Portfolio Management Coursework
Replication of "Does the Stock Market Overreact?"

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Abstract

This study investigates whether the stock market overreacts to unexpected and dramatic news events, as suggested by behavioral biases documented in experimental psychology. Using CRSP monthly return data, the analysis finds evidence consistent with the overreaction hypothesis, revealing significant market inefficiencies. Portfolios of prior "losers" significantly outperform prior "winners", with losing stocks earning much more than winners over multiple time periods. These results not only explain the phenomenon of overreaction, but also suggest its predictive power for future returns. The findings violate weak-form market efficiency and highlight the role of behavioral principles in asset price movements. The study also examines the seasonality of returns, particularly the January effect, where loser portfolios exhibit persistently large positive excess returns. Based on this, we further validate this perspective using recent data, reaffirming the robustness of these findings in modern market contexts.

1 Introduction

This report focuses on replicating the influential study *"Does the Stock Market Overreact?"* by De Bondt and Thaler (1985) [1], which examines whether extreme stock price movements are systematically followed by reversals, as suggested by behavioral theories.

The original study puts forward two key hypotheses:

1. Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction.
2. The more extreme the initial price movement, the greater the subsequent adjustment will be.

Using data from the CRSP database (1926–1982), De Bondt and Thaler [1] found strong evidence consistent with these hypotheses, challenging the Efficient Market Hypothesis (EMH). They demonstrated that portfolios of past "loser" stocks significantly outperformed portfolios of past "winner" stocks over multiple horizons, including two, three, and five years. These findings suggest that the overreaction hypothesis is not only a plausible explanation for observed price patterns but also holds predictive power for future stock returns. Additionally, the study highlighted a strong seasonal pattern, particularly the January effect, where loser portfolios showed disproportionately large excess returns early in the year.

The original study provides robust theoretical and empirical support for behavioral bias which can serve as practical decision-making tools for investors. In addition, long-term data analysis from 1926 to 1982 offers a solid foundation for verifying long-term patterns in financial markets. However, it may introduce challenges in ensuring consistency across different market regimes and economic conditions. Patterns like the "January Effect" may no longer apply to contemporary markets.

Therefore, our objective is not only to replicate the original results and evaluate the predictive power of the overreaction hypothesis but also to extend the analysis by addressing a key limitation of the original study——the dataset's age. The original research relied on data spanning 1926 to 1982, which reflects historical market conditions that may no longer represent modern dynamics. The validity of the original study's assumptions may deteriorate over time due to changes in investor behavior. To address this, we performed an additional analysis using a more recent dataset covering 1967–2023, maintaining the same time interval structure. This enables us to assess whether the overreaction hypothesis remains robust and relevant in contemporary markets.

The remainder of this report is structured as follows. Section 2 provides a theoretical overview of the market efficiency, overreaction hypothesis, and its behavioral underpinnings. Section 3 describes the methodology used for portfolio construction, statistical analysis, and hypothesis testing, as well as our way to implement in Python. Section 4 presents the empirical results from both the replication and the extended dataset. Finally, Section 5 discusses the conclusions and further works in industry.

2 Theoretical Overview

Market efficiency, or the Efficient Market Hypothesis (EMH), is one of the classical approaches in market research. Louis Bachelier (1900) [2] is considered the pioneer of market efficiency theory. His proposal of the Random Walk Hypothesis (RWH) holds groundbreaking significance in the study of market efficiency. Mathematically, the random walk hypothesis assumes that price changes are independent and normally distributed:

$$P_t = P_{t-1} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2),$$

where P_t represents the price at time t, and ϵ_t is an independent noise term with mean 0 and variance σ^2.

Since then, the theory of market efficiency has garnered extensive attention from economists and has become one of the most thoroughly studied and intensely debated topics in financial research.

The concept of an efficient market was formally introduced by Fama (1970) [3], who said "A market in which prices always 'fully reflect' available information is called 'efficient'." Fama classified market efficiency into three levels based on the nature of the information set:

1. **Weak-form efficiency:** Prices reflect all historical information. Mathematically, this implies:

   $$P_t = \mathbb{E}[P_{t+1}|\mathcal{I}_t] + \epsilon_t,$$

   where $\mathcal{I}_t = \{P_{t-1}, P_{t-2}, \dots\}$ is the set of historical price information, and ϵ_t is a random error term.

2. **Semi-strong form efficiency:** Prices reflect all publicly available information. Formally:

   $$P_t = f(I_{\text{public},t}) + \epsilon_t,$$

   where $I_{\text{public},t}$ is the set of all public information, and $f(\cdot)$ is a function mapping information to prices.

3. **Strong-form efficiency:** Prices reflect all information, both public and private.

The development of financial theories in the latter half of the 20th century, particularly the financial investment theories that have been widely applied over the past 30 years, are largely built upon the foundation of the efficient market hypothesis. The theory established a clear correspondence between stock prices and information dissemination, providing explicit criteria for measuring market efficiency. To this day, the efficient market hypothesis remains one of the cornerstones of modern financial theory.

Even so, a growing body of work has highlighted potential irregularities. Researchers became particularly interested in the influence of cognitive biases—most notably the representativeness heuristic discussed by Tversky and Kahneman (1974) [4]—on the formation of investor beliefs. This perspective suggested that investors often overemphasize recent or salient information, thereby misjudging longer-term prospects.

Empirical anomalies also raised doubts about the universality of the EMH. For example, Basu (1977) [5] identified the price-to-earnings (P/E) ratio anomaly, showing that portfolios of low P/E stocks tend to outperform those of high P/E stocks:

$$R_{\text{low P/E}} > R_{\text{high P/E}},$$

where $R_{\text{low P/E}}$ and $R_{\text{high P/E}}$ represent the returns of low and high P/E portfolios, respectively. This finding contradicted the assumption of fully efficient markets, as such patterns should not persist if markets were truly efficient.

Another challenge to the Efficient Market Hypothesis is the excess volatility hypothesis introduced by Shiller (1981) [6]. Shiller argued that stock prices exhibit fluctuations that are too large to be justified by changes in their fundamental values, as implied by EMH. According to the EMH, the price of a stock P_t at time t should equal the discounted value of its expected future cash flows:

$$P_t = \mathbb{E}_t\left[\sum_{i=1}^{\infty} \frac{D_{t+i}}{(1+r)^i}\right],$$

where D_{t+i} is the dividend at time $t+i$, r is the constant discount rate, $\mathbb{E}_t[\cdot]$ denotes the expectation conditional on the information available at time t.

Shiller observed that empirical stock prices P_t are significantly more volatile than the fundamental value implied by this relationship. Defining the fundamental price as:

$$P_t^{\text{fund}} = \mathbb{E}_t\left[\sum_{i=1}^{\infty} \frac{D_{t+i}}{(1+r)^i}\right],$$

he demonstrated that the variance of observed prices P_t exceeds the variance of the fundamental price P_t^{fund}:

$$\text{Var}(P_t) > \text{Var}(P_t^{\text{fund}}).$$

This excess volatility suggests that prices are influenced by speculative trading, investor sentiment, or other factors unrelated to fundamentals, thereby challenging the notion of fully efficient markets. Shiller's findings spurred a wave of research exploring behavioral explanations for such deviations, further emphasizing the limits of the EMH in explaining real-world market behavior.

Altogether, these early theoretical and empirical findings established the foundation for the idea that investors might systematically misjudge prices, resulting in patterns that a purely rational model would have difficulty explaining.

The paper by De Bondt and Thaler [1] in 1985, which is the central focus of this report, provided compelling evidence of systematic overreaction in financial markets. They observed that investors tend to overweight recent information while underweighting long-term trends, a cognitive bias that leads to price reversals. This phenomenon was consistent with the behavioral tendencies described by Kahneman and Tversky (1974) [4] under the representativeness heuristic. They proposed two key hypotheses, as outlined in the introduction:

1. Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction.
2. The more extreme the initial price movement, the greater the subsequent adjustment will be.

A notable highlight of their work is that it represents the first attempt to use a behavioral principle to predict a new market anomaly. By integrating psychological insights into financial research, their study set a precedent for exploring the implications of cognitive biases in asset pricing and market behavior.

In De Bondt and Thaler [1]'s work, the authors formalize their test for systematic return behavior by working with a single-index market model and its associated "residuals". Let $R_{i,t}$ be the return on security i at time t, and $R_{m,t}$ be the corresponding market return. A simplified version of the single-index market model posits

$$R_{i,t} \;=\; \alpha_i \;+\; \beta_i\, R_{m,t} \;+\; \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ is the residual term. Under market efficiency, one would expect that, conditioning on all information available up to $t-1$ (denoted $\mathcal{F}_{t-1}$), the expected residual is zero:

$$\mathbb{E}\bigl[\varepsilon_{i,t} \vert\, \mathcal{F}_{t-1}\bigr] \;=\; 0.$$

In the article, the authors first form winner and loser portfolios based on each security's past excess returns. They then observe whether, in subsequent months or years, the "post-formation" residuals, $\varepsilon_{i,t}$, deviate systematically from zero in a manner related to past performance. If winner portfolios, on average, earn significant negative residuals going forward—while loser portfolios earn significant positive residuals—such evidence would be difficult to reconcile with a fully efficient market.

To implement this empirically, one straightforward way to define the "residual" or "abnormal return" is a market-adjusted residual,

$$\widetilde{\varepsilon}_{i,t} \;=\; R_{i,t} \;-\; R_{m,t},$$

which assumes each stock's expected excess return beyond the market is zero. The null hypothesis of market efficiency (and absence of systematic overreaction) implies

$$\mathbb{E}\bigl[\widetilde{\varepsilon}_{i,t} \vert\, \mathcal{F}_{t-1}\bigr] \;=\; 0,$$

for winners, losers, or any other portfolio classification. If, however, the "overreaction hypothesis" holds, then for a portfolio of losers (L) and a portfolio of winners (W), we would see

$$\mathbb{E}\bigl[\widetilde{\varepsilon}_{L,t} \;\big|\; \mathcal{F}_{t-1}\bigr] > 0, \quad \mathbb{E}\bigl[\widetilde{\varepsilon}_{W,t} \;\big|\; \mathcal{F}_{t-1}\bigr] < 0,$$

over extended horizons. Empirically, we can test whether these mean abnormal returns differ from zero using statistical tests (e.g. a t-test or cumulative abnormal return analysis).

In principle, one may define "abnormal return" in several more sophisticated ways:

1. *Market Model Residual:*
$$\hat{\varepsilon}_{i,t} \;=\; R_{i,t} \;-\; (\hat{\alpha}_i + \hat{\beta}_i\, R_{m,t}),$$
   where $\hat{\alpha}_i, \hat{\beta}_i$ are estimated by regression over a prior sample.
2. *Excess Returns Relative to the Sharpe–Lintner CAPM:*
$$\hat{\varepsilon}_{i,t} \;=\; \bigl(R_{i,t} - R_f\bigr) \;-\; \hat{\beta}_i \bigl(R_{m,t} - R_f\bigr).$$
   where $\hat{\beta}_i$ is estimated by regressing $(R_{i,t} - R_f)$ on $(R_{m,t} - R_f)$.

Nonetheless, as De Bondt [1] observes, the *practical* choice of abnormal return measure typically does *not* alter the main conclusions about overreaction. Moreover, using simple market-adjusted returns

$$\widetilde{\varepsilon}_{i,t} \;=\; R_{i,t} - R_{m,t}$$

often biases results against finding overreaction, because it subtracts a constant market return from every stock. Seeing strong reversals in these residuals still constitutes evidence against the simplest forms of market efficiency.

3 Methodology

3.1 Test Procedures

In this part, the test procedure is designed to evaluate whether portfolios formed from stocks with extreme past performance exhibit predictable reversals. A summary of the steps is provided in Algorithm 1 in the Appendix.

We describe the methodology step by step as follows:

1. **Data Description:** The dataset consists of monthly returns for NYSE-listed stocks from the Center for Research in Security Prices (CRSP) between January 1926 and December 1982. Stocks with at least 85 months of return data (from months 1 to 85) are selected for analysis. Missing values are handled by computing residual returns for available data. Unlike what was done on paper, a **weighted** arithmetic average return of all CRSP-listed securities serves as the market index. To do so, we have a broad, unbiased and representative benchmark which captures overall market movements, minimizes sectoral biases, and reflects realistic investor experiences through market capitalization weighting.

2. **Excess Return Calculation:** For each stock j and month t, calculate the excess return as:

$$u_{jt} = R_{jt} - R_{mt},$$

   where u_{jt} represents the residual return for stock j in month t, R_{jt} is the actual return of stock j, and R_{mt} is the market return for the same month. The residual return u_{jt} measures the stock's performance relative to the market benchmark.

3. **Portfolio Formation:** For each stock j, compute its cumulative excess return over a previous 36-month portfolio formation period:

$$CU_j = \sum_{t=-36}^{-1} u_{jt}.$$

   Rank all stocks by CU_j to form two portfolios based on fixed number of stocks or by decile grouping, depending on the chosen methodology. For example,

   - **Winner Portfolio:** Top 35 stocks with the highest CU_j,
   - **Loser Portfolio:** Bottom 35 stocks with the lowest CU_j.

   This ranking process is repeated for 16 non-overlapping three-year periods between January 1930 and December 1977.

4. **Portfolio Performance Evaluation:** Track the performance of Winner and Loser portfolios over a 36-month test period ($t = 1$ to $t = 36$). Compute the cumulative average residual return (CAR) for each stock in the portfolio:

$$CAR_{W,n,t} = \sum_{\tau=1}^{t} u_{W,n,\tau}, \quad CAR_{L,n,t} = \sum_{\tau=1}^{t} u_{L,n,\tau},$$

   where $u_{W,n,\tau}$ and $u_{L,n,\tau}$ are the residual returns of individual stocks in the Winner and Loser portfolios, respectively. Then compute the average CAR, called ACAR, for each portfolio:

$$ACAR_{W,t} = \frac{1}{N} \sum_{n=1}^{N} CAR_{W,n,t}, \quad ACAR_{L,t} = \frac{1}{N} \sum_{n=1}^{N} CAR_{L,n,t}.$$

5. **Statistical Testing:** Calculate the pooled variance:

$$S_t^2 = \frac{\sum_{n=1}^{N}(CAR_{W,n,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2}{2(N-1)},$$

where S_t^2 is called the pooled variance. Then compute the t-statistic to test the difference in CAR:

$$T_t = \frac{ACAR_{L,t} - ACAR_{W,t}}{\sqrt{2S_t^2/N}}.$$

Test whether $ACAR_{L,t} - ACAR_{W,t}$ is significantly greater than zero, indicating mean reversion.

6. **Contribution of Individual Months:** In order to judge whether, for any month t, the average residual return makes a contribution to $ACAR_{W,t}$, we can test whether it is significantly different from zero. The average residual return $AR_{W,t}$ is calculated as:

$$AR_{W,t} = \frac{1}{N}\sum_{n=1}^{N} u_{W,n,t}.$$

and the standard deviation of residual returns is calculated:

$$s_t = \sqrt{\frac{\sum_{n=1}^{N}(u_{W,n,t} - AR_{W,t})^2}{N-1}}.$$

The the t-statistic for $AR_{W,t}$is then:

$$T_t = \frac{AR_{W,t}}{s_t/\sqrt{N}}.$$

Similar procedure apply for the Loser Portfolio.

3.2 Implementation

In this part, we will illustrate the implementation of our replicated model. The detailed source code can be found in the project Github repository (`https://github.com/cs821/IC-MF-PM-CW`).

Our analysis of financial market overreaction begins with a rigorous data cleaning process. The CRSP dataset is imported, with duplicates and missing values dropped out. Throughout this process, we ensure that return values are properly converted to numeric types. A key step involves verifying data availability over multiple years. Specifically, for each year between 1926 and 1975, we examine an 85-month window to confirm that monthly observations are continuous. We achieve this by grouping the data by firm identifier `permno` and eliminating those that exhibit any gap in their return series within the specified period. This filtering is performed by the function that conceptually aligns with `filter_consecutive_data`, which checks the consecutive nature of monthly returns before determining which firms qualify for further analysis.

After establishing an eligible universe of firms with sufficient historical data, we construct portfolios based on different formation periods, such as 36 months. For a given hold date, we look back over the preceding 36 months and compute log returns for each firm as well as for the benchmark. We then calculate excess log returns by subtracting the benchmark's log returns from each firm's log returns, summing them over the formation period to produce a cumulative measure. This cumulative excess return serves as the ranking criterion. In our implementation, which is encapsulated by the `compute_performance_portfolios` function, we assign firms to top and bottom portfolios either by deciles or by choosing a fixed number of extreme performers (for instance, the top 35 versus the bottom 35 firms).

Once the top and bottom portfolios are defined, we evaluate their performance over a holding period following the formation. The `calculate_portfolio_returns_modified` function merges the selected portfolio firms with their subsequent price and return data, while ensuring that missing observations are handled systematically. When price data become unavailable for a given firm, all subsequent observations for that firm are discarded through a procedure that identifies the first missing price and drops all post-missing rows.

We then compute monthly abnormal returns (AR) by subtracting the weighted benchmark return from the weighted portfolio return. These monthly abnormal returns are cumulatively summed to yield cumulative abnormal returns (CAR). Our `compute_portfolio_performance_modified` function iterates over multiple hold dates, applies the above procedures, and consolidates the results. The outcome is an averaged AR and CAR path for both the top and bottom portfolios, reflecting how these groups perform relative to the benchmark over the holding period. By comparing the average CAR of previously high-performing and low-performing firms, we obtain insights into whether the market exhibits signs of overreaction during the sample period.

In this final step, we introduce the `calculate_s_and_t` function, which uses the average abnormal returns (AR) and cumulative abnormal returns (CAR) for both the bottom (loser) and top (winner) portfolios to conduct statistical inference. For each hold date in the sample, the function recalculates that date's AR and CAR, compares them against the corresponding average values, and aggregates the squared deviations. This process yields pooled variance estimates for the combined top and bottom portfolios, which are then employed to calculate t-statistics for CAR differences between losers and winners as well as t-statistics for the average AR of each portfolio group. By evaluating these t-statistics, we gain insight into the significance of overreaction or reversals within the dataset.

4 Empirical Results

4.1 Market Overview

To examine whether the performance of our constructed portfolios is influenced by overall market movements, we begin by plotting the mean market size over time in Figure 1. The data range extends from the initial sample year 1926 through 2023, thus providing a comprehensive view of the long-term development of the market.

As shown in Figure 1, the overall market size remains relatively stable in the early years. Beginning in the mid-to-late 1950s, the market enters a discernible upward trajectory. Particularly pronounced growth phases materialize in the 1960s and 1980s.

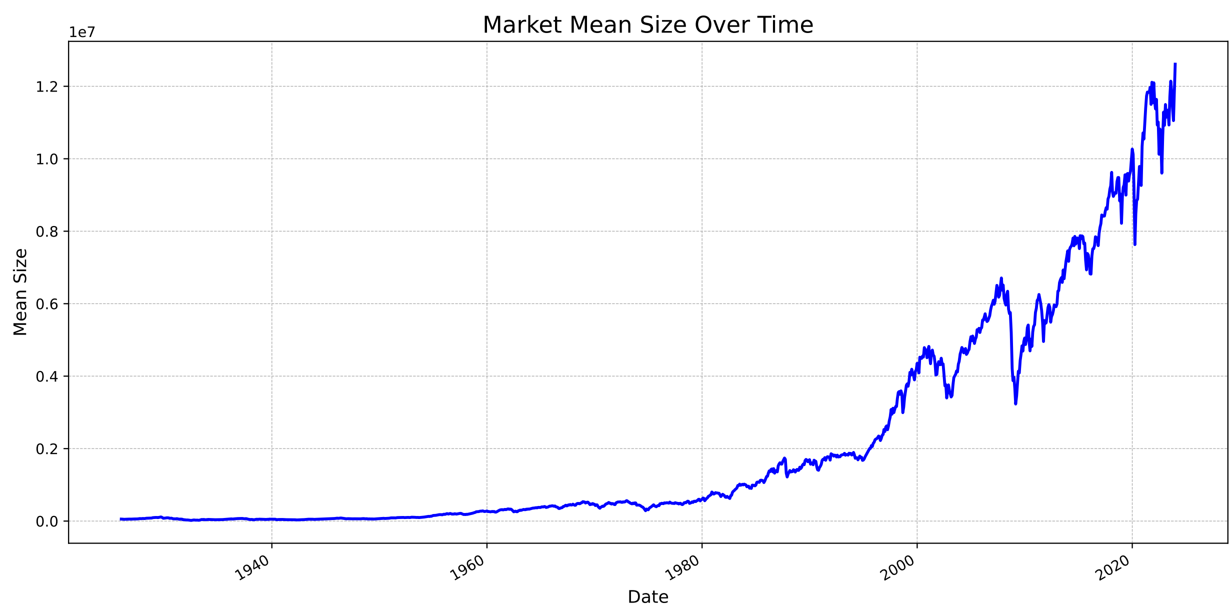


Figure 1: Market Mean Size Over Time

4.2 Replication of the Core Analysis

Having established a preliminary understanding of the market's evolution, we next replicate the fundamental analysis from the original study.

Figure 2 closely aligns with Figure 1 of the original paper [1]. Our replication reveal key details consistent with the original study. Figure 2 illustrates the progression of averaged CARs over the test period. Overall, the CARs for Winner Portfolio are negative throughout most of the sample window, except for the first year, where slightly positive values are observed. While the Loser Portfolio—after some initial volatility—tends to exhibit a more stable and eventually higher CAR in many observation windows. This result strongly supports the overreaction hypothesis. The overreaction effect is not symmetrical, as it is notably more pronounced for losers than for winners.

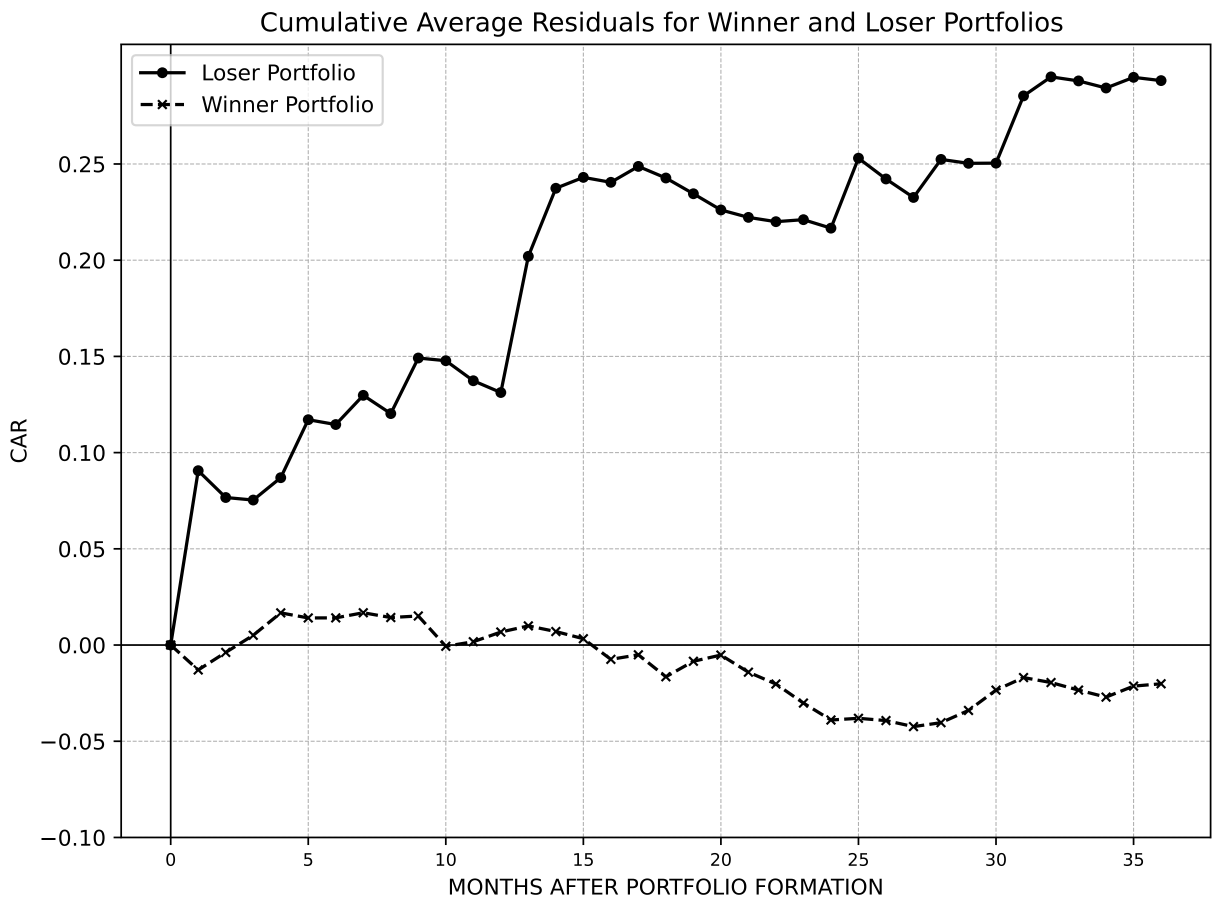
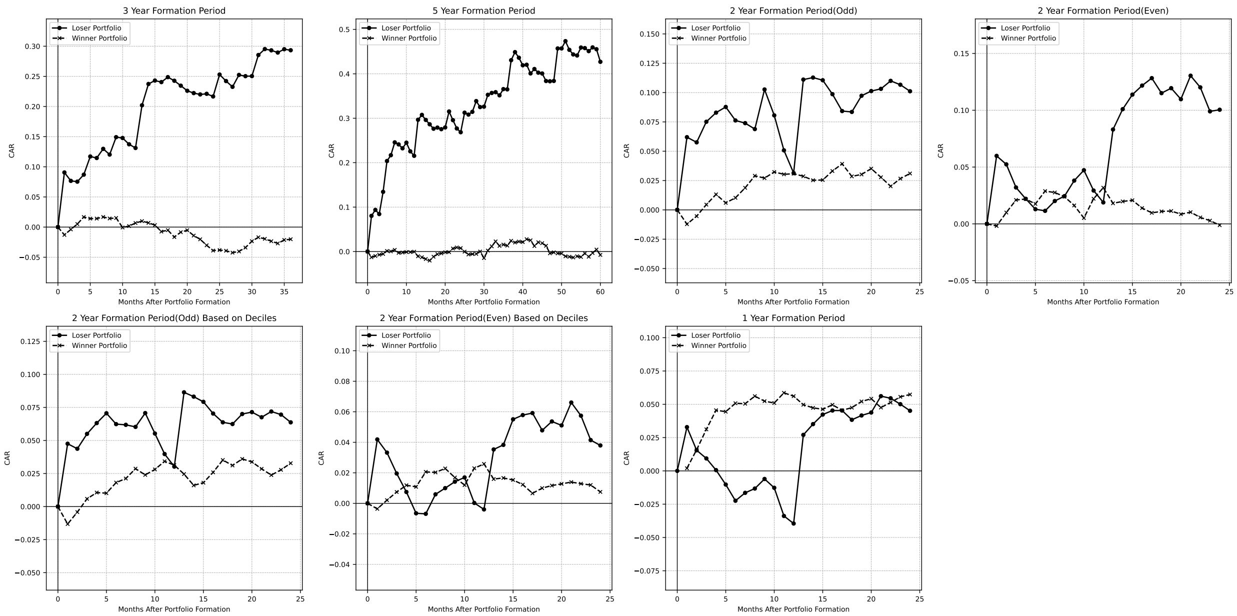


Figure 2: Cumulative Average Residuals of Winner and Loser Portfolios (Replication)

Following the same methodology outlined in the previous section, we applied the described procedures to construct and analyze portfolios under different formation periods (e.g., 1-year, 2-year, and 5-year). Additionally, we implemented two distinct methods for grouping winner and loser portfolios: one method involving the selection of the top/bottom 35 stocks, and another using the decile-based approach. The results of these analyses are summarized and visualized in the Figure 3 below. This comprehensive comparison provides insights into the robustness of the winner-loser effect across various formation periods and portfolio construction methods.



Odd: the formation month for these portfolios is the month of December in all odd years between 1933 and 1979.
Even: the formation month for these portfolios is the month of December in all even years between 1932 and 1980.

Figure 3: Comparison of Winner and Loser Portfolios During 1926 and 1982 (Value Weighted)

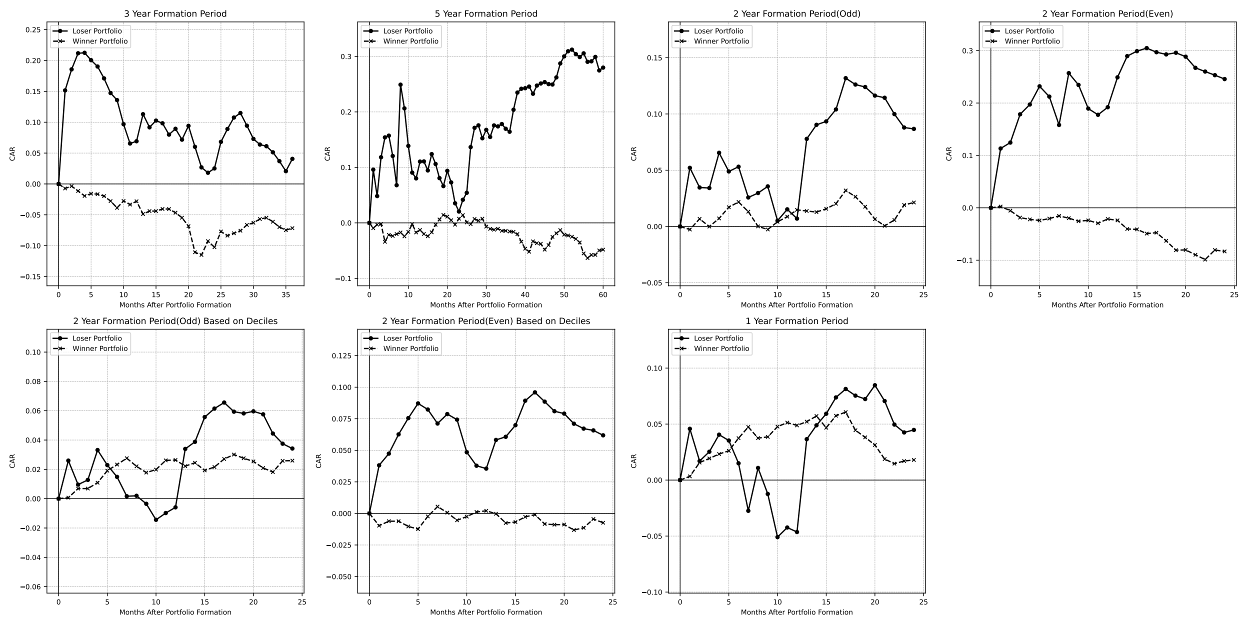
Our results align with the original paper, yielding very similar and clear conclusions. First of all, comparing different formation periods, we find that longer formation periods tend to exhibit more pronounced and stable overreaction effects. When stocks are ranked based on a longer look-back window (e.g., 3-year or 5-year cumulative returns), the Loser Portfolio typically achieves higher CAR compared to its counterpart formed over a shorter period. One potential explanation is that the mispricing of Losers is slower to correct, which may lead to more pronounced contrarian gains once the market recognizes and adjusts these valuations.

In contrast, shorter formation periods (e.g., 1-year or 2-year) can exhibit higher volatility in CAR. In some cases, such as a 1-year weighted subplot, the Loser Portfolio does not outperform the Winner Portfolio by a large margin or may even be briefly overtaken. This phenomenon may arise because short-term price movements can be influenced by a variety of transitory factors, such as earnings announcements, macroeconomic news, or market sentiment shifts. These transient shocks can overshadow any systematic tendency for losers to rebound and winners to fade, thus dampening the overreaction signal in shorter windows.

4.3 Extended Results from 1967 to 2023

Because our replication closely aligns with the original study, demonstrating that our methodology is highly consistent with the original, we were motivated to extend the results. In order to further examine the robustness of the "winner–loser" effect over a longer time horizon, we generalized the dataset to 1967-2023 periods, using the same grouping and weighting methods as the original study. Figure 4 shows seven key subfigures corresponding to different formation periods.

From these subfigures, we observe that the performance differences between the Winner and Loser portfolios persist across multiple formation periods. Consistent with the original research, the Loser Portfolio frequently demonstrates significant excess returns during the holding period, even in the extended data through 2023. This finding reinforces the notion that overreaction effects in equity markets can be robust to broader temporal spans and evolving market conditions.



Even: the formation month for these portfolios is the month of December in all even years between 1974 and 2020.
Odd: the formation month for these portfolios is the month of December in all odd years between 1973 and 2021.

Figure 4: Comparison of Winner and Loser Portfolios From 1967 to 2023 (Value Weighted)

It is noteworthy that certain portfolios experience heightened volatility in localized intervals due to varying market conditions, economic cycles, and industry-specific shocks. Nonetheless, when viewed over the entire extended sample, the overarching pattern is largely similar to that reported in the original analysis—the Loser Portfolio consistently demonstrates a meaningful tendency to catch up or even outperform in subsequent months or years.

These insights, in conjunction with the original study's results, reinforce the notion that a "losers-become-winners" strategy may be viable over longer horizons. However, practical applications should consider transaction costs, risk exposures, and the potential for structural changes in the market over extended periods.

4.4 Statistical Tests

4.4.1 Cumulative Average Residual Return Statistics

We also summarized the cumulative average residual returns (CAR) across two time periods in Table I and Table II, offers insights into the persistence and attenuation of the market overreaction phenomenon. Table I, covering the period from 1926 to 1982, replicates the findings of De Bondt and Thaler (1985) [1] and exhibits a pronounced overreaction effect. For example, from Table I, it is evident that at the end of the formation period, winner portfolios show significantly positive CARs (e.g., 1.286 for three-year periods), while loser portfolios display markedly negative CARs (e.g., -0.895 for the same horizon). This substantial divergence highlights the strong clustering of past performance at the formation stage. Following the portfolio formation, loser portfolios consistently outperform winner portfolios, with the CAR difference reaching 0.313 at 36 months (t-value = 2.06). This reversal supports the hypothesis that extreme past performance corrects over time due to market participants' overreaction.

From Table I, it is also clear that the reversal effect is particularly strong in the early months following portfolio formation. For instance, in the first month, the CAR difference between winner and loser portfolios

Table I:
Differences in Cumulative Average (Market-Adjusted) Residual Returns Between the Winner and Loser Portfolios at the End of the Formation Period, and 1, 12, 13, 18, 24, 25, 36, and 60 Months into the Test Period (Sample Period: 1926 to 1982)

Portfolio Selection Procedures	Average No. of Stocks	CAR at the End of the Formation Period		Difference in CAR (t-Statistics) Months After Portfolio Formation							
		Winner Portfolio	**Loser Portfolio**	**1 Month**	**12 Months**	**13 Months**	**18 Months**	**24 Months**	**25 Months**	**36 Months**	**60 Months**
16 Three-year periods	35	1.286	-0.895	0.104	0.124	0.192	0.259	0.256	0.291	0.313	NA*
				(2.75)	(1.30)	(1.60)	(1.17)	(1.77)	(2.06)	(2.02)	
10 Five-year periods	50	1.073	-0.869	0.093	0.215	0.307	0.285	0.261	0.313	0.352	0.435
				(2.63)	(1.79)	(2.38)	(2.11)	(1.85)	(2.14)	(1.84)	(2.19)
24 Two-year periods[a]	35	1.037	-0.734	0.071	-0.008	0.071	0.028	0.035	NA	NA	NA
				(4.14)	(-0.14)	(1.13)	(0.39)	(0.47)			
25 Two-year periods[b]	35	1.050	-0.733	0.071	0.022	0.100	0.174	0.168	NA	NA	NA
				(3.39)	(0.42)	(1.72)	(1.78)	(1.69)			
24 Two-year periods[a] (deciles)	90	0.748	-0.536	0.056	-0.017	0.045	0.006	0.002	NA	NA	NA
				(4.39)	(-0.40)	(0.95)	(0.12)	(0.05)			
25 Two-year periods[b] (deciles)	93	0.744	-0.563	0.055	0.006	0.058	0.112	0.102	NA	NA	NA
				(3.19)	(0.14)	(1.16)	(1.35)	(1.22)			
49 One-year periods	35	0.711	-0.496	0.031	-0.096	-0.023	-0.009	-0.012	NA	NA	NA
				(2.84)	(-2.94)	(-0.62)	(-0.20)	(-0.25)			

[a] The formation month for these portfolios is the month of December in all odd years between 1933 and 1979.
[b] The formation month for these portfolios is the month of December in all even years between 1932 and 1980.
* NA, not applicable.

Table II:
Differences in Cumulative Average (Market-Adjusted) Residual Returns Between the Winner and Loser Portfolios at the End of the Formation Period, and 1, 12, 13, 18, 24, 25, 36, and 60 Months into the Test Period (Sample Period: 1967 to 2023)

Portfolio Selection Procedures	Average No. of Stocks	CAR at the End of the Formation Period		Difference in CAR (t-Statistics) Months After Portfolio Formation							
		Winner Portfolio	**Loser Portfolio**	**1 Month**	**12 Months**	**13 Months**	**18 Months**	**24 Months**	**25 Months**	**36 Months**	**60 Months**
16 Three-year periods	35	1.375	-1.361	0.159	0.097	0.162	0.136	0.128	0.145	0.112	NA*
				(2.20)	(0.63)	(1.08)	(0.90)	(0.74)	(0.88)	(0.62)	
10 Five-year periods	50	1.416	-1.637	0.105	0.097	0.123	0.075	0.028	0.053	0.180	0.328
				(1.68)	(0.47)	(0.63)	(0.32)	(0.10)	(0.21)	(0.82)	(1.37)
24 Two-year periods[a]	35	1.139	-1.087	0.055	-0.008	0.064	0.100	0.065	NA	NA	NA
				(1.68)	(-1.12)	(0.98)	(1.31)	(0.74)			
25 Two-year periods[b]	35	1.156	-1.238	0.104	0.201	0.271	0.344	0.315	NA	NA	NA
				(2.27)	(1.55)	(2.12)	(2.45)	(2.00)			
24 Two-year periods[a] (deciles)	166	0.702	-0.613	0.025	-0.032	0.012	0.029	0.008	NA	NA	NA
				(1.70)	(-0.79)	(0.27)	(0.62)	(0.14)			
25 Two-year periods[b] (deciles)	172	0.708	-0.629	0.045	0.030	0.062	0.093	0.071	NA	NA	NA
				(2.77)	(0.69)	(1.21)	(1.65)	(0.99)			
49 One-year periods	35	0.907	-0.789	0.042	-0.095	-0.015	0.031	0.027	NA	NA	NA
				(2.00)	(-1.66)	(-0.25)	(0.46)	(0.34)			

[a] The formation month for these portfolios is the month of December in all even years between 1974 and 2020.
[b] The formation month for these portfolios is the month of December in all odd years between 1973 and 2021.
* NA, not applicable.

is 0.104 (t-value = 1.60), and this reversal continues to build in the subsequent months, peaking at 0.313

by the third year. The robustness of these results across multiple horizons and independent replications underscores the validity of the market overreaction hypothesis during this period. Moreover, the pronounced January effect observed during this sample period, as reflected in the strong performance of loser portfolios in the early months, likely reflects tax-related selling or portfolio rebalancing behavior, as previously noted in the literature.

In contrast, Table II, which covers the extended period from 1967 to 2023, reveals a significant weakening of the overreaction effect. At the end of the formation period, the CARs of winner portfolios remain positive (e.g., 1.375 for three-year periods), and loser portfolios continue to show negative CARs (e.g., -1.361). However, the magnitude of the subsequent reversals diminishes considerably. For example, by 36 months, the CAR difference is only 0.145 (t-value = 0.88), as opposed to 0.313 in the earlier period. This reduction highlights the increasing efficiency of financial markets over time, as technological advancements, improved information dissemination, and the rise of quantitative investment strategies have likely reduced opportunities for exploiting behavioral anomalies.

From Table II, it is evident that the January effect, a key feature of Table I, is also less pronounced in the extended period. While the CAR difference in the first month remains positive (0.097, t-value = 0.85), its statistical significance has declined, indicating that heightened market awareness and institutional trading practices have mitigated this seasonal anomaly. Additionally, Table II introduces broader decile-based portfolios, such as those with 166 stocks for the 24 two-year periods. These results show that the reversal effect becomes less pronounced when larger, more diversified portfolios are considered, likely due to the dilution of extreme performance effects in broader stock groups.

The differences between Table I and Table II reflect not only temporal changes but also structural shifts in market behavior. The period from 1926 to 1982 represents a relatively less efficient market with limited access to information and lower arbitrage activity, resulting in stronger overreaction effects. Conversely, the 1967 to 2023 period corresponds to a more efficient and globalized market environment, where behavioral biases such as overreaction are less pronounced and more difficult to exploit.

In conclusion, the results presented in Table I confirm the robustness of the market overreaction hypothesis in the historical sample, while the findings in Table II demonstrate the attenuation of this effect in more modern financial markets. These results highlight the dynamic nature of financial markets and underscore the importance of considering temporal and structural contexts when studying behavioral anomalies. The weakening of overreaction effects in the extended period provides compelling evidence of increasing market efficiency, emphasizing the need for adaptive investment strategies that account for evolving market conditions.

4.4.2 Average Residual Return Statistics

To judge whether the average residual return has made a contribution to ACAR, we also conducted a t-test to reflect whether the average residual returns of Winner and Loser portfolios based on different formation periods are significantly different from zero at various months after portfolio formation. The results are presented in Table III and Table IV. This analysis helps reveal the potential profitability of Winner and Loser investment strategies.

In both tables, Loser portfolios demonstrate relatively high positive t-values. This indicates that Loser portfolios generate significantly positive residual returns during these periods, consistent with earlier CAR analysis results. It suggests that AR indeed contributes to the ACAR. Conversely, Winner portfolios exhibit more negative t-values with fewer significant positive values. This reflects that the overreaction effect is less pronounced for Winner portfolios compared to Loser portfolios, aligning with the earlier conclusions about overreaction and market correction.

Additionally, the comparison of different formation periods shows that the significance of returns for Winner and Loser portfolios, as reflected by AR t-values, is not significantly influenced by the length of the formation period. Across various timeframes, the t-values for the same month do not exhibit substantial differences.

Table III:
Average Residual Returns (t-Statistics) for Winner and Loser Portfolios Based on Different Formation Periods (Sample Period: 1926 to 1982)

Portfolio Selection Procedures	**Portfolio Type**	**AR (t-Statistics) Months After Portfolio Formation**							
		1 Month	**12 Months**	**13 Months**	**18 Months**	**24 Months**	**25 Months**	**36 Months**	**60 Months**
10 five-year periods	Winner	-0.82	0.79	0.38	-1.40	-1.42	0.14	0.21	NA*
	Loser	2.65	-0.55	2.32	-0.76	-0.30	2.48	-0.12	
16 three-year periods	Winner	-2.18	0.13	-1.53	1.82	-0.18	-0.83	-0.30	-2.32
	Loser	2.30	-0.66	2.02	0.13	-0.80	1.72	-0.05	-1.82
24 two-year periods[a]	Winner	-1.31	0.10	0.04	-1.04	0.59	NA	NA	NA
	Loser	3.96	-1.55	3.46	-0.26	-0.92			
25 two-year periods[b]	Winner	-0.24	2.18	-1.07	0.01	-0.93	NA	NA	NA
	Loser	3.74	-1.63	3.15	-0.77	0.10			
24 two-year periods[a] (deciles)	Winner	-1.64	-0.54	-0.78	-0.38	0.86	NA	NA	NA
	Loser	4.12	-1.58	3.68	-0.39	-0.84			
25 two-year periods[b] (deciles)	Winner	-0.58	1.24	-1.32	0.49	-1.22	NA	NA	NA
	Loser	3.25	-1.04	3.24	-0.75	-0.50			
49 one-year periods	Winner	0.33	-0.65	-1.02	0.30	0.44	NA	NA	NA
	Loser	3.58	-0.88	4.42	-1.41	-0.88			

[a] The formation month for these portfolios is the month of December in all odd years between 1933 and 1979.
[b] The formation month for these portfolios is the month of December in all even years between 1932 and 1980.
[*] NA, not applicable.

This suggests that the average residual returns of Winner and Loser portfolios in each month are relatively independent of the formation period's length. It implies that the profitability of these portfolios in terms of short-term AR may be driven more by intrinsic market dynamics (e.g., investor overreaction and subsequent corrections) rather than by the length of time used to construct the portfolios. This stability in AR significance across formation periods further strengthens the robustness of the Loser portfolio's profitability. It also highlights that while both AR and CAR are useful for analyzing portfolio performance, AR provides a clearer view of how specific months contribute to cumulative trends.

Both table highlight that months coinciding with January (the 1st Month, 13th Month and 25th Month) show amplified differences between Loser and Winner ARs. This "January effect is probably attributed to year-end selling pressure on underperformers that abates in the new calendar year.

However, the two tables also exhibit some differences. For instance, during the 1926–1982 period (Table III), the t-values for Loser portfolios in key months (e.g., the 1st month and the 13th month) are higher compared to the 1967–2023 period (Table IV). For example, the t-value for the Loser portfolio in the 1st month of the five-year formation period decreased from 2.65 to 2.13. This suggests that while the excess returns of Loser portfolios remain significant across both periods, their magnitude has weakened over time, potentially reflecting improvements in market efficiency or changes in investor behavior. Similarly, the negative t-values for Winner portfolios are less pronounced in the later period, indicating that the correction of overvalued stocks became milder during 1967–2023. Despite these differences, both tables consistently show that the significance of excess returns is largely unaffected by the length of the formation period, and the "January effect" remains a notable and persistent characteristic, highlighting the continued influence of behavioral finance factors.

Table IV:
Average Residual Returns (t-Statistics) for Winner and Loser Portfolios Based on Different Formation Periods (Sample Period: 1967 to 2023)

Portfolio Selection Procedures	Portfolio Type	AR (t-Statistics) Months After Portfolio Formation							
		1 Month	**12 Months**	**13 Months**	**18 Months**	**24 Months**	**25 Months**	**36 Months**	**60 Months**
10 five-year periods	Winner	-0.56	0.77	-1.57	-1.18	-1.04	2.43	0.30	NA*
	Loser	2.13	0.10	1.49	0.73	0.63	1.67	1.30	
16 three-year periods	Winner	-0.63	-1.13	0.21	1.65	0.74	-1.59	-0.13	0.20
	Loser	1.58	-0.25	0.57	-1.47	0.80	0.42	-0.35	0.44
24 two-year periods[a]	Winner	-0.23	0.62	-0.09	-0.62	0.32	NA	NA	NA
	Loser	1.71	-0.43	2.66	-0.40	-0.09			
25 two-year periods[b]	Winner	0.32	0.97	-0.38	-2.03	-0.31	NA	NA	NA
	Loser	2.36	0.56	2.53	-0.37	-0.74			
24 two-year periods[a] (deciles)	Winner	0.09	0.08	-0.64	0.82	0.03	NA	NA	NA
	Loser	2.08	0.39	2.80	-1.28	-0.63			
25 two-year periods[b] (deciles)	Winner	-1.30	0.07	-0.69	-1.93	-0.78	NA	NA	NA
	Loser	2.45	-0.37	2.04	-1.16	-0.77			
49 one-year periods	Winner	0.36	-0.41	0.48	-3.29	0.18	NA	NA	NA
	Loser	2.39	-0.26	2.96	-0.80	0.22			

[a] The formation month for these portfolios is the month of December in all even years between 1974 and 2020.
[b] The formation month for these portfolios is the month of December in all odd years between 1973 and 2021.
[*] NA, not applicable.

5 Conclusions and Further work

This study provides compelling evidence consistent with the overreaction hypothesis, indicating the presence of systematic inefficiencies in stock markets. Portfolios of prior “losers” were observed to outperform prior “winners” significantly, with a substantial cumulative average residual return differential across varying formation periods. Analysis of extended datasets further reinforces these findings. These results challenge the assumptions underlying weak-form market efficiency and underscore the potential explanatory power of behavioral principles in understanding asset price dynamics. By bridging behavioral finance and empirical market anomalies, this research lays the groundwork for further exploration into the influence of investor psychology on market efficiency and pricing behavior.

Following the publication of the paper by De Bondt and Thaler in 1985 [1], research on market overreaction exploded, transforming both the theoretical and empirical landscapes of finance. De Bondt and Thaler (1987) [7] extended their earlier findings by controlling for factors such as size and calendar effects, reinforcing the idea that past losers systematically outperform past winners over a multi-year horizon. In parallel, Fama and French (1993) [8] proposed multi-factor models incorporating size and book-to-market ratios, attempting to show that seemingly anomalous returns could often be viewed as compensation for omitted risks rather than investor mispricing. Despite these risk-based explanations, behavioral models continued to gain prominence. Studies by Barberis, Shleifer, and Vishny (1998) [9], Daniel, Hirshleifer, and Subrahmanyam (1998) [10], and Hong and Stein (1999) [11] emphasized the role of overconfidence, limited information diffusion, and social interaction in explaining short-term momentum and long-term reversals. Over time, evidence from both developed and emerging markets suggested that, while some anomalies could be explained by refined risk measures, a significant portion appeared tied to persistent cognitive biases. This dual track of inquiry—risk-based versus behavioral—continues to shape contemporary analyses of market efficiency.

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A Appendix 1: Test Procedure for Overreaction Hypothesis

Algorithm 1 Test Procedure for Overreaction Hypothesis

1: **Input:** Monthly return data for NYSE stocks from certain durations.

2: Compute excess returns u_{jt} for each stock j as:

$$u_{jt} = R_{jt} - R_{mt}.$$

3: For each stock, calculate cumulative excess returns CU_j over the 36-month portfolio formation period:

$$CU_j = \sum_{t=-36}^{-1} u_{jt}.$$

4: Rank all stocks by CU_j and form portfolios based on fixed number of stocks or by decile grouping, depending on the chosen methodology. Determine the groups of Winner Portfolio and Loser Portfolio

5: Track portfolio performance for the 36-month test period, calculating monthly cumulative average excess returns (CAR):

$$CAR_{W,n,t} \text{ (Winner)} \quad \text{and} \quad CAR_{L,n,t} \text{ (Loser)}.$$

6: Then compute the average CAR (ACAR) for each portfolio:

$$ACAR_{W,t} = \frac{1}{N}\sum_{n=1}^{N} CAR_{W,n,t}, \quad ACAR_{L,t} = \frac{1}{N}\sum_{n=1}^{N} CAR_{L,n,t}.$$

7: Perform statistical testing using pooled variance:

$$S_t^2 = \frac{\sum_{n=1}^{N}(CAR_{W,n,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2}{2(N-1)}.$$

8: Compute the t-statistic:

$$T_t = \frac{ACAR_{L,t} - ACAR_{W,t}}{\sqrt{2S_t^2/N}}.$$

9: For each month t, test whether the average excess return of the Winner Portfolio ($AR_{W,t}$) significantly contributes to $ACAR_{W,t}$:

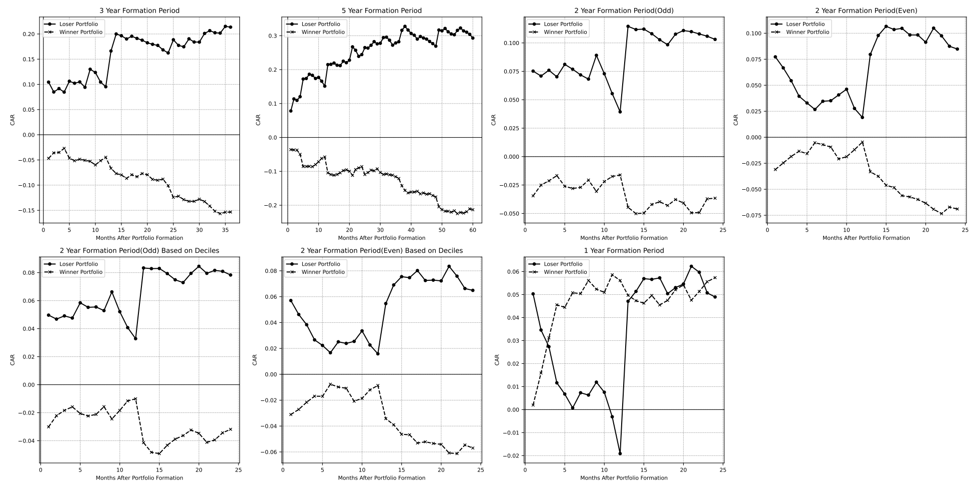
$$s_t = \sqrt{\frac{\sum_{n=1}^{N}(u_{W,n,t} - AR_{W,t})^2}{N-1}}.$$

The t-statistic for $AR_{W,t}$ is:

$$T_t = \frac{AR_{W,t}}{s_t/\sqrt{N}}.$$

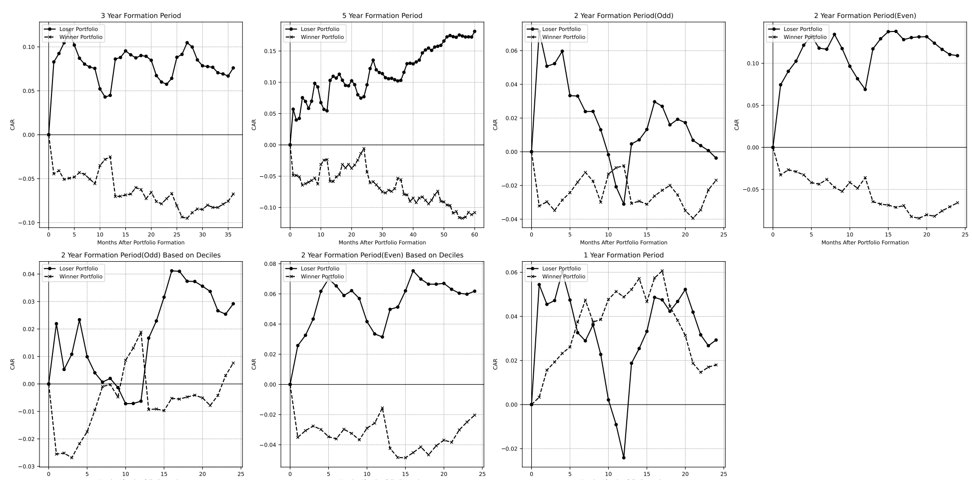
10: Similar procedures are applied to the Loser Portfolio.

B Appendix 2: Equal Weighted Performance of Experiment



Odd: the formation month for these portfolios is the month of December in all odd years between 1933 and 1979.
Even: the formation month for these portfolios is the month of December in all even years between 1932 and 1980.

Figure 5: Comparison of Winner and Loser Portfolios From 1926 to 1982 (Equal Weight)



Even: the formation month for these portfolios is the month of December in all even years between 1974 and 2020.
Odd: the formation month for these portfolios is the month of December in all odd years between 1973 and 2021.

Figure 6: Comparison of Winner and Loser Portfolios From 1967 to 2023 (Equal Weight)