MASTERARBEIT | MASTER'S THESIS

Titel | Title

Bridging the Gap: Short-Term Reversals as a Tool in Medium-Term Momentum

verfasst von | submitted by

lic. Samy Costin-Osan

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2024

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 974
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Banking and Finance
Betreut von | Supervisor:	Univ.-Prof. Mag. Günter Strobl PhD

Acknowledgements

I would like to express my deepest gratitude to Univ.-Prof. Mag. Günter Strobl, PhD, for his guidance and support during my thesis. His "Investments" course inspired me to pursue this topic, and his expertise in the investment field was crucial in overcoming the challenges I faced throughout this process. I am grateful for his assistance and the valuable time he dedicated to helping me.

Abstract

EN In the world of investing, "Momentum" is a key term that often comes up. Investors and hedge funds frequently question its effectiveness and explore ways to improve this strategy. Despite its popularity, investors are still wary if this strategy is still viable today and if it can still be improved. This thesis embarks on an in-depth exploration of momentum investing, with a particular focus on examining its efficacy and opportunities for enhancement. At the heart of this study is an analysis of short-term reversals and their strategic importance within the momentum investing framework. It specifically addresses the critical decision-making process concerning the implementation of a one-month waiting period after the initial formation phase. Challenging traditional views that often interpret short-term reversals as detrimental, this research proposes a novel perspective by considering the potential of incorporating these reversals as advantageous elements to the momentum strategy. Ultimately, this research endeavors to contribute valuable knowledge to the field, offering investors and hedge funds evidence-based strategies to refine their momentum investing approaches in today's market.

DE In der Welt der Investitionen ist 'Momentum' ein Schlüsselbegriff, der oft auftaucht. Investoren und Hedgefonds hinterfragen häufig seine Wirksamkeit und erforschen Wege, diese Strategie zu verbessern. Trotz ihrer Beliebtheit sind sich Investoren immer noch unsicher, ob diese Strategie heute noch tragfähig ist und ob sie noch verbessert werden kann. Diese Arbeit begibt sich auf eine eingehende Untersuchung des Momentum-Investierens, mit einem besonderen Fokus auf die Überprüfung seiner Wirksamkeit und Möglichkeiten zur Verbesserung. Im Kern dieser Studie steht eine Analyse von kurzfristigen Umkehrungen und deren strategischer Bedeutung innerhalb des Rahmens des Momentum-Investierens. Sie spricht insbesondere den kritischen Entscheidungsprozess bezüglich der Implementierung einer einmonatigen Wartezeit nach der anfänglichen Bildungsphase an. Herausfordernd gegenüber traditionellen Ansichten, die kurzfristige Umkehrungen oft als nachteilig interpretieren, schlägt diese Forschung eine neue Perspektive vor, indem sie das Potenzial betrachtet, diese Umkehrungen als vorteilhafte Elemente der Momentum-Strategie zu integrieren. Letztendlich bemüht sich diese Forschung, wertvolles Wissen zum Feld beizutragen, indem sie Investoren und Hedgefonds evidenzbasierte Strategien bietet, um ihre Momentum-Investitionsansätze auf dem heutigen Markt zu verfeinern.

Contents

1. Introduction

Momentum, or the principle that an object in motion tends to stay in motion, is a concept that has extended to the stock market for longer than we know. The idea is that if a stock has been performing well recently, it's likely to continue doing so in the future as well. Conversely, if a stock has been on a downward trend, it will keep losing value. This approach involves buying "winners"—stocks that have outperformed in the past—and selling "losers"—those that have underperformed. According to Jegadeesh and Titman, adopting such a strategy could yield a 12% annual return, showcasing its potential profitability.

Momentum investing introduces a challenge to conventional financial theories, which often struggle to fully explain the dynamics of momentum and reversals. There has been considerable debate on these topics, yet no consensus has been reached. I believe that the phenomena of momentum and reversals are not contradictory but rather complementary explanations for market movements:

- **Rational Explanation:** A view which states that stocks might share exposure to an unidentified risk factor, which causes their prices to move synchronously. For example, companies that suffered in March 2020 could be particularly vulnerable to COVID-related risks, whereas those that prospered were positively aligned with such events. This hypothesis can explain the simultaneous price movements but falls short of justifying the observed premium which can be explained according to the behavioral view.

- **Behavioral Explanation:** On the other hand, this perspective suggests that the market may be sluggish in assimilating new information, causing the prices to adjust to good or bad news gradually over time, commonly referred to as "sticky prices". For instance, the market's reaction to the COVID-19 pandemic was slow, with investors gradually recognizing its impact, but not to the full extent necessary. The consensus among scholars leans towards *behavioral factors* as the primary drivers of momentum.

However, this profit-making method has its limitations. The study by De BONDT and Thaler illustrates that momentum doesn't last indefinitely and can reverse over time. They have managed to demonstrate that stocks often overreact to significant news, leading to an eventual performance reversal. Specifically, stocks that were previously underperforming (losers) have been shown to outperform the (winners) over the next three to five years, with a notable 25% margin in the first three years. Additionally, further analysis by Jegadeesh and Titman build upon their original 1993 findings on momentum. They discovered that the effectiveness of strategies based on momentum for forming portfolios tends to diminish after one year, even turning negative. This update highlights the temporal nature of momentum investing, underscoring the importance of continually reassessing and adjusting strategies to maintain profitability over time.

Building upon insights from Daniel and Moskowitz, this analysis further explores the vulnerability of momentum strategies to significant downturns amidst market volatility. The research by Daniel et al. underscores that while momentum strategies typically generate substantial positive returns across diverse asset classes, they are occasionally subject to rare yet extended periods of negative performance, often referred to as "momentum crashes." These downturns predominantly arise following market slumps, amidst periods of heightened volatility, or during stages of market recovery, which are marked by panic states. This evidence underscores the potential for improvement within momentum strategies, highlighting how reversals could be intricately linked to the broader concept of market momentum. These phenomena, observed both in the short and long term, suggest that momentum and reversals are not mutually exclusive but rather interconnected elements within the market's dynamics. Furthermore, my findings echo those of Daniel et al. as we will see later, where the Winner Minus Loser (WML) portfolio demonstrates a Sharpe ratio of 0.71, significantly outperforming the market's ratio of 0.40. Intriguingly, the WML portfolio exhibits a negative beta of -0.58, leading to an impressive annual CAPM alpha of 22.3% (with a robust t-statistic of 8.5), suggesting its potential to achieve superior risk-adjusted returns even in adverse market conditions. Consequently, this raises the first intriguing question: Can we strategically leverage reversals within the framework of momentum investing to enhance strategy efficacy?

Before we do that, we must first understand how both short-term reversals and value investing fundamentally exploit market inefficiencies through distinct mechanisms. Value investing, as highlighted by Lakonishok et al., aims to leverage the market's propensity to undervalue stocks based on fundamentals in the long run. It states that such undervalued stocks are waiting for their eventual outperformance as the market recognizes their true value. Conversely, short-term reversal strategies capitalize on the immediate effects of market overreactions by purchasing recent underperformers and selling recent outperformers, betting on a swift mean reversion. This approach is based on the well-documented observation, supported by De BONDT and Thaler, that stocks frequently overreact to news, leading to a predictable short-term price correction. By integrating these behavioral insights and risk considerations into the broader momentum strategy framework, a comprehensive approach emerges that adeptly navigates the market's short-term price adjustments and longer-term mispricing.

In contrast, momentum investing strategically prioritizes the recent performance of stocks, typically evaluating the preceding twelve months, to guide portfolio selection decisions. A hallmark of momentum strategies is the deliberate one-month waiting period implemented after identifying a stock's performance trajectory before its integration into a portfolio. This pause aims to fine-tune the entry timing, thereby maximizing the benefits from the stock's continued momentum. Research by Jegadeesh and Titman and Daniel and Moskowitz demonstrates that this approach yields superior outcomes, with Jegadeesh noting enhanced results by omitting the initial week and Daniel and Moskowitz (DM) observing improved performance by excluding the first month all together. I have also used this one-month skip due to the monthly data that will be mentioned later. This practice raises a pivotal question: Why do scholars so readily incorporate this delay into their momentum strategies without exploring alternative tactics, such as capitalizing on the investment opportunities that might arise during this waiting period?

This paper employs the methodology outlined by Daniel and Moskowitz as a fundamental framework for both momentum and reversal strategies, with a nuanced approach to timeframes. Specifically, it examines momentum over an 11-month lookback period and reversals over a 1-month lookback period, cumulatively spanning a 12-month cycle. The term "lookback period" refers to the duration over which one examines the cumulative performance of individual stocks before categorizing them into ranked buckets. The lowest performers are designated as *losers* (bucket 1), and the highest performers as *winners* (bucket 10). To mitigate the impact of short-term reversals commonly observed after the formation period, the strategy incorporates a one-month pause between the formation and holding periods for momentum investments. This adjustment aims to harness the continued momentum while avoiding immediate reversals. Both strategies are dynamic, with monthly rebalancing to adapt to the latest market conditions and performance data.

The findings presented in the referenced studies, as well as the outcomes of my own research, collectively underscore a crucial insight: incorporating a skip month significantly enhances performance when compared to strategies that do not include such a pause. Specifically, the standalone momentum strategy, which looks back over an 11-month period to gauge stock performance but *does not* implement a skip month, yielded an alpha of 13.23% and a beta of -0.60. Alpha, in this context, represents the strategy's ability to generate returns above the market average, while beta indicates the strategy's volatility or risk relative to the market. In contrast, when I introduced a skip month to this strategy—essentially pausing for 1 month after categorizing stocks based on their past performance before initiating trades—the strategy's effectiveness improved noticeably. The adjusted approach delivered an alpha of 19.20% and a beta of -0.52, illustrating not only higher returns but also a more favorable risk profile. The negative betas in both of these strategies could prove to be useful for diversification purposes given that they do not move with the market. These results are very similar to Daniel and Moskowitz, only differing in the time frame taken into account.

Moving on to the analysis of a standalone reversal strategy employing a 1-month lookback period, the strategy yielded an alpha of 3.02% and a beta of 0.23. This indicates the strategy achieved modest gains while assuming relatively low risk, characterized by an alpha significantly lower than more aggressive strategies. Notably, this was the only portfolio that exhibited a positive beta, suggesting it was more aligned with overall market movements. This correlation may be attributed to the brief duration of both the lookback and holding periods, totaling just 1 month each. Such a short timeframe likely allowed market dynamics to exert a more pronounced influence on the strategy's performance. This period provides a limited window for identifying potential reversals, potentially making the strategy more susceptible to prevailing market trends and less insulated against broader market fluctuations.

However, the landscape shifts dramatically when employing a more discerning strategy that requires confirmation signals. This higher-filtered strategy—where both momentum and reversal indicators must agree on whether a stock should be bought, held, or sold—produced significantly higher returns, with an alpha of 45.60% and a beta of -0.18. Although this strategy showcased the potential for remarkable gains, it also introduced a higher level of risk, as evidenced by a standard deviation of 47.17%, which is considerably higher than the 20-35% range associated with the other strategies in this research paper.

A cornerstone of my thesis is the exploration of a short-term reversal strategy during periods traditionally marked by a passive waiting approach in existing literature. Termed "combining strategy or rev_mom(skip)" within my research, this innovative approach has yielded remarkable results, notably an alpha of 30.40% alongside a beta of -0.55. These findings not only validate the effectiveness of the proposed strategy but also highlight the substantial gains achievable through thoughtful modifications to traditional investment tactics. By presenting this strategy, among others, in Table 4.0.4, I facilitate a detailed comparative analysis, offering clear insights into the distinct advantages and limitations inherent in each method. This analysis proves especially insightful in evaluating the benefits of integrating diverse investment strategies over the reliance on singular, isolated approaches.

The empirical groundwork of this study is laid upon a robust dataset sourced from the Center for Research in Security Prices (CRSP), covering an extensive period from 1926 to the end of 2022. This dataset encompasses the entirety of the US market, incorporating data from the NYSE, AMEX, and NASDAQ for various portfolio formations discussed herein. The decision to utilize such an extended time frame was driven by a desire to replicate all the seminal findings of the momentum study by Jegadeesh and Titman, investigate the momentum crashes highlighted in Daniel and Moskowitz, and examine the latest portfolio trends from the Fama and French data site, which will be elaborated upon in Chapter 3. Given the lengthy duration covered by this study, I have chosen to employ cumulative sum returns in my analytical approach. This method allows for the isolation of the strategies' effects without the distortion that might arise from the compounding impact typically observed when performing cumulative product calculations.

To ensure a comprehensive analysis, this study includes results and visualizations for various strategies across multiple holding periods (K=3, 6, 9, 12 months) similar to Jegadeesh and Titman. This approach allows us to evaluate the performance dynamics when these strategies are maintained over different lengths of time. We observe a consistent decrease in alpha as the holding periods are extended, indicating a reduction in excess returns relative to the market. Nevertheless, there is a notable decline in risk, suggesting that longer holding periods may enhance the stability and predictability of the investment outcomes. These findings highlight the dual impact of extended durations on portfolio performance, emphasizing a trade-off between risk and return enhancements.

This paper distinguishes itself from the bulk of existing research by critically examining the potential advantages of engaging in investment activities during the typically inactive one-month interval following stock selection. This approach seeks to leverage short-term reversals that manifest in the interlude between portfolio formation and the subsequent holding phase, a strategy not widely explored in the literature. Additionally, this work evaluates the concept of a "confirming signal," a strategy that synergizes momentum and reversal indicators, in comparison to their independent application. The analysis extends to comparing the impact of using three versus ten buckets on diversification, returns, and risk, and also analyzing what these strategies would like in the 2000s. These detailed examinations are presented in the Appendix. By delving into these areas, the paper pioneers sophisticated techniques that refine and enhance traditional approaches to momentum and reversal investments, paving the way for more intricate investment strategies.

2. Previous Literature

2.1. Pure Momentum Strategy

While researchers like Bird and Casavecchia struggle to pinpoint a clear reason for the short-term underreaction of stocks up to twelve months aligned with the momentum effect, and their subsequent long-term overreaction (leading to contrarian trends), there is a consensus that momentum returns might stem from either investor behavioral biases or more rational factors such as elevated risk levels. Proponents of the behavioral theory argue that it's the reliance on these biases in investment decisions that generate higher returns, painting investors as irrational due to their failure to fully process all available information.

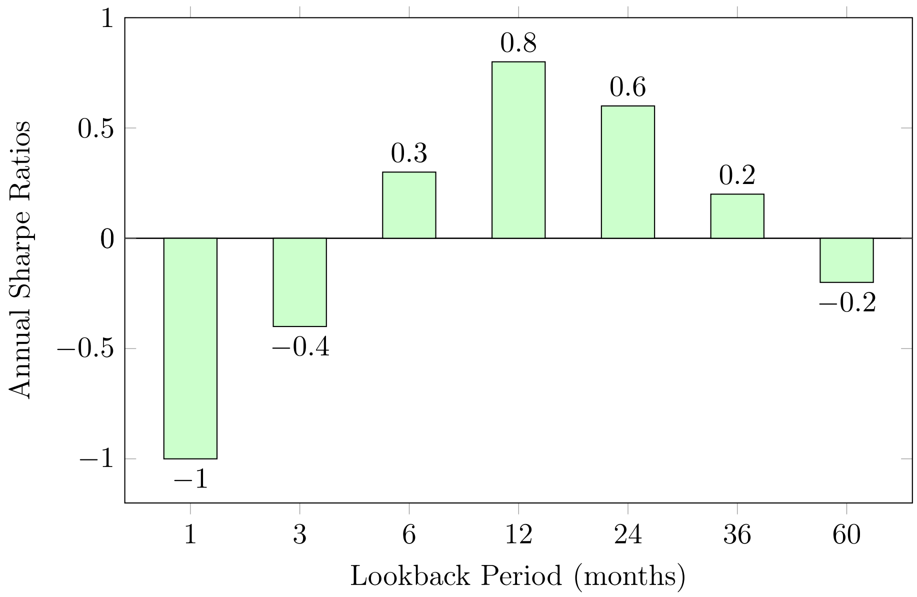
This notion is supported by various studies. For example, Tversky and Kahneman demonstrate that individuals resort to heuristics and biases when faced with uncertain decisions. Additionally, Barberis et al. have noted that individuals tend to react sluggishly to new information. This leads to the assertion that, within short to medium time frames of up to twelve months, people's tendency to underreact to new information causes prices to adjust gradually, as shown by researchers like Frazzini and Kumar and Makhija. On the other hand, it's argued that over more extended periods, individuals' tendency to overreact causes prices to steer excessively in one direction, thereby validating the efficacy of a contrarian strategy as De BONDT and Thaler have suggested.

As mentioned in the introduction, momentum investing is based on the principle that stocks that have exhibited a strong performance in the past are likely to continue their superior performance into the future, whereas stocks with a history of poor performance tend to persist in underperforming. This phenomenon, often referred to as "relative strength," underpins a momentum investment strategy that involves purchasing stocks that have outperformed in the past while selling or shorting stocks that have underperformed.

Empirical evidence supporting the efficacy of momentum strategies is substantial. Jegadeesh and Titman conducted a pioneering study over the period from 1963 to 1990, demonstrating that a strategy that ranked stocks based on their returns over the previous three to twelve months—and subsequently bought the top 10% while shorting the bottom 10% based on this ranking—yielded abnormal annual returns of 12%. This finding underscores the potential of momentum portfolios to capitalize on the cross-sectional continuation of stock performance, betting that a stock's recent relative success or failure is indicative of its future trajectory.

Jegadeesh and Titman have performed these momentum strategies with formation periods (indicated by J) and holding periods (indicated by K) that both range between 3 and 12 months. De BONDT and Thaler have additionally found that profits dissipate over 1 year and even start to reverse after 2–3 years. As shown in Figure 2.1, we can see that the peak of the annual Sharpe Ratio is where the formation period is 12 months. On the outer ends, we will also find the reversal effect (short-term reversal in month 1 and long-term reversal in month 60), with as stronger reversal effect in the short-term reversal of 1 month.

Figure 2.1.: Momentum across different time horizons



In their study, Chan et al. investigate the role of the market's response to information, specifically past earnings news, in the predictability of future stock returns. Their findings indicate that both past returns and earnings surprises are significant predictors of future returns, even after adjusting for other factors. The study explores the origins of this predictability, suggesting that the success of momentum strategies could either stem from the market's medium-term response to earnings-related news or from an overreaction caused by trend-chasing investment strategies. This latter explanation implies that investors amplifying price movements without a fundamental basis could make the returns of previous winners and losers temporary. Chan et al. also note that markets tend to react continuously in the same direction to earnings news, indicating a pattern of initial underreaction.

Barberis et al. build on this discussion by presenting a model that delves into investor sentiment and its impact on earnings expectations. They argue that investors tend to overemphasize the intensity of the evidence presented to them while neglecting its statistical significance, leading to a sluggish adjustment of stock prices to events like earnings announcements, commonly referred to as "sticky prices". With all this proof of overreaction and underreaction in the market, this leaves some room of inefficiency that we can take advantage of with both momentum and reversal.

2.2. Pure Reversal Strategy

In sharp contrast, the concept of a pure reversal strategy is rooted in the observation of short-term reversals in stock prices, where securities that have recently underperformed tend to outperform in the near future, and vice versa. This phenomenon, distinct from the momentum effect, states that stocks exhibit a mean-reverting behavior over shorter periods, such as one month, challenging the momentum strategy's premise that past winners will continue to win and past losers will continue to lose. The reversal strategy, therefore, focuses on capitalizing on the correction of temporary mispricings in the market, which may arise from overreaction or underreaction to news, liquidity pressures, or other market dynamics.

Researchers like Jegadeesh and Lehmann have been pioneers in documenting the short-term reversal effect in stock returns. They argue that the phenomenon is indicative of market inefficiency, where prices temporarily deviate from their fundamental values due to overreaction to recent information or liquidity demands, only to revert to their mean value over time. This view is supported by behavioral finance theories, which suggest that investors' psychological biases and heuristic-driven decision-making lead to predictable patterns of price reversals.

Empirical studies have shown that implementing a strategy based on short-term reversals—specifically, buying stocks that have experienced significant declines and selling stocks that have seen significant gains over a one-month lookback period—can generate significant abnormal returns. For instance, Lo and MacKinlay found that such a strategy, when applied with a one-month holding period, can exploit market inefficiencies and yield positive returns, after adjusting for transaction costs and risks. As we will see in the Methodology and Results chapters, momentum is not always the way to go, and over short periods of time like one month, past winners should actually be shorted and past losers should conversely be longed.

The effectiveness of short-term reversal strategies is based on several key concepts. Firstly, it supports the idea that investors often overreact to new information, causing stock prices to move away from their true value. This means that if a stock's price falls too much due to bad news (or rises too much due to good news), it's likely to eventually return to a more accurate price. Secondly, the strategy benefits from changes in stock demand. Stocks that have recently lost value (or gained value) can see their prices pushed down further (or up) because of investors selling off (or buying) these stocks. This creates a chance to make a profit when these extreme movements correct themselves. Lastly, the strategy uses the bid-ask spread—the difference between the lowest price a seller is willing to accept and the highest price a buyer is willing to pay. Prices can seem to change direction as trades happen at these different prices, further opening opportunities for reversal strategies to work.

In their seminal work, De BONDT and Thaler extend the discussion on reversals to a longer horizon, providing a foundational basis for understanding the mechanics behind price reversals and their implications for market efficiency. They suggest that the long-term reversal effect, observable over three to five years, is primarily driven by investors' overreaction to historical information, leading to a subsequent correction.

Zhang, focusing on the microstructure of the market, examine the impact of trading frictions and market liquidity on the profitability of short-term reversal strategies. Their findings highlight the importance of considering transaction costs and market conditions when implementing such strategies, as these factors can significantly affect the net returns. Despite the undeniable relevance of trading costs in the execution of these strategies, this analysis intentionally omits such costs. The rationale behind this decision is to isolate and evaluate the core performance of both the momentum and reversal strategies, excluding external variables. By omitting the impact of transaction costs, the focus shifts to assessing the strategies performance.

The approach introduced by Novy-Marx, which combines the reversal strategy with a detailed analysis of the stocks themselves, is definitely worth mentioning. They suggest that mixing signals from price trends with fundamental analysis of a company's actual value can make the strategy work better and be less affected by unpredictable market changes. This method shows how a deeper look at reversal strategies, using both price movements and a company's real worth, can help make smarter investment choices. Although this approach has strong benefits, my paper mainly looks at the basic returns from momentum and reversal strategies and leaves out other factors.

The pure reversal strategy, particularly when employing a one-month lookback and holding period, offers a striking comparison to the momentum strategy, highlighting the behavior of stock market movements. This approach seeks to capitalize on short-term market mispricings and investor behavior patterns, potentially leading to enhanced returns. However, it requires an awareness of the associated risks and demands the implementation of advanced risk management practices. By navigating these complexities, investors may unlock the potential for above-average gains.

2.3. Momentum Strategy Crashes

As stated in the introduction and pure momentum strategies section, momentum does not last forever, and there is an optimal time to look back and hold the portfolios. In their paper, Daniel and Moskowitz delve deeper into momentum crashes in times of high volatility. In normal situations, the trend where stock prices continue to move in the direction they have been—either up or down—is both significant and impactful across different stock markets and types of investments. However, during times of panic, after significant market downturns, or when the market is very volatile, stocks that have recently performed poorly become more valuable. As the market begins to recover, these underperforming stocks often see notable increases in value, leading to a problem for strategies that bet against these stocks.

This is where the term "momentum crash" starts to make sense. Their research shows that during tough market conditions, especially when the market is highly volatile, these underperforming stocks don't lose as much value when the market goes down further, but they gain a lot more when the market starts to improve, thereby diminishing the returns coming from the sell-side of momentum and even hurting the momentum strategy altogether. This kind of behavior—similar to having the option to buy or sell at advantageous conditions—isn't typically priced into these stocks. Therefore, these stocks are expected to offer high returns, and the usual momentum strategy doesn't work as well during these times. Interestingly, this pattern isn't mirrored for the stocks that had been performing well during good times, which suggests there's a difference in how winning and losing stocks react to market changes during extreme conditions.

The researchers explore a range of potential explanations for their observations, from the risk of dramatic market crashes to fluctuations in volatility and other market factors like those identified by Fama and French (b). However, they conclude that none of these theories completely explain the phenomena they've observed. While the idea proposed by Merton suggests that equities exhibit option-like returns, an alternative interpretation could be aligned with behavioral finance theories, which suggest that in extreme market conditions, individuals tend to become overly cautious and focus excessively on avoiding losses, often without properly considering the actual probabilities of such outcomes. Whether these behavioral tendencies can fully account for the empirical findings observed across different markets and asset classes remains an open question. This issue points to the need for further research to determine if the behavior of market participants consistently affects these diverse markets, despite the differences in the profiles of average and marginal investors across these domains.

Interestingly and intuitively enough, the volatility might come from the fact that the stocks have high betas. Grundy and Martin build on the work of Kothari and Shanken to analyze price momentum strategies with respect to betas. Their findings highlight a simple yet underappreciated aspect of how these strategies perform in relation to market movements. Specifically, they observe that when the market has experienced a significant decline during the period used to determine momentum (from a 12-month lookback to a one-month lookback period in their study), it's likely that the companies whose stock prices fell alongside the market are those with high sensitivity to market changes (high-beta firms), while those that performed well are less sensitive to market changes (low-beta firms).

Consequently, after a market downturn, a momentum-based investment strategy would typically involve buying stocks of the past winners (low-beta firms) and selling stocks of the past losers (high-beta firms). Their empirical analysis confirms that the beta of stocks in a momentum portfolio can vary significantly over time. They find that, following major market declines, betas for the past-loser decile can rise above 3 and fall below 0.5 for past winners. Therefore, if the market recovers quickly, momentum strategies can fail dramatically because they are positioned in a way that is effectively betting against the market recovery, due to their "conditionally large negative beta." This means that the strategy's overall position becomes more profitable if the market continues to fall, but loses value if the market rebounds. As we have seen with the all-too-unpredictable market situation following the COVID-19 crisis, there have been a number of market rebounds and high volatility environments that deem the momentum strategy ineffective. As we will see in the 2000s results and plots, where there have been multiple crashes, these strategies were not useful in combating market downturns.

2.4. Linking Reversals to Momentum

Conrad and Yavuz, in their creatively-titled book "Does What Goes Up Always Come Down?", hammer down proof that reversals are seen around momentum and state that they are *linked* in one way or another. In other words, Figure 2.1 explains their paper more simply. When investigating the relationship between momentum and reversal patterns, the expectation is that stocks demonstrating momentum in the 0–6 month time-frame are more prone to exhibit reversals in the subsequent 12–24 month period. To explore whether the returns from momentum and reversal are attributed to the same securities, the researchers divide the momentum portfolios into two distinct sub-components:

1. The "realized momentum" component encompasses stocks that have continued their initial momentum in the first 6 months, including those that maintained their winning status and those that remained losers
2. Conversely, the "contrarian/reversal" component consists of stocks that have shown a reversal in the initial 6 months, meaning former winners that turned into losers and vice versa

This division is based on an analysis of monthly returns for winners, losers, and winners-minus-losers portfolios across various holding periods, specifically 0–6, 6–12, 12–24, and

24–36 months. The analysis accounts for a 1-month gap between the portfolio formation period and the following holding period. Merging these separate subgroups of securities makes momentum and reversal patterns appear to be linked.

The studies by Jegadeesh and Lehmann are crucial in identifying and explaining the phenomenon of short-term reversals in stock prices. Their research convincingly shows that stocks experiencing significant price movements over a short period often reverse direction in the following month. This reversal pattern is attributed to the market's tendency to overreact to news or events, which temporarily distorts stock prices. By incorporating a 1-month gap between the period of observation and the commencement of investment, their methodology adeptly navigates the volatility of immediate market reactions. This gap effectively filters out short-term noise, allowing for a more accurate assessment of enduring price movements that materialize after the initial market fluctuations settle.

This approach takes into account how quick and emotional reactions to news in the stock market can obscure the actual worth of a stock. The 1-month buffer is crucial for distinguishing between rapid, emotional market responses and the more gradual, rational adjustments to new information. Their work not only sheds light on the existence of short-term reversals but also offers a strategic approach to capitalizing on these movements. As we move on to the Methodology, we will include a 1 month lag to account for this short-term reversal, use its signal to our advantage in our "confirming" approach, and finally ride the short-term reversal wave by investing in this period as opposed to simply ignoring it.

3. Methodology and Data

3.1. Data

This section outlines the dataset employed in this study and the procedures undertaken for its cleaning and processing, which were essential steps in the development of the investment portfolios. Additionally, it provides insight into the rationale for specific decisions made during this process. Processing of the data and formation of the portfolios was performed with Python and excel.

3.1.1. Data Sources

The dataset comprises monthly records sourced from the Center for Research in Security Prices (CRSP) and spans from 1926 to the end of 2022. It focuses on common stocks, identified by share codes 10 and 11, from major stock exchanges including the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ). These stocks are further categorized by the following exchange codes and definitions:

- *-2, -1, 0*: Halted/suspended/not trading by the NYSE/AMEX/NASDAQ [1]
- *1 and 31*: NYSE
- *2 and 32*: AMEX
- *3 and 33*: NASDAQ

Although the data used particularly focuses on the methodology of using 10 buckets in the period from 1926 to 2022, I will additionally include results from using 3 buckets and experimenting with the different time-frame of 2000-2022 that will be included in the Appendix. In establishing benchmarks, this study draws upon the datasets that were made available by Fama and French (a) and Daniel and Moskowitz.

For those interested in conducting further research, the following resources were invaluable: The Fama French repository, a detailed description of the Fama French data, and the Daniel Moskowitz database. Additionally, for my Python code, I heavily depended on a combination of the following three sources: Alan Moreira, Drechsler, Qingyi (Freda)

[1] These exchange codes were used to address the issue that stocks temporarily stopped trading. Without them, the non-trading months will be tossed out in the output leading to wrong cumulative returns.

S., 2023, Python Programs for Empirical Finance, and Yuhang(Jessie) Jiang (Github). These resources have been vital in accumulating data on portfolio momentum and reversal strategies employing three and ten buckets, as shown in the seminal works by Fama-French (FF) and Daniel-Moskowitz (DM). Finally, the risk-free rate (rf), market rate (mkt) [2], high-minus-low portfolio (HML), and small-minus-big (SMB) portfolio were taken from the FF site.

Fama and French in their papers Fama and Fama and French (b) explain that the mkt, rf, HML, and SMB variables have the following definitions:

- **Market (mkt):** Value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ
- **Risk-free rate (rf):** One-month Treasury bill rate (from Ibbotson Associates)
- **High Minus Low (HML):** The average return on the two FF value portfolios minus the average return on the two FF growth portfolios
- **Small Minus Big (SMB):** The average return on the three FF small portfolios minus the average return on the three FF big portfolios

3.1.2. Data Processing

The initial dataset, sourced directly from CRSP, required several modifications before it could be utilized for portfolio construction. Specifically, instances of missing returns, indicated by the placeholders *-66, -77, -88, -99*, were substituted with *NaN* values. This approach diverges from methodologies in other studies where missing values are replaced with zeros, a practice that I intentionally avoided to prevent the inclusion of stocks with missing returns into the "middle" buckets during the portfolio formation process.

Additionally, to calculate market equity (ME), I performed a multiplication of the stock prices by the shares outstanding. The returns were subsequently transformed into logarithmic returns in order to prepare the data for cumulative calculations over the formation periods. To do this, the monthly dates had to align first. I noticed that the dataset's timestamps were predominantly monthly; however, inconsistencies existed with some dates not aligning with the end of the month. To address this, adjustments were made by adding one to two days to the affected timestamps wherever necessary. This did not alter the data to a large extent but was mostly performed for correct python readability and processing.

The concept of a delisting return (dlret) refers to the performance of a security after its removal from an exchange. In the process of consolidating our dataset, the delisting returns were integrated into the monthly returns for instances where they were absent. In

[2] rf was added back to mkt-rf to result in mkt

cases where both monthly returns and delisting returns were present for a specific date, the combined return was calculated using the following formula:

$$(1 + ret) * (1 + dlret) - 1 \tag{3.1}$$

After completing the data processing, the resulting dataset spans firms from 1926 to 2022, as depicted in Figures 3.1 and 3.2. This visualization categorizes stocks into 10 distinct groups, yet a similar distribution of firms is observed when they are organized into only 3 groups. The pronounced increases in the number of firms in 1964 and 1974 can be attributed to expansions in the coverage of CRSP's flagship databases. Initially, CRSP included common stocks traded on the New York Stock Exchange (NYSE) starting from 1926. It later extended its coverage to incorporate stocks traded on the American Stock Exchange (AMEX) beginning in 1962, and subsequently included those traded on the NASDAQ starting from 1972. Furthermore, a notable event occurred in 2008 when the NYSE acquired AMEX, leading to their unification under a single stock exchange entity.

A close up on the 2000-2022 years as shown in Figure 3.3 shows us a decrease in the number of firms after the peak in 1996, most likely coming from the following 3 reasons:

1. Bankruptcy, failure, or closure of listed firms
2. Delisting of firms going private or acquired
3. Decrease in the number of initial public offerings (IPOs)

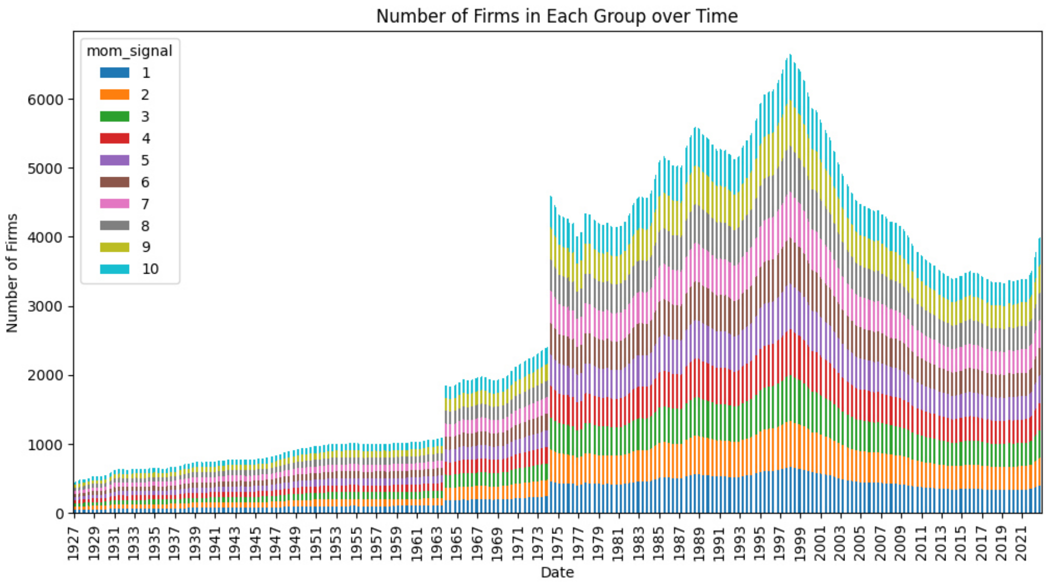


Figure 3.1.: Number of firms over 1926–2022 - 10 buckets

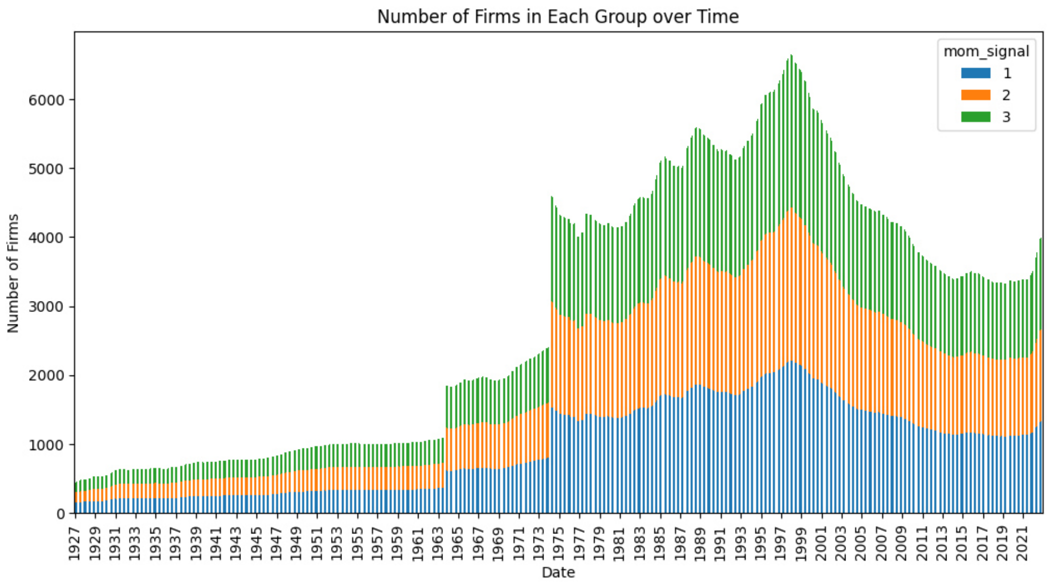


Figure 3.2.: Number of firms over 1926–2022 - 3 buckets

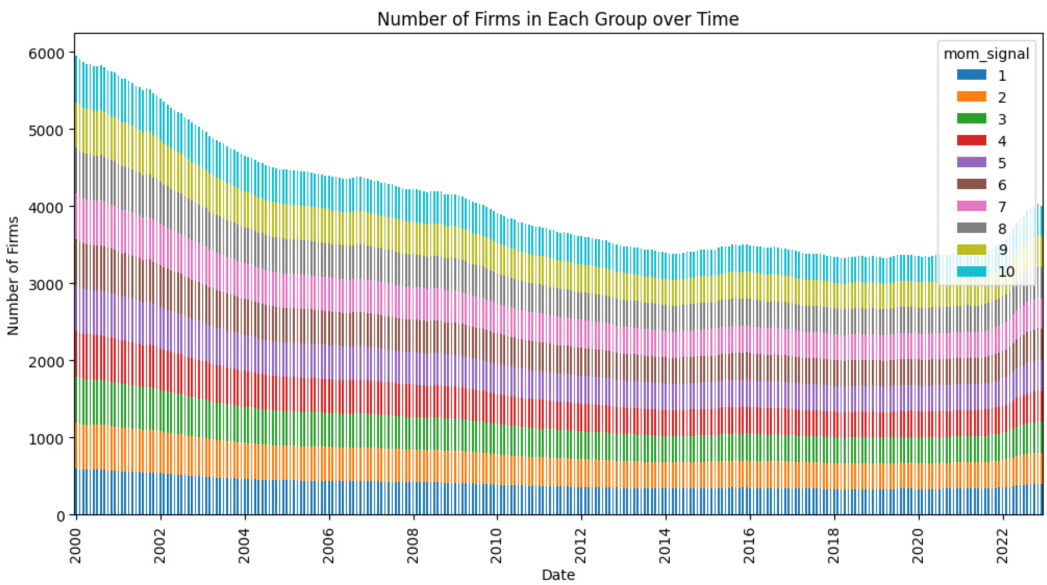


Figure 3.3.: Number of firms over 2000–2022 - 10 buckets

3.2. Methodology

Although Jegadeesh and Titman extensively analyzed various lookback and holding periods of 3, 6, 9, and 12 months each, this study, similar to Daniel and Moskowitz, narrows its focus to examining the outcomes of a 12-month lookback period coupled with a 1-month holding period, featuring monthly portfolio rebalancing. This methodology is adopted to facilitate a direct comparison of results by incorporating the short-term reversal effect during the waiting period, rather than omitting this phase altogether. Nevertheless, I have still calculated the results of the different holding periods and have shown the plots to better visualize the impact that different holding periods have on these strategies, which can be found in section 3.2.4.

To construct the momentum portfolios, stocks are initially sorted by their total returns from the period starting 12 months to 1 month prior to the portfolio formation date (i.e., returns from t-12 to t-1 months). To put this into perspective, if we had 1,000 stocks, we look at their individual performance over the past 11 months and group them into 10 equal buckets, where each bucket represents 100 stocks [3]. In more practical terms, taking this whole 12 month time-frame into account, the first 11 months will be used to judge the performance of the stocks by accumulating returns and placing them into buckets, after which we will wait 1 month, before implementing our strategy to avoid the short-term reversal month as seen in Figure 3.4:

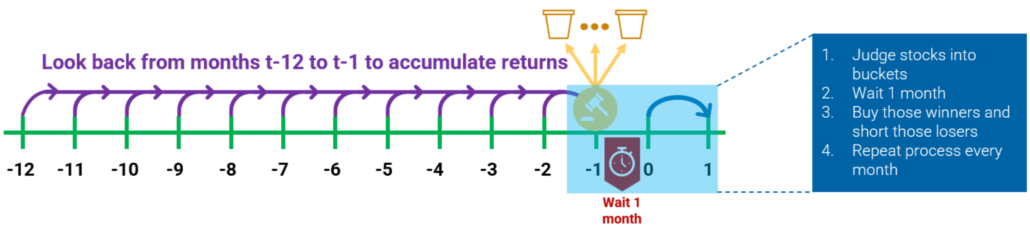


Figure 3.4.: Momentum Daniel-Moskowitz

This method follows established practices in the field Jegadeesh and Titman, Asness, Fama and French (a), incorporating a one-month *waiting period* between the ranking period's conclusion and the holding period's commencement. This buffer is designed to mitigate the impact of short-term reversal effects, as identified in studies by Jegadeesh and Lehmann. Specifically, the analysis will concentrate on stocks falling into the 10% and 90% quantiles of the return distribution, from which we will form portfolios comprising stocks at both the lower and upper extremes of this spectrum. For ease of readability, we will focus mostly on the 10-bucket method ranging from 1926-2022. Nevertheless, the results regarding the 2000s and the 3-bucket approach will be mostly included in the Appendix.

[3] The worst bucket represents the *losers* and the best bucket represents the *winners*

In constructing the momentum and reversal portfolios, I have formulated a step-by-step guide ranging from the lookback period to the implementation of the strategies:

1. **Computation of J Cumulative Returns:** For each stock, the returns are accumulated over the desired period. In our case, $J = 11$–12 months for momentum and $J = 1$ month for reversal

2. **Trading Signals:** Based on these accumulated returns, the stocks are ranked/split evenly into the desired number of buckets (3 or 10 buckets in our case)

3. **Value-Weighting Scheme for Trading Efficiency:** A value-weighting approach is adopted to optimize trading efficiency. This is mathematically represented as:

$$R_{t+1}^{mkt} = \sum_{i}^{I} \frac{m_t^i}{\sum_i^I m_t^i} R_{t+1}^i \tag{3.2}$$

4. **Implementing Strategy:** The momentum strategy will subtract $winners - losers$, while the reversal strategy will subtract $losers - winners$

5. **Statistics:** The statistics are calculated on the excess returns

6. **Cumulative Return Analysis:** The cumulative sum of returns is calculated to provide a graphical representation of the strategy's performance over time

In this paper, my primary focus centers on exploring the outcomes derived from two distinct strategies:

1. Capitalizing on the short-term reversal period by adopting it as a proactive investment approach, rather than viewing it as merely a duration to be "waited out"

2. Employing the short-term reversal signal to confirm/reinforce the momentum signal, thus integrating it as a *verification mechanism* within the investment strategy

To lay a comprehensive foundation for this analysis, I will initially delve into the individual performance of both momentum and reversal strategies, examining their outcomes with and without the inclusion of the intervening period and compare them to the benchmarks from the Fama-French and Daniel-Moskowitz portfolios. This will be followed by an in-depth examination of the efficacy of the reversal signal as a corroborative indicator for momentum. Subsequently, I will explore the synthesis of momentum and reversal strategies into a unified investment approach, evaluating the potential synergies and enhancements this combination may offer.

Considering the strategies span a long period and outliers could greatly affect the analysis results, I have opted to calculate the sum of logarithmic value-weighted returns instead of accumulating the product of the returns (where the compounding effect can kick in). This approach is taken as we're primarily interested in evaluating the returns and comparing the relative performance of the strategies, allowing for effective comparison among them. I have used this calculation approach for the benchmark portfolios from Fama and French (a) and Daniel and Moskowitz, as well as the market and risk-free portfolios.

Plots will be shown in this chapter so that we are better able to visualize the splits and methodology used in the specified strategies. This will shortly be followed by the statistics in the Results chapter where we will dive deeper into the comparison of these approaches, especially taking into account the returns, risks, and other statistical measures of the respective strategies.

3.2.1. Pure Momentum & Reversal

Following the groundwork laid out in Chapter 3, this section will explore the pure momentum and reversal strategies, with a special focus on incorporating a *skip* duration of one month for the momentum strategy. The figures that will follow will include the cumulative returns of the individual groups over time on the left-hand side, and the performance of the specified investment strategy will be shown on the right-hand side.

FF_mom or FF_rev followed by a number represents the portfolios laid out in Fama and French (a), where 3 and 10 represent the number of buckets used for momentum and reversals. The risk-free rate (rf) and market (mkt) are also taken from the Fama-French repository. Finally, the DM_mom_10 portfolio is coming from the Daniel and Moskowitz repository. This is the portfolio I am mainly trying to replicate. The main difference between the Daniel-Moskowitz (DM) and Fama-French (FF) momentum portfolios with 10 buckets is that the FF portfolios use only NYSE breakpoints[4] while DM portfolios use breakpoints of the whole market (NYSE, AMEX, and NASDAQ). While the FF portfolios are constantly updated and range the entire timeframe of this study, the DM portfolios unfortunately are limited to 2016 due to the isolated research for that specific paper. Nevertheless, we can imagine that the portfolio I create follows a similar trend as the DM portfolios into the future given the c.99% correlation I have managed to achieve.

We first start by trying to replicate the DM portfolios; specifically the momentum strategy with a 1-month *skip* mechanism, as illustrated in Figure 3.5. When we examine the left side of the figure, we can clearly see the division of the ten groups based on their performance. The best performers, labeled as *winners (10)*, show the strongest results

[4] FF use only NYSE breakpoints to avoid buying only small-cap stocks in the 1970-1990 era when the NASDAQ stock exchange was just starting out.

over time, whereas the poorest performers, or *losers (1)*, fall behind during the same period. The strategy of buying the winners and selling losers *(Winner Minus Losers - WML)* is represented by the yellow line in the right-hand side of the figure. I try to stick to using yellow for my strategies for the readers to easily locate the trajectory of my portfolios and how they compare to the other benchmarks. Opting to buy only winners might seem like a straightforward path to high returns, but it doesn't fit with the *zero-cost investment strategy* we are aiming to achieve, as discussed in Asness et al..

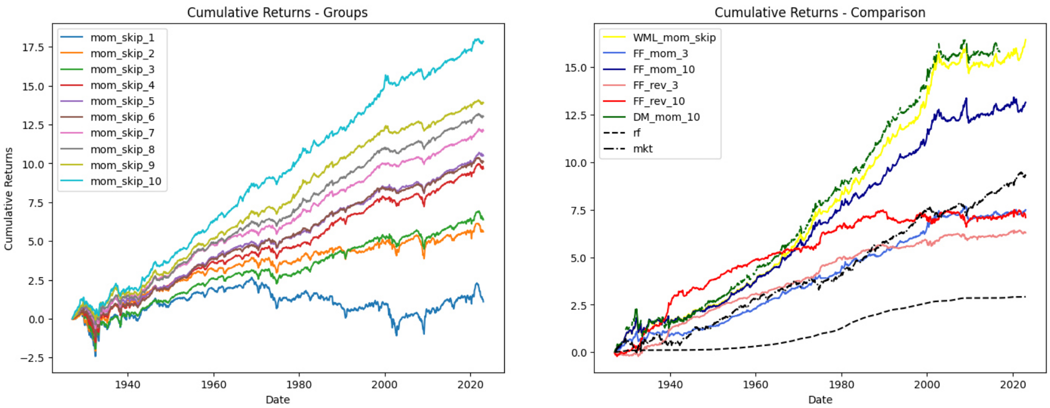


Figure 3.5.: Momentum w/ skip mechanism

To understand the impact of omitting the 1-month waiting period between the formation and holding periods, which is aimed at circumventing the short-term reversal, I directly initiated the strategy following the formation period, bypassing the skip function. In other words, we now use both 11 and 12-month formation periods where we commence the investment instantly as opposed to waiting 1 month before doing so. As one might anticipate, and a key reason why this waiting period is widely adopted in the investment world, the strategy's performance suffers significantly in both of these scenarios, with slightly better results when the formation period is 12 months. This decline is primarily because the short-term reversal undermines the gains coming from the medium-term momentum. Figures 3.6 and 3.7 showcase how this dip in performance can be attributed to the short-term reversal eating away at the gains of the momentum strategy.

With the justification for the waiting period established, it's insightful to also examine the short-term reversal strategy in isolation and compare it to the benchmark Fama-French reversal portfolio **FF_rev_10**, which also categorizes stocks into 10 buckets. This comparison is visualized in Figure 3.8. The short-term reversal is made of a 1-month lookback period and a 1-month holding period. The primary variance between them once again hinges on the selection of breakpoints, though this difference is minor and the replication is quite accurate in my case. In contrast to the momentum portfolios, the reversal strategy showed its peak performance during the early 1940s and 1950s, after which it plateaued and remained relatively stable even up to 2022. This shift could likely

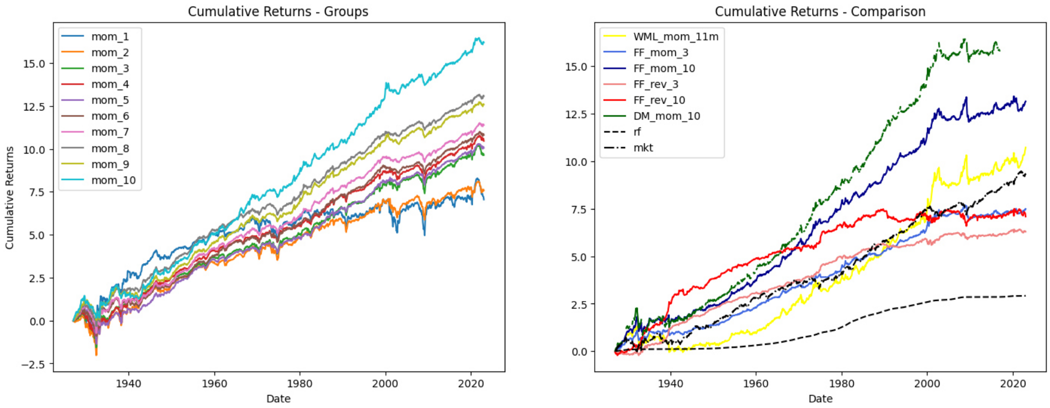


Figure 3.6.: Momentum w/o skip mechanism - J=11 months

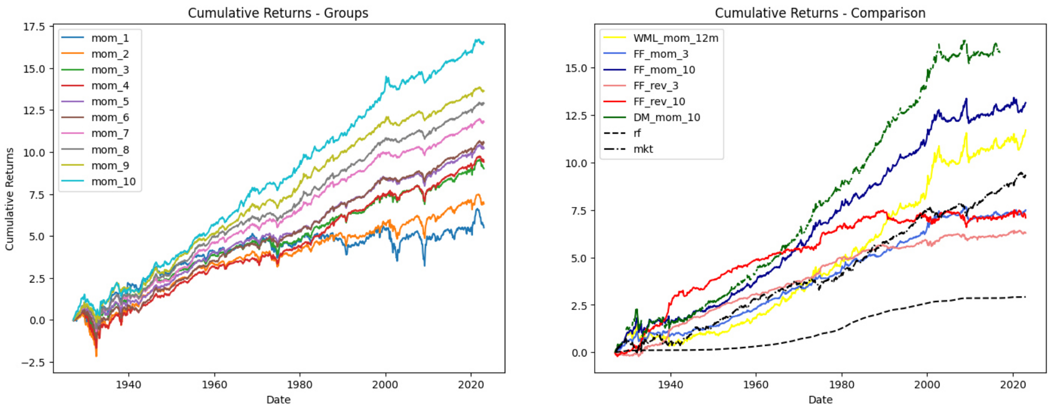


Figure 3.7.: Momentum w/o skip mechanism - J=12 months

be attributed to changes in market participants' behavior—investors have become less reactionary and more informed over time, as shown in Daniel et al..

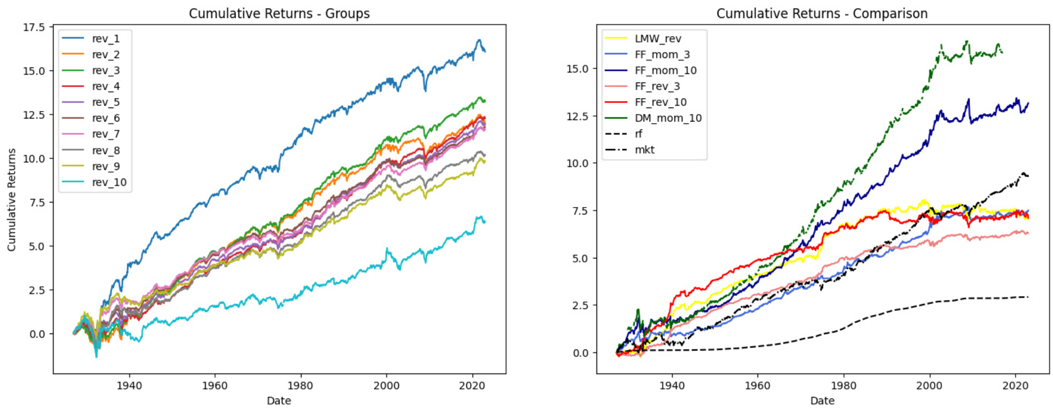


Figure 3.8.: Reversal - Losers Minus Winners

3.2.2. Confirming Signals

Now that we've looked at both pure momentum – with and without the skip mechanism – and reversal strategies, we can now also visualize what it would look like to use the signal that comes from the short-term reversal and implement it into the momentum strategy as seen in Figure 3.9. In other words, this would mean that:

- We initiate a buy action only when both the 1-month lookback signal from the short-term reversal and the medium-term momentum signal agree on a **buy**
- Conversely, we proceed to sell only when both signals agree on a **sell**

It goes without saying that there is no skip mechanism in the momentum strategy as we are using the short-term reversal signal to our advantage, however, we would like to analyze if there is any difference between a lookback period of 11 or 12 months. Before viewing the results, we will first visualize the large decrease in the number of stocks given the larger filter that a stock has to go through in order to be part of the portfolio. It is called a *confirming* signal because it is first set by the signal coming in from medium-term momentum, but it is only included in the final portfolio if it is also confirmed by the short-term reversal. The number of firms with the confirming signal is shown in Figure **??**. Only buckets 1 and 10 are shown since we are only interested in the buy (winners) and sell (losers) signals.

Figures 3.10 and 3.11 show the performance of these two portfolios on the left-hand side and the winner-minus-loser strategy in comparison to the other portfolios on the right-hand side. We see that these portfolio outperform the other portfolios and this is to be expected given the small amount of stocks and the strategy being focused more on extreme winners

ST Reversal / MT Momentum	"Sell"	"Hold"	"Buy"
"Sell"	Strong sell	Weak sell	Weak buy
"Hold"	Weak hold	Strong hold	Hold
"Buy"	Weak buy	Weak buy	Strong buy

Figure 3.9.: Confirming signals - Momentum and Reversal

and losers over such a long period of time. These two strategies of using a lookback period of 11 and 12 months are almost identical in the plots, but they do differ slightly in the statistics as we will see later in Chapter 4. However, as the subsequent statistical analysis will reveal, this strategy does not come without its fair share of increased risk.

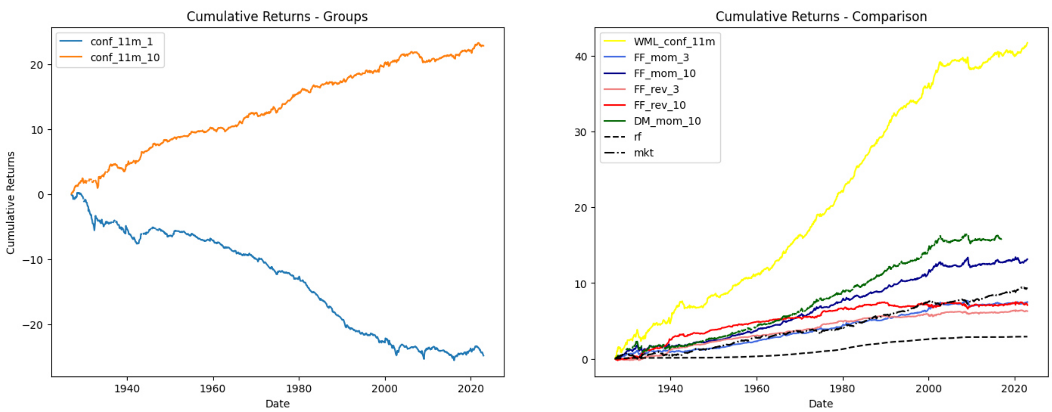


Figure 3.10.: Confirming signal - J=11 months

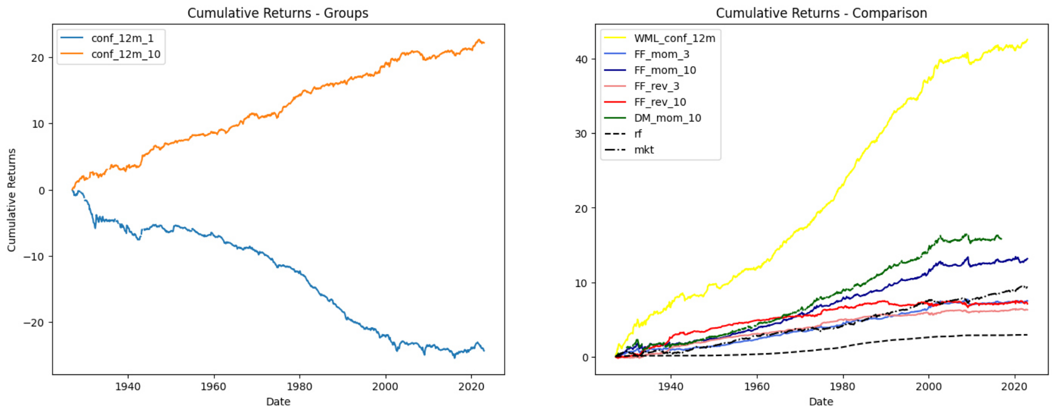


Figure 3.11.: Confirming signal - J=12 months

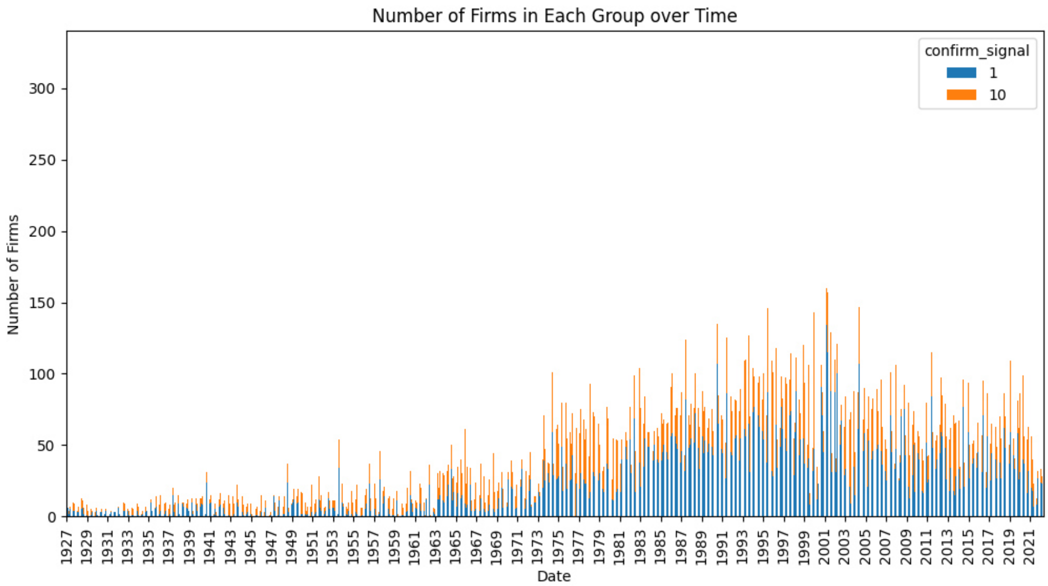


Figure 3.12.: Confirming signal groups

3.2.3. Combining Momentum and Reversal

We can now explore the innovative strategy that intertwines the short-term reversal with the medium-term momentum approach. This strategy diverges from the conventional waiting period outlined in Figure 3.4. Instead of waiting, we actively engage during this period by adopting the short-term reversal strategy, which, like the momentum strategy, operates on a zero-cost basis. This dual-strategy framework introduces three distinct lookback periods: The 11 and 12-month periods for capturing medium-term momentum and the 1-month period for identifying short-term reversals. This approach unfolds into three compelling methodologies:

1. Simultaneous short-term reversal and medium-term momentum, where J=11 months and the strategy is implemented instantly
2. Simultaneous short-term reversal and by medium-term momentum, where J=12 months and the strategy is implemented instantly
3. Short-term reversal followed by medium-term momentum, where J=11 months and there is a one-month pause after the stocks are grouped to allow for the short-term reversal to take place before applying the medium-term momentum strategy

Essentially, these strategies will overlap with each other after the second month and this is what Jegadeesh and Titman and Daniel and Moskowitz admit to as well. Already from the second month onwards, we are involved in both reversal and momentum strategies at the same time that can include overlapping portfolios. As we can see from Figure 3.13, the left-hand side of the figure illustrates pure momentum – 11 and 12-month formation periods with and without the skipping mechanism – and pure reversal, while the right-hand side of the figure showcases the result of bringing short-term reversals into the mix. LMW stands for Losers-Minus-Winners and WML stands for Winners-Minus-Losers.

Notably, the performance improves the most with the implementation of the skip mechanism, followed by the 12 month lookback period and finally the 11 month lookback period, all labeled in shades of yellow. This improvement is logical as we have already mentioned, since it allows for sidestepping the short-term reversal, capitalizing on it through strategic engagement, and then progressing with the known momentum strategy. Interestingly, we also observe a smoothing and steady increase in cumulative returns over time. This trend is likely attributable to the diversification benefits arising from the low correlation between these strategies, a phenomenon discussed in Markowitz.

To illustrate the concept of integrating short-term reversal and medium-term momentum strategies, we adjust the timing of the short-term reversal outcomes by delaying them by one month. This allows us to calculate the combined effect of both strategies at any given point, essentially simulating a holding period of two months. This process is depicted in Equation 3.3. Following this, we proceed to accumulate the results, maintaining consistency with previous calculations, while all other variables remain unchanged. The

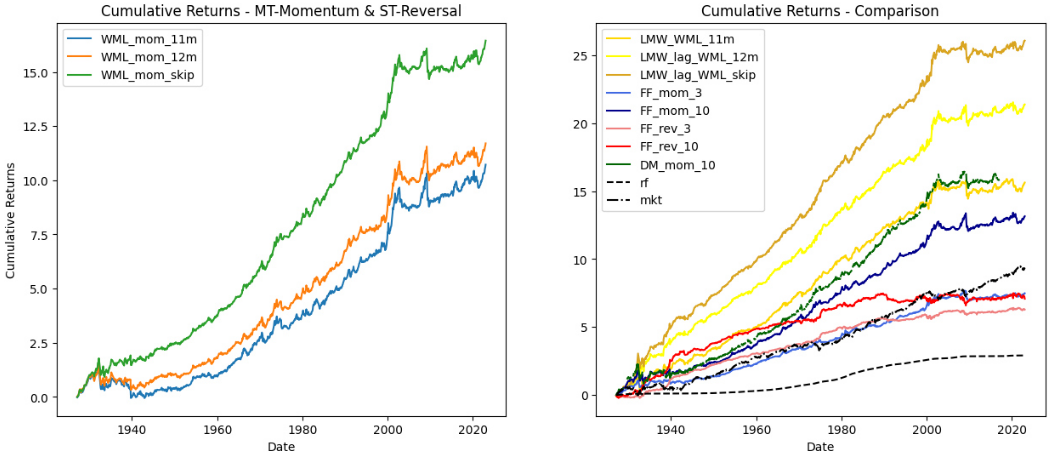


Figure 3.13.: Combining Momentum and Reversal strategies

insights generated by the momentum strategies, both with and without the skip feature, are independent from those of the reversal strategy. It becomes evident that the optimal performance is achieved by merging the momentum strategy, specifically with the skip option, with the short-term reversal data from the preceding month. For a detailed analysis of these outcomes and the interplay between the strategies, refer to Chapter 4.

$$(1 + r_{mom_t}) * (1 + r_{rev_{t-1}}) \tag{3.3}$$

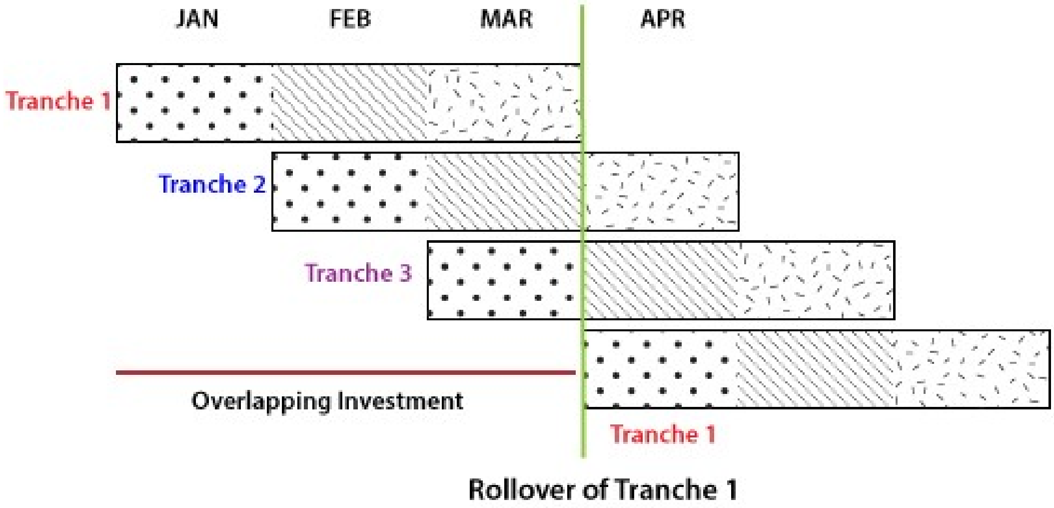


Figure 3.14.: 3 month holding period tranches practical example

3.2.4. Exploring Various Holding Periods

To ensure a comprehensive analysis in this paper, I will explore how different holding periods affect the returns of the portfolios under study. Following the methodology similar to Jegadeesh and Titman, I will examine holding periods denoted as "K" months, specifically over intervals of 3, 6, 9, and 12 months, while maintaining consistency in all other variables. Given that the trends across different analyses are generally consistent, I will limit my detailed examination to the ten-portfolio methods to maintain clarity and conciseness in the presentation of our findings.

In understanding the concept of overlapping portfolios when having multiple months as holding periods, we can look at the following example 3.14. In Jegadeesh and Titman, as well as subsequent studies, the monthly return for a given month, such as March, is calculated by averaging the returns across various tranches for that month. Specifically, the monthly return for March is determined by averaging the returns from Tranche 1 in March, Tranche 2 in March, and Tranche 3 in March. As illustrated in the accompanying diagram, Tranche 1 includes stocks purchased at the end of December and held through January, February, and March. Similarly, the process is applied to the other tranches. While this method is straightforward, it is worth mentioning that it might not capture the full realism of market behaviors or suit everyone's preferences, acknowledging that alternative methodologies could also be viable. In practical terms, this would be the same as having rolling period returns for "K" amount of months and extracting the average over that period of time to avoid any double-counting that can occur.

For the sake of brevity and since all the strategies have the same plots as above, only being different in the fact that they look less risky (or more "smooth") as we increase the holding period, I will post all the results below and you may notice the comparison, that as we move across the different holding periods, the lines smooth out, indicating that increasing the holding period tends to stabilize portfolio returns. This smoothing effect can primarily be attributed to the reduced impact of short-term market volatility on longer-duration holdings. Over extended periods, portfolios are less susceptible to the fluctuations seen in daily or monthly returns, which often reflect immediate market reactions to news or events rather than underlying economic trends. As such, longer holding periods can buffer investors from the market's short-term noise and provide a clearer picture of the investment's performance trend. This can be particularly beneficial for assessing the effectiveness of portfolio strategies over time, offering a more reliable basis for comparison and decision-making. This effect underscores the importance of considering time horizon in investment strategy planning, aligning investor goals with appropriate risk exposure and return expectations. In more practical terms, this can also be attributed to the fact that the average is performed to measure the returns over a certain "K" amount of months and the longer the period is, the longer the period is to average.

For easier readability, the strategies will be posted in the following order with the holding periods being 3, 6, 9, and 12:

1. Momentum w/ skip mechanism
2. Momentum w/o skip mechanism - J=11 months
3. Momentum w/o skip mechanism - J=12 months
4. Reversal - Losers Minus Winners
5. Confirming signal - J=11 months
6. Confirming signal - J=12 months
7. Combining Momentum and Reversal strategie

Momentum w/ skip mechanism

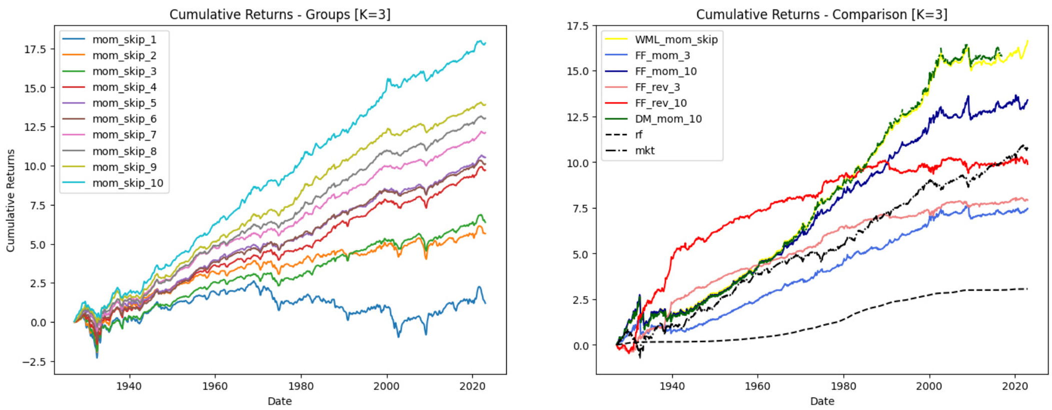


Figure 3.15.: Momentum w/ skip mechanism - K=3 months

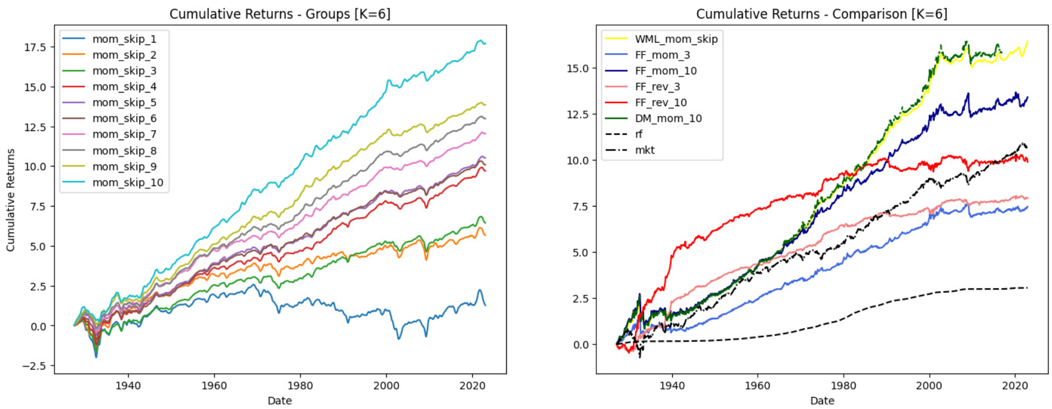


Figure 3.16.: Momentum w/ skip mechanism - K=6 months

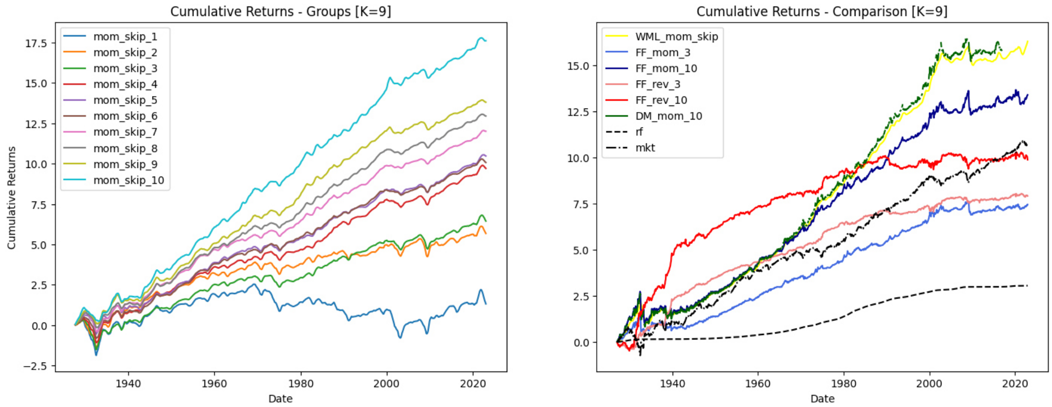


Figure 3.17.: Momentum w/ skip mechanism - K=9 months

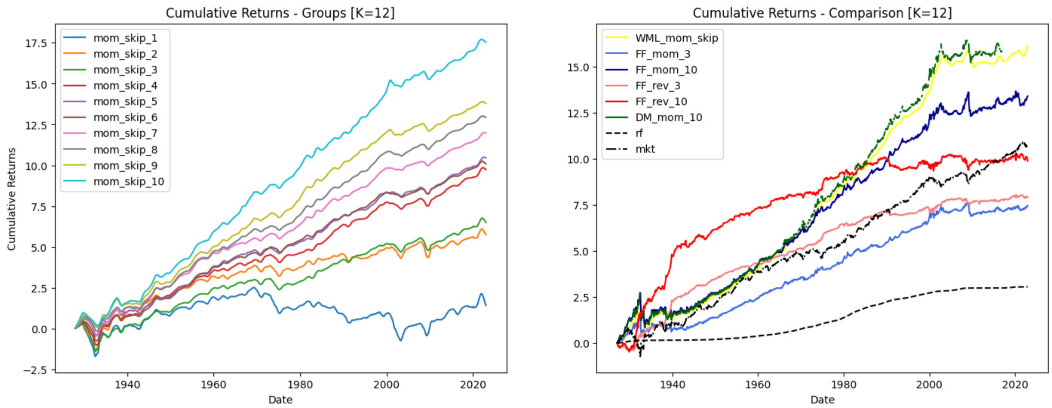


Figure 3.18.: Momentum w/ skip mechanism - K=12 months

Momentum w/o skip mechanism - J=11

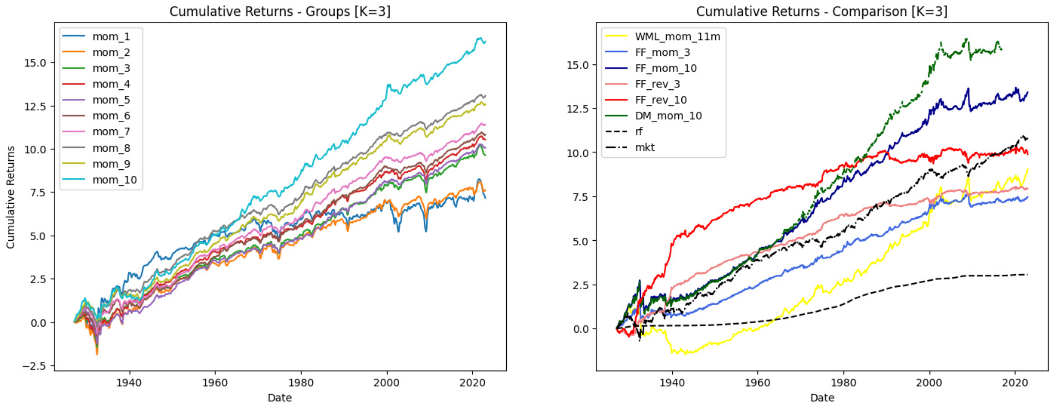


Figure 3.19.: Momentum w/o skip mechanism - J=11, K=3 months

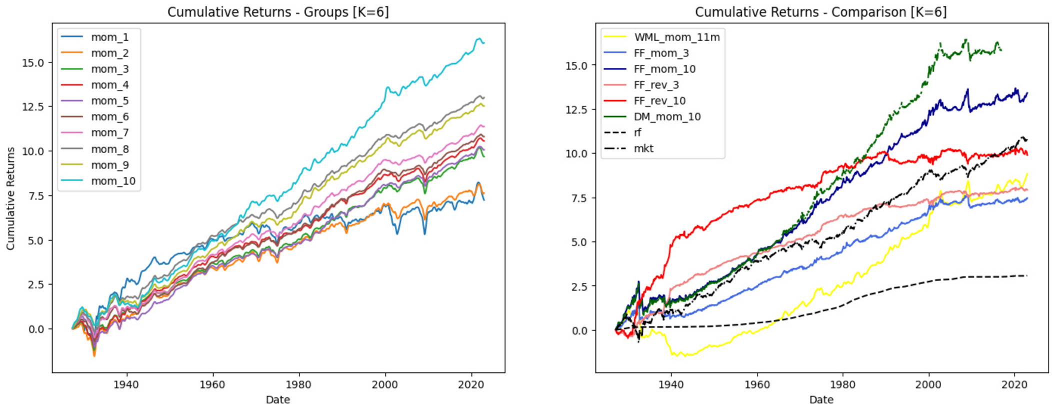


Figure 3.20.: Momentum w/o skip mechanism - J=11, K=6 months

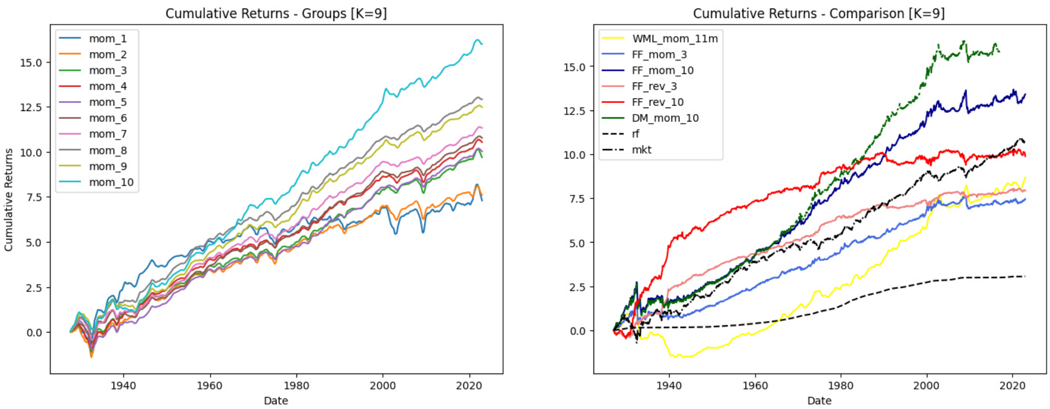


Figure 3.21.: Momentum w/o skip mechanism - J=11, K=9 months

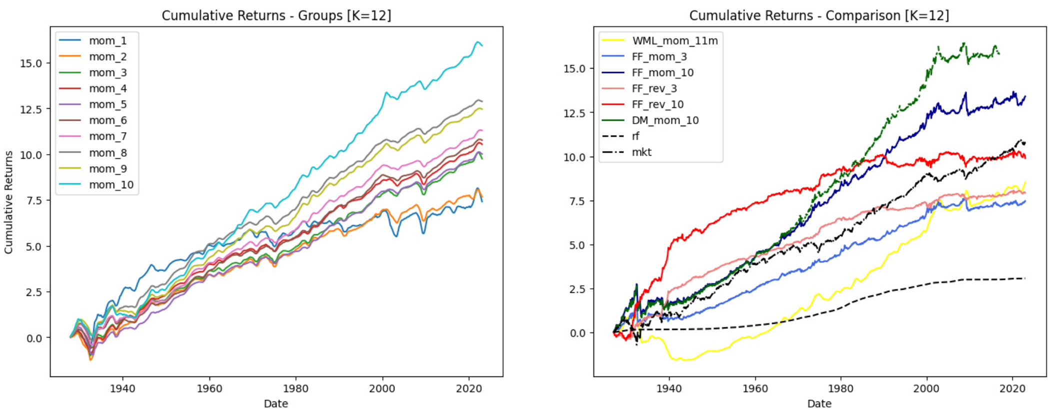


Figure 3.22.: Momentum w/o skip mechanism - J=11, K=12 months

Momentum w/o skip mechanism - J=12

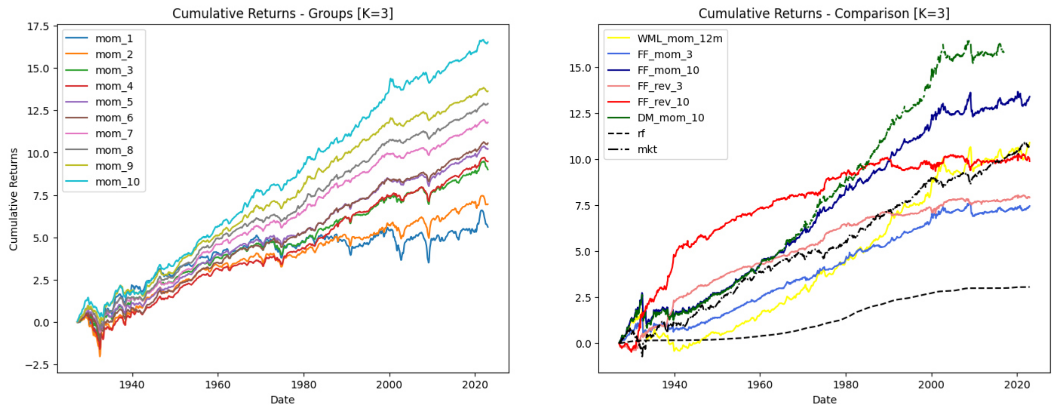


Figure 3.23.: Momentum w/o skip mechanism - J=12, K=3 months

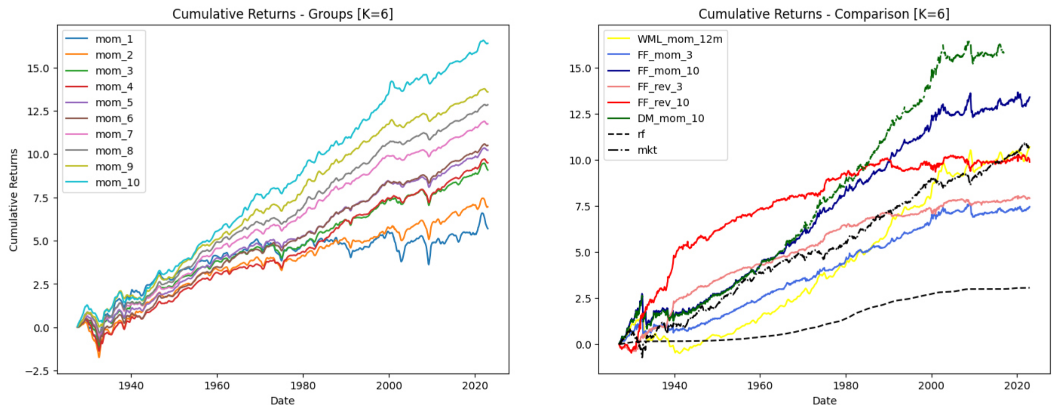


Figure 3.24.: Momentum w/o skip mechanism - J=12, K=6 months

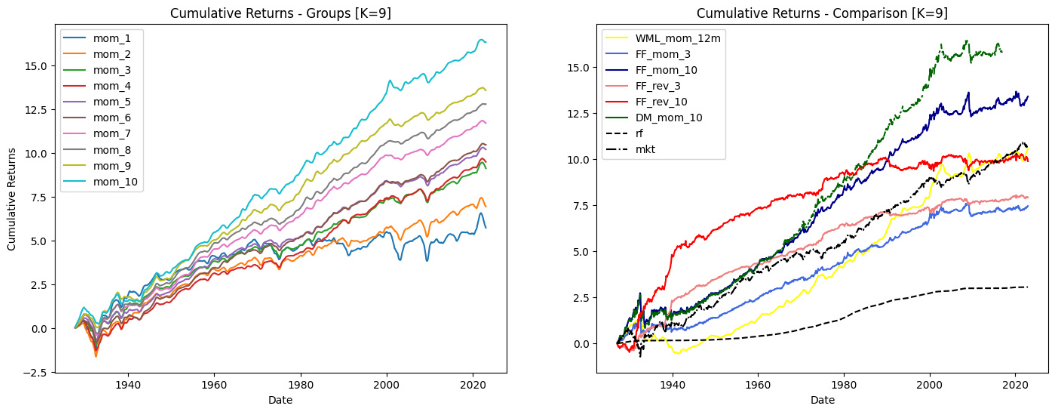


Figure 3.25.: Momentum w/o skip mechanism - J=12, K=9 months

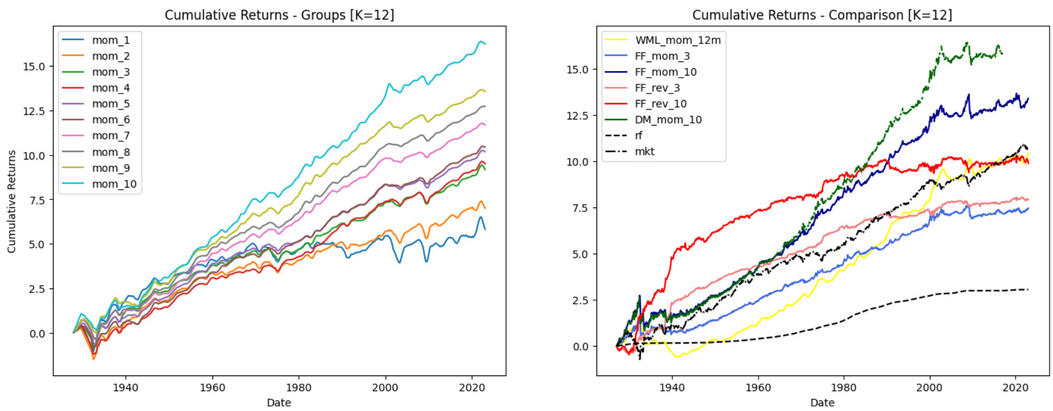


Figure 3.26.: Momentum w/o skip mechanism - J=12, K=12 months

Reversal - Losers Minus Winners

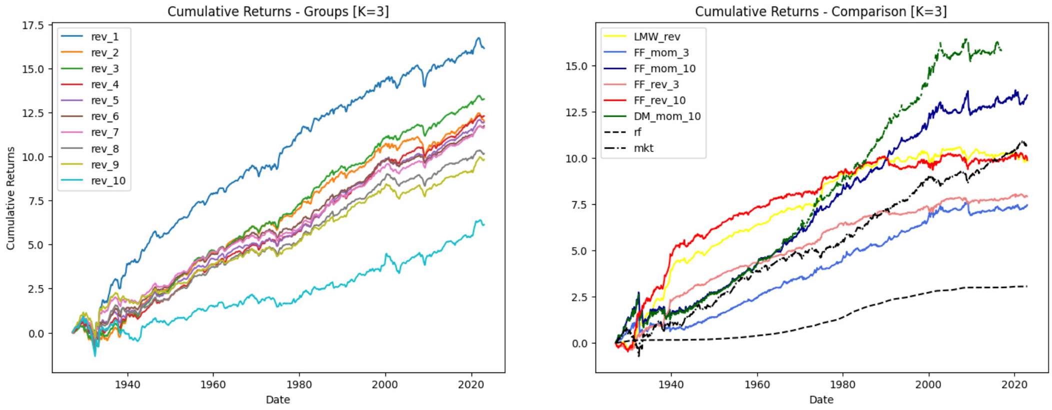


Figure 3.27.: Reversal - Losers Minus Winners - K=3 months

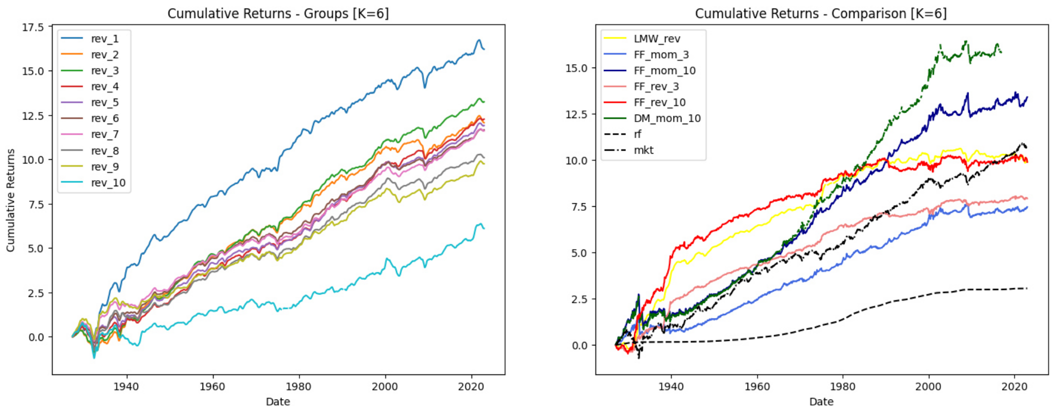


Figure 3.28.: Reversal - Losers Minus Winners - K=6 months

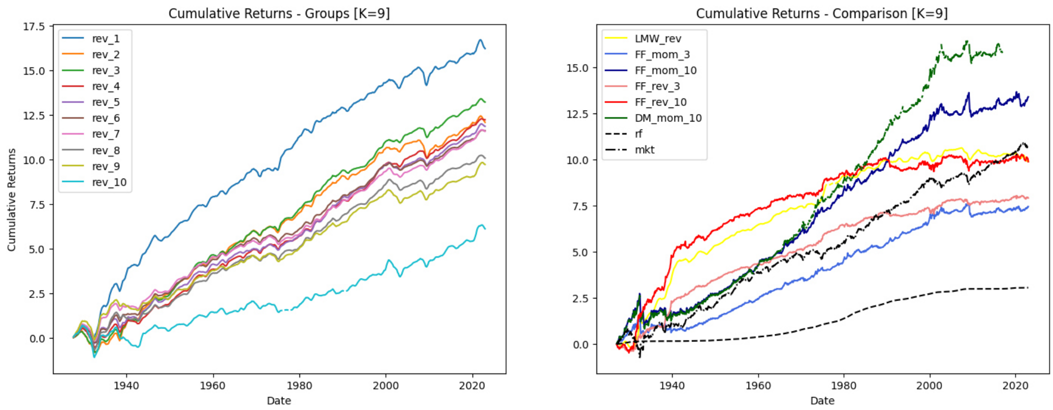


Figure 3.29.: Reversal - Losers Minus Winners - K=9 months

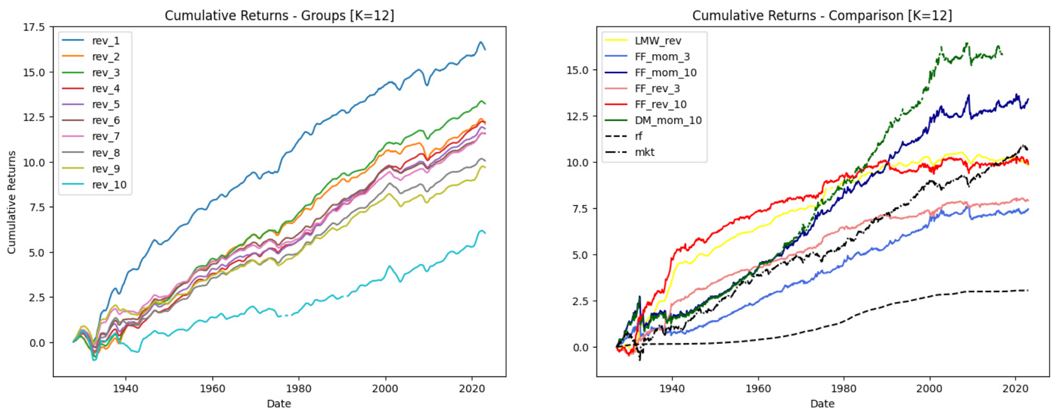


Figure 3.30.: Reversal - Losers Minus Winners - K=12 months

Confirming signal - J=11

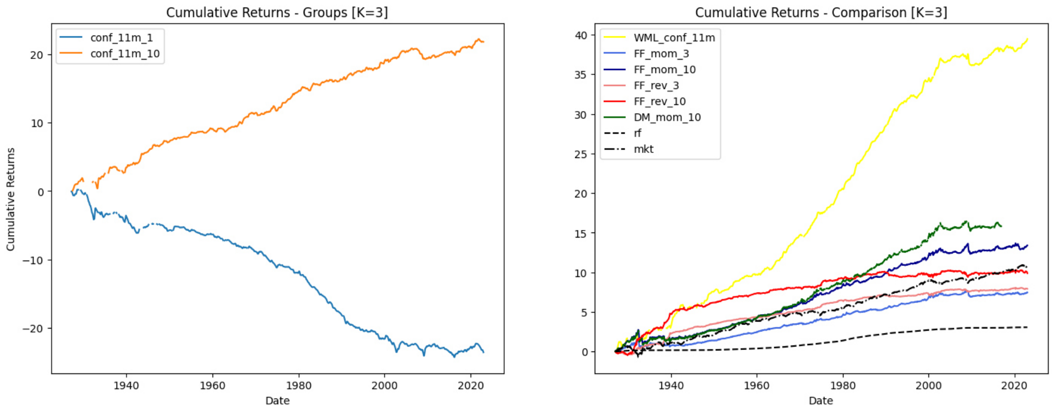


Figure 3.31.: Confirming signal - J=11, K=3 months

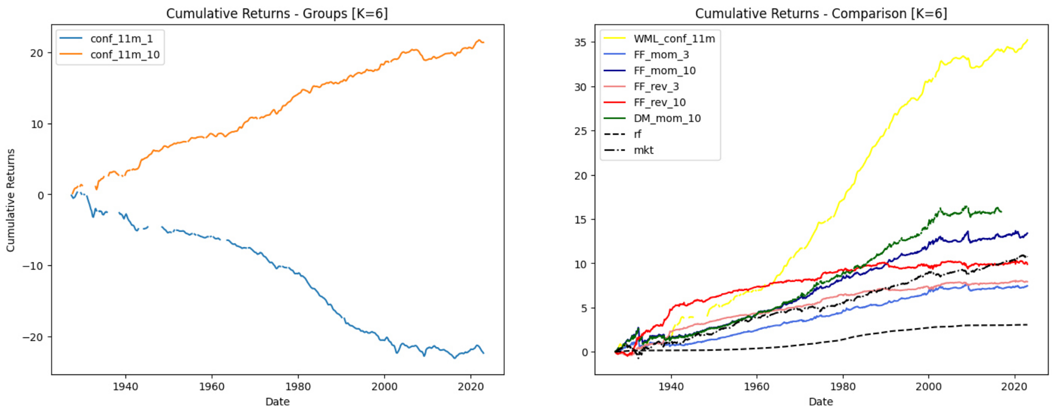


Figure 3.32.: Confirming signal - J=11, K=6 months

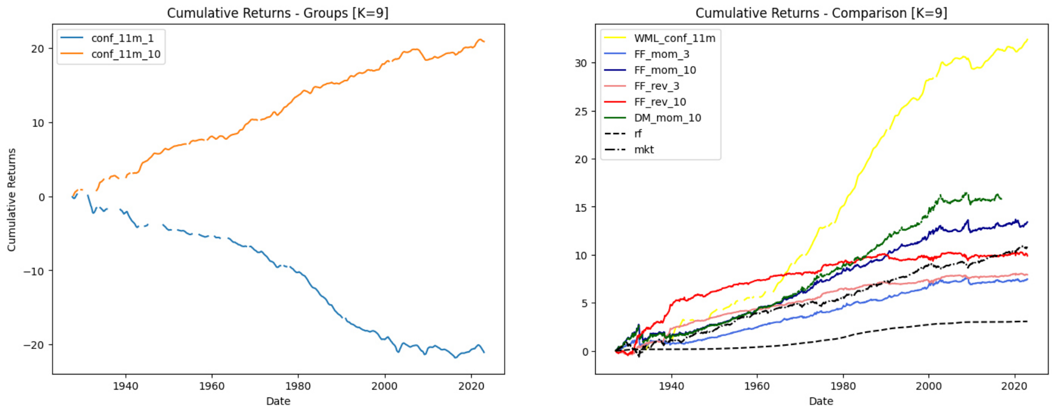


Figure 3.33.: Confirming signal - J=11, K=9 months

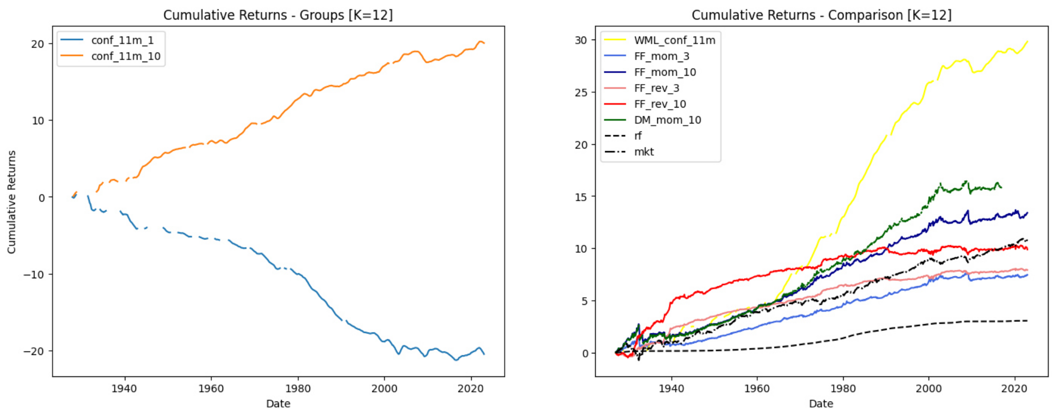


Figure 3.34.: Confirming signal - J=11, K=12 months

Confirming signal - J=12

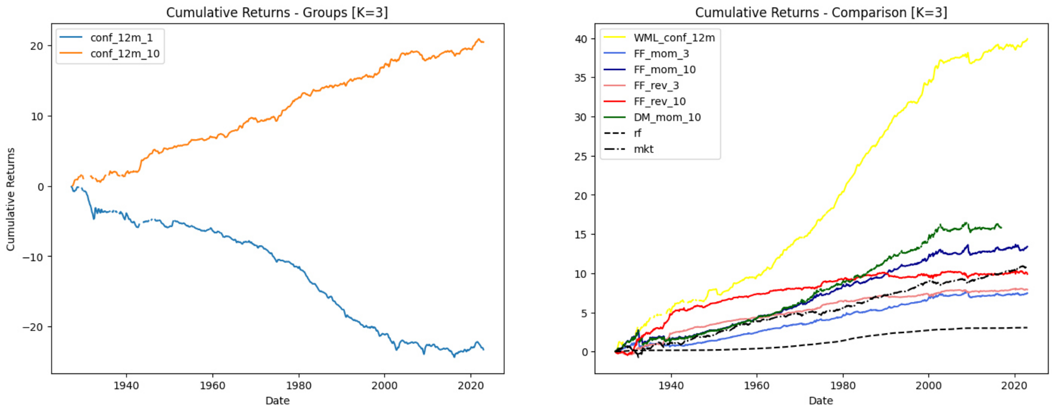


Figure 3.35.: Confirming signal - J=12, K=3 months

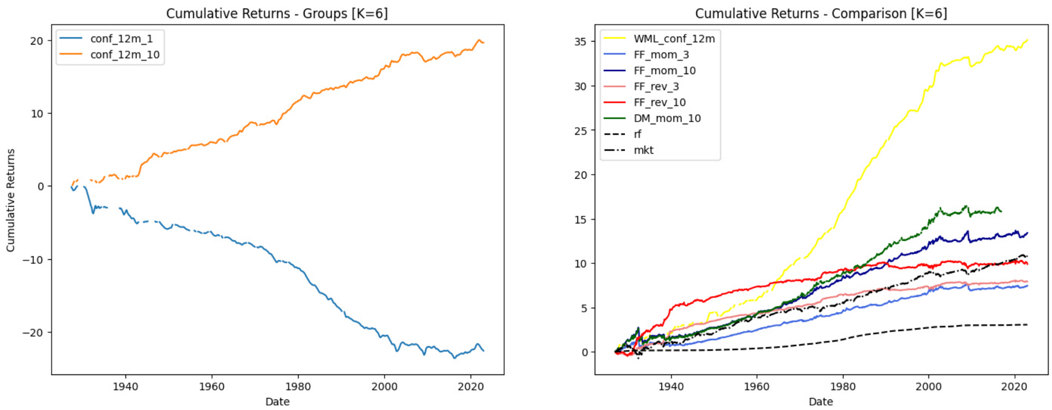


Figure 3.36.: Confirming signal - J=12, K=6 months

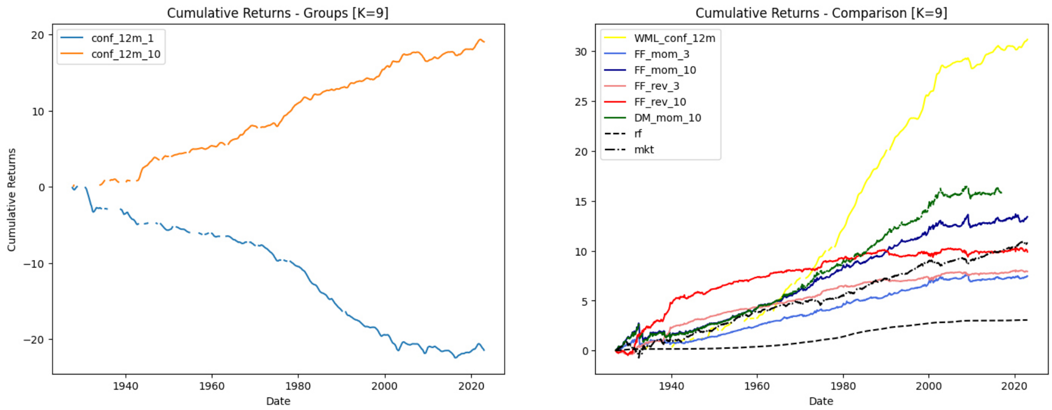


Figure 3.37.: Confirming signal - J=12, K=9 months

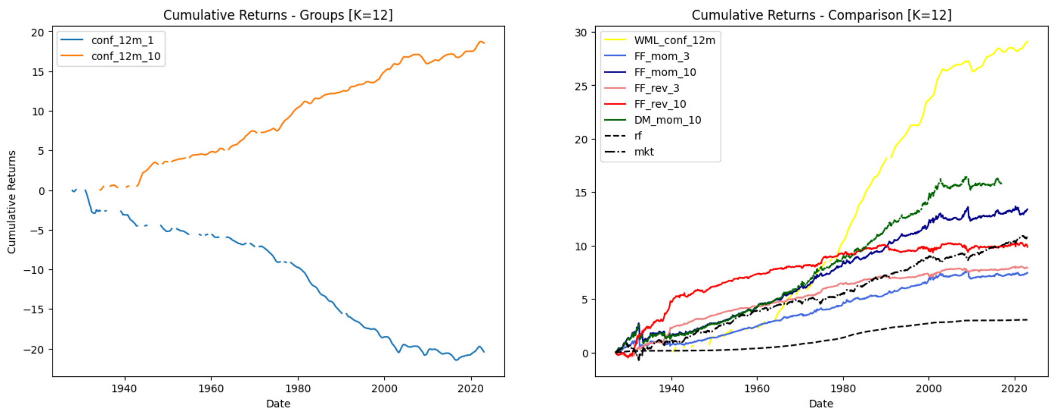


Figure 3.38.: Confirming signal - J=12, K=12 months

Combining Momentum and Reversal strategies

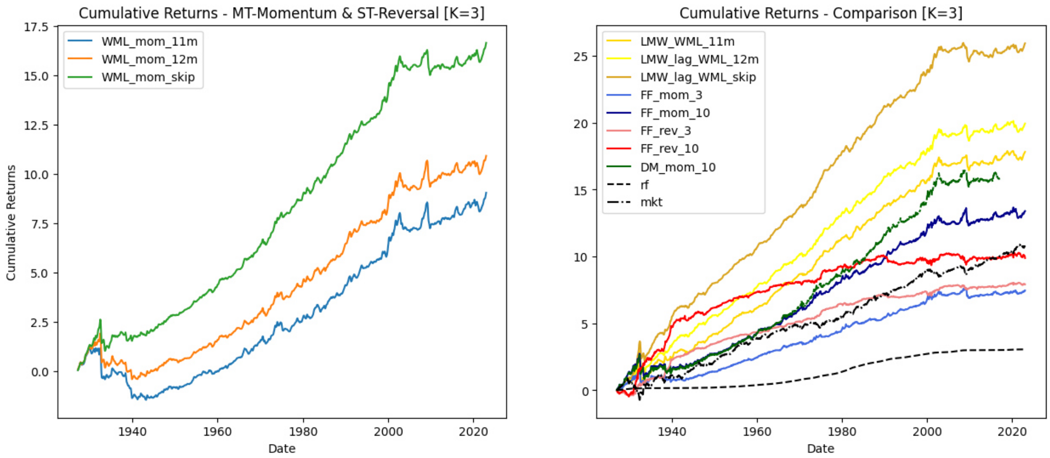


Figure 3.39.: Combining Momentum and Reversal strategies - K=3 months

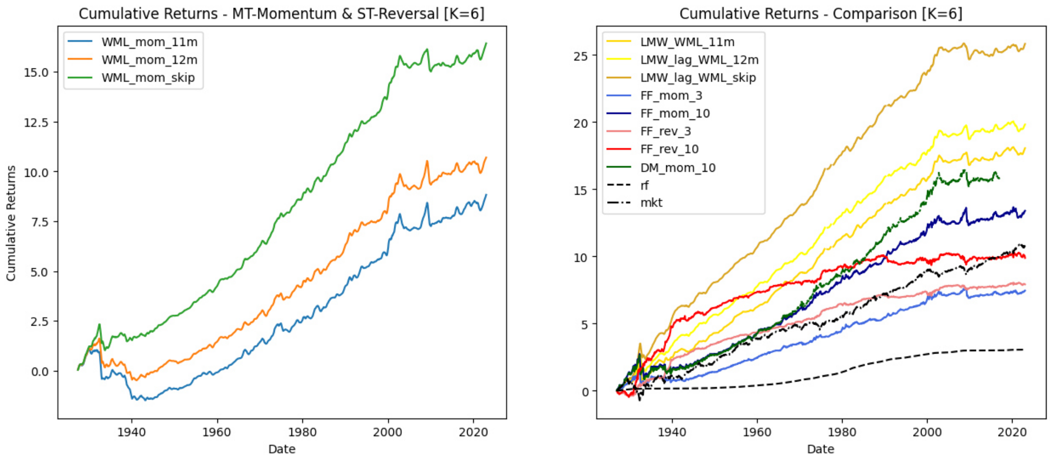


Figure 3.40.: Combining Momentum and Reversal strategies - K=6 months

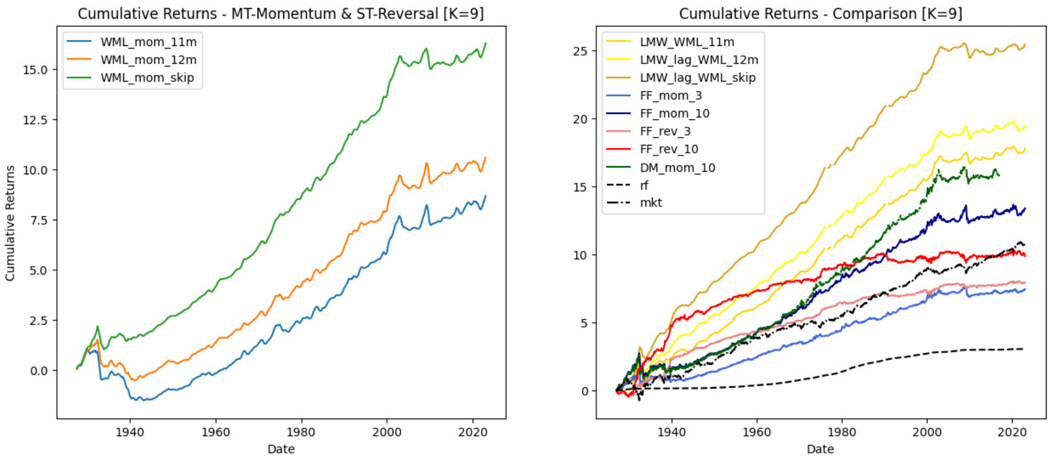


Figure 3.41.: Combining Momentum and Reversal strategies - K=9 months

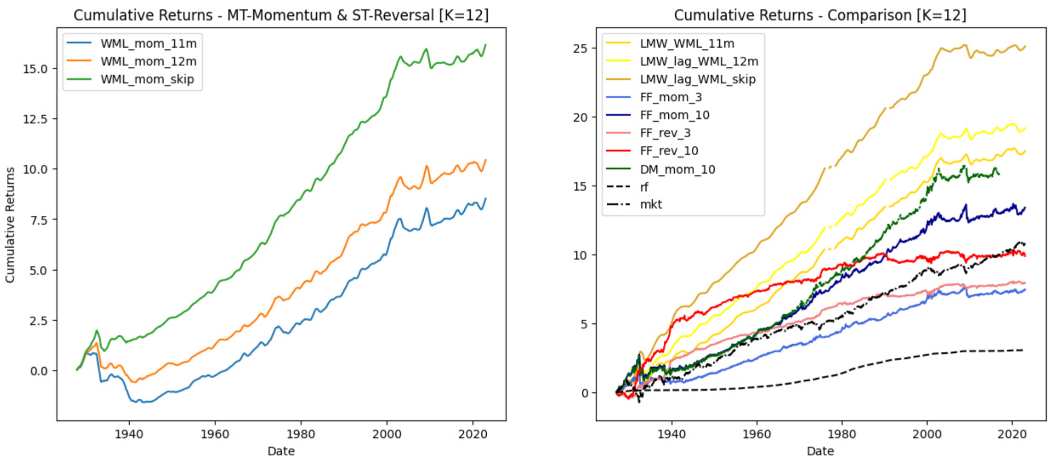


Figure 3.42.: Combining Momentum and Reversal strategies - K=12 months

4. Results

After going through all the methodological steps and visualizing all the plots for the respective strategies in Chapter 3, we get to the results that are split to clearly to differentiate between momentum (skip), momentum with J=11 and J=12 lookback months, reversal, confirming signal, and finally combining momentum with reversal. In the analysis, I have decided to display the portfolios as shown in Daniel and Moskowitz, where the individual buckets are shown on the left side of the table and the specific strategy is shown on the right. 10 buckets are used for the results, but the 3-bucket and 2000s results are also shown in Annex A.

To increase the robustness of the models, I have decided to include both the CAPM Sharpe and the Fama-French 3 factor model Fama and French (a). For the avoidance of doubt, excess returns are used for the calculations, excluding HML and SMB, as these are not excess returns according to formula 4. However, for simplicity and since we are only interested in the sensitivity of this strategy to the market, we will only include the beta with regards to the market. The returns, standard deviations, Sharpe Ratios, and alphas are annualized. Skewness, represented by sk(m) is performed on the monthly log returns similar to Daniel and Moskowitz.

The FF3 (Fama-French Three-Factor) model regression equation is given by:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} \cdot (R_{mt} - R_{ft}) + \beta_{i,SMB} \cdot R_{SMBt} + \beta_{i,HML} \cdot R_{HMLt} + \epsilon_{it}$$

$$\begin{aligned}
R_{it} &: \text{Return on asset } i \text{ at time } t \\
R_{ft} &: \text{Risk-free rate at time } t \\
R_{mt} &: \text{Market return at time } t \\
R_{SMBt} &: \text{Small minus big (SMB) factor return at time } t \\
R_{HMLt} &: \text{High minus low (HML) factor return at time } t \\
\alpha_i &: \text{Intercept (excess return) for asset } i \\
\beta_{i,MKT} &: \text{Sensitivity (exposure) of asset } i \text{ to market factor} \\
\beta_{i,SMB} &: \text{Sensitivity (exposure) of asset } i \text{ to SMB factor} \\
\beta_{i,HML} &: \text{Sensitivity (exposure) of asset } i \text{ to HML factor} \\
\epsilon_{it} &: \text{Error term for asset } i \text{ at time } t
\end{aligned}$$

4.0.1. Pure Momentum Results

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-2.05	2.64	3.45	6.87	7.74	7.34	9.42	10.38	11.29	15.39	15.43
$\sigma(\%)$	36.66	30.15	25.65	22.80	21.16	20.02	19.14	18.77	19.94	23.62	28.38
Sharpe Ratio	-0.06	0.09	0.13	0.30	0.37	0.37	0.49	0.55	0.57	0.65	0.54
sk(m)	0.09	-0.18	-0.17	0.09	-0.09	-0.24	-0.61	-0.51	-0.76	-0.78	-5.11
$\alpha\_mkt(\%)$	-15.08	-8.63	-6.40	-2.11	-0.76	-0.88	1.59	2.80	3.47	7.03	19.20
$t(\alpha)\_mkt$	(-7.13)	(-5.67)	(-5.45)	(-2.29)	(-0.99)	(-1.46)	(2.67)	(4.26)	(4.17)	(5.12)	(6.63)
p-value_mkt	0.000	0.000	0.000	0.022	0.323	0.146	0.008	0.000	0.000	0.000	0.000
β_mkt	1.63	1.41	1.24	1.13	1.07	1.03	0.98	0.95	0.98	1.05	-0.52
$\alpha\_FF3(\%)$	-16.63	-9.86	-7.20	-2.83	-1.31	-1.29	1.52	2.94	3.80	7.85	21.14
t_alpha_FF3	(-8.50)	(-6.83)	(-6.32)	(-3.21)	(-1.79)	(-2.23)	(2.57)	(4.47)	(4.66)	(6.34)	(7.64)
p-value_FF3	0.000	0.000	0.000	0.001	0.073	0.026	0.010	0.000	0.000	0.000	0.000

Table 4.1.: Pure Momentum (skip)

As we can see from the results in Table 4.1, where we implement the skip functionality into momentum, the returns of the portfolios are increasing from the losers to the winners as expected. The results are similar to Daniel and Moskowitz with a slight deviation due to the fact that the DM portfolios have a shorter time range [5]. Nevertheless, the returns across the board only deviate slightly and are very comparable, especially in the trends when scanning the line-by-line items from left to right. As we can see the losers bucket is the only return that is negative, while the winners bucket has the highest returns as previously stated. This is where the momentum strategy comes into fruition, shorting the losers and buying the winners.

Interestingly enough, the risk is the highest for the loser bucket and decreases steadily till the 8th bucket before increasing again for buckets 9 and 10. The winnner-minus-loser (WML) strategy of buying winners and selling losers is thus not surprisingly riskier than most buckets due to the inclusion of the high-risk loser portfolio. Taking both the excess returns and standard deviation into account, we arrive at the Sharpe Ratio, where the trend is increasing from bucket 1 to bucket 10, representing a higher return-to-risk ratio as we shift from losers to winners. The WML portfolio puts us somewhere on the higher end with 0.54 given that we long the winners and short the losers.

Moving along to the alpha and beta with regards to the market where the CAPM was used, we notice an increasing trend from bucket 1 to bucket 10, starting with a -15.08% alpha and ending with a 7.03% alpha. The results are significant on the upper and lower ends, excluding the middle buckets 5 and 6. According to the betas, we notice a decreasing trend from bucket 1 to bucket 8, before increasing back for buckets 9 and 10. The results of the beta seem to be reverting around 1, as this is where the trend stopped and moved the other way. The WML alpha is statistically significant at 19.20%

[5]Daniel-Moskowitz have used 1926-2013 in their famous paper and have additionally provided results up to 2016 on their site.

and the beta is surprisingly negative with -0.52. This is an efficient strategy if investors are looking for strategies that do not move with the market. When adding the FF3 model factors high-minus-low (HML) and small-minus-big (SMB) into the regression, we notice a similar trend with slightly more accentuated results. These results are a good start and well documented in literature, but now we will look at the effects of not taking the skip mechanism into account with J=11 and 12 lookback months.

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	4.15	4.71	6.85	7.70	7.28	8.07	8.67	10.43	9.91	13.68	8.90
$\sigma(\%)$	38.71	30.38	26.40	22.74	20.93	20.11	19.30	19.26	19.68	23.68	30.17
Sharpe Ratio	0.11	0.16	0.26	0.34	0.35	0.40	0.45	0.54	0.50	0.58	0.29
sk(m)	-0.03	-0.38	-0.11	-0.10	-0.36	-0.06	-0.48	-0.29	-0.66	-0.67	-8.38
$\alpha\_mkt(\%)$	-9.33	-6.61	-3.23	-1.15	-1.07	-0.14	0.75	2.65	2.26	5.31	13.23
$t(\alpha)\_mkt$	(-4.01)	(-4.27)	(-2.62)	(-1.17)	(-1.35)	(-0.21)	(1.29)	(3.95)	(2.64)	(3.84)	(4.34)
p-value_mkt	0.000	0.000	0.009	0.243	0.177	0.832	0.197	0.000	0.008	0.000	0.000
β_mkt	1.69	1.42	1.27	1.11	1.05	1.03	0.99	0.97	0.96	1.05	-0.60
$\alpha\_FF3(\%)$	-10.68	-7.50	-3.95	-1.75	-1.53	-0.55	0.52	2.73	2.54	5.99	14.94
t_alpha_FF3	(-4.83)	(-4.99)	(-3.27)	(-1.83)	(-1.98)	(-0.89)	(0.91)	(4.05)	(3.02)	(4.72)	(5.06)
p-value_FF3	0.000	0.000	0.001	0.068	0.048	0.376	0.365	0.000	0.003	0.000	0.000

Table 4.2.: Pure Momentum - J=11 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	2.53	4.01	6.19	6.60	7.44	7.80	9.09	10.24	11.01	14.02	10.02
$\sigma(\%)$	38.56	30.78	26.84	22.79	21.48	19.37	19.15	19.01	20.02	23.52	30.09
Sharpe Ratio	0.07	0.13	0.23	0.29	0.35	0.40	0.47	0.54	0.55	0.60	0.33
sk(m)	-0.06	-0.26	-0.07	-0.17	-0.03	-0.57	-0.45	-0.57	-0.59	-0.70	-7.11
$\alpha\_mkt(\%)$	-10.97	-7.46	-4.02	-2.39	-1.18	-0.08	1.24	2.58	3.16	5.71	14.29
$t(\alpha)\_mkt$	(-4.78)	(-4.76)	(-3.14)	(-2.60)	(-1.52)	(-0.13)	(2.14)	(3.86)	(3.79)	(4.16)	(4.70)
p-value_mkt	0.000	0.000	0.002	0.009	0.129	0.893	0.033	0.000	0.000	0.000	0.000
β_mkt	1.69	1.44	1.28	1.13	1.08	0.99	0.98	0.96	0.99	1.04	-0.59
$\alpha\_FF3(\%)$	-12.49	-8.47	-4.92	-3.06	-1.80	-0.45	1.12	2.66	3.39	6.49	16.19
t_alpha_FF3	(-5.80)	(-5.57)	(-3.99)	(-3.45)	(-2.44)	(-0.73)	(1.96)	(3.97)	(4.11)	(5.24)	(5.53)
p-value_FF3	0.000	0.000	0.000	0.001	0.015	0.465	0.051	0.000	0.000	0.000	0.000

Table 4.3.: Pure Momentum - J=12 months

To realize the advantage of having the skip feature in place, we will notice the decrease in performance when the skip period is not taken into account. In other words, this would mean that we take the whole 11 and 12-month cumulative returns into account as opposed to only taking 11 months and then skipping one period. Everything else remains the same and we can see the results in Table 4.3.

Comparing all 3 tables side-by-side (J=11, J=12, skip), we are able to notice that the results have been diminished when we don't skip (8.90% and 10.02% respectively) and 15.43% in when we skip. The decrease is most likely coming from the fact that the loser bucket (1) is not negative in both of the non-skip strategies. Additionally, we are also able to analyze this visually by comparing Figures 3.6 and 3.7 to 3.5. The Sharpe Ratio is approximately 0.30 in the non-skip scenarios, which is less than the 0.54 that we have seen in the skip scenario. When we look at risk, there is not that big of a difference between the two strategies, although it is worth mentioning that the momentum strategy with the skip has less risk attached to it. This is most likely coming from the fact that we are skipping an additional movement coming from the short-term reversal.

Further, the trends for the alphas are the same, although we note that both the α_mkt and the α_FF3 perform better in the case of momentum where the skip feature is used. The β_mkt similarly has the same trend with reversion around 1 at buckets 8, 9, and 10. The interesting thing to note is that the sensitivity to the market is more significantly negative with approximately -0.60 when we don't skip compared to -0.52 when we do. This can be explained due to the fact that the inclusion of the skip period likely mitigates some of the short-term reversal effects, which typically contribute to the market sensitivity of the strategy. By excluding a month of returns from the calculation, investors potentially avoid the immediate aftermath of a reversal, which often sees losers rebounding and winners pulling back. This immediate reversal is generally attributed to overreaction and subsequent correction in the market, which is less pronounced in the skip methodology. Consequently, the momentum strategy with the skip mechanism appears to be less correlated with the overall market movements, leading to a lower beta.

Moreover, the significant improvement in alpha for the skip strategy suggests that this approach is more effective at identifying true momentum, rather than being influenced by short-term noise. The alpha improvement indicates that, on a risk-adjusted basis, the skip strategy is capable of generating excess returns above the market, which are not explained by its risk profile as measured by beta. This superior performance underscores the value of the skip feature in refining the momentum strategy to better capture the essence of momentum investing—profiting from the continuation of existing trends while avoiding the pitfalls of short-term reversals.

In summary, the analysis clearly demonstrates the benefit of incorporating a skip period into momentum strategies. This approach not only enhances returns but also reduces market sensitivity, offering a more robust and resilient investment strategy. As such, the momentum strategy with the skip feature becomes an attractive option for investors looking to capitalize on long-term trends without the undue influence of short-term market movements. This nuanced understanding of momentum investing, leveraging both the alpha and beta dynamics, provides a compelling case for the adoption of skip strategies in portfolio management.

4.0.2. Pure Reversal Results

Before moving on, we will isolate reversals on their own and see how they perform in relation to the other strategies. The results presented in Table 4.4 provide an insightful look into the performance of pure reversal strategies across 10 buckets, highlighting a fascinating phenomenon where past losers outperform past winners, contrary to the momentum strategy. This reversal effect, where the first bucket (historically underperforming assets) yields the highest return at 13.54%, and the tenth bucket (historically outperforming assets) offers the lowest return at 3.44%, illustrates the opposing nature of a shorter lookback period. The standard deviation (σ) values suggest that the highest returns are also accompanied by the highest risk, particularly noticeable in the first bucket, which carries a significant volatility of 31.04%. Similar to the momentum strategies, the volatility decreases from buckets 1 to 7, before increasing again from buckets 8 to 10. The volatility of the reversal strategies is found to be on par with the momentum strategies, indicating that the reversal strategy, while profitable, does not come without its share of volatility as well.

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	13.54	9.17	10.58	9.58	9.24	9.04	8.90	7.40	7.02	3.44	4.68
$\sigma(\%)$	31.04	24.72	22.10	19.96	19.74	18.77	19.26	20.27	21.54	25.47	21.82
Sharpe Ratio	0.44	0.37	0.48	0.48	0.47	0.48	0.46	0.37	0.33	0.14	0.21
sk(m)	-0.46	-0.48	-0.41	-0.65	-0.22	-0.55	0.21	0.09	0.29	0.02	-1.30
$\alpha\_mkt(\%)$	2.33	-0.31	1.78	1.51	1.17	1.30	1.01	-0.76	-1.45	-5.89	3.02
$t(\alpha)\_mkt$	(1.35)	(-0.27)	(2.10)	(2.21)	(1.91)	(2.46)	(1.72)	(-1.04)	(-1.65)	(-4.33)	(1.31)
p-value_mkt	0.177	0.787	0.036	0.027	0.056	0.014	0.085	0.297	0.100	0.000	0.191
β_mkt	1.41	1.19	1.10	1.01	1.01	0.97	0.99	1.02	1.06	1.17	0.23
$\alpha\_FF3(\%)$	1.85	-0.56	1.70	1.52	0.91	1.26	0.67	-1.00	-1.81	-6.37	2.91
t_alpha_FF3	(1.12)	(-0.50)	(2.03)	(2.22)	(1.52)	(2.37)	(1.19)	(-1.40)	(-2.06)	(-4.85)	(1.26)
p-value_FF3	0.261	0.616	0.043	0.027	0.130	0.018	0.233	0.163	0.039	0.000	0.208

Table 4.4.: Pure Reversal

The Sharpe Ratios across the buckets indicate a decreasing trend in risk-adjusted returns as we move from losers to winners, with the first bucket showing a relatively high ratio of 0.44, reflecting its superior performance on a risk-adjusted basis. This trend reverses as we progress towards the tenth bucket, where the Sharpe Ratio is found at 0.14, suggesting diminishing returns for increased risk. The skewness (sk(m)) of the returns further illustrates the asymmetric risk of investing in reversal strategies, with a noticeable shift from negative values in the lower buckets to positive values as we move to the higher buckets, indicating a transition from left-skewed to nearly symmetric or slightly right-skewed distributions. This transition underscores the changing risk profile across buckets, with lower buckets potentially offering high returns at the cost of higher risk and the possibility of significant negative outcomes.

The analysis of α_mkt and α_FF3 percentages across the buckets reveals that the alpha, or the excess return of an investment relative to the return of a benchmark index, varies significantly, with the first bucket showing a positive alpha of 2.33% according to the market model and 1.85% according to the Fama-French three-factor model (FF3). This positive alpha indicates that the reversal strategy in the first bucket is capable of generating returns that exceed those predicted by market movements and size and value factors alone. However, as we transition to the tenth bucket, the alpha becomes increasingly negative, reaching -5.89% and -6.37% according to the market and FF3 models, respectively. This is the trend we would like to see when we have reversals in mind.

The beta (β_mkt) values, representing the sensitivity of the investment's returns to market returns, decrease slightly across the buckets but remain relatively stable, indicating that while the reversal strategy's returns are somewhat dependent on market movements, this dependency does not vary dramatically across different buckets. The relatively low beta of 0.23 for the reversal portfolio (rev) highlights its potential as a diversification tool, offering returns that do not closely follow the market's ups and downs. Although this beta is not negative like we have seen for the momentum portfolios, it is still a low-beta portfolio that can increase diversification when paired with momentum.

The pure reversal strategy demonstrates a compelling case for contrarian investing, where investors betting against prevailing trends can reap significant rewards, especially in the short term. However, the strategy's effectiveness is nuanced and depends heavily on the risk tolerance and time horizon of the investor. While the high returns in the lower buckets are attractive, they come with substantial risk and volatility. Conversely, the higher buckets offer more stability but at the cost of lower returns. The reversal strategy's ability to generate positive alpha in certain buckets underscores its potential value in a well-diversified portfolio, particularly for investors looking to exploit short-term market inefficiencies and corrections.

Noticing the profitability of this strategy, it is unclear why investors have chosen to skip, or wait, in this period when experimenting with momentum. Capitalizing on this strategy is the scope of this paper. But before we view the results of that strategy, I found it necessary to also include what the results would look like if we would simply use the signal that comes from the short-term reversal, in a sense, to confirm the momentum signal. In other words, we would have two signals, and only when they both agree on an action do we perform that action. This is explained more deeply in Section 3.2.2.

4.0.3. Confirming Signal Results

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-29.14	20.72	44.28
$\sigma(\%)$	47.90	41.45	47.17
Sharpe Ratio	-0.61	0.50	0.94
sk(m)	-0.16	-0.25	-2.32
$\alpha\_mkt(\%)$	-41.20	10.56	45.60
$t(\alpha)\_mkt$	(-10.27)	(3.00)	(9.00)
p-value_mkt	0.000	0.003	0.000
β_mkt	1.51	1.27	-0.18
$\alpha\_FF3(\%)$	-43.33	10.36	47.97
t_alpha_FF3	(-11.35)	(3.24)	(9.66)
p-value_FF3	0.000	0.001	0.000

Table 4.5.: Confirming signals - J=11 months

Now that we have seen the results of both the momentum and the reversal strategies, we will look at a novel approach of utilizing the signals that each offer. To put this into perspective, we will use the two separate momentum signals that comes from the past 11 and 12-month cumulative returns where good-performing stocks over that period will be given the signal "buy", and conversely, bad-performing stocks will be given the signal

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-28.65	20.07	45.26
$\sigma(\%)$	46.21	38.72	45.54
Sharpe Ratio	-0.62	0.52	0.99
sk(m)	-0.23	-0.49	-1.59
$\alpha\_mkt(\%)$	-40.87	10.80	47.30
$t(\alpha)\_mkt$	(-10.99)	(3.28)	(9.71)
p-value_mkt	0.000	0.001	0.000
β_mkt	1.56	1.18	-0.28
$\alpha\_FF3(\%)$	-43.15	11.49	49.88
t_alpha_FF3	(-12.26)	(3.72)	(10.51)
p-value_FF3	0.000	0.000	0.000

Table 4.6.: Confirming signals - J=12 months

"sell". In parallel, we will implement the signal coming from the short-term reversal past 1-month returns that use a mirror-effect approach, where the good-performing stocks receive a "sell" signal and the bad-performing stocks receive the "buy" signal. In the end, we will have two strategies with two signals each for each stock (J=11 momentum with J=1 reversal & J=12 momentum with J=1 reversal), and only when they agree (i.e. both say buy or both say sell) will we perform that action. Notably, there is no skip feature in the momentum approach as this would deem the short-term reversal signal useless.

The explanation of the confirming signal is best visualized in Figure 3.9. "Strong sell" and "Strong buy" are the most important for this strategy as these are the actions that determine the final formula. It is clear to see in Tables 4.5 and 4.5 that only buckets 1 and 10 are used here due to the greater standard that a stock must respect in order to be placed into a portfolio that is either a buy or a sell. Other combinations of different action signals are seen as weak and are not relevant for this confirming signal approach. As mentioned in Chapter 3 and clearly seen in Figure 3.12, this approach will have considerately less stocks all together due to the stricter filter. Although the number of stucks have increased over time, there are still moments where there are very few to no stocks selectred for a particular period.

The advantageous feature of this approach is that the returns and Sharpe ratio are negative in the loser portfolio and positive in the winner portfolio, as we would most prefer when using a WML strategy. As already seen in Section 3.2.2, this is the best-performing portfolio by far, even taking into account all the other portfolios and strategies. However, this does not come without its fair share of risk. Looking at the standard deviation, we notice that it is the greatest among all the strategies talked about thus far. Additionally, this approach is more sensitive to the market compared to momentum, indicated by a slightly less negative beta. Nevertheless, this is not positive like the reversal strategy. The bizarre thing to notice is that the individual portfolios of the losers and winners have a strongly positive sensitivity to the market indicated by the 1.56 and 1.18 respective betas. The negative beta from the WML, however, might be coming from the fact that we are shorting the loser portfolio.

4.0.4. Combining Momentum & Reversal Results

Now comes the focal point of the paper. The results from combining the short-term reversal with the medium-term momentum. As we have already seen in Figure 3.13, two out of the three possible combinations perform better than both the benchmark DM and FF portfolios. Namely, the order from the best to worst-performing portfolio combinations would be the following:

1. **LMW_lag_WML_skip:[6]** The reversal (loser-minus-winner) is implemented exactly one month before the momentum (winner-minus-loser) where the skip mechanism is implemented (11 months lookback with 1 month skip)

2. **LMW_lag_WML_12m:** The reversal is implemented exactly one month before the momentum where there is no skip mechanism implemented, but the whole 12 months are taken into account

3. **LMW_WML_11m:** The reversal is implemented *at the same time with* momentum where there is no skip mechanism implemented, but the whole 11 months are taken into account

For the avoidance of doubt, I will mention that LMW_WML_12m was not implemented because the results were almost identical to LMW_WML_11m and it would just make the plot harder to read. Additionally, I also did not include LMW_lag_WML_11m since it simply would not be relevant for the main range of 11-12 months that we are looking around. Doing that would simply also include the 10-month lookback period, making this case study overly cumbersome.

Showing all the strategies in Table 4.0.4 helps us visualize the statistics side-by-side, especially when it comes to combining different strategies and seeing how they compare to the standalone strategies. Nevertheless, the standout strategy LMW_lag_WML_skip, indicated by rev_mom(skip), not only provided the highest returns at 26.40%, but also offered a strong Sharpe Ratio of 0.70. This indicates that for the level of risk taken, the returns are significantly higher compared to the market. The strategy cleverly waits a month to implement the momentum signal after the reversal strategy was applied 1 month before it, allowing this strategy to capitalize on both the initial reversal and the ensuing momentum. This approach effectively uses the temporary market correction (reversal) as a setup for capturing the longer-term trend (momentum).

On the other hand, the LMW_lag_WML_12m strategy, which directly applies momentum after reversal without the skip, showed returns of 21.05% with a Sharpe Ratio of 0.54. These results are strong but slightly lower than the skip strategy. This difference suggests that waiting 1 month to implement the momentum signal after the reversal can indeed add value, potentially by avoiding the noise coming from the immediate market

[6]The term *lag* is used to shift the reversal one month forward for easier python calculations

reversals.

The LMW_WML_11m strategy, which performs both momentum and reversal within the same month, shows us another perspective. Its performance, while not as high as both of the aforementioned strategies, is still notable. It demonstrates that even without the complexity of timing shifts, combining momentum and reversal signals can yield beneficial results. This approach might appeal to investors looking for a simpler strategy that still outperforms traditional market benchmarks. However, this strategy does not outperform the standalone momentum strategy with the skip mechanism implemented.

Delving into the alpha and beta metrics across these strategies, we observe significant excess returns (alpha) across the board, especially with rev_mom(11m) rev_mom(12m) and rev_mom(skip), which show alphas of 17.05%, 25.49%, and 30.40% for the 11-month, 12-month, and skip strategies, respectively. These high alpha values indicate that these strategies are highly effective at generating returns above the market average, even after adjusting for the risk (beta) taken.

Beta values provide insights into how these strategies move in relation to the market. Negative betas in confirming signals strategies and the LMW_lag_WML_skip strategy suggest these portfolios offer a hedge against market downturns given that they tend to move opposite to the overall market. For example, all these 3 strategies have negative betas of -0.35, -0.61, and -0.55 11-month, 12-month, and skip strategies, respectively. This implies that these strategies could actually gain when the market declines, offering a diversification benefit to investors. This relates back as to how this can improve the momentum strategies in times of volatility.

In conclusion, this analysis underscores the value of incorporating strategically-timed short-term reversals into traditional momentum strategy. The combination of these strategies not only enhances returns but also offers a diversified risk profile, catering to various investor preferences. These findings contribute valuable insights to the financial community, showcasing the potential of these strategies in modern portfolio management. As the financial landscape evolves, it's clear that these nuanced approaches to combining momentum and reversal signals will continue to offer compelling opportunities for investors seeking to maximize their returns while managing risk effectively.

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r - rf)(\%)$	8.90	10.02	15.43	4.68	44.28	45.26	14.50	21.05	26.40	0.00	7.24	3.41	1.96
$\sigma(\%)$	30.17	30.09	28.38	21.82	47.17	45.54	29.62	38.87	37.61	0.00	17.43	11.64	10.37
Sharpe Ratio	0.29	0.33	0.54	0.21	0.94	0.99	0.49	0.54	0.70	NaN	0.42	0.29	0.19
sk(m)	-8.38	-7.11	-5.11	-1.30	-2.32	-1.59	-11.01	-5.12	-3.43	0.00	-0.48	0.89	0.40
$\alpha\_mkt(\%)$	13.23	14.29	19.20	3.02	45.60	47.30	17.05	25.49	30.40	0.00	-0.00	2.70	0.56
$t(\alpha)\_mkt$	(4.34)	(4.70)	(6.63)	(1.31)	(9.00)	(9.71)	(5.47)	(6.34)	(7.77)	NaN	(-13.73)	(2.18)	(0.53)
p-value_mkt	0.000	0.000	0.000	0.191	0.000	0.000	0.000	0.000	0.000	NaN	0.000	0.030	0.596
β_mkt	-0.60	-0.59	-0.52	0.23	-0.18	-0.28	-0.35	-0.61	-0.55	0.00	1.00	0.10	0.19
$\alpha\_FF3(\%)$	14.94	16.19	21.14	2.91	47.97	49.88	18.48	27.29	32.26	0.00	-0.00	-0.00	-0.00
t_alpha_FF3	(5.06)	(5.53)	(7.64)	(1.26)	(9.66)	(10.51)	(6.04)	(6.90)	(8.41)	NaN	(-4.79)	(-5.20)	(-1.50)
p-value_FF3	0.000	0.000	0.000	0.208	0.000	0.000	0.000	0.000	0.000	NaN	0.000	0.000	0.134

4.0.5. Exploring Various Holding Periods - Statistics

We will adopt a method similar to the one used in Section 3.2.4 to enhance readability. Our focus will be on identifying trends observed as we extend the holding period for "K" months in our portfolios, contrasting these findings with the conventional one-month holding period that involves monthly rebalancing. When evaluating the returns from the Pure Momentum (skip) strategy across various holding durations, we note a decline from the initial 15.43% return to 14.14%, 13.94%, 13.80%, and 13.64% for the 3, 6, 9, and 12-month periods, respectively. Similarly, the risk associated with the original Pure Momentum (skip) strategy stands at 28.38%, but it significantly decreases to 17.46%, 11.77%, 9.34%, and 7.90% as the holding periods are extended. To concisely summarize, the trends are consistent across extended holding periods, revealing the following patterns:

- **Mean:** There is a general increase across longer holding periods, with occasional reversals.
- **Risk:** Risk consistently decreases as the holding period lengthens.
- **Sharpe Ratio (SR):** Typically improves with longer holding durations.
- **Skewness (Sk(m)):** Generally shows an upward trend with extended holding periods.
- **Market Alpha (Alpha_mkt):** Tends to decrease over longer holding periods, with some exceptions.
- **Market Beta (Beta_mkt):** Increases with the lengthening of holding periods, barring a few reversals.

Holding Periods Results - K=3 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-1.94	2.70	3.45	6.92	7.77	7.34	9.43	10.38	11.29	15.39	14.14
$\sigma(\%)$	22.84	18.58	15.63	13.71	12.87	12.13	11.39	11.17	11.91	14.39	17.46
Sharpe Ratio	-0.08	0.15	0.22	0.50	0.60	0.61	0.83	0.93	0.95	1.07	0.81
sk(m)	0.53	0.39	0.25	0.43	0.44	0.22	-0.21	-0.27	-0.32	-0.40	-3.60
alpha_mkt (%)	-6.77	-1.44	-0.10	3.67	4.73	4.41	6.69	7.71	8.53	12.36	15.91
t(alpha)_mkt	(-3.31)	(-0.88)	(-0.08)	(3.12)	(4.28)	(4.27)	(6.89)	(8.08)	(8.27)	(9.59)	(9.12)
p-value_mkt	0.0009	0.3799	0.9388	0.0019	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.61	0.52	0.45	0.41	0.38	0.37	0.34	0.33	0.35	0.38	-0.22
alpha_FF3 (%)	-7.41	-2.05	-0.53	3.24	4.41	4.12	6.56	7.60	8.43	12.45	16.65
t_alpha_FF3	(-3.73)	(-1.28)	(-0.40)	(2.81)	(4.03)	(4.05)	(6.78)	(8.01)	(8.35)	(10.02)	(9.64)
p-value_FF3	0.0002	0.2010	0.6913	0.0050	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.7.: Pure Momentum (skip) - K=3 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	4.26	4.73	6.85	7.78	7.30	8.07	8.68	10.41	9.91	13.68	6.22
$\sigma(\%)$	23.78	18.45	15.82	13.58	12.58	12.22	11.69	11.48	11.82	14.61	18.84
Sharpe Ratio	0.18	0.26	0.43	0.57	0.58	0.66	0.74	0.91	0.84	0.94	0.33
sk(m)	0.57	0.19	0.39	0.26	-0.34	0.68	-0.10	0.16	-0.20	-0.14	-4.64
alpha_mkt (%)	-0.68	0.76	3.14	4.59	4.40	5.11	5.79	7.67	7.19	10.60	8.07
t(alpha)_mkt	(-0.32)	(0.46)	(2.31)	(3.93)	(4.03)	(4.93)	(5.90)	(7.82)	(7.01)	(8.09)	(4.28)
p-value_mkt	0.7494	0.6432	0.0213	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.62	0.50	0.46	0.40	0.36	0.37	0.36	0.34	0.34	0.39	-0.23
alpha_FF3 (%)	-1.31	0.30	2.67	4.20	4.18	4.81	5.56	7.49	7.12	10.62	8.72
t_alpha_FF3	(-0.63)	(0.19)	(1.99)	(3.66)	(3.85)	(4.70)	(5.71)	(7.75)	(7.05)	(8.39)	(4.65)
p-value_FF3	0.5313	0.8511	0.0466	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.8.: Pure Momentum - J=11 months, K=3 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	2.66	4.06	6.19	6.68	7.45	7.81	9.09	10.24	11.01	14.02	8.17
$\sigma(\%)$	23.95	18.92	16.19	13.67	12.89	11.60	11.47	11.34	12.15	14.35	18.74
Sharpe Ratio	0.11	0.21	0.38	0.49	0.58	0.67	0.79	0.90	0.91	0.98	0.44
sk(m)	0.54	0.51	0.46	0.22	0.18	-0.25	-0.06	-0.10	-0.01	-0.29	-4.57
alpha_mkt (%)	-2.38	-0.07	2.47	3.44	4.44	5.07	6.31	7.58	8.14	10.99	10.16
t(alpha)_mkt	(-1.11)	(-0.04)	(1.75)	(2.93)	(3.99)	(5.09)	(6.48)	(7.76)	(7.79)	(8.56)	(5.44)
p-value_mkt	0.2672	0.9680	0.0797	0.0034	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.63	0.52	0.47	0.41	0.38	0.34	0.35	0.33	0.36	0.38	-0.25
alpha_FF3 (%)	-3.05	-0.61	1.96	3.03	4.12	4.86	6.14	7.46	7.98	11.08	10.91
t_alpha_FF3	(-1.46)	(-0.37)	(1.42)	(2.62)	(3.75)	(4.91)	(6.35)	(7.71)	(7.78)	(8.94)	(5.90)
p-value_FF3	0.1454	0.7101	0.1567	0.0088	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.9.: Pure Momentum - J=12 months, K=3 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	13.61	9.33	10.61	9.61	9.24	9.03	8.93	7.39	7.04	3.23	7.08
$\sigma(\%)$	18.12	14.69	12.95	11.89	11.73	11.38	11.98	12.52	13.06	16.00	12.98
Sharpe Ratio	0.75	0.64	0.82	0.81	0.79	0.79	0.75	0.59	0.54	0.20	0.55
sk(m)	-0.29	-0.57	-0.27	-0.60	-0.11	-0.07	0.82	0.55	1.07	0.68	-0.06
alpha_mkt (%)	9.31	5.87	7.47	6.74	6.37	6.31	6.01	4.44	3.99	-0.32	6.32
t(alpha)_mkt	(6.00)	(4.64)	(6.80)	(6.66)	(6.43)	(6.49)	(5.93)	(4.12)	(3.54)	(-0.23)	(4.78)
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.8213	0.0000
beta_mkt	0.54	0.43	0.39	0.36	0.36	0.34	0.37	0.37	0.38	0.45	0.10
alpha_FF3 (%)	8.69	5.51	7.19	6.62	6.15	6.18	5.78	4.27	3.68	-0.74	6.15
t_alpha_FF3	(5.84)	(4.45)	(6.71)	(6.62)	(6.27)	(6.41)	(5.78)	(3.99)	(3.31)	(-0.54)	(4.65)
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0010	0.5912	0.0000

Table 4.10.: Pure Reversal - K=3 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-27.82	19.82	38.16
$\sigma(\%)$	28.57	24.03	25.05
Sharpe Ratio	-0.97	0.82	1.52
sk(m)	0.33	0.19	-1.20
alpha_mkt (%)	-31.72	16.39	38.23
t(alpha)_mkt	(-11.34)	(7.00)	(14.84)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.49	0.43	-0.01
alpha_FF3 (%)	-32.43	16.11	38.85
t_alpha_FF3	(-11.70)	(7.27)	(15.09)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.11.: Confirming signals - J=11 months, K=3 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-27.45	18.36	38.64
$\sigma(\%)$	27.87	22.37	24.70
Sharpe Ratio	-0.98	0.82	1.56
sk(m)	0.39	-0.09	-0.72
alpha_mkt (%)	-31.75	15.45	39.27
t(alpha)_mkt	(-11.86)	(7.03)	(15.48)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.55	0.37	-0.08
alpha_FF3 (%)	-32.60	15.52	39.86
t_alpha_FF3	(-12.37)	(7.32)	(15.76)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.12.: Confirming signals - J=12 months, K=3 months

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	6.22	8.17	14.14	7.08	38.16	38.64	15.43	17.64	23.88	0.00	7.97	4.33	2.33
$\sigma(\%)$	18.84	18.74	17.46	12.98	25.05	24.70	17.86	20.00	20.02	0.00	18.58	12.36	11.00
Sharpe Ratio	0.33	0.44	0.81	0.55	1.52	1.56	0.86	0.88	1.19	NaN	0.43	0.35	0.21
sk(m)	-4.64	-4.57	-3.60	-0.06	-1.20	-0.72	-6.30	-4.26	-2.73	0.00	-0.52	1.40	1.17
alpha_mkt (%)	8.07	10.16	15.91	6.32	38.23	39.27	16.52	19.66	25.70	0.00	0.00	3.10	0.84
t(alpha)_mkt	(4.28)	(5.44)	(9.12)	(4.78)	(14.84)	(15.48)	(9.08)	(9.83)	(12.77)	NaN	(0.77)	(2.51)	(0.79)
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.4413	0.0122	0.4325
beta_mkt	-0.23	-0.25	-0.22	0.10	-0.01	-0.08	-0.14	-0.25	-0.23	0.00	1.00	0.15	0.19
alpha_FF3 (%)	8.72	10.91	16.65	6.15	38.85	39.86	16.96	20.29	26.31	0.00	0.00	-0.00	0.00
t_alpha_FF3	(4.65)	(5.90)	(9.64)	(4.65)	(15.09)	(15.76)	(9.33)	(10.19)	(13.11)	NaN	(10.45)	(-2.89)	(2.50)
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.0000	0.0040	0.0124

Holding Periods Results - K=6 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-1.86	2.73	3.53	6.93	7.77	7.33	9.37	10.35	11.25	15.26	13.94
$\sigma(\%)$	15.55	12.61	10.54	9.48	8.86	8.32	7.95	7.80	8.51	10.27	11.77
Sharpe Ratio	-0.12	0.22	0.33	0.73	0.88	0.88	1.18	1.33	1.32	1.49	1.18
sk(m)	0.15	-0.05	-0.36	-0.20	-0.27	-0.28	-0.51	-0.43	-0.26	-0.27	-1.82
alpha_mkt (%)	-4.24	0.69	1.77	5.29	6.24	5.88	8.02	9.05	9.84	13.76	14.80
t(alpha)_mkt	(-2.84)	(0.57)	(1.77)	(5.92)	(7.48)	(7.52)	(10.67)	(12.23)	(12.18)	(13.86)	(12.40)
p-value_mkt	0.0046	0.5678	0.0770	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.30	0.26	0.22	0.21	0.19	0.18	0.17	0.16	0.18	0.19	-0.11
alpha_FF3 (%)	-4.23	0.60	1.76	5.25	6.23	5.89	8.09	9.12	9.87	13.88	14.90
t_alpha_FF3	(-2.83)	(0.50)	(1.76)	(5.87)	(7.44)	(7.51)	(10.73)	(12.30)	(12.18)	(14.03)	(12.45)
p-value_FF3	0.0047	0.6155	0.0793	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.13.: Pure Momentum (skip) - K=6 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	4.35	4.76	6.89	7.81	7.29	8.06	8.65	10.34	9.86	13.55	6.02
$\sigma(\%)$	16.08	12.47	10.60	9.07	8.62	8.53	8.25	8.06	8.39	10.46	12.92
Sharpe Ratio	0.27	0.38	0.65	0.86	0.85	0.94	1.05	1.28	1.18	1.30	0.47
sk(m)	0.30	-0.17	-0.10	-0.21	-0.89	0.23	-0.39	-0.11	-0.28	-0.03	-2.30
alpha_mkt (%)	1.93	2.78	5.07	6.23	5.82	6.57	7.25	8.99	8.54	12.01	6.87
t(alpha)_mkt	(1.25)	(2.33)	(5.07)	(7.31)	(7.15)	(8.19)	(9.31)	(11.78)	(10.63)	(11.87)	(5.23)
p-value_mkt	0.2131	0.0199	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.30	0.25	0.23	0.20	0.18	0.19	0.18	0.17	0.16	0.19	-0.11
alpha_FF3 (%)	1.89	2.77	5.05	6.23	5.87	6.57	7.30	8.99	8.59	12.06	6.97
t_alpha_FF3	(1.22)	(2.32)	(5.04)	(7.30)	(7.19)	(8.17)	(9.34)	(11.75)	(10.66)	(11.94)	(5.29)
p-value_FF3	0.2230	0.0208	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.14.: Pure Momentum - J=11 months, K=6 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	2.75	4.06	6.28	6.71	7.47	7.76	9.05	10.20	10.97	13.90	7.97
$\sigma(\%)$	16.40	12.80	10.79	9.32	8.74	8.07	8.01	7.94	8.65	10.30	12.72
Sharpe Ratio	0.17	0.32	0.58	0.72	0.85	0.96	1.13	1.28	1.27	1.35	0.63
sk(m)	0.16	0.14	-0.09	-0.48	-0.24	-0.67	-0.53	-0.24	-0.02	-0.17	-2.14
alpha_mkt (%)	0.24	2.02	4.46	5.12	5.93	6.37	7.67	8.92	9.55	12.39	8.95
t(alpha)_mkt	(0.15)	(1.65)	(4.37)	(5.82)	(7.22)	(8.38)	(10.16)	(11.79)	(11.62)	(12.45)	(6.95)
p-value_mkt	0.8805	0.0988	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.32	0.26	0.23	0.20	0.19	0.17	0.17	0.16	0.18	0.19	-0.12
alpha_FF3 (%)	0.22	1.97	4.44	5.11	5.91	6.40	7.72	8.97	9.56	12.48	9.06
t_alpha_FF3	(0.14)	(1.61)	(4.33)	(5.79)	(7.19)	(8.39)	(10.19)	(11.83)	(11.60)	(12.58)	(7.02)
p-value_FF3	0.8875	0.1084	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.15.: Pure Momentum - J=12 months, K=6 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	13.69	9.38	10.60	9.59	9.21	8.96	8.90	7.33	6.97	3.26	7.25
$\sigma(\%)$	12.35	10.05	8.93	8.11	8.20	7.87	8.36	8.68	9.03	11.24	9.21
Sharpe Ratio	1.11	0.93	1.19	1.18	1.12	1.14	1.06	0.84	0.77	0.29	0.79
sk(m)	-0.13	-0.67	-0.39	-0.68	-0.46	-0.26	0.31	-0.28	0.37	-0.09	0.41
alpha_mkt (%)	11.53	7.65	9.02	8.19	7.75	7.61	7.47	5.90	5.44	1.53	6.81
t(alpha)_mkt	(9.94)	(8.07)	(10.78)	(10.72)	(10.10)	(10.25)	(9.47)	(7.15)	(6.37)	(1.42)	(7.23)
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1557	0.0000
beta_mkt	0.27	0.22	0.20	0.17	0.18	0.17	0.18	0.18	0.19	0.22	0.05
alpha_FF3 (%)	11.38	7.64	9.03	8.29	7.79	7.68	7.50	5.94	5.42	1.48	6.73
t_alpha_FF3	(9.87)	(8.06)	(10.78)	(10.83)	(10.11)	(10.31)	(9.48)	(7.18)	(6.33)	(1.37)	(7.15)
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1697	0.0000

Table 4.16.: Pure Reversal - K=6 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-26.36	19.43	33.92
$\sigma(\%)$	19.73	16.11	17.32
Sharpe Ratio	-1.34	1.21	1.96
sk(m)	-0.39	0.17	-0.25
alpha_mkt (%)	-28.29	17.97	34.09
t(alpha)_mkt	(-14.26)	(11.05)	(19.14)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.24	0.18	-0.02
alpha_FF3 (%)	-28.24	18.03	34.36
t_alpha_FF3	(-14.21)	(11.17)	(19.25)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.17.: Confirming signals - J=11 months, K=6 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-26.58	17.59	33.87
$\sigma(\%)$	19.03	15.33	16.71
Sharpe Ratio	-1.40	1.15	2.03
sk(m)	-0.46	0.30	0.11
alpha_mkt (%)	-28.66	16.20	34.25
t(alpha)_mkt	(-15.10)	(10.48)	(19.95)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.27	0.18	-0.05
alpha_FF3 (%)	-28.61	16.30	34.46
t_alpha_FF3	(-15.06)	(10.63)	(20.02)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.18.: Confirming signals - J=12 months, K=6 months

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	6.02	7.97	13.94	7.25	33.92	33.87	15.73	17.57	23.82	0.00	7.97	4.33	2.33
$\sigma(\%)$	12.92	12.72	11.77	9.21	17.32	16.71	12.30	13.04	13.66	0.00	18.58	12.36	11.00
Sharpe Ratio	0.47	0.63	1.18	0.79	1.96	2.03	1.28	1.35	1.74	NaN	0.43	0.35	0.21
sk(m)	-2.30	-2.14	-1.82	0.41	-0.25	0.11	-3.00	-2.23	-1.01	0.00	-0.52	1.40	1.17
alpha_mkt (%)	6.87	8.95	14.80	6.81	34.09	34.25	16.14	18.37	24.52	0.00	0.00	3.10	0.84
t(alpha)_mkt	(5.23)	(6.95)	(12.40)	(7.23)	(19.14)	(19.95)	(12.79)	(13.84)	(17.57)	NaN	(0.77)	(2.51)	(0.79)
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.4413	0.0122	0.4325
beta_mkt	-0.11	-0.12	-0.11	0.05	-0.02	-0.05	-0.05	-0.10	-0.09	0.00	1.00	0.15	0.19
alpha_FF3 (%)	6.97	9.06	14.90	6.73	34.36	34.46	16.15	18.24	24.37	0.00	0.00	-0.00	0.00
t_alpha_FF3	(5.29)	(7.02)	(12.45)	(7.15)	(19.25)	(20.02)	(12.75)	(13.69)	(17.41)	NaN	(10.45)	(-2.89)	(2.50)
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.0000	0.0040	0.0124

Holding Periods Results - K=9 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-1.80	2.74	3.54	6.94	7.74	7.32	9.33	10.32	11.21	15.17	13.80
$\sigma(\%)$	12.40	10.15	8.52	7.71	7.19	6.81	6.58	6.47	7.11	8.43	9.34
Sharpe Ratio	-0.15	0.27	0.42	0.90	1.08	1.07	1.42	1.60	1.58	1.80	1.48
sk(m)	-0.16	-0.43	-0.80	-0.57	-0.80	-0.74	-0.84	-0.59	-0.46	-0.36	-1.27
alpha_mkt (%)	-3.46	1.35	2.34	5.84	6.70	6.33	8.41	9.43	10.25	14.17	14.43
t(alpha)_mkt	(-2.86)	(1.36)	(2.82)	(7.80)	(9.62)	(9.61)	(13.15)	(14.95)	(14.77)	(17.00)	(15.21)
p-value_mkt	0.0044	0.1735	0.0048	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.21	0.17	0.15	0.14	0.13	0.12	0.12	0.11	0.12	0.13	-0.08
alpha_FF3 (%)	-3.51	1.25	2.32	5.83	6.70	6.35	8.47	9.50	10.32	14.30	14.62
t_alpha_FF3	(-2.89)	(1.26)	(2.80)	(7.76)	(9.58)	(9.60)	(13.22)	(15.02)	(14.82)	(17.17)	(15.39)
p-value_FF3	0.0039	0.2093	0.0053	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.19.: Pure Momentum (skip) - K=9 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	4.42	4.76	6.93	7.80	7.27	8.05	8.62	10.28	9.83	13.47	5.87
$\sigma(\%)$	12.87	9.95	8.44	7.35	7.04	6.97	6.79	6.69	6.95	8.61	10.39
Sharpe Ratio	0.34	0.48	0.82	1.06	1.03	1.15	1.27	1.54	1.41	1.56	0.56
sk(m)	0.18	-0.51	-0.45	-0.58	-1.32	-0.27	-0.75	-0.33	-0.43	-0.16	-1.81
alpha_mkt (%)	2.74	3.42	5.71	6.71	6.28	7.04	7.65	9.35	8.95	12.42	6.49
t(alpha)_mkt	(2.17)	(3.52)	(6.99)	(9.46)	(9.17)	(10.42)	(11.61)	(14.35)	(13.10)	(14.62)	(6.13)
p-value_mkt	0.0302	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.21	0.17	0.15	0.14	0.12	0.13	0.12	0.12	0.11	0.13	-0.08
alpha_FF3 (%)	2.60	3.35	5.69	6.68	6.32	7.05	7.70	9.40	9.04	12.51	6.72
t_alpha_FF3	(2.06)	(3.43)	(6.93)	(9.39)	(9.20)	(10.40)	(11.64)	(14.37)	(13.19)	(14.71)	(6.35)
p-value_FF3	0.0397	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.20.: Pure Momentum - J=11 months, K=9 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	2.79	4.06	6.33	6.71	7.45	7.72	9.02	10.14	10.96	13.82	7.86
$\sigma(\%)$	13.08	10.27	8.57	7.49	7.10	6.62	6.61	6.64	7.16	8.49	10.05
Sharpe Ratio	0.21	0.40	0.74	0.90	1.05	1.17	1.36	1.53	1.53	1.63	0.78
sk(m)	-0.05	-0.20	-0.52	-0.90	-0.62	-1.05	-0.89	-0.47	-0.24	-0.26	-1.49
alpha_mkt (%)	1.03	2.67	5.11	5.63	6.42	6.79	8.07	9.24	10.01	12.80	8.57
t(alpha)_mkt	(0.81)	(2.66)	(6.14)	(7.76)	(9.33)	(10.56)	(12.60)	(14.26)	(14.29)	(15.26)	(8.40)
p-value_mkt	0.4208	0.0079	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.22	0.17	0.15	0.13	0.13	0.12	0.12	0.11	0.12	0.13	-0.09
alpha_FF3 (%)	0.91	2.58	5.09	5.61	6.42	6.83	8.12	9.30	10.07	12.93	8.82
t_alpha_FF3	(0.71)	(2.56)	(6.10)	(7.70)	(9.30)	(10.58)	(12.63)	(14.32)	(14.34)	(15.42)	(8.65)
p-value_FF3	0.4748	0.0105	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.21.: Pure Momentum - J=12 months, K=9 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	13.70	9.39	10.58	9.55	9.17	8.91	8.87	7.31	6.94	3.32	7.30
$\sigma(\%)$	10.00	8.13	7.19	6.54	6.72	6.43	6.85	7.08	7.41	9.08	7.63
Sharpe Ratio	1.37	1.15	1.47	1.46	1.36	1.39	1.29	1.03	0.94	0.37	0.96
sk(m)	-0.08	-0.72	-0.55	-0.93	-0.73	-0.48	-0.06	-0.77	-0.13	-0.60	0.66
alpha_mkt (%)	12.28	8.29	9.57	8.62	8.20	8.00	7.89	6.32	5.88	2.16	7.04
t(alpha)_mkt	(12.65)	(10.45)	(13.70)	(13.58)	(12.58)	(12.80)	(11.87)	(9.18)	(8.18)	(2.42)	(8.99)
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0157	0.0000
beta_mkt	0.18	0.14	0.13	0.12	0.12	0.11	0.12	0.12	0.13	0.15	0.03
alpha_FF3 (%)	12.12	8.32	9.58	8.66	8.23	8.04	7.92	6.36	5.90	2.20	6.87
t_alpha_FF3	(12.51)	(10.46)	(13.69)	(13.60)	(12.58)	(12.82)	(11.88)	(9.22)	(8.18)	(2.45)	(8.79)
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0143	0.0000

Table 4.22.: Pure Reversal - K=9 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-24.81	18.87	31.15
$\sigma(\%)$	15.51	12.40	14.10
Sharpe Ratio	-1.60	1.52	2.21
sk(m)	-0.65	0.21	0.16
alpha_mkt (%)	-26.06	18.07	31.35
t(alpha)_mkt	(-16.57)	(14.27)	(21.63)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.16	0.10	-0.02
alpha_FF3 (%)	-26.03	18.05	31.52
t_alpha_FF3	(-16.50)	(14.34)	(21.70)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.23.: Confirming signals - J=11 months, K=9 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-25.21	17.01	29.88
$\sigma(\%)$	15.23	12.11	13.61
Sharpe Ratio	-1.66	1.40	2.20
sk(m)	-0.80	0.31	0.35
alpha_mkt (%)	-26.55	16.24	30.18
t(alpha)_mkt	(-17.27)	(13.14)	(21.57)
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.17	0.10	-0.04
alpha_FF3 (%)	-26.50	16.29	30.28
t_alpha_FF3	(-17.18)	(13.24)	(21.59)
p-value_FF3	0.0000	0.0000	0.0000

Table 4.24.: Confirming signals - J=12 months, K=9 months

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	5.87	7.86	13.80	7.30	31.15	29.88	15.52	17.28	23.49	0.00	7.97	4.33	2.33
$\sigma(\%)$	10.39	10.05	9.34	7.63	14.10	13.61	9.70	10.07	10.96	0.00	18.58	12.36	11.00
Sharpe Ratio	0.56	0.78	1.48	0.96	2.21	2.20	1.60	1.72	2.14	NaN	0.43	0.35	0.21
sk(m)	-1.81	-1.49	-1.27	0.66	0.16	0.35	-1.81	-1.18	-0.23	0.00	-0.52	1.40	1.17
alpha_mkt (%)	6.49	8.57	14.43	7.04	31.35	30.18	15.89	17.99	24.13	0.00	0.00	3.10	0.84
t(alpha)_mkt	(6.13)	(8.40)	(15.21)	(8.99)	(21.63)	(21.57)	(15.98)	(17.61)	(21.61)	NaN	0.77	2.51	0.79
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.4413	0.0122	0.4325
beta_mkt	-0.08	-0.09	-0.08	0.03	-0.02	-0.04	-0.05	-0.09	-0.08	0.00	1.00	0.15	0.19
alpha_FF3 (%)	6.72	8.82	14.62	6.87	31.52	30.28	15.94	18.14	24.21	0.00	0.00	-0.00	0.00
t_alpha_FF3	(6.35)	(8.65)	(15.39)	(8.79)	(21.70)	(21.59)	(15.99)	(17.72)	(21.61)	NaN	10.45	-2.89	2.50
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NaN	0.0000	0.0040	0.0124

Holding Periods Results - K=12 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-1.69	2.82	3.60	6.97	7.72	7.34	9.31	10.31	11.21	15.12	13.64
$\sigma(\%)$	10.81	8.78	7.39	6.82	6.23	6.03	5.82	5.67	6.24	7.34	7.90
Sharpe Ratio	-0.16	0.32	0.49	1.02	1.24	1.22	1.60	1.82	1.80	2.06	1.73
sk(m)	0.03	-0.07	-0.56	-0.19	-0.47	-0.38	-0.72	-0.49	-0.41	-0.36	-1.47
alpha_mkt (%)	-3.10	1.65	2.58	6.08	6.90	6.54	8.60	9.64	10.49	14.37	14.28
t(alpha)_mkt	-2.93	1.93	3.58	9.10	11.31	11.08	14.98	17.18	16.97	19.60	17.89
p-value_mkt	0.0034	0.0544	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.18	0.15	0.13	0.11	0.10	0.10	0.09	0.08	0.09	0.09	-0.08
alpha_FF3 (%)	-3.19	1.52	2.54	6.05	6.88	6.54	8.65	9.71	10.54	14.43	14.43
t_alpha_FF3	-3.02	1.77	3.52	9.03	11.24	11.06	15.03	17.26	17.01	19.67	18.11
p-value_FF3	0.0026	0.0764	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.25.: Pure Momentum (skip) - K=12 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	4.56	4.83	7.00	7.81	7.26	8.05	8.61	10.25	9.81	13.43	5.71
$\sigma(\%)$	11.11	8.49	7.22	6.35	6.15	6.16	6.01	5.92	6.09	7.48	8.79
Sharpe Ratio	0.41	0.57	0.97	1.23	1.18	1.31	1.43	1.73	1.61	1.80	0.65
sk(m)	0.25	-0.34	-0.19	-0.50	-1.19	0.05	-0.57	-0.20	-0.40	-0.18	-1.56
alpha_mkt (%)	3.07	3.71	5.96	6.90	6.48	7.26	7.85	9.57	9.18	12.65	6.39
t(alpha)_mkt	2.82	4.47	8.51	11.20	10.73	12.01	13.28	16.32	15.10	16.94	7.19
p-value_mkt	0.0048	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
beta_mkt	0.19	0.14	0.13	0.11	0.10	0.10	0.09	0.09	0.08	0.10	-0.09
alpha_FF3 (%)	2.92	3.63	5.89	6.86	6.51	7.26	7.89	9.60	9.23	12.67	6.57
t_alpha_FF3	2.70	4.37	8.42	11.12	10.73	11.98	13.30	16.33	15.16	16.95	7.41
p-value_FF3	0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.26.: Pure Momentum - J=11 months, K=12 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	2.90	4.13	6.40	6.74	7.44	7.72	9.02	10.10	10.97	13.77	7.70
$\sigma(\%)$	11.33	8.83	7.33	6.51	6.21	5.78	5.86	5.88	6.29	7.38	8.45
Sharpe Ratio	0.26	0.47	0.87	1.04	1.20	1.34	1.54	1.72	1.74	1.87	0.91
sk(m)	0.14	0.03	-0.18	-0.81	-0.26	-0.89	-0.69	-0.38	-0.15	-0.28	-1.41
alpha_mkt (%)	1.37	2.94	5.37	5.85	6.63	6.98	8.28	9.44	10.26	13.01	8.45
t(alpha)_mkt	1.24	3.41	7.54	9.21	10.89	12.30	14.36	16.17	16.44	17.64	9.93
p-value_mkt	0.216	0.0007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
beta_mkt	0.19	0.15	0.13	0.11	0.10	0.09	0.09	0.08	0.09	0.09	-0.09
alpha_FF3 (%)	1.23	2.82	5.32	5.80	6.62	7.01	8.31	9.49	10.30	13.07	8.65
t_alpha_FF3	1.11	3.27	7.47	9.11	10.85	12.31	14.37	16.23	16.46	17.70	10.21
p-value_FF3	0.2652	0.0011	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4.27.: Pure Momentum - J=12 months, K=12 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	13.72	9.44	10.60	9.54	9.16	8.89	8.86	7.30	6.92	3.31	7.24
$\sigma(\%)$	8.68	7.00	6.23	5.69	5.93	5.66	6.11	6.31	6.67	8.02	6.78
Sharpe Ratio	1.58	1.35	1.70	1.68	1.54	1.57	1.45	1.16	1.04	0.41	1.07
sk(m)	0.11	-0.73	-0.46	-0.80	-0.58	-0.40	0.32	-0.44	0.29	-0.50	0.83
alpha_mkt (%)	12.57	8.52	9.80	8.78	8.38	8.20	8.08	6.51	6.07	2.38	7.01
t(alpha)_mkt	14.80	12.42	16.02	15.80	14.42	14.66	13.46	10.49	9.27	2.99	10.08
p-value_mkt	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0028	0.0000
beta_mkt	0.15	0.11	0.10	0.10	0.10	0.09	0.10	0.10	0.11	0.12	0.03
alpha_FF3 (%)	12.45	8.55	9.81	8.80	8.39	8.23	8.07	6.50	6.04	2.33	6.97
t_alpha_FF3	14.71	12.44	16.03	15.79	14.39	14.67	13.41	10.43	9.20	2.93	9.99
p-value_FF3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000

Table 4.28.: Pure Reversal - K=12 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-24.14	18.08	28.57
$\sigma(\%)$	13.21	10.42	12.31
Sharpe Ratio	-1.83	1.74	2.32
sk(m)	-0.85	0.14	0.28
alpha_mkt (%)	-25.32	17.53	28.78
t(alpha)_mkt	-18.99	16.41	22.74
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.15	0.07	-0.03
alpha_FF3 (%)	-25.28	17.50	28.83
t_alpha_FF3	-18.90	16.43	22.69
p-value_FF3	0.0000	0.0000	0.0000

Table 4.29.: Confirming signals - J=11 months, K=12 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-24.00	16.50	27.85
$\sigma(\%)$	13.51	10.29	11.82
Sharpe Ratio	-1.78	1.60	2.36
sk(m)	-0.92	0.32	0.51
alpha_mkt (%)	-25.31	15.92	28.10
t(alpha)_mkt	-18.65	15.13	23.14
p-value_mkt	0.0000	0.0000	0.0000
beta_mkt	0.17	0.07	-0.03
alpha_FF3 (%)	-25.33	15.96	28.10
t_alpha_FF3	-18.64	15.21	23.05
p-value_FF3	0.0000	0.0000	0.0000

Table 4.30.: Confirming signals - J=12 months, K=12 months

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt
$\mu(r-rf)(\%)$	5.710000	7.700000	13.640000	7.240000	28.570000	27.850000	15.250000	16.990000	23.160000	0.000000	7.970000
$\sigma(\%)$	8.790000	8.450000	7.900000	6.780000	12.310000	11.820000	8.190000	8.500000	9.580000	0.000000	18.580000
Sharpe Ratio	0.650000	0.910000	1.730000	1.070000	2.320000	2.360000	1.860000	2.000000	2.420000	NaN	0.430000
sk(m)	-1.560000	-1.410000	-1.470000	0.830000	0.280000	0.510000	-1.390000	-0.980000	-0.290000	0.000000	-0.520000
alpha_mkt (%)	6.390000	8.450000	14.280000	7.010000	28.780000	28.100000	15.730000	17.740000	23.800000	0.000000	0.000000
t(alpha)_mkt	7.190000	9.930000	17.890000	10.080000	22.740000	23.140000	18.840000	20.740000	24.460000	NaN	0.770000
p-value_mkt	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	NaN	0.441300
beta_mkt	-0.090000	-0.090000	-0.080000	0.030000	-0.030000	-0.030000	-0.060000	-0.090000	-0.080000	0.000000	1.000000
alpha_FF3 (%)	6.570000	8.650000	14.430000	6.970000	28.830000	28.100000	15.850000	17.870000	23.880000	0.000000	0.000000
t_alpha_FF3	7.410000	10.210000	18.110000	9.990000	22.690000	23.050000	18.970000	20.880000	24.480000	NaN	10.450000
p-value_FF3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	NaN	0.000000

5. Conclusions and Suggestions for Future Research

5.1. Conclusion

Embarking on a comprehensive exploration of stock market strategies, this study has meticulously scrutinized momentum and reversal approaches over an extensive period from 1926 to 2022. Through a detailed examination of previous studies, application of rigorous methodologies, and careful analysis of outcomes, we have unearthed intriguing insights into the performance of stocks under these strategies over time.

Our investigation reveals that momentum strategies—predicated on the expectation that stocks demonstrating strong past performance will continue their upward trajectory—exhibit considerable efficacy, particularly when employing a one-month waiting period (the "skip" strategy). This strategic delay mitigates the market's occasional knee-jerk reactions, thereby enhancing return potential. Conversely, reversal strategies, which favor underperforming stocks in anticipation of short-term recovery, challenge the conventional wisdom of market efficiency, suggesting there is merit in betting against recent trends for quick gains.

A particularly compelling aspect of our research involved the integration of momentum and reversal tactics. The fusion of these strategies has unveiled a pathway to potentially superior investment outcomes. Notably, our hybrid strategy, characterized by a one-month reversal period followed by a momentum strategy incorporating a wait period ("rev_mom(skip)"), demonstrated remarkable efficacy, boasting a 26.40% return with a Sharpe Ratio of 0.70. This signifies that, relative to the market, the strategy achieves significantly higher returns for the level of risk undertaken.

Furthermore, the "rev_mom(skip)" strategy exhibited an exceptional alpha of 30.4%, underscoring its ability to outstrip market benchmarks after risk adjustment. Its negative beta of -0.55 hints at its potential to offer stability or even gains during market downturns, marking it as a valuable diversification tool. However, it is critical to acknowledge the potential impact of trading fees on the viability and performance of these strategies, given their reliance on active portfolio management.

When also considering longer holding periods (K = 3, 6, 9, and 12 months), we observe distinct trends in the performance metrics. Specifically, the mean, risk, and market alpha generally decrease as the holding period extends, while the Sharpe Ratio (SR), skewness, and market beta tend to increase. This indicates a progressive reduction in volatility and risk alongside an improvement in risk-adjusted returns as portfolios are held for longer durations. Additionally, the increase in skewness and beta suggests that the portfolios are not only becoming more asymmetrical in their returns distribution but also more sensitive to market movements. This comprehensive shift in key performance indicators underscores the strategic advantage of extending holding periods within the Pure Momentum (skip) strategy framework, aligning better with long-term investment goals and risk tolerance. At the end of the day it could be the trade-off between return and risk when it comes to investors choosing their investment time horizon.

In closing, this research not only reaffirms the relevance of both momentum and reversal strategies within the financial literature but also pioneers new avenues for investment strategy by advocating for their combination. The insights gleaned from this study empower investors to better navigate the intricacies of the stock market, leveraging the nuanced application of combined strategies to optimize their market engagement. This blend of old and new wisdom serves as a beacon for future endeavors in the domain of investment strategies, pointing towards a horizon rich with opportunity for both practitioners and scholars alike. By casting a light on the synergistic potential between momentum and reversal strategies, this study sets the stage for further inquiry. The exploration of these combined strategies not only enriches our understanding of market dynamics but also challenges us to rethink traditional investment paradigms. As we look forward, the path is paved with intriguing questions and the promise of innovative investment approaches that await discovery.

5.2. Future Research

This study has opened several paths for further exploration. Here are some ideas for future research that could build on what we've learned:

- **Using daily or weekly data:** This study used data from each month. But, what happens if we look at how stocks do every day or every week? This could give us more detailed insights and possibly better strategies.
- **Trying different holding periods:** I looked at what happens when you hold stocks for one month. But what if we hold them longer, like three, six, nine or even twelve months? This could make our strategy more complex but also more effective.
- **Looking at product returns:** Instead of adding returns together, what if we multiply them, especially over short times like a few years? This could show us how investments really add up over time.
- **Considering trading fees:** Changing your investments every month can cost a lot in fees. It would be interesting to see if these strategies are still worth it after you pay all those costs.

- **Using a different number of groups:** I divided stocks into 3 or 10 groups. Maybe using more groups, or finding the best number of groups, could make our strategies work better.
- **Mixing different time strategies:** Future research could also mix short-term reversal with medium-term momentum, and then add long-term reversal. This could create a more complex, but possibly more rewarding, strategy.

These ideas could help us understand better ways to invest in the stock market and make more money from our investments. In the end, while momentum and reversal strategies each have their unique characteristics and logic, combining them thoughtfully can lead to outstanding investment success. This study not only reaffirms the value of these strategies in academic discussions but also offers actionable insights for investors aiming to make the most of market movements and finally taking advantage of that lazy waiting period!

Bibliography

C. Asness. *Variables that Explain Stock Returns: Simulated and Empirical Evidence*. University of Chicago, Graduate School of Business. URL https://books.google.at/books?id=n2uvGwAACAAJ.

C. S. Asness, T. J. Moskowitz, and L. H. Pedersen. Value and momentum everywhere. 68(3):929–985. ISSN 0022-1082, 1540-6261. doi: 10.1111/jofi.12021. URL https://onlinelibrary.wiley.com/doi/10.1111/jofi.12021.

N. Barberis, A. Shleifer, and R. Vishny. A model of investor sentiment.

R. Bird and L. Casavecchia. Sentiment and financial health indicators for value and growth stocks: The european experience. 13(8):769–793. URL https://ideas.repec.org//a/taf/eurjfi/v13y2007i8p769-793.html. Publisher: Taylor & Francis Journals.

L. K. C. Chan, N. Jegadeesh, and J. Lakonishok. Momentum strategies. 51(5):1681–1713. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1996.tb05222.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1996.tb05222.x.

J. Conrad and M. D. Yavuz. Momentum and reversal: Does what goes up always come down?*. 21(2):555–581. ISSN 1572-3097, 1573-692X. doi: 10.1093/rof/rfw006. URL https://academic.oup.com/rof/article/21/2/555/2670016.

K. Daniel and T. J. Moskowitz. Momentum crashes. 122(2):221–247. ISSN 0304405X. doi: 10.1016/j.jfineco.2015.12.002. URL https://linkinghub.elsevier.com/retrieve/pii/S0304405X16301490.

K. Daniel, D. Hirshleifer, and A. Subrahmanyam. Investor psychology and security market under- and overreactions. 53(6):1839–1885. ISSN 1540-6261. doi: 10.1111/0022-1082.00077. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/0022-1082.00077. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/0022-1082.00077.

W. F. M. De BONDT and R. Thaler. Does the stock market overreact? 40(3):793–805. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1985.tb05004.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1985.tb05004.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1985.tb05004.x.

E. Fama and K. French. Multifactor explanations of asset pricing anomalies. 51(1):55–84, a. URL https://econpapers.repec.org/article/blajfinan/v_3a51_3ay_3a1996_3ai_3a1_3ap_3a55-84.htm. Publisher: American Finance Association.

E. F. Fama. Production of u.s. rm-rf, SMB, and HML in the fama-french data library.

E. F. Fama and K. R. French. Common risk factors in the returns on stocks and bonds. 33(1):3–56, b. ISSN 0304-405X. doi: 10.1016/0304-405X(93)90023-5. URL https://www.sciencedirect.com/science/article/pii/0304405X93900235.

A. Frazzini. The disposition effect and underreaction to news. 61(4):2017–2046. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2006.00896.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2006.00896.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2006.00896.x.

B. D. Grundy and J. S. Martin. Understanding the nature of the risks and the source of the rewards to momentum investing.

N. Jegadeesh. Evidence of predictable behavior of security returns. 45(3):881–898. ISSN 0022-1082. doi: 10.2307/2328797. URL https://www.jstor.org/stable/2328797. Publisher: [American Finance Association, Wiley].

N. Jegadeesh and S. Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. 48(1):65–91. ISSN 0022-1082, 1540-6261. doi: 10.1111/j.1540-6261.1993.tb04702.x. URL https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1993.tb04702.x.

S. P. Kothari and J. Shanken. Stock return variation and expected dividends: A time-series and cross-sectional analysis. 31(2):177–210. ISSN 0304-405X. doi: 10.1016/0304-405X(92)90003-G. URL https://www.sciencedirect.com/science/article/pii/0304405X9290003G.

R. Kumar and A. K. Makhija. Volatility of stock prices and market efficiency. 7(2): 119–122. ISSN 0143-6570. URL https://www.jstor.org/stable/2487167. Publisher: Wiley.

J. Lakonishok, A. Shleifer, and R. W. Vishny. Contrarian investment, extrapolation, and risk. 49(5):1541–1578. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1994.tb04772.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1994.tb04772.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1994.tb04772.x.

B. N. Lehmann. Fads, martingales, and market efficiency. 105(1):1–28. ISSN 0033-5533. doi: 10.2307/2937816. URL https://www.jstor.org/stable/2937816. Publisher: Oxford University Press.

A. W. Lo and A. C. MacKinlay. When are contrarian profits due to stock market overreaction? 3(2):175–205. ISSN 0893-9454. doi: 10.1093/rfs/3.2.175. URL https://doi.org/10.1093/rfs/3.2.175.

H. Markowitz. Portfolio selection*. 7(1):77–91. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1952.tb01525.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1952.tb01525.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1952.tb01525.x.

R. C. Merton. On the pricing of corporate debt: The risk structure of interest rates. 29(2):449–470. ISSN 0022-1082. doi: 10.2307/2978814. URL https://www.jstor.org/stable/2978814. Publisher: [American Finance Association, Wiley].

R. Novy-Marx. Is momentum really momentum? 103(3):429–453. ISSN 0304405X. doi: 10.1016/j.jfineco.2011.05.003. URL https://linkinghub.elsevier.com/retrieve/pii/S0304405X11001152.

W. F. Sharpe. Capital asset prices: A theory of market equilibrium under conditions of risk*. 19(3):425–442. ISSN 1540-6261. doi: 10.1111/j.1540-6261.1964.tb02865.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1964.tb02865.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1964.tb02865.x.

A. Tversky and D. Kahneman. Judgment under uncertainty: Heuristics and biases. 185(4157):1124–1131. ISSN 1095-9203. doi: 10.1126/science.185.4157.1124. Place: US Publisher: American Assn for the Advancement of Science.

X. F. Zhang. Information uncertainty and stock returns. 61(1):105–137. ISSN 1540-6261. doi: 10.1111/j.1540-6261.2006.00831.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2006.00831.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2006.00831.x.

A. Appendix

A.1. 10 Buckets Figures: 2000-2022

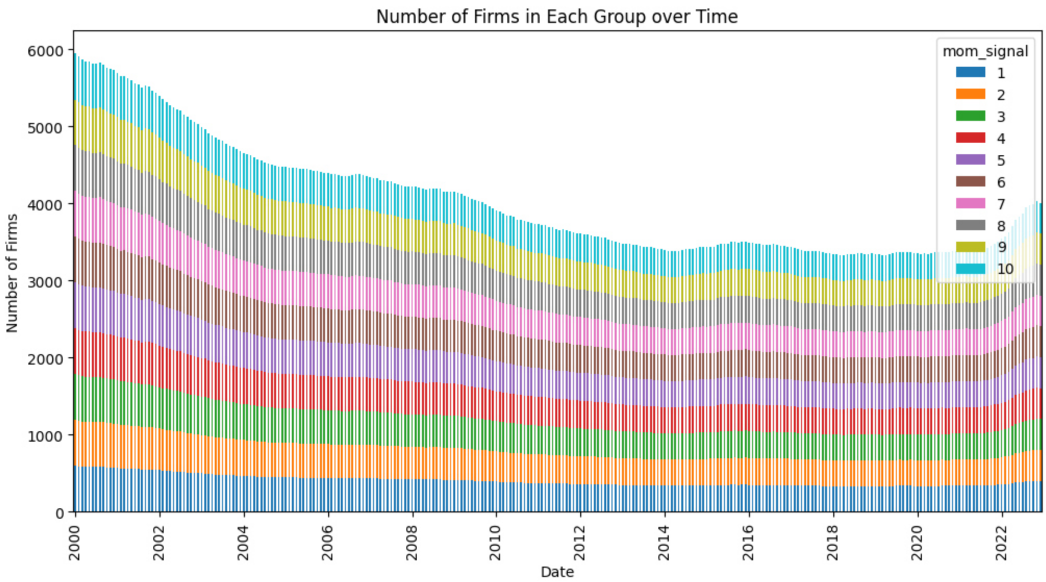


Figure A.1.: Total Groups: 2000-2022

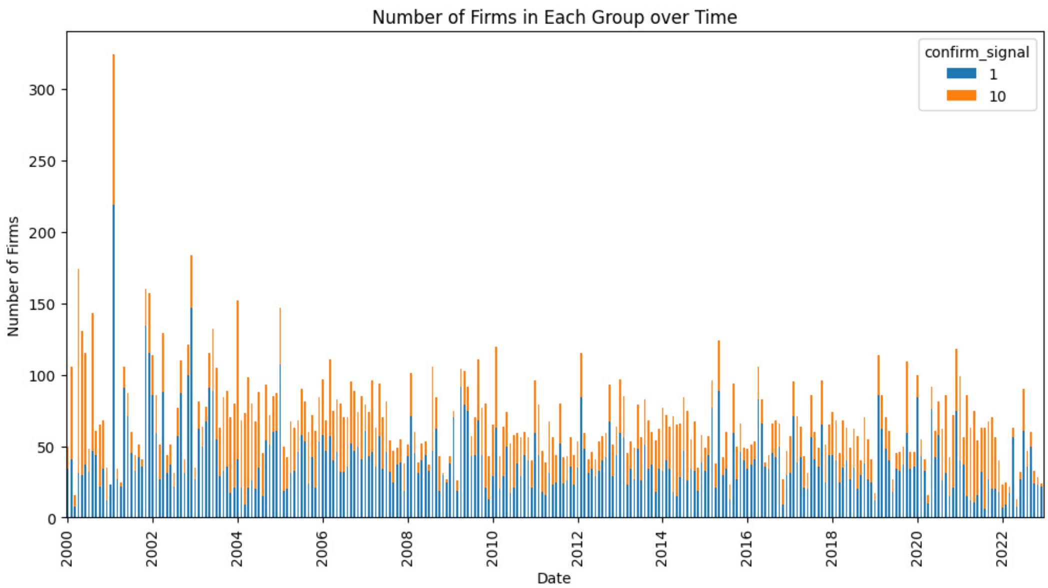


Figure A.2.: Confirming Groups: 2000-2022

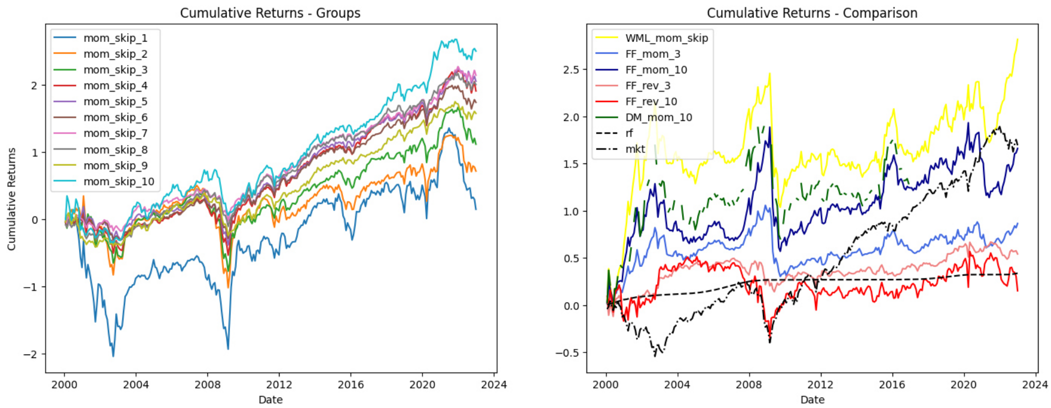


Figure A.3.: Momentum (skip): 2000-2022

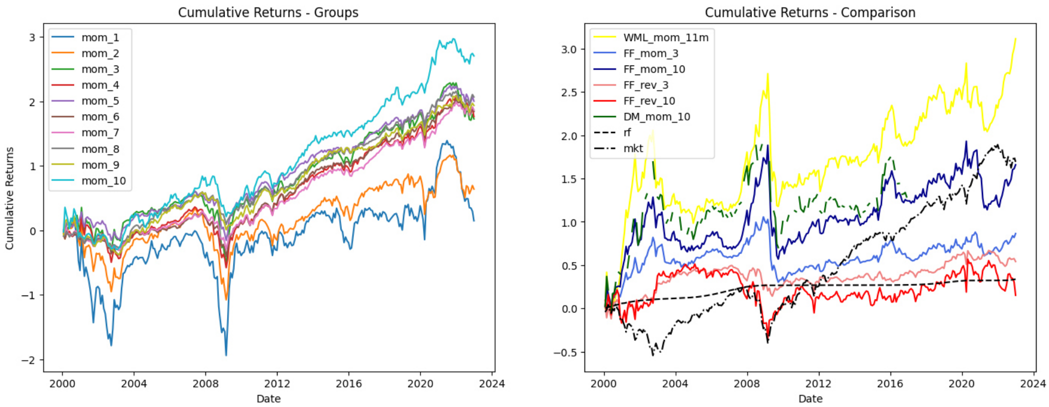


Figure A.4.: Momentum - J=11 months: 2000-2022

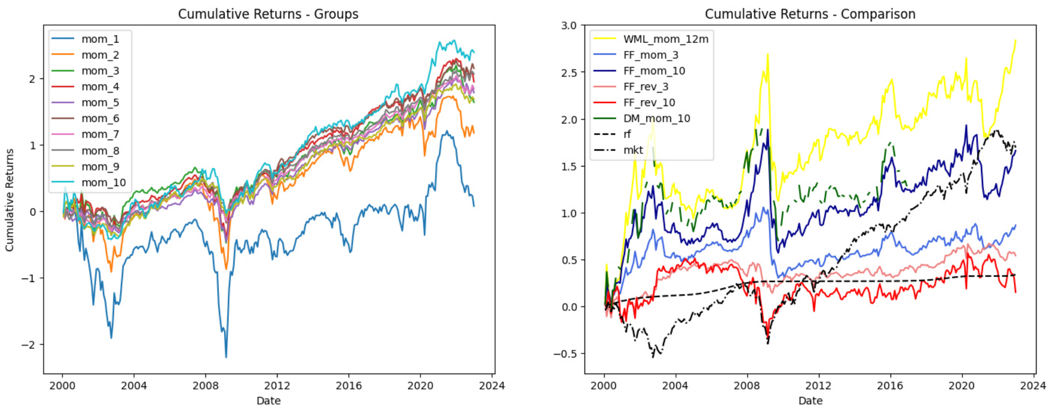


Figure A.5.: Momentum - J=12 months: 2000-2022

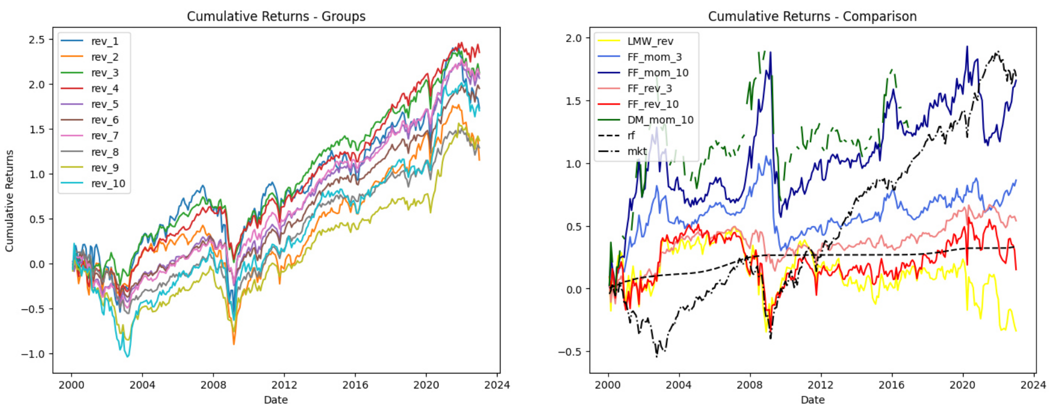


Figure A.6.: Reversal: 2000-2022

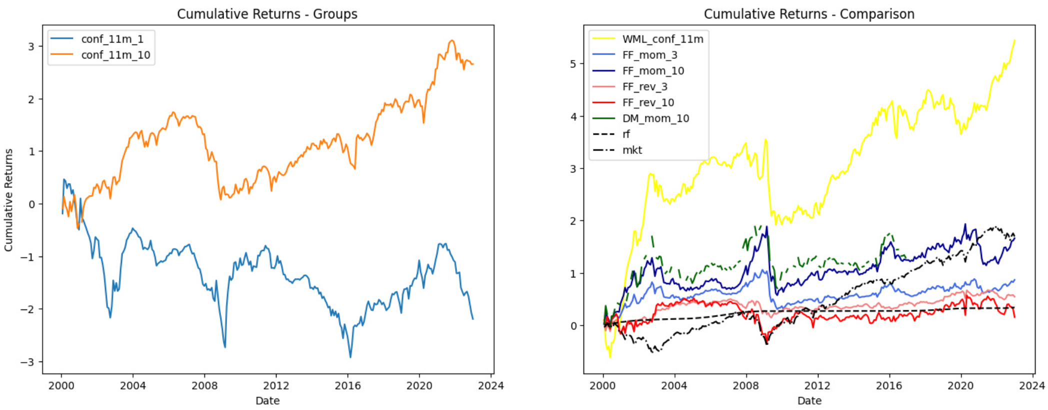


Figure A.7.: Confirming Signal - J=11 months: 2000-2022

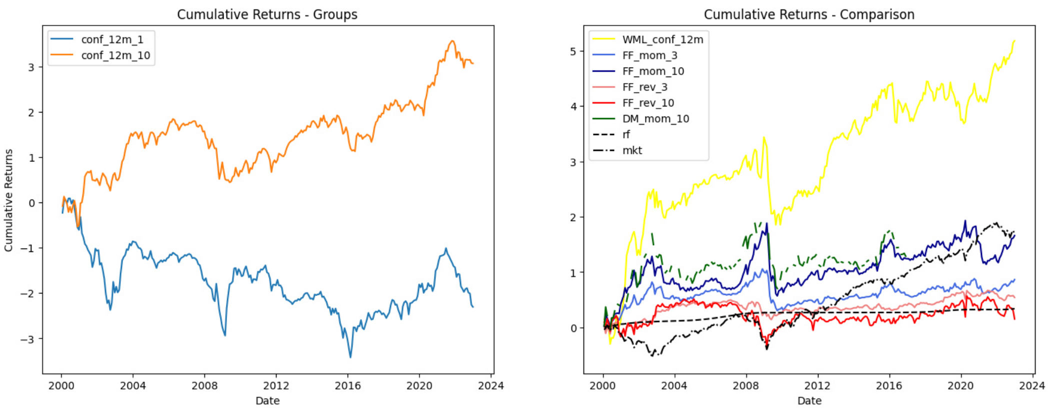


Figure A.8.: Confirming Signal - J=12 months: 2000-2022

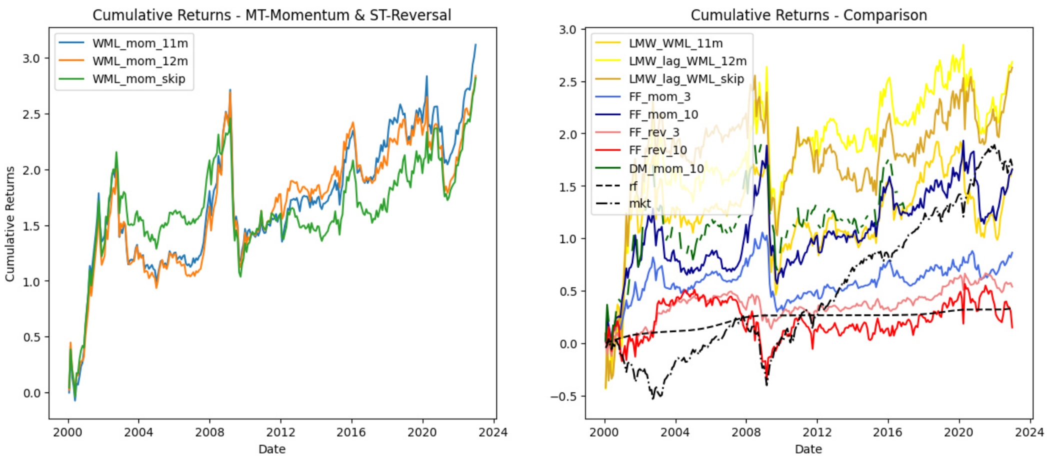


Figure A.9.: Combining Momentum & Reversal: 2000-2022

A.2. 10 Buckets Tables: 2000-2022

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-0.85	1.62	3.36	6.80	7.43	6.06	7.82	7.22	5.35	9.38	10.81
$\sigma(\%)$	42.34	31.46	25.62	21.16	18.59	15.86	14.89	15.36	16.35	23.55	36.25
Sharpe Ratio	-0.02	0.05	0.13	0.32	0.40	0.38	0.53	0.47	0.33	0.40	0.30
sk(m)	0.05	-0.58	-0.49	-0.65	-0.64	-0.55	-0.55	-0.48	-0.86	-0.47	-1.68
$\alpha\_mkt(\%)$	-13.25	-8.24	-4.68	-0.30	1.08	0.54	2.68	1.93	0.03	2.71	16.29
$t(\alpha)\_mkt$	(-2.38)	(-2.27)	(-1.59)	(-0.15)	(0.67)	(0.44)	(2.18)	(1.50)	(0.01)	(0.83)	(2.34)
p-value_mkt	0.018	0.024	0.113	0.881	0.503	0.663	0.030	0.135	0.988	0.405	0.020
β_mkt	2.06	1.64	1.33	1.18	1.05	0.92	0.85	0.88	0.88	1.11	-0.93
$\alpha\_FF3(\%)$	-14.11	-9.18	-5.37	-0.99	0.70	0.21	2.38	1.79	0.14	2.93	17.68
t_alpha_FF3	(-2.55)	(-2.55)	(-1.85)	(-0.54)	(0.46)	(0.19)	(2.07)	(1.40)	(0.08)	(1.10)	(2.60)
p-value_FF3	0.011	0.012	0.066	0.591	0.645	0.852	0.039	0.161	0.935	0.272	0.010

Table A.1.: Pure Momentum (skip)

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-0.85	1.28	6.01	6.16	7.21	6.51	6.62	7.49	6.92	10.26	12.12
$\sigma(\%)$	46.43	32.59	26.71	21.87	18.67	16.16	15.32	14.72	16.56	23.25	39.40
Sharpe Ratio	-0.02	0.04	0.23	0.28	0.39	0.40	0.43	0.51	0.42	0.44	0.31
sk(m)	-0.24	-0.76	-0.50	-0.43	-0.72	-0.54	-0.73	-0.54	-0.39	-0.11	-2.24
$\alpha\_mkt(\%)$	-14.26	-8.96	-2.34	-1.06	0.83	0.94	1.31	2.44	1.69	3.88	18.84
$t(\alpha)\_mkt$	(-2.29)	(-2.40)	(-0.76)	(-0.49)	(0.51)	(0.70)	(1.06)	(1.95)	(0.90)	(1.16)	(2.57)
p-value_mkt	0.023	0.017	0.451	0.628	0.609	0.483	0.290	0.052	0.368	0.245	0.011
β_mkt	2.22	1.70	1.39	1.20	1.06	0.92	0.88	0.84	0.87	1.06	-1.14
$\alpha\_FF3(\%)$	-14.95	-9.87	-2.77	-1.55	0.22	0.73	0.90	2.25	1.59	4.00	19.94
t_alpha_FF3	(-2.41)	(-2.66)	(-0.89)	(-0.74)	(0.15)	(0.59)	(0.80)	(1.80)	(0.87)	(1.45)	(2.76)
p-value_FF3	0.017	0.008	0.373	0.463	0.881	0.558	0.423	0.073	0.383	0.147	0.006

Table A.2.: Pure Momentum - J=11 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	mom
$\mu(r-rf)(\%)$	-1.15	3.64	5.65	6.99	6.28	7.88	6.54	7.50	5.86	8.92	10.90
$\sigma(\%)$	46.60	32.75	26.92	21.41	18.72	16.36	14.89	15.06	16.05	23.38	39.88
Sharpe Ratio	-0.02	0.11	0.21	0.33	0.34	0.48	0.44	0.50	0.37	0.38	0.27
sk(m)	-0.39	-0.64	-0.47	-0.66	-0.70	-0.69	-0.59	-0.47	-0.53	-0.21	-2.08
$\alpha\_mkt(\%)$	-14.74	-6.63	-2.67	-0.22	-0.11	2.20	1.43	2.39	0.67	2.43	17.71
$t(\alpha)\_mkt$	(-2.39)	(-1.76)	(-0.83)	(-0.11)	(-0.07)	(1.68)	(1.13)	(1.77)	(0.39)	(0.74)	(2.38)
p-value_mkt	0.018	0.080	0.405	0.912	0.947	0.093	0.258	0.077	0.694	0.463	0.018
β_mkt	2.25	1.70	1.38	1.20	1.06	0.94	0.85	0.85	0.86	1.08	-1.15
$\alpha\_FF3(\%)$	-15.53	-7.51	-3.59	-0.84	-0.66	1.67	1.26	2.18	0.80	2.61	18.98
t_alpha_FF3	(-2.53)	(-2.00)	(-1.13)	(-0.45)	(-0.45)	(1.45)	(1.11)	(1.63)	(0.49)	(0.95)	(2.60)
p-value_FF3	0.012	0.047	0.258	0.655	0.655	0.149	0.267	0.105	0.622	0.341	0.010

Table A.3.: Pure Momentum - J=12 months

10 BUCKETS	1	2	3	4	5	6	7	8	9	10	rev
$\mu(r-rf)(\%)$	6.02	3.52	7.73	8.72	7.47	6.98	7.66	4.11	4.46	5.90	-2.94
$\sigma(\%)$	33.82	25.60	21.06	18.44	16.57	15.61	15.66	16.46	18.05	23.84	27.48
Sharpe Ratio	0.18	0.14	0.37	0.47	0.45	0.45	0.49	0.25	0.25	0.25	-0.11
sk(m)	-1.08	-1.17	-0.80	-0.58	-0.55	-0.80	-0.63	-0.41	-0.42	-0.22	-0.75
$\alpha\_mkt(\%)$	-4.33	-4.97	0.53	2.28	1.62	1.45	2.17	-1.46	-1.41	-1.08	-6.18
$t(\alpha)\_mkt$	(-1.05)	(-1.97)	(0.29)	(1.61)	(1.37)	(1.33)	(1.85)	(-0.97)	(-0.75)	(-0.35)	(-1.13)
p-value_mkt	0.293	0.050	0.771	0.108	0.172	0.185	0.065	0.334	0.455	0.730	0.260
β_mkt	1.72	1.41	1.19	1.07	0.97	0.92	0.91	0.92	0.97	1.16	0.55
$\alpha\_FF3(\%)$	-4.86	-5.53	0.33	2.25	1.70	1.49	2.21	-1.50	-1.51	-1.31	-6.56
t_alpha_FF3	(-1.23)	(-2.23)	(0.18)	(1.58)	(1.49)	(1.36)	(1.95)	(-1.00)	(-0.80)	(-0.45)	(-1.19)
p-value_FF3	0.221	0.027	0.857	0.115	0.137	0.176	0.052	0.320	0.423	0.656	0.235

Table A.4.: Pure Reversal

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-11.02	10.06	22.27
$\sigma(\%)$	51.99	39.75	49.76
Sharpe Ratio	-0.21	0.25	0.45
sk(m)	0.37	-0.64	-3.12
$\alpha\_mkt(\%)$	-22.94	1.57	25.44
$t(\alpha)\_mkt$	(-2.65)	(0.23)	(2.47)
p-value_mkt	0.009	0.819	0.014
β_mkt	1.98	1.41	-0.54
$\alpha\_FF3(\%)$	-24.63	0.76	26.47
t_alpha_FF3	(-3.02)	(0.12)	(2.55)
p-value_FF3	0.003	0.905	0.011

Table A.5.: Confirming signals - J=11 months

10 BUCKETS	1	10	conf
$\mu(r-rf)(\%)$	-11.51	11.85	21.14
$\sigma(\%)$	47.28	39.71	46.96
Sharpe Ratio	-0.24	0.30	0.45
sk(m)	0.01	-0.57	-1.76
$\alpha\_mkt(\%)$	-22.82	3.00	23.56
$t(\alpha)\_mkt$	(-2.98)	(0.45)	(2.41)
p-value_mkt	0.003	0.655	0.017
β_mkt	1.88	1.47	-0.41
$\alpha\_FF3(\%)$	-24.16	2.43	24.49
t_alpha_FF3	(-3.23)	(0.40)	(2.51)
p-value_FF3	0.001	0.689	0.013

Table A.6.: Confirming signals - J=12 months

10 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	12.12	10.90	10.81	-2.94	22.27	21.14	5.77	10.23	9.99	0.00	5.91	3.26	2.00
$\sigma(\%)$	39.40	39.88	36.25	27.48	49.76	46.96	37.34	51.78	49.03	0.00	16.09	12.01	11.05
Sharpe Ratio	0.31	0.27	0.30	-0.11	0.45	0.45	0.15	0.20	0.20	NaN	0.37	0.27	0.18
sk(m)	-2.24	-2.08	-1.68	-0.75	-3.12	-1.76	-2.30	-1.56	-1.13	0.00	-0.66	0.01	0.26
$\alpha\_mkt(\%)$	18.84	17.71	16.29	-6.18	25.44	23.56	9.24	17.20	15.73	0.00	0.00	3.33	0.94
$t(\alpha)\_mkt$	(2.57)	(2.38)	(2.34)	(-1.13)	(2.47)	(2.41)	(1.21)	(1.70)	(1.61)	NaN	(0.96)	(1.32)	(0.42)
p-value_mkt	0.011	0.018	0.020	0.260	0.014	0.017	0.226	0.091	0.109	NaN	0.338	0.189	0.676
β_mkt	-1.14	-1.15	-0.93	0.55	-0.54	-0.41	-0.59	-1.18	-0.97	0.00	1.00	-0.01	0.18
$\alpha\_FF3(\%)$	19.94	18.98	17.68	-6.56	26.47	24.49	9.76	17.54	16.15	0.00	-0.00	0.00	-0.00
t_alpha_FF3	(2.76)	(2.60)	(2.60)	(-1.19)	(2.55)	(2.51)	(1.29)	(1.74)	(1.66)	NaN	(-3.11)	(0.46)	(-4.76)
p-value_FF3	0.006	0.010	0.010	0.235	0.011	0.013	0.199	0.083	0.098	NaN	0.002	0.645	0.000

A.3. 3 Buckets Figures: 1926-2022

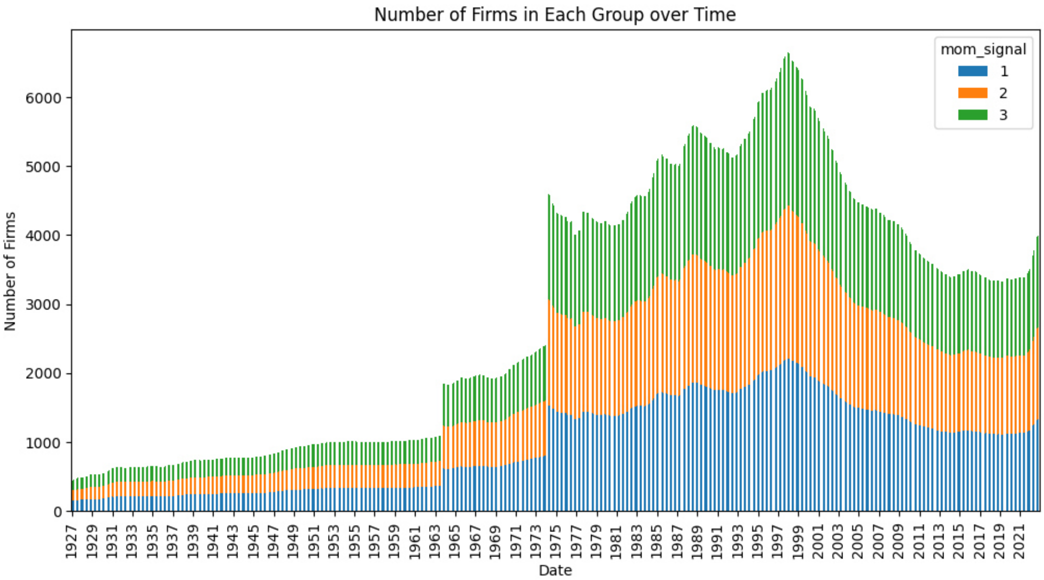


Figure A.10.: Total Groups: 1926-2022

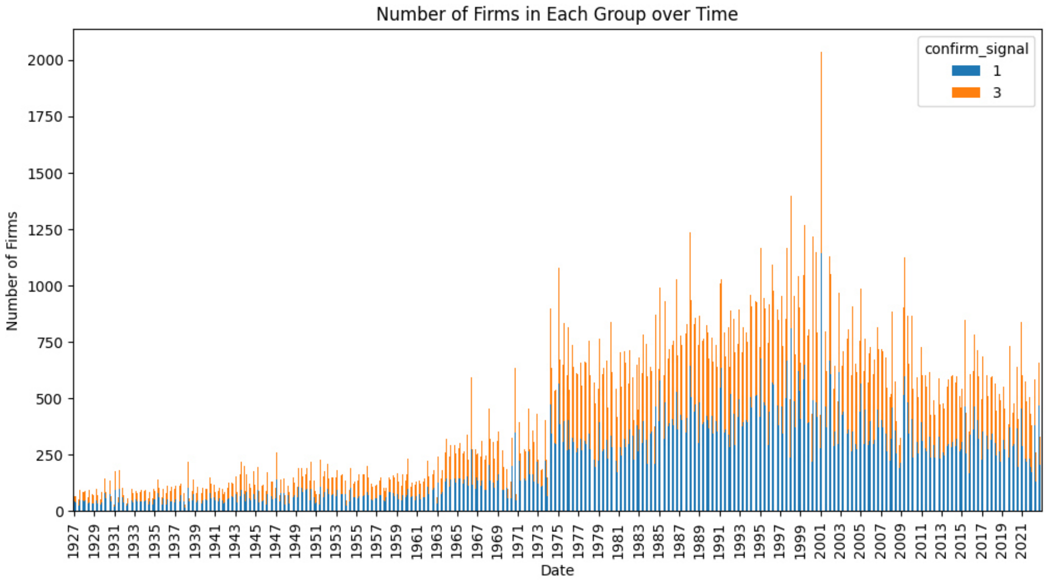


Figure A.11.: Confirming Groups: 1926-2022

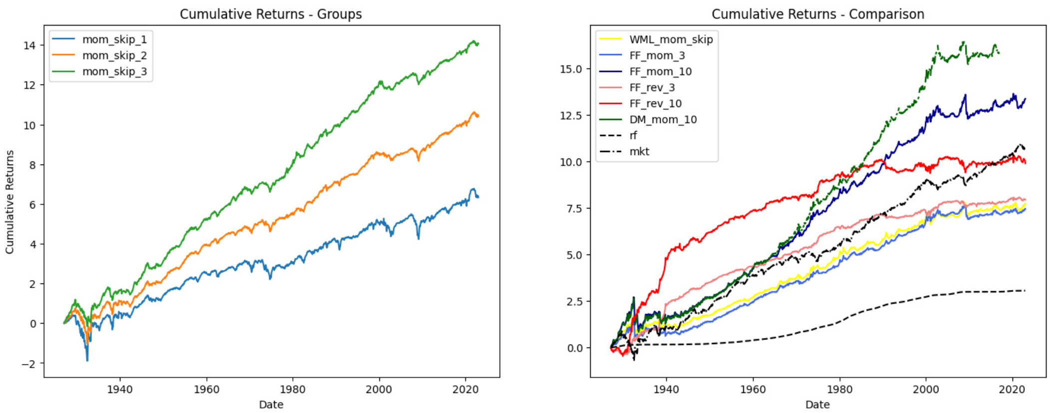


Figure A.12.: Momentum (skip): 1926-2022

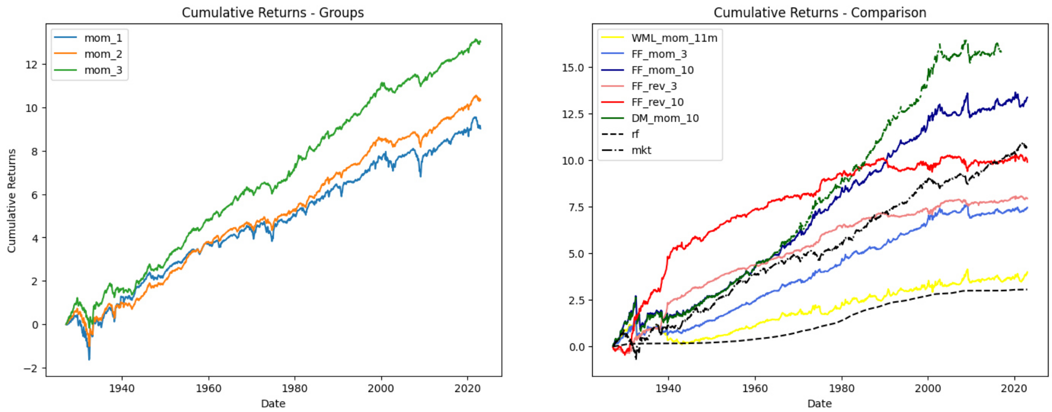


Figure A.13.: Momentum - J=11 months: 1926-2022

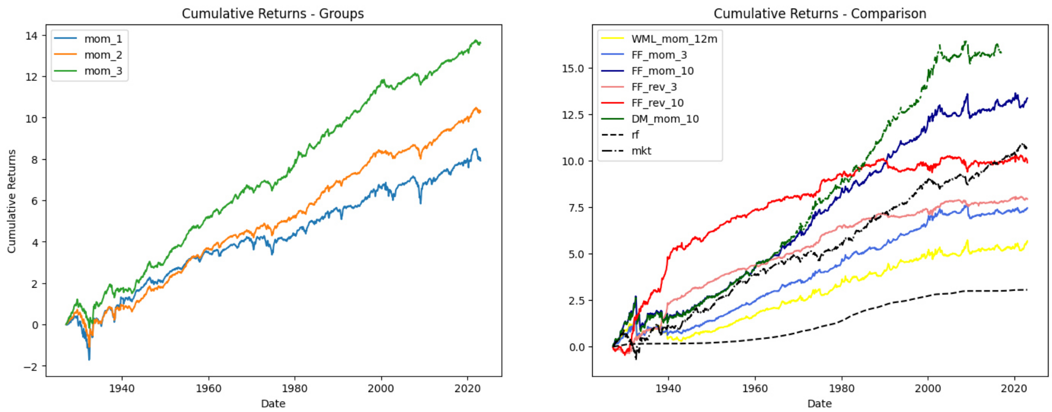


Figure A.14.: Momentum - J=12 months: 1926-2022

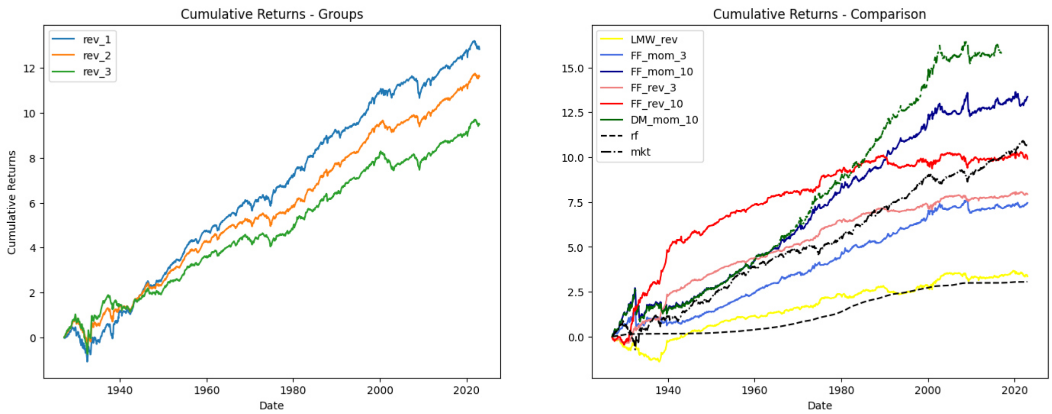


Figure A.15.: Reversal: 1926-2022

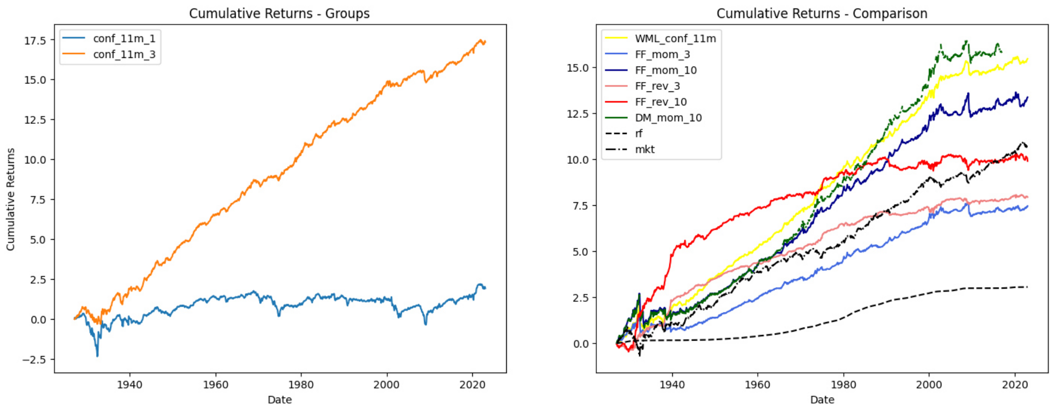


Figure A.16.: Confirming Signal - J=11 months: 1926-2022

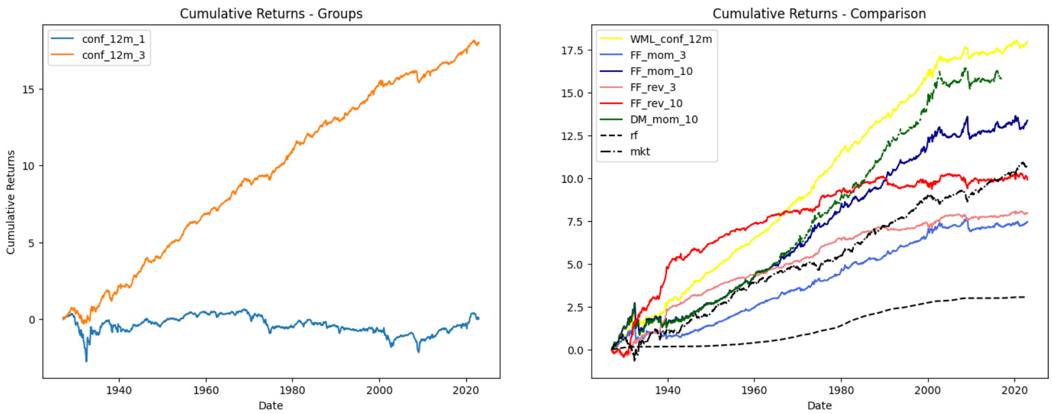


Figure A.17.: Confirming Signal - J=12 months: 1926-2022

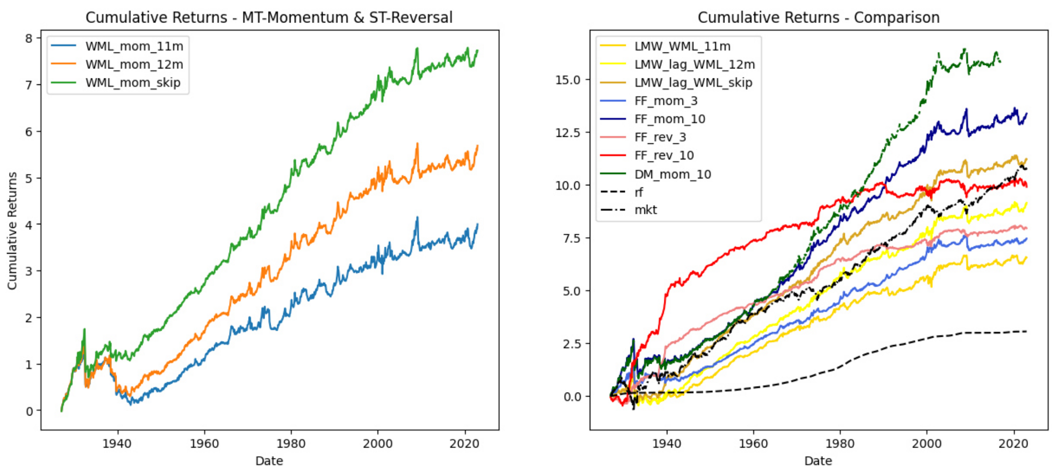


Figure A.18.: Combining Momentum & Reversal: 1926-2022

A.4. 3 Buckets Tables: 1926-2022

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	3.40	7.65	11.45	4.86
$\sigma(\%)$	26.69	19.75	19.20	17.68
Sharpe Ratio	0.13	0.39	0.60	0.27
sk(m)	-0.04	-0.22	-0.73	-3.65
$\alpha\_mkt(\%)$	-6.93	-0.56	3.67	7.38
$t(\alpha)\_mkt$	(-5.83)	(-1.13)	(5.67)	(4.30)
p-value_mkt	0.0000	0.2608	0.0000	0.0000
β_mkt	1.29	1.03	0.98	-0.32
$\alpha\_FF3(\%)$	-7.89	-0.94	4.03	8.69
t_alpha_FF3	(-6.97)	(-2.02)	(6.44)	(5.29)
p-value_FF3	0.000	0.043	0.000	0.000

Table A.7.: Pure Momentum (skip)

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	6.20	7.56	10.37	0.97
$\sigma(\%)$	27.42	19.46	19.29	18.41
Sharpe Ratio	0.23	0.39	0.54	0.05
sk(m)	-0.19	-0.35	-0.64	-3.02
$\alpha\_mkt(\%)$	-4.36	-0.53	2.54	3.68
$t(\alpha)\_mkt$	(-3.50)	(-1.08)	(3.93)	(2.07)
p-value_mkt	0.001	0.282	0.000	0.039
β_mkt	1.32	1.01	0.98	-0.34
$\alpha\_FF3(\%)$	-5.13	-0.87	2.83	4.72
t_alpha_FF3	(-4.24)	(-1.86)	(4.46)	(2.72)
p-value_FF3	0.000	0.064	0.000	0.007

Table A.8.: Pure Momentum - J=11 months

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	5.05	7.51	10.98	2.73
$\sigma(\%)$	27.76	19.65	19.20	18.59
Sharpe Ratio	0.18	0.38	0.57	0.15
sk(m)	-0.07	-0.28	-0.65	-3.42
$\alpha\_mkt(\%)$	-5.63	-0.65	3.18	5.58
$t(\alpha)\_mkt$	(-4.45)	(-1.27)	(5.00)	(3.12)
p-value_mkt	0.000	0.204	0.000	0.002
β_mkt	1.34	1.02	0.98	-0.36
$\alpha\_FF3(\%)$	-6.56	-1.03	3.48	6.81
t_alpha_FF3	(-5.40)	(-2.15)	(5.61)	(3.94)
p-value_FF3	0.000	0.032	0.000	0.000

Table A.9.: Pure Momentum - J=12 months

3 BUCKETS	1	2	3	rev
$\mu(r-rf)(\%)$	10.16	8.90	6.68	0.30
$\sigma(\%)$	22.50	18.46	20.45	13.48
Sharpe Ratio	0.45	0.48	0.33	0.02
sk(m)	-0.54	-0.45	0.22	-1.12
$\alpha\_mkt(\%)$	1.15	1.11	-1.64	-0.41
$t(\alpha)\_mkt$	(1.39)	(3.31)	(-2.47)	(-0.30)
p-value_mkt	0.166	0.001	0.0134	0.767
β_mkt	1.13	0.98	1.04	0.09
$\alpha\_FF3(\%)$	1.10	1.05	-1.96	-0.15
t_alpha_FF3	(1.35)	(3.16)	(-2.99)	(-0.11)
p-value_FF3	0.178	0.002	0.003	0.914

Table A.10.: Pure Reversal

3 BUCKETS	1	3	conf
$\mu(r-rf)(\%)$	-1.20	14.87	12.92
$\sigma(\%)$	28.32	23.44	20.66
Sharpe Ratio	-0.04	0.63	0.63
sk(m)	-0.04	-0.69	-3.28
$\alpha\_mkt(\%)$	-11.66	5.99	14.47
$t(\alpha)\_mkt$	(-7.88)	(5.30)	(6.91)
p-value_mkt	0.000	0.000	0.000
β_mkt	1.31	1.11	-0.19
$\alpha\_FF3(\%)$	-12.96	6.04	15.82
t_alpha_FF3	(-9.38)	(5.63)	(7.79)
p-value_FF3	0.000	0.000	0.000

Table A.11.: Confirming signals - J=11 months

3 BUCKETS	1	3	conf
$\mu(r-rf)(\%)$	-3.16	15.49	15.52
$\sigma(\%)$	28.25	23.27	20.94
Sharpe Ratio	-0.11	0.67	0.74
sk(m)	-0.18	-0.72	-3.32
$\alpha\_mkt(\%)$	-13.58	6.74	17.17
$t(\alpha)\_mkt$	(-9.16)	(5.85)	(8.10)
p-value_mkt	0.000	0.000	0.000
β_mkt	1.31	1.10	-0.21
$\alpha\_FF3(\%)$	-14.93	6.87	18.63
t_alpha_FF3	(-10.84)	(6.28)	(9.12)
p-value_FF3	0.000	0.000	0.000

Table A.12.: Confirming signals - J=12 months

3 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	0.97	2.73	4.86	0.30	12.92	15.52	3.64	6.34	8.49	0.00	7.98	4.29	2.34
$\sigma(\%)$	18.41	18.59	17.68	13.48	20.66	20.94	18.32	23.01	22.41	0.00	18.59	12.36	11.00
Sharpe Ratio	0.05	0.15	0.27	0.02	0.63	0.74	0.20	0.28	0.38	NaN	0.43	0.35	0.21
sk(m)	-3.02	-3.42	-3.65	-1.12	-3.28	-3.32	-5.63	-2.54	-2.48	0.00	-0.52	1.40	1.17
$\alpha\_mkt(\%)$	3.68	5.58	7.38	-0.41	14.47	17.17	5.57	9.24	11.06	0.00	0.00	3.06	0.85
$t(\alpha)\_mkt$	(2.07)	(3.12)	(4.30)	(-0.30)	(6.91)	(8.10)	(3.05)	(4.08)	(4.97)	NaN	(3.44)	(2.47)	(0.79)
p-value_mkt	0.039	0.002	0.00	0.767	0.000	0.000	0.002	0.000	0.000	NaN	0.001	0.014	0.430
β_mkt	-0.34	-0.36	-0.32	0.09	-0.19	-0.21	-0.24	-0.36	-0.32	0.00	1.00	0.15	0.19
$\alpha\_FF3(\%)$	4.72	6.81	8.69	-0.15	15.82	18.63	6.75	10.48	12.38	0.00	0.00	-0.00	-0.00
t_alpha_FF3	(2.72)	(3.94)	(5.29)	(-0.11)	(7.79)	(9.12)	(3.81)	(4.72)	(5.70)	NaN	(6.97)	(-0.72)	(-0.92)
p-value_FF3	0.007	0.000	0.00	0.914	0.000	0.000	0.000	0.000	0.000	NaN	0.000	0.473	0.358

A.5. 3 Buckets Figures: 2000-2022

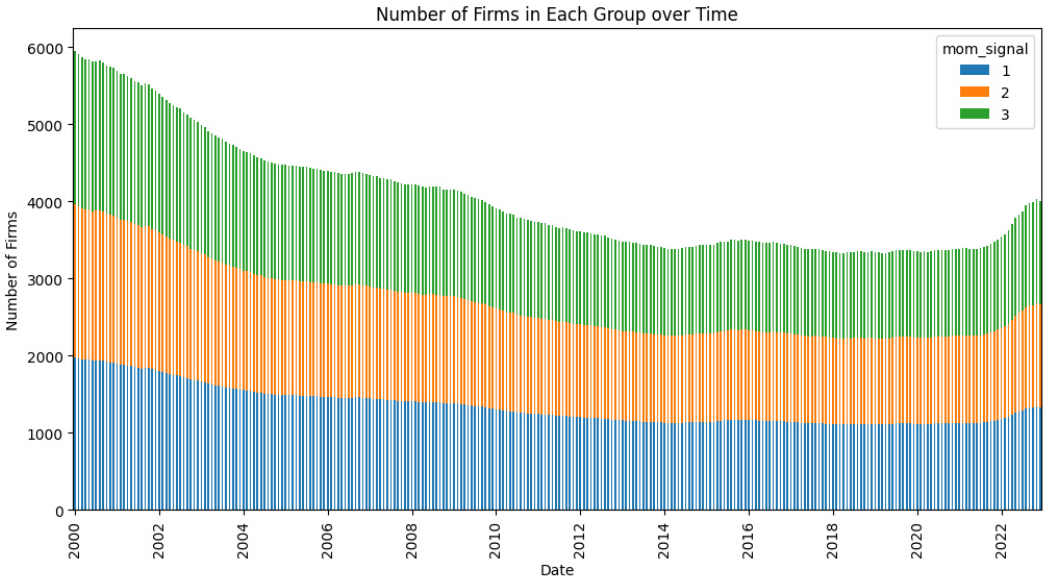


Figure A.19.: Total Groups: 2000-2022

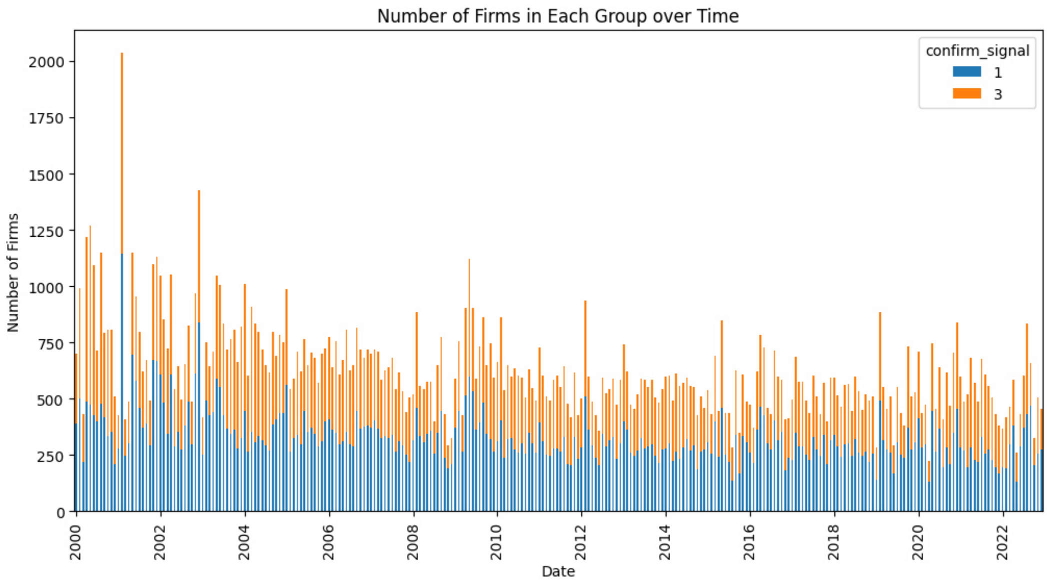


Figure A.20.: Confirming Groups: 2000-2022

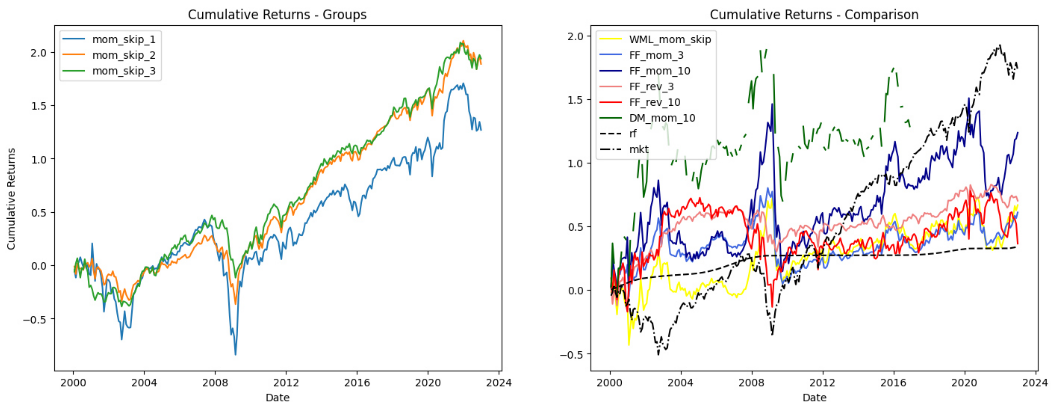


Figure A.21.: Momentum (skip): 2000-2022

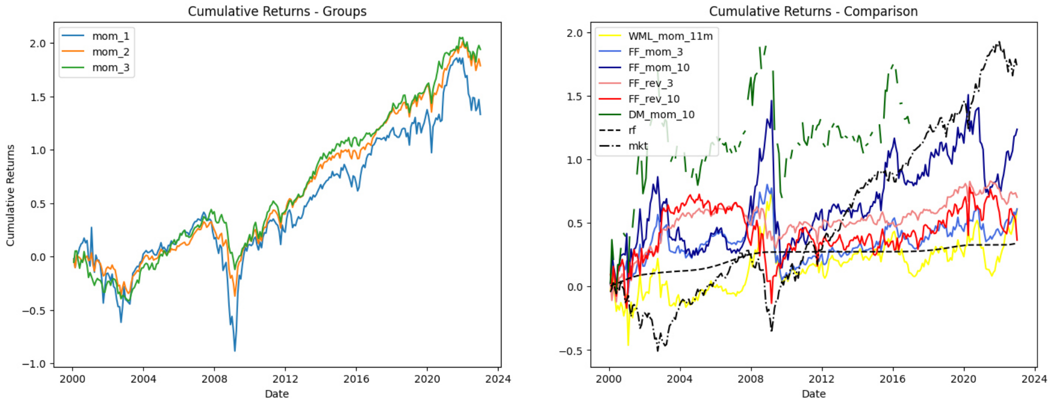


Figure A.22.: Momentum - J=11 months: 2000-2022

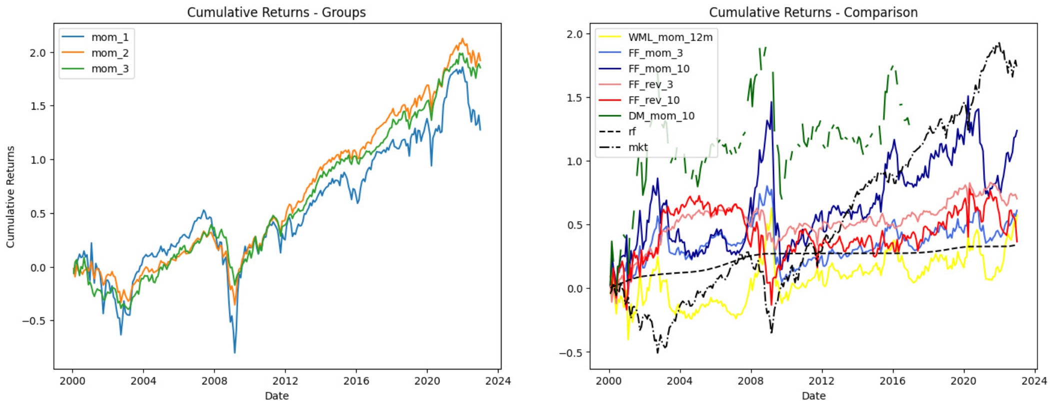


Figure A.23.: Momentum - J=12 months: 2000-2022

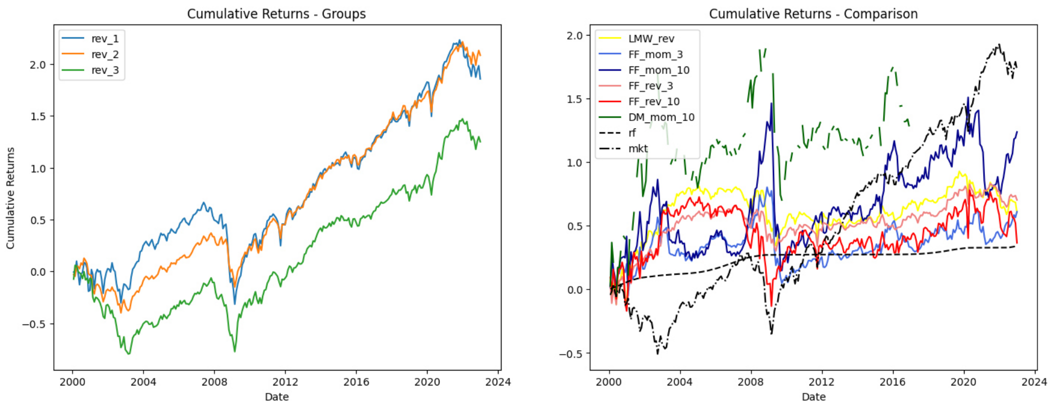


Figure A.24.: Reversal: 2000-2022

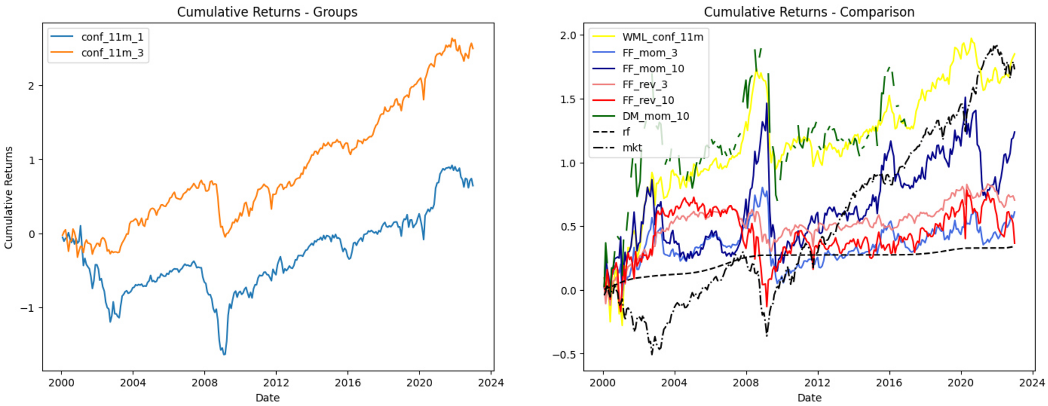


Figure A.25.: Confirming Signal - J=11 months: 2000-2022

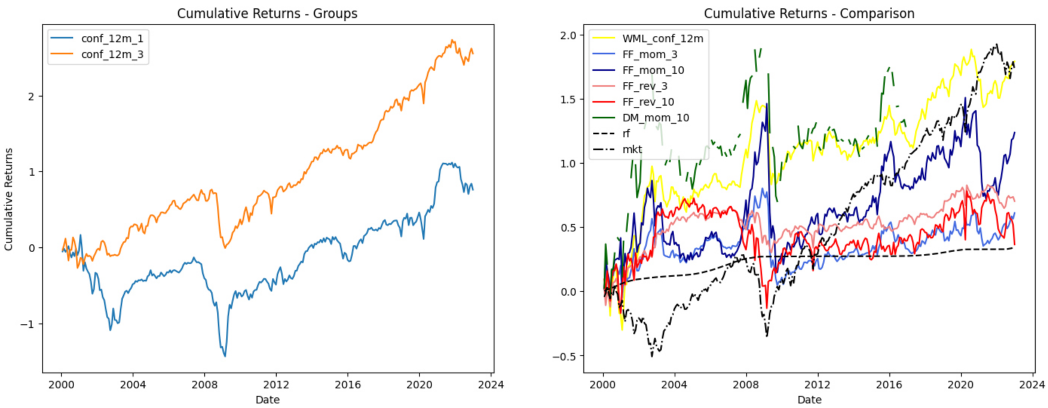


Figure A.26.: Confirming Signal - J=12 months: 2000-2022

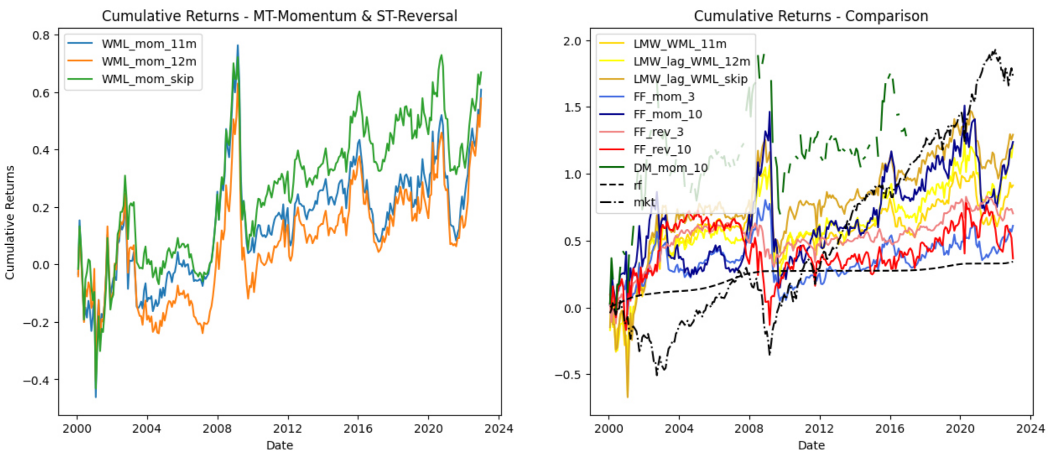


Figure A.27.: Combining Momentum & Reversal: 2000-2022

A.6. 3 Buckets Tables: 2000-2022

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	4.03	6.72	6.93	1.42
$\sigma(\%)$	26.71	16.35	16.16	20.74
Sharpe Ratio	0.15	0.41	0.43	0.07
sk(m)	-0.33	-0.71	-0.57	-2.05
$\alpha\_mkt(\%)$	-4.54	0.87	1.37	4.39
$t(\alpha)\_mkt$	(-1.56)	(0.83)	(1.02)	(1.09)
p-value_mkt	0.120	0.406	0.310	0.277
β_mkt	1.42	0.97	0.92	-0.49
$\alpha\_FF3(\%)$	-5.31	0.54	1.46	5.27
t_alpha_FF3	(-1.85)	(0.60)	(1.13)	(1.33)
p-value_FF3	0.065	0.549	0.261	0.184

Table A.13.: Pure Momentum (skip)

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	4.30	6.28	6.94	1.16
$\sigma(\%)$	28.31	16.56	15.72	22.21
Sharpe Ratio	0.15	0.38	0.44	0.05
sk(m)	-0.43	-0.70	-0.48	-2.34
$\alpha\_mkt(\%)$	-4.82	0.37	1.56	4.87
$t(\alpha)\_mkt$	(-1.58)	(0.35)	(1.15)	(1.16)
p-value_mkt	0.116	0.730	0.250	0.246
β_mkt	1.51	0.98	0.89	-0.62
$\alpha\_FF3(\%)$	-5.29	0.02	1.53	5.32
t_alpha_FF3	(-1.73)	(0.03)	(1.18)	(1.28)
p-value_FF3	0.085	0.979	0.239	0.202

Table A.14.: Pure Momentum - J=11 months

3 BUCKETS	1	2	3	mom
$\mu(r-rf)(\%)$	4.05	6.86	6.57	1.03
$\sigma(\%)$	28.69	16.62	15.68	22.43
Sharpe Ratio	0.14	0.41	0.42	0.05
sk(m)	-0.42	-0.65	-0.51	-2.15
$\alpha\_mkt(\%)$	-5.17	0.93	1.18	4.83
$t(\alpha)\_mkt$	(-1.66)	(0.86)	(0.89)	(1.15)
p-value_mkt	0.097	0.390	0.373	0.251
β_mkt	1.53	0.98	0.89	-0.63
$\alpha\_FF3(\%)$	-5.95	0.57	1.24	5.69
t_alpha_FF3	(-1.93)	(0.62)	(0.98)	(1.37)
p-value_FF3	0.054	0.533	0.330	0.171

Table A.15.: Pure Momentum - J=12 months

3 BUCKETS	1	2	3	rev
$\mu(r-rf)(\%)$	6.58	7.57	3.95	1.14
$\sigma(\%)$	22.44	15.64	16.77	15.25
Sharpe Ratio	0.29	0.48	0.24	0.07
sk(m)	-0.93	-0.66	-0.47	-0.21
$\alpha\_mkt(\%)$	-1.16	1.85	-1.82	-0.85
$t(\alpha)\_mkt$	(-0.62)	(2.51)	(-1.30)	(-0.28)
p-value_mkt	0.534	0.013	0.195	0.776
β_mkt	1.28	0.95	0.96	0.33
$\alpha\_FF3(\%)$	-1.42	1.97	-1.85	-1.06
t_alpha_FF3	(-0.77)	(2.80)	(-1.32)	(-0.35)
p-value_FF3	0.443	0.006	0.189	0.725

Table A.16.: Pure Reversal

3 BUCKETS	1	3	conf
$\mu(r-rf)(\%)$	1.31	9.36	6.56
$\sigma(\%)$	27.37	22.38	22.90
Sharpe Ratio	0.05	0.42	0.29
sk(m)	-0.41	-0.95	-1.34
$\alpha\_mkt(\%)$	-7.09	2.20	7.77
$t(\alpha)\_mkt$	(-2.14)	(0.89)	(1.63)
p-value_mkt	0.033	0.372	0.104
β_mkt	1.39	1.19	-0.20
$\alpha\_FF3(\%)$	-7.53	2.01	8.04
t_alpha_FF3	(-2.27)	(0.86)	(1.72)
p-value_FF3	0.024	0.388	0.087

Table A.17.: Confirming signals - J=11 months

3 BUCKETS	1	3	conf
$\mu(r-rf)(\%)$	1.81	9.61	6.31
$\sigma(\%)$	27.25	22.08	22.90
Sharpe Ratio	0.07	0.44	0.28
sk(m)	-0.35	-0.94	-1.24
$\alpha\_mkt(\%)$	-6.55	2.64	7.67
$t(\alpha)\_mkt$	(-1.99)	(1.05)	(1.61)
p-value_mkt	0.048	0.294	0.108
β_mkt	1.39	1.16	-0.23
$\alpha\_FF3(\%)$	-7.31	2.53	8.35
t_alpha_FF3	(-2.23)	(1.06)	(1.78)
p-value_FF3	0.027	0.291	0.077

Table A.18.: Confirming signals - J=12 months

3 BUCKETS	mom (11m)	mom (12m)	mom (skip)	rev	mom_conf (11m)	mom_conf (12m)	rev_mom (11m)	rev_mom (12m)	rev_mom (skip)	rf	mkt	HML	SMB
$\mu(r-rf)(\%)$	1.16	1.03	1.42	1.14	6.56	6.31	2.48	3.79	4.13	0.00	6.03	3.03	2.28
$\sigma(\%)$	22.21	22.43	20.74	15.25	22.90	22.90	21.82	28.53	27.10	0.00	16.07	12.04	11.11
Sharpe Ratio	0.05	0.05	0.07	0.07	0.29	0.28	0.11	0.13	0.15	NaN	0.38	0.25	0.21
sk(m)	-2.34	-2.15	-2.05	-0.21	-1.34	-1.24	-1.98	-1.43	-1.16	0.00	-0.67	0.01	0.27
$\alpha\_mkt(\%)$	4.87	4.83	4.39	-0.85	7.77	7.67	4.21	7.85	7.37	0.00	0.00	3.11	1.18
$t(\alpha)\_mkt$	(1.16)	(1.15)	(1.09)	(-0.28)	(1.63)	(1.61)	(0.94)	(1.42)	(1.37)	NaN	(17.05)	(1.23)	(0.53)
p-value_mkt	0.246	0.251	0.277	0.776	0.104	0.108	0.348	0.158	0.173	NaN	0.000	0.220	0.599
β_mkt	-0.62	-0.63	-0.49	0.33	-0.20	-0.23	-0.29	-0.67	-0.54	0.00	1.00	-0.01	0.18
$\alpha\_FF3(\%)$	5.32	5.69	5.27	-1.06	8.04	8.35	4.32	7.95	7.48	0.00	-0.00	-0.00	0.00
t_alpha_FF3	(1.28)	(1.37)	(1.33)	(-0.35)	(1.72)	(1.78)	(0.97)	(1.43)	(1.39)	NaN	(-3.24)	(-1.81)	(0.61)
p-value_FF3	0.202	0.171	0.184	0.725	0.087	0.077	0.335	0.153	0.166	NaN	0.001	0.071	0.540