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Profitability of momentum strategies during crisis

evidence from Finland during Covid-19 pandemic

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Abstract:

Extensive research exists to support the profitability of momentum strategies, which rely on the continuation of past price trends. However, the source of the momentum anomaly remains largely unknown. Studies have found that momentum strategies experience significant negative returns during market recovery post periods of high market volatility and uncertainty, referred to as momentum crashes. This thesis examines the impact of COVID-19 on the profitability of momentum strategies in the Finnish stock market. The methodology employs an event study as well as Single Index Models to test whether the returns of momentum portfolios are significantly affected by the COVID-19 crisis.

The findings of this study indicate that cross-sectional momentum strategies were significantly negatively impacted by COVID-19. Deviating from the findings of some existing research, the momentum portfolios did not yield significant negative returns, but performed worse in comparison to the market than before the crisis in or became market neutral. The portfolios with different combinations of observation and holding periods were affected differently, where the portfolios with longer holding periods were typically impacted more in comparison to portfolios with short holding periods. Overall, this study suggests that the existing momentum crash research also applies to the Finnish stock market.

AVAINSANAT: momentum, COVID-19, Finnish stock market, profitability, momentum crash

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Abbreviations

EMH	Efficient Markets Hypothesis
WML	Winner-minus-loser
SIM	Single Index Model
EUT	Expected Utility Theory
DDM	Dividend Discount Model
GGM	Gordons Growth Model
CAPM	Capital Asset Pricing Model

1 Introduction

Financial markets have always been a captivating domain for economic researchers due to their complexity driven by investors' constant strive for abnormal returns. The search for the most accurate theories and models to understand and captivate the behavior of the stock market is ceaseless. Anomalies refer to phenomena that appear to digress from conventional financial models. Among the various observed anomalies in the market, momentum stands out as one of the most persistent and fascinating phenomena.

The momentum refers to the tendency of an asset's past and future price changes to be autocorrelated in a short time horizon. The main types of momentum strategies are the cross-sectional momentum, where the stocks within the stock universe are ranked based on their performance relative to one another (Jegadeesh & Titman 1993), and time series momentum, where the performance of the stock is evaluated according to the individual asset’s historical price trends (Moskowitz, 2012). This study focuses on cross-sectional momentum strategies. The anomaly is yet to be conclusively explained, although it has been widely researched for decades. The anomaly presents a direct discord with one of the most accepted economic theories, the Efficient Market Hypothesis (Fama, 1970). The EMH fundamentally states that the price of an asset correctly and instantly reflects all available information, which is introduced to the market in a random, unpredictable manner. Therefore, it should be impossible to make predictions of future prices based solely on past prices.

Despite momentum’s contradiction to the Efficient Market Hypothesis and lack of an explanation, there is a vast body of evidence to support the profitability of the momentum strategies across markets and assets. Jegadeesh and Titman (1993) introduce a trading strategy that bets on the continuation of past price trends, where portfolios are formed based solely on the past performance of stocks. The best-performing decile of stocks is then bought, and the worst-performing one is sold. Their methodology has been replicated, studied, and altered countless times across countries and asset classes with perpetual significant results in support of the success of the strategy (Rouwenhorst 1998; Barra 2010; Novy-Marx 2012; Moskowitz and Pedersen 2013).

Despite the recurring profitability, the persistent profitability of momentum-based trading strategies appears to be disrupted by periods of significant negative returns post significant economic crisis (Cooper et al. 2004; Daniel and Moskowitz 2016; Grobys 2016). The economic crisis is characterized by heightened volatility, investor anxiety, and significant shifts in market dynamics. The said conditions can significantly impact the profitability of investment strategies in various ways as investors adopt defensive investing approaches.

The outbreak of the COVID-19 pandemic has presented a crisis that profoundly impacted the global economies and financial markets abruptly. COVID-19 was expectational in the sense that no preceding crisis has had an impact as drastic and global arise as suddenly. As the crisis is recent, there is limited research regarding the effect the event had on the profitability of the momentum strategies during and after. This study aims to contribute to existing knowledge by analyzing the performance of momentum strategies during COVID-19 in the Finnish stock market. Through this study, this thesis attempts to add insight to investors and researchers on the dynamics of momentum and its potential during a crisis.

1.1 Purpose of the study

This thesis evaluates the performance of cross-sectional momentum strategies during the latest COVID-19 in the Finnish stock market. This study has been motivated by the existing literature on the effect of the market state on the performance of momentum strategies. More specifically, the studies of market crashes tend to happen after times of high market volatility and stress. For example, Daniel and Moskowitz (2016), Ahmad et al. (2021), and Grobys (2016) find that during the recovery periods after recent financial crises' momentum strategies have yielded significantly lower and, in some cases, persistent negative returns after the market rebounds after a significant decline. Based on the existing literature, similar results could be found during the COVID-19 crisis (Ahmad et al. 2021; Kahn et al. 2023).

This thesis expands the existing literature in several ways. Firstly, COVID-19 was an unprecedented event that shocked the markets globally. In addition to the significant amplitude, its impact was rapid. The market decline and rebound were significantly quicker in comparison to the 2008 financial crisis for instance. Therefore, it should be studied whether a crisis of this speed and amplitude had similar effects on the profitability of momentum strategies as preceding crises. As the crisis of COVID-19 is recent, very limited research exists on the effect it had on investing strategies such as the momentum strategy. Observations of how momentum strategies behave during a crisis can help the pursuit of fully understanding the source of the momentum anomaly which remains unknown. Increased understanding of the behavior of the strategy also benefits practicing investors. Secondly, this study examines the profitability of the momentum strategies specifically in the Finnish stock market. Most of the existing literature on momentum is focused on the United States, thus, studying other smaller markets provides valuable information regarding the robustness of momentum studies and momentum-based strategies' global applicability. Prior literature exists to support the existence of momentum in the Nordic stock market (Leivo 2012; Grobys & Huhta-Halkola 2019; Silvasti, Grobys & Äijö 2021), however, less research has been conducted to evaluate momentum crashes in particular.

1.2 Hypotheses

The source of the momentum anomaly is still debated, and no existing theory can fully explain it. Therefore, the hypotheses of this thesis cannot be justified by any established theory. Instead, the hypotheses are derived from previous findings by various researchers.

Cooper et al. (2004), Stivers and Sun (2010), Daniel and Moskowitz (2016), and Grobys (2016) have found that after times of extreme market uncertainty and volatility cross-sectional momentum strategies tend to yield significant negative returns. None of the previous research has been conducted on data from the Finnish stock market. However, similar results of the profitability of momentum crashes during a crisis appear globally (Grobys, 2016), thus, it is relevant to extend the research to Finland.

H0: Economic crisis does not affect the profitability of cross-sectional momentum strategies in the Finnish stock market
H1: Economic crisis has a significant effect on the profitability of cross-sectional momentum strategies in the Finnish stock market

The null hypothesis is that the COVID-19 crisis did not significantly affect the profitability of momentum strategies in the Finnish stock market. This hypothesis will be accepted in a case where there is no significant difference in profitability found in the empirical study between the periods of COVID-19 and pre-COVID-19. However, if a significant difference in profitability is found, the null hypothesis is rejected, and it can be concluded that the COVID-19 crisis did affect momentum profitability.

1.3 Structure

The remainder of this thesis is structured into five main chapters. The second chapter introduces essential theoretical background relevant to the study, including the efficient market hypothesis, expected utility theory, prospect theory, and asset pricing theorem. These provide the framework for the literature review of chapter three as well as the empirical study of this thesis. In the third chapter, previous literature on the momentum anomaly is introduced and analyzed. This chapter introduces general research on the existence of the momentum anomaly, explores the literature on the effect of the market state on the profitability of momentum strategies, and introduces some potential risk-based and behavioral explanations for the anomaly. The fourth chapter introduces the data and methodology used in the empirical study of this thesis. The fifth chapter consists of the empirical findings derived using the methodology, as well as an analysis of the findings. Lastly, the sixth chapter is the conclusion of the thesis including suggestions for further research.

2 Theoretical background

This section discusses the underlying theoretical concepts vital to understanding the financial markets and the significance of momentum. The first subsection introduces the efficient markets hypothesis, which the existence of the momentum anomaly contradicts. The second subsection introduces the concept of investor rationality, which is the premise of most financial theorems. Investor rationality is also relevant because the unrealistic definition of investor rationality is often theorized to be a possible reason for why the momentum anomaly tends to contradict theories such as the EMH. Lastly, some standard asset pricing theorems are introduced which are commonly employed in research studying momentum returns, as well as in this thesis.

2.1 Efficient markets hypothesis

The Efficient Markets Hypothesis is a widely recognized financial theory introduced by Fama in 1970. It argues that security markets are efficient in the sense that when new price-relevant information is introduced to the market, the security prices reflect the newly available information instantly and appropriately. The shift in price is driven by a body of investors competing over abnormal returns, thus correcting any undervalued stocks to their fundamental price. It is arguably one of the most prominent hypotheses in finance to describe the anatomy of security markets, yet the momentum anomaly presents a direct discord with market efficiency.

The random walk theory was popularized by Burton Malkiel in his book A Random Walk Down the Wall Street (1973), but the theory was studied by various researchers prior, including Fama (1965). The theory implies that the changes in asset prices in the stock market are independent and random. Therefore, past changes in asset prices have no correlation or predictive power of future prices. It also states that at any given time, the price of an asset is the best representation of the investor's best estimate of its intrinsic value. As new information is introduced to the market, the body of investors collectively revises their expectations of the stock's expected earnings, adjusting the stock's price as a result. New information is introduced to the market randomly, which causes the random pattern of price changes of assets. (Fama 1965; Van Horne & Parker 1967.) The EMH is based on the random walk theory. Although closely related, the random walk theory is a mathematical approach to explaining the anatomy of stock price changes, the EMH focuses on explaining the efficiency of the market in accurately processing new information.

Fama (1970) outlines several conditions which may promote or hinder market efficiency. Firstly, Fama recognizes crucial conditions of a market under which market efficiency is attainable.

1. Investors are assumed to be rational agents.
2. In a case where the investor is not rational, their trades are assumed to be random.
3. Rational investors aiming for arbitrage through fundamental analysis are assumed to offset the effect of irrational trades.

In addition, Fama (1970) also outlined assumptions to describe a frictionless market, where if the conditions are not met, it can hinder market efficiency.

1. There are no transaction costs
2. All available information can be accessed by all market participants at no cost
3. All market participants agree with the implications of new information

However, Fama (1970) recognizes that a frictionless market described in the conditions is unrealistic. Despite this, Fama argues that the Efficient Markets Hypothesis is still applicable in real life.

2.1.1 Weak form

The EMH is categorized into three subsets according to the level of information available to the investor. According to Fama (1970), a weak form of market efficiency describes a state where investors only have access to data regarding past prices and volumes of trades.

According to the EMH, all asset prices correctly reflect the available data in the market. Therefore, in weak form, the historical data on volume and prices is already included in all stock prices. Consequently, investors are unable to apply any technical analysis to obtain abnormal profits. As presented by the random walk theory, all price changes are independent and random. Thus, it is impossible to find patterns and make predictions from past price data.

Investors may be able to identify undervalued stocks using fundamental analysis. However, rational investors seeking to beat the market should quickly drive the undervalued stocks to their fundamental level, signifying that there is no long-term advantage in fundamental analysis. According to Fama (1970), the weak form is the most accurate representation of real-world market efficiency.

2.1.2 Semi-strong form

In the semi-strong form, stocks accurately reflect all public information in addition to historical price and volume data. As a firm releases new public information, it is instantly and correctly reflected in the stock's price. Thereupon the advantages of fundamental analysis present in the weak form have diminished. Ultimately the only way to gain above-average returns is to accept above-average risks. (Fama, 1970).

2.1.3 Strong form

In the strong form of market efficiency, all public and private data is available to the investor. Both fundamental and technical analysis will not yield abnormal profits, and the only way an investor could beat the market is by sheer luck. Fama (1991) returned to this form of efficiency later in his studies to conclude that the strong form of market efficiency must be false due to the presence of positive information and trading costs. However, the strong form can still be useful as a benchmark concept for research.

2.2 Rationality

Investor rationality is a vital concept to be established, as momentum returns are often explained by investor irrationality. The EMH along with many other financial theorems relies on the validity of rationality. Rational choice theory (RAT) is a common assumption according to which an individual makes calculated choices that maximize their utility (Boudon, 2003). The assumption of an individual's self-interest and calculated choices has been prevalent in economic research for centuries. The first evidence of this can be traced to the eighteenth century to Adam Smith's theory about the invisible hand, which is composed of a group of individuals who make choices maximizing to their advantage (Smith 1765). Since multiple theories have attempted to economically model rationality to better understand investors' decision-making.

2.2.1 Expected utility hypothesis

The expected utility hypothesis (EUT) is a mathematical concept that defines a framework for a person's decision-making when the outcome of the decision is uncertain. Savage (1951) created the foundation for the hypothesis. His model assumes that any rational agent's primary objective is to maximize their utility. His methodology combines the concepts of personal utility and personal probability distribution. The outcome of each decision is measured by multiplying the expected utility by their respective probabilities. The results of the study show that when an agent adheres to the seven axioms of rationality he defines, the expected utility model can predict the optimal decision under risk and uncertainty.

Whereas Savage (1951) advanced a framework to predict the optimal outcome of a decision made by a rational decision maker, von Neumann and Morgenstern (1953/2007) attempted to define a rational decision maker. They define four axioms specified below, which an agent must satisfy to be considered rational.

1. Completeness: The agent has well-defined preferences.
    - $A > B$ or $B > A$
2. Transitivity: The agent decides consistently
    - If $A > B$ and $B > C$, then we must have $A > C$
3. Continuity: Where there is $A > B > C$, there must be a combination of A and C which is indifferent to B
    - $pA + (1-p)C = B$
4. Independence: The agent's preference of $A > B$ is independent of an irrelevant third outcome C.
    - $tA + (1-t)C > tB + (1-t)C$

However, the expected utility theory was quickly widely criticized due to inconsistencies in empirical testing. For example, the Allais paradox found by Maurice Allais (1953) presented a direct discord to the expected utility hypothesis. His study consisted of two experiments, where the subjects had to decide between a choice of two different gambles with different outcomes. All of the gambles had the same expected utility; however, the probabilities were altered. According to the EUT, a rational agent should have a clear preference for risk. However, Allais finds that people who chose option A in the first experiment often chose option B in the second experiment, which violated the axioms of a rational agent defined by von Neumann and Morgenstern (1953/2007) and Savage (1951). The inconsistency is theorized to be the result of risk aversion and psychological bias.

2.2.2 Prospect theory

Kahneman and Tversky (1979) present a critique of the EUT on the basis that the axioms are rarely satisfied in real life. They propose an alternative model known as the prospect theory, that describes decision-making and investor rationality based on findings from controlled studies conducted on humans.

One of the most significant findings of prospect theory is the asymmetry in how individuals assess loss and gains. Similar to the findings of Allais (1953), Kahneman and Tversky (1979) find that individuals tend to be loss aversive, meaning that the individuals assess the pain of a loss as greater than the pleasure from gaining an equal sum. Therefore, rationality solely based on expected utility is not reflected in actual decision-making.

Kahneman and Tversky (1979) also find that in a scenario where gains are likely, individuals tend to be risk averse. Vice versa, where losses are more likely, individuals tend to choose high-risk. Therefore, in addition to an individual's risk preference, the most likely outcome must also be assessed in predicting choice.

The accuracy of the prospect theory has since been tested since with great success (Barberis, Mukherjee & Wang 2016; Kothiyal, Spinu & Wakker 2014). However, a great limitation of any application of the prospect theory is ultimately the complexity of its mathematics. From this, it can be suggested that the empirical inaccuracy of most of the alternative, strict assumptions of rationality is likely due to the attempt to produce mathematically traceable results.

2.3 Asset pricing models

2.3.1 Dividend Discounted Model

The dividend discount model (DDM) is one of the earliest and simplest methods to estimate a stock's value. DDM is a sum of all firm's future dividends discounted to the present. It can be expressed as a formula shown below. (Gordon & Shapiro, 1956).

$$P_0 = \sum \frac{D_t}{(1+r)^t} \quad (1)$$

In a case where the future dividend is expected to grow at a constant rate until infinity, the formula is often referred to as Gordons Growth Model (GGM) illustrated below (Gordon & Shapiro 1956).

$$P_0 = \frac{D_t}{(r-g)^t} \quad (2)$$

D represents the dividend of the model, t the year, r represents the interest rate, and g represents the growth rate. According to the EMH, all new information should be reflected in the price of an asset immediately after release. Thus, when a firm announces its future dividend, the price of the asset should immediately reflect the fundamental value of the stock correctly. As the announcements of dividends happen randomly, there should not be a pattern or any predictive power in price changes over time. (Fama 1970). Therefore, the discount dividend model does not offer an explanation for the momentum anomaly.

2.3.2 Capital asset pricing model

Capital asset pricing model (CAPM) is another prevalent asset pricing model, that declares that the value of an asset is based on its expected revenue which is based on risk. It was developed by Sharpe (1964), Lintner (1965), Treynor (1962), and Mossin (1966). The model divides risk into two categories: systematic risk and market risk. Market risk refers to the risk-free return and systematic risk to the firm-specific risk represented by β. The idea behind CAPM is that an investor expects to receive an appropriate amount of compensation for the level of risk they take relative to the risk-free rate and market index return. The formula for CAPM can be written as follows:

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f) \quad (3)$$

The accuracy of CAPM has been heavily questioned. One prominent contradiction found is the size-effect. Banz (1981) finds that the CAPM smaller firms appeared to consistently have higher adjusted returns in comparison to large-cap and average-sized firms. Another common critique of the model is that static beta cannot accurately represent expected returns and risk, which tend to be dynamic (French, 2016). Fama and French (2004) argue that CAPM's constant failure in empirical testing shows that the applications of the model are invalid. CAPM, however, remains to be the centerpiece of asset pricing due to its simplicity and easy application.

2.3.3 Single Index Model

Single Index Model is a simple risk and return model by Sharpe (1963) that is used to analyze the performance of an individual asset or a portfolio relative to a market index. The Single Index Model assumes that the returns of stock are mainly driven by the stock's responsiveness to the market.

It can be expressed in two forms: the raw form and the risk-adjusted form. Risk-adjusted formula subtracts the risk-free rate from the market revenues and stock's revenues to get excess returns. The single index model coefficients can be obtained through a linear time-series regression where the analyzed asset or portfolio returns are regressed against the market index returns.

$$R_{WML,i} = \propto_i + \beta_i R_{mt} + \varepsilon_t \quad (4)$$

$$R_{WML,i} - R_f = \propto_i + \beta_i (R_{mt} - R_f) + \varepsilon_t \quad (5)$$

Where $R_{WML,i}$ is the return of the stock i, $\propto_i$ is the intercept of time-series regression of the stock's returns to market returns, β_i is the beta of the stock i, R_{mt} is the return of the market index, R_f is the risk-free rate and ε_t is the error term. Similar to the CAPM, the single index model, the Single Index Model captures both systematic and unsystematic risk of the asset.

The alpha and beta of the Single Index Model allow the investor to assess whether a stock or a portfolio has underperformed or overperformed the market index. In the risk-adjusted form, alpha represents the expected excess return of the stock beyond market movements. A positive alpha, therefore, indicates that the stock has overperformed the market index during the considered time-period even after regard for systematic risk. Beta represents the asset's sensitivity and responsiveness to the market index movements; thus, it measures the systematic risk of the asset. A lower beta generally indicates less risk in comparison to a market index, and vice versa. Lastly, the error term, that is the regression residuals, can be used to explain the idiosyncratic volatility of the asset. In other words, the movements in the asset price cannot be explained by the market returns. (Gruber et al. 2014).

2.3.4 Fama & French Three-Factor Model

Fama and French (1992) created a statistical model in an attempt to describe stock returns more accurately than its predecessors. Instead of using a single variable to represent a risk, Fama and French initially use three variables: size, book-to-market ratio, and market. The Fama and French Three-Factor Model can be formulated as written below:

$$R_{i,t} = \alpha + \beta_{im} R_{mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_t \quad (6)$$

In the formula above, R_{mt} represents the market return. SMB_t is "small minus big", therefore representing the difference in returns between small and large firms in the portfolio. Finally, HML_t is "high minus low", meaning the difference in returns between the high book-to-market value and low book-to-market value firms. α represents the intercept and ε_t the error term. Each term is multiplied by its respective beta values. In empirical testing, the Fama and French Three-Factor Model outperforms the CAPM (Bhatnagar 2013; Bello 2008). However, it is debated whether the success of the model is merely due to a form of data mining to eliminate abnormal returns (Black, 1993; Bhatt & Rajaram, 2014).

Based on Jegadeesh and Titman's (1993) findings of the momentum anomaly, Carhart (1997) suggests an improved version of the model by extending the Three-Factor model by a fourth momentum factor. This model is also known as Carhart's Four-Factor model, and can be expressed mathematically as shown below.

$$R_{i,t} = \alpha + \beta_{im} R_{mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iWML} WML_t + \varepsilon_t \quad (7)$$

The new term WML refers to "winner minus loser", which is the difference in the returns of the winner portfolio and loser portfolio as presented by Jegadeesh and Titman (1993). The winner and loser portfolios are formed based on the historical returns of the stocks. This process is described in more detail in the literature review section. Carhart's (1997) findings show that the four-factor model had a higher explanatory power compared to the original three-factor model.

2.3.5 Fama & French Five-Factor Model

Fama and French continued to develop an extension to their model in an attempt to improve its accuracy to explain anomalies the Three-Factor model failed to account for. Therefore, two factors are added to the original model: RMW and CMA. RMW, meaning robust minus weak, is the difference in returns of firms with robust operating profitability and weak operating profitability. CMA stands for conservative minus aggressive, which is the difference in returns of firms that invest conservatively versus firms that practice aggressive investing. The remaining three of the five factors remain identical to the preceding three-factor model.

$$R_{i,t} = \alpha + \beta_{im} R_{mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iCMA} CMA_t + \beta_{iRMW} RMW_t + \varepsilon_t \quad (8)$$

Empirical tests find that the Five-Factor model has a higher explanatory power than its predecessor (Fama & French, 2015; Hezbi & Salehi 2016). However, Fama and French (2015) find that the model captures return inadequately in a scenario where a small-cap firm invests large amounts despite being less profitable. Despite Carhart's (1997) suggestion, no factor for momentum returns was included in the revised model. Regardless of this, Hezbi and Salehi (2016) find that the Five-Factor model has a higher explanatory power than Carhart’s Four-Factor model.

3 Literature review

This section introduces previous literature on momentum anomaly and momentum strategies. Studies regarding the implications of the economic state on the profitability of momentum strategies are also reviewed, specifically the phenomenon of momentum crashes. The discussion is then extended to possible explanations of the existence of the momentum anomaly.

3.1 Momentum returns

Anomalies refer to empirical findings which appear to be inconsistent with maintained financial theories (Schwert, 2003). According to Schwert, the presence of anomalies typically implies either market inefficiency or inadequacy of the underlying asset-pricing theories. In some cases, the anomalous findings can be the result of data snooping, or excessive focus on surprising findings. Also, Schwert notes that anomalies have the tendency of disappearing or reverting after some time. His findings raise the question of whether anomalies are rather apparent than legitimate.

Momentum anomaly refers to short-term autocorrelation in security prices, where the stocks which have performed well in the past tend to continue performing well in the future. This directly contradicts the efficient markets hypothesis (1970), according to which the past prices of security have no predictive power of its future price even in the weakest form of efficiency. The momentum anomaly has been widely researched, and a large body of empirical evidence over decades seems to suggest that there is a persistent pattern between past and future stock prices.

Levy (1967) explores the concept of intercorrelation of stock prices in his research. His study shows that the changes in stock prices are not in fact statistically independent, contrary to the widely accepted belief. His findings show that investing in securities that performed relatively higher than other stocks in the universe in the past 26 weeks yielded significant abnormal returns.

Jegadeesh and Titman (1993) are often accredited for formulating the momentum trading strategy as it is known today. Their research documents the significant profitability of a trading strategy in which portfolios are formed by buying stocks that have performed well in the past and selling short stocks that performed the worst. Their methodology relies on relative strength rules, which are also referred to as cross-sectional momentum. An alternative to this is the time-series momentum, where assets are bought or shorted according to the individual asset's historical price trends (Moskowitz, 2012).

Jegadeesh and Titman (1993) use data from the United State's stock market from 1965 to 1989. Their methodology can be divided into two parts: formation period J and holding period K. During the formation period J the price changes of stocks are observed, after which they are ranked according to performance. The ranked stocks are grouped into ten equal segments, where the best-performing stocks are considered winners and the worst-performing stocks as losers. The winner minus loser (WML) portfolio is then formed at a time *t* by selling the loser decile and buying the winner decile. The portfolio is held for the duration of K. The durations of J and K consist of different combinations of 3, 6, 9, or 12 months. They find that the strategy yields significant positive returns on nearly all J-K combinations. They also find that profits tend to turn negative when the portfolio is held for over twelve months. This notion is referred to as a return reversal or a price reversal. Different studies have found mixed results on the presence of the return reversal (Chan et al. 1996). Jegadeesh and Titman also find that the positive returns cannot be attributed to systematic risk or lead-lag effects but could be explained by delayed reactions to firm-specific information.

Novy-Marx's (2012) research somewhat contradicts the traditional momentum. He finds that portfolios formed based on past performance of an intermediate time horizon (12 to 7 months) appear to generate higher profits than portfolios based on short-term past performance (6 to 2 months). Thus, he argues that momentum is an inaccurate term to describe the anomaly. His findings also pose difficulties for the most common explanations that attempt to explain momentum, both rational and behavioral. His results are robust across industries and global markets.

The profitability of momentum strategies has thus been tested through numerous empirical tests across countries with mostly significant positive results. For instance, Rouwenhorst (1998) finds that the momentum trading strategy is also profitable in an international setting by finding significant results from 12 different European countries that support Jegadeesh and Titman's (1993) findings. This is supported by the findings of Barra (2010), who finds similar results in Asian, Australian, and New Zealand's stock markets. However, in certain markets, such as Japan, the momentum strategy appears to generate insignificant results. The exception of Japan was also documented by Fama and French (2012) and Asness (2010).

Momentum strategies also appear to be profitable across asset classes. Asness, Moskowitz, and Pedersen (2013) examine eight diverse asset classes and markets globally, including government bonds, currencies, futures, and stock indices. They find momentum strategies to generate significant positive returns in all asset classes. Most recently, evidence suggests that momentum strategies can yield profits in cryptocurrencies (Liu et al., 2022).

3.2 Momentum and market state

Cooper et al. (2004) find that the profitability of momentum strategies is heavily dependent on the market state. More specifically, a six-month momentum portfolio appeared to be profitable only after a period of positive market returns. When the market has experienced prolonged negative returns, the returns of momentum portfolios are diminished, though not eliminated. They also find evidence of the long-run profit reversal, which adds to the body of evidence that suggests that to a degree momentum is the result of overreaction.

Stivers and Sun (2010) also study the effect of market cycles on momentum and value premia and find that high market volatility decreases momentum premium. In other words, the momentum premium and the market state are procyclical. They favor the school of rational factors to explain the phenomenon, at least in part.

Daniel and Moskowitz (2016) conduct an extensive study on the phenomenon of momentum crashes. They also find that momentum strategies have been significantly profitable in the US for the past century, with an annual average return of 17,9% and Sharpe ratio of 0,71 in contrast to an average annual market return of 7,7% and Sharpe ratio of 0,4. However, they also record periods of time where momentum strategies yield significant negative returns persistently. They refer to these occasions as momentum crashes. Daniel and Moskowitz find that these momentum crashes typically occur during periods of high market volatility and stress, which they refer to as "panic states". The losses are particularly prevalent after a high volatility bear-market period when the stock market begins to rebound. The losses are mainly driven by the loser portfolio, as during the stock market rebound the loser portfolios tend to outperform the winner portfolio, resulting in negative returns in the WML portfolio strategy where the losers are shorted.

Grobys (2016) studies the profitability of momentum strategies during economic downturns on a global scale. Similarly to pre-existing literature, his findings support the significant profitability of momentum strategy throughout the sample during the period of 1998 to 2013. His research supports the study of Daniel and Moskowitz (2016), as the findings show that momentum strategies tend to yield significant negative returns during market rebounds following significant market declines. He also extends the study to apply Novy-Marx's (2012) intermediate time-period momentum strategy to the same sample. The results show that although the intermediate momentum strategy did not generate significant negative revenue, the strategy was unprofitable.

Ahmad et al. (2021) study the effect of the financial crisis of 2009 on the performance of momentum in the Jordanian stock market. They find that the returns of the momentum portfolios were significantly lower during the crisis than before. They suggest that the results are due to investors increased risk aversion and increased resentfulness towards the disutility of loss. They also suggest that this in turn is responsible for the momentum returns after the financial crisis. As investors sell the loser stocks in order to limit the disutility of loss, the loser stocks keep rapidly deteriorating, ultimately leading to higher momentum returns.

3.3 Explanatory theories for momentum

The research for the source of momentum anomaly tends to divide into two schools. The first group of researchers attempts to retain investor rationality and thus the validity of theories such as the EMH. They often attribute momentum returns to be a consequence of an unidentified risk factor. The second group of research seeks an answer from psychology and behavioral finance, often dismissing the current understanding of investor rationality and market efficiency as unrealistic.

3.3.1 Risk-based explanations

Berk et al. (1999) use a dynamic model to show that momentum effects can be produced at a long time horizon due to the predictable nature of optimal investment choices of individual firms. They determine that the value and price of a firm are determined by the sum of its discounted cash flows, assets, and the value of its growth potential. Therefore, when a firm detects an attractive low-risk investment, its value is rapidly increased. The expected return has a tendency to lower as the risk decreases over time, which explains short-term return reversals. On the contrary, they find that persistent expected returns and systematic risk tend to generate momentum. Therefore, momentum returns are solely the result of the bias of models that fail to account for these dynamics.

Chorda and Shivakumar (2002) argue that momentum returns can be attributable to a set of macroeconomic variables. They comprise a multifactor model consisting of lagged macroeconomic variables, which is able to capture time-varying returns. Thus, instead of irrational bias, the momentum returns could arise from rational variation in time-varying expected returns. However, Cooper et al. (2004) discredit the macroeconomic model, as they find that the model is not robust to controls for market frictions. They also find that the rational model is unable to forecast out-of-sample time-series momentum returns whereas behavioral models can.

Johnson (2002) proposes that the momentum profits are not the result of investor irrationality, heterogeneous information nor market fiction, but the result of stochastic growth rates. He finds that stock prices tend to highly depend on growth rates in a convex manner, and thus, recent stock performance correlates with the expected growth rate. If the recent positive or negative performance of the stock is due to a shock in growth rate, momentum profits are therefore fair return for the increased growth rate risk.

Avramov and Chordia (2006) argue that it may be premature to reject risk-based explanations for the momentum anomaly. According to their findings, there is a business cycle pattern in momentum returns, which could signal a systematic cause rather than an idiosyncratic one. They also find that the failure of the traditional CAPM is due to its static nature. When beta is allowed to vary in accordance with size, book-to-market, and business cycle, its explanatory power is substantially improved. Whereas the dynamic version of the asset pricing model can explain other market anomalies, the momentum returns remain robust. They suggest there could be an unidentified risk-factor causing the momentum returns instead of cognitive bias.

The suggestions of Avramov and Chordia (2006) are supported by the findings of Antoniou et al. (2007) who applied the described methodology to the European stock market. Their objective is to determine whether the source of momentum can be explained by macroeconomic factors such as the business cycle, or whether the explanation is behavioral. They find similar results in that the cause of momentum returns is the mispricing of assets. However, they suggest that the cause is not the idiosyncratic component of the stock returns, but instead business cycle variables. They extend Avramov and Chordia's (2006) study to incorporate behavioral factors. Based on the partially mixed results, they conclude that behavior is an unlikely cause for momentum and suggest the cause to be an undetected business cycle-attributable risk-factor.

Cooper, Mitrache, and Priestley (2022) motivated by the study of momentum across asset classes by Asness et al. (2013) search for an explanation for the anomaly from unidentified risk factors. Their study supports the hypothesis that the anomalous momentum returns in many asset classes and markets could be the result of exposure to global macroeconomic risk factors.

3.3.2 Behavioral explanations

Chan, Jegadeesh, and Lakonishok (1996) suggest that anomalous momentum returns could be caused by the market's gradual response to new information. They find that a substantial 41 percent of momentum profits occur around earnings announcements. They argue that whether investors surprise positively or negatively, they continue to be surprised in the same direction for the subsequent two earnings announcements. Discordant with the EMH, investors' response to the price-relevant news is not instant, but gradual. This gradual reaction to surprising news could be a source of momentum returns. Chan et al. also show that analysts' delayed adjustments in forecasts also support this theory. Contrary to Jegadeesh and Titman (1993) they do not find evidence to support the existence of return reversal when the portfolio is held for longer than a year, therefore the anomaly cannot be entirely driven by positive feedback trading. Their study shows that the profitability of momentum returns cannot be explained by market risk, size, or book-to-market value.

Barberis et al. (1998) study the prevailing occurrences of overreaction and underreaction. They find that prices persistently overreact to consistent patterns of good or bad news, and contrarily underreact to more mundane news such as earnings announcements. The authors attempt to create a model to capture investor sentiment and how they form their return expectations. They refer to research that has shown what prices tend to underreact to news within a 1–12-month time horizon. New information is incorporated in the prices with delay, thus exhibiting autocorrelating within this time period. They also point out that on a longer time-horizon of 3-5 years, investors tend to overreact to a series of good or bad news and assume continuity. As a possible psychological explanation for the behavior, they refer to the behavioral heuristic representativeness, where individuals view events as typical while ignoring probability. As an explanation for underreaction, they also appoint the conservatism bias, which is the slow updating of models when faced with new information.

Daniel et al. (1998) question the traditional concept of rational asset pricing in their study on the basis of momentum and event-based return predictability. They propose that investors tend to under- and overreact due to two persistent psychological biases: investor overconfidence and biased self-attribution. They find evidence that suggests that investor overconfidence entails negative long-lag autocorrelation, volatility, and event-based return predictability, whereas biased self-attribution results in short-run earnings drift, positive short-lag autocorrelation and negative correlation between past performance and future performance in the long term. They find that if an investor receives positive outcomes from an investment, they often attribute the success to skill and knowledge, whereas negative outcomes are attributed to bad luck. This drives the price of the stock up in the short-term, however, this distortion is fixed in the long-term causing eventual price reversal. These findings are consistent with the findings of Jegadeesh and Titman (1993).

Hong and Stein (1999) propose a model to capture the under- and overreaction of investors in a stock market. They introduce two categories of investors: news-watchers and momentum traders. The news-watchers are characterized as investors who observe price-relevant news and estimate stock prices privately, but not based on historical price data. Private information diffuses across the news-watchers gradually, which leads to an initial underreaction to the news. The other group of investors, the momentum traders, base their investment decisions solely on price data and past performance. The initial delay in the incorporation of information allows the momentum traders to profit from trend-chasing, leading to price increases and eventual overreaction.

Chui et al. (2010) provide supporting evidence for Hong and Stein's (1999) theory. They study the cross-country relationship between momentum profits and the individualism index, which is related to self-attribution bias and overconfidence. Their evidence suggests that the profitability of momentum strategies is highly associated with the level of individualism in a country. Momentum strategies appear to yield higher profits in countries that score relatively higher on the individualism index. The cross-country differences in the level of bias and overconfidence investors are affected by could vary due to cultural reasons. This finding could potentially explain the Japan exception (Fama & French, 2012; Asness, 2010).

4 Data and methodology

This chapter outlines the methodology used in the empirical portion of this thesis. The first portion describes the data which was used, why it was chosen, and how it was obtained. Limitations and adjustments that were made to the data are also disclosed. The next portion describes the event studied in this thesis, which is the crisis caused by the COVID-19 virus. The characteristics of the period are briefly introduced, as well as how the crisis period was limited in this study specifically. The next subsections describe the methodology of the study, which consists of two parts. The first part describes how the Jegadeesh and Titman (1993) methodology was applied in this thesis in constructing the overlapping cross-sectional momentum portfolios. The second part describes how the event study of this thesis was conducted and how the profitability of the constructed portfolios is evaluated before and during the crisis.

4.1 Data

This thesis uses closing price data from stocks of the Finnish stock market between the years 2016 and 2022. The sample includes all stocks listed on the OMX Helsinki stock market, including stocks that have been removed from the market within the data period to avoid survival bias. Survival bias refers to the phenomenon where the results of the study appear (fallaciously) profitable due to the exclusion of delisted stocks, which could have performed poorly due to approaching bankruptcy for instance (Elton et al. 1988). As not all stocks remain in the stock market during the whole study period, the number of observations varies monthly throughout the data sample. In addition, the data is fixed to account for any possible stock splits. Banking and financial service stocks are removed from the sample as was done by Jegadeesh and Titman (1993) in their momentum strategy methodology replicated in this study, and as is common practice in financial research. In the final sample, 208 stocks were listed on the Helsinki stock exchange between the years 2016 and 2022. The number of active stocks varies between 137 and 180.

The data period begins at the beginning of 2016 and ends at the end of 2022. This sample period was chosen to exclude the effects of other preceding crises, as this study focuses solely on the effect of COVID-19. The data period is extended to 2016 in order to get a baseline for the typical profitability of the momentum strategies outside of crisis periods.

This study uses OMX Helsinki Cap as a benchmark index as the indicator of market returns in the Finnish stock market. OMX Helsinki Cap index includes all stocks from Helsinki Stock Exchange, but with the limitation that no single stock's weight surpasses 10%. Any momentum returns exceeding the market returns are considered abnormal. The daily return data of OMX Helsinki Cap are retrieved from Nasdaq. Lastly, the risk-free rate used in this study is the Finnish government benchmark bond yield which is retrieved from the Bank of Finland.

This study excludes the effects of dividends. Although dividends affect the profitability of portfolios in a realistic setting, they are not considered in this study as the momentum anomaly is based solely on the short-term autocorrelation of price. No evidence seems to suggest that the changes in the past prices of an asset have predictive power on upcoming dividends, thus it is unlikely that dividends are the source of the momentum strategy's profitability. Therefore, the presence of momentum and the effect COVID-19 had on the strategy should be measurable solely based on price data, therefore it is not seen as necessary to include dividends in the empirical study.

4.2 Crisis period

At the end of 2019, a new strand of a coronavirus called COVID-19 was discovered. Soon after the infectious disease spread worldwide causing a global pandemic. Due to its elevated mortality rate, many countries imposed extreme measures in an attempt to halt the spread of the virus. These actions along with general panic had substantial effects on all aspects of modern life, including the global economy and financial markets. Before COVID-19, no past pandemic had had a significant impact on the US stock market, yet the recent coronavirus caused unprecedented market moves during the last few years (Baker et al. 2020). Kahn et al (2023) find exceptionally high volatility in financial returns in all six major financial markets, describing the prevailing conditions as “catastrophic” for the investors.

For the purpose of this study, the crisis period is limited from 1.3.2020 until the end of 2022. Although the market crash of COVID-19 was fast lived, the crisis period examined in this study is extended to include the market recovery period. The EURO STOXX 50 Volatility index was used to establish an appropriate crisis start date. The VSTOXX index is based on option prices in the Eurozone and is designed to reflect the expectations of investors in the Euro market through implied variance. The VSTOXX is the European counterpart of the US VIX index. There is no set limit to what VSTOXX level is considered normal. The VSTOXX mean from 2016 to 2022 is 20,83. There is a rapid increase in VSTOXX beginning from 28.2.2020 when the price spikes to 42,24. The highest volatility peak is reached on 16.3.2020 when the VSTOXX price goes up to 85,62. As this study uses monthly returns, the beginning of the crisis period is rounded to start on 1.2.2020 to include the initial shock in the crisis period.

As Daniel and Moskowitz (2016) found, the momentum crash is the most prevalent during the time after the crisis when the market begins to rebound. Therefore, we should expect to find most of the potential negative returns post-crisis. In addition to the COVID-crisis, another global crisis, the Russian attack on Ukraine, happened shortly after. This caused another spike in VSTOXX on 24.2.2022. Thus, it can be presumed that the market remains in a state of elevated crisis from February 2020 until the end of 2022.

4.3 Portfolio construction

The portfolio formation is done based on previous studies on the momentum anomaly, most notably based on the original study by Jegadeesh and Titman (1993). To test autocorrelation in the price changes of stock, they create a trading strategy which consists of two periods J and K, the observation and holding period. T is the moment between observation and the holding period where the best-performing stocks are bought, and worst-performing stocks are sold. In this study the moment t is the first working day of each month. During the observation period J, the stocks in the stock universe are observed for a period of t-3, 6, 9, or 12 months. In this study, the observed stocks are the stocks of the Helsinki Stock Exchange during the years of 2016 and 2022 excluding the banking and financial service stocks. After the observation period, the stocks are ranked from best to worst performing based on their return. The return of a stock is calculated with formula 7 below.

$$R_{it} = P_{it} - P_{it-J} \tag{9}$$

Where R_{it} is the return of the stock at the time t, P_{it} is the price of the asset at the time t, and P_{it-J} is the security price at the beginning of the observation period.

The ranked stocks are grouped into quintiles, after which the best-performing 15% is bought long, and the worst-performing 15% of the stocks are shorted. They bought stocks to create the W portfolio, and shorted stocks are the L portfolio. All stocks are equally weighted in the portfolio. The returns of these two portfolios create the Winner Minus Loser (WML) zero-cost portfolio, which is held for the J period of t+3, 6, 9, or 12 months. Since the data sample includes data from stocks that have been listed or delisted during the observation period, only stocks that have data for the whole portfolio observation and holding period are considered at every formation moment t.

The WML portfolio is constructed and held for all the possible combinations of 3, 6, 9, and 12 months, totaling 16 different portfolio combinations. The portfolio is rebalanced at the end of every holding period J, where the best and worst performing 15% of stocks is bought and shorted based on the performance during the observation period K. Jegadeesh and Titman (1993) use deciles in their original methodology which is replicated in this thesis, however, a portfolio segment of 20% is also very common in momentum research. This study uses 15% as it is the average between the two, and allows to generate portfolios large enough to mitigate radical effects of random variance, but limited enough to possibly differ from the market average.

Jegadeesh and Titman (1993) also present a version of a strategy where the portfolios are rebalanced monthly during the holding period. However, the difference in results was small, and they find the buy-and-hold strategy slightly more profitable, so therefore the buy-and-hold strategy will be the only one tested in this thesis. Corresponding with the study by Jegadeesh and Titman, all 16 combinations of strategies are formed at the beginning of every month on a rolling basis with overlapping holding periods, and the portfolio returns are analyzed based on rolling averages. The overlapping of the portfolios is illustrated below with the example of the J3K3 portfolio.

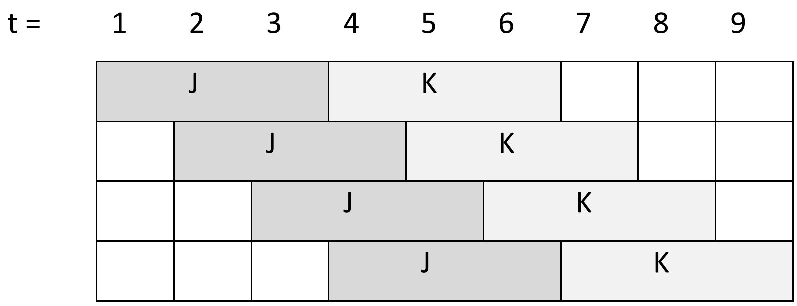


Figure 1. Rolling portfolio formation example J3K3

4.4 Performance evaluation

The profitability of the momentum portfolios is analyzed using several relevant metrics. Firstly, the average arithmetic monthly returns of each portfolio J-K combination are presented in Table 5.1. The loser and winner portfolios are also presented separately to indicate which one generates most of the profit. A paired Student's t-test is used to assess whether the momentum profits significantly vary from the market index or whether they are merely a result of the typical variance. The portfolio returns are calculated with the formula below.

$$R_p = \sum_{i=1}^{n} w_i r_i \quad (10)$$

Where w_i is the weight of the stock, and r_i is the return of the stock.

Abnormal returns refer to revenue that exceeds the expected level. The expected returns are proxied by the OMX Helsinki Cap index realized returns. The abnormal returns are calculated by subtracting the monthly market returns from the monthly portfolio returns as shown in formula 11. The abnormal profits of each portfolio combination are presented both monthly and cumulatively before and during the crisis period.

$$AR_{it} = R_{it} - R_{mt} \quad (11)$$

Student's t-test displayed in formula 12 is used to evaluate the significance of the findings. Student's t-test is a commonly used statistical hypothesis tool that measures whether the means of two groups significantly differ from each other. The null hypothesis states that there is no significant difference between the two means, while the alternative hypothesis suggests that there is a significant difference. Each t-value is compared to its respective critical value to determine whether the null hypothesis can be rejected. If the t-value exceeds the critical value, the null hypothesis can be rejected, and we can assess that evidence suggests the observed group is significantly different from the reference group. If the t-value does not exceed the critical value, we accept the null hypothesis and assume the groups do not significantly differ.

$$t = \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}} \quad (12)$$

Where $\bar{x}$ is the mean of the differences between the two groups, μ is the population mean difference, σ is the standard deviation of the differences and n is the number of paired observations.

A multiple linear regression model is produced based on the Single Index Model presented in chapter two with the following formula:

$$R_{WML,i,t} - R_f = \propto_0 + \beta_1(R_{mt} - R_f) + \beta_2 D_t + \varepsilon_t \quad (13)$$

Where $R_{WML,i,t}$ is the return of the zero-cost portfolio WML at the time t, R_{mt} is the market return at the time t proxied by the OMX Helsinki Cap index return, R_f is the Finnish benchmark yield for 10-year government bonds, and D_t is the dummy variable which takes on the value 1 during crisis, and 0 outside of crisis period. The model is constructed to understand whether the state of crisis had a significant effect on the profitability of the momentum portfolios. A negative dummy coefficient would indicate that the performance of the momentum portfolios was negatively affected during the crisis.

To further assess the momentum strategies' abnormal profits, a risk-adjusted Single Index Model (formula 5) is produced for the pre-COVID-19 period and COVID-19 period portfolios separately. The output allows to inspect the alpha coefficients for excess returns beyond the market index and the beta coefficients show the possible change in risk during the two periods. The differences between coefficients between the time periods as well as the significance levels will be compared.

5 Results

This chapter aims to present and analyze the findings derived from the methodology described in the preceding chapter. The objective is to examine the impact of COVID-19 on the profitability of momentum strategies in the Finnish stock market. Hypothesis H1 posits that there is a significant difference between the profitability of the momentum WML portfolios before to crisis and during the crisis. In the event that the results of the study do not indicate any significant difference, the null hypothesis will be accepted, meaning that COVID-19 did not exert a significant impact on the profitability of the portfolios.

Table 1 presented below displays the average monthly returns for each formation combination for the entire data period. It is important to acknowledge that each formation combination contains a different number of portfolios. The variation arises since the sample period can fit fewer portfolios with longer observation as opposed to shorter observation and holding periods. The best-performing WML portfolio is highlighted in green and the worst-performing in red.

J	K =	3	6	9	12
3	W	1,470 % (1,6346)	1,505 % (2,4847)	1,524 % (2,9915)	1,344 % (2,3967)
	L	0,031 % (-2,9197)	-0,126 % (-5,2763)	0,048 % (-4,5338)	-0,091 % (-5,8775)
	WML	**1,439 %** (1,0679)	**1,631 %** (2,5512)	**1,476 %** (2,0548)	**1,435 %** (1,9541)
6	W	1,653 % (2,4626)	1,620 % (3,4283)	1,520 % (3,453)	1,494 % (3,1492)
	L	-0,116 % (-3,1011)	-0,098 % (-3,9068)	0,041 % (-3,7802)	0,008 % (-4,1144)
	WML	**1,769 %** (1,9255)	**1,718 %** (3,325)	**1,479 %** (2,4122)	**1,486 %** (2,3345)
9	W	1,783 % (3,2429)	1,554 % (3,3372)	1,393 % (2,901)	1,440 % (2,7819)
	L	0,027 % (-2,2192)	-0,104 % (-3,7694)	0,073 % (-3,3473)	-0,024 % (-4,2131)
	WML	**1,756 %** (1,8242)	**1,658 %** (3,1435)	**1,320 %** (1,8683)	**1,464 %** (2,3467)
12	W	1,592 % (2,8571)	1,355 % (2,8862)	1,289 % (2,5153)	1,476 % (2,6259)
	L	-0,016 % (-2,1162)	-0,036 % (-3,1764)	0,048 % (-3,154)	0,086 % (-3,065)
	WML	**1,608 %** (1,5927)	**1,391 %** (2,4055)	**1,241 %** (1,8044)	**1,390 %** (1,991)

Table 1. Average monthly returns of winner, loser, and WML portfolios during the whole data period

The provided table presents the average monthly return of each portfolio expressed as a percentage, along with the corresponding paired t-test value displayed in brackets. As said, portfolio samples consist of a different number of observations due to the different number of portfolios that fit within the time window. Consequently, the degrees of freedom vary from 62 to 80, thus the t-test critical values at the confidence level of 95%

are approximately 1,66-1,67. All paired t-test values except the J3K3WML and J3K3 loser portfolio t-values exceed the critical value. Based on this, it can be concluded that during the entire data period, most of the winner, loser, and WML momentum portfolios yield revenues that differ from the market enough to not be mere results of random variance.

An important observation from the above table is that the winner portfolios consistently exhibit higher returns compared to the loser portfolios. In most cases, the loser portfolios yield negative returns, which results in increased profit in the WML portfolio where the loser stocks are shorted. Even in the cases where the loser portfolio has yielded positive returns, the returns are low. This correlates with most literature on the momentum anomaly, where studies consistently find that the best-performing stocks tend to continue performing well in the near future, and vice versa in the case of the most poorly-performing stocks (Jegadeesh and Titman 1993; Rouwenhorst 1998; Barra 2010).

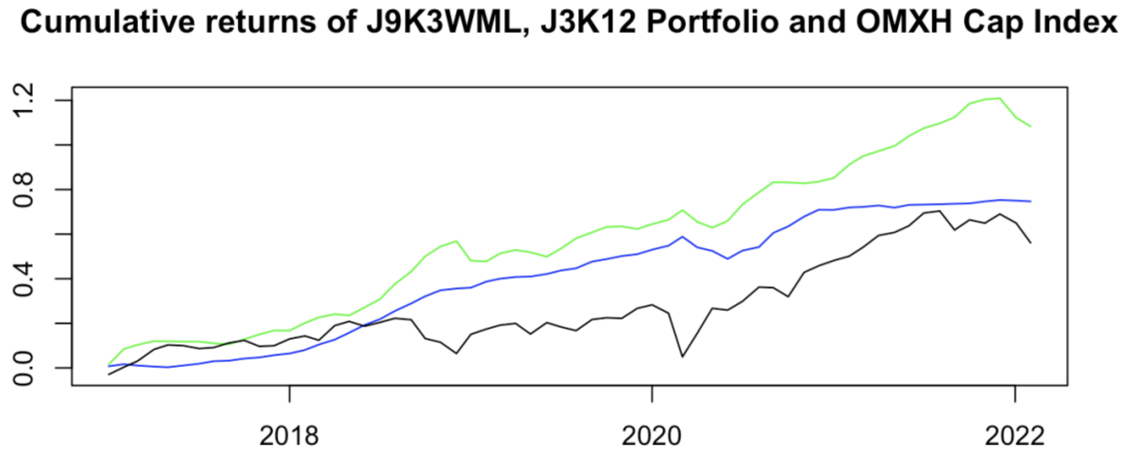
Throughout the entire data period, the monthly return of the OMX Helsinki Cap Index averaged 0,908%. It can be observed that each WML portfolio yielded higher returns on average in comparison to the market’s monthly average. However, it is important to note that the monthly returns are based on averages of multiple overlapping portfolios. Although all momentum portfolios beat the market on average, it does not imply that all individual portfolios performed better than the market. The most profitable WML portfolio combinations based on the monthly averages were the J6K3 and J9K3 portfolios with the monthly average return of 1,769% and 1,756%, respectively. Conversely, the least profitable strategy was the J12K9 portfolio with an average return of 1,241%. These findings are consistent with previous literature that has found momentum strategies to consistently outperform the market. Overall, it can be inferred that momentum strategies are likely to be profitable in the Finnish stock market in general.

Table 2 illustrates the cumulative returns of all zero-cost momentum portfolios during the entire data period. The data period has been adjusted so that the first and last portfolio formation moment t is the same for each portfolio so that there is an equal number of months' returns cumulated in each strategy. The total number of months in this period is 62. Consequently, the cumulative average returns are based on a different number of months than the average monthly returns in Table 1.

J	K =	3	6	9	12
3		85,78 %	98,38 %	90,80 %	74,68 %
6		107,70 %	103,60 %	89,00 %	101,06 %
9		108,29 %	103,47 %	81,51 %	88,93 %
12		102,59 %	87,43 %	79,57 %	86,20 %
Benchmark		56 %			

Table 2. Cumulative returns of WML portfolios during whole data period

Similar to the monthly return table, the portfolio combinations J6K3 and J9K3 emerged as the most successful. Over the entire data period, the most profitable portfolios generated a return of 107,70% and 108,29% as opposed to the benchmark index which yielded a cumulative revenue of 56%. Based on the 62-month cumulative returns the least profitable strategy combination was found to be J3K12, which generated a revenue of 74,68%, outperforming the market, nonetheless. The graph below visualizes the cumulative revenues of the most profitable strategy J9K3, the least profitable strategy J3K12 and the market return.



■ J3K12 WML portfolio cumulative returns

■ J9K3 WML portfolio cumulative returns

■ OMX Helsinki Cap Index cumulative returns

Figure 2. Cumulative returns of J9K3WML, J3K12WML and OMX Helsinki Cap Index

J	K=	3	6	9	12
3	W	1,007 % (1.232)	1,099 % (2.2246)	1,177 % (2.5443)	1,140 % (2.2663)
	L	-0,319 % (-2.9551)	-0,426 % (-5.4069)	-0,406 % (-6.5224)	-0,603 % (-8.496)
	WML	**1,326 %** (1.1711)	**1,525 %** (2.6743)	**1,582 %** (3.314)	**1,744 %** (4.3081)
6	W	1,229 % (2.1629)	1,224 % (2.811)	1,168 % (2.5777)	1,179 % (2.5769)
	L	-0,411 % (-2.3405)	-0,454 % (-3.7106)	-0,542 % (-5.9371)	-0,589 % (-5.77)
	WML	**1,640 %** (1.6343)	**1,678 %** (2.8914)	**1,710 %** (3.9337)	**1,769 %** (4.145)
9	W	1,254 % (2.6457)	1,026 % (2.3365)	0,992 % (2.1511)	1,107 % (2.2546)
	L	-0,610 % (-2.8609)	-0,807 % (-5.4631)	-0,750 % (-6.9103)	-0,739 % (-6.4248)
	WML	**1,864 %** (2.0921)	**1,832 %** (3.5959)	**1,742 %** (4.2419)	**1,846 %** (4.3835)
12	W	0,895 % (1.7233)	0,839 % (2.0493)	0,868 % (2.0435)	1,043 % (2.1662)
	L	-0,883 % (-2.8385)	-0,871 % (-4.6955)	-0,952 % (-7.2184)	-0,761 % (-6.1998)
	WML	**1,779 %** (1.9714)	**1,711 %** (3.8094)	**1,820 %** (4.7734)	**1,804 %** (4.9278)
Benchmark			1,024 %		

Table 3. Average monthly returns before COVID-19 period

Table 3 above displays the average monthly returns of each winner, loser, and winner minus loser portfolio for the time period preceding the COVID-19 crisis. Nearly all portfolios exhibit significant t-values, except for the J3K3 winner portfolio and the J3K3 WML portfolio. Consequently, the null hypothesis must be accepted for these portfolios, meaning that the generated revenues do not significantly deviate from typical market variance.

Each WML portfolio yielded a monthly average higher than the market average, which stood at a monthly average return of 1,024%. The highest revenue is again yielded by the J9K3 portfolio, which is 0,840% higher than the market average. Most winner portfolios generated positive returns either slightly over or below the market index. The loser portfolios consistently yielded negative returns across all strategy combinations. Overall, from the results it can be concluded that most of the winner-minus-loser portfolios were significantly profitable in the Finnish stock market between the dates 1.1.2016 and 31.1.2020.

J	K=	3	6	9	12
3	W	2,096 % (1,2455)	2,107 % (1,7174)	2,095 % (1,8907)	1,719 % (1,1549)
	L	0,504 % (-1,1253)	0,319 % (-2,1255)	0,794 % (-0,81641)	0,853 % (-0,98263)
	WML	**1,592 %** (0,27365)	**1,787 %** (1,0617)	**1,302 %** (0,10573)	**0,866 %** (-0,52416)
6	W	2,190 % (1,6215)	2,169 % (2,2534)	2,060 % (2,313)	2,036 % (1,8832)
	L	0,257 % (-2,0111)	0,396 % (-1,7801)	0,937 % (-0,51003)	1,036 % (-0,5822)
	WML	**1,979 %** (1,0206)	**1,773 %** (1,6727)	**1,123 %** (-0,11856)	**1,000 %** (-0,1794)
9	W	2,404 % (2,2755)	2,236 % (2,5441)	1,964 % (1,9697)	1,972 % (1,6655)
	L	0,776 % (-0,52104)	0,803 % (-0,6528)	1,248 % (0,29519)	1,118 % (-0,34434)
	WML	**1,628 %** (0,43301)	**1,433 %** (0,74328)	**0,716 %** (-0,99258)	**0,853 %** (-0,51971)
12	W	2,351 % (2,3603)	1,971 % (2,0964)	1,846 % (1,5737)	2,117 % (1,6064)
	L	0,928 % (-0,27844)	0,961 % (-0,28466)	1,371 % (0,68601)	1,339 % (0,24899)
	WML	**1,423 %** (0,14107)	**1,010 %** (-0,41974)	**0,475 %** (-1,9573)	**0,778 %** (-0,62722)
Benchmark		0,916 %			

Table 4. Average monthly returns during the COVID-19 period

Table 4. presents the average monthly returns of all winner, loser, and WML portfolios during the COVID-19 crisis period. Nearly all WML portfolios yielded lower returns during crisis in comparison to the control period before. The only exceptions are the portfolios J3K3, J3K6, J6K3, and J6K6. However, none of the mentioned portfolios have a t-value that exceeds the critical value on a 5% significance level, though the J6K6 t-value is

significant on a significance level of 10%. Thus, we must assume that the portfolios are market neutral. This applies to most of the WML portfolios, as the only two WML portfolios that have a t-value that surpasses the critical value are J6K6 and J12K9. Therefore overall, we cannot state that the momentum strategy was significantly different from the ordinary market variance during COVID-19.

Even though the WML results are insignificant, most of the WML portfolios appear to outperform the market despite the assumptions based on previous studies on momentum during crisis. Daniel and Moskowitz (2016) found in their study that WML portfolios tend to yield significant negative revenues post-crisis, often driven by positive loser portfolio revenues. This contradicts the findings of Table 4, as none of the WML portfolios yielded significant negative returns. However, Daniel and Moskowitz's (2016) find that the loser portfolios tend to yield high positive returns during the crisis recovery period, which is consistent with the findings of this thesis. Table 4 shows that the loser portfolios yield positive returns with all observation and holding period combinations which reduce the overall WML profits. However, the loser portfolios' t-values exceed the critical values only in cases of J3K6, J6K3, and J6K6. The positive returns of the rest of the loser portfolios have to be accounted for by random variance.

As said, despite the negative revenues yielded by the shorted loser portfolios, none of the WML portfolios yielded significant negative returns. It appears the negative returns of the loser portfolios were outset by the winner portfolio revenues which were notably higher compared to the pre-COVID-19 time period, as well as the benchmark of the crisis period. Thus, although the shorted portfolio generated negative returns, the positive returns of the winner portfolios were high enough to cause the WML to remain profitable. Most of the winner portfolios yielded highly significant returns. One reason for this could be that the COVID-19 crisis was exceptionally short in comparison to other past crises, thus the effect of the crisis is muted.

The above findings are also consistent with some of the findings of Ahmad et al. (2021) who find that the returns of the zero-cost WML portfolios in their study of the Jordanian stock market yielded significantly lower returns after the financial crisis compared to their returns before the crisis. However, they find that the returns of the WML portfolios were statistically insignificant before to crisis as opposed to during it, where six of the portfolios they tested were significant. This conflicts with the findings of this study, where contrariwise the WML returns before the crisis are statistically significant, and the returns during the crisis are insignificant.

J	K= 3	6	9	12
3	0,540 %	0,804 %	0,831 %	0,966 %
6	0,942 %	1,028 %	1,037 %	1,091 %
9	1,216 %	1,259 %	1,178 %	1,252 %
12	1,235 %	1,288 %	1,361 %	1,289 %

Table 5. Average monthly abnormal returns of momentum portfolios before COVID-19 crisis

The abnormal returns were calculated as expressed in Formula 11 by subtracting the market index revenues from the portfolio revenues. Table 5.5 above presents the average monthly abnormal profits of each portfolio combination during the time-period before COVID-19. All portfolios yielded positive excess returns before the crisis period. The highest excess returns were yielded by the J12K9 portfolio, whereas the lowest abnormal profits were yielded by the J3K3 portfolio.

J	K= 3	6	9	12
3	0,477 %	0,694 %	0,046 %	-0,302 %
6	0,716 %	0,367 %	-0,105 %	-0,168 %
9	0,280 %	0,002 %	-0,585 %	-0,315 %
12	-0,002 %	-0,473 %	-0,767 %	-0,390 %

Table 6. Average monthly abnormal returns of momentum portfolios during COVID-19 period

There is a notable difference in the mean abnormal profits of the zero-cost portfolios during the crisis period. All portfolios yielded less abnormal profits during the crisis than in normal conditions. Most notably the portfolios with the longer hold periods have performed poorly, yielding high negative abnormal returns. The J12K9 portfolio which was the most profitable prior to the crisis has in fact performed the worst during the crisis. This is likely driven by the high positive revenues of the shorted loser portfolio as shown in table 4, which turned highly positive during the crisis.

J	K = 3	6	9	12
3	13,497 %	20,098 %	20,781 %	24,161 %
6	23,562 %	25,691 %	25,931 %	27,271 %
9	30,397 %	31,481 %	29,443 %	31,294 %
12	30,867 %	32,193 %	34,030 %	32,236 %

Table 7. Cumulative abnormal returns before COVID-19

J	K = 3	6	9	12
3	11,936 %	17,341 %	4,381 %	-7,542 %
6	20,447 %	16,995 %	-0,100 %	-4,195 %
9	12,841 %	8,498 %	-10,255 %	-7,872 %
12	7,702 %	-2,091 %	-16,301 %	-9,755 %

Table 8. Cumulative abnormal returns during COVID-19

The cumulative abnormal returns for the period before the crisis and during the crisis are presented in tables 7 and 8. The time periods have been adjusted so that an equal number of observations is calculated for each value. The results are also adjusted so that the cumulative returns before and during the COVID-19 period are comparable. Same as the monthly abnormal returns, half of the portfolios overall yield positive abnormal returns during crisis and half yield negative returns. Shorter holding periods appear more profitable, whereas all the portfolios with a three-month holding period yielded positive abnormal returns even during the crisis. On the contrary, all portfolios with the 12-month holding period yielded negative abnormal returns.

K =	3			6		
J	Alpha	Beta	Dummy	Alpha	Beta	Dummy
3	0,00670*	0,5022***	0,00284	0,0097***	0,3342***	0,0026
	(1,445)	(3,931)	(0,404)	(3,134)	(2,820)	(0,545)
6	0,01021**	0,3983***	0,00292	0,01152***	0,2935***	0,00097
	(2,096)	(3,044)	(0,402)	(3,794)	(2,600)	(0,209)
9	0,01197***	0,5485***	-0,0022	0,0130***	0,32780***	-0,0041
	(2,613)	(4,572)	(-0,322)	(4,784)	(3,325)	(-1,001)
12	0,01190***	0,3946***	-0,0039	0,0121***	0,24423***	-0,0070**
	(-2,502)	(3,270)	(-0,563)	(4,561)	(2,590)	(-1,76)
K =	9			12		
J	Alpha	Beta	Dummy	Alpha	Beta	Dummy
3	0,0104***	0,3741****	-0,0029	0,01166***	0,4349***	-0,0092**
	(3,605)	(2,803)	(-0,623)	(4,342)	(2,851)	(-1,991)
6	0,0121***	0,2713***	-0,0054*	0,01220***	0,41190***	-0,0081*
	(4,923)	(2,436)	(-1,372)	(4,255)	(2,576)	(-1,657)
9	0,0123***	0,3289***	-0,0103***	0,01285***	0,6033***	-0,0128***
	(5,328)	(3,176)	(-2,794)	(4,498)	(3,722)	(-2,603)
12	0,01347***	0,3131***	-0,0137***	0,0129***	0,6856***	-0,0147***
	(6,143)	(3,240)	(-3,959)	(3,716)	(3,527)	(-2,473)

Statistical significance levels: *** 1%, ** 5%, * 10%

Table 9. Extended risk-adjusted Single Index Model for the whole period

Table 9 presents the results of the extended Single Index Model for the whole data period. The t-value is presented in brackets for each respective coefficient. In the Single Index Model, the alpha represents the profits of the assets that exceed the expected market revenue. During the whole period, all portfolios appear to have yielded abnormal profits exceeding the market index, based on the positive alpha coefficients. All the alphas are statistically significant on a 99% confidence level except for J3K3 and J6K3, which are significant on 90% and 95% confidence levels respectively.

The crisis dummy coefficient represents the effect the presence of the COVID-19 period had on the typical performance of the portfolios. The crisis dummy coefficients are mostly negative, except for portfolios J3K3, J3K6, J6K3, and J6K6. However, none of the positive dummies are statistically significant. Thus, the null hypothesis will be accepted and we assume that COVID-19 did not significantly affect the profitability of the portfolios in the cases where the coefficient was positive. The same applies to portfolios J3K9 and J6K9, which both also had an insignificant dummy coefficient, although negative.

However, for all of the statistically significant coefficients, we can reject the null hypothesis and assume that the state of crisis has negatively affected the performance of the portfolio. As an example, the J9K9 portfolio's crisis variable has a coefficient of -0,0103 with a confidence level of at least 99%. Therefore, we can assume that on average any additional unit of revenue yielded from the J9K6 portfolio is lowered by 1,03% during crisis as opposed to normal conditions.

K =	3		6		9		12	
J	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta
3	0,0070* (1,663)	0,4483** (1,945)	0,0119*** (5,473)	-0,1681 (-1,046)	0,0129*** (6,575)	-0,2848* (-1,537)	0,0127*** (5,315)	0,1785 (0,759)
6	0,0115** (2,225)	0,1635 (0,581)	0,0139*** (4,757)	-0,2782 (-1,299)	0,0144*** (6,800)	-0,3916** (-1,961)	0,0136*** (5,520)	0,0129 (0,052)
9	0,0125*** (2,695)	0,4307* (1,686)	0,0149*** (5,75)	-0,2618* (-1,35)	0,0139*** (6,554)	-0,3158* (-1,463)	0,0145*** (5,889)	-0,1422 (-0,493)
12	0,0120*** (2,365)	0,3698 (1,330)	0,0130*** (5,353)	-0,1573 (-0,845)	0,0141*** (6,667)	-0,3063 (-1,273)	0,0141*** (6,372)	-0,3724 (-1,304)

Statistical significance levels: *** 1%, ** 5%, * 10%

Table 10. Risk-adjusted Single Index Model pre-crisis

K =	3		6		9		12	
J	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta
3	0,0095*	0,5189***	0,0113**	0,4996***	0,0056	0,5562***	0,00098	0,54246**
	(1,534)	(3,059)	(2,295)	(2,841)	(1,062)	(2,775)	(0,181)	(2,391)
6	0,0130***	0,4671***	0,0113***	0,4731***	0,0049*	0,4491***	0,0019	0,5700***
	(2,467)	(3,234)	(3,201)	(3,742)	(1,370)	(3,298)	(0,352)	(-2,448)
9	0,0097**	0,5808***	0,0078***	0,4986***	0,00057	0,47305***	-0,0028	0,8156***
	(1,923)	(4,184)	(2,687)	(4,827)	(0,189)	(4,119)	(-0,578)	(3,934)
12	0,0080*	0,4010***	0,0045	0,3518**	-0,0013	0,4218***	-0,0051	0,9267**
	(1,689)	(3,078)	(1,450)	(3,187)	(-0,520)	(4,335)	(-0,773)	(7,830)

Statistical significance levels: *** 1%, ** 5%, * 10%

Table 11. Risk-adjusted Single Index Model during COVID-19 period

Tables 10 and 11 present the results of two Single Index Models divided into two time periods. The results are also robust with earlier findings in the sense that especially the alphas of the portfolios with longer holding and observation periods have been negatively affected by the crisis in comparison to the preceding time period. The alphas pre-crisis are all significant and positive, indicating that the WML portfolios yielded significant abnormal returns before COVID-19. On the contrary, during the crisis, the only alphas with significant positive returns appear with holding periods of 3 and 6 months. This means that during COVID-19 the WML portfolios with longer holding periods did not yield revenues that exceeded the market index.

The alphas of the WML portfolios with longer holding periods all have an alpha close to or below zero. Based on low alpha coefficients and statistically insignificant t-values we can conclude that the WML portfolios with longer holding periods did not yield abnormal revenues during COVID-19. An exception to this is the J6K9 portfolio which has an alpha of 0,0049 which has a significance level of 10%. The J3K9 alpha pre-crisis was 0,0144 with a significance level of 1%, therefore the excess returns of the portfolio were significantly negatively impacted by the crisis.

An interesting observation from the results of the Single Index Models is the changing signs of betas. Before the crisis, many of the betas of the portfolios were negative whereas during COVID-19 all betas were positive. A possible driver for this could be the change in the performance of the loser period before and during the crisis. As seen in tables 3 and 4, the shorted loser portfolios started yielding positive returns during COVID-19. Preceding the crisis, a loser portfolio yielding high negative returns resulted in positive returns for the WML portfolio. Therefore, when a market experienced a drop, the loser portfolios yielded high returns for the WML portfolios. This could result in a negative beta. On the contrary, during COVID-19 the market experienced an extremely brief but extensive drop resulting in short-term loser portfolio profits, after which the market entered a long recovery period. During the recovery period, the loser portfolios experienced positive returns, resulting in negative returns for the WML portfolio. However, as indicated by tables 3 and 4 the increase in the revenues of the winner portfolios was so significant during the recovery that it mitigated the negative returns caused by the loser portfolio. On the contrary, the negative returns yielded by the shorted portfolio reduced the high revenues of the winner portfolio. Overall, the significance of the winner portfolio was amplified during the crisis, causing the WML portfolio revenues to positively correlate with the market.

Additionally, each beta was higher during the crisis whereas before the crisis each beta was closer to zero. This could indicate that before COVID-19, the WML portfolios included less risk in comparison to the crisis period. The betas during COVID-19 were also all statistically significant in comparison to pre-crisis when most betas were statistically insignificant.

The findings of this study correlate with some of the prior research conducted on momentum crashes. As said, studies have found that at times of high market volatility and panic momentum portfolios seem to perform worse (Cooper et al. 2004; Stivers & Sun 2010; Daniel & Moskowitz 2016; Grobys 2016; Ahmad et al. 2021). However, much of the prior research has found that momentum strategies yield significant persistent negative returns during a crisis. This was not the case in this study, as although most portfolios were significantly negatively impacted by the crisis period, the portfolios still appeared to yield overall positive returns. One reason for this could be the short duration of the COVID-19 crisis, due to which the crisis period included too much recovery time after the crisis.

As said, there is yet no conclusive explanation as to what causes momentum returns. Therefore, there is no explanation as to why the momentum strategies experience crashes during a crisis. Ahmad et al. (2021) suggest that investors' increased risk-averseness and conservatism are the driving force behind momentum's declined performance during times of high uncertainty. Other common behavioral explanations for the existence of momentum are the overconfidence of investors and self-attribution bias (Barberis et al. 1998; Daniel et al. 1998). It is possible that as investors begin to receive negative feedback during a crisis, the abnormally high returns cease and are fixed to their fundamental level. Hong and Stein (1999) suggest that momentum exist because investors are divided into two groups: the news-watchers and momentum investors, where the news-watchers observe the market and invest based on the given information although with delay, whereas the momentum traders attempt to gain profits from trend-chasing based solely on past performance. This behavior ultimately causes the prices of stocks to increase above their fundamental level. This theory could also be applied to a state of crisis, where the price of assets is driven below their fundamental level due to Hong and Stein's described investor's habits.

6 Conclusion

This thesis aims to determine whether the COVID-19 pandemic had a significant impact on the profitability of momentum strategies in the Finnish stock market. A vast body of literature has shown that momentum strategies tend to yield persistent positive abnormal returns across different markets and asset classes. However, despite the extensive research the source and behavior of the anomaly are still widely unknown. Research has found that momentum strategies tend to experience what is referred to as a momentum crash at times of high market volatility and uncertainty. In momentum crashes the momentum portfolios have yielded significant negative returns. Most notably, these negative returns seem to occur post-crisis as the market rebounds from a significant drop.

This study used the methodology of Jegadeesh hand Titman (1993) in forming 16 combinations of cross-sectional momentum portfolios from the stocks of the Finnish stock market. The price data collected spanned from 2016 until the end of 2022, during which overlapping portfolios were formed monthly. An event study was conducted on the portfolios to deduce whether the COVID-19 crisis period significantly affected the portfolio returns. The profitability of the portfolios was expressed on a monthly basis, on a cumulative basis, and through abnormal returns. Additionally, a single index model regression was applied.

The average monthly returns during the whole period and the period before the crisis indicated that the momentum strategies are typically statistically profitable in the Finnish stock market. A vast majority of the portfolios yielded significant positive returns, with two exceptions. On the contrary, during the crisis period, nearly all WML portfolios yielded notably lower returns that were statistically insignificant, suggesting that the portfolios were market neutral and likely caused by typical market volatility. The abnormal returns were all negatively impacted by the crisis.

A Single Index Model was conducted on the whole data set with the extension of a dummy variable representing the crisis period. About half of the dummy coefficients were statistically significant, each of which was negative. This suggests at those portfolios performed significantly worse during the crisis. Therefore, although positive crisis coefficients occurred in some of the portfolio combinations, that does not indicate that COVID-19 positively affected their profitability due to statistical insignificance. Each of the portfolios also had a significant positive alpha coefficient, which indicates that all of the WML portfolios typically yield abnormal returns.

Two separate risk-adjusted Single Index Models were produced separately for the two time periods in order to allow comparison between the alpha and beta coefficients. Robust with earlier findings, all alpha coefficients were either lower or statistically insignificant during the crisis in comparison to the control period. This means that the excess returns of all the portfolios were reduced, or the portfolios failed to outperform the market beyond typical market variance during the crisis. Also, the betas of all WML portfolios were significantly higher during the pandemic, which signals increased risk in the portfolio. In a conclusion, the two separate risk-adjusted Single Index Models also indicate that the profitability of the momentum portfolios significantly reduced during the crisis period.

One limitation of this study is the short duration of the crisis. The market crash was extremely quick, and market rebound happened soon after. Therefore, the momentum portfolios should be formed more frequently in order to gain a larger sample of portfolios. Another limitation of this study is the limited sample size due to the small size of the Finnish stock market. Due to the number of stocks listed in the Finnish stock exchange at all times, the winner and loser portfolios which consisted of the winning and losing 15% of the stocks included about 25 stocks each. This could increase the effect of possible outliers and therefore reduce the accuracy and predictive power of the models.

The findings of this study have implications for investors who practicing the momentum strategy with Finnish stocks as well as economic researchers. The findings of this study support the existing literature on momentum crashes during a crisis and confirm that it is also applicable to the Finnish stock market. The event of COVID-19 is recent, and there is still very limited research that has been conducted on the matter. COVID-19 is arguably one of the most substantial occurrences in recent history, as it caused drastic, abrupt consequences globally to an extent never seen before. Therefore, the effect the crisis had should be further researched across countries and asset classes. For further research in the Finnish stock market, the different variations of the strategy, for example, the time-series momentum strategy, should be studied to find whether the results would differ. The study could also be divided into further segments to separate the quick market drop from the recovery period for comparison.

In conclusion, this study finds that many of the WML portfolios were significantly negatively impacted by the crisis. The results that were generated otherwise were most often statistically insignificant. Thus, the overall conclusion of this study rejects the null hypothesis and confirms hypothesis H1 according to which COVID-19 had a significant impact on the profitability of the momentum portfolios. More specifically, the results show that the effect of the COVID-19 and its aftermath on the profitability of the momentum portfolios was negative.

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Appendix

Appendix 1. Portfolio Return Summary Statistics

Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
J3K3W	80	0.015	0.042	-0.075	-0.0094	0.03	0.25
J3K6W	77	0.015	0.033	-0.043	-0.0048	0.028	0.15
J3K9W	74	0.015	0.029	-0.035	-0.0046	0.027	0.1
J3K12W	71	0.013	0.025	-0.024	-0.0051	0.03	0.082
J6K3W	77	0.017	0.042	-0.075	-0.0061	0.036	0.22
J6K6W	74	0.016	0.033	-0.044	-0.0047	0.032	0.12
J6K9W	71	0.015	0.029	-0.036	-0.0055	0.033	0.083
J6K12W	68	0.015	0.028	-0.028	-0.0061	0.034	0.087
J9K3W	74	0.018	0.039	-0.063	-0.007	0.04	0.18
J9K6W	71	0.016	0.032	-0.051	-0.0042	0.033	0.12
J9K9W	68	0.014	0.029	-0.043	-0.0034	0.029	0.093
J9K12W	65	0.014	0.029	-0.03	-0.0057	0.03	0.085
J12K3W	71	0.016	0.038	-0.064	-0.0081	0.037	0.17
J12K6W	68	0.014	0.031	-0.049	-0.0052	0.026	0.1
J12K9W	65	0.013	0.029	-0.044	-0.0061	0.026	0.099
J12K12W	62	0.015	0.032	-0.03	-0.0071	0.032	0.11
J3K3L	80	0.00031	0.042	-0.1	-0.023	0.022	0.14
J3K6L	77	-0.0013	0.028	-0.052	-0.021	0.016	0.069
J3K9L	74	0.00048	0.027	-0.036	-0.02	0.0093	0.12
J3K12L	71	-0.00091	0.024	-0.03	-0.018	0.0078	0.097
J6K3L	77	-0.0012	0.042	-0.1	-0.024	0.019	0.13
J6K6L	74	-0.00098	0.03	-0.053	-0.019	0.01	0.1
J6K9L	71	0.00041	0.029	-0.042	-0.02	0.0089	0.11
J6K12L	68	0.000083	0.027	-0.027	-0.02	0.0064	0.096

J9K3L	74	0.00027	0.046	-0.1	-0.025	0.019	0.18
J9K6L	71	-0.001	0.032	-0.058	-0.019	0.012	0.095
J9K9L	68	0.00073	0.03	-0.042	-0.017	0.0084	0.11
J9K12L	65	-0.00024	0.026	-0.03	-0.019	0.0059	0.092
J12K3L	71	-0.00016	0.047	-0.12	-0.024	0.021	0.18
J12K6L	68	-0.00036	0.031	-0.052	-0.019	0.012	0.086
J12K9L	65	0.00048	0.03	-0.044	-0.016	0.0046	0.1
J12K12L	62	0.00086	0.027	-0.031	-0.016	0.0079	0.11
J3K3WML	80	0.014	0.033	-0.096	-0.0056	0.033	0.14
J3K6WML	77	0.016	0.021	-0.03	0.0064	0.024	0.097
J3K9WML	74	0.015	0.02	-0.062	0.0048	0.025	0.07
J3K12WML	71	0.014	0.019	-0.048	0.0043	0.027	0.063
J6K3WML	77	0.018	0.032	-0.099	0.0042	0.038	0.12
J6K6WML	74	0.017	0.02	-0.037	0.0078	0.031	0.065
J6K9WML	71	0.015	0.016	-0.031	0.0054	0.024	0.048
J6K12WML	68	0.015	0.019	-0.021	0.0032	0.025	0.1
J9K3WML	74	0.018	0.031	-0.087	-0.00057	0.036	0.074
J9K6WML	71	0.017	0.017	-0.026	0.0084	0.026	0.057
J9K9WML	68	0.013	0.016	-0.04	0.0033	0.024	0.041
J9K12WML	65	0.015	0.02	-0.026	-0.00017	0.025	0.11
J12K3WML	71	0.016	0.03	-0.1	0.0036	0.036	0.087
J12K6WML	68	0.014	0.016	-0.03	0.0042	0.025	0.049
J12K9WML	65	0.012	0.015	-0.015	0.0019	0.023	0.043
J12K12LWML	62	0.014	0.023	-0.019	0.00066	0.026	0.15
BM	84	0.0089	0.048	-0.2	-0.015	0.034	0.11
RF	86	0.0055	0.0076	0	0	0.0061	0.031