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Master Thesis Report

Industry Momentum, Momentum Behavior and Market States:

An analysis of different momentum sources under different market states.

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Abstract

Momentum strategies have proved to be very profitable and widely used among investors. Despite this, research has found that they can also experience substantial losses. This thesis focus on studying momentum behavior from different sources under different market states. Exploring over 40 years of data (1980 - 2021) from the US stock market, we find that industry momentum does not suffer the same magnitude of momentum crashes. Further, we find an abnormally high level of momentum returns under the Covid period, not matched by any previous periods in our data set. When studying individual stock momentum within industries, we find market return and market capitalization to be the key drivers behind momentum return. These fail under periods when momentum crashes occur, and they also fail under the Covid period. Lastly, we propose a set of new momentum trading strategies aimed to prevent significant losses under momentum crashes.

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We would like to express gratitude to our excellent supervisor, Zhaneta Krasimirova Tancheva at BI Norwegian Business School, for her sincere engagement and support, as well as valuable input throughout the process of developing and writing this thesis. We would also like to thank BI for the access to facilities, equipment, the possibility to learn MATLAB programming language, and last but not least: five years of excellent teaching, providing us with the knowledge and analytical mindset necessary to develop this thesis.

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1.0 Introduction

In 1993, Jegadeesh and Titman published their seminal paper displaying that investments based on buying stocks that have performed well over the last 3 - 12 months (winners) and selling stocks that have performed poorly over the last 3 - 12 months yield significant returns unexplained by classical financial theory. The fundamental idea behind the strategy, commonly known as individual stock momentum strategy, is that past performance reflects future performance. Over the last 25 years, with the emergence of technology, the strategy has proved to be very popular among traders and money managers worldwide. Although the momentum strategy, on average, yield remarkable positive returns, and favorable risk-reward relationships, it also experiences periods of decline and what is known as momentum crashes (Daniel & Moskowitz, 2016). The crashes tend to occur in the aftermath and recovery periods following significant economic crises and market drawdowns. Daniel & Moskowitz found that these crashes often occur due to past losers performing above and beyond past winners in these periods. As the portfolio holds these losers through short selling, they have a negative impact, leading to negative momentum returns.

Previous studies have found that strategies which buy the winning industries and sell the losing industries yield significant returns similar to individual stock momentum (Moskowitz & Grinblatt, 1999). Hence Moskowitz & Grinblatt suggests that much of the momentum anomaly can be explained by industries and that individual stock performance matter less than previously believed. This thesis aims to identify if the same pattern of momentum crashes in individual stock momentum can be located in industry momentum. We do this by dividing the momentum results into specific definitions of market states, and analyzing the result we get under each market state. Although the crashes are visible in industry momentum, we find the magnitude to be significantly lower when comparing to individual stock momentum.

Our preliminary results suggest an irrational behavior from the individual stock momentum anomaly over the last 10 years when comparing it to the 30 years prior. We identify abnormally low momentum returns in the period after the crisis of 2008, not only during recovery but all the way up to the start of the Covid crisis.

This is interesting as studies have suggested that some of the momentum return stems from investors utilizing the momentum anomaly itself. As the momentum anomaly became more widely used, these findings should indicate that returns from the strategy should rise with time, not slow down.
Following this period, we observe an abnormally high level of momentum returns during the Covid period. On that basis, this thesis aims to provide valuable findings on the momentum anomaly over the last 10 years by examining these periods in detail and analyzing through various risk measurement tools if the same pattern can be located in both individual stock- and industry momentum.

In the aftermath of Jeegadeesh & Titman's paper from 1993, many studies on momentum behavior have been undertaken. Although these are widely spread amongst the different versions and characteristics of momentum, there seems to be a lack of research on individual stock momentum within industries. Hence, to complement our findings from individual stock- and industry momentum and provide further knowledge on momentum and its behavior under the Covid period, this thesis examines individual stock momentum within industries in more detail. Previous studies have suggested a robust link between momentum and credit rating and found that much of the momentum anomaly is located in companies with low market capitalization (Avramov et al., 2007). This thesis builds further on these findings by examining individual stock momentum return within industries and their relationship to industry-specific traits. We study these relationships under different market states to determine their significance under different conditions. We find market returns and market capitalization to be the most influential factors in momentum behavior. However, we also observe that these relationships fail to hold under conditions where momentum crashes occur.

This thesis contributes to the existing literature by providing new and valuable findings on the momentum anomaly in different market segments and under different market conditions. Specifically, the thesis aims to provide new knowledge on momentum behavior under the Covid period and compare it to other major economic crises. Further, we aim to provide knowledge on key drivers of momentum by examining individual stock momentum within industries and their relationship with industry-specific traits. Lastly, we suggest a set of new momentum strategies called Momentum Portfolio Optimization that combines individual stock momentum and industry momentum, to be utilized under distressed market conditions.

This thesis is structured as follows: Section 2 provides an overview of the background and existing literature on the momentum anomaly. Section 3 builds the analytical framework for our hypothesis. Section 4 explains our data set and the subsequent data cleaning. Section 5 provides the methodology we intend to use when conducting the research. Section 6 provides our empirical results. Lastly, section 7 provides a conclusion to our research.

2.0 Background and literature review

2.1 Background

Over the last 35 years, a large amount of research has been conducted on the momentum anomaly. In essence, a momentum strategy consists of buying stocks that, over a certain period, have performed well and short-selling stocks that, over the same period, have performed poorly. According to Moore (2019), "The momentum approach has shown its reliability over the last 200 years, outside of the sample, and across markets and geographies". While this may be true, others have found evidence of a lack of momentum, and momentum crashes over certain periods. Research has found that these periods are often related to distressed market conditions.

While momentum can exist in many asset classes, and subclasses, the main focus in previous research has often been on the US stock market and what is known as individual stock momentum. Individual stock momentum is the momentum anomaly we find over the whole market. Although some research has been undertaken on industry momentum, we feel there is a lack of research supporting momentum within industries.
Additionally, little research on the momentum anomaly under the Covid period has been undertaken. We feel that by exploring these topics in more detail, we can contribute to the current research and provide valuable knowledge that might help in explaining the momentum anomaly.

The next subsection will cover the literature on which our thesis is built. We will start by covering the more individual stock momentum research before looking into the more specific topics related to our thesis.

2.2 Literature review

A variety of articles and research papers have been written on the momentum anomaly. While some researchers focus on the more general components of the anomaly, others go deeper into more specific characteristics.

How people react to the information they are given is frequently used as a steppingstone for discussions among numerous journalists, economists, and psychologists. As a result, a vast number of papers contribute to explaining how momentum behaves and its advantages and disadvantages. Overreaction has often been viewed as a major contributor. De Bondt and Thaler (1985) investigated this phenomenon to see whether or not the market moved in the same direction as people's perception.
The fact that stock markets tend to overreact to information, is a direct extension of the notion presented by De Bondt and Thaler (1985, 1987), and it suggests that counterstrategies (buying previous losers and selling past winners) yield abnormal returns. De Bondt and Thaler (1985) found that over holding periods of three to five years, the returns on equity investments that had lower performance in the preceding three to five years were higher than the returns on equity investments that had higher performance over the same period. However, De Bondt and Thaler's results are still being debated concerning their current interpretation. Some have suggested that the findings of De Bondt and Thaler might be understood through the lens of the systematic risk posed by their contrarian portfolios in conjunction with the size effect. Because the long-term losers passed the long-term winners for the first time in January, it is unclear whether their results may be attributable to an overreaction.

Moreover, De Bondt and Thaler (1985) focus on the long term reversal. Jegadeesh (1990) changed it to a short time period showing short-term return reversals. The research presented in this paper demonstrates that contradictory methods that select stocks based on their results in the week or month prior to the current one yield considerable abnormal returns. Because of this, purchasing stocks based on buying a portfolio containing the most significant companies rather than selling the worst will produce abnormally high returns if adopted over a shorter time horizon.

From Jegadeesh (1990), we know that shifting from a longer to a shorter time period will generate significant abnormal returns. As an extension to this notion, Jegadeesh and Titman (1993) developed a new strategy by analyzing the momentum anomaly over 3- to 12- months, which proved to be highly profitable in their data set from the US stock market. Their strategy selected stocks based on their past results over 3- to 12- months. Their sample includes stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (Amex) between 1965 and 1989. Jegadeesh and Titman (1993) analyzes six potential cost-free investment strategies with the creation and holding durations ranging from one to four quarters, each of which buys and sells the top and bottom ten percent of stocks. Jegadeesh and Titman's portfolio on a 6-months formation period and 6-months holding period yields 0.95 percent without a one-week lag and 1.10 percent with a one-week lag. In total, the 6x6 strategy realizes a compounded excess annual return of 12.01%. However, a backtest done on a sample gathered before 1965 reveals that momentum return suffered a significant mean reversal between 1927 and 1940. Whether the profitability resulted from data mining due to data-snooping or recompense for increasing risk was debatable. In response, Jegadeesh and Titman (2001) expand the scope of the data and give evidence that the profitability of momentum strategies persisted throughout the 1990s.

Knowing the study done by Jegadeesh and Titman (1993) will yield significant returns over short time periods, Moskowitz and Grinblatt (1999) studied the strategy in a very similar pattern. The strategy is based on using industries instead of looking at stocks individually. Through this, Moskowitz and Grinblatt (1999) demonstrate that using a brief time period and spotting industry momentum will create a substantial return. The industry momentum strategy gives a robust methodology and appears profitable among the largest and most liquid stocks. The profitability is dominantly driven by the long positions and not by selling previous losers, mainly among the most illiquid stocks.

The result found by Moskowitz and Grinblatt (1999) explain that the returns are not due to microstructure effects, individual stock momentum, or the cross-sectional dispersion in mean returns because the time period is short, and the analysis is industry-based.

According to a study by DeBondt and Thaler (1985, 1987), past long-term losers outperform past long-term winners over the subsequent three to five years. Jegadeesh (1990) identifies short-term return reversals. Jegadeesh and Titman (1993) bring a new twist to the literature by demonstrating that prior winners continue to outperform past losers over a three- to the twelve-month intermediate horizon, indicating that stock prices have "momentum." In other words, stock prices tend to change in a manner that is consistent with the historical performance of winners. Investing techniques can capitalize on this momentum by acquiring recent winners. Another subset of the momentum literature focuses on the relation between momentum and the business cycle. Daniel and Moskowitz (2016) investigate the impact and potential predictability of momentum crashes, which appear to be a key feature of the momentum anomaly. Similar to previous research, Daniel and Moskowitz (2016) implement the same set of stocks, from January 1927 to March 2013, the monthly momentum zero-cost portfolio generated average annual excess returns of 17.9 percent. Although the market performs exceptionally well, Daniel and Moskowitz (2016) investigate two time periods in depth. The Great Depression (1932–1939) and The Financial Crisis (2009–2013) are two examples where momentum crashes occurred. Those periods represent the most significant sustained drawdown period for the momentum strategy. During the Great Depression, the loser portfolio returned 232 percent, while the winner portfolio returned 32 percent. In the period from March to May of 2009, the loser portfolio returned 163 percent, and the winner portfolio returned 8 percent.
Moreover, robustness is shown across several stock markets and various asset classes. In contrast, price momentum in abnormal environments is weaker than in normal environments. Therefore, in times of distress, after a period of market decrease, and in periods of high market volatility, the prices of former market losers reflect a considerable premium. This is true for both the stock market and the overall economy. When weak market circumstances improve, and the market turns, previous losers experience high gains. This leads to a momentum crash as momentum techniques is short on these assets, which causes losers to experience substantial gains.

When studying momentum crashes, it is vital to understand the key drivers behind the momentum anomaly. Studies suggest that much of the anomaly stems from investors behavioral biases. However, behavioral biases are difficult to measure and hard to quantify. Others have tried to find key drivers behind the anomaly using information that indeed is quantifiable. Avramov et.al. (2007) find a robust link between momentum and credit rating. They document that momentum profits are high in companies with low credit rating, but non-existent in companies with high credit rating. Further, their findings indicate that most of the momentum anomaly stems from companies with low market capitalization. We believe these findings are interesting and deserve further investigation.

3.0 Theory

In economics and finance, many market models often assume no anomalies or other disruptive factors. These models take their basis from the theory that information in the market is complete and accessible to everyone and that all participants in the market are entirely rational. An excellent example of this is the perfect competition model, which in most cases fails to explain real-world scenarios as the model assumes identical goods and low entry and exit costs for participants. Similarly, financial models often fail as information is often reflected in securities prices with a lag. Simultaneously, market participants tend to behave irrationally and follow their own preferences. If these market imperfections are systematic and quantifiable, they are often known as anomalies.

The following section will set the theoretical framework for which this thesis is built upon. We will cover the fundamental hypothesis, theories, and models necessary to give the reader a good understanding of the topic.

3.1 Efficient Market Hypothesis

In 1970, Eugene Fama introduced the Efficient Market Hypothesis, which states that security prices should always incorporate and reflect all relevant market information. The statement implies that new information will affect prices immediately, making it impossible for investors to outperform the market without taking on more risk, as securities are continually trading at fair value. In his study, Fama defines three forms of market efficiency:

Weak; Securities prices include all historical data. *Semi-strong;* Securities prices include all historical data and all publicly available information. *Strong;* Securities prices contain all possible information, including private information. Semi-strong form always include weak form, and strong form always include semi-strong and weak form. From these definitions, one can see that any type of anomalies in the securities prices contradicts even the weak form of market efficiency.

In the aftermath of Fama's study in 1970, other studies in the field have been undertaken. Many have resulted in conflicting findings and criticism of the efficient market theory. It is worth noting that Fama points this out in his original study, saying that perfect markets do not exist. Piotroski (2003) suggests that the market does not react strongly enough to financial statement reports. His study shows that this hypothesis is robust for small and poorly monitored companies.

Schleifer (2000), on the other hand, argues that market efficiency theory assumes that investors' investment strategies are partially irrational and do not correlate with each other. As a result, they should partially cancel each other out, resulting in no substantial effect on the securities' price level. Anomalies, however, disprove this hypothesis as they are evidence of at least some correlation in investors' irrationality.

Fama (1998) argues that the market is efficient despite long-term anomalies, as he claims over- and under-reactions equal themselves out. Hence, according to Fama, anomalies are not relevant in the long run to fulfill an efficient market.

3.2 Capital Asset Pricing Model

Financial theory separates risk into systematic and unsystematic components. To estimate the value and projected return of a security, one must take systematic risk into account. Unsystematic risk is unique to given security. Examples include new competitors and industry regulations. Systemic risk consists of variables impacting the entire economy, such as inflation, exchange, and interest rates. Diversification can diminish unsystematic risk, but not systemic risk.

To determine the value and expected return of a security, one must take systematic risk into account. This is what the Capital Asset Pricing Model (CAPM) does. It is a market equilibrium model that describes the risk and return of assets. The model's simple explanation of risk-reward makes it commonly used for pricing risky assets (Fama and French, 2004). From Markowitz's modern portfolio theory, William F. Sharpe (1964), John Lintner (1965), and Jan Mossin derived the capital asset pricing model (CAPM) (1966). Return on investment is defined by CAPM as follows:

$$E[R_i] = R_f + \beta_i (E(R_{m)} - R_f))$$

Where R_i is expected return on investment, R_f is the risk-free rate, β_i is the beta of investment, and R_m is expected return on the market.

The beta factor differentiates expected investment return from market return and the risk-free rate. It demonstrates the investment's sensitivity to market fluctuations. If beta = 1, the investment is market-tracking. If beta is greater than 1, the investment is more sensitive to market fluctuations. If the beta is negative, the investment has a negative correlation with the market, and a value of 0 indicates the absence of risk. The formula for beta can be written as such:

$$\beta_i = \frac{COV\ (r_i, r_m)}{Var\ (r_m)}$$

Where $COV\ (r_i, r_m)$ is the covariance between the return on asset in and $Var\ (r_m)$ is the market variance (Fama and French, 2004).

As with most models, CAPM has investor and market assumptions.

- Risk-averse investors maximize wealth's expected utility.
- Investors are price takers with uniform expectations.
- Investors can borrow unlimited capital risk-free.
- Marketable, divisible assets are listed.
- The asset market is frictionless, and all information is free.
- No taxes and short-selling restrictions.

These assumptions do not hold, but the CAPM is still considered the most effective way to estimate expected returns.

3.3 Momentum

Scientific papers highlight two primary hypotheses when trying to explain the momentum anomaly. In broad terms, these are risk- behavioral. Risk-based explanations use traditional assets pricing models, such as the capital assets pricing model and the factor models created by Fama and French. These theories emphasize economic risk and fundamental values. The area of investor behavior investigates the premise that market participants, investors, and the market itself does not always behave rationally or sensibly. Investors' irrational conduct often leads to cognitive and psychological errors collectively as behavioral bias.

Momentum remains the anomaly that is most difficult to explain using rational asset pricing models such as the capital asset pricing model (CAPM) when it comes to risk-based explanations. According to Fama and French (1996), their three-factor model's fundamental flaw is that it "fails to capture the continuity of short-term returns." This causes significant distress for the model. Due to the inadequacy of risk-based models in explaining momentum events, researchers have started examining other explanations, such as behavioral. According to the first model, momentum is produced as a result of overreaction, but the other two theories attribute momentum to underreaction, defined as prices reacting too slowly to the news. According to behavioral theories, momentum may be related to cognitive errors made by investors when attempting to assimilate new information. This style is exemplified by the works of Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999).

4.0 Data

4.1 Data description

As the basis for the quantitative part of our thesis we retrieve monthly data from the CRSP monthly Stock file for North America Security Monthly for research purposes. The data we retrieve reaches from 01.01.1980 to 31.12.2021. The New

York Stock Exchange (NYSE), American Stock Exchange, and The Nasdaq Stock Market are selected for the primary stock collection, which we clean and organize using the programming language MATLAB.

For this thesis, the Permanent Number (PERMNO), Price (PRC), Returns (RET), and Standard Industrial Classification code (SICCD) provides the key data. The Permanent Number is an exclusive number assigned to each firm. Thus, it is easy to track the company regardless of whether it changes its name, enters a new industry, or similar. The returns, known as RET, are the return on an investment over a specified period, including the dividends. Standard Industrial Classification is used to establish the economic sector in which a business operates.
The term "Market Capitalization," abbreviated "MCAP," is defined in the data as the product of a company's share price and the number of outstanding shares. In addition, the data contain numerous characteristics that assist the research. These variables include the date, share code, exchange code, ticker, firm name, share classification, Nasdaq index code, shares outstanding, volume, and return excluding dividends. (Table 1).

After reorienting the data, we compute the market capitalization of each stock. We perform the calculation using the value weighted method, whereby each stock is weighted by its market value. Any shares with prices below 5, including negative values, are eliminated. Additionally, the bottom 5 percent market capitalization, along with the top and bottom percentile of returns, are eliminated from the returns. This ensures that the empirical findings are not driven by low and extremely illiquid stocks Avramov, D., Chordia, T., (2006).

The data cleaning procedure gives us an amount of 23 974 unique stocks from the time period 1980 to 2021. Further, the stocks are divided into 21 industries categorized on their Standard Industrial Classification Code (SIC-Code). The industry classifications align with the industries done in Moskowitz and Grinblatt (1999) research paper. We also add two industry categories that are central to the thesis and remove the financial industry as this industry often has irrational stock behavior. The industries we add are "Hotel and Social Services" and "Health and Membership". These industries are central to this thesis as we believe they were severely affected by the Covid-19 pandemic. The summary of the 21 industry portfolios can be found in table 1. It includes the two-digit SIC code we use to form the industries, the average stock amount, minimum quantity of stocks at any point of time (reported in parentheses), and the market capitalization.

4.2 Industry specific ratios

Before studying the industry-specific characteristics of any organization, it is necessary to collect industry-specific data. We collect data on the 21 industries that were initially chosen. We retrieve three distinct ratios for each of the 21 industries; each ratio exhibits a unique link with the relevant industry's stocks. The first ratio is the Quick ratio, commonly known as the liquidity ratio. This ratio measures an industry's ability to meet its short-term obligations using its most liquid assets. The debt ratio was the second measurement taken, reflecting the proportion of an industry's debt to its total assets. The Return on Equity (ROE) represents the proportion of net income returned to shareholders' equity.

$$Quick\ Ratio_{2021} = \frac{(Current\ Assets\ - Investories)}{Current\ Liabilities} = 1.25$$

$$Debt\ Ratio_{2021} = \frac{Liabilities}{Total\ assest} = 0.57$$

$$ROE_{2021} = \frac{Net\ income\ after\ tax}{Shareholde'sequity} = 2.6\%$$

The ratios above are the median industry for all U.S. listed companies[1]. For industry specific data, see Table 2 for a detailed list.

4.3 Benchmark

To determine the relevance of any potential momentum return we find, we will need a good benchmark from the same market that may serve as a point of reference to the momentum strategy itself. The benchmark is extracted from the Kenneth French website, giving the market excess return (R_m.-R_f). It is defined as follows: R_m-R_f, the excess return on the market, value-weight return of all CRSP firms incorporated

[1] https://www.readyratios.com/sec/industry/

in the US and listed on the NYSE, AMEX, or NASDAQ from 1980 to 2021.The data contain monthly returns from July 1926 and up till today. Hence, we extracts the data from 1980 to 2021, to match our initial data set.

5.0 Methodology

5.1 Hypothesis

Daniel & Moskowitz (2016) identify momentum crashes in the recovery periods after both The Great Depression (1929), and The Financial Crisis (2008). These 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 I:

Can we identify similar patterns of momentum crashes in industry momentum and momentum in industries, as previously discovered in individual stock momentum*?*

As the Covid crisis is rather recent, there is a lack of research on how the momentum anomaly behaved under this period. Our preliminary results suggest a rather irrational behavior not identified in any other time periods.

Hypothesis II:

Has the behavior of the momentum anomaly changed substantially under the Covid period compared to previous times?

There is a lack of research on momentum behavior within industries. By applying certain industry-specific traits, we wish to find if there are any significant relationships that might contribute to explain the source of the momentum anomaly.

Hypothesis III:

Can industry-specific traits contribute to explaining the momentum anomaly and how it behaves under different market conditions?

5.2 Momentum portfolios

5.2.1 Individual stock momentum

To get a better understanding of momentum behavior under different market conditions, we start of by calculating the returns from individual stock momentum strategies. The momentum portfolios are formed uniformly with the methodology developed by Jegadeesh and Titman (1993), and the calculations are performed using MATLAB. The methodology initially consists of monitoring and choosing stocks based on 3, 6, 9, and 12 months' past returns and holding the stocks in 3, 6, 9, and 12 months. The formation period is denoted *J*, and the holding period is denoted *K*. To test our hypothesis, it will be necessary to cover a lot of data. In that spirit, we have opted to focus on the 6-6 strategy, which yielded the highest return for Jegadeesh and Titman (1993), and is, in that sense, the strategy that best displays the momentum anomaly. Thus, our $J = 6$ and $K = 6$ throughout the thesis. After collecting data for the formation period, the stocks are divided into ten decile portfolios. The bottom decile consists of the worst-performing stocks (loser), and the top decile consists of the best-performing stocks (winner), all based on their performance in *J*. When the portfolios are established, the trading strategy executes the zero-cost portfolio by buying the winner-portfolio and selling the loser-portfolio. As these are equally weighted, the trading strategy is self-financing and thus known as zero-cost.

To avoid some of the bid-ask spread, price pressure, and lagged reactions that underlie the evidence documented in Jegadeesh (1990) and Lehmann (1990), we skip a month between the formation period and the holding period. Thus, *J* represents months 1-6, while *K* represents months 7-13. To increase the robustness of our research, the strategy we examine includes portfolios with overlapping holding periods. That is, a new formation period will be constructed every new month. Therefore, at any time beyond the first year, the portfolio will consist of 6 separate zero-cost strategies where the new *K* is opened and the old *K* - 6 months is closed out for every new month. Hence, under this strategy, the weights are revised on 1/K of the securities on the entire portfolio in any given month while simultaneously carrying over the rest from the previous month.

5.2.1.1 Return calculations

We start by computing the monthly log returns on all the stocks in our sample. We use log returns as they effectively capture the compounding effect. As covered under section 4.1, our data already gives us the simple monthly return on every stock; hence we only need to convert these.

$$r_{i,t} = ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$$

At the beginning of each month, we rank the stocks in ascending order based on their cumulative return for the past *J* months. The stocks are then divided into ten deciles from best to worst, where *Pzc = P10 – P1*. We then extract the specific *SIC* codes for every portfolio, ensuring that we have identified all relevant stocks. Using our table of extracted *SIC* codes, we run these on the next *K* months to extract the stocks included in each portfolio. We also remember to exclude one month between *J* and *K*, as mentioned above. Further, we calculate the average monthly return in every portfolio in the holding period.

$$P_x = \sum\left(\frac{R_x}{N}\right)$$

We then proceed to construct the zero-cost portfolio, which buys and holds the winner portfolio while simultaneously selling the loser portfolio. This is done on every month during the holding period.

$$P_{ZC} = P10 - P1$$

Lastly, we incorporate the return from the specific period into the extensive portfolio, which consists of formations from the last 6 months while simultaneously dropping out the K - 6 months.

$$t_x = \frac{P_{ZC}t_{x-6} + P_{ZC}t_{x-5} + P_{ZC}t_{x-4} + P_{ZC}t_{x-3} + P_{ZC}t_{x-2} + P_{ZC}t_{x-1}}{K}$$

5.2.2 Industry momentum

Daniel & Moskowitz (2016) identifies momentum crashes during financial turmoil in individual stock momentum strategy. We want to extend this research by examining if the same pattern can be identified in industry momentum. We perform this using the methodology first executed by Moskowitz and Grinblatt (1999) on industry momentum. It shares many similarities with the methodology for individual stock momentum from Jegadeesh & Titman (1993). However, rather than creating ten decile portfolios to find winners and losers, we will use industries. The industries we have defined are displayed in table 2. As with individual stock momentum, our J and K is 6 months. Hence, we divide the stocks into their respective industry. We then proceed to find the three best-performing (winners) and the three worst-performing (losers) industries over period J, as these combined will make up the zero-cost portfolio. When this is established, the trading strategy proceeds to execute the zero-cost portfolio by buying the winner-portfolio and selling the loser-portfolio. As these are equally weighted, the trading strategy is self-financing and thus known as zero-cost.

As with individual stock momentum, we skip a month between formation period and holding period, and the strategy contains portfolios with overlapping holding periods. Hence, the portfolio will, past the first year, always contain 6 separate zero-cost strategies where the new K is opened up and the old K - 6 months is closed out for every new month.

5.2.2.1 Return calculations

We start by computing the monthly log returns on all the stocks in our sample. We use log returns as they effectively capture the compounding effect. As covered under section 4.1, our data already gives us the simple monthly return on every stock; hence we only need to convert these.

$$r_{i,t} = ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$$

Secondly, we divide the stocks into their respective industry through their SIC code. Industries can be found in table 2.

$$Industry = extract(SICCD_{Industry} = SICCD_{Data\ set})$$

The rest of the steps mimic the steps found in 5.2.1.1; hence we will only cover them briefly here. After dividing by industry, we choose and monitor period J and buy the three winners while simultaneously selling the three losers for the period. We incorporate them into the already existing zero-cost strategy and hold them over period K.

5.2.3 Momentum within industries

Daniel & Moskowitz (2016) identifies momentum crashes during financial turmoil in individual stock momentum strategy. We want to extend this research by examining momentum within industries. Specifically, we want to know if there are any industry-fixed effects (leverage ratio, volatility, market cycles) that might affect the robustness of momentum anomaly within industries. To do this, we must first establish that momentum is, in fact, present not only in the market as a whole but also within industries. To do this, we follow the methodology of Jegadeesh & Titman (1993) as we also did with individual stock momentum. However, before performing the strategy, we divide our dataset into the 21 industries defined in table 2. After dividing, we perform the strategy as explained in 5.2.1.

5.2.3.1 Return calculations

We start by dividing the stocks into their respective industry.

$$Industry = extract(SICCD_{Industry} = SICCD_{Data\ set})$$

When this is done, we follow the calculations outlined in 5.2.1.1.

5.3 Statistical significance

5.3.1 T-statistics

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

$$t_{stat} = \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

5.3.2 Jargue-Bera test

The Jarque-Bera test (Bowman & Shenton (1975), Jarque & Bera (1987)) is a test to assess the data's goodness of fit. That is, the test assesses the returns and their departure from normality. The Jarque-Bera takes its fundament from the normal distribution, where the skewness is equal to 0, and the coefficient of kurtosis is equal to 3. The definition of excess kurtosis is the kurtosis coefficient subtracted by 3. Hence, we test if the coefficient of skewness and the coefficient of excess kurtosis are jointly zero (Brooks, 2014).

$$Jarque - Bera \ = \ n \left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

Where n is the sample size, S is the skewness coefficient of the sample, and K is the kurtosis coefficient. Any deviation from the underlying assumptions increases the Jarque-Bera statistics.

5.4 Portfolio performance

5.4.1 Sharpe ratio

The Sharpe ratio is one of the most well-known portfolio performance metrics. Developed by William Sharpe (1966), the Sharpe ratio, also known as the reward to volatility ratio, measures the return on investment against its total risk, their respective standard deviation. A higher Sharpe ratio signals a better risk-adjusted return. The formula can be written as follows:

$$SR_p = \frac{R_p - R_f}{\sigma_p}$$

Where R_p is the average return of the asset, R_f is the risk-free rate, and σ_p is the standard deviation of the asset Sharpe (1966).

The Sharpe ratio is a popular tool for portfolio performance measurement as it is simple and can quickly give the investor a perspective on the portfolio relative to other potential investments. However, it also has its weaknesses. Many have criticized the ratio, stating that past development is a poor future growth prediction. Additionally, the Sharpe ratio assumes that returns are normally distributed. Hence, if there are high spikes, tails, or other abnormalities in the returns, the Sharpe ratio is unable to take this under account. However, Despite possible distortions, we will use the Sharpe ratio as a performance measure due to its simplicity and clarity.

5.4.2 Treynor ratio

Similar to the Sharpe ratio, the Treynor ratio is an easy way to evaluate portfolio performance in relation to risk. Known as the reward to variability ratio, the Treynor ratio was invented by Jack Treynor in 1965. The ratio measures the return less risk-free rate of an investment, divided on the investment's respective CAPM Beta. In other words, the ratio measures the investments return divided by its systematic risk. It can be written as follows:

$$TR_i = \frac{\alpha_i}{\beta_i}$$

Where α_i is excess return, and β_i is the CAPM Beta.

As with the Sharpe ratio, the Treynor ratio is easy to measure, but the simplicity is also its weakness. Hence, one must evaluate the ratio not by itself but together with other risk measurements.

5.4.2 Jensen's Alpha

Michael Jensen developed in 1968 Jensen's Alpha which can be used to measure the risk-adjusted performance of a security/portfolio. It is based on the CAPM model, which we covered under section 3.2, but takes it one step further by introducing the new variable Alpha. If the Alpha is positive and statistically significant, the security/portfolio generates returns above what is expected from the CAPM, considering the level of risk and correlation with the market. Jensen's Alpha is calculated using the following formula:

$$\alpha = R_p - \left(R_f + \beta_p \left(E\left(R_{m)}\right) - R_f\right)\right)$$

Where R_p is the return on the portfolio, R_f is the risk-free rate, and R_m is the market return. The beta on the portfolio (β_p) measures the extent to which the portfolio covaries with the market return.

5.4.3 Maximum Drawdown

Maximum Drawdown (MDD) measures the maximum fall in the value of an investment. This is measured by studying the difference between the value of the lowest through and the value of the highest peak before the through. Hence, if the returns are strictly positive, our MDD will be zero. It is essential for us to study this as it will tell us more about the downside risk exposure of the different strategies and, in that sense, compliment our Sharpe ratios. MDD can be found through the following formula:

$$MMD_p = max \frac{(P - L)}{P}$$

Where P is the peak value before a drop and L is the lowest value before a new peak. The MDD simply measures the size of the most significant loss and gives no indication to the frequency of large losses. Additionally, it gives no indication on the recovery time from the MDD. It is also worth noting that MDD should be studied in relation to the market, as significant losses are often related to the market state.

5.4.4 Defining market states

As mentioned, maximum drawdown gives no indication on the frequency of significant losses and says nothing about the recovery time after the periods. To better understand this, we plot a graph containing all drawdown periods on the market. This is done by eliminating positive returns that go beyond a certain threshold. In other words, if we set our starting point at value 1, all positive returns that make the value go beyond its initial value will be deleted. However, all negative returns will be included, and positive returns up to the initial value. Let us say, for instance, that the initial value is 1 and that we have the following return series:

$T_{+1} = +5\ \%$
$T_{+2} = -6\ \%$
$T_{+3} = +3\ \%$
$T_{+4} = +8\ \%$

$At\ T_{+1} = 1 * (1 + 0.05) = 1.05 = 1$
$At\ T_{+2} = 1 * (1 - 0.06) = 0.94 = 0.94$
$At\ T_{+3} = 0.94 * (1 + 0.03) = 0.9682 = 0.9682$
$At\ T_{+4} = 0.9682 * (1 + 0.08) = 1.0567 = 1$

Consequently, we will quickly see all drawdown periods, their magnitude, and length in time, both in the data and in the graph.
From this, we define three market states based on where the market is on the scale:

- *Down:* This is where the market is on its way down from a peak, the drawdown period
- *Recovery:* This is where the market is recovering from a drawdown but is still not higher than its former peak.
- *Steady:* This is where the market is in a steady state. It is past its recovery phase, and beyond its former peak.

However, we must consider where to draw the line on the drawdowns. In other words, if we define a 2 % downturn in the market as a drawdown period, we will have to divide our dataset into a lot of small datasets. This is not effective and will only confuse the reader.

One of our main goals for this thesis is to analyze how momentum returns behaved before, under, and after the Covid period. Hence, we define a drawdown period as a period with an equal or higher downturn as the downturn of March 2020.

5.4.5 Panel data regression on momentum in industries

To find support for *Hypothesis III*, we perform a panel data regression on the momentum returns we achieve from the industries to try to locate any relationships that might help explain return differences. Hence, the following OLS regression is estimated for all 21 industries over the whole period, August 1980 - December 2021:

$$Momentum\ return_t = \alpha + \beta_1 R_{Mt} + \beta_2 MCAP + \beta_3 DRATIO + \beta_4 VOL + \beta_5 CAPM\beta$$

Where Momentum returns are the dependent variable as constructed in 5.2.3.

R_{Mt} is the independent variable that measures the dependence momentum returns have on market returns.

$MCAP$ is the independent variable that measures the dependence momentum returns have on the average company size in the industry.

$DRATIO$ is the independent variable that measures the dependence momentum returns have on the average leverage ratio in the industry.

VOL is the independent variable that measures the dependence momentum returns have on the average volatility in the industry.

$CAPM\beta$ is the independent variable that measures the dependence momentum returns have on the average CAPM Beta for the industry.

Further, we proceed to run the same regression on the three market states defined in 5.4.5 to identify if any relationships found, hold under all market states.

Lastly, we run the regression on the Covid period alone to see if the momentum returns behave differently. The results from the previous regressions will serve as a benchmark and hence contribute to the analysis.

5.5 Momentum Portfolio Optimization

Our research involves an in-depth look into momentum behavior both across and within industries. As an extension, we wish to locate an optimal zero-cost portfolio that takes both sources of momentum under consideration. We do this by first retrieving the results from 5.2 and 5.3. When we have this, we proceed to locate the winning and losing industries over all months and run these on the winning/losing portfolios within the industries. Our main idea behind these portfolios is that the investor will stay within the winning and losing industries but differ between the winning and losing portfolios within the industries. Hence, we have four possible portfolios:

Winwin/loslos: This strategy buys the winning portfolio (out of ten) in the three winning industries while simultaneously selling the losing portfolio (out of ten) in the three losing industries.

Winwin/winlos: This strategy buys the winning portfolio in the three winning industries while simultaneously selling the winning portfolio in the three losing industries.

Loswin/loslos: This strategy buys the losing portfolio in the three winning industries while simultaneously selling the losing portfolio in the three losing industries.

Loswin/winlos: This strategy buys the losing portfolio in the three winning industries while simultaneously selling the winning portfolio in the three losing industries.

As visualized, we see that the investor never moves out of buying in the winning industries and selling in the losing industries but rather differs on the stocks within the industries. Our idea behind this is that the losing portfolio in the winning industry might help absorb some of the abnormal returns we typically see from the losing portfolios under momentum crashes. In that way, an investor can use these strategies under more distressed market periods.

6.0 Analysis and results

This section will cover the empirical findings from our study. To test our hypothesis, we will explore the results and provide interpretations and comparisons with previous studies.

6.1 Individual stock momentum findings

6.1.1 Whole time-period

All results in this subsection can be found in table 3 in the Appendix.

To build a solid foundation for our findings, we must establish that our dataset contains the momentum anomaly matching previous studies. As this is a small part of our study, we will only cover it briefly. The findings on individual stock momentum are established through the methodology outlined in 5.1.1. Our winner-portfolio achieves a 0.84 percent average monthly return less risk-free rate, while the loser-portfolio achieves a 0.185 percent average monthly return less risk-free rate. Hence, our zero-cost 6-6 (months) portfolio achieves a 0.655 percent monthly average return, statistically significant.

Additionally, we find that returns increase monotonically from losers to winners. Together, these results demonstrate that momentum is present in our data set. However, the momentum returns are lower than our benchmark (the overall market), at a 0.729 percent monthly average return.

Moving on to the risk associated with these returns. Directing our attention to the standard deviation, which measures the overall volatility of the different portfolios, we see that both the winner- and loser-portfolio have higher volatility than the market. On the other hand, the zero-cost portfolio has a substantially lower (2.794 vs. 4.450) volatility rate than both the market and all other portfolios. Hence, one can assume that the winner-and loser-portfolios, to some extent, are correlated and balance each other out. This also gives an indication on where the Sharpe ratio should be at. We can see that the zero-cost portfolio achieves the highest Sharpe ratio above both all other portfolios and the market. This gives the first indication that the zero-cost portfolio not only is self-financing but also achieves a better risk-adjusted return than the market.

The Alpha and Beta with their respective t-stat are found by performing a regression model based on the CAPM. Hence, the Alpha reports Jensen's Alpha. We see that the only portfolio that achieves an Alpha that is statistically significantly different from zero is the zero-cost portfolio. As outlined under "5.4.2 Jensen's Alpha", this indicates that our zero-cost portfolio on the total market generates returns above what is expected from the CAPM. Moreover, we see that our zero-cost portfolio is the only portfolio that achieves a Beta that is not statistically significantly different from zero. Hence we can say that our zero-cost portfolio does not correlate with the overall market. This indicates that the returns from the momentum strategy do not follow the same pattern as the overall market under distressed times. When the Beta is zero, we also see that the Treynor ratio on the zero-cost portfolio is substantially higher than the market and all other portfolios (negative value only because beta is negative, not relevant).

We can also see that all portfolios but *P1* are negatively skewed. This is as predicted, as return series often have long series of positive returns before short but substantially higher negative returns. Further, they all have excess kurtosis, which indicates that the tails of the distribution of returns are higher than the normal distribution. Hence, it signals that the probability of obtaining an extreme outcome is higher than under normal distribution. This brings us over to the Jarque-Bera, which in this case indicates that our data is not normally distributed. This is to be expected as financial return series rarely are.

Shifting our attention to the maximum drawdown, we can see that our zero-cost portfolio suffers the lowest drawdown of all portfolios, including the market. We also see that the maximum drawdown period is only 16 months. For reference, the market suffers a drawdown period of 18 months, whereas our loser-portfolio suffers a drawdown period of 117 months. This is, however, in the strategy's favor as the loser-portfolio is the portfolio in which we sell. It is worth repeating that maximum drawdown simply measures the size of the most significant loss and gives no indication to the frequency of large losses. Additionally, it gives no indication on the recovery time from the drawdown.

6.1.2 Momentum under different market conditions

To get a better understanding of drawdown periods and how the momentum anomaly behaves under different market conditions, we plot a graph containing the accumulated return on both the market and our zero-cost portfolio. This graph can be found in the Appendix under graph 1. However, an accumulated return graph does not visualize early drawdowns proportionally. Hence, we also plot a graph containing only negative periods. This graph can be found in Appendix B, under graph 2. Daniel & Moskowitz (2016) have previously identified momentum crashes under specific market conditions, some of which are visible in the graph. For instance, one can clearly see that the returns from our zero-cost strategy make a rapid shift down of more than 10 percent just as the market is starting to recover from the crisis in the early 2000. Moreover, we see that after the crisis of 2008, our zero-cost portfolio shifts downward and does, in fact, not recover fully until the end of 2021.

Directing our attention back to graph 1, we see that our zero-cost portfolio has beaten the market for nearly the whole time frame, and up until 2018, it was superior. However, we can also see that after the crisis of 2008, the market makes a rapid shift upward and catches up with the returns from the zero-cost portfolio, only to achieve an even more significant gain after the Covid crisis. One can see that the zero-cost returns have also shifted upwards in the time after the Covid crisis. However, we find no obvious answer to why the last 3 years look so different from the previous years, especially the relationship between market returns and zero-cost portfolio returns. This is something we wish to investigate further.

Following the methodology outlined under 5.4.4, we define a drawdown period as a period with a drawdown of more than 20 percent. This is the accumulated negative return achieved under the Covid period. Analyzing the data underlying graph 2, we find five other distinctive periods where a drop of 20 % or more occurred; 1980 - 1982, 1987 - 1987, 1989 - 1990, 2000 - 2002, and 2007 - 2009. except for one of these periods (1987 - 1987), This is in accordance with the Business Cycle Dating from the National Bureau of Economic Research. As the stock market crisis of 1987 is also well documented, we feel confident that all these periods can be evaluated and compared in relation to the Covid crisis. Hence, table 4 display descriptive statistics on both the zero-cost portfolio and the market under these different time periods and market states. Before looking at the statistics, it is worth noting that these downturns all have different characteristics and were developed under different market conditions. Hence, they can, in some cases, not be directly compared.

We start off by looking at the market state which we have called *Down*. In table 4, we see that historically, our zero-cost portfolio has performed well under these market conditions. The average return on all down states for the zero-cost is 0.73 percent, with only one period of average negative returns (1987). This is higher than the average return on the whole dataset (0.66 %) and indicates that the momentum anomaly stays intact under drawdown periods. The down state under the Covid period is fascinating. Although it is a short period (3 months), we can see that, on average, it yields 2.70 percent monthly. This is significantly higher than any of the other down states (the closest is 1989 with 1.53 percent).

Shifting our focus over to the *Recovery* state, which we find in the same tables as above. This is the time period in which Daniel and Moskowitz (2016) discovered momentum crashes due to the loser portfolio yielding substantially higher returns than the winning portfolios. It is not directly comparable as they did limit their time periods more substantially. Nevertheless, we identify the same pattern as their discoveries. The average monthly return on all five recovery periods is 0.34 percent, with the worst period yielding -0.22 percent (2009-2012). these are not statistically significant, which indicates that momentum returns in this state are virtually 0. This is lower than the average monthly return of 0.66 percent. Looking at the returns during the recovery from the Covid period, we identify the same pattern as we did when analyzing the down state. This period yields 0.78 percent, which is substantially higher than the average and is only beaten by the recovery state in 1982 - 1983. Relative to the states during the same period, not substantial. However, relative to the same state under different periods, relatively high.

Moving on to the *Steady* state. This is the state in which the market spends most of its time. Hence, we would assume that this is a place that yields normal returns. Indeed, the average monthly return from the zero-cost portfolio is 0.69 percent which is relatively close to the overall average of 0.66 percent. It is worth noting that the period from 2013 till the end of 2019 yielded substantially low returns for the zero-cost portfolio (only 0.126 percent). This is lower than all other periods in the same state, and something we are interested in exploring more. During the Covid period, however, we see that the returns from the steady state are relatively high and at 1.36 percent, much higher than the average (short time period).

Overall we can see that the momentum anomaly yields high returns up to the crisis of 2008. After this, it yields a substantially lower return before recovering during the Covid period. We find no obvious answer to why it has behaved in such a way and hence need to explore this further.

6.2 Industry momentum findings

6.2.1 Whole time-period

To explore momentum behavior further, we investigate if our data set also contains industry momentum. As mentioned earlier, industry momentum was first discovered by Moskowitz and Grinblatt (1999), and we follow the same methodology as he first developed. The methodology is outlined in 5.2.2, and our results are depicted in table 5. Our winner-portfolio achieves a 1.692 percent average monthly return less risk-free rate, while the loser-portfolio achieves a 0.394 percent average monthly return less risk-free rate. Hence, our zero-cost 6-6 (months) portfolio achieves a surprising 1.298 percent monthly average return. This is considerably more than our benchmark (the overall market), at a 0.729 percent monthly average return.

The results from industry momentum are staggeringly high at an average monthly return of 1.298 percent. This is considerably higher than what we achieve in individual stock momentum. We also note that the standard deviation on our zero-cost portfolio in industry momentum is a bit higher than from individual stock momentum, although still considerably lower than the market (3.655 vs. 4.450). The lower standard deviation from individual stock momentum should indicate that this also has a higher Sharpe ratio. However, due to the high return from industry momentum, the Sharpe ratio is also considerably higher (0.355 vs. 0.234). This signals that the returns from industry momentum achieve a better risk-adjusted return, not only compared to the market but also the individual stock momentum strategy.

As with individual stock momentum, the Alpha and Beta with their respective t-stat reported in the table are found by performing a regression model based on the CAPM. Hence, the Alpha reports Jensen's Alpha. In this case, we see that both the winner and loser portfolios are statistically significantly different from zero, with the winner portfolio attaining a positive alpha and the loser portfolio attaining a negative Alpha. Additionally, our zero-cost portfolio attain a positive Alpha which is expected based on the excess returns compared to the market. Consistent with individual stock momentum, the zero-cost portfolio does not achieve a statistically significant Beta. This indicates that the returns are not correlated with the market. However, we see that the Treynor ratio from industry momentum is significantly lower than the Treynor ratio from individual stock momentum. As the Treynor ratio measures risk compared to the market, one can say that according to this specific measurement, the returns from industry momentum are riskier than the individual stock momentum returns.

The maximum drawdown of the different portfolios is also surprising when comparing it to individual stock momentum. The maximum drawdown from the winning portfolio lasts for 11 months (18 in individual stock momentum), while it lasts for only 23 months on the loser portfolio, which is significantly lower than individual stock momentum at 117 months. This result indicates that both portfolios perform better, and industry momentum is a bit worse when picking losers, but significantly better when picking winners. Consequently, the zero-cost portfolio has a maximum drawdown of only 16 percent over a period of only 6 months, which is significantly lower than the zero-cost portfolio from individual stock momentum (30 percent over 16 months) and the market (49 percent over 18 months). As previously mentioned, maximum drawdown does not say anything about the recovery and frequency of drawdowns. Hence, we need to study the periods more extensively.

6.2.2 Industry momentum under different market conditions

We plot the same two graphs as we did with individual stock momentum. These can be found in the Appendix, where graph 3 contains the accumulated returns from the zero-cost portfolio and the market, and graph 4 contains their respective drawdown periods. As with individual stock momentum, we detect, to some extent, the same pattern of momentum crashes over the same periods when analyzing graph 4. However, they are of a significantly lower magnitude.

Graph 3 visualizes the magnitude of the abnormal returns industry momentum achieves compared to the market. Over the whole time frame, the industry momentum returns are superior and, in contrast to individual stock momentum, are never beaten by the market at any point in time.

As with individual stock momentum, we divide the zero-cost portfolio from industry momentum and the market into the three different market states; *Down*, *Recovery* and *Steady*. Also here our findings yield significant results. They can be found in table 6 in the Appendix.

Starting with the *Down* state, We see that the zero-cost portfolio from industry momentum has historically performed relatively well under these market conditions. The average return on all down states for the zero-cost is 1.43 percent, with no periods of average negative returns. This is higher than the average return on the whole dataset (1.298 percent) and indicates that the momentum anomaly in industries stays intact under drawdown periods. The down state under the Covid period is even more fascinating here. Although it is a short period (3 months), we can see that it, on average, yields 7.704 percent monthly. This is significantly higher than any of the other "down"-states (the closest is 1987 with 2.08 percent).

Moving on to the *Recovery* state. As mentioned, this is the state where Daniel & Moskowitz (2016) identified momentum crashes due to higher returns from the loser portfolio. In industry momentum, we identify the same pattern to a certain extent. The average monthly return on all five recovery periods is 0.87 percent (statistically significant), with the worst period yielding 0.41 percent (1990-1991). This is lower than the average monthly return of 1.298 percent. Contrary to individual stock momentum, we identify a lower return than average in the recovery during the Covid period. Where individual stock momentum yields 0.78 percent on average in this period, industry momentum yields only 0.65 percent. However, this difference has no statistical significance and is virtually 0. Nevertheless, this is the only period where individual stock momentum yields a higher return than industry momentum. We believe this is due to specific industries being harder hit during the Covid period, and hence industry momentum is less "diversified" compared to individual stock momentum during this period.

Lastly we look at the *Steady* state. As mentioned under individual stock momentum, this is the market state in which the market spends most of its time. Hence, in industry momentum, we also expect this to be the state where average returns are close to the average for the whole period. Indeed, on average, our zero-cost portfolio yields 1.28 percent here, which is close to the overall average return of 1.30 percent. In the period where individual stock momentum yields substantially low returns (2013-2019), industry momentum returns were significantly higher at 1.14 percent and only a bit lower than its average. Further, we see that in the same state after the Covid period, industry momentum yielded substantially high returns at 2.09 percent monthly average. As individual stock momentum was also significantly higher during this period, we did expect this.

To summarize the results from industry momentum, we see that in all market states, the returns are significantly higher than what we achieve in individual stock momentum. This is unexpected but must be due to our added time frame and the data sorting and cleaning. We also recognize the same pattern of momentum crashes, though not of the same magnitude as individual stock momentum. In our dataset, Industry momentum investing is a more useful tool for risk-adjusted returns.

6.3 Individual stock Momentum in industries findings

6.3.1 General overview

To further complement our understanding of the momentum anomaly and how it behaved under the Covid crisis, we also conduct several tests for momentum within industries. We do this by using the methodology outlined in 5.2.3 on all the industries employed under the section industry momentum. The results from our calculations can be found in Appendix A, under table 7. While some industries yield returns that are not significantly different from zero, others do, with sufficient numbers on risk measures. Hence, in this section, we will cover the industries and identify if there are any industry-specific traits that might help to explain why some industries achieve a higher momentum than others.

Starting with the industries which deliver negative momentum returns. In this case, it is Paper and Petroleum. We see that they both have relatively high debt ratios. Petroleum is an interesting case to study as the industry has a relatively low number of companies but nearly 27 percent of the total market cap. This means that these 71 companies (on average) make up more than a quarter of the whole market. Previous findings indicate that much of the momentum anomaly can be found in smaller companies, and these findings indicate a similar pattern.

To counteract the findings from Petroleum, we see that Railroads have much of the same qualities, with a high debt ratio, few companies, and relatively high market cap. However, Railroads deliver momentum returns of 0.58 percent, which is above the average of all industries at 0.43 percent. These findings indicate that the leverage effect dominates momentum returns in Railroads.

Opposite to Paper and Petroleum, we find Other and Retail. With average monthly returns of 1,15 percent, Other is in a league of its own due to this industry being a mix of many smaller industries. Hence, in a sense, it replicates the whole market. However, with 583 companies on average, and an average market cap of less than 1 percent, this industry has many small companies with low market caps. This strengthens the idea that much of momentum stems from small companies with low market cap. Retail is also an excellent example of this. with a market cap of below 2 percent, and 1266 companies on average, the industry is well-diversified compared to Other and has the qualities necessary for high momentum returns.

6.3.2 Regression analysis of momentum returns in industries

To determine if the relationships we identified in the section above hold in a statistical state, we perform the regression analysis outlined in 5.4.5. The regression is run on the whole time period. Additionally, we run the regression on the *Down*, *Steady*, and *Recovery* states defined earlier, to identify if the relationships hold under all market conditions.

The regression on the whole time period yields significant findings. It can be found in table 8 in Appendix A. When we run the regression with only the market as the independent variable, we find a small correlation coefficient of 0.039, which is significant at the 1 percent level. Interestingly this coefficient does not change when we introduce industry-specific variables later. Hence, we find that on average, market return contribute to explain a portion of the momentum anomaly. Moving on to company size, we find a negative coefficient of -1.5288, significant at the 1 percent level. Although it loses some of its significance when introducing more variables, we still find it relevant. Intuitively it also confirms what we assumed in the section above, that the momentum returns are dependent on company size.

Further, we find no significant results on the relationship between momentum returns and industry debt ratio. However, interestingly we find that debt ratio seems to have an impact on the dependence of both the constant and company size. It contributes by decreasing the constant to a significance of 0 while simultaneously increasing the dependence on company size.

Volatility seems to have a negative impact on momentum returns, which is at level with financial theory that increased levels of return often come with increased levels of risk. However, we find no statistical significance; hence we conclude that there is no relationship between volatility and momentum returns. This is at par with many of our findings on Sharpe and Treynor ratios in the earlier sections.

There does, however, seem to be a relationship between momentum returns and the industry CAPM Beta. Although the coefficient is low, it is still significant at the 5 percent level. This confirms the relationship between market and momentum returns.

In summary, the regression yields significant results on the relationship between the momentum returns from the different industries, market returns, and industry-specific traits. We now proceed to split the regression into the three respective states to see if the same relationships hold under the different market conditions.

6.3.2.1 Steady state

The regression can be found in table 9 in Appendix A. As previously mentioned, this is where the market spends most of its time (55 percent of the months in our data set). Consequently, we expect this state to be highly influential on the original regression. This is accurate as we see many of the same relationships hold. The correlation coefficient of 0.0576 on the market indicates that momentum returns are more correlated with the market under this state. This is in accordance with the theory of momentum crashes under recovery states.

Further, we find that momentum returns are even more dependent on company size, with a correlation coefficient below -1.8. This may indicate that momentum returns are more dependent on industry-specific traits under this market state. However, we still lack significance on debt ratio and volatility. They do help explain the regression to a certain point, as they lower both the constant and company size, but with no significance, we can not say for certain that they help explain momentum returns. The CAPM Beta coefficient is even more significant and somewhat higher at 0.0192. This indicates that industry momentum returns are even more dependent on its average correlation to the market under this state.

6.3.2.2 Down state

The regression can be found in table 10 in Appendix A. This is where the market spends the least amount of time (18 percent of the months in our data set). It is also the market state with the highest fluctuations in returns. Hence, we must consider the low sample size and high volatility in the different variables when evaluating the regression. Interestingly, we find a higher correlation coefficient of 0.1175 with market returns, statistically significant at the 1 percent level. This is interesting as we often see momentum returns yielding considerably higher returns above the market in these periods. This indicates that momentum within industries is lower under this market state compared to individual stock momentum. Hence, in connection with our previous findings, we conclude that much of the higher return from individual stock momentum achieved under this state stems from industry momentum.

Further, we find that the correlation coefficient on company size is higher at -2.9403 but with a lower level of significance. The lower level of significance may come from the low sample size. Consequently, we conclude that momentum returns are more dependent on company size under this state. Intuitively, this makes sense as smaller companies tend to fluctuate more in distressed periods.

Moreover, we find no statistical significance on the coefficients from debt ratio and volatility. However, as with the original regression, they seem to influence the regression as they lower the constant. Contrary to the regression on steady-state, we find no significance on the coefficient from CAPM Beta. This indicates that the average correlation with the market explains less of the momentum returns in this state.

6.3.2.3 Recovery state

The regression can be found in table 11 in Appendix A. As the medium sample size in the split of the data set (27 percent of the months in our data set), we are more confident on our results under this state than we were under the down state. However, the sample size is still small, so we must take this under consideration when we evaluate. The only place we find a relationship in this state is with the market return. The correlation coefficient is -0.0545, and it is significant at the 5 percent level. Contradictory to the other two states, this coefficient is now negative, which signals the pattern found by previous studies where momentum returns often crash under market recovery periods. The other interesting thing we identify is that under these market conditions, momentum returns in industries are not dependent on any of the industry-specific traits. This is a major finding as it signals that momentum loses this dependence exactly under periods where momentum crashes are experienced.

6.3.3 Momentum within industries under Covid

To get a better understanding of how momentum within industries has performed under the Covid period, we run the same multiple regressions as we did with the whole data set, on 2020 and 2021 alone. These regressions can be found in table 13 in Appendix A. However, although we achieve substantial coefficients, almost none have statistical significance. We conclude that the sample size is too small and that these two years must be analyzed in a more manual way. Hence, table 12 in Appendix A displays the momentum returns from the different industries, including the whole two years and the three different states. It is worth repeating that the sample size is small, but with that being said, the first thing one notices is how much higher these returns are compared to the overall average. Indeed, Covid crisis struck industries differently depending on whether a lockdown was beneficial for the specific industry or not. However, as whole industries were struck, one would assume that this would not affect momentum within industries.

Starting with the whole period, we see that the returns are overall considerably high. Apparel achieves the lowest return at -1.92 percent, where much of their decrease came during the recovery period. This industry has a fair amount of companies with a low market cap and a medium level of leverage. On the other side, we find Railroads with an average monthly return of 3.15 percent. This industry has a low amount of companies with high market cap. and a medium level of leverage. Many similar examples can be found in the table. Hence, we conclude that the relationships found in the section above have failed to hold during the Covid period. Investors primary focus has been on industry-related shocks, not on underlying industry-specific traits.

We also observe that momentum crash in the recovery period does not seem to occur during the recovery from the market fall of 2020. On average, this period yields returns of 1.60 percent, higher than steady state at 0.67 percent. Hence, we conclude that momentum did not suffer the typical crash during the Covid period.

6.3.4 Summarizing results from momentum within industries

Our regression on the whole data set confirms many of the relationships we found in the general overview. We see that after market return, momentum within industries is most dependent on average company size. Hence, our findings confirm the notion that much of momentum can be found in smaller companies with low market cap.

Further, we find that our data set does not support a significant dependence on leverage and volatility. This does not mean that it does not exist, but our model does not capture it. Additionally, we find that these relationships fail to hold under recovery states where momentum often crashes.

Further, we identify that momentum within industries has behaved differently under the Covid period compared to earlier times, with higher volatility in returns, less significant momentum crashes, and less dependence on industry-specific traits.

6.4 Momentum trading optimization

We have now covered our results from individual stock momentum, industry momentum, and momentum in industries. Our preliminary results suggest that most of the momentum anomaly stems from industries and the psychological effect that the current perception of that specific industry has on investors. We can also see that, although some industries behave differently, most display the pattern of momentum crashes during recovery stages in the market. Moskowitz and Grinblatt (1999) concluded that much of the reason for these crashes is that previous loser stocks perform significantly well, yielding returns above what the stocks in the winner portfolio do. We want to test how sensitive the industries are under these conditions. Hence, we perform the four different momentum portfolio optimization strategies based on both industries and momentum within industries. We follow the methodology outlined in 5.5.

As mentioned, our idea for this is to see if the losing portfolio used will have an impact on momentum crashes. If we identify this as significant, we can recommend that investors switch to this alternative strategy during the recovery stages of the market.

Table 14 displays descriptive statistics from the different strategies. We see that *winwin/loslos* perform better than individual stock momentum but worse than industry momentum. The rest perform worse than both industry and individual stock momentum, with *loswin/winlos* yielding negative returns on average. This shows that although industry momentum is more significant than individual stock momentum, it is not absolute, and negative returns can be achieved when you buy the worst from the best and sell the best from the worst. The results here are as expected and not the point of this exercise.

To see if the strategies can have an impact on momentum crashes, we split the strategies into the respective market states which we have defined earlier. For simplicity and a better visual perception, all states are averaged into four tables, displaying the same descriptive statistics we have used over the entire paper. Additionally, we display their statistics under the Covid period to further visualize the deviating behavior of momentum over this period.

Winwin/loslos: Table 15 displays the result. As the strategy buys the top of the top and sells the bottom of the bottom, one would assume this strategy behaves similarly to individual stock momentum. Hence, we do not assume this strategy can provide a "safe haven" for momentum investors during recovery times. Our predictions are indeed accurate. We see that the strategy performs relatively well during down and steady periods, and lower during recovery periods. It is also worth noting that the behavior is reversed under the Covid period, with the highest returns achieved during the recovery period.

Winwin/winlos: Table 16 displays the result. As the strategy that sells the winners of the losers, there should be a certain effect during recovery periods, which it also is. Although the strategy is significantly less profitable, its lowest returns are not achieved during recovery periods but rather during steady periods. Hence, it is a certain "safe haven" effect, probably explained by the winners of the losers not achieving as high returns in this period as the losers of the losers. Also this strategy behaves differently during the Covid period, with a Sharpe ratio of 3.69 during the recovery period.

Loswin/loslos: Table 17 displays the result. Similar to the strategy above, there should also here be a certain effect during recovery times, which it also is. This strategy achieves its highest returns during recovery periods. We can also see that the overall returns are higher for all periods compared to winwin/winlos, and in that sense, it is superior. It also signals that the distance of the differences in returns is more significant for the losers than the winners. As with the other strategies, this also behaves differently during the Covid period with exceptional returns during down and recovery periods, but lower under the steady period.

Loswin/winlos: Table 18 displays the result. As the strategy that buys the losers of the winners and sells the winners of the losers, this strategy contradicts the momentum anomaly in some ways, shifting both what you buy and what you sell closer to the center of the market. Nevertheless, it is here that we find the most significant superiority during recovery periods over down and steady periods. However, as the returns from down and steady are both negative, and recovery is barely positive, we do not see this as a viable strategy.

In summary, momentum crashes are cushioned by utilizing three of the strategies above. However, the returns are not exceptionally high in the three strategies where we find this behavior. Given bid-ask spreads and other inefficiencies in the market, it is doubtful that an investor can achieve any returns above the risk-free rate utilizing these strategies. Hence, we conclude that they are not viable. Nevertheless, it is a good exercise as it reveals interesting behavior of the momentum anomaly, and it highlights the irrational behavior we have seen over the past couple of years.

7.0 Conclusion

Trading strategies based on the momentum anomaly are very popular among investors due to two main factors; they achieve an attractive risk-adjusted return, and they have historically been highly profitable. However, previous studies have identified that these strategies suffer periods of crashes with zero to negative returns. Studying momentum behavior from different sources under different market conditions can help identify critical drivers behind the momentum anomaly and why they fail in specific periods. This thesis aims to provide a better understanding of the anomaly by studying individual stock momentum, industry momentum, and individual stock momentum within industries. Using data from the US stock market spanning from 1980 to 2021, we show that momentum crashes are less prevalent in industry momentum than in individual stock momentum. Further, we find abnormally low returns in individual stock momentum in the steady state leading up to the Covid crisis. Together with other factors, these results lead to a higher return from industry momentum than individual stock momentum in our data set.

Further, we find abnormally high returns from both sources of momentum when analyzing all market states under the Covid period. Through studying individual stock momentum within industries, we find market return and company size to be critical drivers behind momentum return. These relationships hold under both the steady and the down states but fail/become negatively correlated under the recovery state. This supports previous studies that suggest momentum is most prevalent in smaller companies with low market capitalization. Further, we find that these relationships fail to hold under all states during the Covid period. This is a deviation from previous crises, where the relationships have held during the steady and down states. Lastly, we find no significant excess return when performing the portfolio optimization strategies. However, we also find a lack of momentum crashes under some of the portfolios which signals that further research in the area can accomplish more significant results

This field of research is of high importance for investors profitability and future decision-making. Although we did not find any significant support for debt ratio and volatility as critical drivers behind momentum returns, we still believe they are critical and should be studied further. We also believe that by studying the anomaly through individual stock momentum within industries further, one can find other critical drivers of momentum not currently known and accepted. This is a subfield we wish we could have studied further, but lack of time made that impossible. Hence, we hope others will dive deeper into this field.
Further, the abnormal returns achieved during the Covid period need to be studied in more depth as more data comes in with time. Is this shift a permanent change in momentum behavior or a short market shock? A longer time frame may find support for a similar situation in history.

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Appendices

Appendix A: Tables

Table 1: Data variables description

PERMNO	A unique stock (share class) level identifier
Date	Self-explanatory
SICCD	Standard Industrial Classification (SIC) Code
TICKER	Stock ticker
COMNAM	Company name
NSDINX	NASDAQ index code
PRC	Share price
SHROUT	Shares outstanding
VOL	Volume traded
RET	Return with dividends
RETX	Return without dividends
SHRCD	SHRCD is a two- digit code describing the type of shares traded.
EXCHCD	Code indicating the exchange on which a security is listed.
SHRCLS	SHRCLS describes the class of share and is generally blank.

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

Table 2: Industry description and ratio specifics

	Industry	SIC Codes	Quick ratio Average	Dept ratio Median	ROE a/Tax avg	Total Companies
1.	Mining	10-14	3,68	0,49	-13,78 %	833
2.	Food	20	1,49	0,51	-21,40 %	190
3.	Apparel	22-23	2,19	0,53	6,29 %	72
4.	Paper	26	1,18	0,65	17,60 %	41
5.	Chemical	28	5,38	0,35	-113,50 %	1076
6.	Petroleum	29	0,88	0,66	44,90 %	38
7.	Construction	32	1,27	0,54	29,10 %	31
8.	Prim. Metals	33	1,21	0,54	16,50 %	60
9.	Fab. Metals	34	1,68	0,53	9,00 %	78
10.	Machinery	35	2,69	0,52	4,50 %	299
11.	Electrical Eq.	36	3,32	0,41	-18,20 %	487
12.	Transport Eq.	37	4,45	0,54	-27,80 %	156
13.	Manufacturing	38-39	3,66	0,43	-21,79 %	530
14.	Railroads	40	0,77	0,65	488,10 %	13
15.	Other Transport.	41-47	1,68	0,63	5,02 %	162
16.	Utilities	49	0,88	0,66	5,20 %	310
17.	Dept. Stores	53	0,45	0,64	26,10 %	30
18.	Retail	50-52,54-59	1,08	0,66	17,98 %	744
19.	Hotels & Social Ser.	70-79	2,22	0,64	-111,35 %	1538
20.	Health & Membership	80-86	3,43	0,48	-14,49 %	203
21.	Other	87-99	3,39	0,62	-13356,30 %	192

Note: Industry categorization from SIC-code, with market specific ratios selected from *https://www.readyratios.com/sec/industry/*

Table 3: Descriptive statistics – Individual stock momentum

	Momentum portfolios										Market
	P10	P9	P8	P7	P6	P5	P4	P3	P2	P1	P10 – P1	
$r - r_f$	0.84	0.798	0.74	0.691	0.668	0.646	0.574	0.518	0.395	0.185	0.655	0.729
σ	5.061	4.373	3.999	3.779	3.668	3.648	3.783	4.072	4.533	5.286	2.794	4.45
α	0.001	0.001	0.001	0.001	0.001	0.001	0	-0.001	-0.003	-0.006	0.007	0
T-stat (a)	0.979	1.773	1.913	1.791	1.747	1.48	0.203	-0.955	-2.672	-4.34	5.156	Inf
β	1.008	0.899	0.825	0.777	0.752	0.745	0.766	0.819	0.898	1.009	-0.001	1
T-stat (b)	42.586	50.365	51.44	50.466	49.686	48.482	46.114	44.566	41.624	35.785	-0.028	Inf
Sharpe ratio	0.166	0.183	0.185	0.183	0.182	0.177	0.152	0.127	0.087	0.035	0.234	0.164
Treynor ratio	0.008	0.009	0.009	0.009	0.009	0.009	0.007	0.006	0.004	0.002	-8.241	0.007
MDD (%)	464	0.425	0.406	0.391	0.391	0.401	0.413	0.445	0.462	0.566	0.298	0.494
MDD (months)	18	18	23	23	23	23	23	23	23	117	16	18
Skewness	-0.48	-0.68	-0.75	-0.79	-0.694	-0.589	-0.44	-0.31	-0.135	0.01	-0.395	-0.671
Kurtosis	3.787	4.859	5.557	6.11	5.959	5.632	5.225	4.536	4.069	3.53	4.427	5.296
Jarque - Bera	30.441	108.055	180.02	251.701	223.259	177.15	123.775	59.925	26.473	5.934	55.082	146.434
P-value (JB)	0	0	0	0	0	0	0	0	0	0.048	0	0

Note: This table displays descriptive statistics on the individual stock momentum strategy including all portfolios from best (P10) to worst (P1) based on monthly returns.

Table 4: Individual stock momentum under different market states.

	Market States															
	Down 12/1980 - 06/1982		Recovery 07/1982 - 03/1983		Steady 04/1983 - 08/1987		Down 09/1987 - 11/1987		Recovery 12/1987 - 8/1989		Down 09/1989 - 10/1990		Recovery 11/1990 - 05/1991		Steady 06/1991 - 03/2000	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	0.72	-1.88	2.34	3.86	0.93	1.11	-0.65	-11.20	0.85	1.81	1.53	-1.66	0.50	3.82	1.02	1.18
σ	2.80	3.64	4.26	4.73	2.40	4.19	2.85	10.74	2.42	3.23	1.88	4.60	1.31	2.54	2.43	3.78
α	0.01	-	0.04	-	0.01	-	0.02	-	0.01	-	0.02	-	0.01	-	0.01	-
T-stat (a)	1.16	-	2.23	-	2.60	-	8.63	-	0.86	-	4.03	-	1.42	-	3.43	-
β	0.08	-	-0.42	-	0.03	-	0.26	-	0.18	-	0.22	-	-0.22	-	0.17	-
T-stat (b)	0.41	-	-1.40	-	0.34	-	14.00	-	1.08	-	2.21	-	-1.04	-	2.72	-
Sharpe ratio	0.26	-0.52	0.55	0.82	0.39	0.27	-0.23	-1.04	0.35	0.56	0.81	-0.36	0.38	1.50	0.42	0.31
Treynor ratio	0.10	-0.02	-0.06	0.04	0.34	0.01	-0.02	-0.11	0.05	0.02	0.07	-0.02	-0.02	0.04	0.06	0.01
Skewness	-0.27	0.43	-0.27	0.49	-0.37	0.24	-0.41	-0.53	-1.33	0.06	-0.90	0.15	-0.66	-0.19	0.21	-0.83
Kurtosis	2.92	2.15	1.62	2.39	2.42	3.18	1.50	1.50	7.61	1.82	4.45	3.28	2.68	2.16	2.89	5.84

	Market States															
	Down 04/2000 - 09/2002		Recovery 10/2002 - 05/2007		Down 06/2007 - 02/2009		Recovery 03/2009 - 12/2012		Steady 01/2013 - 12/2019		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	0.838	-2.147	0.255	1.179	0.239	-3.231	-0.218	1.759	0.126	1.139	2.699	-7.203	0.777	7.230	1.355	2.588
σ	4.101	5.451	2.644	2.877	4.186	5.485	2.692	4.646	2.656	3.351	2.864	6.688	1.212	5.775	2.747	4.201
α	0.004	-	0.007	-	0.006	-	-0.002	-	0.002	-	0.057	-	0.020	-	0.018	-
T-stat (a)	0.503	-	2.160	-	0.530	-	-0.475	-	0.754	-	5.323	-	1.974	-	2.447	-
β	-0.205	-	-0.415	-	0.104	-	-0.008	-	-0.092	-	0.412	-	-0.173	-	-0.191	-
T-stat (b)	-1.500	-	-3.717	-	0.597	-	-0.089	-	-1.063	-	3.497	-	-1.453	-	-1.222	-
Sharpe ratio	0.204	-0.394	0.096	0.410	0.057	-0.589	-0.081	0.379	0.047	0.340	0.942	-1.077	0.641	1.252	0.493	0.616
Treynor ratio	-0.041	-0.021	-0.006	0.012	0.023	-0.032	0.280	0.018	-0.014	0.011	0.066	-0.072	-0.045	0.072	-0.071	0.026
Skewness	-0.603	0.197	-0.970	0.147	-0.453	-0.721	-0.869	-0.155	0.041	-0.648	0.658	0.250	-0.389	0.482	-0.145	0.352
Kurtosis	3.709	2.086	7.682	3.074	2.950	3.024	3.384	2.628	4.420	3.939	1.500	1.500	1.500	1.500	2.246	3.058

Note: Descriptive statistic of individual stock momentum in different time periods where a drop of 20 % or more occur, *and their market state under those periods.*

Table 5: Descriptive statistics – Industry momentum

	Momentum portfolios			Market
	P10	P1	P10 – P1	
$\tilde{r} - r_f$	1.692	0.394	1.298	0.730
σ	4.740	5.070	3.655	4.450
α	0.010	-0.003	0.013	0.000
T-stat (a)	10.009	-3.001	8.068	Inf
β	0.943	0.998	-0.056	1.000
T-stat (b)	42.332	40.345	-1.508	Inf
Sharpe ratio	0.357	0.078	0.355	0.164
Treynor ratio	0.018	0.004	-0.234	0.007
MDD (%)	37.270	46.990	15.750	49.390
MDD (months)	11	23	6	18
Skewness	-0.311	-0.288	0.189	-0.671
Kurtosis	3.985	5.064	4.424	5.296
Jarque - Bera	27.442	97.866	44.938	146.434
P-value (JB)	0.000	0.000	0.000	0.000

Note: This table displays descriptive statistics on the industry momentum strategy.

Table 6. Industry momentum under different market states

	Market States															
	Down 12/1980 - 06/1982		Recovery 07/1982 - 03/1983		Steady 04/1983 - 08/1987		Down 09/1987 - 11/1987		Recovery 12/1987 - 8/1989		Down 09/1989 - 10/1990		Recovery 11/1990 - 05/1991		Steady 06/1991 - 03/2000	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	1.35	-1.88	2.17	3.86	1.08	1.11	2.08	-11.20	0.78	1.81	1.50	-1.66	0.41	3.82	1.48	1.18
σ	4.18	3.64	5.20	4.73	2.88	4.19	3.60	10.74	2.09	3.23	2.67	4.60	4.04	2.54	3.58	3.78
α	0.02	-	0.04	-	0.01	-	0.04	-	0.01	-	0.02	-	0.01	-	0.01	-
T-stat (a)	1.83	-	1.80	-	3.38	-	3.20	-	1.51	-	3.11	-	0.45	-	4.75	-
β	-0.07	-	-0.25	-	0.01	-	0.21	-	0.03	-	0.01	-	0.05	-	-0.01	-
T-stat (b)	-0.27	-	-0.66	-	0.09	-	2.51	-	0.27	-	0.05	-	0.09	-	-0.20	-
Sharpe ratio	0.52	-0.52	0.63	0.82	0.49	0.27	0.60	-1.04	0.42	0.56	0.92	-0.36	0.41	1.50	0.48	0.31
Treynor ratio	-0.29	-0.02	-0.12	0.04	1.54	0.01	0.07	-0.11	0.22	0.02	3.08	-0.02	0.27	0.04	-0.91	0.01
Skewness	-0.35	0.43	-0.29	0.49	0.23	0.24	-0.65	-0.53	-1.39	0.06	-0.51	0.15	0.54	-0.19	0.16	-0.83
Kurtosis	2.00	2.15	1.89	2.39	3.95	3.18	1.50	1.50	5.88	1.82	2.53	3.28	2.42	2.16	4.33	5.84

	Market States															
	Down 04/2000 - 09/2002		Recovery 10/2002 - 05/2007		Down 06/2007 - 02/2009		Recovery 03/2009 - 12/2012		Steady 01/2013 - 12/2019		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	1.268	-2.147	1.016	1.179	1.602	-3.231	0.560	1.759	1.144	1.139	7.704	-7.203	0.652	7.230	2.086	2.588
σ	5.456	5.451	3.764	2.877	4.756	5.485	4.035	4.646	2.612	3.351	3.267	6.688	4.337	5.775	3.806	4.201
α	0.010	-	0.013	-	0.019	-	0.011	-	0.014	-	0.055	-	0.024	-	0.024	-
T-stat (a)	1.299	-	2.867	-	1.852	-	2.579	-	4.811	-	7.354	-	0.576	-	2.569	-
β	-0.334	-	-0.196	-	0.081	-	-0.184	-	-0.253	-	0.071	-	-0.148	-	-0.136	-
T-stat (b)	-2.456	-	-1.287	-	0.498	-	-2.148	-	-3.146	-	0.854	-	-0.303	-	-0.718	-
Sharpe ratio	0.402	-0.394	0.341	0.410	0.414	-0.589	0.275	0.379	0.416	0.340	6.857	-1.077	0.460	1.252	0.619	0.616
Treynor ratio	-0.052	-0.021	-0.057	0.012	0.200	-0.032	-0.041	0.018	-0.042	0.011	0.706	-0.072	-0.092	0.072	-0.147	0.026
Skewness	-0.103	0.197	0.012	0.147	-0.327	-0.721	-0.882	-0.155	-0.413	-0.648	0.133	0.250	0.701	0.482	1.171	0.352
Kurtosis	2.373	2.086	2.373	3.074	2.019	3.024	4.000	2.628	4.732	3.939	1.500	1.500	1.500	1.500	4.450	3.058

Note: Descriptive statistic of industry momentum in different time periods where a drop of 20 % or more occur*, and their market state under those periods.*

Table 7: Industry returns and statistics

	Industry	SIC Codes	Avg. No of Stocks	Avg. % of Market Cap.	Debt ratio Median	ROE a/Tax avg	$r - r_f$	σ	α	β	Sharpe ratio	Treynor ratio
1.	*Mining*	10-14	698 (112)	3,10 %	0,49	-13,78 %	0,38 %	5,24 %	0,004	-0,02	0,07	-0,16
2.	*Food*	20	246 (74)	7,14 %	0,51	-21,40 %	0,18 %	4,39 %	0,002	-0,03	0,04	-0,06
3.	*Apparel*	22-23	180 (49)	0,81 %	0,53	6,29 %	0,33 %	6,18 %	0,002	0,20	0,05	0,02
4.	*Paper*	26	117 (37)	4,07 %	0,65	17,60 %	-0,08 %	6,14 %	0,000	-0,09	-0,01	0,01
5.	*Chemical*	28	721 (101)	6,51 %	0,35	-113,50 %	0,49 %	4,10 %	0,005	-0,01	0,12	-0,91
6.	*Petroleum*	29	71 (33)	26,89 %	0,66	44,90 %	-0,34 %	7,43 %	-0,004	0,03	-0,05	-0,13
7.	*Construction*	32	100 (36)	1,43 %	0,54	29,10 %	0,29 %	7,66 %	0,002	0,17	0,04	0,02
8.	*Prim. Metals*	33	175 (69)	2,30 %	0,54	16,50 %	0,46 %	5,78 %	0,004	0,06	0,08	0,08
9.	*Fab. Metals*	34	226 (64)	1,50 %	0,53	9,00 %	0,26 %	5,39 %	0,002	0,05	0,05	0,05
10.	*Machinery*	35	761 (128)	3,49 %	0,52	4,50 %	0,36 %	3,90 %	0,003	0,10	0,09	0,04
11.	*Electrical Eq.*	36	955 (109)	3,19 %	0,41	-18,20 %	0,53 %	3,77 %	0,005	0,06	0,14	0,09
12.	*Transport Eq.*	37	230 (60)	5,68 %	0,54	-27,80 %	0,69 %	5,02 %	0,007	-0,02	0,14	-0,37
13.	*Manufacturing*	38-39	736 (72)	1,94 %	0,43	-21,79 %	0,60 %	4,16 %	0,006	-0,01	0,14	-0,86
14.	*Railroads*	40	35 (14)	8,09 %	0,65	488,10 %	0,58 %	7,39 %	0,004	0,29	0,08	0,02
15.	*Other Transport.*	41-47	280 (39)	2,03 %	0,63	5,02 %	0,37 %	5,72 %	0,005	-0,11	0,07	-0,03
16.	*Utilities*	49	371 (154)	5,60 %	0,66	5,20 %	0,47 %	3,82 %	0,006	-0,12	0,12	-0,04
17.	*Dept. Stores*	53	100 (34)	10,19 %	0,64	26,10 %	0,51 %	7,09 %	0,004	0,12	0,07	0,04
18.	*Retail*	50-52,54-59	1266 (118	1,81 %	0,66	17,98 %	0,73 %	3,34 %	0,007	0,03	0,22	0,23
19.	*Hot & So.Ser*	70-79	1745 (82)	2,34 %	0,64	-111,35 %	0,61 %	3,44 %	0,006	0,01	0,18	0,60
20.	*Hea. & Men*	80-86	398 (16)	1,01 %	0,48	-14,49 %	0,37 %	5,70 %	0,003	0,04	0,07	0,09
21.	*Other*	87-99	583 (9)	0,88 %	0,62	-13356,30 %	1,15 %	5,66 %	0,011	0,05	0,20	0,23

Note: This table displays descriptive statistic for each industry category for the industry momentum the time period from 1980-2021

Table 8: Whole time period under all states

	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries
Market return	0.0390***	0.0390***	0.0390***	0.0390***	0.0390***
	(3.24)	(3.24)	(3.24)	(3.24)	(3.24)
Average company size		-1.5288***	-1.7320***	-1.4656*	-1.5769**
		(-2.59)	(-2.69)	(-1.95)	(-2.09)
Average industry debt ratio			0,0051	0,0056	0,0086
			(0.78)	(0.85)	(1.28)
Average volatility				-0,0338	-0,0845
				(-0.68)	(-1.54)
CAPM Beta					0.0136**
					(2.14)
Constant	0.0040***	0.00463***	0,0019	0,0033	0,0038
	(7.33)	(7.75)	(0.53)	(0.80)	(0.93)
R-squared	0,0010	0,0016	0,0017	0,0018	0,0022

*Note: Panel data regression model under all states. The t-statistic are reported in parenthesis. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.*

Table 9: Whole time period under steady state

	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries
Market return	0.0576***	0.0576***	0.0576***	0.0576***	0.0576***
	(3.41)	(3.41)	(3.41)	(3.41)	(3.41)
Average company size		-1.8237**	-2.1979**	-2.0204**	-2.1784**
		(-2.32)	(-2.55)	(-2.01)	(-2.16)
Average industry debt ratio			0,0093	0,0097	0,0139
			(1.08)	(1.11)	(1.56)
Average volatility				-0,0225	-0,0940
				(-0.34)	(-1.29)
CAPM Beta					0.0192***
					(2.26)
Constant	0.0039***	0.0047***	-0,0003	0,0006	0,0013
	(5.36)	(5.84)	(-0.07)	(0.11)	(0.24)
R-squared	0,0020	0,0030	0,0032	0,0032	0,0041

*Note: Panel data regression model under steady state. The t-statistic are reported in parenthesis. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.*

Table 10: Whole time period under down state

	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries
Market return	0.1175***	0.1175***	0.1175***	0.1175***	0.1175***
	(4.80)	(4.80)	(4.80)	(4.80)	(4.80)
Average company size		-2.9403**	-2.9641*	-3,0354	-3,0234
		(-2.02)	(-1.87)	(-1.63)	(-1.62)
Average industry debt ratio			0,0006	0,0005	0,0001
			(0.04)	(0.03)	(0.01)
Average volatility				0,0090	0,0144
				(0.07)	(0.11)
CAPM Beta					-0,0014
					(-0.09)
Constant	0.0071***	0.0083***	0,0080	0,0076	0,0076
	(4.78)	(5.19)	(0.91)	(0.75)	(0.74)
R-squared	0,0121	0,0142	0,0142	0,0142	0,0142

*Note: Panel data regression model under down state. The t-statistic are reported in parenthesis. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.*

Table 11: Whole time period under recovery state

	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries	Momentum return in Industries
Market return	-0.0545**	-0.0545**	-0.0545**	-0.0545**	-0.0545**
	(-2.10)	(-2.10)	(-2.10)	(-2.10)	(-2.10)
Average company size		0,0200	-0,1662	-0,0466	-0,1421
		(0.02)	(-0.14)	(-0.03)	(-0.10)
Average industry debt ratio			0,0046	0,0049	0,0075
			(0.38)	(0.40)	(0.60)
Average volatility				-0,0152	-0,0596
				(-0.16)	(-0.58)
CAPM Beta					0,0119
					(1.00)
Constant	0.0043***	0.0042***	0,0018	0,0024	0,0029
	(3.86)	(3.55)	(0.27)	(0.31)	(0.37)
R-squared	0,0015	0,0015	0,0015	0,0015	0,0019

*Note: Panel data regression model under recovery state. The t-statistic are reported in parenthesis. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.*

Table 12: Individual stock momentum within industries returns under Covid

	Industry	Avg. No of Stocks	Avg. % of Market Cap.	Debt ratio Median	$r - r_1^l$	*Steady*	Down	Recovery
1.	*Mining*	698 (112)	3,10 %	0,49	1,42 %	-0,55 %	4,23 %	10,40 %
2.	*Food*	246 (74)	7,14 %	0,51	0,75 %	1,26 %	1,27 %	-2,88 %
3.	*Apparel*	180 (49)	0,81 %	0,53	-1,92 %	-1,25 %	-0,84 %	-6,99 %
4.	*Paper*	117 (37)	4,07 %	0,65	1,09 %	-0,11 %	4,56 %	4,76 %
5.	*Chemical*	721 (101)	6,51 %	0,35	0,82 %	0,59 %	2,55 %	0,50 %
6.	*Petroleum*	71 (33)	26,89 %	0,66	-1,06 %	-0,99 %	-7,20 %	4,70 %
7.	*Construction*	100 (36)	1,43 %	0,54	2,46 %	1,64 %	-2,95 %	12,76 %
8.	*Prim. Metals*	175 (69)	2,30 %	0,54	0,27 %	0,03 %	3,64 %	-1,69 %
9.	*Fab. Metals*	226 (64)	1,50 %	0,53	1,43 %	0,40 %	3,06 %	5,97 %
10.	*Machinery*	761 (128)	3,49 %	0,52	0,40 %	-0,25 %	0,25 %	4,48 %
11.	*Electrica Eq.*	955 (109)	3,19 %	0,41	1,31 %	1,42 %	2,15 %	-0,20 %
12.	*Transport Eq.*	230 (60)	5,68 %	0,54	1,59 %	1,81 %	-1,01 %	2,84 %
13.	*Manufacturing*	736 (72)	1,94 %	0,43	0,64 %	0,27 %	1,85 %	1,68 %
14.	*Railroads*	35 (14)	8,09 %	0,65	3,15 %	1,76 %	8,53 %	6,13 %
15.	*Other Transport.*	280 (39)	2,03 %	0,63	-0,12 %	0,26 %	6,35 %	-8,90 %
16.	*Utilities*	371 (154)	5,60 %	0,66	0,87 %	-0,25 %	9,85 %	-1,34 %
17.	*Dept. Stores*	100 (34)	10,19 %	0,64	0,09 %	0,51 %	-1,71 %	-0,63 %
18.	*Retail*	1266 (118	1,81 %	0,66	1,02 %	0,84 %	1,32 %	1,76 %
19.	*Hotels & Social Ser.*	1745 (82)	2,34 %	0,64	1,53 %	1,48 %	1,71 %	1,65 %
20.	*Health & Membership*	398 (16)	1,01 %	0,48	2,61 %	3,42 %	2,31 %	-1,93 %
21.	*Other*	583 (9)	0,88 %	0,62	1,59 %	1,71 %	1,85 %	0,60 %

Note: This table displays returns and market states for each industry category for the industry momentum the time period under Covid-19

Table 13: Panel regression under the Covid period

	Whole time period	Steady	Down	Recovery
Market return	-0,0218	-0,1107	0.3577**	0,1028
	(-0.43)	(-1.38)	(2.51)	(0.53)
Average company size	-2,9402	-2,9394	-12,7580	7,9369
	(-0.72)	(-0.64)	(-1.15)	(0.61)
Average industry debt ratio	0,0038	-0,0027	0,1045	-0,0565
	(0.11)	(-0.07)	(1.08)	(-0.49)
Average volatility	0,0226	0,0043	-0,3880	0,4434
	(0.08)	(0.01)	(-0.48)	(0.47)
CAPM Beta	0,0228	0,0237	-0,0351	0,0723
	(0.66)	(0.61)	(-0.38)	(0.66)
Constant	0,0070	0,0111	0,0147	0,0103
	(0.31)	(0.44)	(0.24)	(0.14)
R-squared	0,0023	0,0075	0,1565	0,0509

*Note: Panel data regression model under the Covid period. The t-statistic are reported in parenthesis. ***, ** and * refer to 1%, 5% and 10% significance levels, respectively.*

Table 14: Portfolio optimization strategies

	Strategies				Market
	WINWIN/ LOSLOS	WINWIN/WINLOS	LOSWIN/ LOSLOS	LOSWIN/ WINLOS	
$r - r_f$	0.770	0.232	0.359	-0.179	0.007
σ	5.228	4.089	3.827	3.284	0.045
α	0.007	0.002	0.004	-0.001	0.000
T-stat (a)	3.130	1.094	2.448	-0.787	Inf
β	0.036	0.039	-0.090	-0.086	1.000
T-stat (b)	0.673	0.956	-2.335	-2.606	Inf
Sharpe ratio	0.147	0.057	0.094	-0.055	0.164
Treynor ratio	0.217	0.059	-0.040	0.021	0.007
MDD (%)	53.175	55.108	36.338	71.757	49.394
MDD (months)	10	107	112	296	18
Skewness	-0.381	-0.337	-0.268	-0.111	-0.671
Kurtosis	3.633	4.330	3.819	4.134	5.296
Jarque - Bera	20.339	46.048	19.833	27.682	146.434
P-value (JB)	0.001	0.000	0.002	0.000	0.000

Note: This table displays descriptive statistics on the four portfolio optimization strategies with the market performance.

Table 15: WINWIN/LOSLOS

	Market States											
	Down		Recovery		Steady		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	0.85	-2.58	0.53	1.77	0.69	1.15	6.16	-7.20	6.54	7.23	1.01	2.59
σ	6.40	5.36	5.15	3.75	4.78	3.72	2.70	6.69	1.01	5.77	5.50	4.20
α	0.01	-	0.01	-	0.01	-	0.08	-	0.07	-	0.02	-
T-stat (a)	1.96	-	1.56	-	1.98	-	2.91	-	4.46	-	1.42	-
β	0.24	-	-0.12	-	0.05	-	2.91	-	-0.02	-	-0.43	-
T-stat (b)	1.90	-	-1.06	-	0.59	-	2.91	-	-0.13	-	-1.39	-
Sharpe ratio	0.13	-0.48	0.10	0.47	0.14	0.31	2.28	-1.08	6.45	1.25	0.18	0.62
Treynor ratio	0.04	-0.03	-0.04	0.02	0.14	0.01	0.02	-0.07	-2.92	0.07	-0.02	0.03
Skewness	-0.48	-0.65	-0.39	0.08	-0.23	-0.46	0.14	0.25	0.66	0.48	-0.66	0.35
Kurtosis	3.70	4.64	3.67	3.23	3.22	4.65	1.50	1.50	1.50	1.50	2.54	3.06

Table 16: WINWIN/WINLOS

	Market States											
	Down		Recovery		Steady		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	0.25	-2.58	0.24	1.77	0.18	1.15	2.87	-7.20	1.55	7.23	-0.02	2.59
σ	4.54	5.36	4.59	3.75	3.61	3.72	4.52	6.69	0.42	5.77	4.71	4.20
α	0.00	-	0.00	-	0.00	-	0.01	-	0.02	-	0.01	-
T-stat (a)	0.90	-	0.45	-	0.30	-	0.17	-	2.66	-	0.90	-
β	0.09	-	0.03	-	0.09	-	0.17	-	-0.01	-	-0.44	-
T-stat (b)	1.01	-	0.28	-	1.44	-	0.17	-	-0.18	-	-1.71	-
Sharpe ratio	0.05	-0.48	0.05	0.47	0.05	0.31	0.63	-1.08	3.69	1.25	0.00	0.62
Treynor ratio	0.03	-0.03	0.08	0.02	0.02	0.01	0.17	-0.07	-1.17	0.07	0.00	0.03
Skewness	-0.06	-0.65	-0.42	0.08	-0.50	-0.46	0.00	0.25	0.69	0.48	0.33	0.35
Kurtosis	2.99	4.64	4.63	3.23	4.56	4.65	1.50	1.50	1.50	1.50	2.44	3.06

Note: This table displays the returns from the respective strategy under different market conditions.

Table 17: LOSWIN/LOSLOS

	Market States											
	Down		Recovery		Steady		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	0.31	-2.58	0.39	1.77	0.24	1.15	6.35	-7.20	2.69	7.23	0.40	2.59
σ	4.66	5.36	3.50	3.75	3.66	3.72	2.61	6.69	2.77	5.77	4.12	4.20
α	0.00	-	0.01	-	0.00	-	0.05	-	0.06	-	0.01	-
T-stat (a)	0.66	-	2.20	-	1.54	-	1.62	-	5.52	-	0.81	-
β	0.03	-	-0.18	-	-0.12	-	1.62	-	-0.46	-	-0.21	-
T-stat (b)	0.27	-	-2.32	-	-1.85	-	1.62	-	-3.66	-	-0.88	-
Sharpe ratio	0.07	-0.48	0.11	0.47	0.07	0.31	2.44	-1.08	0.97	1.25	0.10	0.62
Treynor ratio	0.12	-0.03	-0.02	0.02	-0.02	0.01	0.04	-0.07	-0.06	0.07	-0.02	0.03
Skewness	-0.22	-0.65	-0.18	0.08	-0.31	-0.46	-0.06	0.25	-0.71	0.48	-0.53	0.35
Kurtosis	3.18	4.64	4.32	3.23	3.85	4.65	1.50	1.50	1.50	1.50	2.63	3.06

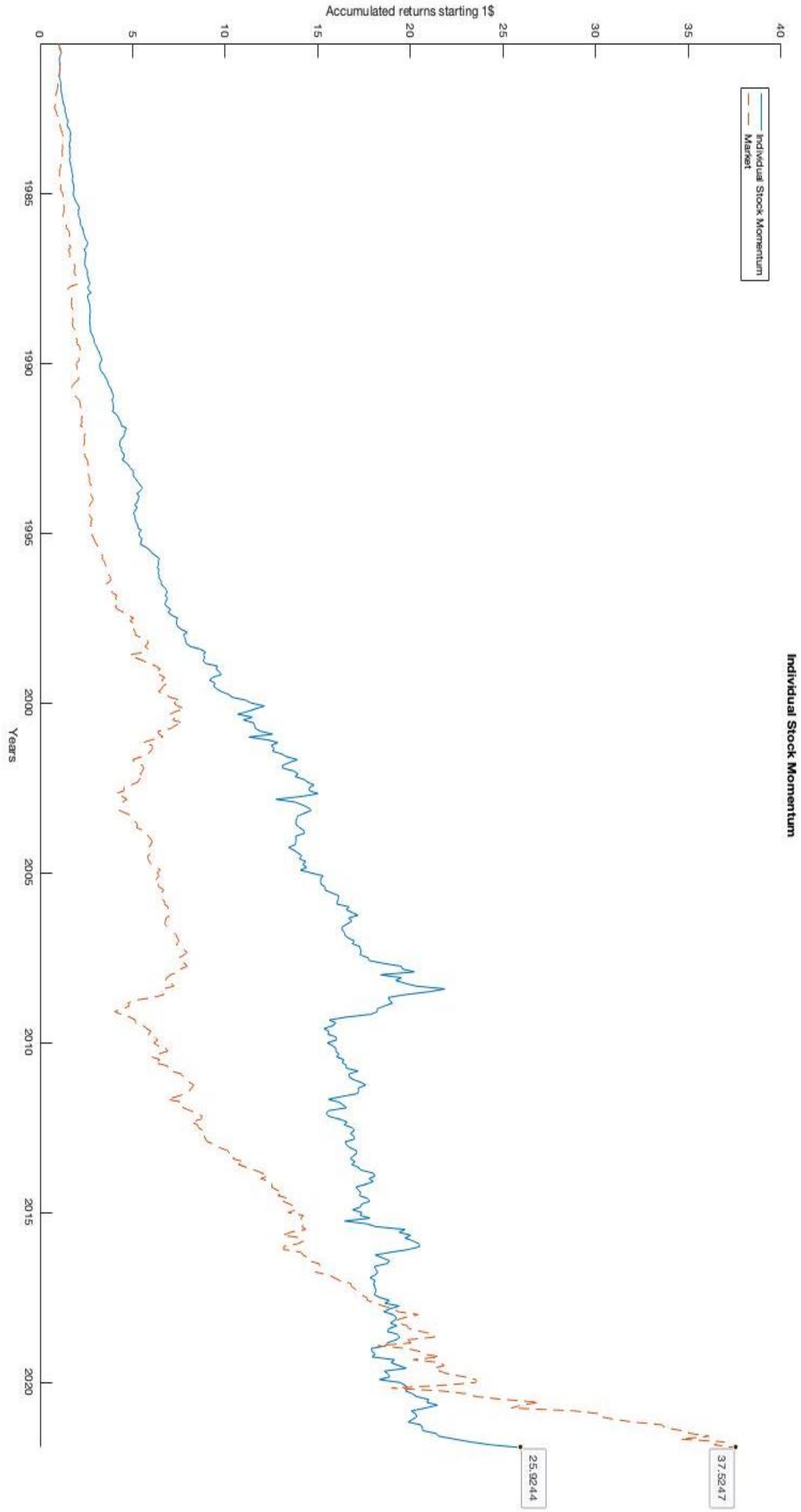
Table 18: LOSWIN/WINLOS

	Market States											
	Down		Recovery		Steady		Down 01/2020 - 03/2020		Recovery 04/2020 - 06/2020		Steady 07/2020 - 12/2021	
	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT	ZC	MKT
$r - r_f$	-0.30	-2.58	0.10	1.77	-0.27	1.15	3.05	-7.20	-2.30	7.23	-0.63	2.59
σ	3.67	5.36	3.26	3.75	3.09	3.72	6.37	6.69	2.62	5.77	3.34	4.20
α	-0.01	-	0.00	-	0.00	-	-0.02	-	0.01	-	0.00	-
T-stat (a)	-1.44	-	0.50	-	-0.90	-	-0.29	-	4.74	-	-0.06	-
β	-0.12	-	-0.03	-	-0.08	-	-0.29	-	-0.45	-	-0.22	-
T-stat (b)	-1.70	-	-0.37	-	-1.42	-	-0.29	-	-18.98	-	-1.17	-
Sharpe ratio	-0.08	-0.48	0.03	0.47	-0.09	0.31	0.48	-1.08	-0.88	1.25	-0.19	0.62
Treynor ratio	0.02	-0.03	-0.04	0.02	0.04	0.01	-0.11	-0.07	0.05	0.07	0.03	0.03
Skewness	-0.30	-0.65	0.17	0.08	-0.35	-0.46	0.64	0.25	-0.56	0.48	-0.13	0.35
Kurtosis	2.39	4.64	4.09	3.23	5.29	4.65	1.50	1.50	1.50	1.50	1.52	3.06

Note: This table displays the returns from the respective strategy under different market conditions.

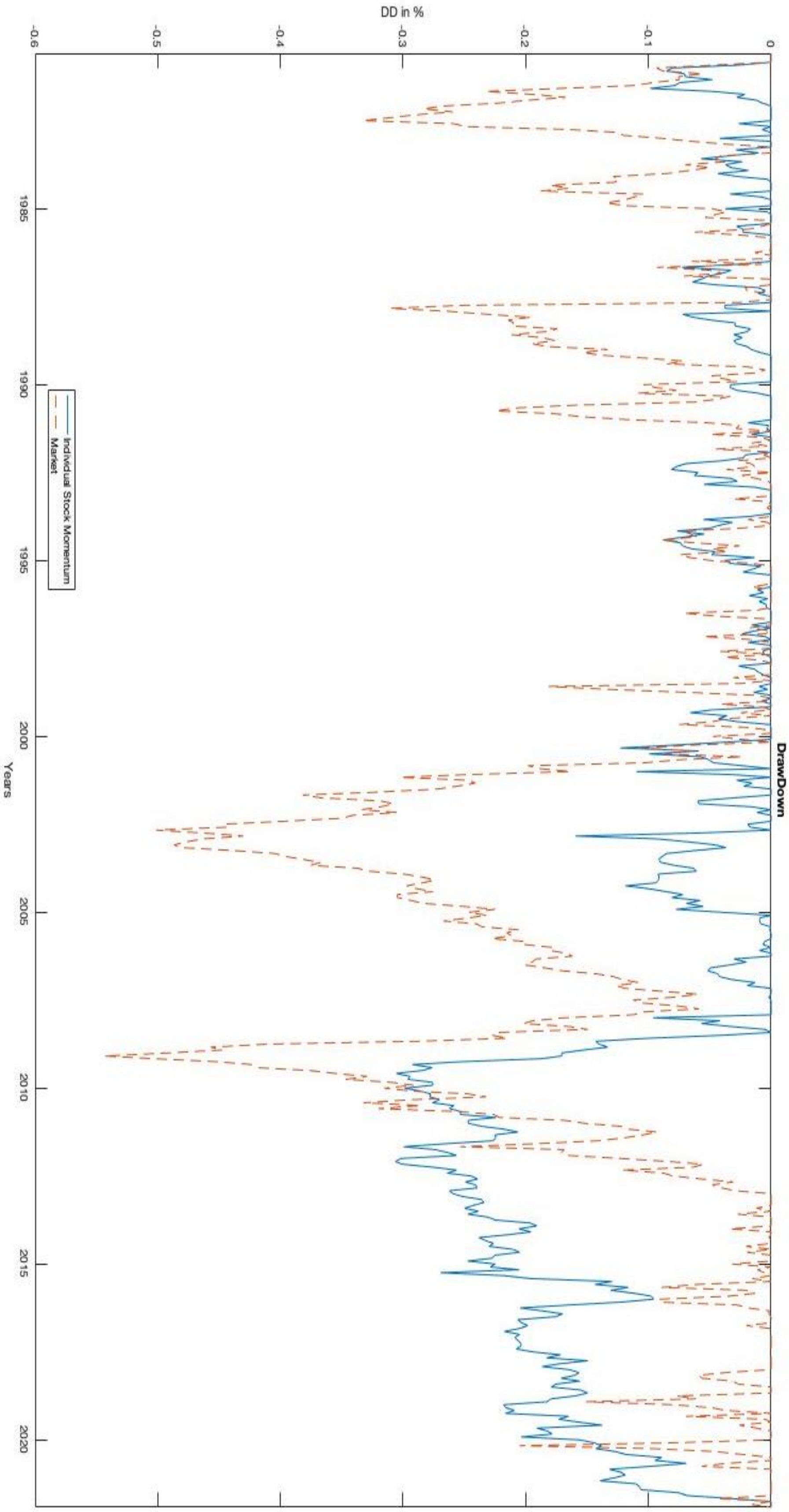
Appendix B: Graphs

Graph 1: Accumulated Individual Stock Momentum



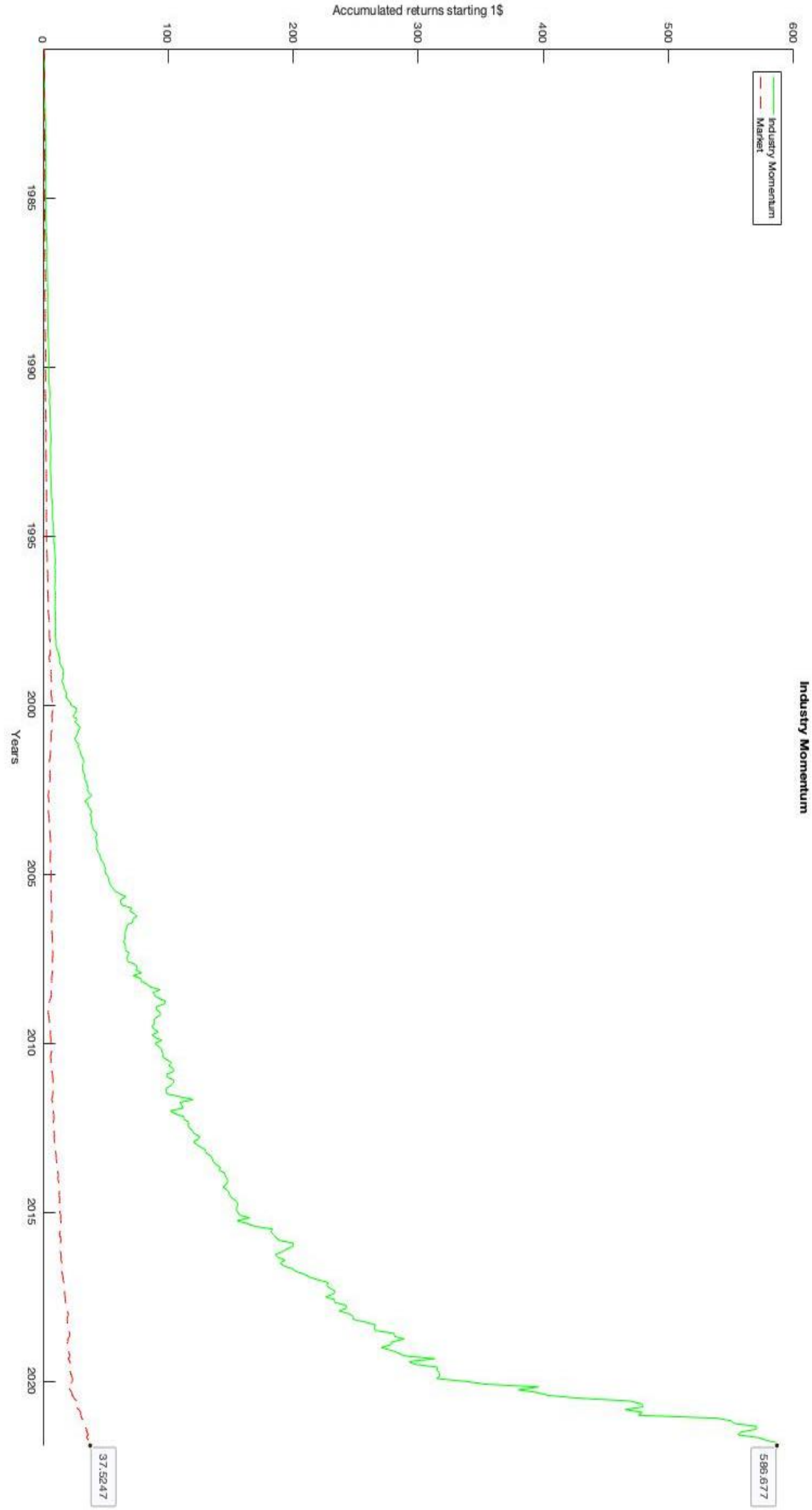
Note: This graph illustrates the return on the accumulated individual stock momentum and the accumulated market return.

Graph 2: DrawDown Individual Stock Momentum



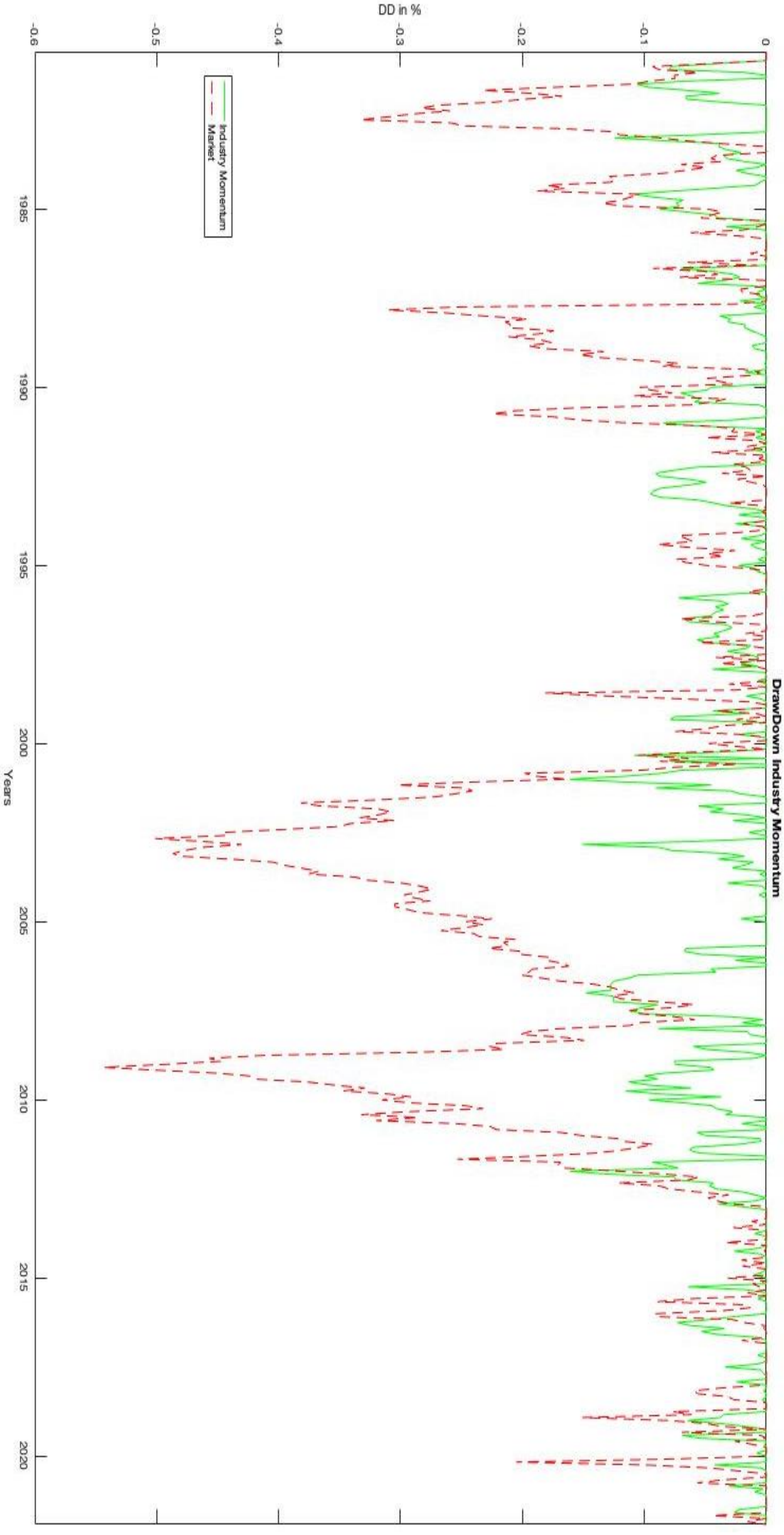
Note: This graph illustrates the drawdown for the individual stock momentum and the market return.

Graph 3: Accumulated Industry Momentum



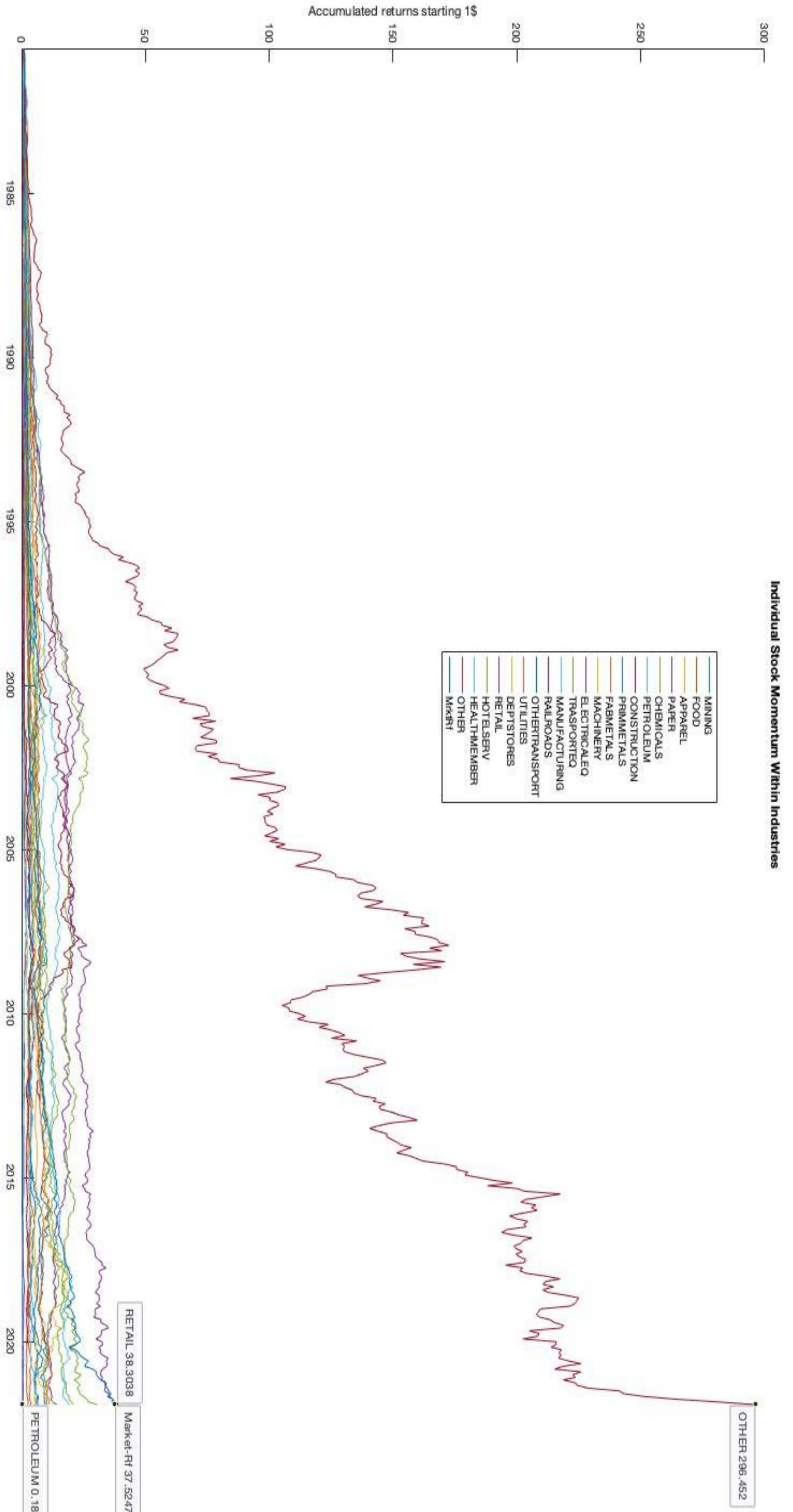
Note: This graph illustrates the return on the accumulated industry momentum and the accumulated market return.

Graph 4: DrawDown Industry Momentum



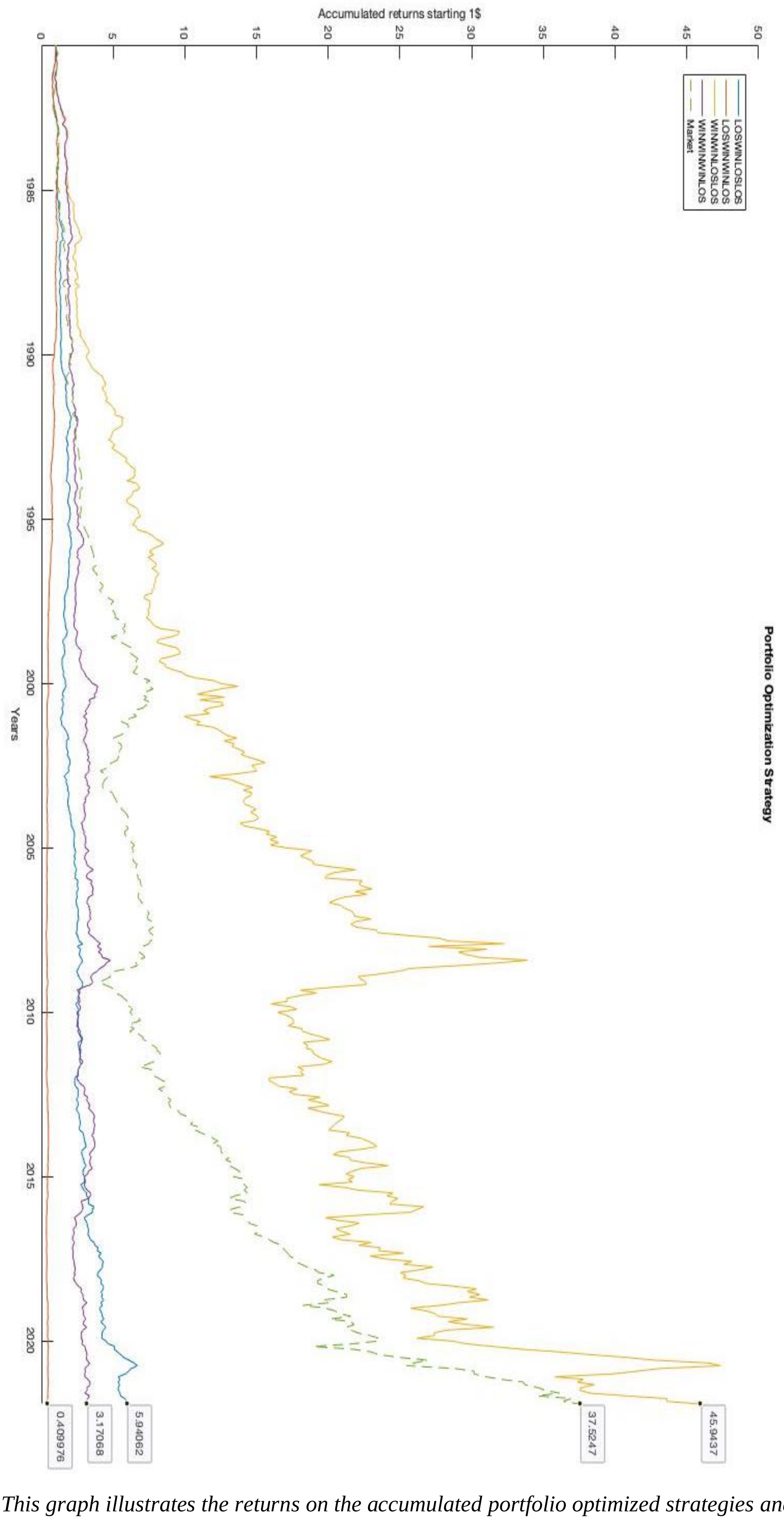
Note: This graph illustrates the drawdown for the industry momentum and the market return.

Graph 5: Accumulated Individual Stock Momentum Within Industries



Note: This graph illustrates the returns on the accumulated Individual Stock Momentum Within Industries and the accumulated market return.

Graph 6: Accumulated Portfolio Optimization Strategy



Note: This graph illustrates the returns on the accumulated portfolio optimized strategies and the accumulated market return.

Appendix C: Individual Stock Momentum (MATLAB-codes)

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

Appendix D: Industry Momentum (MATLAB-codes)

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

Appendix E: Individual Stock Momentum Within Industries (MATLAB-codes)

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

Appendix F: Portfolio Optimization Strategy (MATLAB-codes)

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