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PROFITABILITY OF RISK-MANAGED INDUSTRY MOMENTUM IN THE U.S. STOCK MARKET

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ABSTRACT

This Master’s thesis examines whether risk-managing industry Momentum via the methodology of Barroso and Santa Clara (2015) produces a more profitable strategy than industry Momentum by itself. Industry Momentum is also tested in a previously unexamined period to see whether or not the strategy still produces abnormal returns.

By using data from the U.S. stock market between 1928 – 2015, multivariate regressions that utilize the Fama-French Three and Five Factor Model are run in an attempt to explain returns to industry Momentum and risk-managed industry Momentum. Additionally, robustness tests are conducted in the same vein in subsample time-periods.

The results indicate that risk-managed industry Momentum produces statistically significant abnormal returns in all time-periods tested. Industry Momentum is also still found to be prevalent in the U.S. stock market in producing abnormal returns. Risk-managed industry Momentum is more profitable as well, compared to industry Momentum by measuring Sharpe ratios and abnormal returns for both strategies.

These findings suggest that risk-managing Momentum with the Barroso and Santa Clara methodology works not only for individual stocks, but industries as well. Risk-managing industry Momentum produces significant abnormal returns and a high Sharpe ratio while eliminating negative skewness in return distribution. This arguably eliminates Momentum crashes from industry Momentum completely.

KEYWORDS: Momentum, risk-managed, industry, profitability

1. INTRODUCTION

The search for superior sources of returns is arguably the very crux of investor participation in financial markets. Times change, fads differ, and theory develops but the struggle to find new investment strategies that will aid investors in beating the market never disappears. Though fundamental analysis and portfolio theory (Markowitz, 1953) are the mainstays in screening for investment worthy stocks, there is an increasing amount of quantitative investment strategies that rely on studies produced in academic finance (Asness, Ilmanen, Israel & Moskowitz, 2015). One of these strategies is Momentum investing. Although originally discovered by Levy (1967), Jegadeesh and Titman (1993) sparked widespread academic interest in Momentum, which has created a baffled following of researchers and investors alike, where the former seek to find the source for the strategy's returns and the latter seek to capitalize on those returns. Momentum – or the tendency of winners to keep on winning and losers to keep on losing – has commanded the attention of financial academia. As Momentum bases itself on nothing more than historical price data, it continues to present a serious challenge for the theory of efficient markets (Fama, 1970). This has led to a dichotomy in explanations for Momentum, where in addition to efficient market advocates, behaviorists have joined the fray, in seeking explanations for Momentum returns. Even though Momentum is cornered on both sides by two schools of thought, its mean return origins remain a mystery. It is a common notion to conjecture that once an anomaly's origins are revealed, it subsequently disappears. The continued existence of Momentum thus makes it a strong candidate for an investment strategy to be utilized by investors.

Regardless of the motivation to utilize Momentum, the phenomenon is geographically widespread, prevalent across asset classes, and robust across different time periods (Asness, Frazzini, Israel & Moskowitz, 2014). Industries exemplify the widespread reach of the Momentum effect (Moskowitz & Grinblatt, 1999; Nijman, Swinkels & Verbeek, 2004; Pan, Liano & Huang, 2004; Du & Denning, 2005). Just as with stocks, going long in recent winner industries and selling short recent loser industries, produces abnormal returns. With the rapid rise of Exchange Traded Funds (ETF), investors may access Momentum by buying industries through ETF's, which creates an easy route to harnessing the strategy compared to individual stocks. Therefore, investigating further possibilities of enhancing industry Momentum strategies poses a viable avenue of research.

This success of Momentum makes it a very viable investment strategy capable of producing abnormal returns for investors. As with any popular phenomenon however, there are those who seek to highlight the risks involved. In the case of Momentum, rightly so, as the strategy does suffer from downside risk namely by possessing the built-in risk of Momentum crashes (Daniel & Moskowitz, 2015). These crashes, which are evident in the negative skewness of Momentum return distributions, constrain the profitability of the strategy and steer the more risk-averse investors away. Momentum experiences these crashes when negative market conditions undergo a rebound and the loser stocks climb faster than the winners, resulting in negative returns for the strategy. There is a budding niche in Momentum literature, which seeks to control and minimize the crash risk associated with Momentum (Asness, Moskowitz & Pedersen, 2013; Barroso & Santa-Clara, 2015). In fact, Barroso and Santa-Clara have developed a method of risk-management for stock-based Momentum, which works through scaling the strategy via realized variances of daily returns. This strategy has greatly decreased the negative skewness of Momentum and as a result, the downside effect of Momentum crashes. Needless to say, by decreasing Momentum's risk, the profitability of stock-based Momentum has been enhanced greatly. As a result of the work of Barroso and Santa-Clara, questions arise on the efficacy of their methodology. Mainly, does the strategy apply equally across countries, time-periods, and different securities? It would stand to reason, that if risk-managing Momentum worked in industries for example, this would highlight a previously undiscovered profitable investment strategy, which would be easier to utilize than stock-based Momentum and would potentially trump the profitability of regular industry Momentum. In addition to highlighting a profitable investment strategy, the success of risk-managing industry Momentum would provide further proof, that the findings of Barroso and Santa-Clara are indeed groundbreaking in the field of academic Momentum literature.

1.1. The Purpose of the Thesis

The purpose of this thesis is to investigate whether or not industry Momentum may be risk-managed similarly to individual stock Momentum in Barroso and Santa Clara (2015) and whether this increases the profitability of industry Momentum when compared to its regular non-managed version. This research question is ultimately answered via multivariate regressions using data from the U.S. stock market from 1928 to 2015. To run the regressions, Momentum portfolio sorts are conducted, after which the returns for the strategy are calculated. As a consequence, to the primary purpose, further research questions will be answered concerning the continuing existence of industry Momentum in the U.S. Comparing the findings of this thesis to previous studies of industry Momentum and to the original risk-managed Momentum paper by Barroso & Santa Clara (2015) will reveal whether the risk-managed industry Momentum strategy outperforms regular industry Momentum and risk-managed individual stock Momentum. By answering the purpose of this thesis, a clear contribution to the literature is made. First off, this thesis performs an analysis analogous to the one conducted on stock price Momentum by Barroso and Santa Clara (2015), but in an industry context. Secondly, by investigating the profitability of risk-managed industry Momentum, an entirely new research question will be answered as there are no prior studies that have researched this very topic ever before. At the moment of writing this thesis, the only research conducted on risk-managed Momentum is the original piece of work by Barroso & Santa Clara (2015). Thus investigating its interaction with sector Momentum is the first research expanding beyond regular Momentum and it entails potentially unveiling a new and effective investment strategy that may have real-life implications. Last but not least, this thesis may shed further light on the nature of Momentum, offering for example, further insight into the prevailing debate over whether the return characteristics for individual stock Momentum and industry Momentum are homogenous (Grinblatt & Moskowitz, 1999; Nijman et al., 2004; Pan et al., 2004; Du & Denning, 2005)). After reading through this thesis, the reader will understand whether combining industry Momentum with risk-management via the methodology presented by Barroso and Santa Clara (2015) produces statistically significant abnormal returns and whether this combination outperforms its respective benchmarks in regular industry Momentum and risk-managed individual stock Momentum.

1.2. The Structure of the Thesis

This thesis is divided into nine chapters, each of which may contain a various number of subheadings. This first chapter serves as an introduction to the thesis, shedding light on the purpose of the thesis, the structure, and the research hypotheses that will be investigated. Chapter two will discuss the theory of efficient markets, which is presented as a necessary backdrop in understanding the nature of anomalous returns and thus the nature of Momentum returns. Understanding the Efficient Market Hypothesis (Fama, 1970) (EMH) highlights the importance of potential significant findings. The third chapter discusses how stock prices are formed on a theoretical level in order for the reader to understand how price reactions associated with Momentum may conflict with these principal theories. This is yet again a framework, which should clarify for the reader, the anomalous nature of Momentum returns. Part four introduces the relevant prior research into Momentum, building a historical analysis for what has been done in academic finance in terms of studying the phenomenon. This chapter demonstrates the power of the Momentum effect and describes its prevalence in a wide variety of samples. Chapter five will introduce the relevant prior research related to industry Momentum. This is similar in nature to chapter four and serves to introduce the concepts and methods used in studying industry Momentum, as they will play an important role in understanding the methodologies employed in this study. Chapter six discusses Barroso and Santa Clara's (2015) risk-adjusted Momentum which is the focal point in terms of answering the research question in this thesis. Therefore, it is natural to present the study along with the methodologies used in its own separate chapter, as these methodologies will serve an integral part in the empirical work conducted at the end of the thesis. Chapter seven presents the data and methodologies used in this thesis. It serves to highlight the process followed to reach the eventual results presented. Chapter eight focuses on the results of the study. It will also entail analysis, discussion, and interpretation of said results. Finally, chapter nine will conclude this thesis and summarize the findings and their implications briefly.

1.3. Research Hypotheses

This thesis aims to answer two main hypotheses, each having a null hypothesis and an alternate one. The first hypothesis can be considered a basis for the study to build upon and it aims to investigate whether industry Momentum is still present in the U.S. stock market with up-to-date data from Kenneth French's website (French, 2016). The first hypothesis is as follows:

> H_0: Industry Momentum does not produce statistically significant abnormal returns in the U.S. stock market for the given time period.
>
> H_1: Industry Momentum does produce statistically significant abnormal returns in the U.S. stock market for the given time period.

The second of the hypotheses investigates whether or not risk-managing industry Momentum produces statistically significant abnormal returns and thus can increase the Sharpe ratio of industry Momentum similarly to what Barroso & Santa Clara (2015) show in the case of ordinary stock Momentum. This hypothesis will therefore reveal whether risk-managed industry Momentum is a viable and profitable investment strategy. Additionally, if the conclusion to this hypothesis is that risk-managed industry Momentum produces significant abnormal returns, then the case for the way in which, Barroso and Santa Clara manage the risk of Momentum is strengthened via this out-of-sample test. If the findings support Barroso and Santa Clara's methodology, then it is also a clear indicator that further studies on applying risk-managed Momentum should be conducted for example, in different countries and different asset classes. The second pair of hypotheses are:

> H_0: Risk-managed industry Momentum does not produce statistically significant abnormal returns in the U.S. stock market for the given time period.
>
> H_1: Risk-managed industry Momentum does produce positive statistically significant abnormal returns in the U.S. stock market for the given time period.

The first pair of hypotheses offer no original contribution to the literature as such, but instead aim to confirm previous findings in a slightly different time period in order to form a basis for the inspection of the second pair of hypotheses. The second hypothesis however, contribute to the literature in an original way by combining two different aspects of Momentum that have both been previously studied in finance. Following this, whether or not the hypotheses will be rejected or failed to be rejected, isn't arguably the main concern here, as either way the results of this study begin a stream of research either rebuking or supporting this specific methodology of Momentum risk-management and its ability to decrease Momentum crash risk and increase Sharpe ratios.

2. EFFICIENT MARKETS

Viewing Momentum from the perspective of market efficiency is critical. The anomalous returns from Momentum present a clear challenge to the viability of efficient markets. Therefore, market efficiency is a natural and highly relevant point of view in trying to explain Momentum returns.

2.1. Efficient Market Hypothesis

Eugene Fama not only contributed an important piece of work on efficient markets in 1970, but is often thought of as the founding father of this specific and widespread school of thought. In his paper “Efficient Capital Markets: A Review of Theoretical and Empirical Work” Fama (1970) describes efficient markets as prices always fully reflecting all available information. This Efficient Market Hypothesis (EMH) means that any events or actions with consequences to firms will have an immediate and correct reaction on the firm’s stock price. This way, no one can take advantage of informational asymmetry and profit off of delayed price reactions.

The importance of efficient markets is evident when one considers the functionality of capital markets as a whole. The primary objective of capital markets is to allocate the economy’s capital stock (Fama, 1970). If this doesn’t happen in an efficient way, its consequences will likely lead to disruptions in the markets and therefore disruptions in the economy.

2.2. Three Forms of Market Efficiency

The empirical work on efficient markets by Fama (1970) can be divided into three subsets or levels of efficiency. These subsets or levels can be distinguished by the extent to which “all information” is reflected in the market (Bodie, Kane & Marcus, 2014).

1. Weak-form efficiency asserts that all historical information relating to price and volume are already reflected in stock prices (Fama, 1970). This means that trend or technical analysis based on historical price changes is futile. Using technical analysis in weak-form efficient markets is thus not going to work in providing investors with returns.

2. Semistrong-form efficiency instills the notion that in addition to historical data on price and volume, fundamental information regarding firms is also publicly available (Fama, 1970). This includes company

balance sheets, patent portfolios and earnings forecasts among other things (Bodie et al., 2014) and all of this information is reflected in prices.

3. The strong form efficiency entails that all information available is reflected in stock market prices (Fama, 1970). This means that stock prices efficiently react to even information available only to company insiders (Bodie et al., 2014).

Fama (1970) presents that weak-form tests of market efficiency have been widely conducted and that there is evidence to suggest, that the stock market is indeed weak-form efficient. This assertion is not likely endorsed by advocates of technical analysis, who suggest that historical data can help in timing sales for example and that this may lead to higher returns compared to the market. In the same vein, Momentum, which relies only on historical price data, presents a serious discord in the empirical discussions surrounding even weak-form efficient markets.

On strong form efficiency Fama (1970) concludes that it is not likely to hold true for the stock market. Instead, strong form efficiency, where all available information is reflected in stock prices, should be viewed as a sort of benchmark in studies further investigating market efficiency. Fama touched upon this remark of strong form efficiency again in his 1991 paper where he added that as there are surely positive information and trading costs related to the Efficient Market Hypothesis, strong form efficiency must clearly be false. He also reiterated that even in 1991, the strong form efficient version of the EMH could still serve as a benchmark for further studies (Fama, 1991).

Even though the EMH is confronted by ambiguity through information costs, Fama (1991) claims that the biggest problem to the EMH is the joint-hypothesis approach to testing market efficiency. Market efficiency is by proxy tested through asset-pricing models. If asset-pricing models can explain stock market returns, then by proxy, markets are efficient. Market efficiency per se is not testable in itself and that’s why it is usually tested through these joint-hypotheses. This poses the obvious problem of creating asset-pricing models that are accurate and can explain returns despite where they stem from. Momentum for example, produces anomalous mean returns that no pricing model can wholly explain.

Despite the challenges that tests for market efficiency face, Fama (1991) claims that asset-pricing models are scientifically useful in studying market efficiency. Fama still holds, that despite their usefulness the joint-hypothesis issue leaves much to be desired in drawing precise inferences about market efficiency.

Event studies are often used to study market efficiency (Fama, 1991). The purpose of event studies is to accurately pinpoint and record events to see whether or not they have a direct effect on price changes. These changes are tested for statistical significance and based on the results, they are deemed to offer evidence of market efficiency.

Market efficiency is most often called into question through the existence of anomalous returns to assets. Anomalies in financial markets are returns that cannot be thoroughly explained by asset-pricing models (Schwert, 2002). This in turn is taken as evidence for inefficient markets or inefficient underlying asset-pricing models. The inability to reconcile the source of this inefficiency again highlights the problems surrounding the joint-hypothesis problem.

Schwert (2002) questions the notion of whether or not anomalies are persistent enough to be taken as evidence towards market inefficiency. According to Schwert many anomalies weaken or disappear over time after their academic discovery. Whether this weakening or disappearance can be attributed to being only historically anomalous or the anomalous opportunities being arbitraged away, anomalies in financial markets do not seem to persist. It is important to notice however that the evidence in favor of Momentum seems to persist over time. Schwert claims that this persistence may be explained by a yet unidentified risk factor that accounts for the high returns. The assertion of an undiscovered risk factor explaining Momentum returns seems to be a very popular notion in financial literature, especially held in high regard by representatives of the efficient markets school of thought.

In conclusion to the EMH, all forms have in common the notion, that prices should reflect information (Bodie et al., 2014). The degree of efficiency however seems to be highly debatable. Even Fama (1970, 1991) who created the notion of three forms of market efficiency has been documented as saying that strong form efficiency should serve only as a benchmark. Supporters of technical analysis, or Momentum for that matter, might be willing to argue that even weak-form efficiency isn’t present in stock markets. As the main topic of this thesis, Momentum adds to this conundrum of efficiency by its unexplained anomalous returns.

3. STOCK PRICE THEORY

In discerning the origin of Momentum's returns, it is important to understand the different theories behind stock price formation. Momentum directly relies on stock price changes and therefore understanding the basic principles of how these prices are formed, at the very least on a theoretical level, is crucial to beginning to understand Momentum. Just as information affects the prices of stocks, so do for example future cash flows, future dividends and different risk factors. These are important notions when considering anomalous returns, such as those produced by Momentum, and their underlying causes. In this chapter, five different models of how asset prices – mainly stocks – are formed will be discussed.

3.1. Dividend Discount Model

The dividend discount model (DDM) suggests that a stock's price is formed through its discounted future dividends from present time to perpetuity (Bodie et al., 2014).

(1.) $$V_0 = \frac{D_1}{1+k} + \frac{D_2}{(1+k)^2} + \frac{D_3}{(1+k)^3} + \dots + \frac{D_t}{(1+k)^t}$$

Where, V_0 is the price of stock at time 0, D is the dividend at a certain time t, and k is the return on equity. (Bodie et al., 2014)

The DDM asserts that investors ignore capital gains as such, and that dividends actually already take into account future capital gains. This assertion is based on capital gains being reflected in the dividends at the time the stock is sold. In other words, the DDM states that the stock price is based solely on cash flows incoming to shareholders, and these cash flows are dividends. (Bodie et al., 2014)

Following this logic Momentum should be easily tracked by following announcements concerning firm dividend policy. As announcements affecting dividend policy are available to everyone, Momentum would most likely be arbitraged away. This however is not the case and as returns to Momentum aren't tied to stocks with high dividend yields, the DDM cannot explain why Momentum is so profitable.

3.2. Free Cash Flow Valuation Model

An alternative to the DDM, the free cash flow (FCF) valuation model is essentially based on the same logic as the DDM. Both the DDM and FCF model hold that stock prices are based on cash flows. The DDM asserts that cash flows are nothing more than dividends and therefore relies on discounting future dividends to reveal the current price of a share. The FCF model however differs in the way it discerns what makes up cash flows. In the FCF model free cash flow is what's available to equity holders net of capital expenditures (Bodie et al., 2014). The FCF model works especially well with firms that issue no dividends, but it can be used with any kind of firms and the model may deliver useful information out of the scope of the DDM.

To further enhance the usefulness of the FCF model, instead of using return on equity in the denominator, the weighted average cost of capital (WACC) can be employed. Consequently, debt can be subtracted from the WACC to find the value of equity. After calculating the value of a company this way, the value of a single stock must be derived by dividing with the shares outstanding in the company. (Bodie et al., 2014)

(2.) $$P_0 = \sum_{t=1}^{\infty} \frac{FCF_t}{(1+WACC)^t}$$

Where,
P_0 is the value of the company at time 0, t is the time period, FCF is the free cash flow, and WACC is the weighted average cost of capital (Puttonen & Knüpfer, 2009).

3.3. The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965), is a renowned formula for explaining returns in relation to systematic risk, or Beta. The CAPM was one of the first asset pricing models that became popular in academic research concerning market efficiency. It is still in use and occasionally serves as one of the asset-pricing models in joint-hypotheses when studying market efficiency.

The first part of the CAPM represents the risk-free rate of return. It is then followed by the Beta that acts as a proxy for systematic risk for the stock at hand. The risk premium for a single stock is then calculated by multiplying the risk premium of the market portfolio with the Beta of the stock in question and adding the risk-free rate of return. (Puttonen & Knüpfer, 2009)

(3.) $$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right]$$

Where, $E(r_i)$ is the expected return for stock i, r_f is the risk-free return, B_i is the systematic risk of stock i, and $E(r_m)$ is the expected return for the market (Puttonen & Knüpfer, 2009).

As many models that attempt to describe real world phenomena, the CAPM has a set of assumptions that it relies on to hold true for it to be applicable immaculately. Below is a list of these:

1. Investors are rational mean-variance optimizers.
2. Their planning horizon is a single period.
3. Investors have homogenous expectations.
4. All assets are publicly held and traded on public exchanges, short positions are allowed and investors can borrow or lend at a common risk-free rate.
5. All information is publicly available.
6. Profits aren't taxed.
7. No transaction costs on trades.

(Bodie et al., 2014)

At least three of the assumptions of the CAPM present major challenges to the model. All assets trade, no transaction costs for trades and single period planning horizons are restrictions that have prompted research and development of extensions for the CAPM. There's arguably another set of problems inherent in the use of Beta as a measure for systematic risk. As Beta's are mostly calculated with regressions, they only present a proxy for systematic risk during the very day of calculation. So Beta doesn't take into account possible changes stemming from events taking place with the passing of time. Liquidity is another factor affecting systematic risk as increases or decreases in one stock's liquidity affects every other stock's liquidity. This correlation makes up liquidity risk, which is a component of systematic risk that the CAPM is unable to account for. Even though the CAPM has failed numerous empirical tests, the intrinsic logic behind the model has kept it at the center of financial research through the years. (Bodie et al., 2014)

3.4. Fama & French Three Factor Model

The Fama & French Three Factor Model (FF3) (Fama & French, 1993) is widely regarded as the next step in the evolution of asset-pricing models, superseding the CAPM. The FF3 originally rose out of a need to quantify the size-risk premium (Bodie et al., 2014). The CAPM was never able to fully explain what accounted for the anomalous returns on small-cap value firms and the FF3 was created to answer that challenge.

The FF3 equation relates that all returns excess of the risk-free rate are explained by the sensitivity of said returns to three factors. These factors are: excess returns on a broad market portfolio (R_m - r_f), the difference of returns between a portfolio of small stocks and large stocks (SMB) and the difference of returns between a portfolio of high book-to-market stocks and low book-to-market stocks (HML). (Fama & French, 1993)

If the three factors presented in the FF3 were to be the only risk factors on the market, then the intercept of the regression for every portfolio should be at the very most 0 (Bodie et al., 2014). Fama & French (1996) suggest something along these lines in their most aggressive conclusions as they state that the FF3 could be an equilibrium-pricing model. However, the truth is more likely along the lines of the less aggressive conclusions they draw in suggesting that the FF3 is a liberal explanation for returns and average returns. Regardless of where along this continuum the FF3 lies, it manages to explain variation in cross-sections of average returns and anomalous returns that the CAPM cannot (Fama & French, 1992, 1996).

Even though the FF3 manages to explain many of the anomalies that the CAPM can't, it is important to realize that the FF3 has not been able to account for the anomalous returns of Momentum (Fama & French, 1993, 1996). In trying to do so, Fama and French found the intercepts of Momentum returns to be reliably positive. In fact, the intercepts were greater for the FF3 than they were for the CAPM, which is somewhat puzzling as in general, the FF3 is regarded as a more robust asset-pricing model than the CAPM.

The regression for the FF3:

(4.) $$R_i - R_f = \alpha_i + b_i(r_m - r_f) + s_i SMB + h_i HML + \varepsilon_i$$

Where, R_i is the return on stock/portfolio i, R_f is the risk-free return, a_i is the intercept of the regression for stock/portfolio i, $b_i(r_m\text{-}r_f)$ is the factor beta for market returns multiplied by market index return, s_iSMB is the factor beta for Small Minus Big multiplied by returns for Small Minus Big, h_iHML is the factor beta for High Minus Low multiplied by returns for High Minus Low, e_i is the product of other factors affecting stock/portfolio i (Fama & French, 1996).

3.5. Fama & French Five Factor Model

In a very recent publication Fama & French (2015) refined their FF3 by adding two more risk factors, in the hopes that this revised factor model can further explain variations in average returns. In the Fama-French Five Factor Model (FF5), they have added profitability – as is proposed by Novy-Marx (2013) – and investment-to-market to accompany size and book-to-market factors. Profitability as a factor takes into account the difference of portfolios constructed upon robust and weak profitability (RMW) in firms and investment as a factor takes into account the difference of portfolios constructed upon conservative and aggressive investing (CMA) in firms. The rationale for adding two more factors comes from the purpose of constructing an evaluation model where the risk-factors included act as proxies.

Fama and French (2015) sought out to apply their FF5 to explain returns of prevalent anomalies. They compared their results to the FF3 to see whether the FF5 was more capable of explaining anomalous returns. In addition to this Fama and French investigated whether problems in asset-pricing models didn't derive from separate anomalies but in fact from a single source.

The results of the comparisons of the FF3 and FF5 indicate that in general the FF5 regressions accrued intercepts that were closer to 0 than the FF3, suggesting that the FF5 is indeed a more robust asset-pricing model than its predecessor (Fama & French, 2015). An interesting finding was however that a four-factor model without the HML factor prevailed as well as the five-factor model in explaining variations in average returns. Often the size factor of SMB is considered rather diluted in modern stock markets, so in a way it is rather surprising that the four-factor model without HML prevailed as well as the FF5. Nonetheless, Fama and French estimate that the FF5 explains 71-94% of cross-section variance in expected returns for the portfolios they constructed in accordance to the five factors.

An important takeaway from Fama & French's paper is that the FF5 was unable to explain Momentum profits. This poses the question of how well the model fares in relation to the hypotheses tested later in this thesis. However, it is to be noted that Fama & French never meant to actually explain Momentum profits in their paper directly, but approached the matter through implicit factors. (Fama & French, 2015)

The FF5 equation:

(5.) $R(t) - R_f(t) = \alpha + b\left[R_M(t) - R_f(t)\right] + sSMB(t) + hHML(t) + rRMW(t) + cCMA(t) + \varepsilon(t)$

Where, R(t) is the return on portfolio t, $R_f(t)$ is the return on a risk-free portfolio, a is the intercept of the multivariate regression, $b[R_m(t)-R_f(t)]$ is the factor beta for market returns multiplied by market index return, sSMB(t) is the factor beta for Small Minus Big multiplied by returns on Small Minus Big, hHML(t) is the factor beta for High Minus Low multiplied by returns on High Minus Low, rRMW(t) is the factor beta for Robust Minus Weak multiplied by returns on Robust Minus Weak, cCMA(t) is the factor beta for Conservative Minus Aggressive multiplied by returns on Conservative Minus Aggressive, e(t) is the product of factors affecting portfolio t (Fama & French, 2014).

4. MOMENTUM

4.1. History of Momentum

The discovery of Momentum is attributed to Jegadeesh & Titman (1993) in their seminal paper “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency”. In their paper Jegadeesh and Titman find that sorting stocks into deciles according to their intermediate and recent historical returns and subsequently taking long positions in the top firms and shorting the dismal ones led to abnormal returns in the intermediate future. Jegadeesh & Titman claimed that these abnormal returns couldn’t be explained by systematic risk or delayed reactions to common factors influencing stock prices. They did however find that the abnormal returns from Momentum dissipated if the long and short positions were held for too long after portfolio formation.

The discovery of Momentum has led to an increasing amount of research on the subject matter. Momentum as a phenomenon causes a serious challenge to the EMH as no existing asset-pricing model has been able to explain the source of Momentum profits. Chan, Jegadeesh & Lakonishkok (1996) revisited the possibility of Momentum originating from an underreaction to price information involving stocks, especially an underreaction to past earnings announcements. Chan et al. argued that the build-up of Momentum was similar to the underreactions that build up post-earnings announcement drift (PEAD) and thus could be explained by the same logic. This underreaction hypothesis was the first prospective behavioral explanation for Momentum returns.

Chan et al. (1996) indeed found that approximately 41% of Momentum’s returns within the holding period of the portfolio came around company earnings announcements, which indicates similar underreactions that are found in PEAD. However, some part of the remaining roughly 59% of the returns may have come from underreactions to other types of announcements, such as: stock buybacks, insider trading and new equity issues. The evident drifts in the stock prices however indicate a very realistic probability of an underreacting market.

In conclusion to their study, Chan et al. (1996) however find that the variables in their study, which included past earnings announcements, weren’t reliable in predicting future returns for Momentum. The evidence of their study was sufficient however to suggest that Momentum strategies are affected to some extent by underreaction to different pieces of information. The question thus remains: can underreactions be a reliable explanation for Momentum returns if they cannot predict the returns themselves even if they can partly account for them? Then again, explaining the source of the returns and predicting future returns may indeed be two very different things when it comes to Momentum returns.

Rouwenhorst (1998) was one of the earliest researchers to examine Momentum outside of the U.S. He contributed further evidence that Momentum either can't be captured by asset-pricing models or is the result of underreaction by markets, or both. His evidence backs the claim that Momentum does in fact, provide abnormal returns in other countries besides the United States. Rouwenhorst finds that the evidence he collected from European countries is very similar to the results that Jegadeesh & Titman (1993) originally found in the United States. Rouwenhorst suggests that these results indicate that country specific Momentum is relatively unimportant in explaining the underlying causes for Momentum.

Rouwenhorst continued to investigate the profitability of Momentum out-of-sample in 1999, when he examined Momentum returns in emerging markets. Rouwenhorst again uses international markets in his study to provide further evidence, independent of the U.S., that Momentum could be found in other countries as well. Rouwenhorst rationalizes the use of emerging markets in his study by claiming that emerging markets function in relative isolation from the biggest capital markets in the world, thus providing good independent samples as many emerging markets had only just began lifting restrictions on investments by foreign investors. In his study Rouwenhorst finds that the return factors of Momentum have distinct local character to them: the correlation between emerging markets is relatively low and the exposure to global risk factors do not explain their average returns. Rouwenhorst's study is however, subject to two important biases: the indices he used to gather data mostly consisted of larger and frequently traded stocks in emerging markets. This means that the Momentum effect might have either been diluted or enhanced, depending on the way Momentum commoves with volume and size in emerging markets. The conclusion of the study is that the evidence concerning correlations suggests that the cross-sectional differences between expected returns are primarily driven by local factors. Thus adding to the evidence that Momentum is not dependent on a unifying global risk factor.

Chan, Hameed & Tong contribute to the study of Momentum in out-of-sample settings with their 2000 study "Profitability of Momentum Strategies in the International Equity Markets". Their work investigates three things: whether country selection is useful in applying Momentum strategies to country indices, how exchange rate movements affect the profitability of Momentum and whether trading volume affects the profitability of Momentum internationally. The rationales for these research questions provide further insight into the robustness of the Momentum phenomena. As access to foreign equity markets increasingly becomes available to international equity funds, the question of whether country selection affects Momentum returns in indices is highly relevant. The effect that exchange rate appreciations and depreciations can have on a Momentum portfolio returns might be significant and reduce returns to the anomaly in an international setting. Lastly it is relevant to discern whether trading volume has an effect on Momentum returns in an international setting as it seemingly does in the traditional samples in the United States.

Chan et al. (2000) find that greater trading volume does indeed affect Momentum returns positively, as is the case in the U.S. This finding is in accordance with earlier studies that investigated the relation of trading volume and Momentum. In addition, Chan et al. find that exchange rates play no significant role in Momentum returns and more specifically, it doesn’t have a negative effect. As a final result, Chan et al. find more evidence to back the claim that Momentum returns aren’t confined to developed countries only, but instead are evident in emerging markets as well, lending to the explanation that country selection doesn’t have a huge difference in the profitability of Momentum. In their work Chan et al. also analyzed their results separately for the winner and loser portfolios and saw that the loser portfolios effect on the total returns of Momentum were either insignificant or contributed negatively in their sample. This is a finding that could be affected by country specific circumstances when employing Momentum internationally.

Jegadeesh & Titman (2001) evaluate alternative explanations for Momentum profits. Their work backs the claim that Momentum returns continued in the 1990’s and thus weren’t a result of data snooping bias as was suggested based on the sample they used in their original study. The continuing anomalous returns from Momentum in the subsequent eight years after Jegadeesh and Titman’s first discovery also suggests that investors have not altered their investment strategies in a way that would have eliminated Momentum returns from the market. Jegadeesh and Titman also examined whether Momentum profits could stem from delayed overreactions that eventually reverse instead of underreactions as they first proposed.

In addition to providing further evidence for the robustness of Momentum, Jegadeesh & Titman (2001) also investigated why return reversals happen in the post-holding periods. They found that post-holding period returns are affected by the sample of the study, the sample period, and in some cases whether the post-holding period returns are risk-adjusted. Noteworthy is also the case that if post-holding periods become long enough, then we begin to see a contrarian effect similar to the one described by DeBondt and Thaler (1985). The unstable realization of post-holding period return reversals suggests that behavioral explanations of Momentum cannot account for the anomalous returns by themselves. This indicates that in reality the best explanations for Momentum returns lie somewhere between behavioral models and models of market efficiency.

Griffin, Ji & Martin (2003) examine the effect of macroeconomic risks in explaining Momentum returns globally. They find that Momentum returns commove only weakly among 40 countries, which suggests that if there is a macroeconomic risk factor that explains Momentum, it isn't global but country specific. Griffin et al. also find that the Chen, Roll & Ross (1986) multifactor model – which consists of macroeconomic factors - doesn't produce significant results in explaining pricing or time series in Momentum profits in 17 countries. A third finding by Griffin et al. supports the findings of Chan et al. (2000) in that internationally, winner portfolios earn greater returns than loser portfolios. The fourth finding of the study provides evidence that Momentum returns aren't affected by macroeconomic states and if anything, Momentum returns are slightly higher in negative market cycles. Griffin et al. arrived at this conclusion through comparisons between Momentum portfolio returns in different economic climates determined by GDP growth and aggregate stock market movements. This is to say that Momentum returns aren't rewards for bearing business cycle risk. Griffin et al. deduce that Momentum returns cannot be explained by the macroeconomic variables used in their study. This does not however mean that macroeconomic variables aren't a part of the explanation for Momentum returns, they just aren't the ones used by Griffin et al. Finally, Griffin et al. provide further evidence that Momentum returns undergo a reversal when holding periods last for one to five years. This finding is consistent with the original discoveries of price reversals by DeBondt & Thaler (1985).

In 2006 Antoniou, Lam & Paudyal investigate whether business cycle variables and behavioral biases can explain Momentum returns in three major European markets: UK, Germany and France. Their study incorporates risk-based and behavioral variables in a two-stage model to explain Momentum returns in three European equity markets.

Antoniou et al. find that Momentum could be explained to a certain extent by asset mispricing that is closely linked to global business cycles and is unlikely to be explained by behavioral variables that they used in their study. The results of the study don't indicate a clear role for the behavioral variables according to Antoniou et al. and this in turn supposedly suggests that investor behavior is less likely to be correlated with business cycles. The study also includes the caveat that business cycle risk cannot fully explain Momentum profits, but that it may explain a share of them. This is in contradiction to Griffin et al. (2003) who claimed that Momentum returns are not affected by business cycles.

Chui, Titman & Wei (2010) investigate the effect that cultural differences in different countries may have on Momentum returns. These cultural differences were measured by a global personality index created by Hofstede (2001), who is originally a psychologist, not an academic in the field of finance. The link between the personality index and studying Momentum comes from the assertion that individuality – which is one of the personality traits measured by the index – is correlated with the original behavioral biases related to Momentum: overconfidence and attribution bias. Chui et al. show independent support for the idea that overconfidence appears more often in individualistic cultures by displaying that individualism is correlated with trading volume and volatility. Judging by this, the whole study depends on the original idea that individuality is correlated with overconfidence. This is a rather big assumption to base results upon and in the case that these assumptions are false, all the results of the study come into question in respect to their validity. Chui et al. further argue in their premise that individualism – based on the personality index – is related to the kind of overconfidence discussed in Momentum literature. This is another assumption that this study relies on. It is possible that individualism – as defined originally in Hofstede's work in the field of psychology – isn't correlated at all with the concept of overconfidence as it's been used in the Momentum literature. As a final point, the argument of Chui et al. relies even further on the premise that overconfidence does in fact explain Momentum returns, which it hasn't been distinctly shown to do.

Chui et al. (2010) however find that their results suggest that Momentum profits increase along with the individualism index. At the very least this is self-evident evidence for the positive correlation between Momentum and individuality measured by Hofstede's (2001) index. However, all other possible conclusions are reliant on the aforementioned assumptions to be true. Regardless of the conclusions based on the results, Chui et al. offer other interesting conclusions such as the challenge of risk-based models to explain why Momentum returns are high in the United States and Europe, but not in Japan and most of East-Asia. The challenge on the other hand for behavioral models is to explain why individuals in some countries are prone to the psychological biases that cause Momentum, and in some countries they aren't. Following the logic of the previous conclusion, Chui et al. offer up a final conclusion on their work which suggests that Momentum returns are less evident in Japan and East-Asia because these geographical areas are less individualistic and people in less individualistic countries tend to rely on the opinions of their peers. This means that they are less overconfident and thus don't make investment decisions that generate Momentum.

Novy-Marx (2012) finds evidence that Momentum cannot actually be described through the tendency for prices to stay in motion. In his 2011 work, Novy-Marx presents results that indicate the shortcomings of applying Momentum on the basis of recent returns. According to Novy-Marx, strategies that are based on recent returns do generate positive returns, but are less profitable than strategies based on intermediate past returns. These results aren't strictly new findings, as Jegadeesh & Titman (1993) already found the J/K strategy of 12/3 to be the most profitable. Novy-Marx suggests that his findings are inconsistent with the traditional view of Momentum, in that winners keep winning and losers keep losing. This is to say that Momentum isn't in fact momentum and that intermediate past returns are the driving factor in the Momentum anomaly. As such the findings of these results don't seem to have implications for Momentum as a whole. However, these findings propose serious difficulties for behavioral models that try to explain the origins of Momentum returns. Especially the behavioral models contending that Momentum is the result of underreactions – prices slowly adjusting to information – are called into serious question, as the auto-correlation link between recent and intermediate returns seems to be contradictory to the data. It is important to notice that even though Novy-Marx goes on to demonstrate the lack of auto-correlation – the lack of a link – between recent and intermediate returns, he or no one else for that matter can explain why these intermediate returns cause Momentum profits. As such, the work of Novy-Marx offers insight into what doesn't constitute Momentum returns, but not into what does.

Fama and French (2012) investigate whether asset-pricing models could explain Momentum returns and whether asset pricing is integrated across markets. In the four regions Fama and French investigate, they find Momentum returns in North America, Europe and Asia Pacific but none in Japan. These returns seem to diminish when firm size grows from small to large. In further results Fama and French conclude that integrated pricing across regions is unlikely to be a reality in stock markets and the asset-pricing models used in the study cannot duly explain Momentum returns in the sample regions.

In their work Fama and French (2012) also critique the work of Chui et al. (2010) in that they disagree with the assertion that Japan doesn't present Momentum because of the cultures individuality. Fama and French propose that the conclusion could be reversed in that low individuality could produce Momentum in inherent slow price reactions to information. This seems to suggest that implicitly Fama and French believe to a certain extent in the underreaction theory as a partial explanation at least to Momentum returns.

Interaction patterns between certain stock level characteristics and Momentum returns have been used as a basis for some behavioral explanations of Momentum (Bandarchuk & Hilscher, 2012). Bandarchuk and Hilscher provide evidence in their work that these characteristics (size, R2, turnover, age, analyst coverage, analyst forecast dispersion, market-to-book, price, illiquidity, credit rating) simply proxy for extreme past returns in stocks. These findings propose that explanations for Momentum need not be due to these behavioral assumptions based on characteristics but rather simply due to extreme past returns. Behavioral explanations of Momentum have enlisted characteristic screens in constructing superior Momentum strategies prior to Bandarchuk and Hilscher's work. However, Bandarchuk & Hilscher show that the positive effect of characteristic screens in Momentum strategies disappear when they are controlled for volatility and extreme past returns. Characteristics enhance Momentum returns only because stocks with extreme characteristics tend to have extreme past returns and extreme past returns result in higher Momentum returns. As a result, Bandarchuk & Hilscher suggest that the explanation for Momentum has to begin with discerning the link between volatility, past returns and Momentum.

Asness, Moskowitz & Pedersen (2013) find abnormal Momentum and value returns across eight different markets and asset classes (table 1). Asness et al. also find negative correlation between value and Momentum. Asness et al. incorporate a joint approach to studying Momentum returns. Most studies on the international prevalence of Momentum study sample markets in isolation from the rest of the world. Asness et al. suggest that their approach answers important questions: how much variation exists between Momentum returns across markets and asset classes, how correlated Momentum returns are across markets and asset classes with different geographies, structure, investor types and securities, what are the economic drivers of Momentum and what's the correlation structure like and what is a natural benchmark portfolio for global securities across asset classes? Asness et al. also investigate these aforementioned questions in context to value, but most of this is out of scope for this thesis and will be mentioned only when deemed relevant.

Asness et al. (2013) discover a wide array of results in their work out of which the most striking results come from the discovery of co-movement between value and Momentum across asset classes. Value and Momentum strategies are positively correlated with other value and Momentum strategies across different markets. Asness et al. suggest that this co-movement is indicative of a common global risk factor that works towards explaining returns for both strategies. Regardless of this indication it seems that separate factors for value and Momentum best explain their respective returns when the strategies negative correlation is taken into account. If indeed a common global risk factor could explain the returns for both value and Momentum, it would seem possible that asset-pricing models with value factors would have done a better job of explaining Momentum returns in earlier studies already. Asness et al. do delve further into the explanatory link between value and Momentum and discern that the link between these two is mostly related to liquidity risk and that this risk's importance has increased over time. This seems to be a new discovery as this result can be inferred only from looking across various markets simultaneously instead from isolated sample country studies. In terms of its explanatory power however, funding risk may only explain a fraction of value and Momentum returns. Even more interesting is the fact that combining value and Momentum evenly as an investment strategy negates this liquidity risk and still provides positive abnormal returns. In conclusion, Asness et al. suggest studying value and Momentum as a combination since the mixture of these two are much closer to the efficient frontier than either investment strategy by themselves, which is evident in figure 1 especially in the case of stocks.

	Momentum portfolios			
	P1	P2	P3	P3-P1
U.S. Stocks	8.8%	9.7%	5.4%	7.7%
	(2.96)	(4.14)	(4.82)	(2.08)
U.K. Stocks	9.2%	13.8%	15.2%	6.0%
	(2.32)	(3.81)	(4.04)	(2.37)
Europe stocks	9.2%	13.3%	17.3%	8.1%
	(2.72)	(4.65)	(5.56)	(3.37)
Japan stocks	8.4%	9.9%	10.1%	1.7%
	(2.19)	(2.94)	(2.69)	(0.57)
Global Stocks	8.5%	11.1%	14.1%	5.6%
	(3.10)	(4.82)	(5.46)	(2.94)
Country indices	2.3%	5.8%	11.0%	8.7%
	(0.81)	(2.13)	(3.72)	(4.14)
Currencies	-0.7%	0.3%	2.8%	3.5%
	(-0.40)	(0.20)	(1.91)	(1.90)
Fixed income	3.8%	3.8%	4.2%	0.4%
	(3.42)	(3.49)	(3.28)	(0.35)
Commodities	0.7%	5.8%	13.1%	12.4%
	(0.22)	(2.27)	(3.73)	(3.29)
Global other asset classes	1.6%	3.4%	6.3%	4.6%
	(1.49)	(3.61)	(5.30)	(3.88)
Global all asset classes	4.2%	6.4%	9.2%	5.0%
	(2.74)	(4.88)	(6.09)	(4.18)

Table 1. The percentages represent average raw excess (of the 1-month U.S. T-bill) returns and the numbers within the parentheses are their *t*-statistics. P1, P2 and P3 are portfolios constructed on low, medium and high Momentum respectively. (Asness et al., 2013)

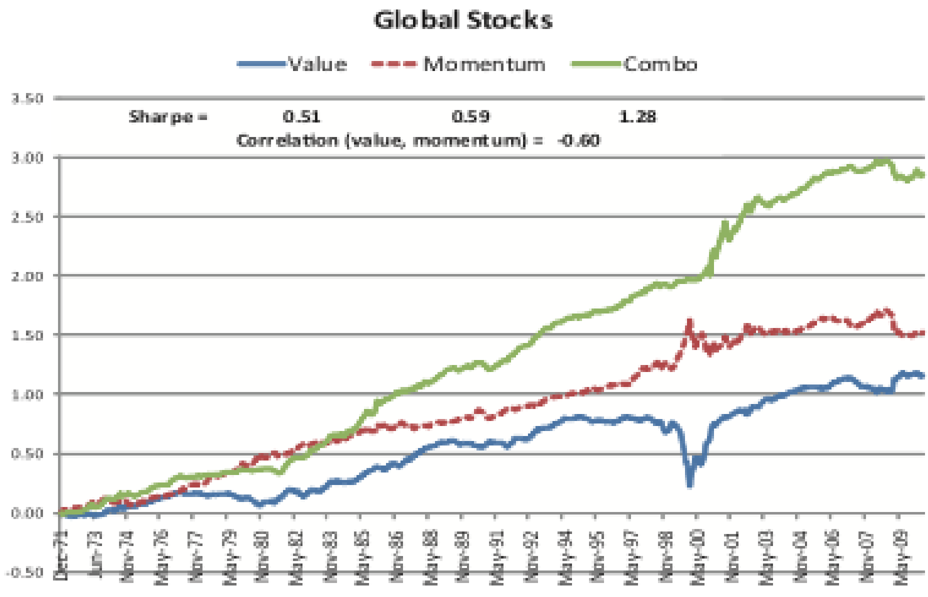


Figure 1. Cumulative returns to portfolios based on value, Momentum and a 50/50 split of both. The sample countries and/or continents listed under "Global" include the United States, the United Kingdom, Europe and Japan. (Asness et al., 2013)

Asness, Frazzini, Israel & Moskowitz (2014) have one of the most recent working papers discussing tweaks to the traditional Momentum strategy and presenting cases for the risk-based vs. behavioral argument over Momentum's returns. Asness et al. in the same vein as Barroso & Santa Clara (2015) suggest a modified version of the Momentum strategy to minimize risk, especially crash risk. The difference being that Asness et al. propose combining Momentum (UMD) with value (HML) to form a split portfolio of the two. In the data Asness et al. used, Momentum's largest negative returns were -77 % and values' -43 % at their most extremes in the time period sample. Combining the two into one portfolio however delivered only -30 % negative returns at its most extreme. Combining these two factors will give investors minimized negative returns and higher positive returns during extreme times, such as crashes, when compared to using both factors by themselves. The value/Momentum investment strategy is another modification to the traditional Momentum strategy that might lead to the utilization of a superior investment strategy. Whenever risk can be managed at the expense of higher returns - which sounds contradictory to the traditional view of risk and return – there will be interest in applying these sorts of strategies.

Asness et al. (2014) present a wide and up-to-date discussion on the already well-established argument over whether risk-based models can explain Momentum or whether it's a behavioral phenomenon. The consensus seems to be that both sides of the argument provide important insight in explaining Momentum's returns and why its premiums continue to persist.

In discussing the behavioral models underlying Momentum, Asness et al. (2014) recount the typical explanations of underreactions – even though they seem to be refuted by Novy-Marx (2012) – and delayed overreactions being responsible for Momentum. Underreactions suggest that information affects stock prices slowly and overreactions rely on investors chasing returns, leading to cyclical amplification, or a feedback mechanism, driving prices higher.

The risk-based view sees the Momentum premium as being compensation for risk (Asness et al., 2014), the idea however being that this risk factor is yet to be discovered and therefore the anomaly persists. The most recent models suggest that this undiscovered risk factor relates to economic risks that affect firm investment and long-term cash flows and dividends through growth rates. This is similar to the two new risk factors in the FF5 (Fama & French, 2014). The underlying mechanism here is that high-momentum stocks are affected by greater cash-flow risk due to their growth possibilities or that they face greater discount rate risk due to their investment horizons causing them to face higher costs for capital. In conclusion to their work Asness et al. propose that the Momentum anomaly will persist – regardless of the explanatory point of view – as long as risks and tastes for risks don't change and as long as biases, behaviors and limits to arbitrage remain stable. Table 2 summarizes the different prospective explanations for Momentum.

Researchers	Explanations
Jegadeesh & Titman (1993)	Overreaction and return persistance.
Chan, Jegadeesh & Lakonishok (1996)	Underreaction to past earnings-announcements.
Rouwenhorst (1998)	Risk-premium, underreaction, or both.
Grundy & Martin (2001)	Unaccounted transaction costs.
Jegadeesh & Titman (2001)	Possible overreactions, but more likely something that accounts for both behavioral and EMH.
Antoniou, Lam & Paudyal (2006)	Mispricing linked to global business cycles.
Chui, Titman & Wei (2010)	Cultural differences explain differences between countries.
Novy-Marx (2011)	Refutes underreactions, but doesn't offer up new explanations.
Bandarchuk & Hilscher (2012)	Volatility and extreme past returns.
Asness, Frazzini, Israel & Moskowitz (2014)	Underreactions and Overreactions as behavioral explanations. Investment risks and cash-flow risks as risk based explanations.

Table 2. A table summarizing the different prospective explanations for Momentum returns as suggested by different academics.

The previous paragraphs gave an overview of the history and evolution of Momentum. Since its discovery in 1993 by Jegadeesha & Titman, numerous studies have been conducted on Momentum. The rest of this chapter will discuss different aspects of implementing the strategy. The purpose is to shed light on different studies that have researched the returns of the many versions of Momentum out there and display the effectiveness of applying Momentum and its variations as a profitable investment strategy.

The Momentum strategy essentially has two parts to it, the formation period (J) and the holding period (K) (Jegadeesh & Titman, 1993). The formation period is a recent to intermediate past time period where data on the success of stocks is gathered. This data is used to rank stocks – usually into deciles – from worst to best performance. Then the top performers are bought long, while the worst performers are sold short for an intermediate time period, known as the holding period.

Jegadeesh and Titman test 32 different Momentum strategies in their original work. The first 16 strategies consist of combinations of three, six, nine and twelve-month formation and holding periods. The second set of 16 strategies are the same as the first with the exception of having a week between formation and holding periods in order to avoid bid-ask spread bounce, price pressure and lagged reactions that might distort the evidence. Jegadeesh and Titman divided up the companies into equal weight decile portfolios according to performance. The top performers were the winners and the worst ones the losers. Each month, they bought the winner portfolio and sold the loser portfolio for K months. The results for all the employed strategies are presented in table 3. (Jegadeesh & Titman, 1993)

		Panel A					Panel B			
J		K =	3	6	9	12	K =	3	6	9	12
3	Sell		0.0108	0.0091	0.0092	0.0087		0.0083	0.0079	0.0084	0.0083
			(2.16)	(1.87)	(1.92)	(1.87)		(1.67)	(1.64)	(1.77)	(1.79)
3	Buy		0.0140	0.0149	0.0152	0.0156		0.0156	0.0158	0.0158	0.0160
			(3.57)	(3.78)	(3.83)	(3.89)		(3.95)	(3.98)	(3.96)	(3.98)
3	Buy-sell		0.0032	0.0058	0.0061	0.0069		0.0073	0.0078	0.0074	0.0077
			(1.10)	(2.29)	(2.69)	(3.53)		(2.61)	(3.16)	(3.36)	(4.00)
6	Sell		0.0087	0.0079	0.0072	0.0080		0.0066	0.0068	0.0067	0.0076
			(1.67)	(1.56)	(1.48)	(1.66)		(1.28)	(1.35)	(1.38)	(1.58)
6	Buy		0.0171	0.0174	0.0174	0.0166		0.0179	0.0178	0.0175	0.0166
			(4.28)	(4.33)	(4.31)	(4.13)		(4.47)	(4.41)	(4.32)	(4.13)
6	Buy-sell		0.0084	0.0095	0.0102	0.0086		0.0114	0.0110	0.0108	0.0090
			(2.44)	(3.07)	(3.76)	(3.36)		(3.37)	(3.61)	(4.01)	(3.54)
9	Sell		0.0077	0.0065	0.0071	0.0082		0.0058	0.0058	0.0066	0.0078
			(1.47)	(1.29)	(1.43)	(1.66)		(1.13)	(1.15)	(1.34)	(1.59)
9	Buy		0.0186	0.0186	0.0176	0.0164		0.0193	0.0188	0.0176	0.0164
			(4.56)	(4.53)	(4.30)	(4.03)		(4.72)	(4.56)	(4.30)	(4.04)
9	Buy-sell		0.0109	0.0121	0.0105	0.0082		0.0135	0.0130	0.0109	0.0085
			(3.03)	(3.78)	(3.47)	(2.89)		(3.85)	(4.09)	(3.67)	(3.04)
12	Sell		0.0060	0.0065	0.0075	0.0087		0.0048	0.0058	0.0070	0.0085
			(1.17)	(1.29)	(1.48)	(1.74)		(0.93)	(1.15)	(1.40)	(1.71)
12	Buy		0.0192	0.0179	0.0168	0.0155		0.0196	0.0179	0.0167	0.0154
			(4.63)	(4.36)	(4.10)	(3.81)		(4.73)	(4.36)	(4.09)	(3.79)
12	Buy-sell		0.0131	0.0114	0.0093	0.0068		0.0149	0.0121	0.0096	0.0069
			(3.74)	(3.40)	(2.95)	(2.25)		(4.28)	(3.65)	(3.09)	(2.31)

Table 3. Monthly average return for Momentum strategies where J represents the formation period duration in months and K represents the holding period duration in months. Panel A does not include a week in between formation and holding periods, whereas Panel B does. t-statistics are reported in parentheses. (Jegadeesh & Titman, 1993)

The most successful portfolio in the original Momentum study is the one with a formation period of 12 months and a holding period of 3 months (Jegadeesh & Titman, 1993). This strategy yielded an average monthly return of 1.31 % without a week in between periods and 1.49 % with a week in between the periods as can be seen in table 3. Converted to yearly returns, this would compound into 16.9 % and 19.4 % respectively. Every strategy that Jegadeesh and Titman investigate results in statistically significant abnormal returns except for the J/K strategy of three and three months. The J/K strategy of six and six months that Jegadeesh & Titman analyze the most realizes excess returns of 12.01 % per year on average.

Jegadeesh & Titman (1993) also take into consideration the turnover rate for their Momentum strategies, as it is clear that with short and intermediate holding periods, there is going to be fluctuations in the contents of the portfolios. On average they find that semiannually the turnover rate was 84.8 %, which as a percentage is high compared to most portfolios and investment strategies. In addition to turnover rates, Jegadeesh and

Titman consider what effect transaction costs would have as a result of high turnover. They consider a 0.5 % one-way transaction cost per year and adjusted the yearly returns of the most common form of the strategy to that cost. They find that even with a 0.5 % one-way transaction cost, yearly returns would be 9.29 %. These risk-adjusted returns after transaction costs are still statistically significant.

In inspecting the profitability of Momentum, Jegadeesh & Titman (1993) also consider seasonality and its effects on returns. January has typically had a positive effect on returns in the stock market. For example, January returns on portfolios based on value have historically had tremendous returns that are often seen as anomalous. Momentum returns during January however deliver on average -7 % returns. This negative monthly effect seems to be restricted to January only, as every other month results in positive abnormal returns. In the sample Jegadeesh and Titman use, Momentum realized positive returns in 67 % of the months. This percentage increases to 71 % when January months are excluded from the sample. The average return for non-January months amount to 1.66 %. Jegadeesh & Titman also provide further evidence to the finding that the size of negative January Momentum returns is inversely correlated with firm size.

January wasn’t the only month that seemed to highlight Momentum returns in some way. Jegadeesh & Titman (1993) found that returns were rather low in August whereas they were fairly high in April, November and December. The monthly differences outside of January were also found to be statistically significant for the whole sample. April in particular seemed to have a strong effect on Momentum returns. 24 out of 25 Aprils (96 %) produced positive Momentum monthly returns on average of 3.33 %. A possible explanation to the consistently positive returns of April may lie in tax deductions. Corporations must transfer money to their pension funds before April. Pension fund portfolio managers may then invest this money into assets. If the portfolio managers follow price momentum in any way, this may add to the price pressure of stocks during the month of April. The significant returns of November and December may benefit from similar price pressure associated with selling losers before years’ end for tax or window dressing related reasons.

The 1999 study by Rouwenhorst that investigated Momentum returns in emerging markets is based on a different kind of Momentum strategy than that of Jegadeesh and Titman (1993). In Rouwenhorst’s strategy stocks are ranked by their past six-month performance, after which the top and bottom five percent are disregarded and then the stocks are compiled not into deciles, but three groups: winners (top 30%), average (middle 30%) and losers (bottom 30%). The holding period however, is again six months.

Chan et al. (2000) provide an interesting variation to Momentum strategies not only in that they long or short indices instead of individual stocks, but because in their results most countries exhibit greatest excess returns for two week holding periods. This seemingly contradicts the typically regarded most profitable J/K strategy of 12/3 months or the most commonly investigated J/K strategy of 6/6 months for that matter.

Grundy & Martin (2001) propose their own variation on using Momentum as an investment strategy. They argue that a Momentum strategy - which bases its formation of winner and loser portfolios on total returns - is outperformed by a portfolio based on stock-specific return components. Grundy & Martin formed portfolios by stock-specific return components and claim that their evidence is strongly in favor of this approach being more profitable.

Novy-Marx (2012) echoes Jegadeesh & Titman (1993) to a certain extent in suggesting intermediate past returns to be more profitable in Momentum strategies. Jegadeesh and Titman find that the most profitable J/K strategy is 12/3 and Novy-Marx agrees in that seven to 12 months' past returns should be considered. Novy-Marx suggests that investors should disregard anything under seven months and everything over 12 months when assessing past returns as this reduces the Momentum strategies performance. According to Novy-Marx the profitability of Momentum increases by ignoring recent performance and this is especially the case in large liquid stocks, which seem to exhibit more Momentum. The increased Sharpe ratio due to ignoring recent performance isn't only limited to stocks. Other strategies that trade industries, investment styles, international equity indices, commodities and currencies all exhibit the advantages of ignoring recent performance. Industry momentums is discussed in greater depth later on in this thesis.

Bandarchuk & Hilscher (2012) propose their own considerations for superior Momentums strategies. Based on their findings, Bandarchuk & Hilscher suggest that it is best to avoid any kind of characteristic screens when evaluating stocks to be included in Momentum portfolios. This means that focusing purely on past returns is sufficient in applying Momentum as an investment strategy.

Asness et al.'s (2014) variation of the Momentum strategy, which was discussed earlier, combines value (HML) and Momentum (UMD) into a single portfolio. Asness et al. find that the optimal ratio of value and Momentum in a portfolio is 60 % and 40 % respectively. This Momentum strategy that combines value and Momentum reduces the negative returns of Momentum crashes and provides higher returns compared to employing a strictly value based or strictly Momentum based investment strategy. See table 4 for further detail on the combinatory portfolio of value and Momentum.

1927-2013	**RMRF**	**SMB**	**HML**	**UMD**	**60/40 HML/UMD**
Sharpe Ratios	0.41	0.26	0.39	0.50	0.80
% Positive, 1-year Rolling Returns	71%	58%	63%	81%	81%
% Positive, 5-year Rolling Returns	82%	65%	89%	88%	92%

Table 4. Sharpe ratios, 1-year rolling returns and 5-year rolling returns expressed as percentages over the time period 1927-2013. Portfolios include the market portfolio (RMRF), size portfolio (SMB), value portfolio (HML), Momentum portfolio (UMD) and value/Momentum portfolio based on a respective 60/40 split (HML/UMD). (Asness et al., 2014)

Even though Momentum has been studied widely after its discovery by Jegadeesh and Titman in 1993, the typical Momentum strategies employed are mostly similar to the ones presented in the original paper. The most these strategies are manipulated pertains to differing the formation and holding periods or including or excluding the most recent month in the formation period. The most interesting developments to Momentum strategies are recent in nature and the value/Momentum combination (Asness at al., 2014) along with risk-managed Momentum (Barroso & Santa Clara 2015), which will be discussed later, are papers that introduce something fundamentally new to Momentum.

Regardless of most Momentum strategies closely resembling each other, there are discrepancies between best practices in implementing Momentum strategies that seem to rise while inspecting different samples utilized for empirical tests of the anomaly. This serves as a cautioning note, that not every strategy should or can be implemented in e.g. each country or each class of security. Some of these contradictions that exist in Momentum strategies are discussed below.

Grundy & Martin (2001) propose that transaction costs cause a decline in Momentum returns resulting in a degree of ineffectiveness in Momentum investing. Asness et al. (2014) on the other hand claim to refute the argument that transaction costs cause any significant ineffectiveness to the strategy. Being separated by 13 years, these differences in views could be attributed to revised samples and research that in fact overturn the evidence of Grundy and Martin. Perhaps the ineffectiveness that Grundy and Martin discuss in their papers is the same kind that Asness et al. (2014) describe as insignificant ineffectiveness. This could also reconcile these two points of views. Yet another point to consider is the fact that transaction costs in general have undergone a tremendous decrease in the era of computerized trading, which has blossomed during the very time period separating these two studies.

Another juxtaposition in evidence seemingly comes from the work of Antoniou et al. (2006) and Griffin et al. (2003). Antoniou et al. suggest that business cycle risk could explain Momentum profits to a certain extent through asset-pricing models. Griffin et al. however find in their study that business cycle risk doesn't explain Momentum returns and if anything, Momentum returns are larger in bear markets. Whether these results are incidental or regardless reconcilable, is hard to tell. For example, Antoniou et al. could be correct in that asset-pricing models may for instance explain the incrementally higher Momentum returns in bear markets that Griffin et al. allude to. Even if this were the case, the marginal explanatory power of business cycle risk could still be relatively low and wouldn't account for proper conducive explanations for Momentum.

More contradictory evidence to the successful applications of Momentum in several stock markets comes again from Antoniou et al. (2006), Griffin et al. (2003) and Chan et al. (2000). Antoniou et al. find that loser portfolios account for the greater share of profits from Momentum portfolios in their sample and that this is the case in general with Momentum. Griffin et al. and Chan et al. however find the exact opposite in that winners, instead of losers, account for most profits in Momentum. Antoniou et al. look at only three countries in their sample, whereas Griffin et al. and Chan et al. have much larger samples. This could be an indication that in general, Griffin et al. and Chan et al. are correct in their assumptions as they have a more representative sample in their studies.

Index based Momentum strategies and stock based Momentum strategies are another puzzle. Countries that appear as top performers in index based Momentum strategies come out as bottom performers in stock based Momentum strategies (Chui et al., 2010; Griffin et al., 2003; Chan et al., 2000; Rouwenhorst 1999). This reverse effect is intriguing and quite frankly, hard to explain without further studies conducted into the matter.

5. INDUSTRY MOMENTUM

Understanding previous research conducted on industry Momentum is an obvious prerequisite to advancing to further chapters in this thesis. This part will thus focus on expanding on the previous research as well as indicating how profitable industry Momentum has been in the past.

5.1. Previous Research

Moskowitz and Grinblatt (1999) were the first to investigate the existence of Momentum payoffs related to industry portfolios. Their article as such did not investigate the absolute or relative profitability of Momentum investing, but rather as many articles before it sought to determine the actual source of these profits. The idea that Grinblatt and Moskowitz (1999) set forth was that abnormal returns from ordinary stock Momentum could actually be attributed to Momentum within industries.

As with regular stock Momentum, the returns to industry Momentum exhibit statistically significant positive returns after controlling for size and book-to-market. However, Grinblatt and Moskowitz (1999) add individual stock Momentum, microstructural influences, and cross-sectional dispersion in mean returns to the control variables and still find that industry Momentum returns are significant. In addition to the results being significant, the overall profitability of industry Momentum actually surpasses that of individual stock Momentum according to their study. Additionally, unlike most individual stock Momentum strategies according to Grinblatt and Moskowitz, the majority of industry Momentum profits come from the long side of the strategy as opposed to the short. Another difference between individual stock Momentum and industry Momentum comes from the profitability in terms of time horizons for holding the portfolios. Industry Momentum is at its most profitable at the one-month period according to Grinblatt & Moskowitz.

For their data Grinblatt and Moskowitz (1999) use Compustat and the CRSP database to form 20 value-weighted industry portfolios based on their two-digit SIC codes that come from stocks listed in NYSE, AMEX, and Nasdaq. Their time period spans from 1963 to 1995. This setup is similar to the one used in many of the industry Momentum articles and thus similar to the setup that will be used in this thesis. With 20 industry portfolios Grinblatt and Moskowitz have an average of 230 stocks per industry which satisfies requirements for being well diversified.

Even though Grinblatt and Moskowitz (1999) find that industry Momentum is at its most profitable with the one-month horizon, they focus much of their analysis on the J/K strategy of six and six, just like the original study by Jegadeesh and Titman (1993). Their methodology both skips and includes the latest month in different analyses and rebalances monthly so that they long the highest 30 % of value-weighted stocks and short the lowest 30 % of value-weighted stocks. The implementation of the top and bottom 30 % strategies differs from the original decile sort used by Jegadeesh and Titman, which, as the name suggests, goes long into the top 10 % and shorts the bottom 10 % of stocks based on historical performance. Regardless, the results for industry Momentum are similar to individual stock Momentum as described by Jegadeesh and Titman, in that profits are strong within holding periods of 3 to 12 months, but if held longer, diminish with time and undergo a similar reversal as described by DeBondt and Thaler (1985).

Individual industries exert patterns in Grinblatt and Moskowitz' (1999) research. For instance, Food & Beverage appears in the winner portfolio 23 % percent, or 80 months, of the time. In the same vein, the loser portfolio exhibits patterns as well. Fabricated Metals appears in the shorted portfolio 83 times. Even though the absolute number of months for these examples are high, the maximum number of consecutive appearances any industry has in either portfolio is five, which – according to Grinblatt and Moskowitz – indicates that no single industry portfolio dominates either of the portfolios.

Overall Grinblatt and Moskowitz (1999) find a persistent Momentum effect in industries that cannot be explained by what they refer to as microstructure effects, cross-sectional mean dispersion in returns, or individual stock Momentum. In fact, industry Momentums subsumes individual stock Momentum at all horizons except the 12-month one and the authors claim that this subsuming effect and thus industry Momentum explains individual stock Momentum returns almost entirely. Regardless of this subsuming effect industry Momentum still attains most of its profits from the long side as opposed to individual stock Momentum. Additionally, industry Momentum also attains most of its profits from large liquid stocks, which again is in juxtaposition to individual stock Momentum. Even though, the authors make a case for explaining that individual stock Momentum returns are explained by industry Momentum and that industry Momentum is profitable, they offer up no real explanations as to why industries have this effect. They are instead content with conjecturing that this effect might be due to investors herding to (from) hot (cold) sectors in the economy and thus creating price pressure.

Grundy and Martin (2001) follow-up on Grinblatt and Moskowitz (1999) and delve deeper into the risks and sources of returns surrounding Momentum. An important finding, they make is that Momentum has been largely stable in the post-1926 time-period when exposed to existing time-varying factors in the stock market. At the time of Grundy and Martins study, different factor models could explain about 95% of the variability of Momentum's returns, but couldn't explain the mean returns from employing Momentum. This distinction is very important, as the mean returns are specifically the anomalous component in Momentum. In the same study Grundy and Martin investigate whether industry risk or cross-sectional differences in returns have a positive effect on Momentum build up. They however conclude that neither of these are the primary cause for Momentum returns.

Grundy & Martin's (2001) conclusions suggest that Momentum doesn't provide arbitrage opportunities relying on the evidence that the risk-adjusted hedged total returns for Momentum are negative in 261 months out of a total of 828. Grundy and Martin also view unaccounted transaction costs as a possible explanation for the 1.3% monthly anomalous returns. Finally, Grundy and Martin go on to suggest that if the Momentum anomaly does not die out, it will sooner or later become a factor comparable to SMB and HML which properties are well understood.

The next top publication concerning industry Momentum after the original Grinblatt and Moskowitz (1999) and Grundy and Martin (2001) paper was authored by Nijman, Swinkels and Verbeek in 2004. Their paper focused on investigating whether either countries or industries or both can explain Momentum returns. Nijman et al. (2004) received results from their study that take a rather opposite view to the findings presented by Grinblatt and Moskowitz. The conclude that Momentum in Europe is explained by individual stock effects and not by industry wide effects and even less so, by country specific effects. The Nijman et al. study serves as a first out-of-sample test for Grinblatt and Moskowitz (1999) with the analysis focusing on countries outside the U.S., which was the center of research for the original industry Momentum effect.

Nijman et al. (2004) use 10 of data from 1990 to 2000, which is a drastically smaller timeframe than what Grinblatt and Moskowitz (1999) use. For this time period they use a portfolio-based regression technique which makes it possible for the authors to determine, which of the effects is most important in explaining excess returns and they find that individual Momentum components account for roughly 60 % of the effect, whereas industry and country specific effects account for 30 % and 10 % respectively. Additionally, the authors claim that controlling for value and size effects in the model confirms that individual Momentum effects dominate industry and country Momentum effects.

In their paper Nijman et al. (2004) focus on large European stocks, as they claim that data for small European firms is not reliably available. This may run the risk of introducing a confirmation bias in the data, as Grinblatt and Moskowitz (1999) note that large stocks tend to exhibit more Momentum in industries as a whole. Thus, if Nijman et al. were to include smaller stocks, this might reduce their findings on the power of industry Momentum in European stocks. In addition to being larger European stocks, the authors require each stock to be covered by analysts from Morgan Stanley Capital International (MSCI) and to have data on their prior 6-month return, market value, and book-to-market ratio. Their total sample thus consists of 1581 stocks, where the least amount of stocks per country is 33 for Ireland and the most is 349 for the U.K. The rest of the countries included in the study are: Denmark, France, Sweden, Finland, Spain, The Netherlands, Norway, Germany, Portugal, Belgium and Austria.

Classifying stocks into industries differs in Nijman et al. (2004) from Grinblatt and Moskowitz (1999) as SIC industry codes aren't available for stocks in Europe. Thus, Nijman et al. use MSCI classifications, which leads them to use 23 different industries which differs from the Grinblatt and Moskowitz study in the amount and composition. This leads to a range of 9 to 260 stocks per industry, where 10 out of 23 industries contain less than 50 stocks while 4 have more than 100.

Nijman et al. (2004) follow a similar portfolio construction method as Jegadeesh and Titman (1993) and Grinblatt and Moskowitz (1999). They form individual, country and industry Momentum portfolios all of which they utilize in their study. The industry Momentum portfolios are formed so that four industries end up in the winner portfolio and four in the loser portfolio. This leaves 15 industries in the middle of the ranking that are excluded. The winners and losers are determined according to prior 6-month returns and are held for a further 6 months. The portfolios are rebalanced monthly and held for the entirety of the holding period. The method is much the same as in Grinblatt and Moskowitz (1999) with the exception of different portfolio rankings in terms of percentiles.

To conclude Nijman et al.'s (2004) study, they find evidence that industry Momentum does not explain individual stock Momentum in Europe, which is directly in opposition to what Grinblatt and Moskowitz (1999) report for the U.S. Additionally, they find that the role of industry Momentum in explaining overall Momentum returns is economically significant, but not statistically so.

Pan, Liano and Huang (2004) published a paper analyzing the sources of profits for industry Momentum. More specifically, they investigate whether industry Momentum profits may be decomposed into own-autocorrelations, cross-autocorrelations and cross-sectional dispersion in mean returns and which of the aforementioned play the most important part in explaining returns. Pan et al. essentially build off of the conclusions of Grinblatt and Moskowitz (1999) in that industry Momentum subsumes individual stock Momentum and thus they try and discern the origins of industry Momentum returns. As a result, they do not set forth any theories or findings to contradict Nijman et al.'s (2004) proposition that the relationship between individual stock and industry Momentum would be reversed. Indeed, if the assumptions of Grinblatt and Moskowitz – and further accepted by Pan et al. – hold true, in that industry Momentum subsumes individual stock Momentum, then risk-managed Momentum (Barroso & Santa Clara, 2015) may produce similar results for industries. Conversely, if the opposite is true for risk-managed Momentum, then one might conjecture that individual stock and industry Momentum stem from different origins. It is important to note however, that even if industry Momentum subsumes individual stock Momentum in that the sample averages are similar and that risk-managing works equally well for industry Momentum, this does not necessarily mean that the stochastic processes underlying those averages share similar properties and as a result stem from the same origins. Pan et al. find evidence to support the fact that industry Momentum produces statistically significant returns only when own-autocorrelations are positive and statistically significant.

Pan et al. (2004) have a similar time frame for their analysis as did Grinblatt and Moskowitz (1999), with the exception that Pan et al. use weekly data instead of monthly in order to increase the power of their tests resulting from larger sample size. They gather their data from the CRSP database using all stocks listed in NYSE, AMEX and NASDAQ. As their data is from the U.S. they use SIC codes to divide companies into 20 industries as did Grinblatt and Moskowitz (1999). Portfolio returns are equally weighted. The biggest difference to earlier studies on industry Momentum is that Pan et al. utilize an alternate J/K strategy as the one most typically used doesn't allow to distinguish the impact of autocorrelations at higher orders for returns. Instead they follow a strategy that buys the sorted portfolios at time *t* where the winners and losers have been sorted based on *t-k*. This construction method allows for decomposing of *k*th order own-autocorrelations and cross-autocorrelations of industry returns. In this way, the authors are able to evaluate industry Momentum returns and in relation to own-autocorrelations and cross-autocorrelations of industry portfolio returns at various lags.

Pan et al. (2004) find evidence that support the notion of industry Momentum profits being positive and statistically significant especially at short-term horizons, namely less than 4 weeks. As mentioned above though, this is only the case when own-autocorrelations are positive and significant. What Pan et al. however cannot account for, is the possibility that industry Momentum returns in their study are the product of spurious autocorrelations in industry portfolios that may be caused by some unknown economic factor. Additionally, the authors acknowledge the fact that transaction costs may once again significantly and detrimentally affect industry Momentum returns, especially so with weekly data as the turnovers for the portfolios increase even further than with monthly data.

Du and Denning (2005) conducted a study which aimed to discern whether industry Momentum could be explained by an asset pricing model which, in addition to contemporaneous factors, included lagged ones as well. The original Jegadeesh and Titman (1993) study addressed this idea as well, but in their study, only a lagged market factor was used in a one factor model, which faired weakly. Thus, Du and Denning add lagged Fama-French factors into their model and conclude that such additions make for an asset pricing model that explains industry Momentum returns to a great extent This addition of lagged variables follows from the idea that Momentum returns may be attributed to initial underreactions by the market. As a result, they conjecture that industry Momentum returns can, in fact, be explained by common risk instead of idiosyncratic risk. These findings directly contradict those of Grinblatt and Moskowitz (1999), who support the idea that industry Momentum is explained by industry specific idiosyncratic risk, which is supported by their findings. Therefore, as with individual stock Momentum, the explanation for industry Momentum returns are heavily disputed and no definitive conclusions seemingly exist.

Du and Denning (2005) do not regress Momentum profits directly on their model of contemporaneous and lagged variables as they claim that it may be an inappropriate approach because the factor loadings of Momentum portfolios change on a monthly basis as they are rebalanced. So they adjust their investment period returns based on their delayed-reaction model. The authors use 30 industries and implement the typical equally-weighted and value-weighted decile ranking for their Momentum strategy inside a sample spanning from 1926 to 2003. Similarly, to this study, Du and Denning gather their data from Kenneth French's website and utilize excess returns, instead of raw returns in their study. They use the J/K strategy of 6/6 and implement a skipped month when analyzing the value-weighted strategy and neglect the skipping when they analyze the equally-weighted strategy. Skipping the latest month, and/or using a value-weighted versus equally weighted strategy makes no relevant difference.

Du and Denning (2005) present interesting arguments as to why individual Momentum and industry Momentum are not the same. First they cite the fact that individual Momentum returns differ greatly when the latest month is skipped in between the ranking and investment periods, as Jegadeesh and Titman (1993) originally displayed, whereas industry Momentum returns do not experience this effect. In the same vein, individual Momentum experiences a strong January effect and industry Momentum has a weak one. Prior to 1963, equally-weighted industry Momentum portfolios had a significant January effect, which the authors conjecture might be explained by the effect of small stocks that may have been pronounced as industry portfolios were rather small in the time period. As a result, the authors focus their analysis on value-weighted portfolios. These arguments for why individual Momentum and industry Momentum differ, offers an ever interesting build-up to the analysis of this thesis, as again, the argument follows that if individual stock Momentum and industry Momentum are different from each other, then risk-managed Momentum (Barroso & Santa Clara, 2015) shouldn't work as such in the case of industry Momentum. On the other hand, if it does, it should serve as a counter argument in the same frame of logic to the argument that the two respective Momentum strategies are different from each other. Then again, even if risk-managing works for industry Momentum as well, this does not have to indicate shared similarities in the origins of individual stock Momentum and industry Momentum, as the potential success of risk-management for both may be occur by chance as well. The same is true for the opposite.

The results that Du and Denning (2005) find imply that the common-factor component using the traditional Fama-French model is incapable of explaining industry Momentum returns as it is 0.01 % per month with a t-statistic of 0.27. However, when the lagged Fama-French factors are added into the model alongside the contemporaneous ones, the explanatory power of returns per month shifts up to 0.23 %, which amounts to 41 % of the raw profits. When allowing for time variation in factor loadings common risk explains an even higher share of industry Momentum profits with the delayed-reaction model. These results point towards the implication that industry Momentum is not the result of idiosyncratic risk relating to industries, but rather more closely linked to common risk.

The main characteristics of the studies on industry Momentum presented above are summarized in table 5.

Authors	Number of Industries	J/K	Returns	Time Period	Country Studied	Data
Grinblatt & Moskowitz	20	6/6	0.43 % (Raw)	1963-1995	US	Monthly
Nijman et al.	23	6/6	0.55 % (Excess)	1990-2000	Europe	Monthly
Pan et al.	20	N / A	0.00173 cents	1962-1998	US	Weekly
Du & Denning	30	6/6	0.56 % (Raw)	1926-2003	US	Monthly

Table 5. The main characteristics of the industry Momentum papers discussed in this chapter. J in J/K refers to the formation period in Momentum strategies and K refers to the holding period. (Grinblatt & Moskowitz, 1999; Nijman et al., 2004; Pan et al., 2004; Du & Denning, 2005)

5.2. Profitability of Industry Momentum

The industry Momentum strategy described above used in Grinblatt and Moskowitz (1999) produces average monthly returns of 0.43 %, which are very similar in magnitude to the returns produced by individual stock Momentum. When control variables for size and book-to-market are added industry Momentum produces average monthly abnormal returns of 0.29 % per month with the strategy discussed above. As was the case with returns, transaction costs are also in line with individual stock Momentum and Grinblatt and Moskowitz approximates annual portfolio turnover for the 6/6 strategy to be around 200 %, which comes down to breakeven transaction costs being 0.75 % per dollar of long and/or short transactions. Transaction costs due to high turnover affect the one-month strategy even more than the six-month strategy, even though the previous one has higher returns. This indicates that for industry Momentum, transactions costs may deter the profitable returns associated with the investment strategy and Grinblatt and Moskowitz propose this to be a subject for further research. Transaction costs will not be associated in the empirical part of this study, as the aim of this research is merely to see if risk-management increases the profitability of industry Momentum, and this doesn't require taking transaction costs into account as such. As with transaction costs being a potential source of limitations for the profitability of industry Momentum, so are limits to arbitrage in the form of the inability to short all necessary stocks. Grinblatt and Moskowitz note that not all stocks are easily borrowed and those that are rarely have short sale proceeds and margins that earn more than the market rate of return.

Further on, from a profitability point of view Grinblatt and Moskowitz (1999) assert that Momentum strategies aren't very well diversified because if industry Momentum does indeed explain returns to individual stock Momentum, it is evident that these returns stem from intra-industry returns that are more often than not highly correlated. However, it is important to note, that according to Grinblatt and Moskowitz, industry Momentum produces higher returns than individual stock Momentum. Does the higher correlation of the stocks that produce Momentum returns, i.e. greater risk as they aren't as diversified as assumed, explain higher returns to industry Momentum as opposed to individual stock Momentum? In other words, does the higher correlation of firms – and thus greater risk because of inefficient diversification – that come from the same industry, that produce industry Momentum returns explain why industry Momentum returns are greater than individual stock Momentum returns?

The Nijman et al. (2004) study suggests that industry Momentum portfolios that are diversified with respect to countries included in their study yield on average an excess monthly return of 0.55 %. The Automobiles industry yields the lowest value-weighted average monthly returns at 0.59 %, whereas the corresponding highest returns come from Software & Services at 2.55 %. As well as having the highest returns, Software & Services also has the highest standard deviation of 9.5 %. Conversely the lowest standard deviation isn't in fact attributed to Automobiles but Utilities, for which it is 4.1 %. By comparison, weighting these returns equally or by value doesn't cause a significant change in the returns.

The takeaway for profitable Momentum investing from Nijman et al. (2004) is that even though individual stock Momentum explains most of the returns to Momentum, investors would still be wise to first sort countries into past winners and losers, then industries and finally stocks. A potential drawback however once again results from transaction costs. Nijman et al. estimate that transaction costs could rise as high as 6 % for Momentum with a turnover of each stock twice a year. This results in approximately cutting the Momentum returns in half.

Du and Denning (2005) find similar results for the profitability of industry Momentum as studies that came before theirs. Both, equally-weighted and value-weighted industry

Momentum strategies are profitable, and value-weighted, which was the author’s focus, produced 0.56 % per month on average, with a t-statistic of 3.81. The authors, however find that in the sub-sample period of 1926 – 1945, this strategy was not profitable.

6. RISK-MANAGED MOMENTUM

Barroso and Santa Clara (2015) unveiled results that may have a lasting impact on Momentum and the academic literature surrounding it. Their findings on the manageability of the risk associated with Momentum begs questions and further research to establish whether their method of managing the risk of Momentum is indeed revolutionary and as robust as the authors claim. This chapter describes the study conducted by Barroso and Santa Clara and fully details it in order to preface the methodologies used in the empirical part of this thesis.

In terms of profitability, Momentum beats other well-known anomalistic investment strategies in value and size, but it is occasionally plagued by crashes that threaten the cumulative returns of the strategy, and thus may deter away investors who fear excess kurtosis and negative skewness (Barroso & Santa Clara, 2015). Barroso and Santa Clara however find, that the risk associated with Momentum is highly predictable and thus manageable. Managing this risk in turn, nearly doubles the Sharpe ratio of Momentum and nearly completely eliminates the crashes Momentum may exhibit.

To highlight the impact of Momentum crashes, it is useful to regard the effects that these crashes have on cumulative returns to the strategy (figure 2). Thus, the importance of eliminating Momentum crashes and consequently improving the profitability of Momentum is evident when prior historical crashes are considered (figure 3). The first example is associated with the Great Depression and more specifically 1932, when Momentum would have delivered -91.56 % returns in just two months (Barroso & Santa Clara, 2015). A more recent record of a Momentum crash comes in the midst of the Financial Crisis, when Momentum delivered a -73.42 % return in three months in 2009. Even though Momentum produces on average, 1.75 % monthly excess returns (Barroso & Santa Clara, 2015), these crashes cause significant losses that take decades to recover from. This highlights the imperative importance of managing the crash risk of Momentum and hence, increasing its profitability.

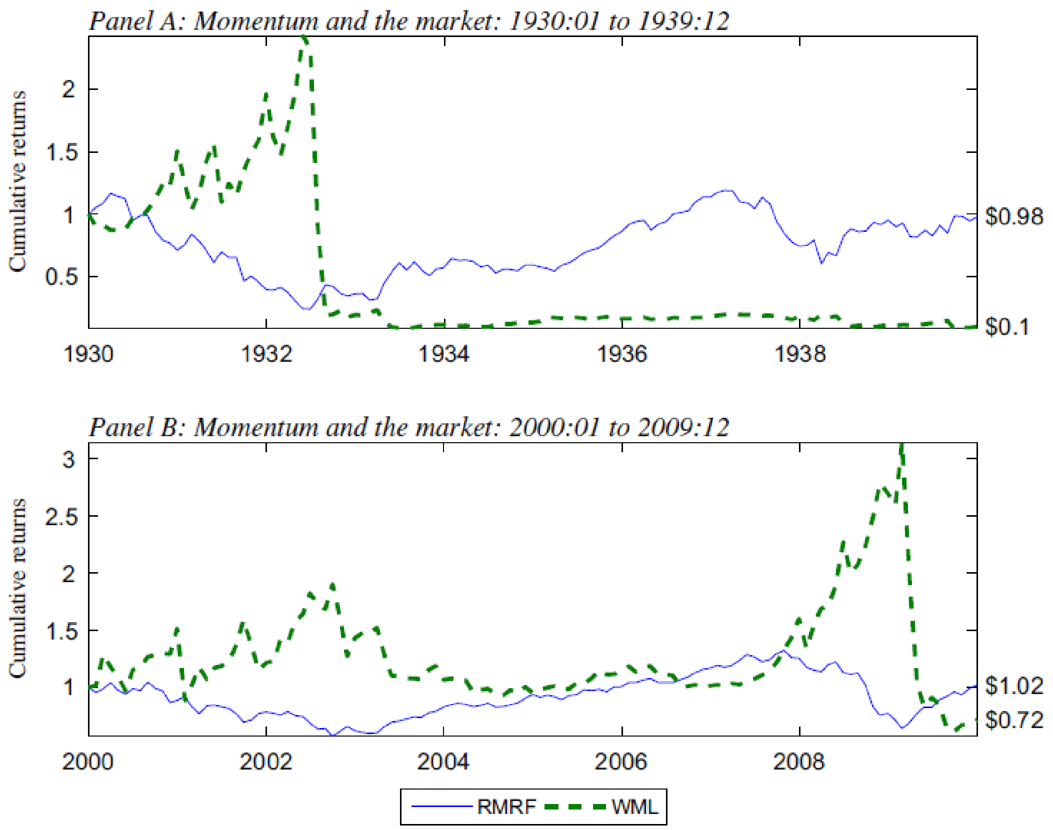


Figure 2. Cumulative returns of regular Momentum and market minus the risk-free rate during periods exhibiting Momentum crashes. (Barroso & Santa Clara, 2015)

The method Barroso and Santa Clara (2015) use to control the risk of Momentum relies purely on ex ante information and is initially based on estimating the risk from daily variances of returns. An autoregressive model of monthly return variances manages to produce and out-of-sample R-square of 57.82 %, which is very high (19.01 percentage points higher) when it is compared to a similar model predicting the market portfolio, which is notoriously predictable with similar models. Next, the weight in the Momentum strategy is scaled according to the realized variance of returns from the past six months, with the aim of maintaining constant volatility. This scaling of the strategy improves the Sharpe ratio from 0.53 for regular Momentum, to 0.97 (table 6) for risk-managed Momentum. This increase in the Sharpe ratio is complemented by a drop in kurtosis from 18.24 to 2.68 and a similar decrease in negative skewness from -2.47 to -0.42. As a result of this decreased risk, the one-month maximum negative return decreases from -78.96 % for regular Momentum to -28.40 % for risk-managed Momentum. Similarly, the maximum drawdown for raw Momentum returns decreases from -96.69 % for regular Momentum, to -45.20 % for risk-managed Momentum.

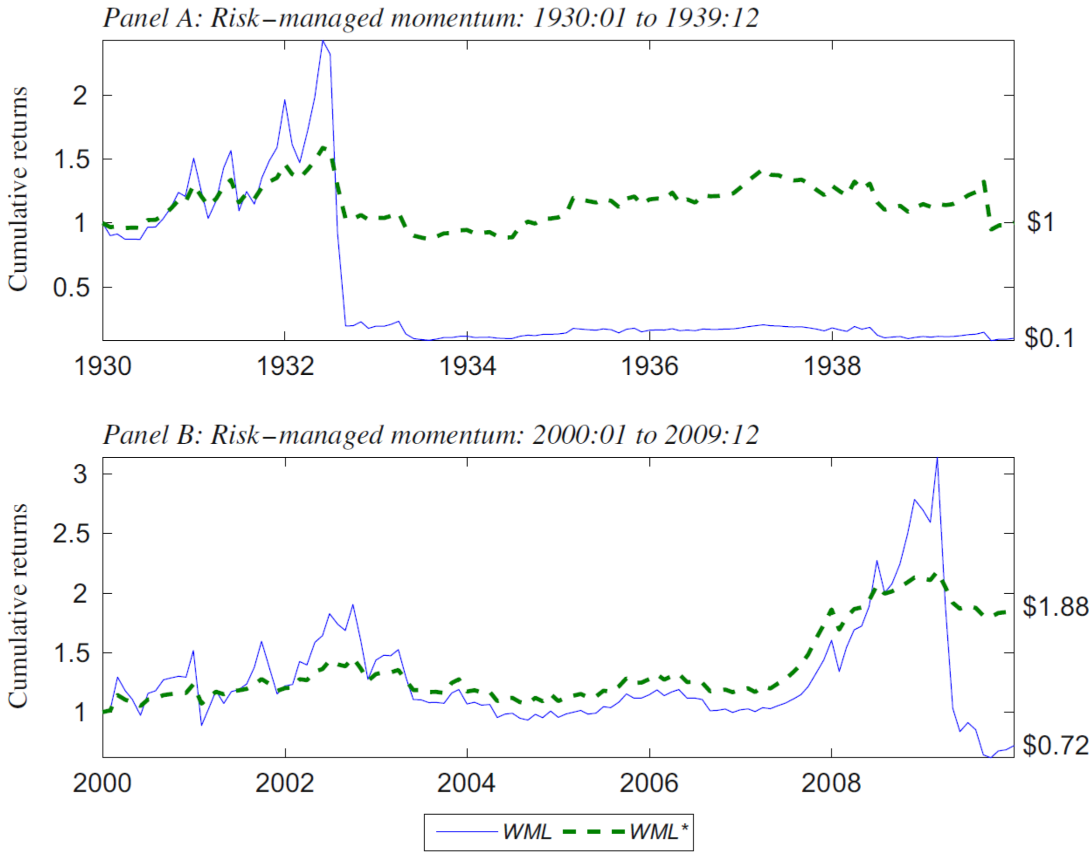


Figure 3. Cumulative returns of regular Momentum and risk-managed Momentum during periods exhibiting Momentum crashes. (Barroso & Santa Clara, 2015)

Portfolio	Maximum	Minimum	Mean	Standard deviation	Kurtosis	Skewness	Sharpe 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

Table 6. The first row (WML) represents the economic performance of regular Momentum and the second row represents the economic performance of risk-managed Momentum (WML*) respectively. The time period extends from March 1927 to December 2011. The mean, standard deviation, and the Sharpe ratio are annualized. (Barroso & Santa Clara, 2015)

Barroso and Santa Clara (2015) also conduct robustness checks, to show that risk-managed Momentum has very similar results internationally, as it does in the U.S. They further show that sub-sample time periods exhibit the same results as in the entire time period, demonstrating that periods with crashes or without crashes to regular Momentum do not alter the results. The authors also address the commonly raised issue of high turnover and consequently high transaction costs eating away Momentum profits, by declaring that as turnover for regular and risk-managed Momentum are similar, due to the higher profitability of risk-managed Momentum, transaction costs are less of an issue for the risk-managed strategy. In fact, according to the estimation of the authors, the turnover rate for risk-managed Momentum is only 100 basis points higher (75 %) per month of trading.

As to why managing Momentum's risk with realized variances works, Barroso and Santa Clara (2015) decompose Momentum's volatility into market and specific strategy based components. This decomposition reveals that the market component risk only accounts for 23 % of the average total risk, thus meaning that the specific component is much larger. As it turns out, this specific component of risk is more persistent and predictable with an out-of-sample R-square of 47.06 % as opposed to an R-square of 20.87 % for the market component. The persistence of realized variances for Momentum is also higher, which is evident from the AR(1) autoregressive model used by Barroso and Santa Clara. The coefficient for Momentum from the AR(1) model is 0.77, which is 0.19 higher than for the market.

In closing, it is important to note that Barroso and Santa Clara (2015) put forth that more than half of Momentum's risk is predictable. No other risk factor in financial academia has a higher predictable portion of risk (Barroso & Santa Clara, 2015). In fact, it is evident from the data that Barroso and Santa Clara use, that the relation between risk and return for Momentum is negative. As before, risk-managed Momentum relies purely on ex-ante information, which digresses from many potentially profitable trading strategies in that it can actually be utilized in real-time. Additionally, Barroso and Santa Clara find no credence in that statement that Momentum has died down in roughly the last 10 years. Instead they conjecture that the period may have withheld a number of high risk episodes that may have affected the performance of Momentum. The work of Barroso and Santa Clara may prove to be the most profitable Momentum strategy applicable to real-life markets. Thus it warrants more research on the topic to assess the validity of its potential.

7. DATA AND METHODOLOGY

7.1. Data Collection and Description

The data for this thesis comes from Kenneth French's website. The website has readymade monthly and daily return data sets for industry portfolios in the U.S., out of which the set for 30 industry portfolios is used here. The time period for the data set is from July 1926 to December 2015, which means 89 years and 5 months' worth of data. The stocks in the data set come from NYSE, AMEX and NASDAQ where each stock is assigned to an industry based on their four-digit SIC code. This assignment to specific industries is done at the end of June of year t. The SIC codes originally come from Compustat and for year t, t-1 SIC codes are used. Whenever the Compustat SIC codes are unavailable CRSP SIC codes are used. Returns are then computed from July of year t, to June of t+1. (French, 2016) The monthly returns are used to calculate monthly returns for the industry Momentum portfolios and the daily returns are used to calculate daily industry Momentum returns which are then utilized to calculate the realized variances for the risk-managed industry Momentum strategy. These realized variances are utilized in calculating the time-varying weights for the risk-managed industry Momentum strategy.

The Fama-French Three Factor Model values are from Kenneth French's website as well. They too, are monthly observations and span from July 1926 to December 2015. The factors themselves are formed by value-weighting 6 portfolios on size and book-to-market. SMB is formed by subtracting the average returns of three big portfolios from the average returns of three small portfolios. HML is calculated by subtracting the average returns of two growth portfolios from the average returns of two value portfolios. The Rm-Rf factor is formed by all CRSP stocks incorporated in the U.S. and listed on NYSE, AMEX, and NASDAQ. The returns are value-weighted and each stock has to have a CRSP share code of 10 or 11 at the beginning of month t, good price and share data at the beginning of month t, and good data on returns for t minus the one-month Treasury bill. The Treasury bill rate originally comes from Ibbotson Associates. (French, 2016)

The data for the utilization of the Fama-French Five Factor model are downloaded from Kenneth French's website similarly to the previous data. The composition of the factors differs slightly from the FF3 even for the identically named factors. The time period for the FF5 factors differs as well, which results in unavoidably differing time periods for the actual regressions later on. The FF5 factors account for the years from July 1963 to

December 2015. The SMB factor in the FF5 is computed by subtracting the average return of nine big stock portfolios from the average return to nine small stock portfolios. The HML factor is formed identically to that of the FF3. RMW or Robust Minus Weak is calculated by subtracting the average returns to two weak operating profitability portfolios from the average returns to two robust operating profitability portfolios. CMA or Conservative Minus Aggressive is the difference between the average returns of two conservative investment portfolios and two aggressive investment portfolios. The Rm-Rf factor is formed in similar fashion as in the FF3. (French, 2016)

The data for the three and five factor models is adequate in its downloaded form as it is serving as the independent variables for the study and thus need no further refinement. The return data however is further manipulated to form Momentum portfolios. The manipulation begins with computing rolling past six-month returns for all of the industry portfolios for the duration of the time periods utilized. This reflects the ranking window of six months or J = 6 in our J/K strategy of 6/1. Next, the top decile of industries is assigned to a winner portfolio each month – as the strategy rebalances monthly – and the bottom decile of industries are assigned to a loser portfolio respectively. This is repeated every month without skipping the most recent formation month, as Du and Denning (2005) point out that skipping the latest formation month doesn’t affect returns either statistically or in magnitude. Deciles are used here instead of e.g. top and bottom 30 % as in Grinblatt and Moskowitz (1999) because a prevailing theme in this thesis is indeed profitability. As such, a finer ranking procedure should produce higher profitability in the subsequent Momentum strategy. This formulation is used to calculate returns for the winner portfolio and loser portfolios separately. Equal weighted portfolios are used here, not because there’s specific motivation to do so, but simply because Nijman et al. (2004) conclude that value weighting or equal weighting industry Momentum portfolios makes no difference in terms of the magnitude or significance of returns. Finally, the returns to the loser portfolio are simply subtracted from the returns to the winner portfolio and thus we end up with returns to the industry Momentum portfolio for June 1927 to December 2015.

After the time-series of returns for industry Momentum have been calculated, the process of risk-managing the returns is the next step. We apply the methodology of Barroso and Santa Clara (2015) directly, which require utilizing daily returns of the industry Momentum strategy to form time-varying weights for participation in the strategy itself. This is done with the following formula:

(6.) $$\sigma^2_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j} \,/126$$

Where $r_{WML,t}$ represents the monthly returns to Momentum, $r_{WML,d}$ the daily returns to Momentum, and d_t the dates of the last trading sessions each month for the time series.

To be more specific, the formula entails first calculating the sum of past six-month daily trading day returns at the beginning of each month. These are then multiplied by 21 and divided by 126. This gives us the variance forecast which is needed in the next formula.

The forecasted variances are used to calculate the weights, relating the estimates to the constant amount of risk that is targeted with the following formula:

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

Where $r_{WML,t}$ is the unscaled plain Momentum, $r_{WML*,t}$ is risk-managed Momentum, and the numerator represents the targeted level of volatility. Barroso and Santa Clara (2015) choose a target of annualized volatility equal to 12 %. What this then means is that the square root of the variance forecasts is taken and divided by the monthly target volatility derived from the 12 % annualized volatility, which is 3.46 %. The target of 3.46 % is divided by the volatility estimates to end up with weights that determine how vested the position in industry Momentum should be for each month. This process is repeated at each turn of the month for the whole time period.

Finally, to arrive at the actual return series, the monthly returns to industry Momentum are simply multiplied with the corresponding monthly weights. This scales the participation of the strategy. Throughout the time period utilized in the sample, the weights for risk-managed industry Momentum vary between 0.26 and 4.18, whereas the original paper by Barroso and Santa Clara (2015) report weights varying between 0.13 and 2.00. Conjecture for the difference in weight ranges between risk-managed industry and individual Momentum is presented later in this thesis.

7.2. Methodology

The methodology used to test the two hypothesis presented in the beginning of this thesis are reliant on multivariate regressions, where the FF3 and FF5 factors act as independent variables. In order to conclusively reject the null hypotheses both factor models should be unable to explain the Momentum returns. Conflicting findings would result in a need for further research on the topic. The regression to test the first hypothesis has industry Momentum returns as the dependent variable and the FF3 factors as the independent variables. This same regression is also run with the FF5 factors as the independent variables. The latter of these is presented below as it holds the first one within it as well.

(8.) $R_{IM} = \alpha + \beta_1\left(R_M - R_f\right) + \beta_2(SMB) + \beta_3(HML) + \beta_4(RMW) + \beta_5(CMA) + \varepsilon$

R_{IM} represents the returns for industry Momentum, $R_m - R_f$ stands for risk-adjusted market returns, SMB is returns to small firms minus returns to large ones, HML means returns to value minus returns to growth, RMW stands for robust profitability returns minus weak profitability returns and finally CMW stands for the difference between portfolios constructed on conservative and aggressive firm returns. (Fama & French, 2015)

The same type of regression is also used to test whether risk-managed industry Momentum produces significant abnormal returns. The only difference being the dependent variable, which in the case of testing the second hypothesis is the monthly returns from risk-managed industry Momentum. In the same vein, these returns are regressed on the FF3 factors and subsequently on the FF5 factors. The second of these regressions is once again presented below and the first one is not, as it is inherent in the latter one as well, simply excluding the last two factors.

(9.) $R_{RMIM} = \alpha + \beta_1(R_M - R_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(RMW) + \beta_5(CMA) + \varepsilon$

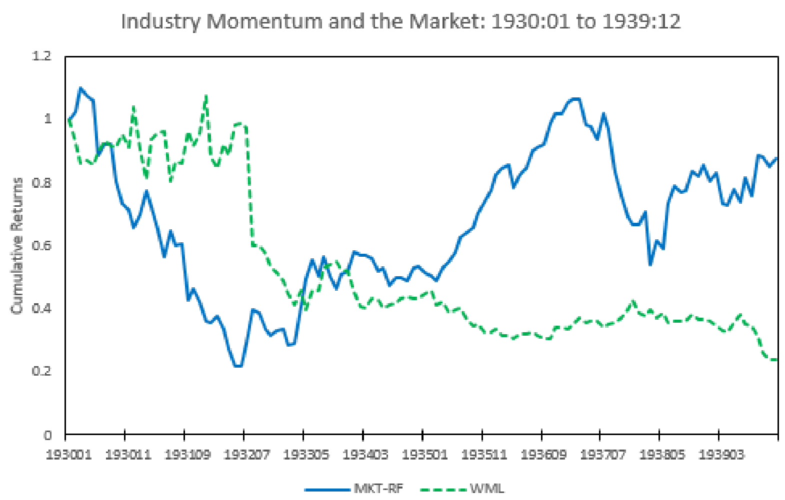
R_{RMIM} represents the risk-managed industry Momentum returns. All of the independent variables are identical to those already explained above.

8. RESULTS

The focus of this chapter is in describing the results from the empirical models that were presented previously. First, graphs depicting the cumulative returns for the market (MKT-RF), industry Momentum (WML), and risk-managed industry Momentum (WML*) will be presented and discussed, then descriptive statistics will be presented pertaining to the original hypotheses. This is followed by the actual regression results and finally evidence from robustness tests are displayed and discussed.

Figure 4 graphs the cumulative returns of industry Momentum and the market during crash periods. The graphs span from January 1930 to December 1939 and January 2000 to December 2009, thus withholding the Momentum crash of 1932 and likewise the Momentum crash that occurred during the global financial crisis in 2009.

Panel A



Panel B

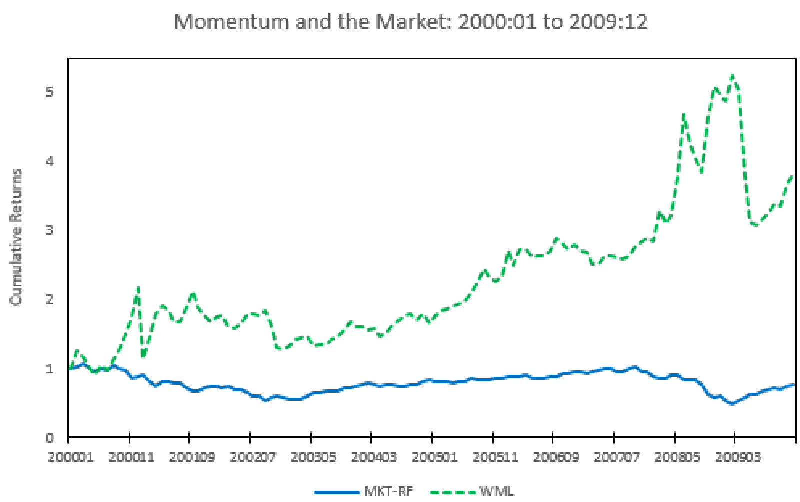


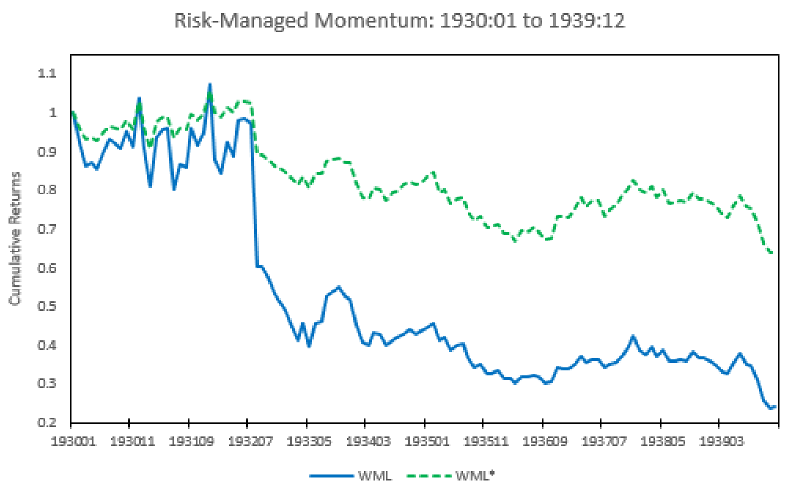
Figure 4. Panel A depicts the cumulative returns of the market minus risk-free rate (MKT-RF) and industry Momentum (WML) during the period January 1930 – December 1939. Panel B depicts the same in the period January 2000 – December 2009.

Panel A in figure 4 plots the cumulative returns to industry Momentum and the market from January 1930 to December 1939. This graph is essentially a duplicate of the Barroso and Santa Clara (2015) graph that plots cumulative returns to Momentum and the market and is thus, meant to be compared to it as well. The Momentum crash of 1932 is clearly exhibited in industry Momentum in the graph and it is highly similar to the crash to individual stock Momentum. As with individual stock Momentum, industry Momentum crashes in 1932, subsequently experiencing a small rebound before it continues a steady downward drift in the post-crash years, which ends in a slight dip at the eve of World War II. The overall cumulative return pattern between individual stock Momentum and industry Momentum is thus roughly the same, with the exception of individual stock Momentum crashing to a near zero level, whereas industry Momentum briefly recovers after the 1932 crash, only to drift down to a level of 0.24. Panel A also indicates what is known from Barroso and Santa Clara (2015), in that the market recovers from the 1932 crash at a faster rate than Momentum, whether it be individual stock or industry Momentum. The magnitude of the 1932 crash for industry Momentum witnesses a drop of -59.85 % from 0.99 to 0.40 through June 1932 to May 1933. Even though the magnitude of the crash is large for industry Momentum, it compares favorably with the -91.59 % returns that individual stock Momentum experiences in just two months in 1932 (Barroso and Santa Clara, 2015).

Panel B in figure 4 graphs the same cumulative returns as above with the exception, that the time period now spans from January 2000 to December 2009. This is again, an almost exact duplicate from Barroso and Santa Clara (2015), where they illustrate the Momentum crash of 2009 and its effects on cumulative returns to Momentum. As with individual stock Momentum, industry Momentum suffers the same crash in 2009. From its peak of 5.24 in February 2009 industry Momentum suffers a drop to a trough of 3.08 which equals a -41.24 % drop in cumulative returns, producing a less severe drawdown on Momentum returns compared to the 1932 crash. Overall the return pattern in the graph for industry Momentum is similar to that of individual stock Momentum as presented by Barroso and Santa Clara. Of notice however, is the fact that cumulative returns on individual stock Momentum drop by -73.42 % in three months, which is a much higher drop than what industry Momentum experiences. Industry Momentum also begins its recovery much faster in the post-crash period, which is also evident from panel B.

Figure 5 graphs the cumulative returns to industry Momentum and risk-managed industry Momentum for the same years, as the figure before it. This is essentially the same comparison Barroso and Santa Clara (2015) made between Momentum and risk-managed Momentum. The aim here is to graphically illustrate the ability of risk-managing industry Momentum to decrease the downside risk of the strategy, and more specifically to decrease the downside of crash risk.

Panel A



Panel B

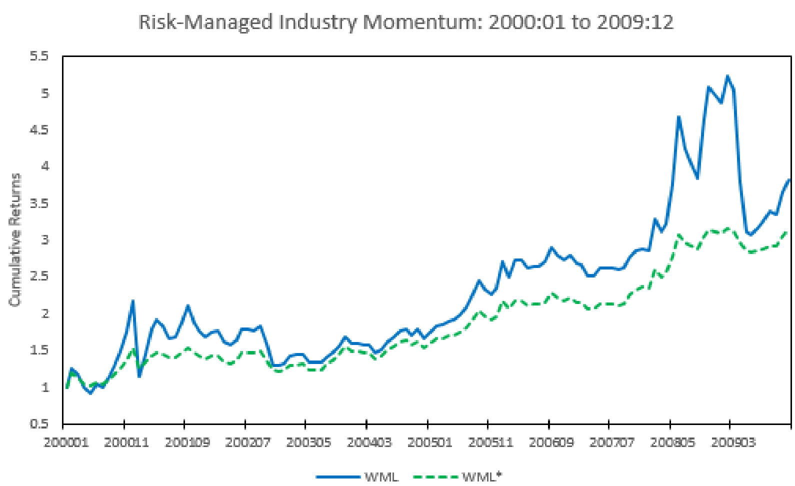


Figure 5. Panel A depicts the cumulative returns of industry Momentum (WML) and risk-managed industry Momentum (WML*) in the period January 1930 – December 1993. Panel B depicts the same in the period January 2000 – December 2009.

Panel A in figure 5 plots the cumulative returns of industry Momentum and risk-managed industry Momentum from January 1930 to December 1939. The pattern of the two lines in the graph are noticeably similar almost throughout the figure with a few exceptions. WML* produces higher returns up until the crash of 1932, whereupon both strategies suffer drops in cumulative returns. However, whereas WML dropped 59.85 %

WML*'s drop is contained to a severely smaller loss, the cumulative returns only dropping by -21.59 %. The drop WML* suffers is 61.74 % smaller than the drop WML undergoes. Risk-management hence brings about a large reduction in the downside of the 1932 Momentum crash. After the crash, both WML and WML* cumulative returns tread downwards at similar rates, the difference however being, that WML*'s cumulative return line slides at a much higher level than the returns to WML.

Panel B presents the final graph, which plots industry Momentum and risk-managed industry Momentum cumulative returns from January 2000 to December 2009. As before, the meaningful course of action is to view how much downside risk-management in Momentum brings when compared in cumulative returns. For the first half of the graph both WML and WML* returns develop at similar rate. Halfway through however, WML cumulative returns rise higher than WML* returns and before the crash they are indeed almost 52 % higher. Then the Momentum crash of 2009 ensues and WML suffers a -41.24 % drop, while WML* suffers only a dramatically reduced -7.72 % decline. The returns to WML* suffer a decline that is 81.28 % smaller than the decline that WML suffers in 2009. This is a second demonstration of the ability of risk-managed industry Momentum to greatly limit the downside on industry Momentum. Even though the time period in panel B ends with WML producing higher cumulative returns than WML*, it does so with the cost of inherently evident crash risk, which is clearly exhibited in the 2009 crash. Thanks to the evidence in figure 4 and 5, a strong case can be made for the reduction of crash risk when risk-managing industry Momentum.

Table 7 presents the descriptive statistics for the whole sample time periods for both, the time period involved in the FF3 regressions and the time periods involved in the FF5 regressions. As was already mentioned before, these time periods differ as the original data from Kenneth French's website is different for the FF3 and FF5 data sets. For the time period involving the FF3 model (January 1928 to December 2015) the annualized mean return for industry Momentum is 15.49 % whereas the annualized mean return for risk-managed industry Momentum is 17.74 %. Thus, the annual mean return for the risk-managed counterpart of industry Momentum is roughly 200 basis points higher, which is a clear indication that risk-managed industry Momentum is definitely more profitable in terms of mean returns than regular industry Momentum. However, the time period involving the FF5 model (July 1963 to December 2015) produces very similar annualized mean returns for both, industry Momentum and risk-managed industry Momentum, as the annualized mean return for industry Momentum is 23.29 % and the equivalent annualized mean returns for risk-managed industry Momentum is 23.14 %. Now only a 15 basis point difference is evident in the returns between the two strategies. The returns for the FF5 model time period may be higher than for the FF3 model time period because of the fact that the previous period only exhibits one Momentum crash as the latter exhibits two, both in 1932 and 2009. As a result, WML returns in the FF5 time period may appear more favorable in terms of annualized mean returns compared to the FF3 time period, as there is essentially only one crash to risk-manage in the time period. Regardless of the higher returns for the FF5 model time period, 1 dollar invested with the annualized mean return of 17.74 % for risk-managed industry Momentum from the FF3 model time period would have compounded into 1 480 440 dollars over the 87 years that the data spans.

Statistic	Whole Sample (FF3)		Whole Sample (FF5)	
	WML	WML*	WML	WML*
Maximum	26.13	26.56	26.13	26.56
Minimum	-47.06	-18.32	-47.06	-18.32
Mean	15.94	17.74	23.29	23.14
Standard Deviation	20.83	16.19	22.34	17.75
Kurtosis	10.80	5.24	10.51	5.11
Skewness	-0.60	0.45	-0.57	0.39
Sharpe Ratio	0.60	0.89	0.82	1.03

Table 7. The table presents the descriptive statistics for industry Momentum (WML) and risk-managed industry Momentum (WML*) in two different time periods. The first time period (FF3) spans January 1928 – December 2015. The second time period spans July 1963 – December 2015. Reported figures are monthly except for the mean, standard deviation and Sharpe ratio, which are annualized.

Risk-managing industry Momentum has a clear effect of minimizing the downside of negative returns for the regular industry Momentum strategy. The minimum monthly return for industry Momentum in the larger time period is -47.06 % while it is only -18.32 % for risk-managed industry Momentum in the same time period. This is almost 3000 basis points smaller, which is a very noticeable difference. Interestingly the -47.06 % drop for industry Momentum comes in January of 2001, which is eight years removed from 2009, the year of the second infamous, less dramatic Momentum crash. Coincidentally, the largest monthly minimum returns for WML* occur during the same month in the same year. As the largest negative monthly return for risk-managed industry Momentum and its non-managed counterpart comes in January 2001, it may be reasonable to conjecture that the bursting of the tech bubble contributed massively to this downturn. The drop of January 2001 for industry Momentum however is at odds with the traditional view that the market crash of 1932 exhibits the worst month for Momentum. Regardless of the traditional view however, the January 2001 drop for industry Momentum is highly likely linked to the bursting of the tech bubble as its effects were felt at the time and this may be magnified by incorporating the whole industry as a portfolio in the strategy. Interesting to note however, is the fact that while industry Momentum suffered a -47.06 % and risk-managed industry Momentum a -18.32 % drop, the returns for the whole market went up by 3.67 % during the same month.

While the downside of industry Momentum can be seemingly effectively controlled by risk-management, the upside of the strategy appears to be beneficially affected as well. This is alluded to by the maximum returns for both time periods. In the FF3 (FF5) time period, industry Momentum has maximum monthly returns of 26.13 % (26.13%) and risk-managed industry Momentum has maximum monthly returns of 25.56 % (26.56 %). A widely known fact in finance is that the largest gains in the stock market often directly follow large drops. As risk-managed Momentum is scaled by realized variances, there may be a lag effect that decreases participation in the strategy during those high gain days on account of high realized variances in recent market drops. However, this potential lag effect works both ways, as the realized variances may increase participation during rises in mid-bull markets, leading to higher maximum monthly returns despite smaller participation in the immediate bull days following market troughs. This may be able to explain why maximum returns to WML* outperform maximum returns to WML, as was the case with minimum returns

The annualized standard deviations of industry Momentum compared to risk-managed industry Momentum in both time periods are noticeably higher. The annualized standard deviations for the FF3 (FF5) model time period are 20.83 (22.34) for industry Momentum and 16.19 (17.75) for risk-managed industry Momentum. This finding differs somewhat from the original findings for individual stock Momentum by Barroso and Santa Clara (2015). In their paper, they report an annualized standard deviation of 27.53 for Momentum and 16.95 for risk-managed Momentum, meaning that the relative decrease in standard deviation is larger in risk-managed individual stock Momentum. It then follows that in Barroso and Santa Clara’s findings the Sharpe ratio of risk-managed Momentum increases both because of an increase in mean returns and a decrease in standard deviation. This much is true for industry Momentum and risk-managed industry Momentum as well, however, risk-managed industry Momentum’s Sharpe ratio increases comparatively more from an increase in mean returns and less so due to a decrease in standard deviation. The standard deviation for industry Momentum – whether it be regular or risk-managed – is closer to the standard deviation of risk-managed individual stock Momentum than individual stock Momentum. This might be an implication of using portfolios – in this case industries – for the Momentum strategy instead of individual stocks. Portfolios tend to inherently have a greater amount of stocks within them already and thus the standard deviation of returns is smaller. As risk-managing industry Momentum still deals with portfolios, the reason for a relatively smaller change in standard deviation – compared to what Barroso and Santa Clara (2015) report – may lie within the same logic. Therefore, risk-managing Momentum in industries doesn't increase profitability as measured by the Sharpe ratio, as much in the case of industries as it does in individual stocks.

This leads us on to perhaps the most interesting finding within the descriptive statistics – and arguably the most interesting finding in this thesis – which is concerned with skewness. The negative skewness of Momentum is perhaps the most widely cited downside to the strategy as a whole. The crashes inherent to Momentum may erase away massive amounts of cumulative returns which take decades to recover from (Barroso & Santa Clara, 2015). This is exactly the reason why Barroso and Santa Clara's finding of Momentum risk-management is so exciting. However, Barroso and Santa Clara aren't arguably able to rid Momentum from its crash risk entirely. This argument is buffed by the fact that risk-managed individual stock Momentum still retains its negative skewness even though it decreases from -2.47 to -0.42. Risk-managing industry Momentum however dissipates the negative skewness of the return distribution entirely. This leads the foray in arguing that risk-managing industry Momentum indeed entirely rids its respective Momentum from crash risk. In the FF3 (FF5) model time period skewness is -0.60 (-0.57) for industry Momentum and for risk-managed industry Momentum the skewness is surprisingly positive at 0.45 (0.39). It is obvious that this whole argument relies on the semantics of defining what truly constitutes a Momentum crash, but constraining the largest negative monthly returns to -18.32 % and completely eliminating negative skewness acts as a strong argument in favor of this statement. Indeed, the largest negative monthly returns for MKT-RF in the FF3 time period are more negative (-29.13 %) than for the worst month for risk-managed industry Momentum. I thus conjecture, that this is evidence for the first Momentum strategy which completely eliminates crash risk.

As with risk-managed individual stock Momentum, risk-managed industry Momentum decreases the kurtosis of the returns distribution to near normal levels. Kurtosis for industry Momentum is 10.80 in the FF3 time period and 10.51 in the FF5 period. However, for risk-managed industry Momentum kurtosis is only 5.24 for the FF3 time period and 5.11 for the FF5 period. This reduced kurtosis and near zero skewness indicates that the returns to risk-managed industry Momentum present an investment strategy that produces mean monthly returns of 1.37 % with a near-normal distribution.

Finally, the descriptive statistics display the Sharpe ratios for both time periods for both Momentum strategies. First, it is clear that risk-managed industry Momentum is more profitable with a Sharpe ratio of 0.89 (1.03) compared to a Sharpe ratio of 0.60 (0.82) for regular industry Momentum in the FF3 (FF5) time period. The Sharpe ratio for risk-managed industry Momentum – and for industry Momentum for that matter – in the FF3 time period is greater than the Sharpe ratio for individual stock Momentum, which is 0.53 in the Barroso and Santa Clara (2015) study. However, the Sharpe ratio of risk-managed individual stock Momentum is higher (0.97) than the Sharpe ratio for risk-managed industry Momentum. It should be noted however, that Barroso and Santa Clara (2015) do not subtract the risk-free rate from mean returns in their Sharpe ratio calculations, whereas this is done in the Sharpe ratio calculations presented here. Overall, the increase in the Sharpe ratio for industry Momentum and risk-managed industry Momentum is 48.33 % (25.61 %) higher in the FF3 (FF5) time period, which makes for a substantive increase. The increase is smaller however compared to the one that Barroso and Santa Clara report for risk-managed individual stock Momentum and its unmanaged counterpart (83.02 %).

The regression results that answer the hypotheses of this thesis are presented next. They are found in table 8 and consist of the FF3 and FF5 regressions with alternating dependent variables of industry Momentum and risk-managed industry Momentum returns. All of the regressions run in this thesis are Newey-West corrected for heteroscedasticity and autocorrelation.

It is clear outright from table 8 that the null of the first hypothesis presented at the very beginning of this thesis is rejected at a 5 % significance level and even at a 1 % level. The alpha intercepts for both the FF3 and FF5 regressions where WML is the dependent variable are positive and statistically significant with p-values < 0.00. The alpha intercepts of both regressions communicate that WML has on average 1.39 % abnormal monthly returns in the FF3 time period and 1.61 % abnormal monthly returns in the FF5 time period. As for the second hypothesis, an almost identical conclusion is reached: the null of the second hypothesis is rejected at both 5 % and 1 % significance levels.

WML* produces on average 1.43 % abnormal returns on a monthly basis when regressed on the FF3 factors and 1.73 % abnormal returns when regressed on the FF5 factors. Both alpha intercepts have p-values < 0.00. These null rejections mean that in

	Whole Sample				
	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.39	0.00	Alpha	1.43	0.00
MKT-RF	-0.13	0.04	MKT-RF	-0.04	0.27
SMB	-0.09	0.50	SMB	-0.04	0.66
HML	-0.11	0.42	HML	-0.05	0.55
Adj. R2	0.03	-	Adj. R2	0.00	-

	Whole Sample				
	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.61	0.00	Alpha	1.73	0.00
MKT-RF	-0.07	0.44	MKT-RF	-0.01	0.88
SMB	0.04	0.82	SMB	-0.03	0.87
HML	-0.54	0.03	HML	-0.26	0.17
RMW	0.21	0.55	RMW	-0.03	0.87
CMA	1.00	0.02	CMA	0.44	0.10
Adj. R2	0.05	-	Adj. R2	0.01	-

Table 8. The table reports the results of the Fama-French three factor model regressions and the Fama-French five factor model regressions for their respective time-periods (1928-2015 & 1963-2015). Alpha is the intercept of the regression, MKT-RF is the market return minus the risk-free rate, SMB is the returns to Small minus Big stocks, HML is the return to High book-to-market minus returns to Low book-to-market, RMW is the returns of Robust minus Weak operating profitability portfolios, and CMA is the returns to Conservative minus Aggressive investment portfolios. WML is the return to industry Momentum and WML* is the return to risk-managed industry Momentum. All regressions are Newey-West (1987) corrected for heteroscedasticity and autocorrelation.

both time periods industry Momentum and risk-managed industry Momentum service as profitable investment strategies capable of providing abnormal returns. For industry Momentum, this serves as yet another out-of-sample test, but for risk-managed industry Momentum this provides first ever results of its anomalous performance in producing returns. Further, the abnormal returns WML* provides are higher than those that WML provides, which is consistent with the Sharpe ratio being higher for WML*. WML* is a more profitable investment strategy than WML both in terms of abnormal returns and

Sharpe ratios. With these results it is safe to say that the research question of this thesis is now answered. However, further investigation and robustness tests will follow, to further test the evidence that has been presented thus far.

To divulge rest of the information from table 8, it is obviously of interest to look at the factor loadings, whether they are significant, and what is the explanatory power of the models themselves. First and foremost, all of the coefficients of all of the independent variables in the models associated with WML* are not significant. Thus, the FF3 and FF5 models do a poor job at explaining the returns to WML*. The closest any independent variables' coefficient comes to being able to explain returns, is in the FF5 model for WML* returns. In this model CMA has a loading of 0.44 and a p-value of 0.10, which is beyond the scope of 5 % significance and additionally its loading in relation to the alpha intercept is not economically high. This is to say that companies with conservative investments do not reliably explain returns to risk-managed Momentum at an industry level. The FF3 and FF5 do a better job in terms of explaining returns to WML. In the FF3 model, a single coefficient of an independent variable is significant and this is the MKT-RF variable. It has a loading of -0.13 with a p-value of 0.04. This indicates that WML returns slightly negatively co-move with the market and as such the model provides limited insight into what makes up WML returns. The significance of MKT-RF may simply stem from the fact that wide portfolios of industries are held, which accounts for relatively large parts of the market. As a whole however, the explanatory power of the model is low, as the adjusted R-squared is only 0.03, meaning that the model only explains 3 % of the returns to WML. The FF5 model explaining WML returns does an incrementally better job than the FF3 model in explaining WML returns. This model has statistically significant coefficients for HML and CMA. Both coefficients have relatively high loadings when compared to the Alpha intercept, with HML being -0.54 and CMA 1.00 respectively. HMLs p-value is 0.03 and CMAs 0.02 indicating that both are statistically significant at the 5 % level. The indication in these results is that WML returns are to a certain extent explained by growth firms – as a result of the negative loading – and firms that make conservative investments. The models explanatory power in terms of adjusted R-squared is higher at 5 % compared to the FF3 model which managed to explain 3 % of the WML returns. However, this magnitude of explanatory power is low for a factor model, if it is to be taken seriously, but this should not come as a surprise considering the overall weak statistical significance of the coefficients of the independent variables. In general, however, both the FF3 and FF5 models did a better job at explaining returns to WML, than WML*.

As the main research questions and hypotheses of this thesis have been now answered, room is left for conducting robustness tests to provide further evidence in support of the findings presented previously. These robustness tests rather closely follow those that Barroso and Santa Clara (2015) put forth in their study of risk-managed Momentum. This is intended so that comparison of robustness between risk-managed Momentum and risk-managed industry Momentum is more clear and concise.

Barroso and Santa Clara (2015) test risk-managed Momentum in different time periods or subsamples in order to see to what extent the two Momentum crashes of both 1932 and 2009 drive their results. First, they divide the time period into two halves as a simple robustness test. As each half however contains a crash, they also conduct the same tests on a full time period without the crash years of 1932 and 2009. Finally, they investigate the time period of January 1945 to December 2005, which is often referred to as the post-war years, which were rather benign in economic nature, but where traditional Momentum faired rather well. This exact same logic is followed here. The two main differences stem from the overall slightly differing time period for the FF3 model and the differing time period associated with the FF5 model. Regardless, all of the robustness checks described above are conducted on both the FF3 model time period and the FF5 model time period. Panel A in table 9 presents the descriptive statistics for the FF3 model subsample time periods and panel B presents the same information for the FF5 model subsample time period.

Panel A

Statistic	First Half		Second Half		No-Crash		Post-War	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	18.65	14.69	26.13	26.56	26.13	26.56	26.13	26.56
Minimum	-38.15	-13.26	-47.06	-28.41	-47.06	-18.32	-47.06	-18.32
Mean	9.12	14.3	23.14	21.27	17.46	18.44	20.27	23.44
Standard Deviation	17.61	14.49	23.50	17.70	20.08	16.23	18.45	17.26
Kurtosis	10.32	3.92	10.1	5.50	10.09	5.18	14.82	5.01
Skewness	-0.89	0.30	-0.56	0.48	-0.29	0.47	-0.50	0.40
Sharpe Ratio	0.41	0.85	0.78	0.92	0.86	1.12	0.85	1.10

Panel B

Statistic	First Half		Second Half		No-Crash		Post-War	
	WML	WML*	WML	WML*	WML	WML*	WML	WML*
Maximum	19.62	26.56	26.13	18.54	26.13	26.56	26.13	26.56
Minimum	-16.70	-15.84	-47.06	-18.32	-47.06	-18.32	-47.06	-18.32
Mean	25.05	32.92	21.41	14.16	24.16	23.73	23.73	25.78
Standard Deviation	17.21	19.88	26.52	15.02	22.01	17.86	20.83	18.42
Kurtosis	4.58	4.38	9.76	5.42	10.75	5.06	13.07	5.00
Skewness	0.24	0.47	-0.72	-0.14	-0.47	0.38	-0.59	0.41
Sharpe Ratio	1.06	1.31	0.69	0.74	1.08	1.31	0.86	1.09

Table 9. Panel A displays the descriptive statistics for the FF3 time-period (1928-2015) subsamples. First half covers 1928-1971, second half covers 1971-2015, no-crash is the period 1928-2015 without the crash years 1932 and 2009, and post-war covers 1945-2005. Panel B displays the descriptive statistics for the FF5 time-period subsamples. First half covers 1963-1989, second half covers 1989-2015, no-crash is the period 1963-2015 without the crash year of 2009, and post-war covers 1963-2005. All statistics are monthly except mean, standard deviation, and Sharpe ratio which are annualized.

The results in table 9 mostly tell the same story as the table with the descriptive statistics for the whole sample periods. In panel A the maximum return is mostly in favor of risk-managed industry Momentum with the exception of the first half, which spans from January 1928 to December 1971, having a higher maximum return for WML. In the same time period the annualized mean returns for WML are also noticeably lower than in the rest of the time periods. In fact, in the first half MKT-RF had annualized mean returns of 9.12 %, making it at face value an equally profitable investment with WML. In the second half however, WML makes up for its prior weak returns by encompassing WML* with mean returns of 23.14 %, which slightly eclipse the 21.27 % mean returns of WML*. If the post-war years were profitable for individual stock Momentum (Barroso & Santa Clara, 2015), then the same argument can be made for industry Momentum, but even more so for risk-managed industry Momentum. WML* has annualized mean returns of 23.44 % in the post-war era, which are the highest mean returns of all the subsamples.

Skewness in panel A for WML in each period is negative and conversely for WML* it is positive in each period. This robustness of positive skewness in WML* returns is important in adding further evidence to the fact that risk-managed industry Momentum truly eliminates the crash risk associated with Momentum. Much the same can be said for kurtosis, in that in each period the statistic is dramatically lower for WML* than for WML. Finally, the Sharpe ratio for WML* is higher in each period than for WML, which adds robustness to the superior profitability of WML* as an investments strategy.

Panel B displays descriptive statistics for four additional time periods which are identical to those used in conjunction with the FF5 model. Noteworthy in panel B is the fact that the first half exhibits minimum returns that are almost identical for WML and WML*. This indicates that out of all the time periods analyzed in this thesis, from July 1963 to September 1989 the largest single negative return month is almost unaffected by risk-managing the maximum drawdowns of Momentum. Mean returns are split in favor of both Momentum strategies. The annualized mean returns for the first half and the post-war period are higher for WML* and conversely the annualized mean returns for the second half and the no-crash period are higher for WML. The annualized mean returns for the first half in particular are very high for WML* (WML) reaching 32.92 % (25.05 %) returns.

Skewness again presents some interesting results at first glance. For the first half WML exhibits positive skewness for the first time in any time period utilized. Careful consideration however, would point to the fact that the first half contains no instances of Momentum crashes, which would be liable to explain this finding. Equally interesting is the notion that skewness for WML* is negative – the only instance of negative skewness for WML* in any of the time periods utilized – in the second half. However, juxtaposed to the first half, the second half contains the crash of 2009. In addition, the halves are rather much shorter due to the constrained full sample time period derived from the FF5 model time period. This means that the crash of 2009 has a higher impact on the return distribution of the data and thus will exhibit negative skewness in the returns. As this time period is indeed the only one with negative skewness in WML* returns, I am quick to dismiss it due to the magnified effect of the 2009 crash in the data. The Sharpe ratio again is unequivocally in favor of WML* over WML, again adding to the evidence suggesting that WML* is indeed more profitable than WML.

In summary of all the descriptive statistics investigated in all of the time periods utilized, it can be argued that the findings in the original descriptive statistics are quite robust. Out of 10 time periods, WML* reduced minimum negative returns in each of them, in all 10 cases WML* reduced kurtosis, in nine out of 10 cases skewness was positive for WML* and in all 10 cases the Sharpe ratio was higher for WML*. In light of these descriptive statistics, it is fair to conjecture that these findings are robust across time periods.

As for the descriptive statistics, robustness tests are performed similarly for the regressions that were run with the initial time periods. Here, the only difference to the regressions run earlier, are the time periods. The time periods identically match those that were utilized in the descriptive statistics and therefore no further added commentary on the nature of the following out-of-sample tests is needed. Table 10 entails FF3 regressions run on WML and WML* in all the alternate time periods and table 11 entails FF5 regressions run on WML and WML* in their respective alternate time periods.

Split Sample - 1st Half

WML	Coeff.	p-value	WML*	Coeff.	p-value
Alpha	0.89	0.00	Alpha	1.18	0.00
MKT-RF	-0.08	0.28	MKT-RF	-0.04	0.23
SMB	-0.19	0.09	SMB	-0.09	0.28
HML	-0.11	0.28	HML	0.00	0.99
Adj. R2	0.05	-	Adj. R2	0.01	-

Split Sample - 2nd Half

WML	Coeff.	p-value	WML*	Coeff.	p-value
Alpha	1.90	0.00	Alpha	1.70	0.00
MKT-RF	-0.20	0.03	MKT-RF	-0.06	0.35
SMB	0.00	0.99	SMB	-0.02	0.93
HML	-0.14	0.61	HML	-0.11	0.50
Adj. R2	0.01	-	Adj. R2	0.00	-

No-Crash

WML	Coeff.	p-value	WML*	Coeff.	p-value
Alpha	1.44	0.00	Alpha	1.46	0.00
MKT-RF	-0.10	0.11	MKT-RF	-0.03	0.38
SMB	-0.07	0.62	SMB	-0.04	0.74
HML	-0.05	0.76	HML	-0.03	0.78
Adj. R2	0.01	-	Adj. R2	0.00	-

Post-War

WML	Coeff.	p-value	WML*	Coeff.	p-value
Alpha	1.52	0.00	Alpha	1.77	0.00
MKT-RF	-0.05	0.44	MKT-RF	0.00	0.98
SMB	0.02	0.93	SMB	-0.02	0.90
HML	0.14	0.57	HML	0.03	0.87
Adj. R2	0.00	-	Adj. R2	0.00	-

Table 10. The table reports the results of the Fama-French three factor model regressions for its sub-sample time-periods. First half covers 1928-1971, second half covers 1971-2015, no-crash is the period 1928-2015 without the crash years 1932 and 2009, and post-war covers 1945-2005. Alpha is the intercept of the regression, MKT-RF is the market return minus the risk-free rate, SMB is the returns to Small minus Big stocks, and HML is the return to High book-to-market minus returns to Low book-to-market. WML is the return to industry Momentum and WML* is the return to risk-managed industry Momentum. All regressions are Newey-West (1987) corrected for heteroscedasticity and autocorrelation.

The first result that should be noted in table 10 is that the alpha intercepts in all the regressions, both for WML and WML*, are significant at the 5 % and 1 % levels as all p-values < 0.00. Thus, all abnormal returns are significant and range between 1.44 % to 1.90 % for WML and 1.18 % to 1.77 % for WML* at monthly levels. The abnormal returns are higher for WML* in each subsample time period excluding the second half, where WML abnormal returns are 1.90 % and WML* abnormal returns are 1.70 %. This is mostly consistent – excluding the second half, where the WML alpha was higher than that of WML* – with the findings in the whole sample time periods in that both industry Momentum and risk-managed industry Momentum produce significant abnormal returns and that risk-managed industry Momentum produces higher abnormal returns than its unmanaged counterpart.

In these shorter subsample time periods, the FF3 model prevails with equally questionable success at explaining the returns to WML and WML*. For the FF3 models explaining returns to WML, only one coefficient is statistically significant for any of the independent variables. MKT-RF has a loading of -0.20 with a p-value of 0.03 in the second half time period. The loading is small in relation to the Alpha intercept of 1.90, but none-the-less this suggests that returns to WML somewhat negatively co-moved with the market during 1971 – 2015. The MKT-RF coefficient was statistically significant for the FF3 model in the whole sample time period, but it seems that as the first half time period exhibits non-significance for MKT-RF, the negative co-movement of WML with MKT-RF is mostly evident during 1971 – 2015. In other words, in times of market upsurges the winner portfolio decreased and the loser portfolio increased and vice versa for market downturns. This would suggest that in the time period examined, loser stocks are those with positive market Beta's and winners are those with negative market Beta's. As before though, the second half time period is the only subsample where market returns are significant as an explanatory variable. For WML* returns, the FF3 model yet again fails to provide any statistically significant coefficients for any explanatory variables. With unilaterally near-zero adjusted R-squared statistics as well, it is safe to say that the FF3 model does a poor job as an asset pricing model in explaining WML* returns.

For the robustness tests concerning the FF5 model (table 11) the first finding to note – just as it was with the FF3 model robustness tests – is the fact that all alpha coefficients in all regressions are significant at the 1 % level, with p-values < 0.00. All abnormal returns are thus significant and range between 1.47 to 2.00 for WML and 1.11 and 2.57 for WML* respectively. Abnormal returns are again larger in every subsample time period for WML* than for WML, with the exception of the second half time period, which is also found in the FF3 model subsample time periods. These findings hence corroborate those found in the whole sample time period in that WML and WML* abnormal returns are positive and statistically significant and that WML* abnormal returns are indeed higher than similar returns to WML in the majority of cases.

In the discussion above concerning the FF5 model regressions on the whole sample time period, it was indicated that the FF5 model does a better job at explaining WML returns, than the FF3 model. This much is true for the robustness tests. Statistically significant coefficients of explanatory variables can be found in two of the four subsample time periods. The first is found in the second half time period, where HML has a negative loading of -0.66 with a p-value of 0.03, exhibiting a relatively high loading when compared to the respective Alpha of 1.47. This finding proposes the notion that returns to growth stocks played a part in contributing to industry Momentum returns in the time period spanning 1971 to 2015. The assertion could be put forward that the loser portfolio consists of value stocks and the winner portfolio consists of growth stocks, as industry Momentum overall exhibits a negative relation with the HML factor in the second half of the sample data. The second subsample time period with statistically significant coefficients is the period with no crashes. Here HML again is significant with a loading of -0.50 and a p-value of 0.05 and now too CMA is significant with a loading of 0.95 and a p-value of 0.03. In the case of HML, before looking at the no-crash period, one could have conjectured that HML gains in explanatory power in more recent years when controlling for more than just the FF3 model factors. However, this conjecture is not as straight forward when viewed in the light of the significance of HML in the no-crash period. This would indicate that HML fairs well also outside recent years as long as there are no crashes that take away from the story of growth stocks explaining WML returns. The second half subsample time period however, includes a crash and this is confounding for the story presented earlier. This only raises further questions as to the varying significance of HML in explaining WML returns in relation to the characteristics of tested time periods. CMA on the other hand presents significance when industry Momentum prevails without crashes. This could be indicative of firms with conservative investments exhibiting Momentum. The loading of CMA is relatively high (0.95) so this could be plausible, but the observation of including crashes in time periods takes away from this theory, as it would seemingly break down when Momentum indeed crashes. This break down could be intuitively attributed to rebounding loser industries making a sudden change to conservative investments instead of aggressive ones, which they have committed to earlier in this scenario. This explanation however, seems highly arbitrary in nature and as with HML, only raises further questions to be answered via further potential research. Finally, the FF5 model leaves much to be desired when it comes to explaining WML* returns. As for the whole sample time period, none of the coefficients for explanatory variables are significant at the 5 % level in the subsample time periods. The closest any coefficient comes to 5 % significance is the MKT-RF factor in the second half time period, where it has a loading of -0.14 with a p-value of 0.06. Even though the factor is close to the cut off rate for statistical significance, the economic magnitude is small in relation to the Alpha coefficient of 1.11. Thus, nothing truly insightful can be said of market returns explaining returns to risk-managed industry Momentum in the second half time period. As such, the findings of WML* producing abnormal returns that cannot be explained by the FF3 or FF5 model remain robust to different time periods.

Split Sample - 1st Half

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	2.00	0.00	Alpha	2.57	0.00
MKT-RF	0.10	0.23	MKT-RF	0.12	0.23
SMB	-0.24	0.27	SMB	-0.24	0.31
HML	-0.36	0.19	HML	-0.29	0.39
RMW	-0.38	0.26	RMW	-0.41	0.27
CMA	0.44	0.22	CMA	0.21	0.58
Adj. R2	0.03	-	Adj. R2	0.01	-

Split Sample - 2nd Half

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.47	0.00	Alpha	1.11	0.00
MKT-RF	-0.24	0.07	MKT-RF	-0.14	0.06
SMB	0.18	0.35	SMB	0.11	0.34
HML	-0.66	0.03	HML	-0.26	0.13
RMW	0.32	0.34	RMW	0.02	0.93
CMA	1.16	0.07	CMA	0.44	0.15
Adj. R2	0.08		Adj. R2	0.04	-

No-Crash

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.67	0.00	Alpha	1.77	0.00
MKT-RF	-0.06	0.51	MKT-RF	-0.01	0.86
SMB	0.04	0.80	SMB	-0.03	0.86
HML	-0.50	0.05	HML	-0.27	0.18
RMW	0.19	0.59	RMW	-0.04	0.85
CMA	0.95	0.03	CMA	0.43	0.11
Adj. R2	0.04	-	Adj. R2	0.01	-

Post-War

	WML			WML*	
	Coeff.	p-value		Coeff.	p-value
Alpha	1.55	0.00	Alpha	1.89	0.00
MKT-RF	0.02	0.84	MKT-RF	0.02	0.79
SMB	0.06	0.75	SMB	-0.03	0.87
HML	-0.35	0.21	HML	-0.23	0.33
RMW	0.13	0.74	RMW	-0.07	0.75
CMA	0.96	0.06	CMA	0.45	0.14
Adj. R2	0.04	-	Adj. R2	0.01	-

Table 11. The table reports the results of the Fama-French five factor model regressions for its sub-sample time-periods. First half covers 1963-1989, second half covers 1989-2015, no-crash is the period 1963-2015 without the crash year of 2009, and post-war covers 1963-2005. Alpha is the intercept of the regression, MKT-RF is the market return minus the risk-free rate, SMB is the returns to Small minus Big stocks, and HML is the return to High book-to-market minus returns to Low book-to-market, RMW is the returns of Robust minus Weak operating profitability portfolios, and CMA is the returns to Conservative minus Aggressive investment portfolios. WML is the return to industry Momentum and WML* is the return to risk-managed industry Momentum. All regressions are Newey-West (1987) corrected for heteroscedasticity and autocorrelation.

9. CONCLUSIONS

Momentum returns have been dated back 212 years to the Victorian age in the United Kingdom, in over 20 years of out-of-sample data, in over 40 countries and in more than a dozen asset classes. Even further, some of the evidence concerning Momentum predates academic research in financial economics, possibly suggesting that the phenomenon has been a part of markets ever since they came into existence. (Asness et al., 2014)

Asness et al. (2014) provides a strong case for utilizing Momentum as an investment strategy. As they point out, Momentum has been shown to prevail in not only individual stocks, but in out-of-sample data expanding outside the realm of traditional individual stock Momentum. This includes industries, where Momentum also succeeds in producing abnormal returns (Grinblatt & Moskowitz, 1999; Pan et al., 2004; Nijman et al., 2004; Du & Denning, 2005). However, even the most skeptic opposition of Momentum have found fault in its negative skewness that is prone to crashes. This is precisely why the findings of Barroso and Santa Clara (2015) are so significant: they manage to decrease the downside effect on Momentum returns by managing its crash risk with realized variances of its daily returns. This risk-management arguably doesn’t rid Momentum of crashes entirely, but it manages to dull down the effects they have on returns. As the methodology of Barroso and Santa Clara is full of potential and real-life implications, it begs for out-of-sample tests, which is why studying their risk-management methodology in industry Momentum is so important. Whether or not this provides evidence of the profitability of risk-managed industry Momentum, the repercussions affect possible implications of trading strategies, the future research on risk-managing Momentum, and the overall importance of industry Momentum.

Risk-managed industry Momentum is profitable in the U.S. stock market. This effectively concludes the research conducted and presented in this thesis. The results that were found rejected the null hypotheses and are remarkably robust to a handful of out-of-sample tests concerning different time periods. These results are interesting not only because they offer up a new contribution to financial academic literature, but also because they have a potential real world impact. It is more than feasible to see risk-managed industry Momentum as an investment strategy for example for mutual funds or hedge funds. After all, there is no shortage of strategies that produce 17.74 % average annualized returns with positive skewness and kurtosis values that indicate near normal distribution of returns. Additionally, the Sharpe ratio of the strategy implemented here (0.89) trumps that of traditional industry Momentum (0.60) by 48.33 %. From an academic point of view, the effectiveness of risk-managing industry Momentum using realized variances of daily returns supports the case of Barroso and Santa Clara (2015). Risk-managing Momentum returns is now a much more widespread phenomenon as its efficacy has been shown not only in individual stock Momentum, but in industries as well. The prevalence of risk-management in both Momentum classes offers up evidence as well for the argument that the source of returns for individual stock Momentum and industry Momentum is the same, which is an issue of heated discussion (Grinblatt & Moskowitz, 1999; Nijman et al., 2004; Pan et al., 2004; Du & Denning, 2005). There is logic in arguing for the source of returns being the same as the same method of risk-management works for both classes of Momentum. What that source may be however, is still a mystery that requires solving.

Suggestions for further research are numerous. Now that risk-managing Momentum has been expanded into industries, different asset classes warrant a look as well. How does risk-managing Momentum in currencies or fixed income securities fare for example? This presents an interesting research question not only because of its real-life applications to trading, but because it would again act as out-of-sample testing for Barroso and Santa Clara (2015). Studying risk-managed industry Momentum in different countries is a natural continuation of this thesis as well. Barroso and Santa Clara conducted out-of-sample tests in 21 different countries in total. Doing the same extensive international testing would arguably be too strenuous a task for a Master's thesis and as such is left for further research at this time. Even further still, using realized variances of daily returns may be used to test risk-management in other strategies that suffer from crash risks. Currencies were mentioned earlier and carry trades in the FOREX market might make for an interesting research topic, as it too suffers from crashes inherent in its negatively skewed return distribution. Is risk-management via realized variances applicable to carry trades? These are just some ideas that would make for suitable future research in the wake of the completion of this thesis.

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