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Profitability of Risk-Managed Momentum in Equity Markets

Global Evidence

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Title of the Thesis:	Profitability of Risk-Managed Momentum in Equity Markets : Global Evidence
Degree:	Master of Science in Economics and Business Administration
Programme:	Master's Degree Programme in Finance
Supervisor:	Vanja Piljak
Year:	2020 **Pages:** 77

ABSTRACT:

The plain momentum strategy has been a profitable investment strategy for investors in many countries. Despite the success of the momentum strategies, the plain momentum is prone to momentum crashes. The momentum crashes can wipe out the returns of the decades, and it might take years that the plain momentum recovers from the crash. To improve momentum profitability and avoid the momentum crashes, Barroso and Santa-Clara (2015) present a risk-managed momentum strategy. This thesis examines whether the risk-managed momentum produces positive abnormal returns in European and global (North America, Japan and Asia-Pacific) equity markets. Furthermore, this thesis takes a deeper look at how managing the risk of the momentum reduces the momentum crash risk and increases the profitability measured by the Sharpe ratio.

This thesis utilizes only the data from the largest stocks, which comprise 90 % of the total market capitalization. All the data are downloaded from Kenneth French's website, and the time period that is used is from January 1995 to December 2019. To construct the risk-managed momentum portfolios, this thesis uses the same procedure as Barroso and Santa-Clara (2015). In order to test the positive abnormal returns of the risk-managed momentum, the Ordinary Least Squares (OLS) regressions that utilize the Fama-French three-factor model (FF3) and Fama-French five-factor model (FF5) are run. Moreover, robustness tests are formed by dividing the whole sample period into four different subsamples.

The results of the whole sample period indicate that the risk-managed momentum strategy produces statistically significant positive abnormal returns in Europe and Asia-Pacific but not in North America and Japan. Even though managing the risk of the momentum does not produce statistically significant positive abnormal returns in all research regions, it provides other benefits for the investors. The risk-managed momentum produces higher Sharpe ratio compared to the plain momentum. The Sharpe ratio results are robust in every subsample and every research region. Usually, high kurtosis values are related to plain momentum strategy, but this thesis provides results that the risk-managed momentum drops the kurtosis values near to normal distribution. Furthermore, managing the risk of the momentum improves whole sample skewness values in every research area and even provides positive skewness values. Thus, this indicates that the risk-managed momentum virtually eliminates the momentum crashes.

KEYWORDS: Momentum, risk-managed momentum, profitability, Fama-French three-factor model, Fama-French five-factor model

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Abbreviations

APT	Arbitrage Pricing Theory
CAPM	Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
DDM	Dividend Discount Model
FCF	Free Cash Flow Model
FF3	Fama & French Three-Factor Model
FF5	Fama & French Five-Factor Model
HML	High Minus Low
SMB	Small Minus Big
RMRF	Market Return Minus Risk-Free Rate
RMW	Robust Minus Weak
WML	Momentum Portfolio
WML*	Risk-Managed Momentum Portfolio

1 Introduction

During history, investors have developed different strategies to beat the market. Jegadeesh and Titman (1993) present the momentum strategy, and their findings aroused the interest of researchers all around the world. They find that previous winners tend to rise in the future, and the previous losers tend to decrease in the future. Their finding raises questions towards Fama's (1970) efficient market hypothesis, which suggests that all past information is already in the stock prices. Therefore, it is not possible to earn positive abnormal returns by creating a strategy based on past returns.

The earliest momentum studies were in the U.S. market, but the Rouwenhorst (1998) presents the first momentum study outside of U.S. Later many momentum studies are presented in globally (Chan, Hameed and Tong 2000; Griffin, Ji and Martin 2003; Fama and French 2015). The wide popularity of the momentum strategy in equity market inspire researchers to study momentum strategy in different asset classes. Researchers show that the momentum works in commodities, stock indices, currencies, across asset classes, industry portfolios and many other asset classes (Asness, Liew, and Stevens 1997; Bianchi, Drew and Fan 2016; Menkhof, Sarno, Schmeling and Schrimpf 2012; Moskowitz and Grinblatt 1999; Okunev and White 2003). Momentum strategy works by alone and combined with other strategies. For example, researchers combine momentum and value investing (Bird and Whitaker 2004). Furthermore, there are widely known opposite strategy for the momentum, contrarian strategy, where investors buy past losers and sell past winners (Ryan and Overmyer 2004).

Despite the success of the momentum strategy in various countries and asset classes, the crash risk is related closely to the momentum strategy. The negatively skewed return distribution makes momentum strategy more vulnerable to the crashes than most of the other strategies. The momentum strategy suffered -91,59 % losses in 1932, and -73,42 % loses in 2009 (Barroso and Santa Clara 2015). The momentum crashes appear when collapsed market starts to increase rapidly and cause a high rise of loser stocks returns (Daniel and Moskowitz 2016). To reduce the negative skewness and the probability of

the momentum crash, Barroso and Santa-Clara (2015) present a risk-managed momentum strategy. They estimate the momentum risk by the realized variance of daily returns and find that managing the risk reduces negative skewness, eliminates crashes and almost doubles a Sharpe ratio. The findings raise questions, does the risk-managed momentum work in different countries, asset classes and time periods?

1.1 The purpose of the study and contribution

This thesis aims to test with three-factor (FF3) and five-factor (FF5) models, does the Barroso and Santa-Clara's (2015) risk-managed momentum strategy produce positive abnormal returns in European and global equity markets. These two main research questions will be answered in the results section. The investigation of the risk-managed momentum abnormal returns is not the only purpose of this thesis. The thesis takes a deeper look at momentum and risk-managed momentum in Europe and examines how managing the risk of the momentum reduces the momentum crash risk and increases the profitability measured by the Sharpe ratio. Globally, the thesis also examines the same things that in the European market but focuses more on the investigation, whether risk-managed momentum produces positive abnormal returns globally.

The clear contribution to the previous literature is made in this thesis. Barroso and Santa-Clara's (2015) paper is one of the few studies which focuses on managing the risk of the equity plain momentum while most of the studies focus on managing the risk of the industrial momentum. The first contribution is made in research area selection. This thesis examines the risk-managed momentum globally more widely (European, North America, Japan and Asia-Pacific) than the previous literature. Especially this thesis provides new information about risk-managed momentum in Asia-Pacific due to the lack of previous studies. On other words, wider evidence will be presented whether or not the risk-managed momentum works. The second contribution is made in the time period selection, where this thesis uses the most recent data from the past 25 years. Therefore, this thesis provides the most recent performance of the risk-managed momentum.

1.2 Research hypotheses

In this thesis, the hypotheses are derived from the previous studies on momentum. Rouwenhorst (1998) shows that momentum produces positive abnormal returns in the European market. Therefore, the first hypothesis investigates whether or not the momentum still produces positive abnormal returns in the European market. The first hypothesis is written as follows:

H0: Momentum strategy does not produce positive abnormal returns in Europe.

H1: Momentum strategy does produce positive abnormal returns in Europe.

Barroso and Santa-Clara (2015) examine the risk-managed momentum strategy in the UK, France and Germany and show that it is a profitable investment strategy in all three countries. In this thesis, the second hypothesis examines whether or not the risk-managed momentum produces positive abnormal returns in Europe and also answers one of the main research questions of this thesis. The first hypothesis act as a great benchmark for a second hypothesis. The second hypothesis is presented as follows:

H2: Risk-managed momentum strategy does produce positive abnormal returns in Europe.

Barroso and Santa-Clara (2015) show that the risk-managed momentum also works globally. Therefore, in this thesis, the third hypothesis investigates whether or not the risk-managed momentum produces positive abnormal returns in globally and provides the answer for the research question. The third hypothesis is presented as follows:

H3: Risk-managed momentum strategy does produce positive abnormal returns in North America, Japan and Asia-Pacific.

1.3 Limitations and assumptions

In this thesis, the limitations lie on the chosen data and time period. The thesis utilizes only the large stocks data, and therefore the risk-managed momentum returns might differ if small and medium-size stocks would have been included into data. The second limitation is related to time period length. Most of the risk-managed momentum studies use a longer time period compared to this thesis. As discussed earlier, other researchers have proven that the risk-managed momentum strategy is profitable. Therefore, positive abnormal returns of the risk-managed momentum can be expected in this thesis. However, there are not many studies that are related to risk-managed momentum. Thus, it is hard to say whether or not the risk-managed momentum produces positive abnormal returns in every research area.

1.4 Structure of the thesis

The rest of the thesis is structured as follows: The second chapter will discuss the theoretical background, which includes the theory of the efficient market, asset pricing models and portfolio performance measures. The third chapter covers the previous literature and gives the reader a wide understanding of how momentum studies have been developed. The fourth chapter presents the data and methodology that is used in this thesis. The fifth chapter presents the results of the thesis and answers to the research questions. Finally, the last chapter draws a conclusion from the whole thesis.

2   Theoretical background

In this chapter, theory and models which are related to this thesis are presented. First, the efficient market hypothesis is presented. Second, the widely known asset pricing models are presented. Finally, portfolio performance measures are presented.

2.1   Efficient market hypothesis

Efficient market hypothesis plays a vital role in financial theory. It was first introduced by Eugene F. Fama (1970), and he shows that the efficient market hypothesis can be divided into three categories based on the feature of information. The categories are weak-form, semi strong-form and strong-form. The efficient market hypothesis shows that stocks are correctly priced, and therefore, it is impossible to gain excess returns on stocks. More precisely, any actions which affect firms are immediately in stock prices so no excess returns can be earned. (Fama 1970.)

The first efficient market hypothesis is called the weak-form hypothesis, which means that stock prices already reflect all the past information regarding stocks. For example, the past information could be trading volumes, short interests or stock prices from the past. The past stock price data must be costless to obtain and publicly available. The weak-form hypothesis suggests that trend analysis is useless. (Bodie, Kane and Marcus 2014: 353-354.)

The second efficient market hypothesis is called semi strong-form, which means that all the past information of stocks and also all the publicly available information regarding companies' prospects are already in stock prices. For instance, the information could be earning forecast, patents held and quality of management. (Bodie et al. 2014: 354.)

The third efficient market hypothesis is called strong-form, which means that all relevant information to the company is already in stock prices. This also includes the company's

insider information. All three efficient market hypothesis share one common feature which is that stock prices should reflect available information. (Bodie et al. 2014: 354.)

Even though the efficient market hypothesis is widely known among financial practitioners, anomalies challenge market efficiency. The weak-form category is challenged by momentum anomaly. The weak-form category asserts that all the past information is already in the stock prices. Therefore, no positive abnormal returns can be earned based on past information, as discussed earlier. However, momentum anomaly considers only past information and Jegadeesh and Titman (1993) show that momentum generates positive abnormal returns. The semi strong-form category is challenged by firm size and book-to-market (value) anomalies. The semi strong-form category suggests that positive abnormal returns cannot be earned by using past and publicly available information. However, small-firm portfolios provide a higher average return than large-firm portfolios, and high book-to-market firms provide higher average return than low book-to-market firms (Fama and French 1996.) Thus, these anomalies act as evidence that markets are not efficient.

The strong-form category cannot be true due to trading costs and positive information. However, it could be used as a benchmark. Moreover, the biggest problem regarding the efficient market hypothesis is a joint-hypothesis problem. Market efficient is not testable by itself so that must be tested jointly with the equilibrium model, for example, an asset pricing model. (Fama 1991.)

Results of the anomalies are inconsistent with asset-pricing theories. The anomalies show that either the asset pricing models are deficient or the market is inefficient. Often when anomalies are observed and presented in the academic literature, the anomalies effect tend to attenuate or disappear. This raises questions among the financial practitioners that are the anomalies statistical aberrations or do the anomalies only exist in the past because investors utilize the anomalies until the anomalies disappear or attenuate. Thus, investors' behaviour makes the market more efficient. (Schwert 2002.)

2.2   Asset pricing models

2.2.1   Divident Discount Model

Dividend discount model (DDM) is a popular stock valuation model among stock market analysts. Analysts use the model to determine stocks intrinsic value. To calculate the stock's intrinsic value, the dividend discount model takes into account future dividends from the current moment to perpetuity. Then the future dividends are divided by the required rate of return. (Bodie et al. 2014: 591-596.)

The formula of the DDM can be written as follows:

$$V_0 = \frac{D_1}{1+k} + \frac{D_2}{(1+k)^2} + \cdots + \frac{D_t}{(1+k)^t} , \qquad (1)$$

Where V_0 is current share price, D_t dividend at time t and k required rate of return. (Bodie et al. 2014: 595-596.)

The drawbacks of equation 1. is that it needs dividend forecasts for every year into the indefinite future. To make the dividend discount model more practical, the constant-growth DDM has been developed, also known as the Gordon model. Instead of forecasting dividends for every year in the future, the constant growth DDM estimates constant growth of dividends. (Bodie et al. 2014: 596-597.)

The formula of the constant-growth DDM can be written as follows:

$$V_0 = \frac{D_1}{k-g} , \qquad (2)$$

Where g is estimated constant growth rate of dividends. (Bodie et al. 2014: 596-597.)

2.2.2 Free Cash Flow Model

Free cash flow model (FCF) provides an alternative method to calculate a stock price. Comparing the free cash flow model to the dividend discount model, the free cash flow model can evaluate a firm's stock price if the firm does not pay dividends. The free cash flow model estimates a firm's free cash flows year by year and discount them with the weighted-average cost of capital (WACC). Finally, it takes into account a terminal value. The formula gives the current value of a firm, and the firm value must be divided by the number of outstanding shares to get a stock price value. (Bodie et al. 2014: 617-618.)

The formula of the free cash flow model can be written as follows:

$$P_o = \sum_{t=1}^{T} \frac{FCF_t}{(1+WACC)^t} + \frac{V_t}{(1+WACC)^t}, \tag{3}$$

$$V_t = \frac{FCF_{t+1}}{WACC-g}, \tag{4}$$

Where P_o is the current value of the firm, FCF is the free cash flow, t is the time period, $WACC$ is the weighted-average cost of capital, g is the growth rate of cash flows. (Bodie et al. 2014: 617-618.)

2.2.3 Capital Asset Pricing Model

The capital asset pricing model (CAPM) was presented by William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966). It is one of the earliest asset pricing models which has gained popularity among finance practitioners. The asset pricing model predicts the relationship between risky asset and its expected return. It lays on Harry Markowitz (1952) modern portfolio theory. The modern portfolio theory expects that all investors optimize their portfolios (Bodie et al. 2014: 291).

CAPM can be portrayed graphically as a security market line (SML) which shows expected returns against beta. Beta plays in a central role in CAPM where the beta measures a systematic risk which cannot be eliminated by diversifying a stock portfolio. The market beta is 1, and therefore SML slope is a risk premium of the market portfolio. The fairly priced stocks are precisely on SML, and if the stocks are underpriced, they plot above the SML and overpriced stocks plot under SML. (Bodie et al. 2014: 298-299.)

The formula of the capital asset pricing model can be written as follows:

$$E(R_i) = R_f + \beta(R_M - R_f)\,, \tag{5}$$

Where $E(R_i)$ is the expected return on asset, R_f is the risk-free rate, β is the market beta and R_M is the expected return of market portfolio. (Fama and French 2004.)

Assumption of the CAPM:
- Investors are rational and risk-averse
- Investors have a single planning horizon
- Investors have homogeneous beliefs and expectations
- Investors can lend or borrow at the common risk-free rate, all short positions are allowed, and all assets can be traded on public exchanges
- All information is publicly available for everyone at the same time
- No taxes
- No transaction costs. (Bodie et al. 2014: 304.)

Three of unrealistic CAPM assumptions listed above create challenges to CAPM. These are, all assets can be traded, there are no transaction costs and investors have a single planning horizon. These challenges of CAPM assumptions have motivated other finance practitioners to study the unrealistic assumptions, thus leading CAPM failing in many empirical tests. (Bodie et al. 2014: 305.) Furthermore, CAPM fails to explain certain patterns in stock returns which are called anomalies. Even though the CAPM sometimes

fails to explain stock returns, it stays popular among the investors due to its simple logic. (Fama and French 1996; 2004.)

2.2.4   Arbitrage Pricing Theory

The arbitrage pricing theory (ATP) was presented by Stephen Ross (1976). The ATP is developed to overcome the CAPM weaknesses. The CAPM assumes that the stock market is perfectly efficient, whereas ATP assumes that markets can misprice the stocks. The arbitrage opportunity can be noted when the net investment is not needed, and investors can make profits without risk. However, the arbitrage opportunity can vanish quickly because investors can set large positions on arbitrage trades, thus forcing prices up and down until the arbitrage opportunities vanish. (Bodie et al. 2014: 324-328.)

Returns of stocks are affected by two different risk factors that are a macroeconomic risk factor and firm-specific risk factor (Bodie et al. 2014: 325). Macroeconomic changes have a different effect on different types of stocks. For example, some stocks are more sensitive to changes in interest rate, and some stocks are more sensitive to changes in oil prices. (Harrington 1978: 188-189.)

APT assumptions can be written as:
- Investors maximize their wealth and are unwilling to take risks
- Investors can take loan with risk-free rate
- No transaction costs, no taxes and short positions are allowed. (Harrington 1978: 193.)

The formula of the APT can be written as follows:

$$R_i = r_f + b_{i1}F_{i1} + b_{i2}F_{i2} + \cdots + e_i \, , \qquad\qquad (6)$$

Where R_i is the return of asset, the r_f is the risk-free rate, the b_i is the factor sensitivity or loading, F_i is the value of factor and e_i is the noise error. (Brealey, Myers and Allen 2017: 207.)

2.2.5 Fama & French Three-Factor Model

One of the most common asset pricing models is the three-factor model which is developed by Fama and French (1993). The model is used to explain the average excess returns of securities. The three-factor model is formed by using three different factors which are a market factor, size factor and book-to-market ratio factor. The market factor is excess return on the market (RMRF), the size factor is small minus big (SMB) which measures the excess return of small stocks compared to large stocks, and the book-to-market ratio is high minus low (HML) which measures the excess return of value stocks compared to growth stocks. (Fama and French 1993.)

Fama and French (1993) show that the three-factor model is a good model to measure size and book-to-market portfolio returns. In a later study, Fama and French (1996) state that the three-factor model explains better the average variations and abnormal returns than the Capital Asset Pricing Model.

The formula of the three-factor model can be presented as follows:

$$R_i - R_f = \alpha_i + b_i(R_m - R_f) + s_i SMB + h_i HML + \varepsilon_i \, , \qquad (7)$$

Where R_i is the expected return of portfolio, R_f is the risk-free rate, α_i is the estimated alpha, $b_i(R_m - R_f)$ is the factor sensitivity or loading for excess market returns multiplied by excess returns of market portfolio, $s_i SMB$ is the factor sensitivity or loading for small minus big multiplied by returns of small minus big, $h_i HML$ is the factor sensitivity or loading for high minus large multiplied by returns of high minus large and ε_i is the random error variable. (Fama and French 1996.)

2.2.6 Fama & French Five-Factor Model

A three-factor model has faced criticism that it does not explain all the average excess returns of securities. For that reason, Fama and French (2015) developed a five-factor model where the two new factors are profitability (RMW) and investment (CMA). The RMW factor is the difference of returns between robust profitability and weak profitability portfolios, and the CMA factor is the difference of returns between conservative and aggressive portfolios.

The five-factor model can be used to explain anomalous returns, and it provides better results than the three-factor model. However, the five-factor model can not explain low average returns on small stocks when companies have low profitability and companies' returns behave like companies that invest a lot. (Fama and French 2015.)

The formula of the five-factor model can be presented as follows:

$$R_i - R_f = \alpha_i + b_i(R_m - R_f) + s_i SMB + h_i HML + r_i RMW + \qquad (8)$$
$$c_i CMA + \varepsilon_i ,$$

Where R_i is the expected return of portfolio, R_f is the risk-free rate, α_i is the estimated alpha, $b_i(R_m - R_f)$ is the factor sensitivity or loading for excess market returns multiplied by excess returns of market portfolio, $s_i SMB$ is the factor sensitivity or loading for small minus big multiplied by returns of small minus big, $h_i HML$ is the factor sensitivity or loading for high minus large multiplied by returns of high minus large, $r_i RMW$ is the factor sensitivity or loading for robust minus weak multiplied by returns of robust minus weak, $c_i CMA$ is the factor sensitivity or loading for conservative minus aggressive multiplied by returns of conservative minus aggressive and ε_i is the random error variable. (Fama and French 2015.)

2.3 Portfolio performance measures

2.3.1 Sharpe Ratio

The Sharpe ratio, also known as a reward-to-volatility ratio, was introduced by William Sharpe (1966). The Sharpe ratio compares a portfolio's excess return to the portfolio's risk, which is a standard deviation of excess return. The higher the Sharpe ratio is, the more excess return the portfolio generates compared to its risk. Investment managers performance is often evaluated by the Sharpe ratio. (Bodie et al. 2014 134.) Even though the Sharpe ratio is widely used there are some drawbacks. According to Sharpe (1994), the Sharpe ratio does not take under consideration the correlation with other securities in the portfolio or current liabilities, and Sharpe ratio only takes into consideration the portfolio's excess return. Despite the drawback of the Sharpe ratio, it can be used to improve investment portfolio.

The formula of the Sharpe ratio can be written as follows:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_\alpha}, \tag{9}$$

Where R_p is the return of portfolio, R_f is the risk-free return and σ_α is the standard deviation of the excess return. (Bodie et al. 2014: 134.)

2.3.2 Treynor Ratio

Treynor and Mazuy (1966) present the Treynor ratio to measure mutual funds performances where the Treynor ratio measures the excess return per unit of risk. The excess return can be calculated by a portfolio's return minus risk-free return, and the risk is the portfolio's beta (Treynor and Mazuy 1966). Both the Treynor ratio and the Sharpe ratio have grown popularity among investors. The difference between the Sharpe ratio and

the Treynor ratio is that as the risk, Sharpe ratio uses the standard deviation of the excess return, whereas the Treynor ratio uses the portfolio's beta.

The formula of the Treynor ratio can be written as follows:

$$Treynor\ ratio = \frac{r_p - r_f}{\beta_p}, \tag{10}$$

Where r_p is the return of a portfolio, r_f is the risk-free rate and β_p is the beta of a portfolio. (Bodie et al. 2014: 840.)

2.3.3   Jensen's Alpha

To measure portfolio performance Michael Jensen (1968) presents the Jensen's alpha. The Jensen's alpha is based on the CAPM, and it measures that how much average returns portfolio has earned over the market returns when portfolio returns are predicted with CAPM. If the portfolio's alpha is positive, then the manager has earned excess returns. In other words, the portfolio manager has earned more than expected by a given level of riskiness of the portfolio. On the other hand, if Jensen's alpha is negative, then the portfolio manager has not earned any excess return. (Jensen 1968.)

The formula of the Jensen's alpha can be written as follows:

$$\alpha = R_i - [R_f + \beta_i(R_M - R_f)], \tag{11}$$

Where α is the Jensen's alpha, R_i is the return of the portfolio i, R_f is the risk-free rate, β_i is the beta of the portfolio i, R_M is the return of the market portfolio. (Jensen 1968.)

2.3.4 Information Ratio

Information ratio (IR) is a widely used portfolio measurement tool among investors. It helps investors to compare active portfolio's relation to the benchmark, and in addition, it shows how much the active portfolio has generated excess returns relative to the benchmark. The information ratio divides portfolio's alpha by tracking error where the portfolio's alpha is portfolio's return minus benchmark's return, and the tracking error is the standard deviation of the difference between portfolio's return and benchmark's return. (Goodwin 1998.)

The formula of the information ratio can be written as follows:

$$Information\ ratio = \frac{\alpha_p}{\sigma(e_p)}, \tag{12}$$

Where α_p is the portfolio alpha and $\sigma(e_p)$ is the tracking error. (Bodie et al. 2014: 840.)

3   Literature review

This chapter first presents the previous momentum studies where the momentum development, benefits and drawbacks are discussed. Second, the biggest drawback, momentum crash, is discussed. Finally, to mitigate the momentum crashes the risk-manage momentum strategy is presented.

3.1   Previous studies of momentum

Jegadeesh and Titman (1993) show a strategy where they sell poorly performed stocks in the past and buy well-performed stocks in the past generating significant positive returns over 3- to 12- month holding periods. For example, Jegadeesh and Titman (1993) select stocks based on their prior 6-month returns and hold them for 6 months. As a result, the strategy generated a compounded excess return of 12,01% per year on average. Furthermore, they prove that the profitability of the momentum strategy is not due to delayed stock price reaction to a common factor or to momentum strategies' systematic risk.

Jegadeesh and Titman (1993) state a common opinion that overreaction and underreaction of stock returns are too simplistic. To explain the pattern of returns, a more sophisticated model to measure investors' behaviour is needed. They propose that stock price overreaction is caused by investors who buy past winners and sell past losers, causing a temporary price distortion. This opinion is consistent with the study of DeLong, Shleifer, Summers, and Waldman (1990). From the other standpoint, Jegadeesh and Titman (1993) state that market underreacts to firms' short-term prospects and overreacts to firms' long-term prospects.

The results of the momentum strategy made by Jegadeesh and Titman (1993), aroused the interest of other researchers. For instance, Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999) study the momentum

phenomenon, and they present behavioural models which claim that inherent biases cause momentum profits. In addition, Conrad and Kaul (1998) claim that momentum strategy profitability is caused by cross-sectional variation in expected yields not predictable time-series variations in stocks yields.

As a later study Jegadeesh and Titman (2001) evaluate various explanations for momentum strategy profitability which was documented in their earlier study (1993). They find that the results of momentum profits in their newest study is similar to their previous study, even though the sample period is eight years subsequent. It can be used as real evidence that the profits of momentum are not entirely due to data snooping biases. Furthermore, Conrad's and Kaul's (1998) hypothesis of momentum profits source is rejected by Jegadeesh and Titman (2001). The behaviour models are the best partial explanation to momentum profits, however, the behaviour models should be used caution because momentum profits might sometimes associate with postholding period reversals (Jegadeesh and Titman 2001).

Rouwenhorst (1998) studies return patterns of momentum strategy within markets and across markets by using data from 1978 to 1995 and investigating 2190 stocks from 12 European countries. The paper focuses only on medium-term returns. As a result, internationally diversified past winners portfolio outperformed about 1 % per month compared to past losers portfolio. Rouwenhorst (1998) finds that the momentum strategies are loaded negatively on conventional risk factors as the market and the size, thus leading inconsistent of asset pricing models and joint hypotheses of market efficiency. Furthermore, in Europe, small companies provide higher momentum returns compared to large companies, and momentum strategies return in Europe are significantly correlated to the relative strategies in the United States.

Chan, Jegadeesh and Lakonishok (1996) examine past returns of stocks to find factors which affect future stock returns predictability. To construct a portfolio, they use data from January 1977 to January 1993, and they rank the lowest stocks by abnormal

announcement returns and the highest stocks based on prior returns. As a result, the past winners' return is higher than average returns in the first subsequent year, however, returns are almost the same in the second and third following years. This raises questions about the quality of the risk-based explanation for the profitability of the momentum strategy. Chan et al. (1996) find an alternative explanation that momentum returns are related to new information in the market. They focus on how the market reacts when information of earnings is released, and they find out that earnings announcements have an impact on momentum strategy returns. In the first six months, about 41 % of price momentum strategy returns appear around earnings announcements dates. Moreover, if markets face good or bad earnings news surprise, the market average returns tend to move to the same direction at least next two announcements. Also, other information surprises tend to move market stock returns, for instance, new equity issues, stock buy-backs and insider trading.

Using a hedging strategy to minimize a dynamic exposure to a market and size factor can decrease monthly returns variability by 78,6 % as Grundy and Martin (2001) show in their study. They prove that the historical average return will not be sacrificed even the hedging strategy reduces monthly returns variability. Moreover, the significant risk-adjusted return is over 1,3 % per month when it is measured with a two-factor asset pricing model from August 1926 to July 1995 and three-factor Fama-French model from August 1966 to July 1995. The risk-adjusted return is stable across subperiod but unhedged strategy in January exposure to a size factor and performs poorly. All in all, Grundy and Martin (2001) suggest that the profitability of momentum strategy can not be explained entirely by either reward of bearing industry risk or cross-sectional variability in required returns.

Rouwenhorst (1998) states in his earlier paper that momentum strategies are profitable in 12 European countries. In Rouwenhorst's (1999) later study, he proves that the momentum strategy works as well in emerging countries. Chan, Hameed and Tong (2000) examine the momentum strategy in global equity markets. By including stock market

indices in a momentum portfolio, they examine that does the country selection benefit the momentum strategy. Second, they investigate how exchange rate movement affects to returns of international momentum strategies. They investigate that does international momentum generate profits due to interdependence because profits of international momentum depending on the interrelationship between equity and currency market. The third main question in their paper is that does the trading volume information affect to momentum strategies profitability. They argue that a low trading volume can cause an underreaction to stock prices, thus generating a profitable momentum strategy opportunity.

As a result, Chan et al. (2000) find significant results of momentum strategy profitability in a short time period. The evidence shows that momentum profits can be increased by exploiting exchange rates. However, the major source of increased momentum profits come from price continuations in individual stock indices. Also, evidence shows that nonsynchronous trading does not explain the profits of momentum completely, and profits are not confined to emerging markets. Furthermore, Chan et al. (2000) implement the momentum strategy to markets where trading volume increases in the previous period, and they measure higher profits of the momentum strategy.

Several studies suggest that high macroeconomic risk is the reason for momentum profits. Griffin, Ji and Martin (2003) use large international data over 40 countries to examine the relation between momentum and macroeconomic risk. First, they document large profits of momentum strategy when there is weak comovement between countries. The result indicates that if momentum returns are explained by country-specific risk. Second, they use the unconditional model of Chen, Roll and Ross (1986) to measure profits of momentum in 17 markets. The result indicates no significant profits in abroad or in the United States. Third, they measure momentum profits in 16 markets by using a conditional forecasting model of Chordia and Shivakumar (2002). They document that winner stocks earn higher returns in future than loser stocks. Fourth, momentum profits are compared with different economic climates like GDP growth and aggregate stock market

movements. As a result, Griffin et al. (2003) document positive profits of momentum in all macroeconomic states. Furthermore, documents indicate that profits reverse after investment period and in longer horizons, profits become negative.

Antoniou, Lam and Paudyal (2007) examine in their paper that can behaviour biases and cycle variables explain profitable of momentum strategies in three main European countries as Germany, France and the UK. They use Avramov and Chordia (2006) conditional asset pricing model to investigate how business cycle patterns show profits of momentum in the markets of three European countries. Also, they investigate how to use business cycle variables to predict momentum profits in European markets. Second, Antoniou et al. (2007) enchase the Avramov and Chordia (2006) conditional model to explain how investors behaviour affects to time series and cross-sectional patterns of stock returns by including behavioural characteristics to conditional model. As a result, Antoniou et al. (2007) show that European momentum returns can be explained by asset mispricing that systemically varies with global business conditions. This indicates that stock return idiosyncratic risk does not explain the returns of the momentum strategy in Europe. Moreover, their result shows that behaviour does not explain momentum returns and is not correlated to the business cycle. Also, the momentum patterns are risk-based and behavioural variables does not affect them.

Chui, Titman and Wei (2010) investigate in their paper how momentum strategies are affected by cultural differences. They use the individualism index, developed by Hofstede (2001), to investigate cross-country differences, and more specifically, they examine how behavioural biases affect momentum returns. They indicate significant results of cross-country differences in momentum. Countries which have generated the most momentum returns in the first half tend to generate the most momentum returns in the second half, however, some these differences can be explained by adding the Hofstede individualism measure. Explaining cross-countries differences in momentum returns challenge the risk-based and behavioural theories. The risk-based theory explains why momentum returns are risky in Europe and the U.S. but not in most East Asian countries and Japan.

The behavioural theory explains why some countries are affected by psychological biases that cause momentum. Furthermore, the evidence in the paper shows that culture has an important role in stock return patterns. Correlation between cultural differences and momentum profits is that cultures which are less individualistic trust less to information created by themselves and trust more to information made by their peers. (Chui et al. 2010.)

Many studies have measured momentum returns everywhere. Fama and French (2012) use four regions North America, Europe, Japan and Asia Pacific to examine the value premiums in average stock returns. They document value premiums in all regions, and strong momentum returns in all regions except Japan. Moreover, they find evidence that firm size affects international value premiums and momentum returns, however, in Japan, the value premiums are larger to small stocks. The spread of winner minus loser in momentum returns reduce from smaller to bigger stocks, but in Japan, there are no momentum returns documented in any size group.

Many researchers show that specific characteristics of stocks affect to momentum strategy returns. Momentum profits tend to be higher with stocks that have high market-to-book ratios (Kent and Titman 1999), low analyst coverage (Hong et al. 2000) and high analyst forecast dispersion (Zhang 2006; Verardo 2009). Stocks' certain characteristics that affect momentum returns support the behaviour theory (Bandarchuk and Hilscher 2013). Many researchers also document that momentum returns tend to be higher during a high turnover of stocks (Lee and Swaminathan 2000) and high-risk credit ratings of stocks (Avramov, Chordia, Jostova and Philipov 2007).

Bandarchuk and Hilscher (2013) argue in their paper that there is a common channel which can explain that momentum returns are higher with specific characteristics. First, they show that there is no benefit to determine a momentum strategy on stock-level characteristics. Therefore, in the investment point of view, to maximize momentum returns the strategy should focus on past returns. Second, momentum explanation has to

consider momentum profits, volatility and past return as a starting point. Furthermore, they argue that information uncertainty like analyst forecast dispersion and analyst coverage does not affect to abnormal returns of momentum when their connection in the past is observed.

Asness, Moskowitz and Pedersen (2013) study value and momentum investing globally across asset classes and find evidence of a common structure among their profits as returns correlate strongly across asset classes. The behaviour theories have difficulties to explain the strong correlation structure among value and momentum strategies across asset classes. Value and momentum portfolios' high Sharpe ratio of a global across asset classes and high profits also cause difficulties to explain the value and momentum strategies' returns by rational risk-based models. Furthermore, they show that a correlation structure is explained partially by funding liquidity risk.

Asness, Frazzini, Israel and Moskowitz (2014) study different myths related to momentum in their paper, and they use the simplest data from Kenneth French's website. They present annualized mean spread returns and Sharpe ratios for RMRF, SMB, HML and UMD portfolios. The RMRF represents the equity market risk premium, SMB represents the size portfolio, HML represents the value portfolio and UMD represents the momentum portfolio. The sample periods are divided into three periods. The first period uses data from 1927 to 2013, the second period uses data from 1963 to 2013 and the third period uses data from 1991 to 2013.

Sample	Returns				Sharpe Ratios			
	RMRF	SMB	HML	UMD	RMRF	SMB	HML	UMD
1927–2013	7.7%	2.9%	4.7%	8.3%	0.41	0.26	0.39	0.50
1963–2013	6.0%	3.1%	4.5%	8.4%	0.39	0.29	0.45	0.57
1991–2013	8.2%	3.3%	3.6%	6.3%	0.54	0.29	0.32	0.36

Table 1. Returns and Sharpe ratios of Factor Portfolios in different time periods. (Asness et al. 2014.)

In table 1, UMD portfolio presents the highest returns and Sharpe ratios in the sample period 1927 – 2013 and 1963 – 2013. In the period 1991 – 2013, Sharpe ratio and returns are highest for the RMRF portfolio. Momentum benefits in terms of Sharpe ratio are a little smaller than in terms of raw spread returns. This has caused some critics among the researches. All in all, the Sharpe ratio and raw returns for the UMD portfolio are higher than for the other portfolios in the fulltime sample. (Asness et al. 2014) Despite the success of the momentum strategy, many researchers argue that trading costs limit the profitability of the momentum strategy, for example, Korajczyk and Sadka (2004) use intraday data, and they prove that trading costs limit the momentum strategy returns.

Novy-Mark (2012) examines a momentum returns and use all stocks price information in the Center for Research in Securities Prices universe from January 1926 to December 2010. The portfolio is constructed each month by selling losers and buying winners. As a result, recent winners that were losers in an intermediate horizon underperformed significantly to recent losers which were winners in the intermediate horizon. The result does not support the traditional momentum where winners tend to rise, and losers tend to fall. Moreover, the results show that momentum strategy works in the US securities, currencies, international equity indices, investment styles, industries and commodities when momentum portfolio is constructed based on the intermediate horizon.

The deviation between the intermediate horizon and traditional momentum results makes it difficult to explain momentum by models. The most common explanations are

based on biases, thus interpret of investors information generate positive short-lag autocorrelation in prices, for example, news affect slowly in security prices, causing price momentum. According to a rational explanation, a positive correlation is measured between risk exposure and past performance which generate a short-lag autocorrelation in prices. Furthermore, to improve a profitably of a momentum strategy, understanding the intermediate horizon role in momentum portfolio construction is important because it does improve not only profitability but also a Sharpe ratio. (Novy-Marx 2012).

Strategies based on the intermediate horizon are more profitable than strategies based on recent past performance (Novy-Marx 2012). Gong, M Liu and Q Liu (2015) study in their paper these two momentum strategies in 26 major international markets and the US. They exclude prior months 2 and 12 from recent and intermediate past horizons and compare these strategies. As a result, they document that the effect of the intermediate past return momentum is overestimated. However, including prior month 2 in the recent past horizon underestimates the recent momentum strategy's effect. Furthermore, by excluding two specific months from these two momentum strategies, they find that the profitability is small and insignificant between these recent and intermediate past horizon strategies.

Recent and intermediate momentum strategies are also investigated in international stock markets. Excluding prior months 2 and 12 from momentum construction, the intermediate momentum is not more profitable than the recent past momentum in any market. Thus, an investor should take advantage of the recent past momentum. However, these two momentum strategies contain different information and therefore, cannot replace each other. There is not a significant difference in strategies' predictability based on the returns of stocks from past 3-11 months. (Gong et al. 2015)

After a panic state when markets are recovering, the loser stocks are gaining more than winner stocks, causing a momentum crash to momentum strategies. When market volatility is high in the bear market, past losers' up-market betas are large, but down-market

betas are low. Thus, past losers expected returns are very high, and the momentum effect is reversed. During the good times, the attribute does not exist in the winner stocks, but during the extreme times, an asymmetric exists in loser and winner exposure to returns of the market. (Daniel and Moskowitz 2016.)

Daniel and Moskowitz (2016) examine the impact and potential predictability of momentum crashes in multiple time periods and get consistent results in eight different markets and asset classes in their paper. They use ex-ante volatility estimates and bear market indicators to forecast a conditional mean and variance of momentum strategies. As a result, they double a Sharpe ratio of a static momentum strategy by creating a simple dynamically weighted momentum portfolio. Moreover, they prove that momentum crash periods are predictable.

Using a cumulative monthly return from 1927 to 2013 in a momentum portfolio, the winners significantly outperform the losers. The winner strategy excess return on average is 15,3 % per year, and the loser strategy average excess return per year is -2,5 % while the average excess return of the market is 7,6 %. For the winner portfolio, the Sharpe ratio is 0,71 and for the market that is 0,40. A beta of the winner minus loser portfolio, over the sample period, is -0,58 and unconditional capital asset pricing model alpha is 22,3 % per year for the WML portfolio. An ex-post optimal combination of the WML and market portfolio has a double Sharpe ratio compared to the market. Thus, the result is consistent with the high alpha. (Daniel and Moskowitz 2016.)

In recent years, many researchers have study how macroeconomic risks affect momentum returns. Ji, Martin and Yao (2017) use data from 1947 to 2014 in the United States to study how the momentum profits can be explained by macroeconomic risks. They find that losers and winners have different macroeconomic loadings in January when the losers overcome the winners. However, the different factor loadings disappear at the end of the year if the momentum does exist. Furthermore, they show that macroeconomic risk can not explain the momentum profits.

Maio and Philip (2018) estimate in their paper that are macroeconomic variables valid factors in multifactor asset pricing models to explain momentum-based anomalies. They build a two-factor model where the second factor represents macroeconomic variables that are directly related to economic activities, and the other factor represents Merton's (1973) Intertemporal CAPM. As a result, Maio and Philip (2018) show that two-factor ICAPM model can explain both industrial momentum and price momentum.

Garcia-Feijoo, R. Jensen and K. Jensen (2018) study how the macroeconomic factors affect momentum returns. More specifically, they examine how funding condition affects momentum returns. They find that winners tend to overcome losers during restrictive funding states, but during expansive states, winners and losers perform similarly. A plausible reason for momentum returns behaviour is that loser stocks are more illiquid during restrictive states and for loser stock liquidity risk is priced higher during the restrictive states (Garcia-Feijoo et al. 2018).

3.2 Momentum crash

A momentum strategy average returns are significant and large, but during history, there have been periods when the momentum strategy has underperformed dramatically. Two main crashes are measured from June 1932 to December 1939 and from March 2009 to March 2013. In these two periods, the loser portfolio outperforms compared to winner portfolio. In the period from March 2009 to March 2013, the loser portfolio generates twice as much profit than winner portfolio. In the period from June 1932 to December 1939, the losers generate 50 % more profit than the winners. Even though the winner portfolio outperforms the loser portfolio over time, the alpha and the Sharpe ratio suffer significantly from the crashes. When winner portfolios are compared to loser portfolios, the winner portfolio is more negatively skewed in extreme deciles. Winner portfolio monthly skewness is -0,82, and daily skewness is -0,61 while loser portfolio monthly skewness is 0,09 and daily skewness is 0,12. (Daniel and Markowitz 2016.)

The momentum crashes occur after a panic state when markets are recovering. The loser stocks are gaining more than winner stocks, causing a momentum crash to momentum strategies. The biggest losses of momentum strategy are measured during the two biggest crashes in the stock market. In July and August 1932, the momentum strategy faces the worst months. A market decreases by 90 % from the peak of 1929. Furthermore, the April and May in 1933 are the sixth and 12th worst momentum months. The March and April in 2009 are the seventh and fourth worst momentum months and three of the ten worst momentum months are measured in 2009. (Daniel and Moskowitz 2016.)
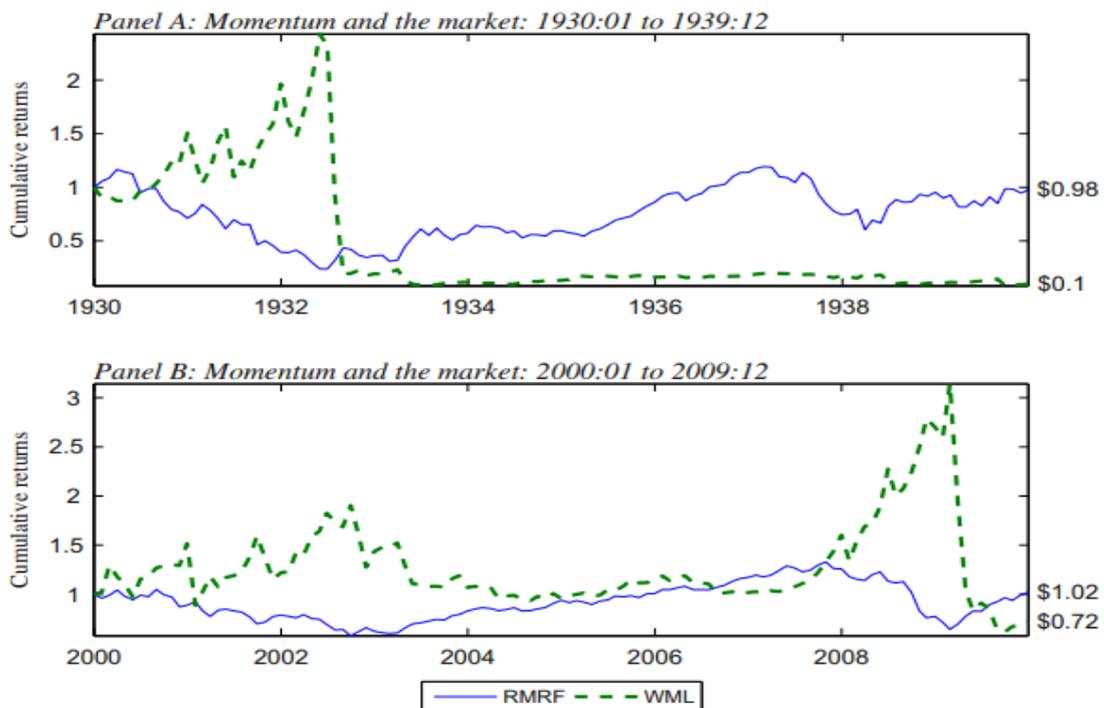
Figure 1. Cumulative returns of the market minus risk free-rate portfolio (RMRF) and the plain momentum portfolio (WML) during the momentum crashes. (Barroso and Santa-Clara 2015.)

Figure 1 presents the performance of momentum strategy in the 1930s and the 2000s. In July and August 1932, the momentum strategy's cumulative return is -91,59 %, and from March to May in 2009, momentum strategy suffers from the crash and has a cumulative return of -73,42 %. These crashes have a permanent effect on momentum strategy returns. For instance, 1 dollar invested in a momentum strategy in July 1932, takes 31

years that the value recovers from the crash. This constructs a risk of momentum invest-
ing. (Barroso and Santa-Clara 2015.)

3.3 Risk-managed momentum

Barroso and Santa Clara (2015) use a risk-managed momentum strategy to improve the
profitability of the momentum portfolio. To do so, the risk of momentum is calculated
from the realized variance of daily returns. From the realized variance, they calculate
realized volatility in the previous six months and target to constant volatility. They scale
the momentum portfolio by the ratio of the constant volatility target divided by realized
volatility. As a result, the Sharpe ratio and skewness values improve greatly.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Kurtosis	Skewness	Sharpe ratio	Information ratio
WML	26.18	−78.96	14.46	27.53	18.24	−2.47	0.53	−
WML*	21.95	−28.40	16.50	16.95	2.68	−0.42	0.97	0.78

Table 2. The first row presents the economic performance of the plain momentum, and the sec-
ond row presents the economic performance of the risk-managed momentum. The mean, stand-
ard deviation, Sharpe ratio and information ratio are annualized, and others are given in monthly
figures. The time period is from 1927:03 to 2011:12. (Barroso and Santa-Clara 2015.)

Table 2 shows the result of the risk-managed momentum portfolio from 1927 to 2011.
The risk-managed momentum has a higher average return of 2,04 % per year and 10,58 %
less standard deviation compared to plain momentum. The risk-managed momentum
almost doubles the Sharpe ratio from 0,53 to 0,97, and Information ratio has a high value
of 0,78. (Barroso and Santa-Clara 2015.)

Barroso and Santa-Clara (2015) argue that increasing turnover in risk-managed momen-
tum might offset the risk-managed momentum's benefits after transaction costs. They
control this by calculating risk-managed momentum and plain momentum turnovers

from the firm size and stock-level data on returns from 1951 to 2010. As a result, the turnover of the momentum per month is 74 %, and the risk-managed momentum turnover per month is 75 %. The turnover increases only 1 % and an AR(1) coefficient of 0,97, which is constant from month to month. Therefore, the increase in turnover is not adequate to eliminate volatility scaling benefits. Furthermore, they use round-trip cutoff cost to find what is the cost of transactions for momentum strategies. They find that transaction costs reduce the risk-managed momentum returns significantly, and the transaction costs are smaller for the plain momentum.

In turbulence times, the risk-managed momentum benefits are important. The risk-managed momentum strategy decreases the skewness from -2,47 to -0,42 and lowers the excess kurtosis from a value 18,24 to 2,68. Figure 2 shows that managing the risk of the momentum during momentum crashes in 1930-1939 and 2000-2009 provides significant benefits. The risk-managed momentum managed to maintain its value in the 1930s, however, the plain momentum lost 90 % of investment value. From 2000 to 2009 the plain momentum lost 28 % of its value due to the momentum crash. The risk-managed momentum value is 88 % higher in 2009 than it was in 2000 because it managed to avoid the momentum crash. (Barroso and Santa-Clara 2015.)
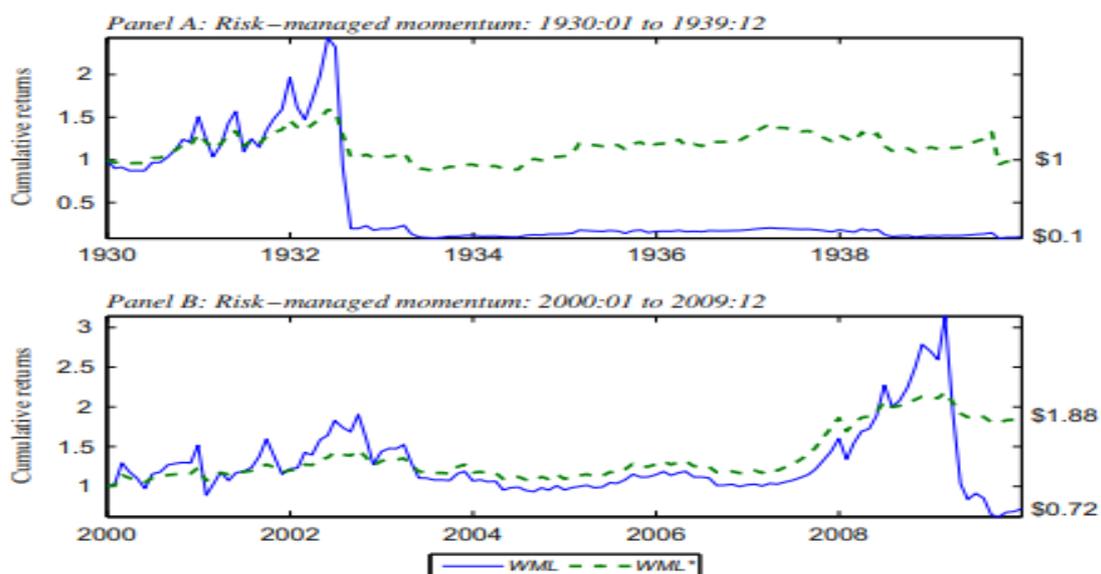

Figure 2. Cumulative returns of the plain momentum portfolio (WML) and the risk-managed momentum portfolio (WML*) during the momentum crashes. (Barroso and Santa-Clara 2015.)

4 Data and methodology

4.1 Data

In this thesis, all the data is obtained from Kenneth French's website. The datasets contain daily and monthly returns for the stock portfolios in Europe, North America, Japan and Asia-Pacific. The European portfolio includes stocks from Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great-Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal and Sweden. The Japan portfolio only includes stocks from Japan. The North America portfolio includes stocks from Canada and the United States. The Asia-Pacific portfolio includes stocks from Australia, Hong Kong, New Zealand and Singapore. The time period for the datasets is from January 1995 to December 2019. Stocks are divided into five size groups based on the market cap. The highest size group is constructed of the largest stocks from the market that comprise 90 % of the total market capitalization. Then the momentum quintiles are formed by subdividing each size group into five momentum quintiles. The momentum quintile return is stock's cumulative return from t-12 to t-2. The lowest momentum quintile represents the bottom 20 % lowest stocks, and the highest quantile momentum represents the top 20 % highest stocks. The portfolios are formed at the end of the month t-1, and the same portfolio construction procedure is used every month. In each portfolio, the individual stocks are value-weighted, and all returns are in U.S. dollars. (French 2020.) Chaves' (2012) international momentum study avoid the illiquid stocks by selecting only the largest and the most liquid stocks. Therefore, in this study, I focus only on the biggest size group.

The Fama-French three-factor model values for all four regions are downloaded from Kenneth French's website. Datasets contain monthly returns and the time period is from January 1995 to December 2019. The market factor is constructed by calculating the returns on region's value-weighted portfolio minus the one-month risk-free rate, which is the U.S. one-month T-bill rate. The SMB factor is constructed by calculating the average of the returns on the three small stock portfolios for the region and subtracting the

average of the returns on the three big stock portfolios for the region. The HML factor is constructed by calculating the average of the returns on the two high B/M portfolios for the region and subtracting the average of the returns on the two low B/M portfolios for the region. All returns are in U.S. dollars. (French 2020)

The Fama-French five-factor model values for all four regions are downloaded from Kenneth French's website. Datasets contain monthly returns. The same risk-free rate and time period are used than in the previous three-factor model. The market and HML factors are constructed in the same way than in the three-factor model. The SMB factor is constructed by calculating the average return on the nine small stock portfolios and subtracting the average return on the nine big stock portfolios. The RWM factor is constructed by calculating the average return on the two robust operating profitability portfolios and subtracting the average return on the two weak operating profitability portfolios. The CMA factor is formed by calculating the average return on the two conservative investment portfolios and subtracting the average return on the two aggressive investment portfolios. All returns are in U.S. dollars. (French 2020)

4.2   Methodology

To calculate the risk-managed momentum returns, the momentum portfolio returns are calculated first. It is widely known that the momentum portfolio returns can be calculated by winner stocks minus loser stocks. Therefore, in this thesis, the momentum portfolio daily and monthly returns of the largest stocks are calculated by the highest quintile (past winners) minus the lowest quintile (past losers).

After the momentum portfolio returns have been calculated, it is time to calculate the risk-managed momentum returns. In this thesis, I follow Barroso and Santa-Clara (2015) procedure to form and calculate the risk-managed momentum returns. First, they calculate for each month a variance forecast from previous six-month daily returns of momentum portfolio. They also use one-month, three-month realized variances and

exponentially weighted moving average. As a result, they notice that all the options give nearly similar results. Therefore, in this thesis, the simplest one-month realized variance is used to calculate the variance forecast. Below is the formula for the variance forecast (Barroso and Santa-Clara 2015):

$$\hat{\sigma}^2_{WML,t} = 21 \sum_{j=0}^{20} r^2_{WML,d_{t-1}-j} / 21 , \qquad (13)$$

Where, the $\hat{\sigma}^2_t$ is forecasted variance of the month t and the $r^2_{WML,d_{t-1}-j}$ is squared daily returns in the previous month.

To calculate the risk-managed momentum returns Barroso and Santa Clara (2015) scale the monthly returns of the plain momentum portfolio by the ratio of the constant volatility target level divided by forecasted volatility. The momentum strategy can be scaled without constrains because it is a zero-investment and self-financing strategy. Below is the formula for the risk-managed momentum returns (Barroso and Santa-Clara 2015):

$$r_{WML*,t} = \frac{\sigma_{target}}{\sigma_t} r_{WML,t} , \qquad (14)$$

Where $r_{WML*,t}$ is the return of risk-managed momentum, σ_{target} is the constant volatility target level, σ_t is the annualized forecasted volatility which can be calculated by multiplying square root twelve with the square root of the monthly forecasted variance, $r_{WML,t}$ is the return of the plain momentum portfolio.

The ratio between constant volatility target level and annualized forecasted volatility represents weights for the risk-managed momentum, and the weights vary every month. Barroso and Santa-Clara (2015) choose to use 12 % as the level of the constant volatility target. In this thesis, I use the annualized market average volatility as the level of the constant volatility target. It is calculated by using volatility from the whole market monthly data and then multiplied the obtained volatility by square root twelve. The

constant volatility target level for Europe is 16,96 %, for North America it is 15,03 %, for Japan it is 17,18 % and for Asia-Pacific it is 20,02 %.

Fama and French (2015) use asset pricing models to test whether the momentum portfolios produce positive abnormal returns. Therefore, to test the three hypotheses of this thesis, the Ordinary Least Squares (OLS) regression is used. The FF3 and FF5 factors act as independent variables of the regressions. Monthly returns of the plain momentum and risk-managed momentum act as dependent variables. In order to accept the hypotheses 1-3, both FF3 and FF5 factor models' dependent variables should be statistically significant at the 5 % level. In this thesis, all regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity.

5   Results

In this chapter, the results of the empirical models are presented, and all the hypotheses will be answered. First, the cumulative returns of the plain momentum, risk-managed momentum and market minus risk-free rate portfolio in the most turbulence time are plotted in the figure 3. Second, the results of the plain momentum and the risk-managed momentum in Europe are presented and discussed. Third, global results of the plain momentum and risk-managed momentum are presented and discussed.
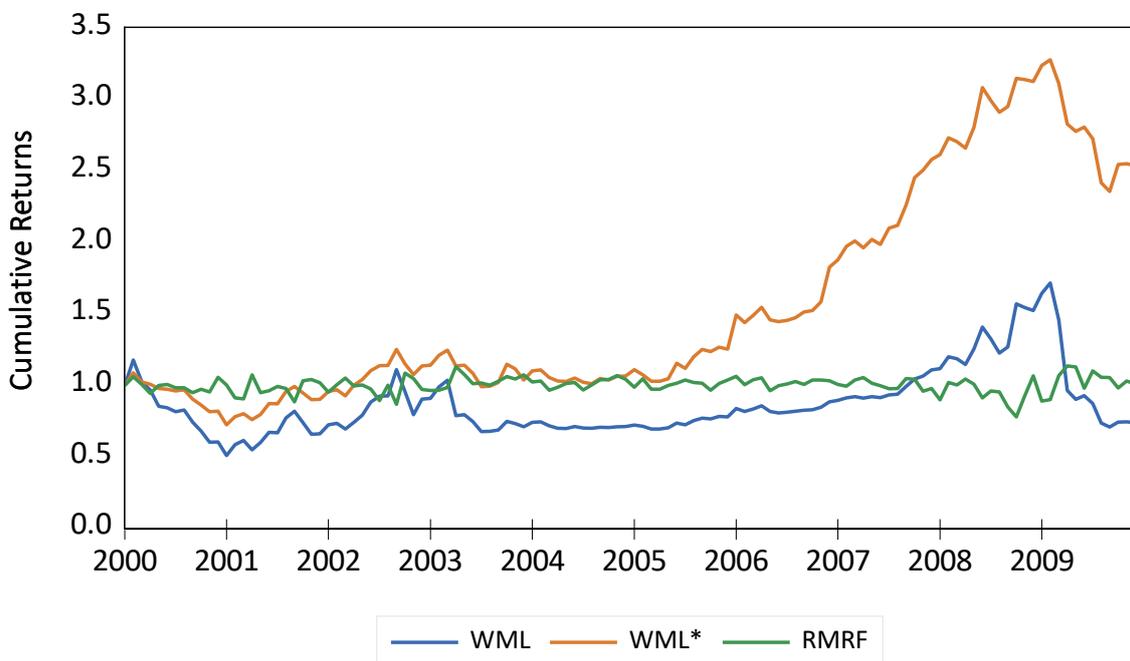
Figure 3. Cumulative returns of the plain momentum (WML), the risk-managed momentum (WML*) and the market minus risk-free rate portfolio (RMRF) during the period January 2000 – December 2009.

Figure 3 represents cumulative returns of the plain momentum, the risk-managed momentum and the market minus risk-free rate portfolio in the most turbulent time in the 2000s. The time period spans from January 2000 to December 2009, and it shows how a dollar investment has developed during the time period. A dollar invested in the plain momentum portfolio at the beginning of time period is worth of 0,74 dollars at the end of the time period whereas the market minus risk-free rate portfolio is worth of 1,01

dollars and risk-managed momentum portfolio is worth of 2,54 dollars. Figure 3 shows a momentum crash risk related to plain momentum strategy. Before the financial crisis in 2009, the cumulative return of the plain momentum portfolio is 1,72 dollars. Due to the financial crisis, the plain momentum portfolio return suffers a drop, and it ends up with a lower value than market minus risk-free rate portfolio which is similar than Barroso and Santa Clara's (2015) results in U.S. market. Because of the riskiness of plain momentum strategy, it is interesting to compare cumulative returns development of the risk-managed momentum and the plain momentum. Both portfolios' cumulative returns behave at approximately the same way. In the early 2000s, both cumulative returns decrease, but the plain momentum portfolio suffers a higher decline in returns. At the end of the sample period, both portfolios' cumulative returns growth, however, cumulative returns of the risk-managed momentum portfolio increase faster. Before the financial crises, the risk-managed momentum returns have a value of 3,28 dollars, and due to financial crises, the risk-managed momentum portfolio suffers a 28,12 % drop while the plain momentum portfolio suffers a 58,66 % drop. Thus, it can be said that this provides one evidence that risk-managed momentum limits a crash risk of momentum strategy.

Table 3 presents a descriptive statistic for the plain momentum (WML) and risk-managed momentum (WML*) in the full sample period. It is interesting to compare that is the risk-managed momentum more profitable and less risky strategy than the plain momentum strategy in Europe. First, the WML* provides higher single month maximum return and lower single month minimum return than the WML strategy. The maximum return month is 1,67 % higher for WML*. The WML* suffers -22,25 % drop in returns, whereas the WML suffers -33,70 % drop in returns. The result of the minimum month return is in line with Barroso and Santa Clara's (2015) findings. However, they find that the maximum month return is higher for the plain momentum strategy. This might be a result with the different market area, time period, momentum portfolio construction or target volatility level of risk-managed momentum.

Statistic	Europe	
	WML	WML*
Maximum	23.76	25.43
Minimum	-33.70	-22.25
Mean	6.59	13.89
Standard Deviation	22.02	20.33
Kurtosis	7.03	4.36
Skewness	-0.57	0.26
Sharpe Ratio	0.30	0.68

Table 3. Descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*). The mean average excess return, the standard deviation and the Sharpe ratio are annualized, and others are given in monthly figures. The time period is from 1995:01 to 2019:12.

In table 3, the mean average excess return per year is 13,89 % for the WML* strategy, and for the WML strategy, the mean average excess return per year is 6,59 %. Thus, it can be said that the risk-managed momentum is a more profitable strategy in terms of mean return. The annualized standard deviation of the WML* is 20,33 %, and the annualized standard deviation of the WML is 22,02 %. Thus, the risk-managed momentum provides a smaller dispersion to returns than the plain momentum. Barroso and Santa Clara (2015) get similar results, and they measure the annualized average excess return of 16,50 % for the risk-managed momentum and annualized standard deviation of 19,95 %. For the plain momentum, they measure the annualized average excess return of 14,46 % and annualized standard deviation of 27,53 %.

Managing the risk of the WML strategy improves the kurtosis and skewness. In table 3, the WML* strategy lowers the kurtosis from 7,03 to 4,36 and improves the skewness from -0,57 to 0,26. Barrosso and Santa Clara (2015) get roughly the similar results, however, they report that the skewness of the risk-managed momentum is negative even though the skewness is improved when managing the risk of the momentum. They argue that improvement in kurtosis and skewness lower the momentum crash risk greatly.

Therefore, the risk-managed momentum in Europe reduces the momentum crash risk substantially and even virtually eliminates it due to positive skewness and kurtosis values near to normal distribution. Moreover, the WML* enhances the Sharpe ratio from 0,30 to 0,68. The increase in Sharpe ratio is mostly due to an increase in annualized mean return and not due to a decrease in annualized standard deviation. The improvement in Sharpe ratio tells that the risk-managed momentum is a more profitable strategy than plain momentum strategy, which is in line with the Barroso and Santa Clara's (2015) results and also similar than Grobys, Ruotsalainen and Äijö's (2018) risk-managed industrial momentum results.

Next, table 4 presents the results that answer to hypothesis 1 and 2. The FF3 regression's alpha intercept for the WML is statistically significant at the 1 % level and produces a significant abnormal monthly return of 0,936 %. The FF5 regression's alpha intercept for the WML is not statistically significant. Thus, this thesis rejects the hypothesis 1 and the hypothesis 0 holds, which means that the plain momentum strategy does not produce statistically significant positive abnormal returns in Europe. The FF3 and FF5 regressions show that the alpha intercepts for the WML* are statistically significant at the 1 % level. The FF3 regression shows that the WML* produces a significant abnormal monthly return of 1,374 %, and the FF5 regression shows that the WML* offers a significant abnormal monthly return of 1,095 %. Thus, this thesis accepts the hypothesis 2, which means that the risk-managed momentum produces statistically significant positive abnormal returns in Europe. Now to one of the main research questions has been answered. All in all, the risk-managed momentum provides higher alpha intercepts than plain momentum strategy when the intercepts are measured by FF3 and FF5 regressions. Thus, it can be said that risk-managed momentum is more profitable investment strategy than the plain momentum. Moreover, the results are consistent with the Sharpe ratios in table 3.

	Whole Sample					
	WML				**WML***	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.936 ***	0.003		Alpha	1.374 ***	0.000
RMRF	-0.389 ***	0.004		RMRF	-0.129	0.135
SMB	0.146	0.517		SMB	0.067	0.720
HML	-0.616 *	0.054		HML	-0.527 **	0.027
Adj.R2	0.178			Adj.R2	0.065	

	Whole Sample					
	WML				**WML***	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.367	0.253		Alpha	1.095 ***	0.001
RMRF	-0.289 ***	0.006		RMRF	-0.120	0.173
SMB	0.193	0.374		SMB	0.075	0.688
HML	-0.270	0.552		HML	-0.210	0.534
RMW	1.121 **	0.011		RMW	0.605 **	0.041
CMA	0.014	0.980		CMA	-0.259	0.587
Adj.R2	0.224			Adj.R2	0.079	

Table 4. The table summarizes the Fama-French 3-factor model (FF3) regression and Fama-French 5-factor model (FF5) regression whole sample results from 1995:01 to 2019:12. Alpha is the intercept of the regression, and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big), HML (high minus low), RMW (robust minus weak) and CMA (conservative minus aggressive). WML is the plain momentum and WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level.

It is interesting to look at the factor loadings in table 4. More specifically, that are the factor loadings significant and what is the explanatory power of the FF3 and FF5 models. When WML returns are explained by FF3 model, only one independent variable has a significant coefficient at the 1 % level, and that is RMRF. It has a factor loading of -0,389, and that indicates that WML returns move partially to the opposite direction than

market returns. The HML factor loading is statistically significant at the 10 % level and has a loading of -0,616. When WML* returns are explained by FF3 model, the HML coefficient is significant, and it has a factor loading of -0,527 and p-value of 0,027. Negative loading of HML means that WML* returns can be explained by growth firms. All other coefficients are insignificant in FF3 model. When WML returns are explained by FF5 model, the RMRF and RMW have significant coefficients, and other independent variables have insignificant coefficients. The RMRF factor has a negative loading of -0,289 and p-value of 0,006. It indicates that MWL returns have a negative co-movement with the market. The RMW factor has a positive loading of 1,121 and p-value of 0,011 which means that firms that are operating profitable explain the WML returns. When the FF5 model explains WML* returns, only the RMW coefficient is statistically significant among the other coefficients of the independent variables. It has a positive factor loading of 0,605 and p-value of 0,041. It indicates that WML* returns can be explained by firms that are operating profitably. Furthermore, the FF5 model has better explanatory power than the FF3 model. For the WML returns the FF5 model adjusted R-squared is 0,224 whereas FF3 model adjusted R-squared is 0,178. This means that the FF5 model explains 22,4 % of the WML returns, whereas FF3 model explains 17,8 % of the WML returns. Both models explain better the WML returns than the WML* returns. The FF3 model only explains 6,5 % of WML* returns and the FF5 model do a little bit better job and explains 7,9 % of WML* returns.

Barroso and Santa Clara (2015) test the robustness of the risk-managed momentum by dividing the whole time period into different subsamples. Their first subsample is from 1927:03 to 1969:12, the second subsample is from 1970:01 to 2011:12, the third subsample is from 1945:01 to 2005:12 and fourth subsample is from 1927:03 to 2011:12 where the crashes in 1932 and in 2009 are excluded. In this paper, the whole time period is divided into four different subsamples to check the plain momentum and risk-managed momentum results in Europe. The first subsample (first-period) is from 1995:01 to 2003:04, the second subsample (second-period) is from 2003:05 to 2011:08, the third

subsample (third-period) is from 2011:09 to 2019:12 and the fourth subsample (no crash) is from 1995:01 to 2019:12 where the financial crisis in 2009 is excluded.

Statistic	First period		Second period		Third period		No crash	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	19.85	25.43	23.76	19.04	13.35	15.81	23.76	25.43
Minimum	-23.91	-22.25	-33.70	-13.75	-12.84	-9.77	-23.91	-22.25
Mean	9.76	19.80	4.80	14.34	5.22	7.53	9.41	15.26
Standard Deviation	27.57	24.79	21.57	17.95	15.43	17.46	20.63	20.34
Kurtosis	3.56	4.04	12.82	5.59	3.28	2.69	5.30	4.39
Skewness	-0.28	0.08	-1.41	0.36	0.11	0.34	-0.04	0.27
Sharpe Ratio	0.35	0.80	0.22	0.80	0.34	0.43	0.46	0.75

Table 5. Descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*) in different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and the no crash period covers 1995:01-2019:12 where the financial crisis in 2009 is excluded. The mean average excess return, the standard deviation and the Sharpe ratio are annualized, and others are given in monthly figures.

In table 5, the results are mostly the same as in the whole sample descriptive statistics table 3. The maximum return of the month is higher for the WML* than the WML in every subsample except in the second period. In the second period, the maximum month return is 4,74 % lower for the WML*. The minimum month returns are better for the WML* in every subsample. In the point of minimum month return, the WML* provides the biggest benefits in the second period. The minimum month return is -13,75 % for WML* whereas the minimum month return is -33.70 % for the WML. The minimum month return results are in line with Barroso and Santa Clara's (2015) findings.

The annualized mean excess returns in table 5 are higher in every subsample for the WML* and the results support the whole sample descriptive results. The biggest annualized mean excess return for the WML* is 19,80 % which is measured in the first period. The lowest annualized mean excess return for the WML* is 7,53 % in the third period. The WML suffers the lowest annualized mean excess return 4,80 % in the second period, which is mostly caused by the financial crisis in 2009. In the same period, the WML*

produces annualized mean excess return of 14,34 %. This support the assumption that risk-managed momentum mitigates the negative effect of the momentum crash. Moreover, the annualized standard deviation is lower for the WML in the third period, but in all other periods, the WML* produces lower standard deviations.

Kurtosis in table 5 is lower for the WML* than the WML except in the first period. The biggest reduction of the kurtosis happens in the second period when kurtosis drops from 12,82 to 5,59 when managing the risk of the momentum. The WML produces mostly negative skewness values in all subsample periods while WML* can improve skewness of WML and it produces only positive skewness values in all subsample periods. This is robust evidence that risk-managed momentum eliminates virtually the crash risk associated with plain momentum. Furthermore, WML* generates higher Sharpe ratio in all subsample periods compared to WML. The biggest difference of the Sharpe ratio is in the second period when Sharpe ratio of WML is only 0,22, and Sharpe ratio of WML* is 0,80. Even in the no crash period, the WML* almost doubles the Sharpe ratio. The higher Sharpe ratio, in every period, is robust evidence that risk-managed momentum is a more profitable strategy than the plain momentum strategy and these results are also in line with Barroso and Santa Clara's (2015) findings.

Next, the robustness tests are formed to FF3 and FF5 regressions and the same subsample periods are used than in the descriptive statistics robustness test. Table 6 shows the FF3 regression's robustness test results for the WML and WML* and table 7 presents the FF5 regression's robustness test results for the WML and WML*.

First period

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.449 *	0.083	Alpha	2.086 **	0.011
RMRF	-0.549 *	0.059	RMRF	-0.244	0.226
SMB	0.136	0.667	SMB	-0.181	0.481
HML	-0.602	0.231	HML	-0.541	0.200
Adj.R2	0.106		Adj.R2	0.021	

Second period

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	0.863 *	0.081	Alpha	1.304 ***	0.004
RMRF	-0.182	0.189	RMRF	0.061	0.520
SMB	-0.050	0.853	SMB	0.274	0.271
HML	-1.293 ***	0.003	HML	-0.959 ***	0.009
Adj.R2	0.286		Adj.R2	0.113	

Third period

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	0.509	0.171	Alpha	0.637	0.122
RMRF	-0.301 **	0.024	RMRF	-0.222 *	0.097
SMB	0.125	0.619	SMB	0.263	0.320
HML	-0.620 ***	0.004	HML	-0.617 ***	0.006
Adj.R2	0.213		Adj.R2	0.124	

No crash

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.069 ***	0.001	Alpha	1.455 ***	0.000
RMRF	-0.318 **	0.017	RMRF	-0.107	0.238
SMB	0.222	0.344	SMB	0.101	0.603
HML	-0.494	0.130	HML	-0.481 *	0.054
Adj.R2	0.123		Adj.R2	0.046	

Table 6. The table summarizes the Fama-French 3-factor model (FF3) regression results in different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and the no crash period covers 1995:01-2019:12 where the financial crisis in 2009 is excluded. Alpha is the intercept of the regression, and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big) and HML (high minus low). WML is the plain momentum and WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level.

The alpha intercepts of the WML strategy are mostly statistically significant in table 6. In the first and the second period, the alpha intercepts are statistically significant at the 10 % level, but in the third period, the alpha intercept is not statistically significant. The no crash period provides the statistically significant alpha intercept at the 1 % level and 1,069 % monthly excess return. The FF3 model shows that the WML alpha intercept was statistically significant at the 1 % level in the whole sample period, but the robustness test results show that alpha intercepts are not statistically significant in every subsample period. The alpha intercepts of the WML* are statistically significant at the 5 % and 1 % levels in every subsample period expect in the third period where the alpha intercept is insignificant. Once again, the whole sample alpha intercept is statistically significant at the 1 % level, but it is not statistically significant in every subsample period for the WML* strategy. The highest significant monthly abnormal return for the WML* is 2,086 %, and the lowest significant monthly abnormal return is 1,304 %. All in all, WML and WML* do not produce significant monthly abnormal returns in every subsample period, however, WML* produces higher monthly abnormal returns in every subsample period than the WML.

The FF3 model independent variables explain the returns of WML and WML* strategies in table 6. In the first period, RMRF has a coefficient that is statistically significant at the 10 % level for the WML, and the RMRF factor has a negative loading of 0-549. For the WML* there are not significant coefficients that can explain the WML* returns in the first period. In the second period, HML has statistically significant coefficient at the 1 % level for the WML, and the HML factor has a negative loading of -1,293. The same factor is statistically significant at the 1 % level for the WML* and it has a negative factor loading of -0,959. These factors have high loadings compared to their alpha intercepts. This finding suggests that growth stocks can explain some of the WML and WML* returns in the second period. In the third period, there are two statistically significant coefficients at the 5 % and 1 % levels for the WML. These are RMRF and HML. The RMRF has a negative factor loading of -0,301 and p-value of 0,024, whereas the HML factor has a negative loading of -0,620 and p-value of 0,004. The same coefficients are statistically significant

at the 10 % and 1 % levels for the WML*. The RMRF factor has a negative loading of -0,222 and p-value of 0,097, whereas the HML factor has a negative loading of -0,617 and p-value of 0,006. The RMRF factor suggests that WML and WML* returns move partially to the opposite direction than RMRF returns. The HML loadings are high again compared to alpha intercepts. In the no crash period RMRF has a statistically significant coefficient at the 5 % level for WML and the RMRF factor has a negative loading of -0,318. The HML has statistically significant coefficient at the 10 % level for WML* and the HML factor has a negative loading -0,481. It is important to notice that FF3 model's independent variable's coefficients do not significantly explain WML and WML* returns in every subsample period. Even though, FF3 model in the whole sample suggests that RMRF factor explains WML returns at the statistically significant level at 1 % and HML factor explains WML* returns at the statistically significant level at 5 % in the whole sample. Another important notice is that FF3 model explains better the WML returns than the WML* returns, however, the FF3 model's total explanation power of the WML returns is not high.

Table 7 presents the FF5 regression's robustness test for the WML and WML*. The first finding is that the alpha intercepts to WML are not statistically significant in any subsample period. The robustness test results for the alpha intercepts of the WML are in line with the whole sample FF5 results. The alpha intercepts of the WML* are statistically significant in the second period and the no crash period but not in the first and the third period. In the second period, the alpha intercept is statistically significant at the at 5 % level and in the no crash period it is statistically significant at the 1 % level. A significant monthly abnormal return is 1,28 % in the second period and 1,178 % in the no crash period. The robustness test shows that the WML* alpha intercept is not statistically significant in every subsample period even though it is statistically significant in the whole sample period (table 4).

The FF5 model's independent variables explain the returns of WML and WML* strategies in table 7. In the first period, three coefficients are statistically significant at the 10 %, 5 % and 1 % levels for the WML. The RMRF factor has a negative loading of -0,440 and p-

value of 0,028, the RMW factor has a positive loading of 1,922 and p-value of 0,001 and finally CMA factor has a negative loading of -1,127 and p-value of 0,069. Negative and significant RMRF factor means that WML returns moves to the opposite direction than RMRF returns. The positive and significant RMW factor implies that WML returns can be explained by profitable companies' returns. The negative and significant CMA factor implies that companies that are investing aggressively can explain the WML returns. In the first period, RMW has a statistically significant coefficient for the WML*. The RWM factor has a positive loading of 1,124 and p-value of 0,009. In the second period, there are statistically significant coefficients at the 5 % and 10 % levels for the WML portfolio. HML factor has a negative loading of -1,600 and p-value of 0,034, whereas CMA factor has a positive loading of 1,180 and p-value of 0,074. Also, the HML factor is statistically significant for the WML* in the second period. It has a negative loading of -0,112 and p-value of 0,011. The HML factor is also economically significant compared to WML* alpha intercept.

Table 7. Table summarizes the Fama-French 5-factor model (FF5) regression results in different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and the no crash period covers 1995:01-2019:12 where the financial crisis in 2009 is excluded. Alpha is the intercept of the regression and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big), HML (high minus low), RMW (robust minus weak) and CMA (conservative minus aggressive). WML is the plain momentum and WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level. The table on the next page.

First period

	WML				WML*	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.045	0.946		Alpha	1.236	0.112
RMRF	-0.440 **	0.028		RMRF	-0.239	0.156
SMB	0.188	0.550		SMB	-0.167	0.531
HML	0.507	0.342		HML	0.294	0.626
RMW	1.922 ***	0.001		RMW	1.124 ***	0.009
CMA	-1.127 *	0.069		CMA	-0.952	0.168
Adj.R2	0.295			Adj.R2	0.111	

Second period

	WML				WML*	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.585	0.332		Alpha	1.280 **	0.025
RMRF	-0.039	0.678		RMRF	0.095	0.211
SMB	0.111	0.602		SMB	0.309	0.214
HML	-1.600 **	0.034		HML	-1.112 **	0.011
RMW	0.051	0.940		RMW	-0.114	0.799
CMA	1.180 *	0.074		CMA	0.249	0.542
Adj.R2	0.331			Adj.R2	0.100	

Third period

	WML				WML*	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.393	0.323		Alpha	0.706	0.137
RMRF	-0.192	0.162		RMRF	-0.108	0.506
SMB	0.235	0.270		SMB	0.279	0.276
HML	-1.007 **	0.015		HML	-1.526 **	0.013
RMW	-0.037	0.949		RMW	-0.844	0.249
CMA	0.910	0.115		CMA	1.045	0.120
Adj.R2	0.226			Adj.R2	0.150	

No crash

	WML				WML*	
	Coeff.	p-value			Coeff.	p-value
Alpha	0.479	0.130		Alpha	1.178 ***	0.000
RMRF	-0.242 **	0.024		RMRF	-0.103	0.258
SMB	0.248	0.268		SMB	0.105	0.586
HML	0.054	0.887		HML	-0.101	0.777
RMW	1.288 ***	0.003		RMW	0.650 **	0.035
CMA	-0.307	0.516		CMA	-0.361	0.459
Adj.R2	0.198			Adj.R2	0.065	

The third period shows that only the HML factor is statistically significant at the 5 % level for the WML in table 7. It has a negative loading of -1,007 and p-value of 0,015. The same factor is also statistically significant at the 5 % level for the WML* and it has a negative loading of -1,526. In the no crash period RMRF and RMW have statistically significant coefficients at the 5 % and 1 % levels for WML. The RMRF factor has a negative loading of -0,242 and p-value of 0,024. The RMW factor has a positive loading of 1,288 and p-value of 0,003. The coefficient of the RMW is statistically significant at the 5 % level for the WML* and the positive loading of the RMW factor is 0,650. FF5 model's factors RMRF and RMW explain the WML returns significantly in the whole sample, and also RMW factor explains the WML* returns significantly in the whole sample. However, the robustness test shows that FF5 model's factors do not explain WML and WML* returns significantly in every subsample period. Furthermore, FF5 does a better job at explaining the WML returns than WML* returns, and the FF5 model explains better the WML and WML* returns than FF3 model.

Now the large stocks' plain momentum and risk-managed momentum results in Europe have been examined. It is time to investigate the risk-managed momentum globally. First, the descriptive statistics for the plain momentum and risk-managed momentum in North America, Japan and Asia-Pacific will be presented. Then the worldwide risk-managed momentum returns will be investigated by FF3 and FF5 regression models, and finally, the robustness tests will be presented.

Table 8 presents a whole sample period descriptive statistic for the plain momentum and risk-managed momentum in North America, Japan and Asia-Pacific. The MWL* has a lower single month maximum return in all research regions than WML has. The biggest difference between single month maximum return is in North America, where the difference is 18,79 %. The WML suffers a worse single month minimum return in every research region compared to MWL*. The biggest difference between single month minimum return is in Asia-Pacific, where the different is 35,13 %. The results are in line with

the Barroso and Santa Clara's (2015) findings in the U.S., France, Germany and Japan. However, in this paper, the maximum month return findings globally are different than in Europe. This might be a result of many variables, as discussed earlier.

Statistic	North-America		Japan		Asia-Pacific	
	WML	WML*	WML	WML*	WML	WML*
Maximum	36.09	17.30	25.60	20.14	25.78	25.51
Minimum	-30.01	-13.71	-25.65	-20.22	-57.33	-22.20
Mean	6.19	7.46	1.97	5.39	-0.60	8.92
Standard Deviation	23.52	17.96	24.04	21.62	25.19	24.85
Kurtosis	8.06	3.49	4.76	4.04	16.93	4.20
Skewness	0.01	0.24	-0.13	0.16	-1.99	0.14
Sharpe Ratio	0.26	0.42	0.08	0.25	-0.02	0.36

Table 8. Descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*). The mean average excess return, the standard deviation and the Sharpe ratio are annualized, and others are given in monthly figures. The time period is from 1995:01 to 2019:12.

The annualized mean excess return is higher for WML* than WML in every research region in table 8. The best benefit of managing the risk of momentum is reached in Asia-Pacific. The annualized mean excess returns increase from -0,60 % to 8,92 %. This is clear evidence that the risk-managed momentum is more profitable than the plain momentum in terms of the mean return. The annualized standard deviation is lower for the WML* than WML in every research region. In North America the WML* strategy provides 5,56 % lower annualized standard deviation and in Japan WML* strategy provides 2,42 % lower annualized standard deviation. In Asia-Pacific, the annualized standard deviation decreases 0,34 % when WML* is used. Barroso and Santa-Clara (2015) get globally similar findings.

Managing the risk of momentum improves kurtosis and skewness in every research region in table 8. In Japan, the WML* only decreases the kurtosis from 4,76 to 4,04, but in Asia-Pacific, the kurtosis decreases from 16,93 to 4,20. The lowest kurtosis is in North America after managing the risk of momentum. Risk-managed momentum increases skewness in every research period, and skewness gets only positive values. Once again,

these results imply that the risk-managed momentum virtually eliminates the crash risk, as discussed earlier. Furthermore, after managing the risk of momentum, the Sharpe ratio increases in North-America from 0,26 to 0,42, in Japan from 0,08 to 0,25 and in Asia-Pacific from -0,02 to 0,36. Barroso and Santa-Clara (2015) also find that risk-managed momentum improves the Sharpe ratio globally. Thus, it can be said that risk-managed momentum is globally more profitable strategy than the plain momentum strategy.

Table 9 presents the results that answer to the hypothesis 3. Panel A shows the FF3 regression results and panel B shows the FF5 regression results. In North America, the FF3 regression's alpha intercept for WML* is statistically significant at the 1 % level and produces a significant abnormal monthly return of 0,782% but the FF5 regression's alpha intercept for WML* is not statistically significant at the 5 % level. In Japan, both FF3 and FF5 regressions' alpha intercepts for WML* are insignificant. Thus, the hypothesis 3 is rejected for North America and Japan. In Asia-Pacific, the FF3 and FF5 regressions show that the alpha intercepts for the WML* are statistically significant at the 5% and 1% levels. The FF3 regression shows that the WML* produces a significant monthly abnormal return of 1,136%, and the FF5 regression shows that the WML* offers a significant monthly abnormal return of 0,858 %. Thus, the hypothesis 3 is accepted for the Asia-Pacific. Now to the last main research question has been answered. All in all, risk-managed momentum produces statistically significant positive abnormal returns only in the Asia-Pacific when the research areas in North America, Japan and Asia-Pacific are considered.

Panel A

	North-America		Japan		Asia-Pacific	
	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	0.782 ***	0.002	0.595	0.112	1.136 ***	0.007
RMRF	-0.156 *	0.064	-0.192 *	0.083	-0.135	0.129
SMB	0.060	0.658	-0.085	0.665	0.261 *	0.063
HML	-0.374 **	0.030	-0.461 **	0.013	-0.432 **	0.011
Adj.R2	0.057		0.049		0.053	

Panel B

	North-America		Japan		Asia-Pacific	
	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	0.536 *	0.066	0.333	0.344	0.858 **	0.049
RMRF	-0.081	0.356	-0.078	0.458	0.003	0.977
SMB	0.259	0.107	-0.037	0.822	0.370 ***	0.007
HML	-0.545 ***	0.002	-0.136	0.509	-0.536 ***	0.005
RMW	0.528 ***	0.005	0.960 ***	0.001	0.134	0.522
CMA	0.015	0.955	0.132	0.649	0.571 **	0.018
Adj.R2	0.090		0.102		0.074	

Table 9. Panel A presents the Fama-French 3-factor model (FF3) regression results and Panel B presents the Fama-French 5-factor model (FF5) regression results. Time period is from 1995:01 to 2019:12 in both regressions. Alpha is the intercept of the regression, and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big), HML (high minus low), RMW (robust minus weak) and CMA (conservative minus aggressive). WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and hetero-scedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level.

In table 9, the FF3 model's independent variables explain the returns of the WML* strategy. In North America, two coefficients are statistically significant at the 10 % and 5 % levels for the WML*. The RMRF factor has a negative loading of -0,156, and the HML factor has a negative loading of -0,374. The negative HML factor implies that WML* returns can be explained by growth firms. In Japan, the same factors are statistically significant at the 10 % and 5 % levels than in North America. The RMRF factor has a negative loading of -0,192, and the HML factor has a negative loading -0,461. In Asia-Pacific, two coefficients are statistically significant at the 10 % and 5 % levels for the WML*. The SMB factor has a positive loading of 0,261 and p-value of 0,063. The HML factor has a negative

loading of -0,432 and p-value of 0,011. It is interesting to notice that growth firms explain WML* returns in every research region when WML* returns are measured by FF3 model.

The FF5 model's independent variables explain the returns of the WML* strategy in table 9. In North America, two coefficients are statistically significant at the 5 % and 1 % levels for the WML*. The HML factor remains statistically significant with a negative loading of -0,545. The RMW factor has a positive loading of 0,528. This means that firms that are operating profitably can partially explain the WML* returns. In Japan, there is only one coefficient that is statistically significant at the 1 % level for the WML*. The RMW has a positive loading of 0,960. In Asia-Pacific, three coefficients are statistically significant at the 5 % and 1 % levels for the WML*. The SMB factor has a positive loading of 0,370 and p-value of 0,007. This denotes that large firms' risk-managed momentum return move to the same direction than small firms' return. This might be a result of that the large firms' winner stocks move to the same direction than the small firms' stocks and the large firms' loser stocks move to the opposite direction than the small firms' stocks. At the same time, large firms' risk-managed momentum strategy has a long position on winner stocks and short position on loser stocks. The HML factor remains statistically significant with a negative loading of -0,536, and the CMA factor has a positive loading of 0,571. The positive CMA factor implies that firms with conservative investments explain the MWL* returns. The FF5 model factors HML and CMA are economically significant compared to WML* alpha intercept in Asia-Pacific. Furthermore, the FF5 model does a better job at explaining the WML* returns in every research region than the FF3 model, however, the explanatory power is quite low.

The robustness test for the plain momentum and the risk-managed momentum in North America, Japan and Asia-Pacific is presented in table 10. The same subsample periods are used than in the European's robustness test. Panel A presents the robustness test for North America, panel B presents the robustness test for Japan and panel C presents the robustness test for Asia-Pacific.

Panel A in table 10 shows that in North America the WML has a higher month maximum return than the WML* in every subsample period except in the third period. Whereas, the monthly minimum return is better for the WML* than the WML in every subsample period except in the third period. The annualized mean excess return is higher for the WML* in the second and third period but lower in the first and no crash period. This means that the whole sample annualized mean excess return result is not robust, and annualized mean excess returns vary in different time periods. The annualized standard deviation is lower for the WML* in every subsample period except in the third period. This also means that the time periods affect to annualized standard deviation results. The different outcome in the third period compared to other periods may depend on that fact that the third period in the stock market is quite calm and bullish compared to other periods. Kurtosis in panel A is lower for the WML* than the WML, however, in the third period, the kurtosis is lower for the WML. The WML*'s skewness is positive in every subsample period, and it is also better in every subsample period except in the third period. The Sharpe ratio improves in every subsample period when managing the risk of momentum. The Sharpe ratio results are in the with the whole sample results and Barroso and Santa Clara's (2015) findings.

Panel B in table 10 shows that in Japan, the maximum month return is higher for WML in the first and no crash periods. To the WML* the maximum month return is higher for in the second and the third period. The minimum month return is better for the WML* in every subsample period and this result is consistent with the Japan's whole sample minimum month result. The annualized mean excess return is higher for the WML* in every subsample period except in the first period. In the first period, the annualized mean excess return is only 1,59 % higher for the WML. The WML* reduces the annualized standard deviation in every time period expect in the third period. The kurtoses are almost identical between WML and WML*. The WML's kurtosis is lower in the first period but higher in the other periods. The WML* has only positive skewness values, and it improves the skewness values in every subsample period. The Sharpe ratio is higher for the WML* in every subsample period. The skewness and the Sharpe ratio results are in

line with Japan's whole sample results and mostly in line with Barroso and Santa Clara's (2015) findings in Japan.

Panel C in table 10 shows that in Asia-Pacific the maximum month return is higher for the WML in the first period and no crash period whereas, the maximum month return is higher in the second and the third period for the WML*. The minimum month return is better for the WML* in every subsample period except in the third period. In the first period, the WML suffers from a minimum month return of -55,33 % and WML*'s minimum month return is -22,20 % in the first period. The annualized mean excess return is higher for the WML* in every subsample period, thus annualized mean excess return is consistent with the whole sample result. The annualized standard deviation is higher for the WML in the first and the no crash period whereas, the WML* has a higher annualized standard deviation in the second and the third period. The WML* has lower kurtosis in the first and the no crash period, but the WML has lower kurtosis in the second and the third period. The WML* has better skewness and the Sharpe ratio in every subsample period. Thus, the skewness and the Sharpe ratio results are consistent with the whole sample result.

Panel A

Statistic	First period		Second period		Third period		No crash	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	36.09	17.30	13.99	14.93	8.52	16.49	36.09	17.30
Minimum	-27.67	-13.56	-30.01	-10.85	-9.88	-13.71	-27.67	-13.71
Mean	12.31	10.73	2.62	5.96	3.64	5.68	8.07	7.90
Standard Deviation	31.91	19.52	21.15	16.96	14.16	17.43	22.64	18.08
Kurtosis	5.40	3.51	8.26	3.02	2.55	3.62	7.94	3.49
Skewness	0.30	0.33	-1.33	0.10	-0.10	0.19	0.34	0.23
Sharpe Ratio	0.39	0.55	0.12	0.35	0.26	0.33	0.36	0.44

Panel B

Statistic	First period		Second period		Third period		No crash	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	25.60	20.14	17.99	18.66	12.01	16.70	25.60	20.14
Minimum	-25.65	-20.22	-18.63	-15.35	-14.73	-12.92	-25.65	-20.22
Mean	8.93	7.34	-2.52	5.38	-0.49	3.44	3.95	6.14
Standard Deviation	32.47	25.95	20.47	19.21	16.28	19.19	23.74	21.70
Kurtosis	3.39	3.64	4.41	4.15	3.92	3.43	4.91	4.07
Skewness	-0.16	0.01	-0.31	0.48	-0.29	0.10	-0.11	0.14
Sharpe Ratio	0.27	0.28	-0.12	0.28	-0.03	0.18	0.17	0.28

Panel C

Statistic	First period		Second period		Third period		No crash	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	25.78	22.11	16.27	25.51	14.25	22.78	25.78	22.51
Minimum	-57.33	-22.20	-16.36	-14.43	-16.13	-21.04	-57.33	-22.20
Mean	-0.62	15.34	-2.77	6.52	1.58	4.89	1.38	10.31
Standard Deviation	34.69	25.67	18.62	22.34	19.14	26.49	25.22	25.06
Kurtosis	13.67	4.08	4.24	4.74	3.22	3.96	17.64	4.19
Skewness	-2.23	-0.17	-0.34	0.70	-0.17	0.07	-2.08	0.10
Sharpe Ratio	-0.02	0.60	-0.15	0.29	0.08	0.18	0.05	0.41

Table 10. Panel A presents descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*) in North America. Panel B presents descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*) in Japan. Panel C presents descriptive statistics for the plain momentum (WML) and the risk-managed momentum (WML*) in Asia-Pacific. Time period is divided into four different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and no crash period covers 1995:01-2019:12 where the financial crisis in 2009 is excluded. The mean average excess return, the standard deviation and the Sharpe ratio are annualized, and others are given in monthly figures.

The most interesting findings in table 10 are presented next. Most of the time the annualized mean excess returns are globally better for the risk-managed momentum than the plain momentum. Sometimes the plain momentum produces negative annualized mean excess returns, whereas, the risk-managed momentum produces only positive annualized mean excess returns. Globally the risk-managed momentum reduces the high kurtosis values. In Japan, the kurtosis values are almost identical in different subsample

periods. The risk-managed momentum improves the skewness globally in every subsample period except in the no crash period in North America. The skewness for the risk-managed momentum is negative in the first period in the Asia-Pacific, but otherwise globally it is positive for the risk-managed momentum. The Sharpe ratio is globally higher for the risk-managed momentum than plain momentum in every subsample period. This is a robust result that risk-managed momentum produces a higher return for every taken unit of risk.

Next, the robustness tests are formed to FF3 and FF5 regressions and the same subsample periods are used than in the descriptive statistic's robustness test. Panel A presents the robustness test for North America, panel B presents the robustness test for Japan and panel C presents the robustness test for Asia-Pacific. Table 11 shows the FF3 regression's robustness results for the WML* and table 12 presents the FF5 regression's robustness results for the WML*.

Table 11 shows the FF3 regression's alpha intercepts for the WML*. In the first and no crash periods, the alpha intercepts are statistically significant at the 5 % and 10 % levels for North America in panel A. The monthly abnormal return is 1,132 % in the first period and in the no crash period the monthly abnormal return is 0,808 %. Panel B shows that Japan has only one statistically significant alpha intercept at the 10 % level in the no crash period. Panel C shows that the Asia-Pacific has two statistically significant alpha intercepts at the 1 % level. In the first period the WML* produces a monthly abnormal return of 1,891 % and in the no crash period the WML* produces a monthly abnormal return of 1,310 %. The alpha intercept of the whole sample is statistically significant at the 1 % level in North America and Asia-Pacific, but in the robustness test, the results are not statistically significant in every subsample period.

Panel A

	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	1.132 **	0.038	0.322	0.449	0.486	0.219	0.808 ***	0.002
RMRF	-0.197	0.134	-0.037	0.774	-0.335 **	0.015	-0.148	0.107
SMB	0.019	0.917	0.707 **	0.012	-0.132	0.519	0.058	0.680
HML	-0.234	0.268	-0.523 *	0.072	-1.216 ***	0.000	-0.370 **	0.046
Adj.R2	0.008		0.121		0.348		0.049	

Panel B

	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	0.391	0.634	0.176	0.781	0.034	0.942	0.678 *	0.074
RMRF	-0.321 **	0.026	0.090	0.601	-0.059	0.764	-0.189	0.103
SMB	-0.459 **	0.037	0.368	0.136	0.439 **	0.047	-0.086	0.664
HML	-0.393	0.130	0.304	0.209	-0.786 ***	0.001	-0.501 ***	0.007
Adj.R2	0.140		0.011		0.201		0.056	

Panel C

	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	1.891 ***	0.005	0.536	0.367	0.399	0.628	1.310 ***	0.002
RMRF	-0.290	0.094	0.117	0.377	-0.181	0.288	-0.107	0.249
SMB	0.460 ***	0.008	-0.057	0.801	-0.010	0.984	0.302 **	0.035
HML	-0.460 **	0.032	-0.470 **	0.049	0.182	0.683	-0.509 ***	0.003
Adj.R2	0.202		0.030		-0.017		0.063	

Table 11. Panel A presents the Fama-French 3-factor model (FF3) regression results in North America. Panel B presents the Fama-French 3-factor model (FF3) regression results in Japan. Panel C presents the Fama-French 3-factor model (FF3) regression results in Asia-Pacific. Time period is divided into four different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and the no crash period covers 1995:01-2019:12. Alpha is the intercept of the regression, and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big) and HML (high minus low). WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level.

In table 11, the FF3 model independent variables explain the returns of WML* strategy. FF3 model in the whole sample shows that North America has two significant coefficients at 10 % and 5 % levels for the WML*. In panel A the robustness check shows that none of the independent variable coefficients is statistically significant in every subsample period. The closest is the HML factor, which is statistically significant in the second, third and no crash period. Furthermore, the lowest adjusted r squared 0,008 is in the first

period, and the highest adjusted r squared 0,348 is in the third period. All in all, in North America the FF3 model does not do a good job at explaining the WML* returns.

FF3 model in the whole sample shows that Japan has two significant coefficients at 10 % and 5 % levels for the WML*. In table 11 the panel B shows that in Japan, none of the independent variable coefficients is statistically significant in every subsample period. In the whole sample, the SMB factor is not statistically significant, but in the subsamples, the SMB factor is statistically significant in the first and third period. In the first period, the SMB factor has a negative loading of -0,459, and in the third period, it has a positive loading of 0,439. Thus, it can be said that sometimes large firms and sometimes small firms explain the WML* returns. Moreover, in Japan, the FF3 model does not do a good job of explaining the WML* returns.

In the whole sample, the FF3 model shows that in Asia-Pacific, two coefficients are statistically significant at 10 % and 5 % levels for the WML*. The robustness check in table 11 shows that none of the independent variable coefficients is statistically significant in every subsample period in Asia-Pacific. The closest is the HML factor, which is statistically significant in the first, second and no crash period. In the third period, there are not statistically significant factors but is not a surprise because the adjusted r squared is slightly negative. The negative adjusted r squared means that the FF3 model is useless in the third period. All in all, the FF3 model does not do a good job at explaining the WML* returns in Asia-Pacific.

The FF5 model's alpha intercepts for the WML* are presented in table 12. Panel A shows that North America has a statistically significant coefficient at the 10 % level only in the no crash period. In the no crash period, the monthly abnormal return is 0,588 % for the WML*. Panel B shows that there are not statistically significant alpha intercepts in Japan. Panel C shows that the Asia-Pacific has two statistically significant alpha intercepts at the 5 % level. In the first period WML* produces a monthly abnormal return of 1,372 % and in the no crash period WML* produces a monthly excess return of 1,024 %. The alpha

intercept of the whole sample is statistically significant at the 10 % level in North America and statistically significant at the 5 % level in Asia-Pacific, but in the robustness test, the alpha intercepts are not statistically significant in every subsample period.

In table 12, the FF5 model shows that North America has two significant coefficients in the whole sample period at the 1 % level for the WML*. The robustness check in panel A shows that none of the independent variable coefficients is statistically significant in every subsample period. The closest is the RMW factor, which is statistically significant in the second, third and no crash period at the 10 % and 1 % levels. The HML factor is statistically significant in the third and no crash period at the 1 % level. Moreover, the adjusted r squared is negative in the first period, which means that the FF5 model is useless. In all other periods, the adjusted r squared is positive, even though the FF5 model does not have high explanatory power.

In the whole sample, the FF5 model shows that in Japan, the RMW coefficient is statistically significant at the 1 % level for the WML*. In table 12, the robustness check shows that the RWM coefficient is only statistically significant in the third and no crash period. Furthermore, the adjusted r squared vary from 0,014 to 0,268. This means that FF5 model does not have good explanatory power.

FF5 model results in the whole sample show that in the Asia-Pacific, there are three statistically significant coefficients at the 5 % and 1 % levels for the WML*. The robustness check in panel C shows that none of the independent variable coefficients is statistically significant in every subsample period. The closest is the HML factor, which is statistically significant in the first, second and no crash period. Moreover, the FF5 model does not explain the WML* returns well and in the third period adjusted r squared is slightly negative like it is also for the FF3 model robustness check in the third period.

Panel A

Statistic	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	1.047	0.111	-0.045	0.919	0.456	0.281	0.588 *	0.051
RMRF	-0.170	0.261	0.001	0.994	-0.333 **	0.011	-0.082	0.381
SMB	0.111	0.598	0.827 ***	0.002	-0.339	0.106	0.269	0.108
HML	-0.294	0.281	-0.439	0.214	-1.439 ***	0.000	-0.523 ***	0.005
RMW	0.254	0.340	0.694 *	0.084	-0.638 *	0.092	0.540 ***	0.005
CMA	-0.080	0.839	-0.223	0.616	0.410	0.506	-0.030	0.911
Adj.R2	-0.001		0.173		0.356		0.083	

Panel B

Statistic	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	-0.059	0.932	0.167	0.783	-0.265	0.591	0.447	0.211
RMRF	-0.184	0.195	0.124	0.499	0.137	0.535	-0.079	0.479
SMB	-0.283 *	0.092	0.340	0.159	0.463 **	0.024	-0.030	0.861
HML	0.273	0.439	0.147	0.604	-0.611 **	0.046	-0.140	0.507
RMW	0.371	0.425	0.534	0.332	1.164 *	0.093	0.834 ***	0.007
CMA	-0.728	0.167	0.457	0.245	1.101 ***	0.005	-0.012	0.967
Adj.R2	0.218		0.014		0.268		0.100	

Panel C

Statistic	First period		Second period		Third period		No crash	
	WML*	p-value	WML*	p-value	WML*	p-value	WML*	p-value
Alpha	1.372 **	0.035	0.442	0.525	0.370	0.694	1.024 **	0.021
RMRF	-0.072	0.700	0.200	0.244	-0.125	0.447	0.008	0.932
SMB	0.567 ***	0.002	-0.047	0.845	0.001	0.998	0.392 ***	0.006
HML	-0.583 **	0.011	-0.766 ***	0.006	-0.086	0.860	-0.591 ***	0.002
RMW	0.212	0.397	-0.274	0.408	-0.301	0.689	0.133	0.546
CMA	0.777 ***	0.006	0.467	0.330	0.748	0.341	0.490 **	0.048
Adj.R2	0.264		0.026		-0.021		0.077	

Table 12. Panel A presents the Fama-French 5-factor model (FF5) regression results in North America. Panel B presents the Fama-French 5-factor model (FF5) regression results in Japan. Panel C presents the Fama-French 5-factor model (FF5) regression results in Asia-Pacific. Time period is divided into four different subsamples. The first period covers 1995:01-2003:04, the second period covers 2003:05-2011:08, the third period covers 2011:09-2019:12 and the no crash period covers 1995:01-2019:12. Alpha is the intercept of the regression, and the factor loadings are RMRF (market return minus risk-free rate), SMB (small minus big), HML (high minus low), RMW (robust minus weak) and CMA (conservative minus aggressive). WML* is the risk-managed momentum. All regressions are Newey-West (1987) corrected for autocorrelation and heteroscedasticity. Statistically significant: 1) *** on a 1 % level, 2) ** on a 5 % level, 3) * on a 10 % level.

All in all, the whole sample FF3 and FF5 regressions' alpha intercepts are statistically significant for the WML* in North America and Asia-Pacific. However, the robustness checks show that the alpha intercepts are not statistically significant in every subsample

period. The robustness checks also prove that the independent variables' coefficients are not statistically significant in every subsample period. Furthermore, the FF3 and FF5 models do not explain well the abnormal returns of the WML*. Most of the times the FF5 model explains better the abnormal returns of the WML* than the FF3 model does.

6 Conclusion

The plain momentum strategy is prone to momentum crashes, and the crashes could wipe out the decade of the momentum returns (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). Barroso and Santa-Clara (2015) show that managing the risk of the momentum by its realized variance of daily returns can mitigate the crash risk and improve profitability. Therefore, this thesis examines abnormal returns of the risk-managed momentum first in Europe and subsequently globally in North America, Japan and Asia-Pacific by using the Fama-French 3- and 5-factor OLS regressions. Moreover, this thesis investigates how much risk-managed momentum improves the Sharpe ratio and negative elements of the plain momentum in the whole sample period and subsample periods.

In this paper, the most important findings are found in the regression results. The risk-managed momentum generates statistically significant positive abnormal returns at least at 5 % level in Europe and Asia-Pacific but not in North America and Japan. Thus, these results give answers to the main research questions, as discussed earlier. Even though the risk-managed momentum strategy is not able to generate statistically significant positive abnormal returns in every research area, it provides many benefits for investors when the risk-managed momentum is compared to plain momentum. The results in this paper show that managing the risk of the momentum strategy improve the skewness greatly and even provide positive skewness values in Europe and globally. These skewness results are mostly in line with Barroso and Santa-Clara's (2015) findings. Also, in this paper, it is observed that the risk-managed momentum improves kurtosis of the momentum and provides near the normal distribution kurtosis values in every research area. The Sharpe ratio is improved in Europe and globally when the risk of the momentum is managed. These results are robust in every subsample period and also in line with Barroso and Santa-Clara's (2015) and Grobys, Ruotsalainen and Äijö's (2018) results. The biggest improvement of the Sharpe ratio is in the Asia-Pacific where the plain momentum first provides a negative Sharpe ratio value of -0,02, and the risk-managed momentum increases the Sharpe ratio to 0,36. Furthermore, in the most turbulence

times, the risk-managed momentum improves the plain momentum performance and mitigates the momentum crash risk.

Overall, this paper shows that risk-managed momentum solves the main problems related to the plain momentum in Europe and globally. Therefore, it is more safety and profitable strategy for investors. In the field of risk-managed momentum, there are many topics where future research could be related to. The risk-managed momentum has been now investigated globally in the equity markets, and therefore, it could be interesting to investigate risk-managed industrial momentum globally. Studying the risk-managed momentum in different asset classes such as fixed-income securities and currencies could be interesting. Furthermore, it could be interesting to investigate the risk-managed momentum differences in large companies compared to small companies.

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