all available price data. In *semi-strong form* efficient markets, prices fully reflect historical price and return data, as well as other publicly available information including annual reports, new security issues, and so forth. Lastly, in *strong form* efficient markets, prices fully reflect all information, including non-public information.

In order to determine whether a market is efficiently pricing assets, asset pricing models are needed. One of the earliest and most well-known examples of an asset pricing model used to determine the intrinsic value of an asset is the Capital Asset Pricing Model (CAPM). The CAPM, developed by Sharpe (1964), Treynor (1962), Litner (1965), and Mossin (1966), is consistent with the basic portfolio theory that investors wish to maximize the return of their investments while minimizing the standard deviation, or risk, of said investments.[1] In equilibrium, the CAPM dictates that the expected return of an asset is calculated as $E_i = r_f + \beta(E_m - r_f)$, where the expected return of asset i is equal to the sum of the risk free rate and a market risk premium. This premium is denoted as $E_m - r_f$, where β is the sensitivity of the asset's return to the market's return and $E_m - r_f$ is the difference between the expected return of the market and the risk free rate[2].

De Bondt and Thaler (1985) use the CAPM and other techniques to test for market inefficiencies and predictability in stock returns. They provide empirical evidence of substantial weak form inefficiencies in the U.S. stock market. They find that "loser" portfolios which are comprised of the prior poorest performing stocks significantly

[1]See Markowitz (1952) for prior work on portfolio theory.
[2]Also see Perold (2004).

outperform "winner" portfolios comprised of the prior best performing stocks. They also show evidence that these systematic price reversals persist as late as five years after portfolio formation for loser portfolios. They show that loser portfolios outperform the market by, on average, 19.6% 36-months after portfolio formation. They find that most of these positive abnormal returns are realized in January. January abnormal returns totaled 17.7% during the first 36-months after formation. They credit this phenomenon to investor overreaction, arguing that investors tend to overreact to unexpected and dramatic news events.

They also test their hypothesis using the CAPM, as well as simpler market-adjusted excess returns, and market model residuals. Notably, they find no significant differences in the results of the three models, and ultimately display results for the market-adjusted excess returns model, denoted as $\hat{u}_{it} = R_{it} - R_{mt}$ where the residual for asset i in time t is equal to the difference between the asset's return and the market's return over corresponding periods of time. De Bondt and Thaler (1987) build on this methodology by testing alternative hypotheses for these systematic price reversals. They find that the price reversals in their original research cannot be explained by differences in idiosyncratic risk or firm size.

Although they credit these forward return differences to investor overreaction, the outsized impact of January returns on total forward returns cannot be ignored. In a later paper, Lakonishok, Shleifer, Thaler, and Vishny (1991) argue that pension fund managers tend to oversell stocks in the fourth quarter that have performed poorly in order to "window dress" their portfolios, making them appear more impressive. Research by D'Mello, Ferris, and Hwang (2003) instead suggests that this "January effect" is driven by tax-loss selling. They find that abnormal selling pressure at year end by poor performing stocks is primarily the result of investors' desire to realize capital losses. Conversely, investors delay realizing capital gains by postponing the sale of capital gain stocks until the new year.

The January effect is not the only explanation for the price reversals discovered in De Bondt and Thaler (1985). Conrad and Kaul (1993) argue that the apparent long-term outperformance of prior underperforming stocks is in-part due to measurement errors, including a bid-ask spread effect, which caused an upward bias when cumulated over 36-months. They find that this upward bias increases significantly for low-priced stocks. Using a buy and hold performance measure, they also find that non-January returns of an arbitrage portfolio of losers and winners did not outperform. They argue that all outperformance can be explained by abnormal positive January returns, which are unrelated to past performance. In a later study of momentum trading strategies, Jegadeesh and Titman (2001) eliminate all stocks priced below $5 per share to avoid the upward bias issue originally discussed in Conrad and Kaul (1993).

In a separate study, Daniel, Hirschleifer, and Subrahmanyam (1988) also look into the issue of investor under- and overreactions to measure a relationship between past returns and future returns originally investigated in De Bondt and Thaler (1985). They show evidence that self-attribution biases can cause short- positive autocorrelation of returns, but that, consistent with De Bondt and Thaler (1985), investor overreaction can result in a negative relationship between future returns and long-term past stock market and accounting performance.

Vayanos and Woolley (2013) also find evidence of a pattern of momentum and reversal. However, they arrive at a different explanation for this pattern. They note that in modern financial markets, investors can hold assets through an index fund or an actively-managed fund. They argue that outflows of active funds can cause a price drop for actively-held assets, which is generally expected to continue. This momentum later reverses over the long-run as investors take advantage of prices that fell below their intrinsic values. More recent work confirms a pattern of momentum followed by the long-run price reversals. Daniel and Hirschleifer (2015) also find a persistent pattern of momentum and reversal. This study argues that this pattern may be explained in part by investor overconfidence, rather than traditional price and accounting measures per se.

However, conclusions about market efficiency may be limited by the asset pricing models they rely on. Since this work by De Bondt and Thaler, significant contributions have been made to the literature regarding asset pricing. Most notably, Fama and French (1992) develop a three-factor asset pricing model that is far more explanatory of expected stock returns than the CAPM. They test many easily measured variables, including size, book-to-market equity, leverage, and earnings-price ratios to determine whether any significantly explain the cross-sectional variation in average excess stock returns. Ultimately, they find that portfolios of small market capitalization stocks tend to outperform portfolios of large market capitalization stocks and that portfolios of high book-to-market stocks tend to outperform portfolios low book-to-market stocks. They measure these effects and combine them with the market risk premium developed in CAPM to explain the variation in excess returns of stocks.

Carhart (1997) confirms that this Fama-French three-factor model is highly explanatory of equity mutual fund performance. However, Carhart also argues that momentum, when included as a fourth factor, is also explanatory of persistence in equity mutual fund performance. In fact, the only significant persistence that remains unexplained is concentrated in strong underperformance by the worst performing equity mutual funds. More recently, Fama and French (2015) also argue for an expanded version of their original three-factor model. They find that, in addition to the factors included in their three-factor model, differences in profitability and investment patterns can explain an additional degree of the cross-sectional variation in stock returns.

3 Data and Empirical Methodology

3.1 Data

To investigate price reversals in the U.S. stock market, I begin with monthly return data for U.S. listed stocks from January 1964 to December 2018, compiled by the Center for Research in Security Prices (CRSP). The monthly return data, rather than daily return data, are used to avoid issues highlighted in the literature, including issues with infrequent trading and bid-ask spreads. Data for the factors included in the Fama-French and Carhart models are gathered from the Kenneth R. French Data Library.

For each of the 50 portfolio formation periods, the investment universe is narrowed to stocks that have six years or more of uninterrupted return data; three years trailing the portfolio formation date, and three years following the portfolio formation date. I then generate a portfolio of "winning" stocks and a portfolio of "losing" stocks for each time period, placing the 35 stocks with the highest trailing three-year Cumulative Abnormal Return (CAR) into an equal-weighted winner portfolio, and the 35 stocks with the lower trailing three-year CAR into an equal-weighted loser portfolio. CARs are calculated as:

$$CAR_i = \sum_{t=-35}^{t=0} R_{it} - R_{mt} \tag{1}$$

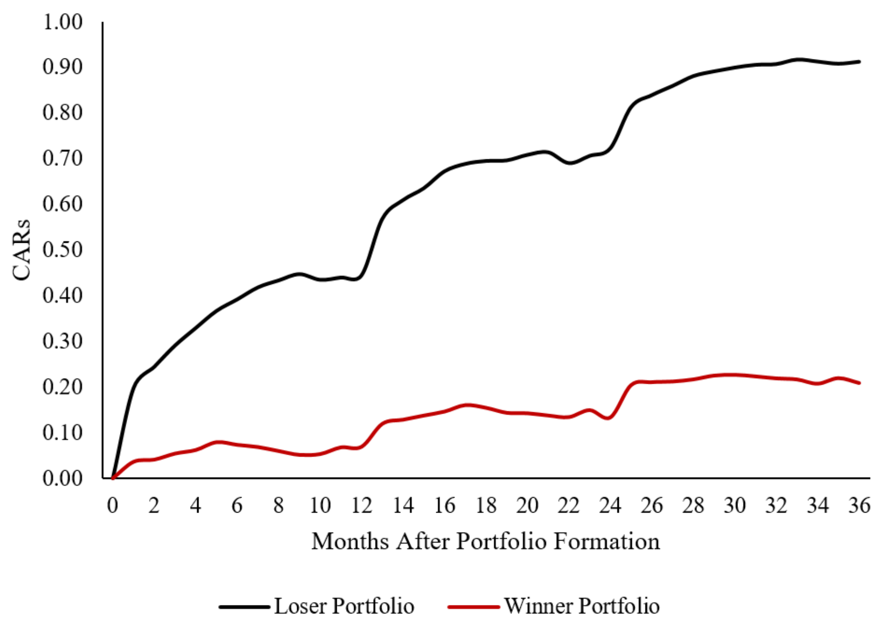
R_{it} is the return of security i in month t. R_{mt} is the return of the market index in month t. An equally weighted arithmetic average rate of return of all CRSP listed securities serves as the market index. These abnormal returns, $R_{it} - R_{mt}$, are cumulated for the 36-months prior to the portfolio formation date. For each time period i, the 35 stocks with the highest CAR are placed in an equally weighted "winner" portfolio, and the 35 stocks with the lowest CAR are placed in a "loser" portfolio. All remaining stocks are removed from the data for that time period.

This process is repeated 50 times, with the first portfolio formation period on

January 1966, and the final portfolio formation period on January 2015. Overlapping time series are used in order to generate a sample size that is large enough to provide reliable estimators. The empirical methodology section describes the estimation procedure used to address issues that arise as a result of overlapping time series.

Figure 1 shows the average CARs of 50 loser portfolios ($ACAR_L$) and 50 winner portfolios ($ACAR_W$) during the first 36-months after portfolio formation. Using an investment universe of all CRSP listed securities, loser portfolios significantly outperform winner portfolios. 36-months after portfolio formation, the average cumulative abnormal return for loser portfolios is 91.3%, while the average cumulative abnormal return for winner portfolios is 20.9%. The cumulative abnormal return differences between these extreme portfolios after 36-months ($ACAR_L - ACAR_W$), 70.4%, is far larger than the original 36-month cumulative abnormal return difference calculated in De Bondt and Thaler (1985), which totaled 24.6%[3].

Figure 1: Average CARs of 50 Loser Portfolios and 50 Winner Portfolios from January 1964 to December 2018



[3]The original calculation in De Bondt and Thaler (1985) was measured using the average of 16 loser and winner portfolios, rather than 50

As in De Bondt and Thaler (1985), January returns in the updated sample period still comprise an outsized share of average abnormal return differences between the extreme portfolios. Average abnormal returns during January ($t = 1$, $t = 13$, and $t = 25$) totaled 25.5%, and account for more than one-third of the abnormal return differences between these extreme portfolios.

Table 1 shows the summary statistics for these winning and loser portfolios collectively. Note that forward portfolio returns assume an automatic monthly rebalancing. Panel A represents portfolios generated using all CRSP listed securities as the investment universe. There are several notable characteristics of these portfolios. During the portfolio formation month, the mean share price across winning and loser portfolios is \$10.76, while the mean market capitalization is \$418 million. The minimum mean share price for a portfolio in the data is \$0.08, while the minimum mean market capitalization is less than \$3.2 million. Therefore, when using all CRSP listed securities as an investment universe for generating winning and loser portfolios, there are many nano-cap and micro-cap stocks that enter the portfolios, as well as many stocks with remarkably low share prices.

In order to test for systematic price reversals on a more typical investment universe, I create Panel B, which generates portfolios based on an investment universe of CRSP listed securities with a market capitalization over \$300 million at portfolio formation. Therefore, Panel B includes large-cap, mid-cap, and small-cap stocks, but excludes micro-cap and nano-cap stocks. Others have argued that the inclusion of low-priced stocks may cause the return differences illustrated in De Bondt and Thaler (1985).[4] Therefore, I create Panel C, which generates portfolios based on an investment universe of CRSP listed securities with share prices at or above \$5 during the portfolio formation month. Note that when market capitalization and share price thresholds are established, the mean forward monthly return decreases, while the

[4]See Conrad and Kaul (1993) and Jegadeesh and Titman (2001).

mean trailing three-year CAR increases. The mean monthly volume also increases.

Table 1: Summary Statistics

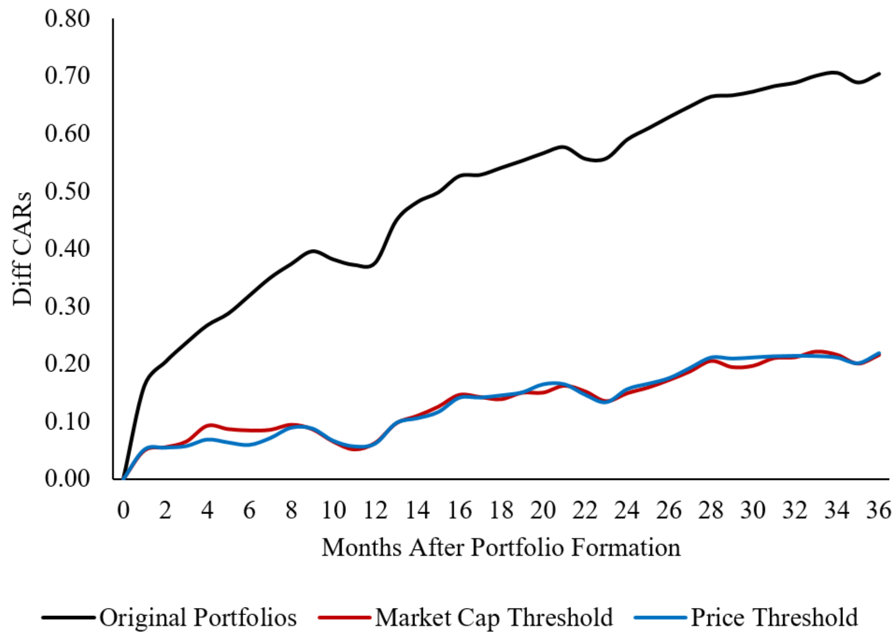
	(1) Mean	(2) Std. Dev.	(3) Min.	(4) Max.
Panel A: Original Portfolios				
Monthly Return	0.016	0.091	-0.335	0.731
Monthly Volume	8,951,110	15,100,000	30,936	149,000,000
Trailing 3-Year CAR	0.52	2.76	-2.79	5.34
Share Price (at formation)	10.76	13.58	0.08	65.26
Market Cap. (at formation)	418,354	1,081,466	3,168	8,612,038
Panel B: Market Capitalization Threshold				
Monthly Return	0.010	0.078	-0.366	0.534
Monthly Volume	32,300,000	69,100,000	237,526	913,000,000
Trailing 3-Year CAR	0.50	1.70	-1.81	4.53
Share Price (at formation)	31.33	19.09	5.56	94.59
Market Cap. (at formation)	1,818,652	1,819,310	648,461	15,900,000
Panel C: Share Price Threshold				
Monthly Return	0.008	0.078	-0.363	0.575
Monthly Volume	14,400,000	37,300,000	59,146	688,000,000
Trailing 3-Year CAR	0.70	2.20	-2.39	5.04
Share Price (at formation)	19.31	12.14	6.92	67.37
Market Cap. (at formation)	745,512	1,572,465	20,784	13,500,000

Table 1. N=3,600 for all variables. Market capitalizations are in thousands.

Figure 2 compares the differences in average cumulative abnormal returns between losing and winner portfolios for each of these three panels. Panel A, which is the set of original portfolios generated from the entire universe of CRSP listed securities experiences an exceptionally large performance difference between loser and winner portfolios. The difference in cumulative abnormal returns 36-months after formation is 70.4%, which shows significant outperformance for loser portfolios. When all securities with a market capitalization under $300 million upon formation are removed from the sample and new portfolios are generated, the difference in cumulative abnormal returns after 36-months falls to 21.6%. Similarly, when stocks priced below

$5 per share are removed from the sample, the difference in cumulative abnormal returns falls to 21.9%. Loser portfolios still appear to outperform, though to a far lesser degree.

Figure 2: Differences in Average CARs from January 1964 to December 2018



Figures 3 and 4 in the Appendix offer an alternative illustration of the relationship between forward 36-month CARs and average market capitalization. When no market capitalization threshold is established, most portfolios have very low market capitalizations, often resulting in very high CARs. A clear negative relationship between mean market capitalization and forward 36-month CAR emerges. As Figure 4 shows, when stocks with market capitalizations under $300 million are removed from the investment universe, 36-month CARs moderate, and the relationship between mean market capitalization and forward 36-month CAR is less clear.

Figures 5 and 6 in the Appendix illustrate the relationship between forward 36-month CARs and mean share prices. As with market capitalization, when there is no threshold for share prices, many portfolios are formed with very low share prices and a clear negative relationship between mean share price and forward 36-month CAR emerges. As Figure 6 shows, when the investment universe is limited with respect to share price, this relationship becomes less extreme.

3.2 Empirical Methodology

De Bondt and Thaler (1985) estimate investor overreaction and systematic price reversals by constructing a series of "winning" and "losing" portfolios based on trailing three-year CARs. They compute t-statistics based on the difference in forward three-year performance of the winning and loser portfolios.

For this study, I apply the Fama-French five-factor model, and the Carhart four-factor model to determine whether there are statistically significant return differences between winning and loser portfolios after controlling for other contributors to expected stock returns. I introduce a dummy variable to each factor model. Equation 2 represents the Fama-French specification, while Equation 3 represents the Carhart specification.

$$\begin{aligned} R_{it} - R_{Ft} = \alpha_i + \beta_0 + \beta_1(R_M - R_F)_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} \\ + \beta_4 RMW_{it} + \beta_5 CMA_{it} + \beta_6 Loser_{it} + u_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} R_{it} - R_{Ft} = \alpha_i + \beta_0 + \beta_1(R_M - R_F)_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} \\ + \beta_4 MOM_{it} + \beta_5 Loser_{it} + u_{it} \end{aligned} \tag{3}$$

In both specifications, the dependent variable is a risk premium for security i where R_{it} is the return for security i in time t and R_{Ft} is a risk-free rate in time t. The risk-free rate is the yield on a one-month U.S. Treasury bill rate. As with the CAPM, $R_M – R_{Ft}$ is the market risk premium denoted as the risk-free rate, subtracted from the return of a market index in time t. SMB_t denotes the size premium in time t. That is, the average return of three small market capitalization portfolios minus the average return of three large market capitalization portfolios. HML_t represents the value premium, that is the average return difference between portfolios of high book-to-market "value stocks" and low book-to-market "growth stocks."

RMW_t is the profitability premium in time t, which represents the average return of two portfolios of robust operating profitability stocks minus the average return of two portfolios comprised of weak operating profitability stocks. CMA_t, an investment premium, represents the return difference between two conservative investment portfolios minus the average return on two aggressive investment portfolios. The independent variable of interest, $Loser_t$, is a dummy variable that takes the value of 1 if the observation is a portfolio of stocks with a low trailing three-year CAR, and takes the value of 0 if the observation is a portfolio of stocks with high trailing three-year CAR.

Specification three does not include RMW and CMA factors. Instead, it includes MOM_t, which is the average return on two high prior return portfolios minus the average return on low prior return portfolios. Note that momentum is a measure of shorter-run autocorrelation, and does not capture autocorrelation of returns over a period of several years, which is the aim of this paper.

3.3 Generalized Least Squares

Many studies use overlapping time series data to improve estimation reliability. For the purposes of this study, a three-year estimation period is used from January 1967 to December 1969, another from January 1968 to December 1970, and so on. The overlapping time series approach can make OLS parameter estimates less reliable. Past studies have applied Newey-West standard errors to OLS in order to address this issue. However, Harri and Brorsen (2009) summarize the various estimation techniques and conclude that generalized least squares (GLS) estimators are generally preferred for handling the overlapping sample horizon issue.

GLS estimators are also more efficient than OLS estimators when heteroscedasticity is present. To determine whether heteroscedasticity is present, I run the Breusch-Pagan test. For the original panel of data, which uses an investment universe of all CRSP listed securities, the Fama-French five-factor model produces a p-value of 0.0028, while the Carhart four-factor model produces a p-value of 0.0000. Results are similar when tested on other panels, which exclude low market capitalization stocks and low-priced stocks. Therefore, these results soundly reject the null hypothesis of homoscedasticity.

GLS estimators allow for more efficient estimation of samples with overlapping time series and also allow for more efficient estimation of the models given the presence of heteroscedasticity. Accordingly, the GLS estimation technique has been used in several recent studies on expected stock and hedge fund returns.[5]

3.4 Multicollinearity

Table 2 shows the correlation coefficients for Panel A, portfolios based on a universe of all CRSP listed securities. Coefficients for the other panels are similar. Hanke and Winchern (2008) explain that correlations among independent variables between -0.5 and 0.5 do not result in estimation issues. Correlations between independent variables are generally low for these data, but one issue does arise. A correlation coefficient of 0.7 arises between factors HML and CMA. Ordinarily, this may indicate the presence of multicollinearity. I report GLS estimates for both the Fama-French five-factor model and the Carhart four-factor model. The Carhart four-factor model does not include the CMA factor, which alleviates these concerns. Moreover, the GLS estimates for these models are quite similar.

[5]See Fu (2009) and Bali, Brown, and Caglayan (2012).

Table 2: Correlation Coefficients

Panel A: Original Portfolios							
	MktRF	SMB	HML	MOM	RMW	CMA	Loser
MktRF	1						
SMB	0.279	1					
HML	-0.255	-0.067	1				
MOM	-0.174	-0.093	-0.187	1			
RMW	-0.249	-0.359	0.054	0.124	1		
CMA	-0.393	-0.095	0.697	-0.001	-0.022	1	
Loser	0.003	-0.002	-0.008	-0.005	0.0005	-0.009	1

4 Results

GLS regressions are on the monthly risk premia, $R_{it}{-}R_{Ft}$, on 50 winner portfolios and 50 loser portfolios in each of the first 36-months after formation. The first column displays the GLS estimates for the Fama-French five-factor model, on a universe of all CRSP listed securities. The coefficient estimate for the Loser dummy variable is positive and statistically significant at the $p < 0.01$ level. The coefficient estimate indicates that, and holding Fama-French factors constant, loser portfolios outperform winner portfolios by 3.2% per month in each of the first 36-months after formation. Results for the Carhart model are similar, showing that loser portfolios outperform winner portfolios by about 3.1% per month.

However, as the third and fourth regressions show, when securities with a market capitalization of less than $300 million are removed from the data, the dummy variable is no longer statistically significant. Therefore, on a standard investment universe consisting of low-cap, mid-cap, and large-cap stocks, there is no statistically significant difference between investing portfolios of prior winning stocks and portfolios of prior losing stocks.

Table 3: GLS Estimates

	Original Portfolios		Market Capitalization Threshold		Share Price Threshold	
	(1)	(2)	(3)	(4)	(5)	(6)
MktRF	0.015***	0.014***	0.016***	0.015***	0.015***	0.013***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
SMB	0.013***	0.013***	0.007***	0.007***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HML	−0.008***	−0.012***	−0.006***	−0.009***	−0.008***	−0.011***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MOM		−0.010***		−0.008***		−0.009***
		(0.001)		(0.001)		(0.001)
RMW	−0.004		−0.002		−0.001	
	(0.003)		(0.002)		(0.002)	
CMA	−0.001		0.000		0.000	
	(0.004)		(0.003)		(0.004)	
Loser	0.032***	0.031***	0.008	0.008	0.011	0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	−0.396***	−0.388***	−0.392***	−0.386***	−0.396***	−0.389***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	3,600	3,600	3,600	3,600	3,600	3,600
Wald Chi^2	369.54	435.42	355.90	416.53	358.56	420.21
Prob. > Chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3. Stars denote statistical significance (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$) respectively.

Likewise, the fifth and six regressions show that there is also no statistically significant difference between winning and loser portfolios when securities priced below \$5 per share upon portfolio formation are removed from the data. P-values for these coefficient estimates can be found in Table 5 in the Appendix. Overall, while it initially appears that there are significant positive returns to investing in stocks with prior poor returns, these returns appear to be driven by nano-cap and micro-cap stocks, as well as low-priced stocks

Consistently, the market risk premium, the size premium, and the value premium are all statistically significant at the $p < 0.01$ level. The momentum factor, which was included in the Carhart four-factor model is also consistently statistically significant. While prior three-year CARs do not appear indicative of future returns on the restricted investment universes in regressions three through six, the market risk premium and the size premium do contribute positively to stock returns. In this sample, the value premium and the momentum factor contribute negatively to returns.

Table 3 also displays the results of the Wald Chi-Squared test of joint significance for these models. The results show that, collectively, the independent variables are explanatory of the risk premium, and that the models are well-fitting. These results are also robust to different quantities of securities placed in portfolios. Table 3 displays results for equal-weighted portfolios of 35 stocks. To demonstrate robustness, these regressions were performed on winner and loser portfolios comrpised of different numbers of securities. Table 6 in the Appendix shows that when 15 stocks, rather than 35 stocks, are placed in each portfolio, the results are quite similar. Additionally, when the top and bottom percentiles of stocks according to trailing 36-month CARs are placed in winner and loser portfolios respectively, estimates remain consistent.

5 Conclusion

Using the methodology originally used in De Bondt and Thaler (1985), the data show that the apparent pattern of prior poor performing stocks outperforming portfolios of prior well-performing stocks persists. However, these return differences are driven by nano-cap and micro-cap stocks, as well as by low-priced stocks. On investment universes that consist only of small-cap, mid-cap, and large-cap stocks, or consisting of stocks with share prices above $5, there is no statistically significant difference between winning and loser portfolios.

The January effect is also an outsized contributor to the investment performance of loser portfolios that are not limited by market capitalization and share price. Though the January effect on this updated dataset is less extreme than in De Bondt and Thaler (1985), it still accounts for more than one-third of the difference in forward 36-month CARs between loser and winner portfolios.

The results suggest that these return differences are not evidence of investor over-reaction or of a systematic and exploitable long-run return pattern. Rather, when using the broadest possible U.S. investment universe, loser portfolios are often comprised of very small and very low-priced stocks. Price changes in these stocks are unlikely to impact index returns, they are likely overlooked by institutional investors, and their shares tend to be less liquid and subject to infrequent trading. Moreover, arbitrage portfolios that aim to exploit this apparent pattern would likely leave investors highly exposed to distressed companies and stocks that experience infrequent trading.

Though these results allow for additional criticism of De Bondt and Thaler (1985), there are several limitations. Consistent with their original methodology, this paper cumulates, rather than compounds, trailing three-year abnormal returns. Moreover, forward three-year portfolio returns assume an automatic monthly rebalancing. This assumption is rigid, and it may be preferable to calculate portfolio returns based on weights that that change based on performance, and are not rebalanced on a monthly basis. Beyond this, there are additional factor models that could be tested, and additional econometric techniques that could be applied. Furthermore, the GLS results are robust to different portfolio compositions, it would be beneficial to test different numbers of test periods. Results would also be more robust if different test period durations were tested.

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Appendix

Figure 3: Market Capitalization and 36-month CARs for 50 Loser Portfolios and 50 Winner Portfolios
(Investment Universe: All CRSP Securities)

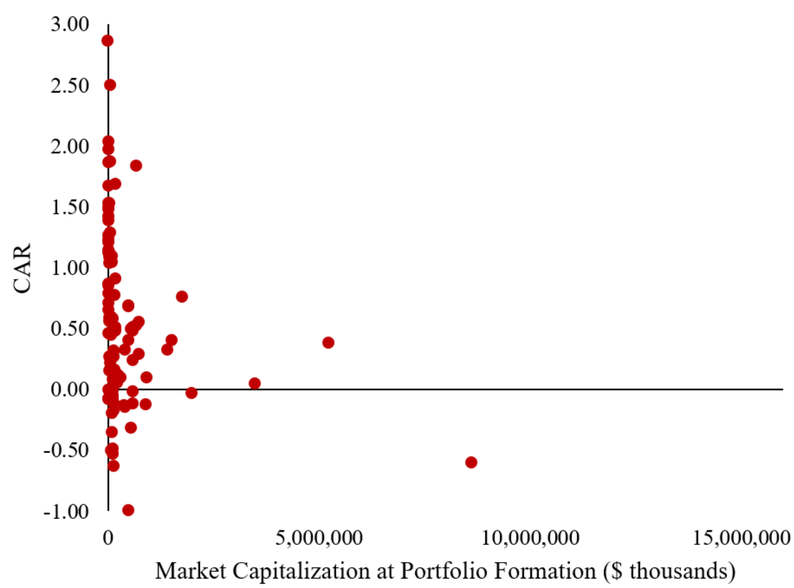

Figure 4: Market Capitalization and 36-month CARs for 50 Loser Portfolios and 50 Winner Portfolios
(Investment Universe: Securities with Market Capitalizations above $300 million)

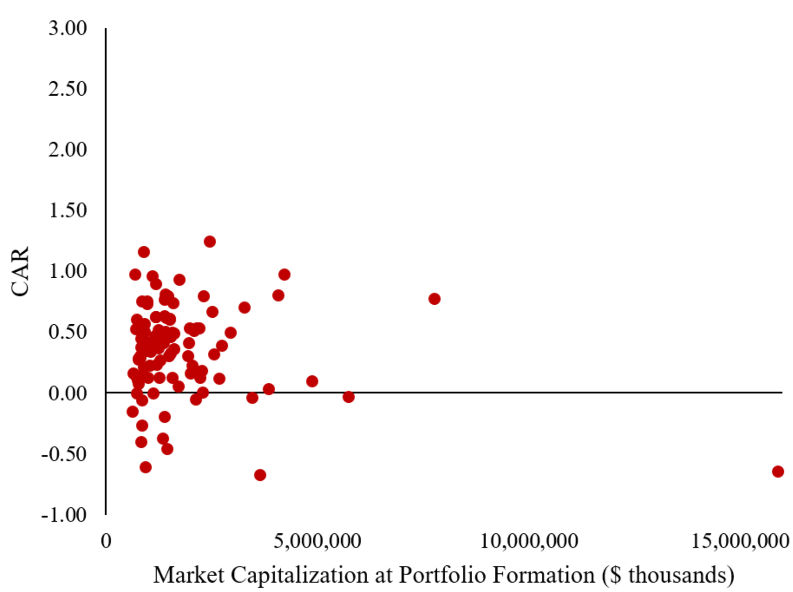

Figure 5: Share Price and 36-month CARs for 50 Loser Portfolios and 50 Winner Portfolios
(Investment Universe: All CRSP Securities)

Figure 6: Share Price and 36-month CARs for 50 Loser Portfolios and 50 Winner Portfolios
(Investment Universe: Securities with Share Prices above $5)

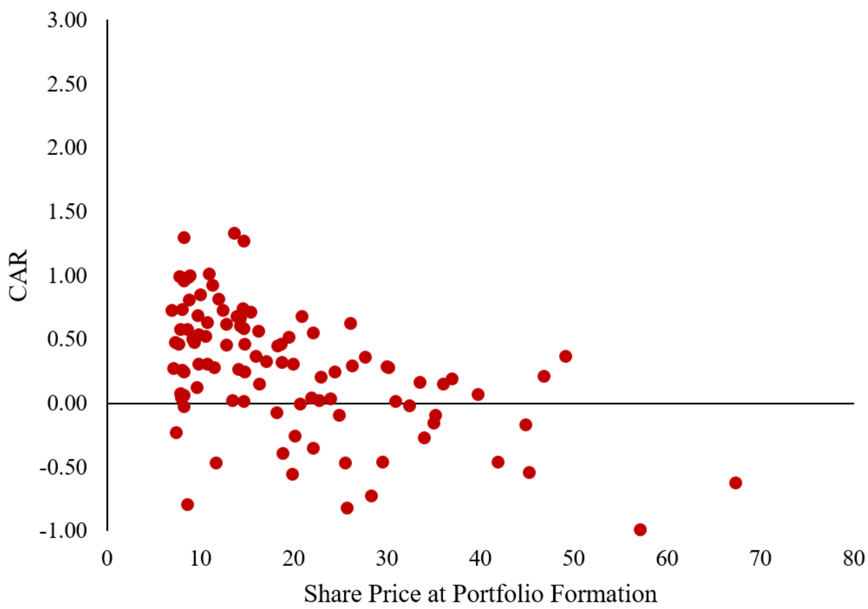

Table 4: Correlation Coefficients (All Panels)

Panel A: Original Portfolios							
	MktRF	SMB	HML	MOM	RMW	CMA	Loser
MktRF	1						
SMB	0.279	1					
HML	-0.255	-0.067	1				
MOM	-0.174	-0.093	-0.187	1			
RMW	-0.249	-0.359	0.054	0.124	1		
CMA	-0.393	-0.095	0.697	-0.001	-0.022	1	
Loser	0.003	-0.002	-0.008	-0.005	0.0005	-0.009	1
Panel B: Market Capitalization Threshold							
	MktRF	SMB	HML	MOM	RMW	CMA	Loser
MktRF	1						
SMB	0.272	1					
HML	-0.276	-0.079	1				
MOM	-0.136	-0.056	-0.191	1			
RMW	-0.236	-0.368	0.079	0.104	1		
CMA	-0.399	-0.090	0.704	-0.005	-0.010	1	
Loser	0.001	-0.001	-0.001	-0.000	-0.002	-0.002	1
Panel C: Share Price Threshold							
	MktRF	SMB	HML	MOM	RMW	CMA	Loser
MktRF	1						
SMB	0.270	1					
HML	-0.278	-0.080	1				
MOM	-0.147	-0.073	-0.193	1			
RMW	-0.237	-0.363	0.072	0.105	1		
CMA	-0.40	-0.094	0.703	-0.009	-0.0129	1	
Loser	0.001	-0.003	-0.006	-0.002	-0.001	-0.007	1

Table 5: P-values for Loser Dummy Variable

	Original Portfolios		Mkt. Cap. Threshold		Price Threshold	
	(1)	(2)	(3)	(4)	(5)	(6)
z	3.49	3.47	0.85	0.86	1.25	1.24
$P > \|z\|$	0.000	0.001	0.394	0.390	0.210	0.215

Table 6: GLS Estimates for Alternative Portfolio Compositions

	Panel A: Original Portfolios					
	35 Stocks		15 Stocks		Top Percentile	
	(1)	(2)	(3)	(4)	(5)	(6)
MktRF	0.015***	0.014***	0.016***	0.014***	0.015***	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
SMB	0.013***	0.013***	0.012***	0.012***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HML	−0.008***	−0.012***	−0.008***	−0.013***	−0.008***	−0.012***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
MOM		−0.010***		−0.011***		−0.010***
		(0.001)		(0.001)		(0.001)
RMW	−0.004		−0.005*		−0.004	
	(0.003)		(0.003)		(0.003)	
CMA	−0.001		0.002		−0.001	
	(0.004)		(0.004)		(0.004)	
Loser	0.032***	0.031***	0.036	0.035***	0.032***	0.032***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Constant	−0.396***	−0.388***	−0.398***	−0.390***	−0.397***	−0.389***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	3,600	3,600	3,600	3,600	3,600	3,600
Wald Chi^2	369.54	435.42	344.79	414.83	374.66	441.38
Prob. > Chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 6. Stars denote statistical significance (***p < 0.01, **p < 0.05, *p < 0.1) respectively.