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Abstract

This paper documents investment strategies that buy the best-performing stocks and sell the worst-performing stocks based on past returns. The momentum anomaly has proved to be a profitable and widely used strategy among investors. Research has found that momentum investment also experiences substantial losses, called momentum crashes. This thesis investigates the behavior of cross-sectional and industry momentum during and succeeding recessions. Exploring data in the US Stock market during 1965-2022, we find that individual stock momentum, especially within industries, tends to result in more excessive returns, and therefore experience more extreme crashes compared to industry momentum. Covid-19 shows indications of the same pattern of a momentum crash during the market rebound, as with earlier studies of crises and the Dot-Com Bubble. We observe no distinct patterns between the most affected industries and individual stock momentum within industries.

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Table of Contents

1.0 Introduction

The profitability of momentum strategies is well demonstrated in the academic literature. Momentum investment in asset pricing has persisted across diverse asset classes and geographical regions for an extended period. These strategies operate on the fundamental principle that asset prices tend to maintain their positive performance in the future. Consequently, the zero-cost portfolio entails to buy the best-performing assets while selling the underperforming assets over a defined period, typically spanning 3 to 12 months. Empirical evidence by Jegadeesh and Titman (1993) supports the notion that momentum portfolios can generate a Sharpe ratio surpassing that of the broader market. These strategies have shown profitable outcomes, with average monthly returns of approximately 1 percent. Daniel and Moskowitz (2016) discovered that the momentum approach occasionally experiences downturns and collapses even if the strategy normally delivers strong average returns and a positive risk-reward relationship. Momentum crashes typically occur in periods of recovery shortly after recessions. After being significantly more undervalued than winners during the crises, losers rebound strongly, leading to momentum crashes.

Buying winning industries and selling the losers might produce huge profits like individual stock momentum (Moskowitz and Grinblatt, 1999). According to Moskowitz and Grinblatt, industries can account for a substantial part of the momentum anomaly, thus individual stock performance is less important than previously thought. Existing literature, which includes a variety of forms and qualities, concentrates on momentum in its broadest meaning. Little analysis has been done on the precise momentum displayed by certain stocks within industries. The current study, which builds on earlier results on individual stock momentum and industry momentum, strives to close this gap by thoroughly examining the momentum of individual stocks within industries. This thesis aims to find whether momentum crashes follow recessions, as documented in individual stock momentum also occur in industry momentum and individual stock momentum within industries. By expanding the scope of the investigation, we aim to enhance our understanding of the dynamics and behavior of momentum in different market conditions. We will study the phenomenon covering the US stock market, running from 1965 to 2022, during the Dot-Com Bubble and the Financial Crisis and the primary focus will be on the Covid-19 pandemic.

Our primary results show that the momentum anomaly strategy has historically been attractive to investors, providing favorable risk-adjusted returns. However, it is subject to periods of crashes with zero to negative returns. Through our analysis of individual stock momentum, industry momentum, and individual stock momentum within industries we find similar patterns of momentum crashes across these dimensions. We also find that individual stock momentum, particularly within industries, tends to experience more extreme crashes compared to industry momentum. Regarding the Covid-19 pandemic, our study shows indications of a similar momentum pattern observed in the Dot-Com Bubble and earlier crises. However, the lack of statistically significant support limits our ability to make precise interpretations of the momentum portfolios during Covid-19.

Moreover, we will examine which industries were positively and negatively affected during the different market states. We want to see whether we can find a similar pattern between those industries and the industries that experienced momentum profit and those that suffered momentum crash using individual stock momentum within industries. We will use the same industries as Moskowitz and Grinblatt (1999), however including industries that we know were affected by the pandemic. We find no distinct patterns between the most affected industries, comparing average stock returns within industry groups with individual stock momentum within industries. Thus, similarities observed indicate coincidence rather than apparent causal connections. Additionally, we find that the Covid-19 recession witnessed the most extreme momentum crash.

The Covid-19 crisis, being a recent event, opens the opportunity to research the behavior of the momentum anomaly during this period. This thesis contributed to the existing literature by providing new and insightful research on the momentum anomaly in different crises and market states. Specifically, the thesis aims to investigate whether consistent patterns or deviations in the momentum anomaly emerged in the US stock market during the Covid-19 crisis and compare those to the patterns observed in the Dot-Com Bubble and the Financial Crisis. By looking at individual stock momentum within industries and industry momentum, we also hope to bring insight into any linkages between the industries that were affected by the crises.

The pandemic had diverse and intricate effects on industries, underscoring the significance of adaptability and resilience. Industries that swiftly adjusted to changes in customer behavior fared better than those slower to respond, experiencing greater challenges and losses. Industries reliant on in-person interactions, such as entertainment, hospitality, and travel, suffered substantial financial setbacks and closures due to social distancing regulations. Conversely, e-commerce, online learning, and telemedicine saw rapid growth during the crisis, capitalizing on their ability to adapt to evolving customer behavior. The challenges faced by industries during the crisis, encompassed diminished demand, disruptions in supply chains, labor and operational issues, and market instability. Consequently, several industries underwent significant transformations and restructuring to thrive in the new normal.

This thesis has been structured as follows: Section 2 overviews previous literature. Section 3 contains the theoretical foundation supporting our hypothesis. Section 4 provides the gathering of data. Section 5 explains the research methods we apply. Section 6 provides our empirical findings. Lastly, Section 7 provides a conclusion to our research.

2.0 Literature Review

Buying assets that have performed well over an extended amount of period and similarly shorting assets that have performed poorly over the same period represent a popular momentum strategy. Numerous articles and academic papers have been published because of the momentum anomaly's great academic interest. Some researchers have concentrated their studies on the fundamental features of the anomaly, while others have investigated its more specific features. Jegadeesh and Titman (1993) and Asness (1994) were the first to demonstrate momentum investing, which includes sorting companies based on 1 to 4 quarters of past returns, by studying the US common equity returns between 1965 and 1989. Subsequently, Jegadeesh and Titman (2001) show the continued efficiency of US equity portfolios on the momentum anomaly in common equity returns spanning 1990 to 1998. Israel and Moskowitz (2013) proved the robustness of momentum strategies pre and post those research papers during 1927-1965 and 1990-2012. Moore (2019) asserts that this momentum strategy has been consistent over the past two hundred years, transcending the sample data and spanning several markets and geographical areas. It is crucial to keep in mind that other academics have discovered evidence of momentum shortcomings and occurrences of momentum collapses within periods (Daniel and Moskowitz, 2016).

Jegadeesh and Titman (1993) and Asness, Moskowitz, and Pedersen (2013) have sought to elucidate the behavior of momentum, delineating its advantages and disadvantages. Factors often cited as contributors to momentum are instances of overreaction, which have been identified as significant drivers of this phenomenon by Grinblatt and Han (2004). De Bondt and Thaler (1985) investigated this issue to see whether the market followed public perception. Stock markets frequently overreact to information is a direct extension of the theory provided by De Bondt and Thaler (1985, 1987), and it indicates that counterstrategies (buying past losses and selling prior winners) produce unusual returns. De Bondt and Thaler (1985, 1987) found that with holding periods of three to five years, the returns on stock investments that had lower performance in the preceding three to five years were higher than the returns on stocks that had higher performance over the same period. De Bondt and Thaler's results are still debated concerning their current interpretation. It is unclear whether their results may be attributed to an overreaction due to the long-term losers passing the long-term winners for the first time in January. Carhart (1997) uses the difference between the winner and loser stocks from the prior period to generate a proxy for the momentum effect.

We know that shifting from a longer to a shorter period will result in considerable anomalous returns (Jegadeesh, 1990). Jegadeesh and Titman (1993) created a new strategy by extending this idea and studying the momentum anomaly over a 3- to 12-month period. The methodology chooses stocks based on their performance over the previous 3 to 12 months. This method was highly profitable in their data set from the US stock market, including stocks listed on New York Stock Exchange (NYSE) and American Stock Exchange (Amex) between 1965 and 1989. Jegadeesh and Titman (1993) analyzed six potential cost-free investment strategies with formation and holding periods ranging from 3 to 12 months. The methodology sells and buys the bottom and top ten percent of stocks. Jegadeesh and Titman's (1993) momentum strategy with a 6-month formation period and 6-month holding period yielded 0.95 percent without a lag of one week and 1.10 percent with a week of one lag. In total, the strategy realized a momentum excess annual return of 12.01 percent. It was arguable whether the profitability was the product of data mining brought on by data spying or compensation for rising risk. Jegadeesh and Titman (2001) responded by extending the breadth of the data and providing evidence that momentum strategy profitability remained throughout the 1990s.

Moskowitz and Grinblatt (1999) studied the strategy in a similar pattern. The research is based on industries instead of individual stocks. Moskowitz and Grinblatt indicate that implementing a brief period and recognizing industry momentum will result in a sizable return. Among the largest and most liquid equities, the industry momentum approach offers a reliable technique and seems rewarding. Selling prior losers, especially those among the most illiquid equities, does not contribute to profitability; long holdings do. Moskowitz and Grinblatt (1999) provide evidence that returns are not due to individual stock momentum, microstructure effects, or the cross-sectional dispersion in mean returns because there is a brief period, and the analysis is industry-based.

While the momentum approach often produces impressive returns and favorable risk-reward correlations, the strategy can sometimes endure downturns and collapses. Effects and prediction of momentum crashes are important aspects of the momentum anomaly (Daniel and Moskowitz, 2016). Daniel and Moskowitz used the same selection of stocks from 1927 to 2013 as in previous research. Average yearly excess returns from the monthly momentum zero-cost portfolio were 17.9 percent. Despite the market's remarkable performance, they thoroughly looked at two periods. Examples of momentum crashes include the Great Depression (1932–1939) and the Financial Crisis (2009–2013). Those periods reflect the most significant continuous decline periods. The loser portfolio made a return of 232 percent during the Great Depression, while the winning portfolio made a return of 32 percent. The loser portfolio made a return of 163 percent from March to May 2009, while the winning portfolio made a return of 8 percent. Barroso and Santa-Clara (2015) applied similar research on the anomaly and documented the presence of momentum crashes during the same period. What separates Barroso and Santa-

Clara (2015) from Daniel and Moskowitz's (2016) analyzes is their different suggestion for a hedging strategy for overcoming the severe declines in those periods.

Additionally, resilience is demonstrated across several stock markets and different asset types. In contrast, price momentum is weaker under unusual circumstances than in normal circumstances. During challenging times, when the market experienced a downfall and uncertainty, the prices of stocks that performed poorly before tending to increase by a significant amount. This pattern can be observed in both the stock market and the overall economy. Previous losers observe large returns when market conditions start to recover after a period of weakness. This generates a momentum collapse since momentum approaches are deficient in these assets, which results in enormous profits for losers.

3.0 Theory

3.1 Efficient Market Hypothesis

In 1970, Eugene Fama proposed the Efficient Market Hypothesis (EMH), which declares that asset prices should always represent all pertinent market information. This suggests that added information will change prices right away, and since riskier assets always sell at their fair value, investors cannot beat the market without acquiring more of them. The three types of market efficiency that Fama finds are weak, semi-strong, and strong form. Semi-strong efficiency suggests that stock prices represent all accessible public information about a firm, while the weak form suggests that stock prices reflect all past data that is now available. The strong form is when the market is efficient and stock prices reflect all relevant information. Momentum is a violation of weak form market efficiency.

3.2 Capital Asset Pricing Model

Risks are divided into systematic and unsystematic components according to financial theory. Investors must consider systematic risk when estimating the value and expected return of an investment. Individual security has its own unsystematic risks. Two examples are new competitors and industry rules. Interest rates, currency rates, and inflation are examples of systemic risks since they affect the whole economy. The unsystematic risk may be reduced through diversification, while systematic risk cannot.

The Capital Asset Pricing Model (CAPM) considers the notion of systematic risk. It presents a framework that illustrates the relationship between risk and returns for assets within a market equilibrium model. This model is commonly used to determine the pricing of high-risk assets, as it provides a clear understanding of the risk-reward trade-off (Fama and French, 2004). The development of the CAPM can be attributed to the collaborative efforts of William F. Sharpe (1964), John Lintner (1965), and Jan Mossin (1996), who incorporated elements of Markowitz's modern portfolio theory into their work.

3.3 The Fama-French Three & Five-Factor Model

The Fama-French Three-Factor Model extends the traditional Capital Asset Pricing Model (CAPM) by incorporating size and value as additional factors. These models attempt to explain that the chance distribution of stock returns influences academic finance. According to the Fama-French Three-Factor model, the expected return of a stock can be explained by three factors. The first factor is market risk, which is represented by the excess return of the overall market. This factor captures the systematic risk that affects all stocks. The second factor is size, which reflects the historical tendency of small-cap stocks to outperform large-cap stocks. The model suggests that smaller companies have higher expected returns compared to larger companies. The third factor is value, which captures the historical tendency of value stocks (those with low price-to-book ratios) to outperform growth stocks (those with high price-to-book ratios). The model implies that value stocks have higher expected returns compared to growth stocks. In the Three-Factor Model, the expected return of a stock is determined by a combination of these three factors, with the intercept representing the stock's alpha or excess return not explained by the factors (Fama and French, 1992).

The Fama-French Five-Factor Model expands the Three-Factor Model by adding two additional factors: profitability and investment. The profitability factor captures the historical tendency of highly profitable companies to outperform less profitable companies, suggesting that highly profitable stocks have higher expected returns. The investment factor reflects the historical tendency of companies with low levels of investment to outperform those with elevated levels of investment, indicating that stocks of companies with low investment have higher expected returns. By incorporating these additional factors, the Five-Factor Model provides a more comprehensive explanation of stock returns than the Three-Factor Model (Fama and French, 2015).

3.4 Momentum

The academic literature finds two primary categories of explanations for the factors driving momentum profitability: risk-based explanations and behavioral explanations. Risk-based explanations draw upon established asset pricing models such as the CAPM and the factor models developed by Fama and French. These models shed light on the underlying reasons and mechanisms that make momentum strategies potentially profitable. On the other hand, behavioral explanations revolve around the presence of irrational behavior exhibited by market participants, often attributed to behavioral biases. In this study, the emphasis is placed on exploring risk-based explanations as the primary determinant of momentum profitability.

While momentum strategies have historically generated strong returns, the anomaly also comes with risks, including the potential for crashes or abrupt reversals in market trends. Risk-based explanations for momentum crashes suggest that these crashes are driven by systematic factors or risks that affect a particular industry or asset class (Geczy and Samonov, 2015). Overall, risk-based explanations for momentum crashes suggest that investors need to pay close attention to the specific risks that are affecting the industry or asset class. By understanding these risks, investors can make more informed decisions about when to buy or sell assets, and potentially avoid the worst effects of a momentum crash.

When it comes to risk-based explanations, momentum continues to be the anomaly that is hardest to explain using rational asset pricing models like the capital asset pricing model (CAPM) and the multiple Fama-French models. Fama and French

(1996) claim that their three-factor model has difficulties because it "fails to capture the continuity of short-term returns.", and therefore experiences distress.

4.0 Data

For the quantitative part, we retrieved data from WRDS, using monthly data from CRSP focusing on the US stock market. The sample period spans the period from January 1965 to March 2022. The primary stock collection is a sample of common shares from NYSE, AMEX, and NASDAQ (with CRSP share codes of 10 and 11). Any shares with a price below 5 are eliminated from the sample, as well as the 1 percent top and bottom percentile of returns. This is to ensure that empirical findings are not motivated by low and illiquid assets. Variables that include key data can be found in Table 1.

The cleaning of data gives an amount of 25 476 unique stocks from the period 1965 to 2022. To analyze industry momentum the stocks are divided into twenty-four industries categorized on their Standard Industrial Classification Code (SIC-Code). The industry classifications align with the industries studied in Moskowitz and Grinblatt's (1999) research paper. Three industry categories central to the thesis have been added: *Air Transportation*, *Hotel & Social Services*, and *Health & Membership.* These are central to the thesis as the industries were severely affected by the Covid-19 pandemic. Table 2 includes a summary of the industry portfolios and the two-digit SIC code used to form the industry groups.

One of our main goals for this thesis is to analyze how momentum returns behaved during and post, the Financial Crisis, the Dot-Com Bubble, and the Covid-19 pandemic. We will also include a period of the Covid-19 pandemic spanning January 2020 to December 2020 to cover more data during the disruption. NBER's list of past recessions defines the length of the economic downturns. We have included data for the whole month the recession started and the whole month the recession ended. NBER defines a recession as a significant decline in economic activity that is spread throughout the economy and lasts longer than a couple of months. There is no standard way of defining the period after the recession, so we have chosen 12 months as recovery time.

To determine the performance of the potential momentum returns, we extract relevant factors from the Kenneth French website. Including the market excess return (Rm-Rf), SMB, HML, RMW, and CMA. The factors are defined in 5.3.3. The factors are monthly spanning 1965 to 2022 gathered from the US Stock market and listed on the NYSE, AMEX, or NASDAQ.

5.0 Methodology

5.1 Hypothesis

Daniel and Moskowitz (2016) discovered momentum crashes in market states of recovery. The findings are well documented in individual stock momentum. However, there is a lack of research on whether this behavior is present in industry momentum and momentum within industries.

Hypothesis 1: *Can we find patterns of momentum crashes, in the US stock market, in industry momentum, and individual stock momentum within industries that reflect those previously identified in individual stock momentum?*

Covid-19 is a recent crisis. There is a lack of research on how the momentum anomaly behaved during this period. We want to explore whether there are any consistent patterns or deviations in the momentum anomaly during the Covid-19 crisis in the US stock market, in comparison to past crises and existing research on market states of distress and recovery.

Hypothesis 2: *Do we observe the same momentum anomaly during Covid-19 compared to previous crises and earlier studies?*

There is a lack of research on industry momentum and individual stock momentum within industries. We know that industries were affected by the restrictions and the lockdown during the pandemic. Thus, we want to analyze which industries that have been negatively affected and which industries that have been positively affected across crises. The hypothesis seeks to explore whether there are any patterns or trends in how industries perform using industry momentum within individual stock momentum compared to how they perform under industry momentum.

Hypothesis 3: *Do we observe any similarities between positively and negatively affected industries across crises under industry momentum and individual stock momentum within industries?*

5.2 Momentum Portfolios

5.2.1 Individual Stock Momentum

To better understand the momentum behavior under different market conditions, we first calculate the returns from individual stock momentum strategies. The trading strategy is based on buying stocks that performed well in the past (winners) and selling those that performed poorly (losers). This strategy has shown, over time, to yield positive returns, violating what is to be considered the most fundamental hypothesis within the financial theory, the Efficient Market Hypothesis. The momentum portfolios are constructed using the methodology developed by Jegadeesh & Titman (1993), and the calculations are performed using STATA.

The methodology consists of observing and selecting stocks based on their previous performance over the past 1 to 4 quarters and then holding the stocks for 1 to 4 quarters. The formation period is denoted J, and the holding period is denoted K. We have opted to focus on the $J = 6$- and $K = 6$-period strategy, which yielded the highest return for Jegadeesh and Titman (1993), thus the strategy which best displays the momentum anomaly.

After the data is collected and the formation period is formed, we divide the stocks into ten decile portfolios. The top decile consists of the best-performing stocks (winners), and the bottom deciles consist of the worst-performing stocks (losers), based on their performance in J. By selling the loser portfolio and buying the winner portfolio, it constructs the zero-cost portfolio. The strategy is known as zero-cost as the portfolios are equally weighted, and therefore self-financing. Jegadeesh (1990) and Lehmann (1990) show that we must skip one month between the formation period *J* and the holding period *K* to avoid short-term reversals. We have chosen to not use overlapping portfolios in our research. The use of overlapping periods during the holding period is based on the methodology of Jegadeesh and Titman (1993). However, they argue that it should have no significant impact on outcomes whether one chooses to use overlapping or non-overlapping periods.

5.2.1.1 Return Calculations

We use log returns to effectively capture compounding effects. The data already give us the monthly holding period return on all stocks. At the beginning of each month, we rank the stocks based on their past *J* = 6 months return. The securities are divided into ten deciles from best to worst. The equally weighted average return is calculated for each decile portfolio in the holding period.

$$\boldsymbol{r_{W,t}} = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{K} r_{i,t}^{W}\right]$$

$$\boldsymbol{r_{L,t}} = \frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=1}^{K} r_{i,t}^{L}\right]$$

Where $r_{W,t}$ is the winner portfolio, $r_{L,t}$ is the loser portfolio, and N is the number of stocks in each portfolio.

We then construct the zero-cost portfolio ($\boldsymbol{r_{ZC}}$), where the strategy is to buy and hold the best-performing portfolio ($r_{W,t}$) every month while simultaneously selling the worst-performing portfolio ($r_{L,t}$).

$$\boldsymbol{r_{ZC}} = r_{W,t} - r_{L,t}$$

Finally, we calculate the average return for the winner portfolio and the loser portfolio and the average return of the zero-cost portfolio.

5.2.2 Industry Momentum

We use the methodology executed by Moskowitz & Grinblatt (1999) to examine industry momentum. The strategy shares similarities with Jegadeesh & Titman's

(1993) methodology on individual stock momentum, however, we use industries rather than creating ten decile portfolios finding winners and losers. The industries are displayed in Table 2. J = 6 and K = 6, as with individual stock momentum. The stocks are divided into their respective industries. The zero-cost portfolio will consist of the three best-performing (winners) industries and the three worst-performing (losers) industries over period J. The trading strategy proceeds to buy the best-performing portfolio and sell the worst-performing portfolio. The trading strategy is self-financing. Between the formation period and the holding period we skip one month, as with the individual stock momentum.

5.2.2.1 Return Calculations

As we already have the holding period return for our sample, we start by dividing the stocks into their respective industry through their SIC code. The rest of the steps mimic the steps in 5.2.1.1, thus we will only cover them briefly here. After forming industry groups, we form the formation period based on J = 6 months and then construct the zero-cost portfolio by buying the three winners while simultaneously selling the three losers for the period.

5.2.3 Individual Stock Momentum within Industries

We then extend Daniel & Moskowitz's (2016) research by examining momentum within industries. We want to examine the momentum anomaly during Covid-19 but also compare the affected industries to the Financial Crisis and the Dot-Com Bubble. First, we establish that momentum is also present within industries. We follow Jegadeesh & Timan's (1993) methodology, as we did with individual stock momentum. The only difference is that we divide our dataset into the twenty-four industries before performing the strategy as we explained in 5.2.1.

5.3 Significance Test and Performance

5.3.1 T-statistics

To evaluate the validity of the results, we test for statistical significance to assess whether the results occur by chance or not. To assess whether the portfolios have yielded returns greater than zero, we will use a two-sided t-test because of the possibility of negative values from the strategies.

$$t_{stat} = \frac{m - \mu}{\frac{s}{\sqrt{n}}}$$

5.3.2 Sharpe Ratio

The Sharpe ratio measures the combined risk-reward relationship (William Sharpe, 1966). The ratio measures the return on investments against its total risk, and their respective standard deviations. The higher the Sharpe ratio the better risk-adjusted return. The following formula calculates the Sharpe ratio:

$$SR = \frac{R_P - R_f}{\sigma_P}$$

R_P is the average return of the portfolio, R_f is the risk-free rate, and σ_P is the standard deviation of the portfolio.

The ratio is the most well-known portfolio performance metric. It gives a quick perspective of the portfolio relative to other investments. The ratio has been criticized for its weaknesses. Criticizers state that the ratio has a poor future growth prediction, and it does not inform anything regarding the kurtosis or the skewness of the returns, which affects the standard deviation and its validity. The Sharpe ratio will be used to measure the performance of the portfolio because of its clarity and simplicity.

5.3.3 Fama-French Three-Factor Model

To use a more formal test of the dynamic portfolios' performance we will conduct a spanning test by including the three-factor model, developed by Fama and French (1993). Fama and French have identified three factors that can be useful in predicting future expected returns. Any returns above the risk-free rate can be attributed to the sensitivity of investments to these three factors. These factors include the excess return of the market ($R_m - R_f$), size (SMB), and book-to-market (HML).

$$R_P - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \varepsilon_i$$

R_P is the return of portfolio i, R_f is the risk-free rate, α_i is the intercept, $(R_m - R_f)$ is the excess return on the market portfolio (index), SMB is the return spread of small minus big stocks, HML is the return spread of high book-to-market firms minus low book-to-market firms, ε_i is the influence of other factors affecting the portfolios price, and $\beta_{\mathbf{1,2,3}}$ is the factor coefficients.

5.3.4 Fama-French Five-Factor Model

The five-factor model is an expansion of the three-factor model by adding two more factors: profitability (RMW), and investment patterns (CMA). The five-factor model produces intercepts that are closer to zero than the intercepts of the three-factor model, which suggests that the five-factor model performs better in explaining stock returns.

$$R_P - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_i$$

R_P is the return of portfolio i, R_f is the risk-free rate, α_i is the intercept, $(R_m - R_f)$ is the excess return on the market portfolio (index), SMB is the return spread of small minus big stocks, HML is the return spread of high book-to-market firms minus low book-to-market firms, RMW is the return spread of portfolios with robust profitability minus portfolios with weak profitability, CMA it the return spread of conservatively invested portfolios minus aggressively invested portfolios, ε_i is the influence of other factors affecting the portfolios price, and $\beta_{\mathbf{1,2,3,4,5}}$ is the factor coefficients.

6.0 Empirical Findings

In this section, we provide the findings of our empirical study. We will review the findings, offer interpretations, and make comparisons to earlier research.

6.1 Individual Stock Momentum Findings

6.1.1 Whole Period

Results in this subsection can be found in Table 3. The table presents characteristics of momentum return for each decile portfolio ranging from P1 to P10, and the WML portfolio, over the full sample length. The WML portfolio corresponds to long portfolio P10 and short portfolio P1. We must demonstrate that our dataset has the momentum anomaly reflecting earlier studies to provide a solid foundation for our conclusions. 5.2.1. shows a description of the approach.

Firstly, the pattern is consistent with the existing literature on individual stock momentum. Empirical evidence by Jegadeesh and Titman (1993) showed monotonically increasing profitable outcomes with average monthly returns of approximately 1 percent with the 6-6 strategy. Thus, supporting our results that momentum is present in our data, with a substantial momentum return that appears over the last century. The winner portfolio has statistically outperformed the loser portfolio with mean returns of 1.59 percent against 1.08 percent. Our WML portfolio achieves a 0.51 percent monthly momentum return, with a t-statistic of 6.99 which supports the robustness of the performance.

Furthermore, the WML portfolio has produced greater risk-adjusted returns than a risk-free asset with a Sharpe ratio of 0.14. The Fama-French three-factor (FF3) and the Fama-French five-factor (FF5) models report alphas with increasing magnitudes and high t–statistics suggesting that these portfolios consistently outperform the models' expectations. Both alphas for the WML portfolio (0.14 percent for the three-factor model and 0.15 percent for the five-factor model) are positive, which shows that the investment generates excess returns beyond what can be explained by the respective models. However, the slightly higher alpha of 0.15 percent in the five-factor model suggests that the added factors (profitability and investment) contribute to the performance of the portfolio. We find evidence of a self-financing and profitable individual stock momentum strategy from July 1965 to October 2021.

6.1.2 Crises - Individual Stock Momentum

5.2.1. shows a description of the approach. To identify individual stock momentum, we calculate the monthly raw returns, Sharpe ratios, FF3 and FF5 for each state of the crises. The crises include the Dot-Com Bubble, including the recession (03:2001 - 10:2001) and the 12-month post-recession period (12:2001 - 10:2002), the Financial Crisis, including the recession (12:2007 - 12:2009) and the 12-month post-recession period (07:2009 - 16:2010), and Covid-19, including the recession (02:2020 - 03:2020), the 12-month post-recession period (05:2020 - 04:2021), and the disruption (01:2020 - 12:2020). These results can be found in Appendix A. Table 4 covers the Dot-Com Bubble, Table 5 covers the Financial Crisis, and Table 6 covers Covid-19. We compare the crises to get a better understanding of drawdown periods and how the momentum anomaly behaves during cross-sectional periods.

<u>Recession</u>

A recession is a period in which the market experiences a significant decline in economic activity. During the recession of the Dot-Com Bubble, the winner portfolio outperformed the loser portfolio, suggesting successful performance. Thus, the WML portfolio shows an insignificant momentum return of 0.45 percent, with a Sharpe ratio of 0.12. FF3 and FF5 provide no evidence to state that the WML portfolio performed other than what the models expected. The statistics consistently indicate the superior performance of the higher-numbered portfolios. This suggests that the strategy successfully captures momentum effects in individual stock performance during the recession, even though the results for the WML portfolio are insufficient.

During the recession of the Financial Crisis, we find from losers to winners, monotonically decreasing statistics, which is surprising. The pattern demonstrates a shift from positive to negative returns as the crisis progresses, thus the assets that have been displaying positive returns suddenly and unexpectedly reversed their trend and experienced a sharp decline. Our WML portfolio stands out with its highly statistically significant monthly average return of -3.75 percent. In addition, a poor risk-adjusted performance with a Sharpe ratio of -0.96. The negative alphas of -3.55 and -3.71 obtained from the FF3 and FF5 models, respectively, suggest that the portfolio's performance is significantly worse than what would be expected based on its exposure to the models' factors. The statistics show evidence of a severe momentum crash showing that the loser portfolio outperformed the winner portfolio, thus the momentum strategy did not yield profits.

All portfolios during the Covid-19 recession have positive returns and Sharpe ratios, suggesting successful performance. The WML portfolio has a statistically insignificant momentum profit of 0.63 percent. The time-specter is limited, hence there are very few observations which could be the explanation for insignificant returns. The WML portfolio shows a Sharpe ratio of 0.33, suggesting that the momentum portfolio has generated excess returns above the risk-free rate. FF3 and FF5 do not provide any results because of collinearity caused by the Fama-French variables SMB, HML, and RMW, which are omitted. Our strategy consists of having portfolio returns every 6 months only, hence, the collinearity might be caused by a lack of observations and therefore correlated. There is no evidence to claim that the momentum anomaly yields any profit or loss due to insignificant returns. Based on statistically significant monthly raw returns did the winner portfolio perform slightly better than the loser portfolio, however, the loser portfolio received a more robust return.

Post-Recession

The momentum strategy's average returns are high and highly statistically significant, but since 1927 there have been a number of extended periods over which momentum under-performed dramatically, typically post-recession. A time of recovery is the period Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015) discovered momentum crashes due to the worst-performing portfolio yielding higher returns than the best-performing portfolio.

Post-recession of the Dot-Com Bubble, the results show that the whole market experienced a sharp decline in market returns as all portfolios show negative statistics and the winning portfolio performing the worst. The WML portfolio shows a statistically insignificant mean return of -0.80 percent and provides returns below the return of a risk-free asset with a Sharpe ratio of -0.56. Significant alphas of -1.21 and -1.38 from both the regression models FF3 and FF5, respectively, show evidence of a significant amount of the return not explained by the models. The results suggest that the loser portfolio outperformed the winner portfolio such that we experienced a momentum crash, thus the strategy has not been successful during the period.

Post-recession of the Financial Crisis is known to be one of the largest sustained drawdown periods using the momentum strategy. Daniel and Moskowitz (2016) discovered that the loser portfolio strongly outperformed the winner portfolio from March 2009 to March 2013. We do however limit our recovery period to 12 months post the recession spanning from July 2009 to June 2010, thus not directly comparable. The portfolio returns, Sharpe ratios, and the Fama-French models are monotonically increasing from losers to winners, which is a shift in the trend from the recession. The WML portfolio obtains a highly statistically significant positive momentum return of 0.70 percent and show good risk-adjusted performance with a Sharpe ratio of 1.22. The significant alphas of 0.72 and 0.59 obtained from the FF3 and FF5 models, respectively, suggest that the strategy's performance on average exceeded what would be predicted by the models. We find during this period that the winner portfolio outperformed the loser portfolio. Thus, the strategy was successful in generating momentum profits, contrary to the finding in the research by Daniel and Moskowitz (2016).

During the Covid-19 12-month post-period, there is a decreasing trend of statistically significant positive raw monthly returns from the loser decile to the winner decile. This demonstrates a shift in stock returns as the crisis progresses, similar to the Dot-Com Bubble. Thus, this suggests that the assets that previously displayed deficient performance suddenly and unexpectedly reversed their trend and experienced a sharp rise. All deciles result in overall superior portfolio returns and Sharpe ratios during this period, compared to the other crises. The WML portfolio, however, obtains a statistically insignificant mean return of -0.99 percent. The raw returns provided suggest that the loser portfolio is superior to the winner portfolio with returns of 5.02 percent and 4.03 percent, respectively, however, the winner portfolio obtains a more robust return. The strategy has not been effective as the portfolio generated lower returns than a risk-free asset, given the level of risk taken, with a Sharpe ratio of -0.43. None of the Fama-French models are statistically significant, however suggesting underperformance. The statistics suggest that the strategy does not result in momentum returns. We cannot tell whether the momentum strategy experienced a momentum crash during the recession of Covid-

19 as the return of the WML portfolio is insignificant. Nevertheless, we observe indications of a momentum crash.

Disruption of Covid-19

Disruption of Covid-19 covers both the recession of Covid-19 and a part of its recovery from the downfall. This is to analyze a broader part of the pandemic. We observe a decreasing trend of portfolio returns, however with a shift of performance in the middle. Nevertheless, the loser decile is the superior portfolio. Thus, the WML portfolio obtains a (statistically insignificant) mean return of -1.19 percent, with an insufficient risk-adjusted performance with a Sharpe ratio of -0.56. None of the alphas from the FF3 and FF5 are statistically significant, however, the statistics suggest that the portfolio underperformed.

Investing in winners and avoiding losers did not yield profitable momentum returns during the disruption. The loser portfolio consistently outperformed the winner portfolio. The Covid-19 pandemic and the following period have been challenging and stormy periods in which financial markets experienced high fluctuations and uncertainty and went through a “flash” but painful bear market. Since the disruption period in our dataset covers both the recession of Covid-19 and a part of its recovery from the downfall, the market condition ameliorates, and the market starts to rebound. The worst-performing stocks experienced strong gains, which resulted in a “momentum crash” as momentum strategies short these.

Overall, we observe that the Financial Crisis is the only crisis that provides sufficient evidence to claim that the strategy experienced a momentum crash during the recession and momentum profits post-recession. The other periods received momentum returns that are virtually zero, nevertheless, we see indications of its performance. Implications of momentum crashes are present post-recession and during the disruption of Covid-19 and the post-recession period of the Dot-Com Bubble. Thus, we find a similar pattern during those periods, as Daniel and Moskowitz discovered during periods of recovery, where the loser deciles experience a sudden reverse in their trend and then experience a sharp rise. In the Financial Crisis, the pattern deviates and we find evidence of momentum crash during the recession and not in the subsequent 12-month period. The finding is interesting, but several factors could contribute to this phenomenon. We also observe that Covid-19 yields higher portfolio returns and risk-adjusted returns (P1 to P10) compared to the portfolios of the other crises. Due to the Covid-19 period's lack of statistically significant returns, we see the need for further research to accurately state the crises performance.

6.2 Industry Momentum Findings

Using individual stock momentum, we observed a similar pattern of momentum returns during Covid-19 and the Dot-Com Bubble, as with earlier research, with a deviating pattern during the Financial Crisis. We further want to investigate whether the same momentum patterns we observe with individual stock momentum are also present using industry momentum.

6.2.1 Whole Period

We analyze to see whether our data collection over the full sample period also contains industry momentum to further examine momentum behavior. As already mentioned, Moskowitz and Grinblatt (1999) were the ones who initially identified industry momentum, and we use the same methodology as them. 5.2.2. shows a description of the approach. Table 7 shows all results for this subsection. The table presents characteristics of momentum return for each decile portfolio ranging from P1 to P8, and the WML portfolio, over the full sample length. The WML portfolio corresponds to long portfolio P8 and short portfolio P1.

Consistent with earlier research, the strategy generates statistically significant positive monthly raw returns that are monotonically increasing. The winners (P8) significantly outperform the losers (P1). Consistent with existing literature, by shorting the loser portfolio and going long the winner portfolio our strategy yields a monthly raw momentum return of 0.35 percent. The return is however lower than the return of our individual stock momentum return (0.35 vs 0.51). We do however observe that the WML portfolio has a negative Sharpe ratio of -0.01, which is poor and lower than for a risk-free asset. Indicating that the momentum strategy has a poor risk-adjusted performance. The WML portfolio’s Fama-French alphas indicate that the performance of the strategy is in line with the model’s expectations. We find that industry momentum does yield a momentum return during this period, however the anomaly is not as profitable as with the individual stock momentum strategy.

6.2.2 Crises - Industry Momentum

We analyze industry momentum during the recession period, and the post-recovery period of the Dot-Com Bubble and the Financial Crisis to further develop our understanding of momentum behavior and compare it to the Covid-19 crisis. Tables 8, 10, and 12 provide monthly average raw returns, Sharpe ratio, FF3, and FF5. Table 8 shows the results for the Dot-Com Bubble, Table 10 shows the Financial Crisis, and Table 12 shows the results for Covid-19.

<u>Recession</u>

During the Dot-Com Bubble recession the winner and loser portfolios received closely aligned returns, resulting a momentum return of 0.03 percent. Thus, the winner portfolio did outperform the loser portfolio. Furthermore, the strategy yielded a poor risk-adjusted return indicated by the negative Sharpe ratio of -0.20, and The Fama-French models also showed that the strategy failed to exceed the models' expectations. Moving to the Financial Crisis, we observe monotonically decreasing patterns. The WML portfolio experienced a significant loss of -1.80 percent and obtained a poor risk-adjusted performance of -0.72. The Fama-French models also revealed underperformance, indicating that the strategy failed to meet the models' expectations, further supporting evidence of a momentum crash. We find that industry momentum yields a low momentum profit during the recession of the Dot-Com Bubble, while we find evidence of a momentum crash during the recession of the Financial Crisis, consistent with the findings from the individual stock momentum. The loss was however more severe with the individual stock momentum, whilst the recession of the Financial Crisis experienced over double the loss.

During the recession period of the Covid-19 crisis, there were no distinct patterns that emerged in terms of average returns. The WML portfolio protrude as the only portfolio with a significant alpha, with an average monthly return of 1.06 percent. Additionally, the portfolio shows a superior Sharpe ratio of 1.69, which suggest that the strategy had a good risk-adjusted performance. FF3 and FF5 do not provide any results due to collinearity (see section 6.1.2). We find that industry momentum during the recession of Covid-19 result in momentum profits, and had a superior performance compared to individual stock momentum, contrary to the other crises. Also, the strategy receives an abnormally prominent level of momentum returns, not matched by any of the previous periods in our dataset.

Post-recession

Analyzing the post-recession periods of the crises sheds light on the momentum behavior during these phases. During the Dot-Com Bubble recovery, there was a reversal in returns, with all portfolios suggesting negative returns. The WML portfolio experienced a momentum crash, as indicated by its statistically significant average return of -0.70 percent. Followed by a negative Sharpe ratio of -0.86, suggesting subpar risk-adjusted returns. The Fama-French models also revealed underperformance for the portfolio, indicating that the strategy failed to meet the models' expectations. Turning to the Financial Crisis post-recession period, we observe an increasing pattern. Moving from losers to winners demonstrates favorable risk-adjusted performance and positive and statistically significant momentum development. The WML portfolio shows a statistically significant momentum return of 0.57 percent and a risk-adjusted return of 0.85 above that of a risk-free asset. FF3 shows outperformance, while the lack of significant alpha for the FF5 model indicates that the strategy's returns align with the model's predictions. Overall, we find evidence of a momentum crash during the recovery of the Dot-Com Bubble, and positive momentum returns during the post-recession of the Financial Crisis, consistent with the findings with individual stock momentum.

During the post-recession period of the Covid-19 crisis, all portfolios provide highly statistically significant returns, with the loser portfolio outperforming the winner portfolio in terms of raw returns throughout the period. This indicates a reversal in momentum and subpar performance for the WML portfolio. However, the return of -0.49 percent is not statistically significant, preventing any definitive claims about profit or loss for the strategy. Also, the portfolio underperforms with a negative Sharpe ratio of -0.30. None of the alphas from the Fama-French models demonstrate statistical significance, implying that all returns align with the models' expectations. Given the statistics we cannot tell anything regarding the strategy's performance, however, we see indications of underperformance suggesting a momentum crash or no returns. Thus, during the post-recession period of the Covid-19 crisis, we find that industry momentum shows a similar pattern to individual stock momentum.

Disruption of Covid-19

We find that during the disruptive period of Covid-19, a parallel can be drawn between the observed outcomes and patterns seen in individual stock momentum. The loser portfolio outperformed the winner portfolio, resulting in an average monthly momentum return of -0.25 percent, however, not statistically significant. The WML portfolio exhibits a Sharpe ratio of -0.16, indicating unfavorable risk-adjusted performance for the strategy. None of the alphas from the FF3 and FF5 models demonstrate statistical significance, implying that all returns align with the models' expectations. Thus, based on statistical analysis, the strategy appears to underperform during the disruptive period like the post-recession period, although not as severely as with individual stock momentum. Interestingly, we find that individual stock momentum results in more prominent momentum returns compared to industry momentum during all periods, meaning that individual stock momentum shows more severe crashes.

6.2.2.1 Average Stock Returns within Industry Groups

All results in this subsection are shown in Tables 9, 11, and 13. Table 9 show the results for the Dot-Com Bubble, Table 11 show the results for the Financial Crisis, and Table 13 shows the results for Covid-19. The tables contain the average stock return for each industry, during each period. In addition, the tables show the number of times each industry won and lost during the formation period of the crises.

By examining the average stock returns within the industries, we observe both similarities and differences between positively and negatively affected industries. During the Dot-Com Bubble recession, several industries experienced positive returns, which is surprising. Contrarily, during the Financial Crisis recession and Covid-19, most industries experienced negative returns, reflecting the widespread impact of the crises. We observe similarities between the recessions, where *Air Transportation* and *Mining* are amongst the most negatively affected industries.

Contrary, *Chemical* and *Department Stores* are resilient during all three recessions. Also, Covid-19 and the Financial Crisis shows common affected industries, where *Petroleum, Finance, Transport Equipment,* and *Hotels & Social Services* are among the most severely hit industries. Differences between the recessions are seen with *Health & Membership, Hotels & Social Services, Manufacturing,* and *Retail* exhibiting particularly robust performance during the recession of the Dot-Com Bubble. We find it interesting that *Technology* had positive returns during this period, however, the bubble burst already in 2000 and had a brief period of market rise in early 2001 which could explain the positive returns. During the recession of Covid-19, we also find that industries such as *Apparel, Construction,* and *Primary Metals* also were particularly hard-hit, with significant declines in average stock returns.

During the Dot-Com Bubble, almost all industries experienced positive returns post-recession and are somehow lower than the returns during the bubble burst, which we find interesting. However, we observe that the stock market already started to collapse in March 2000, and did not fully recover until April 2015. Contrary, in the post-recession period of the Financial Crisis and Covid-19 and the disruption, there was a shift from negative to positive returns across industries. These states show that the market displays signs of recuperation from the recession. During Covid-19 we observe exceptionally high returns compared to the other crises, however, the recession also did suffer more severe losses, indicating an elevated level of volatility during the pandemic. *Mining, Apparel, Retail, Technology,* and *Hotels & Social Services* perform well during all recoveries, in addition, *Air Transportation,* and *Primary Metals* also had a superior performance during the recovery of Covid-19. We find the lowest stock returns for *Food, Petroleum,* and *Utilities,* which we find are common in all post-recessions and the disruption.

There are also differences between the recoveries. During the post-recession of the bubble, we find that *Other Transportation, Transport Equipment,* and *Finance* performed well during this period. While *Chemical* and *Transportation* also suffered with negative returns, suggesting ongoing challenges for these industries. Post the recession of the Financial Crisis, the market started to recover from the fall with *Paper, Machinery, Transport Equipment, and Transportation,* in addition to the ones mentioned above, which had the highest returns. The pandemic of Covid-

19 had wide-ranging impacts on industries typically associated with "high-contact" activity, due to lockdown measures. Conversely, industries characterized by "low-contact" activities have thrived during the pandemic. Industries such as *Other, Technology, Electrical Equipment, Mining,* but also *Retail*, show superior stock returns during the disruption. These observations underscore the diverse responses of industries to economic downturns, which we also see are common during recessions. Thus, we observe both similarities and differences between negatively and positively affected industries across market states.

Overall, our empirical findings on industry momentum reveal variations in statistically significant performance. During the Dot-Com Bubble, industry momentum did not generate substantial returns. Subsequently, during the recovery phase, a momentum crash occurred. During the recession caused by the Financial Crisis, our analysis provides evidence of a momentum crash, followed by a period of momentum profit in the next 12 months. During the Covid-19 recession, there is evidence of momentum profit, which was followed by indications of a momentum crash in the subsequent period. Conversely, the strategy did not yield favorable outcomes during the disruption and prove a momentum crash. Thus, we see the same pattern of momentum crashes during Covid-19 as with earlier studies and the Dot-Com Bubble. We also find that returns during Covid-19 were significantly higher compared to returns during other crises.

The data shows that individual stock momentum tends to result in more extreme crashes, such that industry momentum has an overall inferior performance in comparison. However, we find a consistent pattern of winner-minus-loser returns with both strategies. Due to the disruption and the post-recession periods of Covid-19's lack of statistically significant returns, we see the need for further research, to accurately tell the crises performance. Furthermore, our analysis highlights the differences and similarities in the performance of industries cross-sectional, where the Financial Crisis and Covid-19 had more in common. During the recessions, *Air Transportation* and *Mining* were among the most negatively affected industries, while *Chemical* and *Department Stores* were resilient. *Mining, Apparel, Retail, Technology*, and *Hotels & Social Services* performed well during all recoveries. We find the lowest stock returns for *Food, Petroleum,* and *Utilities.*

6.3 Individual Stock Momentum Within Industries

We also run more analyses for momentum within industries to further strengthen our knowledge of the momentum anomaly and how the anomaly behaved during Covid-19, the Financial Crisis, and the Dot-Com Bubble. To do this, we apply the methods described in 5.2.3. Table 14 shows the findings for this section.

We conclude that the sample size is small and that these years require a more manual approach to analyze. Thus, the momentum returns from the various industries, spanning the years and distinct periods. One notable observation is the substantial deviation of certain momentum returns from the average, as evident in our analysis encompassing individual stock momentum and industry momentum. *Transportation* and *Construction* did not provide results during Covid-19 and the Financial Crisis because of insufficient data. Thus, those industries require further investigation for correct judgments.

<u>Recession</u>

During the Dot-Com Bubble recession, most momentum portfolios had limited returns, but most portfolios showed momentum profits, thus, the pattern follows earlier findings. Detailed analysis, as presented in Table 9 shows that *Hotels & Social Services* and *Health & Membership* had superior average stock returns and momentum profits within their industries. *Construction* and *Transportation* displayed remarkable momentum returns, while *Department Stores* and *Primary Metals* experienced momentum crashes.

In contrast, the Financial Crisis recession was marked by significant momentum crashes across all industries, consistent with earlier findings. Notably, the *Primary Metals*, *Fabricated Metals*, *Transport Equipment*, *Health & Membership*, and *Mining* industries experienced extreme momentum crashes with average returns ranging between -3.85 to -7.46 percent, resulting in severe losses and a considerable divergence between stocks that fared well and those that suffered. Furthermore, the *Finance* industry showed a statistically significant momentum loss, which was followed by a momentum crash during the recovery. These findings highlight a time of market distress and significant challenges faced by industries during the recession. Comparing these results with average stock returns in Table 11, we find that both results are marked by negative returns, however we find no parallels between the ones that were most severely hit during the market downfall.

During the Covid-19 crisis, the application of the momentum strategy yielded limited statistically significant returns across industries, making the identification of discernible patterns challenging. Notably, over half of the momentum portfolios showed indications of a momentum crash, however not statistically significant. *Apparel* suffered the most severe momentum crash among the industries, with a negative average return of -11.38 percent. In Table 13, we also find that *Apparel* was the most negatively affected industry. Additionally, we also see indications of crashes for *Primary Metals, Air Transportation,* and *Health & Membership*. Conversely, *Paper* and *Transport Equipment* showed the highest average monthly momentum profits, with returns of 12.58 percent and 8.84 percent, respectively.

<u>Post-recession</u>

The post-recession period following economic crises had varied effects on industries. After the Dot-Com Bubble, there were significant momentum crashes, but some industries showed positive momentum returns. In contrast, in Table 9, we find that most industries had positive average stock returns. We find no clear link between their performance. *Construction, Machinery, Manufacturing, Department Stores, Electrical Equipment*, and *Technology* experienced notable momentum crashes. The presence of positive momentum returns in certain industries shows investment potential during the recovery.

The Financial Crisis recovery period saw a notable shift, with previously challenged industries emerging as winners. Thus, there are now lucrative profits to be made from momentum investing due to continuance of existing trends in the market. *Mining, Machinery, Utilities, Retail*, and *Other* industries displayed favorable momentum returns, capitalizing on the recovery. Conversely, *Other Transportation, Finance, Air Transportation,* and *Health & Membership* faced severe momentum crashes. We find no patterns of affected industries, showed in Table 11, and those that experienced momentum crashes or momentum profits with individual stock momentum within industries.

In the post-recession period of the Financial Crisis, there were a consistent pattern of momentum profits. However, following the recessions of the Dot-Com Bubble and Covid-19, the periods showed a diverse range of performances across industries, with however most frequent crashes. *Primary Metals, Manufacturing, Retail, Transport Equipment,* and *Apparel* industries experienced momentum crash. The severe losses ranged between -2.33 to -5.41 percent. Certain industries proved strong rebounds and displayed robust post-recession performance, while others encountered obstacles and struggled to adapt to the evolving business environment.

Disruption of Covid-19

During the Covid-19 pandemic, industries showed varied performances throughout different periods. Notably, the *Apparel* industry appeared as one of the hardest-hit industries, experiencing severe and persistent momentum crashes throughout all three periods of Covid-19. Furthermore, the *Primary Metals* industry also saw a notable momentum crash, reflecting a negative return of -3.49 percent. Conversely, *Utilities* stood out as the sole industry to show a significant momentum profit. We find an absence of a straightforward relationship between industry performance and average stock returns within industries. The pandemic disrupted both industry momentum and individual stock momentum, leading to underperformance and momentum crashes. This highlights the challenges faced by industries and individual stocks, resulting in unfavorable performance.

Our findings are of particular interest as they shed light on the significant challenges met by the industries during the Covid-19 crisis. The impact on industries varied, with mixed performance patterns reflecting the diverse challenges and opportunities they encountered, which can be attributed to unique circumstances and market forces that influenced momentum returns. The findings show varied momentum returns across industries and market states. Significant economic incidents occurred during the Covid-19 crisis, the Financial Crisis, and the Dot-Com Bubble, suffering long-lasting effects in the financial markets. While some industries experienced significant momentum collapses, others showed recoveries, high profits, or inconsistent results. Even while every period had its distinctive characteristics, a comparison reveals some significant parallels and variations.

Overall, individual stock momentum within industries reveals parallels between individual stock momentum and industry momentum. The Financial Crisis had notable momentum profits and crashes. While Covid-19 and the Dot-Com Bubble showed mixed insignificant results, however frequent momentum crashes during the post-recession period. It is important to note that statistical significance was lacking during especially Covid-19 and the Dot-Com Bubble, highlighting the need for further research to fully understand the dynamics of individual stock momentum within industries during these periods. We do however find that both individual stock momentum strategies result in more severe momentum crashes compared to industry momentum, however in turn also greater profits, indicating a riskier strategy. These findings emphasize the importance of considering specific stock dynamics within industries when pursuing momentum opportunities.

We find that few of most affected industries, in terms of average stock returns within industries, also experienced the most severe crashes or most profitable returns using individual stock momentum within industries, however we find no distinct patterns overall. Thus, similarities indicate coincidences rather than apparent causal connections. We suggest further research and analysis to accurately interpret any linkages.

7.0 Conclusion

Momentum anomaly is a popular trading strategy among investors due to two main factors. The strategy achieves an attractive risk-adjusted return, in addition to having historically been highly profitable. Nevertheless, earlier research has found that the anomaly suffers periods of crashes with zero to negative returns. By studying momentum behavior under different market states, one could help find why some investments fall short in specific periods. This research seeks to provide a better understanding of the anomaly by analyzing individual stock momentum, industry momentum, and individual stock momentum within industries, in the US stock market spanning from 1965 to 2022.

We do find similar patterns of momentum crashes in industry momentum and individual stock momentum within industries as with individual stock momentum. However, we do find that individual stock momentum, especially within industries, tends to result in more prominent returns, and therefore experience more extreme crashes. We observe that Covid-19 shows indications of the same pattern of momentum results as with the Dot-Com Bubble, and earlier studies of times of recovery. Although, we lack statistically significant support for correct interpretations of the momentum portfolios during Covid-19.

When looking at individual stock momentum within industries, we see that despite the Financial Crisis recession experiencing most collapses, the Covid-19 recession experienced the most extreme crash. Further, we find abnormally high returns for Covid-19 when analyzing the market states. We find no distinct patterns between affected industries and individual stock momentum within industries; thus, similarities indicate coincidences rather than apparent causal connections.

Our data shows inconsistent outcomes for some momentum portfolios, highlighting the need for further investigation and considering the specific statistical tests and data context for accurate interpretations. We recognize the limitation of our chosen sample length to study the momentum anomaly during Covid-19. For further research, it would be interesting to investigate a longer sample to include the full length of the Covid-19 pandemic. Another implication for further research would be to investigate deeper into individual stock momentum within industries and why certain industries show more pronounced momentum crashes during recessions compared to others. This analysis could shed light on the underlying factors and dynamics that contribute to the varying degrees of resilience and vulnerability observed within different industries during economic downturns. By examining the specific characteristics of individual stocks within industries, such as their fundamental attributes, market positioning, and investor sentiment, researchers can gain insights into the mechanisms driving momentum crashes and find potential indicators or predictive factors for future occurrences.

8.0 References

Asness, C. S. (1995). The Power of Past Stock Returns to Explain Future Stock Returns. http://dx.doi.org/10.2139/ssrn.2865769

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. The Journal of Finance, 68(3), 929–985. http://www.jstor.org/stable/42002613

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics, 116(1), 111-120. https://doi.org/10.1016/j.jfineco.2014.11.010

Benchmark. (2022). Industry Portfolios. Kenneth R. French. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Bernanke, B., & Gertler, M. (1989). Agency Costs, Net Worth, and Business Fluctuations. The American Economic Review, 79(1), 14–31. http://www.jstor.org/stable/1804770

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. The Journal of Finance, 52(1), 57–82. https://doi.org/10.2307/2329556

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. Journal of Financial Economics, 122(2), 221-247. https://doi.org/10.1016/j.jfineco.2015.12.002

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? The Journal of Finance, 40(3), 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. The Journal of Finance, 42(2), 427-465. http://www.jstor.org/stable/2329112

Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics, 33(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. Journal of Economic Perspectives, 18(3), 25-46. http://dx.doi.org/10.1257/0895330042162430

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. The Journal of Finance, 51(1), 55-84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. Journal of Financial Economics, 116(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

French, R. K., (2023). Fama/French 5 Factors (2x3). https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Grinblatt, M., & Han, B. (2004). The Disposition Effect and Momentum. NBER Working Papers 8734, National Bureau of Economic Research, Inc.

Israel, R., & Moskowitz, T.J. (2013). The Role of Shorting, Firm Size, and Time on Market Anomalies. Journal of Financial Economics, 108(2), 275-301. https://doi.org/10.1016/j.jfineco.2012.11.005

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. The Journal of Finance, 45(3), 881-898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. The Journal of Finance, 56(2), 699–720. http://www.jstor.org/stable/222579

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1), 65–91. https://doi.org/10.2307/2328882

Jensen, M. C. (1968). The Performance of Mutual Funds in the Period 1945–1964. The Journal of Finance, 23(2), 389-416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Johnson, T. C. (2002). Rational Momentum Effects. The Journal of Finance, 57(2), 585-608. https://doi.org/10.1111/1540-6261.00435

Lehmann, B. N. (1990). Fads, Martingales, and Market Efficiency. The Quarterly Journal of Economics, 105(1), 1-28. https://doi.org/10.2307/2937816

Lintner, J. (1965). Security Prices, Risk, and Maximal Gains From Diversification. The Journal of Finance, 20(4), 587–615. https://doi.org/10.2307/2977249

Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? The Journal of Finance, 54(4), 1249–1290. http://www.jstor.org/stable/798005

Moore, S. (2019, 27. January). A Deeper Look At Momentum Strategies. Forbes. https://www.forbes.com/sites/simonmoore/2019/01/27/a-deeper-look-at how-momentum-strategies-work/?sh=72d9c63f5ae3

Mossin, J. (1966). Equilibrium in a Capital Asset Market. Econometrics, 34(4), 768–783. https://doi.org/10.2307/1910098

NBER, (n.d.). Business Cycle Dating. NBER. https://www.nber.org/research/business-cycle-dating.

Sharpe, W. F. (1966). Mutual Fund Performance. The Journal of Business, 39(1), 119–138. http://www.jstor.org/stable/2351741

CRSP. (2023). Monthly Stock. Wharton University of Pennsylvania. https://wrds-www.wharton.upenn.edu/

Appendices

Appendix A: Tables

Table 1: Data variables described.

PERMNO	A unique stock (share class) level identifier
DATE	Self-explanatory
SHRCD	A two-digit code that describes the type of shares traded
EXCHCD	A code that indicates the exchange on which a security is listed
SICCD	Standard Industrial Classification (SIC) code
PRC	Share price
RET	Holding period return
SHROUT	Shares outstanding

Note: The table gives a brief explanation for all data variables included in the raw data set.

Table 2: Industry groups with their respective SIC codes.

	Industries	SIC Codes
1.	Mining	10-14
2.	Food	20
3.	Apparel	22-23
4.	Paper	26
5.	Chemical	28
6.	Petroleum	29
7.	Construction	32
8.	Primary Metals	33
9.	Fabricated Metals	34
10.	Machinery	35
11.	Electrical Equipment	36
12.	Transport Equipment	37
13.	Manufacturing	38-39
14.	Transportation	40
15.	Other Transportation	41-44, 46-47
16.	Air Transportation	45
17.	Utilities	49
18.	Department Stores	53
19.	Retail	50-52, 54-59
20.	Finance	60-69
21.	Technology	73
22.	Hotels & Social Services	70-72, 74-79
23.	Health & Membership	80-86
24.	Other	87-99

Table 3: Individual Stock Momentum

The table reports the monthly return for momentum portfolios based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 10 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P10 and short portfolio P1. The table shows the average raw monthly return in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three-Factor (FF3) Model and the Fama-French Five-Factor (FF5) Model is reported. t-statistics are in parentheses below the mean monthly return. ***, ** and * refers to 1%, 5% and 10% significance levels, respectively.

Individual Stock Momentum
(July 1965 – October 2021)

	Raw return	Sharpe ratio	FF3	FF5
P1	1.08	0.24	0.59	0.60
	(9.61)		(5.44)	(5.40)
P2	1.14	0.30	0.64	0.65
	(11.62)		(6.88)	(6.70)
P3	1.16	0.33	0.66	0.66
	(12.80)		(7.70)	(7.39)
P4	1.19	0.36	0.69	0.69
	(13.80)		(8.50)	(8.15)
P5	1.21	0.39	0.72	0.71
	(14.68)		(9.21)	(8.78)
P6	1.23	0.41	0.74	0.73
	(15.41)		(9.88)	(9.46)
P7	1.23	0.41	0.74	0.74
	(15.49)		(9.96)	(9.55)
P8	1.28	0.42	0.79	0.79
	(15.57)		(10.32)	(10.00)
P9	1.35	0.43	0.86	0.88
	(15.28)		(10.48)	(10.30)
P10	1.59	0.44	1.11	1.13
	(14.99)		(11.10)	(11.03)
WML	0.51	0.08	0.14	0.15
	(6.99) ***		(1.97)*	(2.02)*

Table 4: Individual Stock Momentum during the Dot-Com Bubble

The table reports the monthly return for momentum portfolios during the Dot-Com Bubble, divided into the recession period and the 12-month post-recession period. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period Each portfolio from 1 (loser portfolio) until 10 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P10 and short portfolio P1. The table shows the average raw monthly return in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three-Factor (FF3) model and the Fama-French Five-Factor (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refers to 1%, 5% and 10% significance levels, respectively

The Dot-Com Bubble - Individual Stock Momentum

	Recession Period (March 2001 – November 2001)				**Post-Recession Period** (December 2001 – November 2002)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	FF3	FF5
P1	1.38	0.42	1.27	1.53	-0.24	-0.14	0.16	0.88
	(1.64)		(1.21)	(1.04)	(-0.31)		(0.21)	(1.12)
P2	1.07	0.38	0.97	1.38	-0.61	-0.37	-0.39	0.05
	(1.64)		(1.17)	(1.26)	(-1.04)		(-0.69)	(0.08)
P3	1.24	0.47	1.14	1.61	-0.54	-0.46	-0.44	-0.16
	(1.93)		(1.38)	(1.54)	(-1.28)		(-1.12)	(-0.32)
P4	1.22	0.51	1.08	1.47	-0.59	-0.57	-0.53	-0.33
	(2.10)		(1.40)	(1.47)	(-1.60)		(-1.66)	(-0.82)
P5	1.23	0.59	1.05	1.43	-0.55	-0.48	-0.52	-0.26
	(2.42)		(1.54)	(1.62)	(-1.33)		(-1.27)	(-0.50)
P6	1.56	0.80	1.40	1.73	-0.44	-0.37	-0.41	-0.08
	(3.06)		(2.14)	(1.99)	(-0.99)		(-0.90)	(-0.14)
P7	1.53	0.84	1.39	1.75	-0.37	-0.33	-0.35	-0.05
	(3.26)		(2.30)	(2.34)	(-0.83)		(-0.75)	(-0.08)
P8	1.65	0.88	1.44	1.83	-0.58	-0.38	-0.50	-0.04
	(3.30)		(2.19)	(2.19)	(-1.07)		(-0.88)	(-0.06)
P9	1.67	0.85	1.50	1.92	-0.84	-0.48	-0.72	-0.25
	(3.20)		(2.30)	(2.41)	(-1.43)		(-1.16)	(-0.33)
P10	1.83	0.92	1.71	2.00	-1.04	-0.58	-0.91	-0.36
	(3.36)		(2.45)	(2.10)	(-1.79)		(-1.50)	(-0.51)
WML	0.45	0.12	0.14	0.18	-0.80	-0.56	-1.21	-1.38
	(0.99)		(0.27)	(0.25)	(-1.65)		(-2.56)*	(-2.58)*

Table 5: Individual Stock Momentum during the Financial Crisis

The table reports the monthly return for momentum portfolios during the Financial Crisis, divided into the recession period and the 12-month post-recession period. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 10 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P10 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) model and the Fama-French Five (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refers to 1%, 5% and 10% significance levels, respectively.

Financial Crisis - Individual Stock Momentum

	Recession Period (December 2007 – June 2009)				**Post-Recession Period** (July 2009 – June 2010)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	FF3	FF5
P1	1.87	0.28	2.69	3.55	1.52	1.13	1.40	1.55
	(1.31)		(1.87)	(1.99)	(3.92)		(3.84)	(2.41)
P2	0.59	0.09	1.52	2.27	1.47	1.16	1.45	1.59
	(0.48)		(1.24)	(1.52)	(4.03)		(4.00)	(2.50)
P3	0.21	0.02	1.06	1.77	1.57	1.24	1.54	1.66
	(0.19)		(0.99)	(1.33)	(4.33)		(4.50)	(2.77)
P4	0.00	-0.02	0.92	1.54	1.45	1.56	1.42	1.41
	(0.00)		(0.89)	(1.22)	(5.44)		(5.45)	(3.10)
P5	0.03	-0.02	0.70	1.29	1.57	1.30	1.54	1.63
	(0.03)		(0.79)	(1.21)	(4.54)		(4.59)	(2.83)
P6	-0.24	-0.09	0.47	1.10	1.60	1.37	1.58	1.61
	(-0.27)		(0.58)	(1.12)	(4.77)		(5.34)	(3.09)
P7	-0.42	-0.15	0.25	0.77	1.62	1.29	1.60	1.72
	(-0.53)		(0.34)	(0.88)	(4.48)		(4.78)	(3.01)
P8	-0.76	-0.24	0.02	0.60	1.76	1.28	1.74	1.78
	(-0.95)		(0.02)	(0.69)	(4.47)		(4.84)	(2.85)
P9	-1.15	-0.34	-0.35	0.24	2.00	1.34	1.96	1.91
	(-1.38)		(-0.46)	(0.27)	(4.65)		(4.94)	(2.74)
P10	-1.87	-0.44	-0.77	-0.09	2.22	1.37	2.13	2.14
	(-1.82)		(-0.75)	(-0.07)	(4.76)		(5.37)	(3.12)
WML	-3.75	-0.96	-3.55	-3.71	0.70	1.22	0.72	0.59
	(-4.00)***		(-3.49)**	(-2.83)*	(4.27)**		(4.77)**	(2.54)*

Table 6: Individual Stock Momentum during Covid-19

The table reports the monthly return for momentum portfolios during Covid-19, divided into the disruption period, the recession period and the 12-month post-recession period. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 10 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P10 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) model and the Fama-French Five (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.

COVID-19 - Individual Stock Momentum

	Disruption Period (January 2020 – December 2020)				**Recession Period** (February 2020 – March 2020)		**Post-Recession Period** (May 2020 – March 2021)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	Raw return	Sharpe ratio	FF3	FF5
P1	5.83	2.01	7.16	7.98	4.13	2.19	5.02	1.40	5.09	5.34
	(7.11)		(4.89)	(5.98)	(4.01)		(4.86)		(3.30)	(2.82)
P2	4.45	1.47	5.39	6.13	2.06	0.95	4.58	1.80	4.38	4.50
	(5.21)		(3.71)	(4.35)	(1.76)		(6.25)		(3.90)	(3.21)
P3	3.73	1.23	4.92	5.61	1.30	0.48	4.13	1.83	3.96	4.23
	(4.36)		(3.68)	(4.37)	(0.92)		(6.34)		(3.88)	(3.40)
P4	3.30	1.13	4.25	5.02	0.92	0.35	3.91	2.13	3.72	3.84
	(4.01)		(3.19)	(4.20)	(0.68)		(7.38)		(4.48)	(3.73)
P5	3.13	1.03	4.23	4.99	0.62	0.21	3.86	2.06	3.60	3.86
	(3.68)		(3.07)	(3.92)	(0.42)		(7.15)		(4.26)	(3.78)
P6	3.05	1.06	3.71	4.45	0.81	0.28	3.76	2.28	3.23	3.43
	(3.78)		(3.09)	(4.44)	(0.55)		(7.89)		(4.65)	(4.05)
P7	3.28	1.14	4.04	4.77	1.51	0.42	3.71	2.03	3.28	3.60
	(4.08)		(3.32)	(4.67)	(0.79)		(7.05)		(4.17)	(3.92)
P8	3.28	1.20	3.59	4.35	2.20	0.62	3.53	1.94	2.89	3.12
	(4.28)		(2.96)	(4.40)	(1.14)		(6.73)		(4.03)	(3.63)
P9	3.69	1.50	3.80	4.48	2.93	0.82	3.72	2.16	3.05	3.29
	(5.36)		(3.48)	(4.96)	(1.49)		(7.47)		(4.66)	(4.26)
P10	4.64	1.95	4.67	5.34	4.76	1.36	4.03	1.78	3.21	3.47
	(6.91)		(4.03)	(5.21)	(2.45)		(6.19)		(3.78)	(3.37)
WML	-1.19	-0.56	-2.53	-2.67	0.63	0.33	-0.99	-0.43	-1.88	-1.88
	(-1.87)		(-2.08)	(-1.85)	(0.69)		(-1.47)		(-2.22)	(-1.83)

Table 7: Industry Momentum

Industry groups have been formed based on a two-digit sic code. The table reports the monthly return for momentum portfolios based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 8 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P8 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) Model and the Fama-French Five (FF5) Model is reported. t-statistics are in parentheses below the mean monthly return. ***, ** and * refers to 1%, 5% and 10% significance levels, respectively.

Industry Momentum

(July 1965 – October 2021)

	Raw return	Sharpe ratio	FF3	FF5
P1	1.18	0.31	0.68	0.68
	(11.69)		(7.03)	(6.81)
P2	1.26	0.35	0.74	0.73
	(12.82)		(8.00)	(7.56)
P3	1.31	0.37	0.81	0.82
	(13.32)		(8.60)	(8.45)
P4	1.33	0.38	0.83	0.80
	(13.74)		(8.98)	(8.38)
P5	1.40	0.40	0.90	0.89
	(14.34)		(9.66)	(9.32)
P6	1.39	0.41	0.87	0.87
	(14.48)		(9.75)	(9.40)
P7	1.44	0.43	0.94	0.93
	(15.04)		(10.47)	(9.98)
P8	1.53	0.42	1.03	1.03
	(14.49)		(10.36)	(10.04)
WML	0.35	-0.01	-0.02	-0.02
	(4.87)***		(-0.31)	(-0.33)

Table 8: Industry Momentum during the Dot-Com Bubble

The table reports the monthly return for momentum portfolios during the Dot-Com Bubble, divided into the recession period and the 12-month post-recession period. Industry groups have been formed based on a two-digit SIC code. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 8 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P8 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) model and the Fama-French Five (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.

The Dot-Com Bubble - Industry Momentum

	Recession Period (March 2001 – November 2001)				**Post-Recession Period** (December 2001 – November 2002)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	FF3	FF5
P1	1.30	0.52	1.17	1.63	-0.17	-0.14	0.03	0.51
	(2.08)		(1.56)	(1.76)	(-0.27)		(0.05)	(0.66)
P2	1.88	0.84	1.70	2.12	-0.39	-0.33	-0.26	-0.06
	(3.09)		(2.17)	(2.06)	(-0.84)		(-0.57)	(-0.11)
P3	2.02	0.64	2.07	2.65	-0.57	-0.40	-0.43	0.17
	(2.31)		(1.80)	(1.75)	(-1.12)		(-0.87)	(0.37)
P4	1.61	0.53	1.50	2.06	-0.58	-0.38	-0.56	-0.15
	(2.01)		(1.39)	(1.47)	(-1.05)		(-0.94)	(-0.21)
P5	1.21	0.40	0.82	1.23	-0.88	-0.44	-0.69	-0.33
	(1.62)		(0.82)	(0.94)	(-1.31)		(-1.02)	(-0.39)
P6	1.66	0.80	1.47	1.67	-0.61	-0.31	-0.46	-0.16
	(3.00)		(2.24)	(1.81)	(-0.89)		(-0.74)	(-0.20)
P7	2.16	1.03	2.02	2.43	-0.87	-0.49	-0.94	-0.79
	(3.63)		(2.80)	(2.70)	(-1.48)		(-1.50)	(-0.93)
P8	1.34	0.57	1.29	1.76	-0.87	-0.48	-0.81	-0.39
	(2.23)		(1.61)	(1.83)	(-1.44)		(-1.33)	(-0.53)
WML	0.03	-0.20	-0.18	-0.16	-0.70	-0.86	-0.98	-1.05
	(0.07)		(-0.49)	(-0.91)	(-2.49)*		(-3.54)**	(-3.04)*

Table 9: Industry Returns During the Dot-Com Bubble

The table documents the number of times each industry (numbered from 1-24) appears in the winners- and losers-portfolios (table 12) in the industry momentum strategy during the period given. Stock return is the average monthly percentage return for each industry group during its given time-period.

The Dot-Com Bubble - Industry Momentum

		Recession Period (March 2001 – November 2001)			**Post-Recession Period** (December 2001 – November 2002)		
	Industry	Wi	Lo	Stock return	Wi	Lo	Stock return
1.	Mining	1	4	-0.78	0	2	1.07
2.	Food	2	0	2.22	5	0	0.94
3.	Apparel	2	0	2.53	6	0	2.19
4.	Paper	0	0	1.26	0	0	0.74
5.	Chemical	1	1	2.91	0	5	-0.12
6.	Petroleum	3	0	2.34	0	0	0.14
7.	Construction	0	0	1.90	1	0	0.86
8.	Primary Metals	2	0	1.59	0	5	0.40
9.	Fab. Metals	0	0	1.16	1	0	1.37
10.	Machinery	0	0	1.03	0	0	1.38
11.	Electrical Eq.	0	7	1.58	0	6	0.06
12.	Transport Eq.	0	0	1.63	3	1	1.95
13.	Manufacturing	0	0	3.19	0	0	0.71
14.	Transportation	3	0	0.75	1	0	-0.28
15.	Other Transport.	2	0	1.98	5	0	2.27
16.	Air Transportation	0	5	-0.24	2	7	0.16
17.	Utilities	0	3	0.49	0	3	-0.24
18.	Dept. Stores	1	0	0.94	0	0	0.40
19.	Retail	1	0	3.24	2	0	1.43
20.	Finance	1	0	2.15	5	0	1.69
21.	Technology	0	3	2.56	2	3	1.16
22.	Hotels & Social Ser.	3	0	3.44	2	0	1.14
23.	Health & Membership	4	0	3.11	1	1	0.42
24.	Other	1	4	2.69	0	3	0.04

Table 10: Industry Momentum during the Financial Crisis

The table reports the monthly return for momentum portfolios during the Financial Crisis, divided into the recession period and the 12-month post-recession period. Industry groups have been formed based on a two-digit SIC code. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 8 (winner portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P8 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) model and the Fama-French Five (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refers to 1%, 5% and 10% significance levels, respectively.

The Financial Crisis - Industry Momentum

	Recession Period (December 2007 – June 2009)				**Post-Recession Period** (July 2009 – June 2010)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	FF3	FF5
P1	0.56	0.08	1.57	2.28	1.38	0.98	1.37	1.35
	(0.44)		(1.20)	(1.42)	(3.43)		(3.19)	(1.79)
P2	0.56	0.10	1.32	2.06	1.54	1.16	1.47	1.48
	(0.52)		(1.31)	(1.67)	(4.05)		(4.02)	(2.35)
P3	-0.02	-0.02	0.91	1.72	1.76	1.48	1.72	1.74
	(-0.01)		(0.80)	(1.24)	(5.15)		(6.44)	(3.72)
P4	0.18	0.02	1.00	1.81	1.86	0.93	1.81	2.04
	(0.17)		(0.98)	(1.42)	(3.24)		(3.61)	(2.32)
P5	-0.09	-0.04	0.68	0.97	2.07	1.55	1.94	2.34
	(-0.09)		(0.67)	(0.81)	(5.37)		(5.21)	(4.27)
P6	0.09	-0.00	1.33	2.10	1.92	1.50	1.91	1.67
	(0.07)		(1.17)	(1.51)	(5.22)		(5.31)	(2.70)
P7	-0.31	-0.09	0.59	1.70	2.44	1.46	2.30	2.45
	(-0.31)		(0.59)	(1.46)	(5.09)		(5.12)	(3.31)
P8	-1.24	-0.24	0.04	0.52	1.94	1.18	1.88	1.57
	(-0.97)		(0.03)	(0.35)	(4.10)		(4.40)	(2.13)
WML	-1.80	-0.72	-1.63	-1.85	0.57	0.85	0.51	0.21
	(-2.94)**		(-2.42)*	(-2.17)*	(2.97)*		(3.51)**	(1.16)

Table 11: Industry Returns During the Financial Crisis

The table documents the number of times each industry (numbered from 1-24) appears in the winners- and losers-portfolios (table 10) in the industry momentum strategy during the period given. Stock return is the average monthly percentage return for each industry group during its given time-period.

The Financial Crisis – Industry Momentum

		Recession Period (December 2007 – June 2009)			**Post-Recession Period** (July 2009 – June 2010)		
	Industry	Wi	Lo	Stock return	Wi	Lo	Stock return
1.	Mining	8	7	-0.53	5	1	2.66
2.	Food	2	0	-0.12	1	0	2.01
3.	Apparel	1	6	-0.61	7	0	3.40
4.	Paper	0	0	-0.14	6	0	4.00
5.	Chemical	3	0	0.32	0	0	2.43
6.	Petroleum	2	7	-2.40	0	11	0.97
7.	Construction	1	5	-0.92	3	6	2.12
8.	Primary Metals	2	5	-1.12	2	1	1.46
9.	Fab. Metals	0	0	-0.84	0	0	2.81
10.	Machinery	1	1	-1.20	1	0	3.35
11.	Electrical Eq.	0	1	-0.34	1	0	2.58
12.	Transport Eq.	0	1	-1.25	4	0	3.56
13.	Manufacturing	0	0	-0.73	0	0	2.62
14.	Transportation	8	3	-0.91	2	2	3.40
15.	Other Transport.	2	2	-0.44	0	2	2.02
16.	Air Transportation	0	3	-1.88	1	0	2.56
17.	Utilities	6	1	-0.95	0	7	1.15
18.	Dept. Stores	4	5	0.04	0	2	1.64
19.	Retail	2	0	-0.07	1	0	2.67
20.	Finance	3	3	-1.39	0	2	1.65
21.	Technology	1	0	-0.34	1	0	2.51
22.	Hotels & Social Ser.	0	7	-1.34	0	0	3.01
23.	Health & Membership	8	0	-0.06	0	1	1.61
24.	Other	3	0	-0.09	0	1	1.39

Table 12: Industry Momentum during Covid-19

The table reports the monthly return for momentum portfolios during Covid-19, divided into the disruption period, the recession period and the 12-month post-recession period. Industry groups have been formed based on a two-digit SIC code. The returns are based on a 6-month formation period and a 6-month holding period, including 1-month lag between the holding period and the formation period. Each portfolio from 1 (loser portfolio) until 8 (winner-portfolio) are ranked into decile portfolios according to their return during the formation period. WML is long portfolio P8 and short portfolio P1. The table shows the average raw monthly profits in percentage for each portfolio during the holding period, as well as the momentum strategy return. Next, the Sharpe ratio of each portfolio is reported. In the two last columns the Fama-French Three (FF3) model and the Fama-French Five (FF5) model is reported. T-statistics are in parentheses below the mean monthly return. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.

Covid-19 - Industry Momentum

	Disruption Period (January 2020 – December 2020)				**Recession Period** (February 2020 – March 2020)		**Post-Recession Period** (May 2020 – March 2021)			
	Raw return	Sharpe ratio	FF3	FF5	Raw return	Sharpe ratio	Raw return	Sharpe ratio	FF3	FF5
P1	4.28	1.09	5.83	6.94	1.43	0.43	4.77	1.58	4.37	4.97
	(3.86)		(3.20)	(4.76)	(0.81)		(5.49)		(3.12)	(3.05)
P2	3.77	1.02	4.63	5.47	0.87	0.24	4.42	1.85	4.37	4.49
	(3.62)		(2.55)	(2.97)	(0.47)		(6.41)		(4.27)	(3.54)
P3	4.02	1.20	4.58	5.20	2.72	0.63	4.20	1.97	4.05	4.20
	(4.26)		(3.28)	(3.68)	(1.15)		(6.83)		(4.40)	(3.71)
P4	4.54	1.68	4.66	5.47	3.03	1.14	4.45	1.83	3.50	3.81
	(5.97)		(4.07)	(7.27)	(2.08)		(6.34)		(3.93)	(3.56)
P5	3.81	1.27	4.69	5.52	1.25	0.41	4.30	2.00	3.88	4.05
	(4.52)		(3.15)	(4.09)	(0.76)		(6.94)		(4.06)	(3.43)
P6	3.76	1.42	4.19	4.98	2.64	0.91	3.99	1.84	3.24	3.53
	(5.05)		(3.51)	(5.43)	(1.67)		(6.38)		(4.21)	(3.88)
P7	3.95	1.49	4.18	4.97	2.64	0.77	4.12	1.96	3.34	3.57
	(5.30)		(3.30)	(4.91)	(1.67)		(6.79)		(4.06)	(3.58)
P8	4.03	1.44	4.79	5.53	2.65	0.76	4.28	2.13	3.73	3.93
	(5.12)		(4.18)	(6.07)	(1.40)		(7.38)		(4.27)	(3.66)
WML	-0.25	-0.16	-1.07	-1.44	1.06	1.69	-0.49	-0.30	-0.65	-1.05
	(-0.46)		(-1.02)	(-1.32)	(3.42)*		(-1.01)		(-0.81)	(-1.18)

Table 13: Industry Returns During Covid-19

The table documents the number of times each industry (numbered from 1-24) appears in the winners- and losers-portfolios (table 8) in the industry momentum strategy during the period given. Stock return is the average monthly percentage return for each industry group during its given time-period.

Covid-19 Industry Momentum

		Disruption Period (January 2020 – December 2020)			**Recession Period** (February 2020 – March 2020)			**Post-Recession Period** (May 2020 – March 2021)		
	Industry	Wi	Lo	Stock return	Wi	Lo	Stock return	Wi	Lo	Stock return
1.	Mining	1	5	3.39	0	3	-2.37	3	1	7.79
2.	Food	1	1	1.17	0	1	-2.37	1	4	3.51
3.	Apparel	1	6	1.10	0	0	-11.53	4	5	6.93
4.	Paper	3	1	1.08	2	0	-5.93	0	1	4.58
5.	Chemical	5	0	2.90	0	0	0.31	5	0	4.57
6.	Petroleum	0	8	-0.52	0	3	-4.13	1	7	3.95
7.	Construction	2	1	1.45	0	1	-9.63	2	0	6.10
8.	Primary Metals	0	2	1.86	0	0	-8.23	1	2	7.51
9.	Fab. Metals	0	0	2.69	0	0	-5.04	0	0	5.68
10.	Machinery	1	0	2.61	1	0	-5.09	0	0	5.90
11.	Electrical Eq.	2	0	3.72	1	0	-1.66	1	0	5.40
12.	Transport Eq.	0	0	2.91	0	0	-5.95	0	0	5.69
13.	Manufacturing	0	0	2.80	0	0	-3.06	0	0	4.94
14.	Transportation	3	0	2.38	2	0	-4.78	1	2	4.68
15.	Other Transport.	4	0	3.35	0	0	-4.44	3	1	6.26
16.	Air Transportation	1	3	1.32	0	1	-11.02	3	2	6.77
17.	Utilities	0	2	0.60	0	0	-5.50	0	5	2.80
18.	Dept. Stores	0	0	2.76	0	0	-2.85	1	0	5.77
19.	Retail	4	0	3.44	1	0	-3.66	2	0	6.80
20.	Finance	0	3	0.57	0	0	-7.24	0	3	4.32
21.	Technology	1	0	3.51	0	0	-2.72	1	0	5.06
22.	Hotels & Social Ser.	0	3	1.86	0	0	-8.77	2	3	6.51
23.	Health & Membership	4	0	2.85	1	0	-2.82	3	0	4.78
24.	Other	3	1	4.12	1	0	-1.74	2	0	4.93

Table 14: Individual Stock Momentum Within Industries

Table 14: Individual Stock Momentum Within Industries during Covid-19, The Financial Crisis and The Dot-Com Bubble

The table reports the monthly individual stock momentum returns within industries for each winner-minus-loser momentum portfolio. The portfolios are based on a 6-month formation period and a 6-month holding period in each respective industry group, including 1-month lag between the holding period and the formation period. The table shows the average raw monthly profits (Mom. Profits) in percentage for each winner-minus-loser portfolio during the holding period. T-statistics are presented beside the monthly average return. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.

	Covid-19						The Financial Crisis				The Dot-Com Bubble			
	Disruption		Recession		Post-Recession		Recession		Post-Recession		Recession		Post-Recession	
Industry	Mom. profits	t-stat	Mom. profits	t-stat	Mom. profits	t-stat	Mom. profits	t-stat	Mom. profits	t-stat	Mom. profits	t-stat	Mom. profits	t-stat
1. Mining	0.18	0.09	-0.35	-0.06	0.64	0.40	-4.45	-3.26**	2.02	4.46***	-1.88	-1.55	0.96	1.74
2. Food	-0.42	-0.51	-1.17	-0.63	1.54	2.45*	-1.69	-2.51*	0.52	0.85	-1.93	-2.15	0.25	0.37
3. Apparel	-7.96	-4.97***	-11.38	-4.76*	-5.41	-3.46**	-3.65	-2.11*	0.06	0.05	-0.66	-0.45	-1.12	-0.86
4. Paper	0.10	0.03	12.58	3.12*	-2.41	-1.19	-0.72	-0.37	0.49	0.46	1.30	1.15	-0.55	-0.78
5. Chemical	-0.63	-0.74	-0.06	-0.16	-0.09	-0.09	-4.09	-5.17***	1.37	1.94	0.13	0.20	-0.07	-0.09
6. Petroleum	0.30	0.12	-0.85	-0.21	0.68	0.22	-3.59	-1.85	2.35	1.89	0.88	0.80	-3.11	-2.93
7. Construction	NA		NA		2.81	0.73	NA		NA		8.78	3.20*	-1.60	-3.30*
8. Primary Metals	-3.49	-3.01*	-3.22	-2.17	-3.97	-4.35**	-7.46	-6.75***	1.21	1.22	-2.10	-1.89	-2.07	-1.45
9. Fab. Metals	-1.58	-1.95	-1.05	-0.57	-1.33	-1.70	-6.91	-5.58***	-0.40	-0.49	0.87	0.63	-0.02	-0.02
10. Machinery	-0.28	-0.34	2.48	1.86	-1.05	-1.93	-2.96	-2.64*	1.54	2.57*	0.47	0.34	-1.52	-3.09*
11. Electrical Eq.	1.33	1.81	1.63	0.83	0.36	0.44	-2.85	-3.87**	0.27	0.52	-0.61	-0.64	-2.35	-2.84*
12. Transport Eq.	-1.95	-0.80	8.84	7.15*	-4.86	-3.28**	-4.26	-5.21***	-0.71	-0.90	1.14	1.16	-1.18	-1.05
13. Manufacturing	-1.64	-1.60	2.17	4.39*	-2.33	-2.68*	-2.35	-3.02**	1.30	3.88**	-1.30	-1.31	-1.30	-3.04*
14. Transportation	NA		NA		NA		NA		NA		3.30	1.59	1.78	1.84
15. Other Transport.	-0.89	-0.64	0.45	0.25	-1.74	-1.36	-1.60	-1.50	-2.35	-4.58***	0.48	0.48	0.95	1.17
16. Air Transportation	-2.70	-1.91	-2.70	-0.70	-2.64	-2.07	-3.42	-2.00	-1.89	-1.43	2.14	1.29	0.56	0.38
17. Utilities	1.96	2.64*	4.74	2.78	0.34	0.70	-2.80	-3.92***	0.56	2.81*	0.77	0.88	1.11	1.81
18. Dept. Stores	-4.28	-1.35	-3.79	-1.09	0.55	0.15	-2.90	-1.45	-1.50	-1.29	-3.01	-3.24*	-2.18	-2.76*
19. Retail	-2.40	-1.40	3.88	6.48*	-3.45	-2.40*	-3.96	-3.86**	0.78	3.82**	0.32	0.57	0.17	0.32
20. Finance	-1.31	-1.57	1.77	2.68	-1.60	-2.12	-2.37	-2.04*	-0.88	-2.76*	0.72	2.70*	0.15	0.42
21. Technology	-1.29	-1.68	-0.48	-0.39	-0.14	-0.13	-2.15	-3.27**	0.55	1.49	0.55	0.54	-2.03	-3.45**
22. Hotels & Social Ser.	-2.39	-1.54	-0.99	-0.56	-1.70	-1.15	-2.08	-1.41	0.52	0.58	4.52	4.50**	0.15	0.21
23. Health & Membership	-2.20	-1.86	-3.91	-1.91	0.24	0.24	-3.85	-4.41***	-1.11	-2.09	3.54	5.30***	-0.95	-1.01
24. Other	-0.98	-2.78*	-1.31	-1.43	-0.04	-0.09	-2.48	-2.73*	2.33	3.98**	1.46	1.80	-0.60	-0.75

Appendix B: Individual Stock Momentum (STATA-codes)

Please see the attached file for full description of codes used to obtain the results in the corresponding section.

Appendix C: Industry Momentum (STATA-codes)

Please see the attached file for full description of codes used to obtain the results in the corresponding section.

Appendix D: Individual Stock Momentum Within Industries (STATA-codes)

Please see the attached file for full description of codes used to obtain the results in the corresponding section.