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Momentum Anomaly in Finland

Evidence from the Helsinki Stock Exchange

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ABSTRACT:

The momentum phenomenon, a short-term continuation of previous returns, has proved to be a constant challenge to researchers. It is one of the most examined and robust anomalies found in financial markets. Momentum appears widely across different markets, asset classes, and time-periods, however empirical evidence on the sources behind the anomaly is mixed. Competing theories suggest diverse explanations for momentum and researcher perform continuous re-examinations on the issue. The simple momentum strategy where recent best-performing stocks are bought and worst-performing stocks are sold short, remains a highly profitable investment strategy in all parts of the world.

The purpose of this thesis is to examine whether momentum exists in the Finnish stock market. The examination utilizes data of all stocks listed in the Helsinki stock exchange during a time-period between January 2006 and December 2022. Momentum portfolios are constructed monthly from stocks with the largest and smallest returns during the last 2 to 12 months. Stocks with the largest prior 2-12 returns form the winner portfolio and stocks with the smallest prior 2-12 returns form the loser portfolio. The portfolios are then held for the subsequent 3-, 6-, 12- and 13 to 24 months. Momentum returns for these holding periods are calculated by subtracting the returns of the loser portfolio from the returns of the winner portfolio. The winner minus loser momentum returns are tested with the CAPM and Fama & French asset pricing models to capture the abnormality of the returns.

The results indicate that the momentum strategy produces large and statistically significant abnormal returns in the Finnish stock market. The returns are higher for shorter holding periods and cannot be explained by the examined regression models. All models generate significant alphas for the 3 to 12 month holding periods, evidencing strong short- to intermediate-term momentum in Finnish stocks. When adjusted to risks, the 6-month holding period strategy is the most compelling with the highest Sharpe ratio. The 13 to 24 month holding period does not produce significant returns for the momentum portfolio, thus indicating the existence of reversal effect in Finland.

These findings suggest that momentum investing is profitable in Finland and excess profits can be made with a strategy based on past stock returns. The results support vast global incidence of momentum and the notion that momentum returns are not caused by risk captured with traditional asset pricing models.

KEYWORDS: Momentum, Anomaly, Asset Pricing, Profitability

VAASAN YLIOPISTO**Laskentatoimen ja rahoituksen yksikkö**

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TIIVISTELMÄ:

Momentum-ilmiö, eli lyhyen aikavälin tuottojen jatkuvuus, on todistetusti pysyvä haaste tutkijoille. Se on yksi tutkituimmista ja vahvimista anomaliaista rahoitusmarkkinoilla. Momentumia esiintyy laajalti eri markkinoilla, eri omaisuuserissä ja eri ajanjaksoina, mutta empiiriset todisteet anomalian taustalla vaikuttavista tekijöistä ovat sekalaiset. Kilpailevat teoriat esittävät monipuolisia selityksiä momentumille ja tutkijat tekevät jatkuvasti uusia tutkimuksia aiheeseen liittyen. Yksinkertainen momentum-strategia, missä viimeaikaisia parhaiten menestyneitä osakkeita ostetaan ja huonoiten menestyneitä osakkeita myydään lyhyeksi, on edelleen erittäin kannattava sijoitusstrategia ympäri maailman.

Tämän tutkielman tarkoituksena on selvittää, esiintyykö momentumia Suomen osakemarkkinoilla. Tutkimuksessa käytetään dataa kaikista Helsingin pörssiin listatuista osakkeista aikaväliltä tammikuu 2006 – joulukuu 2022. Momentum-portfoliot rakennetaan kuukausittain osakkeista, jotka ovat ansainneet suurimmat ja pienimmät tuotot viimeisen 2–12 kuukauden aikana. Osakkeet, joiden tuotot viimeisen 2–12 kuukauden aikana ovat olleet suurimmat, muodostavat voittajaportfolion ja osakkeet, joiden tuotot viimeisen 2–12 kuukauden aikana ovat olleet pienimmät, muodostavat häviäjäportfolion. Portfolioita pidetään tämän jälkeen seuraavat 3, 6, 12 ja 13–24 kuukautta. Momentum-tuotot näille hallussapitojaksolle lasketaan vähentämällä häviäjäportfolion tuotot voittajaportfolion tuotoista. Voittaja miinus häviäjä -tuotot testataan CAP-sekä Faman ja Frenchin omaisuuserien hinnoittelumalleilla ylituottojen havainnoimiseksi.

Tulokset osoittavat, että momentum-strategia synnyttää suuret ja tilastollisesti merkittävät ylituotot Suomen osakemarkkinoilla. Tuotot ovat suuremmat lyhyemmille hallussapitojaksolle, eikä niitä voida selittää käytetyillä regressiomalleilla. Kaikki mallit tuottavat merkittävät alpha-arvot 3–12 kuukauden hallussapitojaksolle, mikä indikoi vahvaa lyhyen ja keskipitkän aikavälin momentumia Suomen osakkeissa. Kun tuottoja riskikorjataan, 6 kuukauden hallussapitajakso on kaikista houkuttelevin strategia korkeimmalla Sharpe-luvullaan. Momentum-portfolio ei saa aikaan merkittäviä tuottoja 13–24 kuukauden hallussapitajaksolla, osoittaen reversal-ilmiön olemassaoloon Suomessa.

Nämä tulokset viittaavat momentum-sijoittamisen kannattavuuteen Suomessa ja siihen, että ylituottoja voi saada aikaan viimeaikaisiin tuottoihin perustuvalla strategialla. Tulokset tukevat laajaa maailmanlaajuista momentumin esiintyvyyttä sekä perinteisten hinnoittelumallien kykenemättömyyttä selittää momentumista aiheutuvia tuottoja.

AVAINSANAT: Momentum, Anomalia, Omaisuuserien hinnoittelu, Kannattavuus

Table of Contents

1	Introduction	6
1.1	Purpose of the Thesis	7
1.2	Structure of the Thesis	7
2	Market Efficiency	9
2.1	The Efficient Market Hypothesis	10
2.1.1	Different Forms of Market Efficiency	12
2.1.2	Discussion and Criticism of the EMH	13
2.2	Asset-Pricing Models	14
2.2.1	Capital Asset Pricing Model	15
2.2.2	Three-Factor Model	16
2.2.3	Five-Factor Model	18
2.2.4	Six-Factor Model	19
3	Momentum	20
3.1	Introducing the Momentum Effect	20
3.2	Overreaction and Underreaction to Information	23
4	Literature Review	27
5	Data and Methodology	41
5.1	Data	41
5.2	Portfolio Formation	42
6	Results	44
6.1	Momentum Returns	44
6.2	Descriptive Statistics	47
6.3	Regression Analysis	49
7	Conclusions	54
	References	57

List of Figures

Figure 1, Efficient Price Formation	10
Figure 2, Overreaction to Private Information (Daniel et al.1998).....	26

List of Formulas

Formula 1, Capital Asset Pricing Model	15
Formula 2, Three-Factor Model	17
Formula 3, Five-Factor Model	18
Formula 4, Six-Factor Model	19
Formulas 5, 6, 7, DHS Model	25
Formula 8, Monthly Stock Returns	42
Formula 9, Cumulative Stock Returns	43
Formula 10, One Sample t-test	43

List of Tables

Table 1, Market Dynamics and Momentum Profits (Asem & Tian, 2010)	30
Table 2, Profits of Overconfidence Portfolios (Adebambo & Yan, 2016)	35
Table 3, Continuing Overreaction Portfolio Returns (Byun et al. 2016)	37
Table 4, Momentum Returns in the Helsinki Stock Exchange	44
Table 5, Return Reversals in the Helsinki Stock Exchange	46
Table 6, Descriptive Statistics of Momentum Portfolios	47
Table 7, CAPM Regression	49
Table 8, FF3 Regression	50
Table 9, FF5 Regression	51
Table 10, FF6 Regression	52

1 Introduction

Academic research in finance has discovered several anomalies in financial markets. Anomalies represent differences between the observed data and the expected data based on existing theories. Observed anomalous data patterns cause challenges to financial theories and are a continuous interest of researchers. One of the most examined and robust anomalies is called the momentum phenomenon (Asness, Moskowitz & Pedersen, 2013). Momentum refers to short time periods where previous success of stocks tends to continue the same. Previous winner stocks tend to keep raising in value and previous loser stocks tend to keep decreasing in value in the short-term future. This relation between stock's return and its recent performance is called the momentum effect.

Unlike many asset pricing anomalies, momentum is confirmed by scientific replication Hou et al. (2020). This recurring finding has received great academic interest since its initial discovery approximately 30 years ago. It questions the well-known theory of efficient markets which suggests that current stock prices reflect all available information. Therefore, generating abnormal returns should not be possible by predicting future returns through the information about past returns, and the only way to gain higher returns is to take higher risks (Fama, 1965; 1970).

Contradictory to the efficient market's theory, there is substantial global evidence of the momentum effect in stocks and other assets (Jegadeesh & Titman, 1993; Asness, Moskowitz & Pedersen, 2013, Hou et al. 2020), and it continues to be a subject of regular re-examinations. Although it exists widely across different markets, time periods and market states, there is no comprehensive theory explaining the phenomenon. Traditional financial theories offer mainly risk-based explanations to momentum (Conrad & Kaul, 1998; Bulkeley & Nawosah, 2009), whereas theories of behavioral finance propose that the momentum effect in finance largely results from individual behavioral biases (Daniel, Hirshleifer & Subrahmanyam, 1998; Jegadeesh & Titman, 2002).

1.1 Purpose of the Thesis

This thesis examines whether this well documented anomaly exists in Finland. Evidence of momentum is searched from the Helsinki stock exchange, where all listed companies are examined for the time-period of January 2006 to December 2022. Empirical evidence on momentum in Finland is rather non-existent in the financial literature as the small Finnish market is not a very popular target of examination. However, it has been studied in a larger scale in Europe and this thesis offers a concentrated approach of momentum in a local scale.

The aim is to clarify if excess returns can be made with a momentum strategy in the Helsinki stock exchange with recent data. Possible excess momentum returns are tested with the capital asset pricing model (CAPM) and Fama & French models (FF3, FF5 and FF6), which are introduced later, to clarify their relation to risks. Regressions with asset pricing models show whether there are risk factors causing the momentum effect or if the momentum is caused by other phenomena. Implications of previous literature lead to the following hypothesis.

H0: Momentum does not produce significant abnormal returns in the Finnish stock market.

H1: Momentum does produce significant abnormal returns in the Finnish stock market.

1.2 Structure of the Thesis

This thesis is divided into seven chapters and is organized as follows. The next chapter is an introduction to the concept of market efficiency, which is essential when trying to understand different functions of financial markets. It works as a foundational theory for modern finance and has a controversial relationship with anomalies such as momentum. Chapter three concentrates on momentum and behavioral features of finance. It

deepens on some possible sources for momentum, whereas the fourth chapter contains the literature review of past momentum research. The literature review reports previous findings on momentum by going through studies concerning the subject. Chapter five introduces the data and methodology of the thesis and explains the type of a momentum strategy that is used through the portfolio formation process. Chapter six presents the obtained results. Results are divided into three parts; plain momentum returns, descriptive statistics of the returns, and regression analysis. Finally, conclusions of the thesis are presented in the seventh chapter with a summary of the results. The summary offers an answer to the presented research hypothesis.

2 Market Efficiency

As long as stock markets have existed, investors have been interested in prices of stocks and how they are developing. Investors try to maximize their profits by making best possible investment decisions. Figuring out which stocks are likely to raise in value and which stocks are likely to decrease in value in the future is a rational way to accomplish this task. In front, economists and statisticians have tested different models and created theories for stock price behavior. Some of these theories have worked as a foundation for modern finance.

Modern finance is resulting largely from the history of battling between rationality versus irrationality and efficiency versus inefficiency (Cochrane, 2005). The assumption of rationality applies in the classic paradigm of finance when dealing with market efficiency (Cosmides & Tooby, 1994), however the concept of efficiency has multiple aspects attached to it. Financial markets contain operational efficiency including costs of market transactions and taxes, allocative efficiency which measures the transmit of assets between lenders and borrowers, and informational efficiency in which informational impacts on markets are examined. From these, the informational efficiency has been at the center of financial studies due to the impact that information and people reacting to it have on markets. Primarily, when studies allude to efficiency, the term stands for informational efficiency.

Financial markets are full of information. Information is diverse, it comes from various sources and at different moments in time. Investors are trying to reach their objective of maximizing profits by using existing information on markets at the prevailing time. Information can be used in multiple ways and investors create their own strategies on the basis of it. This is often done by applying either technical or fundamental analysis or both of them together. Technical analysis is a method that seeks to find statistical trends and patterns from history of stock prices. It evaluates investments merely on past prices and their trading volume. Fundamental analysis focuses on company's intrinsic value. It

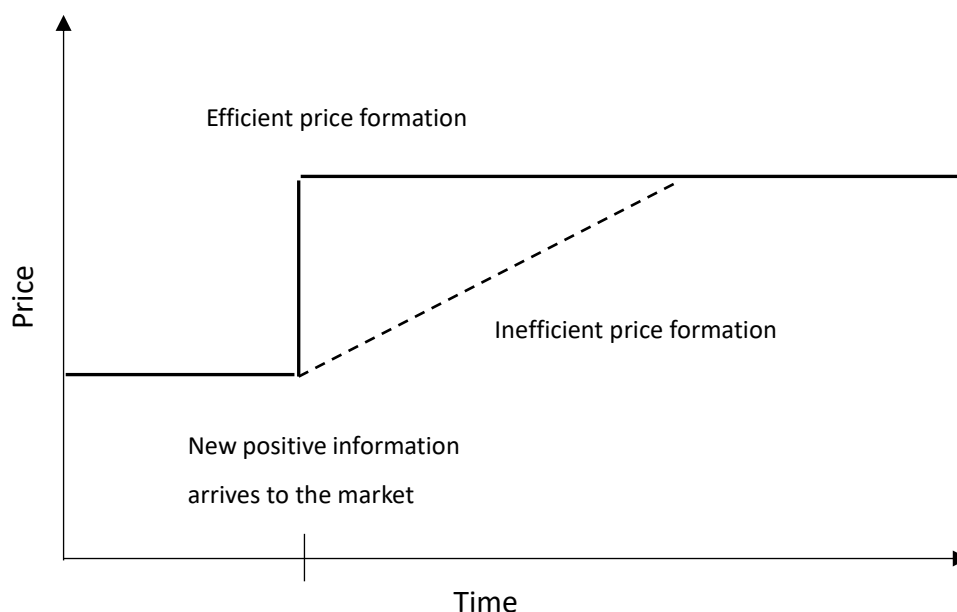
factors in basically everything that can affect the value of a stock including variables from the microlevel and the macrolevel of the economy. (Bodie, Kane & Marcus, 2014.)

Investors who seek to profit from their investments make efficient markets. No matter how they choose to react to prevailing information, or what type of analysis they use to handle it, they have an influence on a market and its efficiency. Keys to how efficient a market is, are the number of participants on a market, what kind of information there is available to public and how investors react to available information.

2.1 The Efficient Market Hypothesis

Today's financial theories are largely based on Eugene Fama's idea of the efficient market hypothesis (EMH). Fama (1965) defines the market to be efficient when stock prices fully reflect all available information. Anytime new relevant information appears, prices of stocks adapt to it without any delay. This requires numerous of market participants to happen. The more profit-maximizers there are on a market the more efficient the market is. Information is available to competing investors, who drive prices towards their correct value. Therefore, at any given time, stocks trade at their fair value and it is impossible for single investor to make abnormal profits without taking any abnormal risks (Fama, 1970).

Figure 1, Efficient Price Formation



In figure 1, the solid line presents efficient price formation when new positive information arrives to the market. There is no delay in the reaction of price, and it moves straight from its former level to a new correct and higher level. The dashed line presents inefficient price formation, where the price adapts to new information gradually and reaches its correct level after some amount of time has passed. During this time, the asset is mispriced and can be exploited to gain excessive returns. In the case of new negative information, the reactions would be similar but to the opposite direction.

There are three sufficient conditions listed by Fama (1970) for achieving efficient markets. First, there aren't any transaction costs for trading stocks. Transaction costs twist stock prices and therefore drive markets towards inefficiency. Secondly, all information is available to all market participants for free. Any costs for gaining information also undermine efficiency. Finally, everyone agrees on the implications that current information causes for the price and the distribution of each stock. Fama (1970) reminds that although these conditions are sufficient for efficient markets, they are not always completely necessary. As long as market participants factor in all available information, single cases for costs in transactions or in gaining information aren't by themselves signifying that stock prices will not fully reflect available information. However, in large scale these conditions have to apply for achieving efficient markets.

The efficient market hypothesis emerged after studies about random walk were created and discussed. Proposed by statisticians, the idea of stock prices changing randomly without following any systematic patterns was later labeled as the random walk theory. Consistent with the EMH, stock prices react to new information immediately and change independently. Because information is randomly entered into markets, stock prices fluctuate randomly and thus are unpredictable (Kendall, 1953; Fama, 1965). This means that each stock is as likely to move up as they are to move down and there are no clear predictions to be drawn from previous success of a stock. Later, Burton Malkiel expressed this idea figuratively that a blindfolded chimpanzee could select a portfolio by throwing darts which would perform as well as ones selected by experts (Malkiel, 1999).

2.1.1 Different Forms of Market Efficiency

In his paper “Efficient Capital Markets: A Review of Theory and Empirical Work” (1970), Fama divided efficient markets into three categories. He stated that the way in which markets process information effects directly into efficiency. Therefore, the three forms of market efficiency are divided by how each market deals with information and how it impacts the prices of stocks. (Fama, 1970). The weak form covers historical prices of stocks and is concerned only by how well past prices predict future prices. When a market reaches the weak form efficiency, beneficial predictions of future prices cannot be made from past prices. The weak form hypothesis includes that if previous stock price data at any time indicated the future performance of stocks, it would be widely known by investors and conclusions made from it would have no value. Thus, according to the weak form theory, technical analysis which objective is to analyze previous trends of stocks and draw conclusions for the future through them, is useless.

The second form of efficiency is called the semi-strong form. It includes all publicly available information and assumes that stock prices already reflect it. In addition to past prices, public information includes financial statements, quality of management, dividend policy, stock splits, patents held and accounting practices, among other features of companies. Investors cannot gain any excessive profits by using this kind of information for the same reason as in the weak form they could not by using information of past prices. Any public information indicating some stock to be over- or undervalued, loses value instantly as information is available to all investors and the stock price concerned immediately increases. (Bodie et. al. 2014; Fama, 1970.)

The most extreme form of efficiency is the strong form. It states that investors have monopolistic access to any information regarding the company, including all the private and insider information. Again, this is already reflected in the stock price and there is no way for investors to benefit from either public or private information. The strong form hypothesis presents a perfectly efficient situation in a market, where all information is not only available simultaneously to everyone but also factored in correctly by everyone and

thus not one stock is over- or undervalued. In other words, excessive profits are impossible to gain, at least without taking any significant risks. This kind of frictionless situation sounds somewhat impossible to accomplish and seems to be hardly the one we meet in practice. Along the way of developing modern view of market efficiency, the strong form hypothesis as well as the whole theory of the EMH has been under a lot of challenging, testing and criticism.

2.1.2 Discussion and Criticism of the EMH

Quickly after the theory of EMH was introduced, it gained extensive support and endorsement from financial academics. Testing of the theory began immediately in the 1960's and most of the conducted studies supported the hypothesis (Lee & Yen, 2008). There were concerns about prices truly reflecting all available information, but the hypothesis seemed to hold its ground at least in the weak and semi-strong forms. Despite some early questioning, the theory was widely accepted throughout the academic circles in the 1970s (Malkiel, 2003; Shiller, 2003).

Moving towards the 21st century, the dominance of the EMH became less and less acknowledged. In the 1980s discussion of excess volatility undermined the efficient markets theory by implying that changes of prices occur more for psychological reasons rather than any fundamental reasons (Shiller, 2003). However, econometric analyses were very favorable at the time and it wasn't until the 1990s that the real surge of behavioral finance shifted the academic focus to theories including psychological and sociological aspects of human behavior. Studying price formations in markets, researchers found more and more anomalies that were supported by solid empirical evidence. Behavioral elements of stock price determination have raised questions and caused critique towards market efficiency. Over time these findings have changed the definition of market efficiency so that it is not as absolute anymore. (Malkiel, 2003; Shiller 2003.)

In general, many financial economists today believe that prices of stocks can be at least partly predictable (Malkiel, 2003, Bodie et al. 2014). This enables investors to find over-

and undervalued stocks, which is the reason for existence of many investment strategies. After the rise of the EMH, views regarding efficient markets have split up by two different schools of finance. Advocates of the efficient market theory have showcased evidence in favor of the EMH and supporters of behavioral finance have presented evidence controversial with it. The main difference between these two circles around the definition of market efficiency. Those who support the EMH focus more on the absence of arbitrage and highlights the possibility of markets being efficient despite some random flaws of prices not fully reflecting all available information. Those in favor of behavioral finance tend to define efficient markets in a more unconditional manner (Shefrin 2005).

2.2 Asset-Pricing Models

Investors aim to find misvalued stocks from financial markets. Gaining excess returns by exploiting misvaluations is a primary goal for many investors. There are plenty of analysts and financial experts trying to do the same as well. In order to define which stocks might be priced incorrectly and have some missed value to benefit from, investors have to evaluate the companies. This can be done using fundamental or technical analysis. Asset pricing in financial studies focus on technical analysis by comparing and calculating different kinds of numerical data and mostly leaves the companies fundamentals out of the examination. There are numerous valuation models developed for this task.

Understanding the basic principles of stock price formation is necessary when moving on to the momentum effect. As introduced in the theory of efficient markets, information is a major contributing factor in stock prices. However, it is not the only thing affecting these prices. Many other technical factors, for example dividends, other future cash flows and various risk factors have their own impact on valuation of stocks. Different valuation models factor in these matters differently. The following presents a few common asset-pricing models in the finance literature regarding momentum. Presented models are also ones that are used in the empiric research part of the thesis.

2.2.1 Capital Asset Pricing Model

The capital asset pricing model (CAPM) is one of the most widely known and commonly used valuation model in finance. It provides a framework for answering a fundamental question of how the risk of an investment affects its returns. Simply put, it predicts the relationship between systematic risk and expected return of some asset. The model was developed a little over 10 years after Harry Markowitz disclosed his work of modern portfolio management in 1952. In 1964 William Sharpe, in 1965 John Lintner and in 1966 Jan Mossin independently published papers regarding asset pricing and they all introduced similar models. (Perold, 2004; Bodie et al. 2014.)

CAPM:

$$(1) \quad E(r_i) = r_f + \beta_i [E(r_m) - r_f]$$

where,

- $E(r_i)$ = expected return of portfolio i
- r_f = risk free return
- β_i = beta coefficient of portfolio i
- $E(r_m)$ = expected return of market portfolio

The basic from of CAPM presents its general idea, where the investments expected returns and risk go hand in hand. The higher the systematic risk for the investment is, the higher are also the expected returns. Similarly with all models that try to describe real world situations, the CAPM has many simplifying assumptions that it relies on. These assumptions are mostly unrealistic in practice, but they are necessary when trying to understand the risk-return relationship. The list of assumptions that are used in the CAPM after Bodie et al. (2014) are the following.

1. Investors are rational, mean-variance optimizers
2. Investors have homogenous expectations
3. Investors planning horizon is a single period
4. Investors can borrow or lend at a risk-free rate
5. Short positions are allowed
6. All information is publicly available
7. There are no taxes or transaction costs

These assumptions have raised some questioning of the model. As usual, when unrealistic circumstances are presented to hold true, critique is inevitable. However, the CAPM has been very useful when applying it to different valuation situations and when trying to figure out how much different types of risks affect returns of an investment. Also, challenges regarding the CAPM have motivated researchers to create a set of extensions for the model. The basic form has served as a fundament for more practically successful forms of the model. These matters make the CAPM extremely popular.

2.2.2 Three-Factor Model

As well as the CAPM presents the relationship between risk and return of an investment, it uses only the beta factor to compare a portfolio with the market portfolio. Eugene Fama and Kenneth French constructed a study of US stocks from the time-period of 1963-1990 and found out that average stock returns could not be explained only with beta (Fama & French, 1992). They focused primarily on two categories of stocks, which outperformed the market. The first one was small companies and the other one was companies with high book value to market value ratio. In order to explain the above average returns in a more convenient way, the authors created risk factors to represent their findings and developed the three-factor model.

The three-factor model states that all returns exceeding the risk-free return can be explained by the three factors used in the model. These factors are a market factor that is used in the CAPM, a size factor and a value factor. Market factor consists from excess

returns and is formed by subtracting the risk-free rate from the market return ($r_m - r_f$). Size factor compares the returns of small stocks with the returns of big stocks. It is the difference between those two (small minus big, *SMB*). Value factor compares the returns between high book value to market companies and low book value to market companies and is the difference between those two (high minus low, *HML*).

Three-factor model:

$$(2) \quad E(r_i) = r_f + \beta_1 MKT + \beta_2 SMB + \beta_3 HML$$

where,

<i>(MKT)</i>	=	expected premium of market return
<i>(SMB)</i>	=	expected premium of size
<i>(HML)</i>	=	expected premium of value
β_1	=	factor loading on market return
β_2	=	factor loading on size
β_3	=	factor loading on value

Similar to the CAPM, this model shows the relationship between risk and return of an investment. Interpreting the factors, the smaller the company and the bigger its book value to market value ratio is, the more risk it carries. Therefore, a small company with high book value to market value ratio tends to earn greater returns than the market in general (Fama & French, 1992). The three-factor model works well when portfolios are formed based on earnings, cash flow and sales growth for example. It can explain many of the anomalous findings that the CAPM hasn't been able to and performs well in predicting returns of small stocks. Also, it turns over many of the anomalous long-term returns. However, it hasn't been able to explain the returns originating from momentum. (Fama & French 1996.) Due to the fact that there are still some clear anomalous returns that can't be explained with these three factors, Fama and French created the five-factor model.

2.2.3 Five-Factor Model

In 2015, Fama and French introduced the five-factor model. Two more factors, profitability and investment, were added to their previous three-factor model. Profitability contains the difference between returns of companies with high profitability and companies with low profitability (robust minus weak, RMW). Investment is the difference between low investment companies and high investment companies. Low investment companies are seen as conservative and high investment companies as aggressive (conservative minus aggressive, CMA). (Fama & French, 2015.)

Five-factor model:

$$(3) \quad E(r_i) = r_f + \beta_1MKT + \beta_2SMB + \beta_3HML + \beta_4RMW + \beta_5CMA$$

where,

RMW	=	expected return of profitability
CMA	=	expected return of investment
β_4	=	factor loading on profitability
β_5	=	factor loading on investment

With the two added factors, Fama and French found explanations to more variations of excess returns that were previously left unanswered. They saw that profitability and investment were the two best factors to be added into the model and to answer many of the questions regarding different anomalous returns. (Fama and French, 2015.) The five-factor model has been used to the same purpose as the three-factor model but with a more extensive manor. Both models have been very popular in the financial research over the years due to offering solid explanations to many anomalous returns. However, there are still situations where these valuation models cannot explain certain return patterns found in markets.

2.2.4 Six-Factor Model

In their paper “Choosing factors” (2018) Fama and French add yet another factor to their previous model. They add the momentum factor UMD (up minus down), that measures the difference between stocks with positive momentum and stocks with negative momentum. The factor contains the excess return of a portfolio that buys stocks with the best previous performance and sells stocks with the worst previous performance. Momentum factor in regressions is also known as WML (winner minus loser) or MOM (momentum) and it was first introduced by Mark Carhart in 1997 when he examined the persistence of mutual fund performance (Carhart, 1997). By adding the momentum factor to their previous five-factor model, Fama and French answered to some popular demand in trying to explain the momentum in stocks.

Six-factor model:

$$(4) \quad E(r_i) = r_f + \beta_1MKT + \beta_2SMB + \beta_3HML + \beta_4RMW + \beta_5CMA + \beta_6UMD$$

where, UMD = expected return of momentum
 β_6 = factor loading on momentum

This model more or less designed to answer questions regarding momentum, now takes the previous success of stocks into account. Basically, adding factors to evaluation models makes them more accurate, and in Fama and Frenches’ tests six-factor models are reliably better than five- or three-factor models. However the authors state that simply adding factors also leads to serious multiple comparisons problem. With more and more factors meaningful statistical inference is made impossible due to multiple comparisons issues. Therefore the number of factors in an evaluation model should be limited and the authors were first somewhat reluctant to add the sixth factor. (Fama & French, 2018.)

3 Momentum

3.1 Introducing the Momentum Effect

Moving on from the 1970s when the EMH was at the height of its dominance, to the 2000s and beyond, different anomalies have stood out in the financial research. Behavioral finance has had a great role in this rush, proposing new theories based on other sciences, such as psychology and sociology, in trying to explain the observed anomalies (Shiller, 2003). Taking an alternative perspective to finance, theories of behavioral finance state that individual psychological, social, emotional and cognitive factors matter in the financial decision-making (Kahneman & Tversky 1979). Behavioral studies have introduced a great amount of human biases that drive investors to do certain decisions somewhat consistently, enabling the existence of anomalies. Traditional financial theories have been struggling with some of these systematic phenomena which has been the main reason for the rise of behavioral finance and it's becoming a part of mainstream finance (Baker & Nofsinger, 2010).

According to the theory of efficient markets, it shouldn't be possible to earn above-average returns from investments by using publicly available information. However, after years of financial research, it has become clear that this is not always the case in practice. Reported anomalies state that excess returns occur and can be exploited with certain types of investment strategies. This is challenging to traditional financial theories including the EMH and the random walk theory that are successful in explaining various financial situations (Park & Sohn, 2013). Many of these anomalies are noticed to possibly be a consequence of behavioral differences of individuals. Humans have limited processing ability and experience personal biases that affect their financial decisions suggesting that not all decisions in financial markets are made by perfectly rational investors (Kent & Titman, 1999; Baker & Nofsinger 2010). Examining how investors make decisions and acknowledging their indifferencies in interpreting specific information have led to a shift in academic discussion more towards anomalies and behavioral finance (Shiller, 2003; Park & Sohn, 2013).

Since the extensive popularity of the EMH, substantial evidence of different anomalous return patterns has been reported globally in finance. Of all recognized anomalies, this thesis concentrates momentum as it is one of the most widely recognized among researchers (Asness, Moskowitz & Pedersen 2013). As stated before, momentum is also considered as one of the most robust anomalies in the financial markets and holds true after scientific replication (Hou et al. 2020). The momentum effect, a relation between stock's return and its recent performance, has led to a creation of investment strategies called momentum strategies, in which investors buy stocks that have recently succeeded and sell stocks that have recently struggled. All kinds of variations of momentum strategies have received lots of academic interest in the financial community within the past decades (Jegadeesh and Titman 1993, 2001; Novy-Marx 2012; Asness, Moskowitz & Pedersen 2013, Bodie et. al 2014.)

Stock price momentum and its capability to produce abnormal returns was first documented by Narasimhan Jegadeesh & Sheridan Titman in 1993. Before their study, a new discovery that stock returns are predictable with the information of past returns had been reported in the finance literature. Debono & Thaler (1985, 1987) find that portfolios conducted from prior loser stocks outperform portfolios conducted from prior winner stocks over the long term. In addition, both Jegadeesh (1990) and Lehmann (1990) report that previous winners and losers experience strong reversal effects over the short-term supporting the stock return predictability theorem.

In their paper "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" Jegadeesh & Titman (1993) conducted a study of U.S. stocks from a time-period of 1965 to 1989, sorting them by their recent past performance. Long positions were taken in stocks that had done well in the recent 3 to 12 months and short positions were taken in stocks that had been done poorly during the same period. They find that this strategy leads to significant positive returns for individual stocks in the subsequent 3 to 12 months. The momentum effect holds up to a year and in longer time periods the positive effects disappear and returns turn to either insignificant or negative. The

authors state that in longer holding periods the momentum effect is reversed and return reversals are an important implication in their examination. In 2001, the authors conducted a new study with more recent data and had very similar results confirming their findings from the initial study.

After the initial discovery of the phenomenon, the effect where recent previous success of stocks extends for the near future is noticed to exist across different markets and over time (see also, Rouwenhorst, 1998; Asness et al. 2013; Byun et al. 2016; Yang et al. 2018). Momentum studies have developed through the years and there have been numerous of different momentum examinations. In addition to market samples, differences in momentum examinations affiliate mostly with the time periods that are used when constructing the momentum portfolios and with the attempt to capture the underlying source of the phenomenon and its relation to risk.

Regarding the time periods, there are two periods that are considered when performing a momentum examination. These are the formation period and the holding period. When looking at the past performance of stocks, a formation period in which previous stock returns are calculated has to be determined. Formation periods differentiate between studies, however it is common to use a formation period somewhere between the most recent month $t-1$ and month $t-12$, which is 12 months back from the current month. Some studies skip the most recent month or two to account for short-term reversal effects (Jegadeesh & Titman, 1993; 2001). Holding periods that determine how long the momentum strategy is kept differentiate mostly between 3 and 12 months after the formation period. It is common to use some combination of 3-, 6-, 9-, and 12 month holding periods. Longer holding periods are used only when examining longer term return reversals.

The attempt to capture sources for momentum has led to different ways of constructing the formula for past return calculations. The underlying cause is usually in some way incorporated to the formula and depending on the results, it is evidence either for or

against the possible cause for momentum. Traditionally significant returns are often viewed as a compensation for higher risks (Conrad & Kaul, 1998; Bulkley & Nawosah, 2009; Park, Kyung-In & Kim, 2014, Fama & French, 2018) and they are tested with different risk factors. Since the sources for momentum are usually divided into behavioral explanations and these traditional risk-based explanations, it is beneficial to clarify one basic idea behind the behavioral explanations. Regardless of the behavioral reason, they all lead one way or another to investors either overreacting or under-reacting to information. Next, this is explained in more detail. More on past momentum studies follows in chapter four.

3.2 Overreaction and Underreaction to Information

As introduced, the EMH states that prices of stocks react immediately to new information and set on their new correct level. Due to numbers of market participants and high competition, prices form efficiently without the possibility of arbitrage. A question of investors always reacting to new information at the right extent was raised by researchers challenging the EMH theory. What is an appropriate reaction and is it possible for some investors to react too strongly or too weakly to available information? Humans react differently to different matters and concepts of overreaction and underreaction are familiar to our intuitive and emotional species. People have a tendency to overreact to unexpected and extreme events (Kahnemann, 2011). On the contrary, certain events might not feel significant at the first glance and the importance of that event emerges sometime after the initial underreaction.

There are two hypotheses describing and explaining over- and underreactions. The overreaction hypothesis states that investors react too strongly at the moment of a positive or negative shock and correct their reaction by opposite actions afterwards. The underreaction hypotheses states that investors react too weakly at the moment of a shock and correct their reaction by opposite actions afterwards. (Stefanescu, Dumitriu & Nistor, 2012.) In addition to personal behavioral differences, there are other circumstances that can impact the investors reactions. For example, the size of a firm can significantly affect

reactions to shocks (Clare & Thomas, 1995), as well as the time when the shock occurs. Generally, smaller firms are more prone to experiencing stronger reactions to shocks than larger firms and if the market experiences turbulent times, one shock has far less significant reactions attached to it than it would have during stable and quiet times (Stefanescu et al. 2012).

As a major implication for these two hypotheses is market inefficiency. Stock market overreaction implies that underperformed stocks over a recent period of time will outperform the market over a subsequent, similar period of time. Conversely, stock market underreaction implies the underperformance of stocks that have recently outperformed the market (Bassiouny & Ragab, 2014). The first evidence of overreaction was reported by Debondt & Thaler (1985), who find that the US stock market experiences too strong rises and falls of stock prices in relation to good and bad news. Due to investors tendency to exaggerate, this phenomenon can be exploited by using a contrarian trading strategy in which past winner stocks are sold and past loser stocks are bought (Stefanescu et al. 2012; Bassiouny & Ragab, 2014). Empirical evidence of underreaction was first introduced by Jegadeesh and Titman in 1993. They showed that underreaction patterns due to conservatism and gradual adaption to recent news can be exploited by using a momentum trading strategy.

Examining these over- and underreactions and their effects to stock return predictability is well introduced by Daniel et al. (1998) in their study "Investor Psychology and Security Market Under- and Overreactions". In their model, later named as the DHS model, the authors present the impact of private information on prices. Equilibrium stands at time $t = 0$. At $t = 1$, the investor receives noisy private information and at $t = 2$, the price of a stock is revealed. The private information signal that the investor receives at $t = 1$ is,

$$(5) \quad S_1 = \theta + \epsilon$$

where, θ = terminal value of the stock, with mean = θ and variance = σ_θ^2
 ϵ = error term ($0, \sigma_\epsilon^2$), uninformed investors correctly assess the error variance, but informed investors underestimate it to be $\sigma_C^2 < \sigma_\epsilon^2$

Two different price formations are now considered at $t = 2$. In the case of uninformed and fully rational investors, the estimated price is,

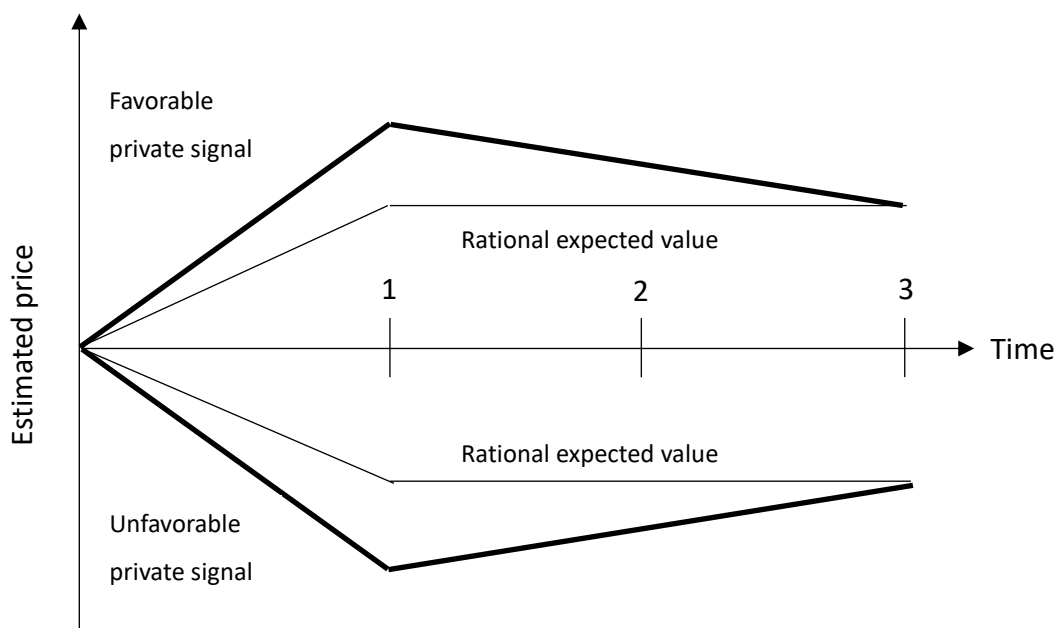
$$(6) \quad P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2} (\theta + \epsilon)$$

And in the case of informed investors and their overconfident assessments, the estimated price is,

$$(7) \quad P_2 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_C^2} (\theta + \epsilon)$$

Due to the overconfidence of investors and their variance underestimation $\sigma_C^2 < \sigma_\epsilon^2$, prices move now more significantly $P_2 > P_1$. Overconfidence in the private information makes investors overreact and estimate the price incorrectly. Thus, prices are affected more by the private information than is rational.

Figure 2, Overreaction to Private Information (Daniel et al.1998)



In figure 2, the overreaction to a noisy private signal is illustrated. Bolded lines present the overconfident investors average reaction to favorable and unfavorable private information. Thinner lines present the fully rational price level. At $t = 1$, overconfidence in private signals causes prices to overreact to new information. After $t = 1$, noisy public information signals arrive correcting the inefficient deviation between the fully rational price level and the price level driven by overconfident investors. The correction happens gradually suggesting that overconfident investors underreact to public information signals after their initial overreaction. The fully rational correction would happen immediately at the time the public information arrives.

4 Literature Review

After the discovery of stock return predictability with past return data, the commonly known momentum research was initiated by Jegadeesh & Titman's (1993) study regarding past winners and past losers continuing their recent trend. Since then, an extensive amount of finance literature has been addressing the topic. Majority of studies document strong performance of momentum strategies around the world. Regardless of asset classes, time-periods, industries etcetera, strategies exploiting the momentum effect keep generating abnormal excess returns in different markets globally. As a financial phenomenon, momentum has become so prominent that it is included in the basic factor investing characteristics alongside value and size for example. Nowadays, momentum investing is a well-recognized style of investing and momentum is included as a factor in asset pricing models by Carhart (1997) and Fama & French (2018) to better explain the returns earned from momentum strategies.

The lack of the existing asset pricing models' success in explaining the momentum returns remains an attractive question for researchers. The quest for the unclear source of momentum profits keeps producing new examinations constantly every year. This chapter reviews some of the previous studies related to momentum. Focus is on well-known papers and studies with similar findings are highlighted together. Studies are gone through in a somewhat chronological order and few of the more recent ones are explained in more detail. There are some tables of momentum returns presented to display the similar demonstration of returns used later in the results section of the thesis.

In 1996, Fama & French test the average returns of stocks generated from different firm characteristics with their three-factor model. They try to explain the anomalous returns documented in previous financial literature related to size, earnings, cash flow, equity, sales, long-term returns, and short-term returns. Since the CAPM has not been able to explain these anomalous returns reported by researchers, the authors add the SMB and HML factors to their model. They find that the anomalies largely fade away in the three-factor model except for the momentum. The continuation of short-term returns cannot

be explained with the model, while the returns based on all other examined criteria have large and significant loadings of SMB and/or HML (Fama & French, 1996). This is one of the first important findings that offers strong support for momentum. Due to the incapability of capturing momentum returns, Fama & French note however that the model is just a model and it's far from complete in respect of explaining average returns.

Chan, Jegadeesh & Lakonishkok (1996) examine the return predictability of past returns with their underreaction hypothesis in the U.S. They argue that with investors underreaction to information, especially to past earnings announcements, future returns can be predicted. Chan et al. (1996) report an approximately 41 % share of momentum returns arriving from dates around companies' earnings announcements. This evidence of the relationship between past earnings news and future returns cannot be explained with market risk, size, or book-to-market effects. The authors conclude that the market does not effectively respond to new information and is subject to experiencing momentum in stock returns.

Using similar research hypotheses, Daniel et al. (1998) show that overconfident investors overreact to private information and underreact to public information. They use the model introduced in chapter 3.2 in their examination. The detected over- and underreactions result in negative long-lag autocorrelations, positive short-lag autocorrelations, excess volatility and return predictability in stock prices. Positive short-lag autocorrelation signifies momentum over the medium term and the authors find it resulting mainly from underreactions detected after the initial overreaction. In addition, public signals in line with the private signals increase investor confidence because of biased self-attribution and trigger further overreaction. Thus, investor overconfidence and momentum profits are likely to be higher when the market continues in the same direction than when the market reverses. The authors propose that momentum is sensitive to market dynamics and can be a result continuing investor overreaction, in contrast with the common correspondence.

In addition to Daniel et al. (1998), Hong & Stein (1999), Cooper, Gutierrez & Hameed (2004), and Sagi & Seasholes (2007) all suggest that momentum profits are higher when market continues in the up states than when it shifts direction. However, none of these studies suggest higher profits in continuing down markets. Evidence connecting market dynamics partially to momentum profits made Asem & Tian (2010) consider way to investigate momentum in different market states. In order to clarify this asymmetry, Asem & Tian (2010) examine the effects of market reversals following both up and down markets.

In the Asem & Tian (2010) study “Market Dynamics and Momentum Profits” market state is defined through past market performance as follows. A Market is considered as an up market when the past 12-month value-weighted return for Center for Research in Security Prices (CRSP) is positive or 0. A down market is when the similar past 12-month return is negative. The authors classify momentum profits following both up and down markets into 2 groups. When the value weighted CRSP return is positive or 0 in the subsequent month, the market continues in the same state and when the CRSP return is negative in the subsequent month, the market reverses from an up state to a down state and vice versa.

The authors construct 10 portfolios by sorting firms into deciles based on their returns from previous 5 months. The biggest loser stocks are assigned to portfolio 1 and biggest winner stocks to portfolio 10. A momentum portfolio is winners minus losers ($P_{10} - P_1$) and the holding period for all portfolios is 6 months. The following table presents the mean monthly returns of the discussed portfolios in different market dynamics.

Table 1, Market Dynamics and Momentum Profits (Asem & Tian, 2010)

Portfolio	Subsequent UP Markets		Subsequent DOWN Markets	
	Holding Period A	Formation Period	Holding Period B	Formation Period
Past UP Markets				
P1	3.24	-4.65	-4.71	-4.74
P10	5.33	10.67	-4.72	11.10
P10 - P1	2.09		-0.01	
Past DOWN Markets				
P1	8.03	-8.52	-9.02	-9.35
P10	5.48	6.82	-5.49	6.93
P10 - P1	-2.54		3.53	

Table 1 shows that the returns of winner and loser portfolios are higher in subsequent up markets than in subsequent down markets. Following up markets, the mean return for the momentum portfolio is 2.09% per month when the subsequent market is up, and -0.01% per month when the subsequent market is down. This result is consistent with previous studies and suggests that momentum profits are significantly higher when markets continue in up states than when they transition to down states. Following down markets, the mean return for the momentum portfolio is 3.53% per month when the markets continue in down states and -2.54% when the markets transition to up states. This also indicates that momentum profits are higher when markets continue in the same direction than when they reverse. In continuing down markets this is particularly interesting since previous empirical studies show nonexistent momentum profits following down markets.

One of the first momentum studies outside of the U.S. was Rouwenhorst's "International Momentum Strategies" (1998). Rouwenhorst expands momentum research into 12 European countries and examines the return patterns both within and across these 12 markets. The sample period of 1978 – 1995 is independent of previous research apart from a partial overlapping with the Jegadeesh & Titman (1993) and Fama & French (1996) U.S.

samples. Using the same methodology as Jegadeesh & Titman (1993), Rouwenhorst finds that the previous winners outperform the previous losers in all 12 markets and the Jegadeesh & Titman (1993) momentum strategy earns an approximately 1 % monthly return for an internationally diversified portfolio. The abnormal return is not limited to a particular market and increases after controlling for market risk.

Momentum in international stocks lasts for one year and is not an attribution of conventional risk measures. The return continuation is a bit stronger in smaller firms, however the detected momentum in returns holds across size divergence. These findings are very similar with previous findings reported in the U.S. suggesting that country specifics are relatively negligible when trying to explain the cause for momentum. Rouwenhorst (1998) concludes that momentum profits can be driven by exposure to some common factor.

After investigating momentum in Europe, Rouwenhorst (1999) broadens into emerging markets. His new sample consists of 1750 individual stocks from 20 emerging countries such as Taiwan, Zimbabwe, and Brazil. The purpose of the study is to find if the factors related to size, value or momentum explain the return variations in expected stock returns, and whether these factors are similar between the developed and emerging markets. Rouwenhorst (1999) uses a different method when constructing the momentum portfolios and includes 30 % of stocks into both the top and the bottom portfolios. With this larger portion from the prior return distribution, the author reports slightly weaker evidence of momentum than in Jegadeesh & Titman (1993) and in Rouwenhorst (1998). The prior winners still significantly outperform the prior losers producing excess momentum returns of 0,39 % with equally weighted stocks and 0,58 % with equally weighted countries.

Strong evidence in international markets and a renewed U.S. study of Jegadeesh & Titman (2001) with more recent sample period back up the momentum effect in stocks. Griffin, Ji & Martin (2003) add to the conjecture by testing, whether the momentum is a

result of macroeconomic risks. Using several methods and an international sample setting of 40 countries in their examination, Griffin et al. (2003) report large positive momentum profits with no evidence of co-movement among different countries. Profits remain generally positive in all macroeconomic states. The authors claim that if the profits are driven by risk, the risk is country specific. Macroeconomic factors are not significant for pricing or for time series in any of the tested countries.

Moving on to the 2010s, Novy-Marx (2012) provides international evidence of momentum being generated more from intermediate past performance than from recent past performance. The author finds that stock returns from prior 12 to 7 months explain the momentum returns more significantly than stock returns from the prior 6 months and seem to better predict future returns. The examined strategies based on intermediate past performance significantly outperform the strategies based on recent past performance. Despite the latter strategies also generating positive returns, the returns of the outperforming strategies have significant alphas in the Fama & French regressions and the prior 6-month strategies have not. On average, stocks that have been recent winners and intermediate losers are inferior to stocks that have been recent losers and intermediate winners. These results are inconsistent with the established idea that recent winners keep winning and losers losing thus suggesting that describing momentum through the tendency of stock prices to stay in motion is not accurate.

In 2012, Fama & French re-examines the capability of asset pricing models to explain returns related to size, value, and momentum. They contribute with four international regions (North America, Europe, Japan, and Asia Pacific) and recent data. The main findings related to momentum showcase its' strong existence in all regions except Japan. Two years prior, Chui, Titman & Wei (2010) report similar findings regarding the lack of momentum in Japan and East-Asia, and suggest it being a result of less individualistic investors in these areas. Chui et al. (2010) show support to the idea that individualistic cultures drive people to be more overconfident, which is seen in individualism being correlated with trading volume and volatility. The link between individualism and

investor overconfidence is an uncertain assumption and Fama & French (2012) debate that actually the Chui et al. (2010) argumentation could go the other way. In opposite reasoning, low individuality could produce momentum through stock prices reacting slowly to information. This is consistent with Chan et al. (1996) and Daniel et al. (1998) underreaction hypotheses. Regardless of the aforementioned contradiction, Fama & French (2012) evaluation models again fail to capture momentum with both local and global perspective in the regions where momentum was detected.

Asness, Moskowitz & Pedersen (2013) investigate value and momentum, two of the most prominent phenomena in capital markets at the time, together. The returns from value and momentum are examined jointly across different markets and asset classes. In addition to stocks, the effect of value and momentum is investigated for government bonds, commodities, and currencies. Asness et al. (2013) find significant returns resulting from both phenomena with strong co-movement of strategies across asset classes. Momentum strategies are positively correlated with other momentum strategies globally, however they are negatively correlated with value strategies. Positive correlation between different asset classes suggests the presence of common global risk factors explaining the returns.

The authors investigate the possible common global factor structure with a simple three factor model consisting of a global market index and zero-cost strategies for value and momentum. The model captures the co-movement and the cross section average returns both within and across asset classes. It also captures the returns to the Fama & French U.S. portfolios. The separate factors for momentum and value work better in explaining the returns rather than a single factor for both phenomena. When investigating the source for the common macroeconomic factor structure, Asness et al. (2013) find that there are only weak links to default risk, business cycle and consumption. However, there is a strong positively correlated link between liquidity risk and momentum that offers a partial explanation for momentum in different asset classes.

Adebambo & Yan (2016) empirically examine the overconfidence hypotheses and its effects on momentum. Several empirical papers before them give support the idea that overconfidence impacts momentum (Asem & Tian, 2010; Chui, et al. 2010), however directly measuring the influential behavioral bias had not yet been comprehensively implemented. The authors focus on the overconfidence of mutual fund managers and test whether the momentum effect is stronger in stocks owned by more overconfident managers.

The utilization of mutual fund managers is useful for many reasons. First, overconfidence tends to be stronger among professionals. Second, mutual fund managers are more likely to possess private information than an everyday investor. Finally, mutual funds hold a large portion of the U.S. stock market, and the detailed data is readily available for them and their managers. To measure overconfidence, which is difficult to directly observe, the authors construct an overconfidence index including proxies for manager's gender, manager's tenure, portfolio turnover, portfolio concentration, prior performance and idiosyncratic risk. They use a portfolio approach in measuring the relation between the momentum effect and manager overconfidence.

The following presents a table of momentum profits across overconfidence portfolios after Adebambo & Yan (2016). It reports the average monthly portfolio returns over the subsequent 6 months. The stock-level overconfidence measure is the weighted average overconfidence index of fund managers holding the stock, including those six proxies mentioned. OC1 (OC3) is a tercile containing stocks with the lowest (highest) value of the stock level overconfidence measure. PR1 (PR3) is a tercile containing past loser (winner) stocks.

Table 2, Profits of Overconfidence Portfolios (Adebambo & Yan, 2016)

<u>Prior Return</u>	<u>All Stocks</u>	<u>OC1 (low)</u>	<u>OC2 (med)</u>	<u>OC3 (high)</u>	<u>OC3 - OC1</u>
PR1	0.84** (2,56)	0.99*** (3.27)	0.90*** (2.70)	0.66* (1.68)	
PR2	1.13*** (4.60)	1.19*** (5.04)	1.12*** (4.29)	1.02*** (3.30)	
PR3	1.21*** (4.00)	1.15*** (4.21)	1.20*** (4.00)	1.26*** (3.40)	
PR3 - PR1	0.36* (1.85)	0.16 (0.99)	0.30* (1.76)	0.60*** (3.05)	0.44*** (3.74)

Table 2 shows that the full sample average monthly return from the momentum strategy is 0,36 %. Looking at the overconfidence portfolios, the momentum profits are insignificant 0,16 % for the low-level overconfidence portfolio, marginal 0,30 % for the medium-level overconfidence portfolio, and significant 0,60 % for the high-level overconfidence portfolio. The difference in returns between the high and low overconfidence portfolios is 0,44 % per month, or 5,28 % annually.

The authors determine whether the difference in momentum profits between overconfidence portfolios is compensation for risk with the three-factor model. They estimate the three-factor model for the monthly returns of overconfidence portfolios and find that the difference in profits is not a compensation for high factor loadings. They also test the return reversals of the overconfidence portfolios. Daniel et al. (1998) propose that momentum profits reverse in the long run due to more information becoming available and the market starting to correct the mispricing. Therefore, the expectation is that the reversal is stronger with stocks held by more overconfident investors. Examining this proposition, the authors show that the high-level overconfidence portfolio exhibits strong and significant reversals whereas the low-level overconfidence portfolio does not exhibit statistically meaningful reversals.

After testing the relation between overconfidence and momentum profits with their regression, controlling some key stock-level characteristics and running some robustness tests, the authors conclude that stocks held by more overconfident managers exhibit higher momentum profits than stocks held by less overconfident managers. This result is robust and not a compensation for risks detected with the asset pricing model. In addition, stocks held by more overconfident managers experience return reversals that are strong and significant, while stocks held by less overconfident managers experience no notable return reversals.

Byun, Lim & Yun (2016) focus on the Daniel et al. (1998) suggestion that continuing overreaction, triggered by increased investor confidence after the arrival of favorable public signals, causes momentum. Their study "Continuing Overreaction and Stock Return Predictability" examines whether future returns can be predicted with a measure of continuing overreaction. The authors point out that a direct measure of continuing overreaction would be a better predictor of future returns than just past returns. They introduce a new measure based on trading volumes and the direction the overreaction. Trading volume is a useful proxy for both investor overconfidence and continuing overreaction as many studies show strong evidence of investor overconfidence causing increased trading volumes on markets (Odean, 1998; Grindblatt & Keloharju, 2009).

Although knowing the level of investor overconfidence is valuable when predicting future returns, even more essential is to capture the trend in overconfidence. Continuing overreaction is defined by an upward trend in investor confidence and Daniel et al. (1998) show that momentum appears when investors become increasingly more confident, not when the level of overconfidence stays constant. Therefore, the authors put more weight on trading volumes of recent months and capture the trend rather than the level of overconfidence.

In addition to the trend, identifying the direction of investor overreaction is essential when predicting future returns. In the case of high trading volume, increased stock price

indicates continuing overreaction to positive information and predicts higher future price, while decreased stock price indicates continuing overreaction to negative information and predicts lower future price. The authors construct a signed volume that subsumes the direction of either upward or downward overreaction by multiplying the trading volume by the sign of the contemporaneous stock returns.

Using this measure, Byun et al. (2016) sort stocks into 10 portfolios based on their monthly returns and trading volumes over the past 12 months. Their sample includes stocks traded on NYSE, AMEX and NASDAQ exchange from the period of January 1965 to December 2009. Stocks with the highest degree of continuing overreaction on the positive side are placed in the top decile (Portfolio 10) and stocks with the highest degree of continuing overreaction on the negative side are placed in the bottom decile (Portfolio 1). The following table presents the raw average monthly returns for the 10 portfolios constructed. Returns are noted for 3-, 6-, and 12-month holding periods.

Table 3, Continuing Overreaction Portfolio Returns (Byun et al. 2016)

Portfolio	Holding Periods		
	3 Months	6 Months	12 Months
1 (Downward)	0.52 (1.93)	0.59 (2.17)	0.80 (2.93)
2	0.75 (2.68)	0.82 (2.97)	1.00 (3.93)
3	0.90 (3.33)	0.95 (3.52)	1.09 (4.03)
4	1.01 (3.81)	1.04 (3.96)	1.14 (4.34)
5	1.11 (4.31)	1.16 (4.50)	1.19 (4.61)
6	1.23 (4.85)	1.22 (4.81)	1.22 (4.85)
7	1.29 (5.19)	1.28 (5.17)	1.26 (5.09)
8	1.40 (5.68)	1.39 (5.65)	1.32 (5.39)
9	1.49 (6.10)	1.45 (5.91)	1.36 (5.51)
10 (Upward)	1.63 (6.12)	1.59 (5.95)	1.38 (5.13)
10 – 1	1.11 (6.25)	1.00 (6.25)	0.58 (4.07)

As can be seen from table 3, the returns of upward-continuing overreaction portfolios are consistently higher than the returns of downward-continuing overreaction portfolios. The table also reports the returns of zero-investment portfolio that buys the highest

positive overreaction portfolio and shorts the highest negative overreaction portfolio. This is marked as the difference between the returns of portfolios 10 and 1, and for all holding periods, the zero-investment portfolio yields positive and statistically significant returns. For shorter holding periods the monthly returns of this strategy are 1,11 % and 1,00 %. For the whole year holding period, the strategy yields lower but still significant returns. These results suggest that long-short trading strategies can be implemented by using continuing overreaction as a measure for investor overconfidence and gain notable profits in the medium term.

The continuing overreaction measure is designed to directly capture the underlying driver of return predictability used in the DHS model. In the case of continuing overreaction predicting future returns better than past returns do, such evidence offers strong support for the DHS model. The authors compare their continuing overreaction strategies with price momentum strategies and find that the returns of their strategies are not only robust when using momentum-adjusted returns, but the returns of all of the momentum portfolios except for the loser portfolio become insignificant after being adjusted for continuing overreaction. Continuing overreaction predicts future returns very well even after adding different determinants of the cross section of stock returns, such as beta, size, book-to-market ratio, liquidity and turnover. Based on these results, continuing overreaction is a better predictor of future returns than past returns.

Motivated by the Byun et al. (2016) results and the finding that there is a clear difference in return predictability between the U.S and Japan, Yang, Chu, Ko & Lee (2018) examine the effectiveness of Byun et al. (2016) strategy outside of the U.S. Their study investigates whether continuing overreaction predicts future returns in the Taiwan stock market. This particular market is chosen for two main reasons. First, evidence shows the lack of momentum in the Taiwan stock market (Hameed & Kusunadi, 2002; Du, Huang & Liao, 2009). Second, unlike investors in Japan, Taiwanese investors are suggested to exhibit overconfident trading behavior, and there is an imposition of price limits, a trading

mechanism preventing overreaction to information, for individual stocks in the Taiwan stock market.

Yang et al. (2018) begin by testing the effectiveness of the Byun et al. (2016) continuing overreaction measure in predicting returns for stocks listed in the TWSE. Their sample consist of 519 firms per month on average for the time-period of January 1971 to December 2015. A similar examination with Byun et al. (2016) reveals higher returns for the winner (upward) portfolios than loser (downward) portfolios for all the 3- to 12-month holding periods and significant monthly momentum profits of 0,364 % and 0,307 % for the long-short trading strategy over the 3- and 6-month holding periods. For the 12-month period, the profits of the long-short strategy become lower and insignificant. The profitability of the continuing overreaction strategy in Taiwan persist only up to 9 months and the authors suggest it to be a result of Taiwanese investors' stronger preference toward mean revision as discussed by Shu, Yeh, Chiu & Chen (2005).

Next the authors examine the difference on trading mechanism between the U.S. and Taiwan markets and its impact on the return predictability based on continuing overreaction. The imposition of price limits in TWSE is important because if investors are overconfident in their private information, their trading likely triggers price limit events. When trading is not allowed beyond the limit price, trading volume is limited at the upper and lower boundaries even if the level of investor overconfidence is high. In this case, the signed volume in Byun et al. (2016) measure would be underweighted at price limit events. Thus, Yang et al. (2018) develop two momentum strategies based on signed volumes of non-hit days and limit-hit days.

They find that the non-hit strategy yields significant positive returns in the intermediate term and strong reversals in the long term. The limit-hit strategy however yields negative returns in both intermediate and long terms. This evidence suggests that continuing overreaction exists only among stocks with more signed volumes at non-hit days. High signed volumes at limit-hit days seem to cool down investors trading, leading to rapid

price corrections, hence the imposition of price limits seems to restrain overreactions in Taiwan.

The outstanding performance of momentum strategies does not come without any setbacks. As a significant negative concern regarding momentum, its crashes are more than noteworthy. The risk-managed momentum introduced by Barroso & Santa-Clara (2015) tackles the concept of momentum crashes. The authors state that momentum strategies produce sudden and dramatic crashes following large previous market declines. In 1932 following the great depression, a traditional momentum strategy produced a return of -91,59 % in two months. In 2009 following the financial crisis, the momentum return was -73,42 % in three months. These extremely sudden crashes would take decades to get compensated even with large momentum returns (Barroso & Santa-Clara, 2015).

Taken these crashes into account, momentum investing seems far less compelling even if the investor is not risk averse. Due to the possibility to lose over 90 percent of the assets' value, the crash risk should preferably be managed. To manage the risk, Barroso & Santa-Clara (2015) propose a method of scaling the momentum portfolio by its realized volatility in the prior 6 months and targeting a strategy that has constant volatility. This method leads to the following benefits in their international examination. It raises the Sharpe ratio from 0,53 to 0,97, it drops the kurtosis from 18,24 to 2,68, and it improves the negative skewness from -247 to 0,42. The authors add that the minimum one-month return for the risk-managed momentum strategy is only -28,40 % when the same return for a raw momentum strategy is -78,96 %. With these results, Barroso & Santa-Clara (2015) argue that the crash risk of momentum is predictable and highly variable over time. It can be managed by scaling momentum with prior volatility and this kind of risk-managed momentum eliminates its exposure to crashes.

5 Data and Methodology

This chapter describes the data and methodology used in this thesis. First, the main characteristics of the sample data are introduced. Second, the portfolio formation and return calculations are explained in detail. Regression tests and eventual performance evaluation follows in chapter six.

5.1 Data

The data for this thesis is collected from the Thomson Reuters database and the Kenneth R. French data library. Daily data for stock prices is from the Thomson Reuters database. The sample consists of all stocks listed in the Helsinki stock exchange. The sample period is 17 years, spanning from January of 2006 to December of 2022. There were 93 stocks listed in the Helsinki stock exchange in the beginning of 2006 and 140 stocks by the end of 2022. Due to the relatively small sample size, no stocks were left out of the sample based on size, industry, or other criteria.

Factor data for asset pricing models is downloaded from the Kenneth R. French data library. Datasets for evaluation models include monthly values for all six factors used in the models. This thesis uses the European factors available on the data library. The market factor is the return on a regions value-weight market portfolio minus the one-month T-bill rate of the U.S. For other factors, the database has constructed different portfolios from which the factors are calculated. Small minus big (SMB) factor is the average return on small stock portfolios minus the average return on big stock portfolios. High minus low (HML) factor is the average return on value portfolios minus the average return on growth portfolios. Robust minus weak (RMW) factor is the average return on robust operating profitability portfolios minus the average return on weak operating profitability portfolios. Conservative minus aggressive (CMA) factor is the average return on conservative investment portfolios minus the average return on aggressive investment portfolios. Momentum (WML) factor is the average return on winner portfolios minus the

average return on loser portfolios. The momentum portfolios used to calculate the WML factor also use the 2-12 formation period that is explained in the next chapter.

5.2 Portfolio Formation

Monthly returns for stocks are calculated by dividing the price at end of the month t with the price at the beginning of the month t . Logarithmic returns are used to get more normally distributed returns by using the following formula.

$$(8) \quad R_{S,t} = \ln \left(\frac{P_t}{P_{t-1}} \right)$$

where,

$R_{S,t}$	=	Return of a stock in month t
\ln	=	Natural logarithm
P_t	=	Stock price at the end of the month t
P_{t-1}	=	Stock price at the beginning of the month t

Stocks are divided into portfolios based on their past performance. Stocks with the highest returns in the previous 12 months excluding the most recent month make the top (winner) portfolio and stocks with the lowest returns in the previous 12 months excluding the most recent month make the bottom (loser) portfolio. Excluding the most recent month prevents the effect of short-term reversals and thus limits the capability to produce abnormal returns (Jegadeesh & Titman 1993, 2001). The 2-12 formation period is one commonly used method in momentum examinations. 14 stocks with the largest cumulative returns during the formation period make the winner portfolio and 14 stocks with the lowest cumulative returns during the formation period make the loser portfolio. These momentum portfolios are reconstructed monthly for all months of the sample period.

In momentum strategies the winner portfolio is bought and the loser portfolio is sold, and this strategy is then held for the subsequent K months. The cumulative returns for the winner and loser portfolios are calculated for four different holding periods. Holding periods used to capture the short-term momentum in stocks are 3 months ($K = 3$), 6 months ($K = 6$) and 12 months ($K = 12$). In order to investigate possible return reversals, returns for a fourth holding period ($K = 13-24$) are also calculated. In this case the holding period is the second year after the portfolio formation. The following formula is used when calculating the formation period and the holding period returns of stocks.

$$(9) \quad CR_{s,t}(k) = \sum_{t=1}^k r_{s,t}$$

where, $CR_{s,t}$ = Cumulative return for a stock in month t
 k = number of months in a reviewed period

For all holding periods, the WML portfolio returns are calculated by subtracting the returns of the loser portfolio from the returns of the winner portfolio. The performance of the momentum portfolio is tested with all asset pricing models introduced in chapter 2. When evaluating the statistical significance of the results, a two-sided one sample t-test is used for the WML returns. It is possible for both the winner and the loser portfolio to generate positive or negative returns and therefore a two-sided test is more suitable for the examination. The chosen t-test with $n - 1$ degrees of freedom is the following.

$$(10) \quad t = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{n}}}$$

where, t = t-value of the returns
 $\bar{x} - \mu_0$ = difference between the sample mean and the hypothesized mean
 σ = the standard deviation of the sample
 n = number of observations in the sample

6 Results

The results section is divided into three parts. First, plain momentum returns are presented for the 3-, 6- and 12-month holding periods of the WML portfolio. In this section, these holding periods are referred as momentum periods and returns in these periods are referred as momentum returns. The last K=13-24 holding period is referred as reversal period and the return reversals are presented in the first part of the section, right after the momentum returns. Second, some descriptive statistics of the portfolios are introduced. The CAPM and Fama & French regressions come in the third part of the chapter. All interpretations of the results come in the paragraphs following the tables.

6.1 Momentum Returns

The following table presents the average monthly returns on the winner portfolio, loser portfolio and the WML portfolio for the whole sample. The values of t-statistics are reported in the parentheses, and ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels respectively. First, the returns are reported for 3-month, 6-month and 12-month holding periods to show the differences between shorter- and longer-term momentum.

Table 4, Momentum Returns in the Helsinki Stock Exchange

Portfolio	Holding period		
	3 months K=3	6 months K=6	12 months K=12
Winner	0,809 % (-0,85)	0,624 % (-1,93)	0,361 % (-3,82)
Loser	-1,079 % (-6,41)	-0,983 % (-7,93)	-0,744 % (-9,14)
WML	1,888 % (3,38)***	1,607 % (3,02)***	1,104 % (0,59)

As can be seen from table 4, the winner portfolio significantly outperforms the loser portfolio in the Helsinki stock exchange between years 2006 and 2022 in all holding periods. The winner portfolio generates positive returns for all holding periods and the loser portfolio generates negative returns for all holding periods. The momentum effect is more significant in the shorter 3- and 6-month holding periods than it is in the 12-month holding period. For the 3-month period, both the positive average monthly return of 0,809 % of the winner portfolio and the negative average monthly return of -1,079 % of the loser portfolio are the highest (lowest) of all holding periods. The average monthly WML return for the 3-month holding period is a 1,888 % with statistical significance at the 1 % level. The momentum effect slightly weakens for the 6-month holding period where the momentum portfolio produces a highly statistically significant positive monthly return of 1,607 %. The lowest 1,104 % return for the K=12 period is no longer statistically significant, implicating that the prominent effects of momentum do not quite endure the whole 12 months.

The WML returns indicate strong short-term momentum in the Helsinki stock exchange between years 2006 and 2022. The momentum returns table shows that the large average monthly returns are generated more strongly from the negative returns of the loser portfolio than from the positive returns of the winner portfolio. In other words, the loser stocks tend to follow their previous success more robustly than the winner stocks in the Helsinki stock exchange during the sample period. The intrinsic value of the returns for the loser portfolio is greater in all holding periods than it is for the winner portfolio. The next table illustrates the reversal effect linked to momentum by reporting the portfolio returns for the first year (K=12) and the year 2 (K=13-24) holding periods.

Table 5, Return Reversals in the Helsinki Stock Exchange

Portfolio	Holding period	
	Year 1, K=12	Year 2, K=13-24
Winner	0,361 % (-3,82)	-0,059 % (-5,90)
Loser	-0,744 % (-9,14)	-0,126 % (-6,35)
WML	1,104 % 0,59	0,067 % (-7,88)

Despite the lack of statistical significance of the returns, table 5 reveals a common feature of the momentum effect in return reversals. The winner portfolio yields a negative average monthly return of -0,059 % in the year 2 holding period. The momentum effect clearly disappears after 12 months and the returns for the best performing stocks turn negative in year 2. The loser portfolio also yields a negative return of -0,126 % for the year 2 holding period, however the difference of 0,618% to year 1 returns show that the negative returns start to decrease and move towards the positive side. It is common for the worst performing stocks to yield positive returns when moving on to year 2 and onwards from the portfolio formation period. Although the year 2 holding period returns remain negative, the trend is distinguishable. The WML portfolio yields an insignificant positive monthly return of 0,067 % or less than 1 % annually for the year 2 holding period, where the first-year return was 1,104 % per month.

6.2 Descriptive Statistics

Before going through the regression tests of the momentum portfolios, some descriptive statistics are introduced. The following table presents the descriptive statistics of the WML portfolios for the full sample period. Statistics are calculated for all four WML strategies and they are presented separately in side to side comparison. The mean average excess return is calculated by subtracting the monthly risk-free rate from the average monthly returns. The Sharpe ratio is calculated by dividing the mean excess return with the standard deviation. These three values, the mean excess return, the standard deviation and the Sharpe ratio are annualized, other values are given in monthly figures for all WML portfolios.

Table 6, Descriptive Statistics of Momentum Portfolios

<i>Statistic</i>	Portfolio			
	<i>WML 3</i>	<i>WML 6</i>	<i>WML 12</i>	<i>WML 13-24</i>
Mean	22,30	19,11	13,16	0,71
Standard Deviation	42,58	32,16	24,60	18,72
Kurtosis	3,65	3,07	2,69	0,01
Skewness	-0,73	-0,85	-1,11	-0,07
Minimum	-14,31	-10,83	-7,77	-5,07
Maximum	12,57	9,74	5,02	3,69
Sharpe Ratio	0,52	0,59	0,53	0,04

Table 6 shows that the annual mean excess return for the WML portfolio is 22,30 %, 19,11 %, 13,16 % and 0,71 % for the 3-, 6-, 12- and 13-24 -month holding periods respectively. Annually the most profitable strategy is to keep the winner and loser stocks for three months, however it bears more risk than the longer holding periods do. This is seen in the annual standard deviation figures, which are 42,58 %, 32,16 %, 24,60 % and 18,72 % for the holding periods in the same order respectively. The more the returns deviate from their mean value, the more volatile and therefore riskier they are. Adjusted to the risk, the 6-month holding period can be seen as the best strategy with the highest

Sharpe ratio of 0,59. The year 2 holding period clearly contains the weakest profitability and Sharpe ratio values showing the reversal effect after a strong short-term momentum in the Helsinki exchange's stocks.

Interpreting the Kurtosis and the skewness values, the Kurtosis of the 3- 6- and 12-month holding periods is very similar. Kurtosis of 3 is seen as neither high nor low as it is the same as in the normal distribution. Higher kurtosis implies more extreme price fluctuations and therefore the WML 3 strategy exhibits a bit more kurtosis risk than the WML 6 and the WML 12 strategies, though the differences and the risk altogether can be considered small. All the momentum strategies have negative skewness values. Negative skewness implies that the most extreme values are found further on left side of the return distribution denoting that the largest losses are more extreme than the largest gains. This is also seen in the momentum returns table, where the loser portfolio has higher negative returns than the winner portfolio has positive returns in all holding periods. Skewness of less than -1 means that the return distribution is highly skewed. It makes sense that the longer WML 12 strategy returns are more skewed since there are more extremes to be found when the market continues in the same direction for longer periods of time.

The largest maximum (12,57) and the smallest minimum (-14,31) values come from the WML 3 strategy. Similarly with the mean returns, the maximum and minimum values decrease in the longer holding periods. The smallest minimum values for all strategies come from the time-period between 2009 and 2010, right after the financial crises. This is consistent with the Barroso & Santa-Clara (2015) evidence of momentum crashes, where the most extreme momentum setbacks occur as the market is rebounding from huge declines. In this case, the biggest loser stocks during the 2008 financial crisis gain strong rise in value the following year and the WML portfolio generates large negative returns.

The largest maximum values come from different time-periods depending on the holding period. The maximum values for WML 3 and WML 6 strategies come from the 3-month and 6-month periods right at the end of the financial crisis between the end of 2008 and January of 2009, where the previous loser stocks keep falling drastically generating strong positive returns for the WML portfolio. The maximum value of 60,22 for the WML 12 strategy comes from the time-period of April 2019 – April 2020. This 12-month period contains the Covid-19 crash making the previous loser stocks fall significantly. Also, the previous winner stocks earn strong positive returns right before the crash and together these incidences cause the WML 12 strategy gain the biggest return in the sample period.

6.3 Regression Analysis

Next, the results of the CAPM and the Fama & French 3-factor, 5-factor and 6-factor regression models are introduced. All following tables are presented in the same manner, where the WML strategies are in contiguous columns, the intercept alphas and the factor values are in their own rows. The focus of interpreting the results is in the momentum returns. The reversal values for the year 2 holding period (WML 13-24) are presented as well to show the differences in the momentum and reversal effects, however less attention is given to their interpretation. Again, the values of t-statistics are reported in the parentheses, and ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % levels respectively.

Table 7, CAPM Regression

CAPM	WML 3	WML 6	WML 12	WML 13-24
Alpha	1,93*** (7,52)	1,65*** (8,51)	1,11*** (7,22)	0,04 (0,32)
MKT	-0,12 (-2,52)	-0,10 (-2,83)	-0,02 (-0,86)	0,04* (1,86)

Table 7 reports the CAPM regression results. The alpha intercept for the WML 3, WML 6 and WML 12 strategies produces significant abnormal returns of 1,93 %, 1,65 % and 1,11 % per month respectively and is statistically significant at the 1 % level for all these holding periods. The factor loading for MKT is very small, negative, and not statistically significant for all momentum strategies. It is a positive 0,04 and statistically significant at the 10 % level for the reversal period showing that the reversal period returns move fractionally in the same direction with the market and in the opposite direction of the momentum returns. However, the MKT values are so small that it has next to none effect on the momentum returns as an independent variable.

Table 8, FF3 Regression

FF3	WML 3	WML 6	WML 12	WML 13-24
Alpha	1,90*** (7,33)	1,65*** (8,35)	1,10*** (7,04)	0,01 (0,09)
MKT	-0,08 (-1,53)	-0,09 (-2,10)	-0,01 (-0,17)	0,06** (2,14)
SMB	-0,13 (-0,93)	-0,09 (-0,87)	-0,09 (-1,13)	0,11 (1,59)
HML	-0,14 (-1,24)	-0,05 (-0,53)	-0,07 (-0,95)	-0,06 (-1,00)

Table 9, FF5 Regression

FF5	WML 3	WML 6	WML 12	WML 13-24
Alpha	1,95*** (7,70)	1,81*** (9,10)	1,20*** (7,43)	0,07 (0,54)
MKT	0,09 (1,44)	-0,03 (-0,62)	0,004 (0,10)	0,05* (1,67)
SMB	0,03 (0,22)	-0,07 (-0,65)	-0,10 (-1,22)	0,09 (1,22)
HML	-0,83 (-4,67)	-0,51 (-3,62)	-0,27 (-2,30)	-0,14 (-1,34)
RMW	-0,51 (-2,07)	-0,68 (-3,51)	-0,38 (-2,41)	-0,16 (-1,17)
CMA	1,15*** (5,11)	0,37** (2,07)	0,04 (0,29)	-0,04 (-0,34)

Tables 8 and 9 report the results of Fama & French 3- and 5-factor regressions. The results for the momentum strategies in both models are very similar with the CAMP regression results as the alpha intercepts are almost identical and all statistically significant at the 1 % level. Both regressions show significant abnormal returns for the momentum portfolio in the 3-, 6- and 12-month holding periods. For the 5-factor model, the alpha intercepts are a bit higher than for the 3-factor model since the HML and RMW factors affect more negatively to the dependent variable in the 5-factor model. The highest abnormal momentum returns of 1,95 % comes from the alpha intercept of the WML 3 strategy in the 5-factor model, and the smallest abnormal momentum return of 1,10 % comes from the alpha intercept of the WML 12 strategy in the 3-factor model. The reversal period returns are again minimal and not statistically significant.

Generally, the independent variables don't have statistically significant effect on the momentum returns in either model. In the FF3 model, all factor values are very small and not statistically significant excluding the market factor for the reversal period returns. In the FF5 model however, the factor loadings for HML, RMW and CMA are all a little larger and therefore have more effect on the momentum returns. The CMA factor has a value of 1,15 with significance at the 1 % level for the WML 3 strategy. This means that a 1 % change in the CMA factor has a positive 1,15 % effect on the momentum returns in the 3-month holding strategy. The CMA factor is the only independent variable that explains the momentum returns to some extent. It has a positive value of 0,37 with significance at the 5 % level in the WML 6 strategy as well, although the effect is a bit weaker and not as statistically significant. For the WML 12 strategy, the effect disappears.

Table 10, FF6 Regression

FF6	WML 3	WML 6	WML 12	WML 13-24
Alpha	1,71*** (7,00)	1,67*** (8,48)	1,10*** (6,84)	0,03 (0,21)
MKT	0,10* (1,81)	-0,02 (-0,43)	0,01 (0,29)	0,05* (1,79)
SMB	-0,01 (-0,10)	-0,10 (-0,95)	-0,12 (-1,47)	0,08 (1,13)
HML	-0,44 (-2,37)	-0,26 (-1,69)	-0,08 (-0,67)	-0,07 (-0,64)
RMW	-0,48 (-2,05)	-0,66 (-3,51)	-0,36 (-2,33)	-0,16 (-1,15)
CMA	0,83*** (3,71)	0,16 (0,88)	-0,10 (-0,72)	-0,10 (-0,85)
WML	0,36*** (4,65)	0,23*** (3,76)	0,16*** (3,24)	0,07* (1,70)

Table 10 reports the Fama & French 6-factor model results. Similarly to the other regressions, the intercept alphas show high and extremely statistically significant abnormal returns of 1,71 %, 1,67 % and 1,10 % for the WML 3, WML 6 and WML 12 strategies respectively. According to the alphas, the WML 3 strategy is again the most profitable but the difference with the WML 6 alpha is smaller than in the other models. The t-statistic for the WML 6 strategy alpha is consistently largest in all regression models implying its attractiveness as the best strategy to choose from. The same is noticed in table 6 Sharpe ratios.

As can be seen from the FF6 table, the added momentum factor in the 6-factor model has small and highly statistically significant effect to all momentum returns. The factor loadings are larger in shorter holding periods, all effecting positively to the dependent variable. From all other independent variables only the CMA factor for the WML 3 strategy has a statistically significant effect on the momentum portfolio returns. Consequently, the excess returns can be explained only to some extent with the momentum factor and in the case of the WML 3 strategy with the momentum and investment factors. Of all factors, the momentum factor is strongest and although the performance of the FF6 model is also weak, due to the WML factor the FF6 model performs the best in explaining the momentum returns in the Helsinki stock exchange.

7 Conclusions

The phenomenon of momentum, classically defined as something that is moving in one direction keeps moving in that direction, is prominent in financial markets. Momentum research dates back to at least 30 years ago, when Jegadeesh & Titman published their study on recent winners and recent losers in 1993. There were some reported evidence of stock return predictability through past returns even earlier and with momentum's dominant incidence throughout the years, it is not crazy to assume that momentum in stocks has been around for much longer.

As presented, momentum has persevered through time and remains a significant financial anomaly around the world. The bulk of previous research support the possibility to earn above average returns with a simple strategy that buys previous winners and sells short previous losers. Although momentum strategies have developed and differ with each other, the basic idea remains the same and produces abnormal returns. The excess returns gained from momentum strategies refuse to be derived from common factors generally used in asset pricing models. The underlying source for the returns remains unproven making it a popular subject among researchers.

This thesis examines momentum in the Helsinki stock exchange. In a time-period spanning from 2006 to 2022 and with a sample that consists of all stocks listed in the Helsinki stock exchange, the plain 2-12 momentum strategy produces significant raw returns. The monthly momentum returns are highest 1,888 % for the shortest 3-month holding period, second highest 1,607 % for the 6-month holding period and lowest 1,104 % for the 12-month holding period. The WML returns are highly statistically significant for the 3- and 6-month holding periods and not statistically significant for the 12-month holding period, showing that the momentum effect in Finnish stocks is stronger in the short-term than in the long term. In addition, the monthly return for the year 2 holding period is only 0,067 % showing evidence of the reversal effect.

When adjusted to risks, the 6-month holding period strategy seems the most attractive of the examined strategies. It produces slightly lesser returns than the 3-month holding period strategy but with less risk. The 0,59 Sharpe ratio of WML 6 is higher than the 0,52 of WML 3, due to the monthly returns deviating less around the mean return. The skewness is similar, but WML 6 has less kurtosis risk. Additionally, there is less crash risk with the minimum value of WML 6 being approximately 3,50 % higher than in WML 3. Also, the WML 6 alphas have the highest t-values in all regression models.

The abnormality of the returns is tested with the CAPM and Fama & French 3-, 5-, and 6-factor models. The alpha intercepts of the examined regression models show high abnormality of the returns. The intercepts are consistent among all models; they all decrease in value as the holding periods get longer and show similar statistical significance. The highest intercept values come from the FF5 model with 1,95, 1,81, 1,20, and 0,07 for the WML 3, WML 6, WML 12, WML 13-24 strategies respectively. Large alpha values in all models with statistical significance at the 1 % level suggest highly significant abnormal returns for the momentum strategy in 3 to 12 month holding periods. In the reversal period, the values are miniscule and not statistically significant offering more evidence on the return reversals one year after the portfolio formation.

In general, the independent variables in the CAPM and Fama & French regressions have very little explanatory power over the observed momentum returns. The models' coefficients are systematically small and not statistically significant. Considering strategies as a whole, the WML momentum factor has the most significant effect on the returns of all the factors. In fact, it is the only factor which to some extent explains the returns statistically significantly for all holding periods. The CMA factor in the FF5 and FF6 models has the largest coefficient in the 3-month holding strategy, however in longer strategies, its effect severely decreases. None of the other factors exhibit significant loadings. These results indicate that none of the regression models perform well in explaining the abnormal returns earned from the momentum strategy. The best-performing model from the examined ones is the FF6 model, which neither cannot capture the excess returns.

These main findings confirm the hypothesis of this thesis and reject the null hypothesis. Momentum clearly produces significant abnormal returns in the Finnish stock market. Up to 22,30 % annual profits can be made by exploiting the momentum effect between years 2006 and 2022 in the Helsinki stock exchange. The returns cannot be explained by the examined Fama & French factors. These results are consistent with most of the previous studies introduced in chapter four. Momentum keeps producing abnormal returns in different markets and this thesis offers evidence of that in Finland. In addition to the large returns and the asset pricing models incapability to capture them, the stock price behavior seems similar to the U.S. market as in Barroso & Santa-Clara (2015) for example when the most extreme negative returns come right after the period of crisis when the market is recovering, and loser stocks gain strong profits.

Overall, the source for momentum remains unclear. It might originate from some behavioral phenomenon or other risks that are not examined in this thesis. Suggestions for further research could be to combine momentum with other measures such as value or quality, or to build a momentum strategy based on overconfidence or over- and underreactions. Understanding the fact that the small Finnish market is not the most compelling target of research, further evidence of momentum in Finland is welcomed.

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