Is Financial Investment a Matter of Skill?

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Empirical Evidence from Asness's et al. Combo Investment Strategy

Moritz Vetter

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– Empirical Evidence from Asness's et al. Combo Investment Strategy

Author: Moritz Vetter

Católica-Lisbon School of Business and Economics

Abstract

I present empirical evidence that Asness's et al. (2013) Combo investment strategy, consisting equally of value and momentum, yields significant returns and Jensen alphas in 13 of 18 markets analyzed. In these markets, Combo yields Sharpe Ratios ranging from 0.42 to 0.93. The market portfolio produces significant returns only in three markets. I conduct a pair-wise bootstrap analysis finding that across 17 of 18 markets the Combo investment conclusively outperforms the market taking into account Sharpe Ratio, skewness and kurtosis. My dissertation further shows that US investors can significantly improve their investment's risk-return profile by investing internationally. My findings question the efficient market hypothesis for two reasons. First, the Combo strategy's risk-adjusted investment performance is better than the market. Second, the strategy cannot be reconciled as a common risk factor. The momentum portfolio is not grounded in fundamental risk and Gerakos and Linnainmaa (2018) present evidence that neither is the value portfolio. My empirical analysis suggests that the theory needs to be recalibrated. While the strong correlation structure of two seemingly unrelated behavioral effects remains a puzzle, my analysis suggests that, under the premises of current theory, financial investment is a matter of skill. An investor can predictably outperform the market without risk exposure to fundamentals and robust to non-parametric simulation.

Abstrato

A presente dissertação apresenta evidências empíricas de que a estratégia de investimento "Combo" de Asness et al. (2013), que é igualmente constituída por valor e momentum, produz retornos significativos e alphas de Jensen em 13 dos 18 mercados analisados. Nestes mercados, à estratégia Combo estão associados Sharpe Ratios que variam de 0.42 a 0.93. O portfólio de mercado produz retornos significativos apenas em três mercados. Uma análise pair-wise bootstrap é realizada, constatando-se que, em 17 de 18 mercados a estratégia Combo supera o mercado no que respeita ao Sharpe Ratio, assimetria e curtose. Esta análise verifica, também, que os investidores americanos podem melhorar significativamente o seu perfil risco-retorno ao investirem internacionalmente. As inferências aqui retiradas questionam a hipótese de eficiência dos mercados por dois motivos. Primeiramente, a estratégia Combo tem um desempenho claramente superior ao do mercado. Segundamente, a estratégia não pode ser reconciliada como um fator comum de risco. O portfólio de momentum não está assente em risco fundamental, e Gerakos and Linnainmaa (2018) apresentam evidências de que o mesmo acontece com o portfólio de valor. A minha análise empírica sugere uma necessidade de recalibração da teoria. Enquanto a estrutura de forte correlação de dois efeitos de comportamento aparentemente não-relacionados permanece um puzzle, a minha análise sugere que, no contexto da teoria existente, o investimento financeiro é uma questão de habilidade, uma vez que o investidor pode previsivelmente obter um desempenho superior ao do mercado sem exposição ao risco fundamental e de forma robusta numa simulação não-paramétrica.

Keywords: Financial Investment, Value, Momentum, Bootstrap

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First, I thank my experiential environment, since I have been born. I have the eternal privilege to have had a loving father and I have a wonderful mother. There is no one like her. I have lived through some moments, which casted enormous personal doubts on my abilities. If it were not for her, my brothers Julius and Felix, and my grandfather (Opi), I would not be here.

As a collective, we seem to glorify self-determination, achievement, and sovereignty of the individual. We often refer to this as the meritocracy. It appears to me like a self-sustaining justification for lack of responsibility for others and one's personal superiority. It conflates uniformly distributed human value with unevenly distributed human economic value. They are not the same. IQ tests come with a standard deviation. I understand everybody who is successful giving in to the narrative. It is a reasonable, but I consider it a post-rationalization. Recent neuroscience provides clear-cut evidence that our imagination forms upon episodic memory. Even our ideas are the product of our experiences and our environment – talk about ownership. This is why I owe for the fortunate experiential environment into which I was born, which shaped me, and of which I am a reflection. Therefore, I bare responsibility for others. I am happy to have written this master's thesis and I hope it is a contribution to academia. I am certain there is more to do. I hope to contribute further to society with my modest capacity. We can create better incentives. We can become a more inclusive society. We can treat people as humans and not solely like economic human resources. We are team human. It starts with us.

Aside from scientific discourse, productive disagreement, and long nights of hard work, I formed many friendships during my time here at Católica Lisbon SBE: Lucas, Daniel, Hiwa, Lilia, Max, Azeddine, Juliana, Gregorio, Rita, Richard, and Francesco to name a few. I will not forget Amelia, the angle of our school. Pierre has become a mentor and a role model.

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Here, I leave with a poem for my mother:

"Com três letrinhas apenas / Se escreve a palavra mãe. / Que é das palavras pequenas, / A maior que o mundo tem." – Heloísa Cid

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1 Introduction

Asness's et al. (2013) Combo investment strategy presents contradicting evidence to Fama's (1970) seminal paper on the efficient market hypothesis (EMH). The EMH and its implications dominate the scientific discussion among financial economists. Two implications in particular are subject to debate: first, since a stock price reflects all available information, stock price changes, or returns, are unpredictable. Since the 1990's, this implication of the EMH is empirically refuted with wide academic consensus (Fama and French, 1988; Lo and MacKinlay, 1988, 1990a). Stock prices do not follow random walks. Second, one cannot find an investment strategy that outperforms the market's risk-return profile, since market prices reflect full information. Hence, there is also no justification for active portfolio management if the EMH holds. This is why I ask in this dissertation: is financial investment a matter of skill?

This is precisely the setup for conflict between academics defending the EMH and investment practitioners that aim to realize returns, which the market does not explain. Thereby, Asness's et al. (2013) paper "Value and Momentum Everywhere" presents a great case-in-point to examine this problem empirically.

Therefore in this dissertation, I assess Asness's et al. (2013) Combo investment strategy. The investment rationale equally combines the well-known value and momentum portfolios. Asness et al. (2013) find a strong negative correlation structure between the two portfolios and provide empirical results that their proposed strategy yields high risk-adjusted returns.

I apply the Combo investment strategy to a set of 18 stock markets, thereby empirically testing the robustness of the results for the four markets in Asness et al. (2013). Studying a wider set of stock markets increases the robustness of the results. I find statistically significant Combo effects across 13 of the 18 markets, while market excess returns only produce significant returns in three markets with the same set of securities. Like Asness et al. (2013), I find negative correlation between value and momentum portfolios. This generates Combo effects because the correlation substantially reduces the volatility of the joint portfolio. Further, I find that Combo returns show better risk-adjusted return profiles in terms of Sharpe Ratio. I show that the market portfolio does not explain the Combo returns, generating strong and significant alphas in all 13 markets with significant returns. I increase the robustness of these results by conducting a bootstrap analysis with 10,000 resampled replicates of Combo and market return pairs. I find that the Combo investment strategy is superior to a passive investment in the market portfolio. All my results are currency-adjusted to the US dollar and hence my results are comparable across markets. I find that US investors can significantly improve their investment performance by investing outside of the United States or internationally.

The Combo investment strategy is well suited for my research question for the following reasons: first, the Combo strategy follows a straightforward investment rationale. Second, Asness et al. (2013) find that the strategy yields high risk-adjusted performance not explained by market returns, hence generating market model alphas. Third, researchers cannot reconcile the momentum strategy with the EMH. This market anomaly may constitute a short-term underreaction to new market information (De Bondt and Thaler, 1985; Jegadeesh and Titman, 1993). Fourth, the value portfolio is under scientific scrutiny. Gerakos and Linnainmaa (2018) find that past changes in market value of equity explain the value portfolio's return, not their book-to-market ratio. Hence, a joint portfolio of momentum and value portfolio cannot be reconciled as a common risk factor. My replication study is valuable because, if such an investment strategy confirms its superior performance to the market over time, meaning it persists, then the second implication of the EMH and further widely accepted models building upon it are seriously in question.

As mentioned, the researchers empirically refute the first implication of full unpredictability in stock price changes. Yet, there are claims that reconcile these findings with the spirit of the EMH. In their introduction, Boudoukh et al. (1994) refer to three schools of thought, which interpret the empirical finding of stock price predictability differently: the loyalists, revisionists, and heretics. The loyalists argue that the EMH holds – meaning markets process information rationally – and that market frictions determine autocorrelations and cross-correlations (e.g. Cohen et al., 1980; Fama and French, 1996; Lo and MacKinlay, 1990b). The revisionists believe the EMH holds, but these correlations are due to changes in fundamentals, e.g. changing market risk premiums over time. For these first two schools of thought, either market anomalies would not exist in truly perfect markets or these anomalies may reveal other common risk factors (e.g. Fama and French, 1992, 1993). However, the heretics claim that markets are not rational and that they over- and underreact to information. This third school of thought claims that market anomalies can in fact constitute market inefficiencies and thereby, through the lens of an investor, investment opportunities. If the heretics are right indeed, then such market anomaly based investment strategies may not only be revealed but may also persist (De Bondt and Thaler, 1985; Jegadeesh, 1990; Jegadeesh and Titman, 1993). I like the picture of these three schools of thought and will refer to it in my conclusion.

First, I will provide a detailed review of the literature on modern portfolio theory, market anomalies, Asness's et al. (2013) paper and all relevant metrics to evaluate investment performance.

Second, I present my stock market sample and the methodology I use to implement the Combo investment strategy across all markets. I analyze a set of 18 stock markets, which comprises countries and regions among the top twenty of either GDP per capita or absolute GDP worldwide. I use Thomson Reuters Datastream's LTOTMK* constituent lists because they comprise between 75-80% of the market capitalization of each particular market. With larger market capitalization, the probability to have a possibility to short sell a stock heavily increases – a feature, which is necessary to build value and momentum portfolios. Large capitalized stocks also yield lower returns on average compared to small capitalized stocks. In addition, I implement a set of constraints to ensure highly reliable results, e.g. by filtering penny stocks, instituting diversification requirements, restricting sample periods, and denying portfolio predictor and weighting optimization. I currency-adjust all data to the US dollar. With these steps, I mitigate the risk of data snooping and ensure conservative and fully comparable results across markets.

Third, I detail the results of my empirical study. In 13 of the 18 markets, I find statistically significant Combo returns, while I only find significant market returns in three markets. In markets with significant Combo effects, the Sharpe Ratios to the US dollar vary from 0.42 to 0.93. Further, I find that the market portfolio does not explain Combo returns within the 18 markets. In all markets where I find statistically significant Combo returns, the linear CAPM time-series regressions also generate statistically significant alphas. The Combo strategy outperforms the market and the market neither explains the Combo returns. Then, I show a detailed picture of the correlation structure among value and momentum portfolios across different markets individually. I carefully analyze their joint correlation over each market's sample period and its variation over time with a three-year rolling window. I find substantial variation in the correlation structure, but this variation does not explain the Combo return. Next, I analyze the persistence of the value and momentum portfolio composition. I find that both portfolios' compositions are stable over time, a fact that one can leverage in practice to reduce transaction costs.

Fourth, I conduct a pair-wise bootstrap analysis to compare the Combo investment with the market portfolio in each market. With this analysis, I quantify the degree of robustness of my prior results. Both, Combo and market returns are not normally distributed and do not follow the same probability distribution. A bootstrap analysis respects that fact. It does not assume a probability distribution or a model and follows only the realized data of the sample. It assigns each month's realized Combo and market return pair the same probability to be drawn and then one draws a replicate of the initial sample size. In this simulation, I draw 10,000 replicates. On these 10,000 resampled versions of the initial data, I calculate the investment performance statistics Sharpe Ratio, skewness, and excess kurtosis. With this information, I compute Combo superiority probabilities, which reflect to what percentage the Combo investment strategy performs strictly better than the market. I find that with fair attention to all metrics, the Combo investment is superior to the market. I run time-series regressions to determine whether the statistically significant alphas persist on the resampled data of the bootstrap simulation. In the bootstrap regression analysis, I find that all prior significant alphas persist.

Fifth, I test two novel strategies. First, I study an international Combo investment by aggregating the 18 markets I study into one universe of stocks. Since all data are currency-adjusted, the approach is straightforward. I find that the international Combo clearly outperforms the market. Further, a US investor significantly improves her investment performance by investing internationally. Second, I test the intersectional Combo investment strategy. In this strategy, I do not separate the predictor screens. I only long stocks, which are both high in value and recent winners, and I short sell stocks that are both low value stocks and recent losers. Among the 11 markets, in which this strategy has significant returns, it achieves alphas varying between 9.7% and 30.8%. In terms of Sharpe Ratio, the intersectional Combo strategy performs comparable to the classic Combo strategy.

Sixth, I conclude with a summary of my findings and an outlook stating extensions for performance improvement and future research opportunities upon the insights of my study. Since I confirm Asness's et al. (2013) main findings, my dissertation questions the second implication of the EMH. I do side with the heretics given that the Combo strategy persists in outperforming the market. My work presents a strong argument to recalibrate the theory. My dissertation provides empirical evidence that an investor can implement a simple rationale to predictably outperform the market without risk exposure grounded in fundamentals. Therefore, I claim financial investment is indeed a matter of skill.

This dissertation is structured as follows: Section 2 provides a picture of the relevant literature. In section 3, I present my data and methodology. In section 4, I present the results of my study. Section 5 shows the results of my bootstrap analysis. In section 6, I study two novel strategies. In section 7, I summarize my findings, conclude, and provide an outlook for future research.

2 Literature Review

In this section, I present the goal of the financial investor. I review portfolio theory. Next, I present the CAPM, the differentiation of market anomalies between common risk factor and market inefficiency. A market inefficiency may constitute an investment opportunity through an investor's lens. I exemplify this with the momentum portfolio. Then, I present Asness's et al. (2013) finding of negative correlation between momentum and value portfolio and their derived investment strategy. Last, I explain the relevant measures that are widely accepted among researchers and practitioners to assess investment performance.

2.1 The goal of the financial investor and portfolio theory

Rational investment behavior implies one unifying principle for all financial investors: every investor aims to maximize her return at the lowest systemic risk exposure and is thus trying to outperform the return of the market. Since the emergence of stock exchanges, investors seek such returns. In addition, researchers inquire to develop portfolio theories and empirically test investment strategies.

There are two major portfolio theory approaches: the traditional theories, namely Dow and Random Walk Theory (Cootner, 1964; Fama, 1965; Samuelson, 1965), and Modern Portfolio Theory (Markowitz, 1952). I focus on the widely adopted and taught Modern Portfolio Theory since Dow's theory merely focuses on price trends and Random Walk Theory states that stock market behavior is fully unpredictable. Both theories are rejected by empirical evidence (Cowles, 1933; Fama and French, 1988; Lo and MacKinlay, 1988, 1990a).

Markowitz (1952) assesses a wide set of portfolios comprised of different risky securities and develops a theory to select the most efficient portfolio. The modern portfolio theory proposes that the most efficient portfolio is mean-variance optimized. Hence, an efficient portfolio yields either the highest return (mean of expected return) at a given level of risk (variance of expected return) or the lowest amount of risk at a given level of return. For a given set of risky assets, for each specified level of return one can minimize the portfolio's variance by changing the weights of all securities in the optimization problem. This process generates the efficient frontier of mean-variance optimized portfolios. Sharpe (1964), Lintner (1965), and Black (1972) find that the market portfolio is mean-variance efficient under a set of specific assumptions by which all investors essentially solve an identical optimization problem.

2.2 CAPM, market anomalies and "risk factor-market inefficiency" differentiation

In financial economics, rational pricing is a core assumption and sets the basis for asset pricing theory. Gordon (1959) proposes the rational asset price of a stock is equal to the sum of all future cash flows that are then disposable for shareholder distribution. Hence, a stock is worth the present value of its future dividends properly discounted conditional to all available information (Grossman and Shiller, 1981). Further, in a Modigliani-Miller (1958) economy, dividend timing is irrelevant and thus a holding period return is the most effective measure for investor's compensation. Therefore, the accurate determination of the required rate of return is important. This calculation is subject to rigorous scientific research. Derived from Markowitz's (1952) modern portfolio theory, Sharpe (1964), Lintner (1965), and Black (1972) find that the market portfolio is mean-variance efficient provided a set of several assumptions. They claim that the capital market line explains the relationship between risk and the required rate of return of a stock and present the Capital Asset Pricing Model[1] (CAPM):

$$E(r_i) = r_f + \beta_i\left[E(r_M) - r_f\right] + e_i \tag{1}$$

The expected return $E(r_i)$ of an asset is explained by the risk-free rate r_f, its market exposure β_i multiplied by the expected market excess return $E(r_m) - r_f$ and a firm-specific deviating error term e_i. In this model, the covariance of the stock's excess return with the market excess return explains the stock's required rate of return. The error term is the stock's specific risk or idiosyncratic random shock risk with a mean of zero. Hence, in a regression one can compute the market beta of a stock that according to Sharpe (1964), Lintner (1965), and Black (1972) determines a stock's expected return, yet with the caveat of controlling or assessing the effect on past returns.

A major implication of CAPM is that a portfolio or stock uncorrelated to the market returns can only yield the risk-free rate or zero, if there is no risk-free asset in the economy, over time. This notion is subject to criticism because it inherently claims that there is only one type of common risk, meaning systemic and undiversifiable. It implies there cannot be any portfolio formed that consistently achieves excess returns unexplained by market risk. Ross (1976) therefore proposes the arbitrage pricing theory (APT) that allows for more types of common risk:

$$E(r_i) = r_f + \beta_{i,k}F_{i,k} + e_i \tag{2}$$

[1] Throughout the thesis, I may refer to the CAPM as market model or SLB model. I use these terms interchangeably.

In this model, the stock return is explained by a vector of sensitivities, the respective β_k, to systematic risk factors F_k, which may include but are not limited to the market risk premium. As opposed to the CAPM, this model allows flexibility and argues that investors choose portfolios on more risk domains than market risk only.

Fama and French (1992, 1993) find that regressions using a market beta have only limited explanatory power for common stock returns when testing the CAPM empirically. They show that two additional portfolios are significant in explaining stock returns. These portfolios are constructed based on size of a stock's market value of equity, known as size or small minus big (SMB) portfolio (see also Banz, 1981), and based on a stock's book-to-market equity, known as value or high minus low (HML) portfolio (see also Rosenberg et al., 1985; Lakonishok et al., 1994). These portfolios have positive excess returns and the market return does not explain them. While the SMB and HML portfolios may not be risk factors of themselves, according to Fama and French, they may be effective proxies for more fundamental risk structures. Therefore, Fama and French argue that these portfolios constitute risk premiums, which aligns their FF3 model with Ross's (1976) APT. Hence, according to Fama and French there are at least three common risk factors.

Some researchers empirically test further risk factors based on fundamental risk proxies, e.g. profitability, investment, and quality factors (Fama and French, 2015; Asness et al., 2019). On the other hand, financial investors aim to create portfolios that produce positive excess returns, which common risk factors do not explain. These prior market anomalies to the CAPM can be reconciled with Ross's (1976) APT. However, the preferred outcome for the financial investor is to find an investment rationale, a clear pattern, or strategy that consistently produces excess returns not explained by risk factors – market anomalies that are not a proxy for fundamental risk and further are not explained by risk factors.

Jegadeesh and Titman (1993) find one such investment strategy referred to as momentum or winners minus losers (WML), grounded in the findings of De Bondt and Thaler (1985). They show that a portfolio taking a long position in stocks with recently high cumulative returns and a short position in stocks with low cumulative returns achieves statistically significant excess returns.

Several researchers provide empirical evidence that an investor can significantly improve the financial performance of the momentum portfolio by slightly adapting or managing the strategy

(George and Hwang, 2004; Blitz et al., 2011; Moskowitz et al., 2012; Barroso and Santa-Clara, 2015).

According to Jegadeesh and Titman (1993), their findings suggest a stock market inefficiency, namely a market underreaction to good news (De Bondt and Thaler, 1985). Carhart (1997) uses the WML factor in explaining mutual fund returns along with the common risk factors along the market excess return, HML and SMB. Yet, there is no scientific agreement that the momentum market anomaly is a common risk factor and thus can be reconciled with Ross's (1976) APT. Since the momentum portfolio is constructed solely on past cumulative stock returns, the portfolio is not grounded in fundamentals.

With regard to common risk factors and investment strategies, there is rigorous scientific discourse about which portfolios may constitute undiversifiable risk or on the other hand signal market inefficiencies and thereby investment opportunities. This dissertation and its scope cannot terminate this debate. I strictly view the possibility whether implementing a simple investment rationale of portfolio construction can predictably outperform the market. If such a pattern is identifiable and the CAPM cannot explain these returns, then the market model is not efficient. Further, if the strategy cannot be modeled as a source of systemic risk, it arguably confirms that portfolio selection and financial investment is a matter of skill.

2.3 Value, momentum, and their negative correlation

Prior to the here examined paper "Value and Momentum Everywhere" (Asness et al., 2013), researchers extensively study the value effect and momentum strategy, first in the US stock market.[2] Fama and French (1998) find a positive risk premium for the value portfolio across twelve of 13 selected stock markets. Prior Chan et al. (1991) find a value premium in Japan. Further, there is evidence that momentum strategies consistently yield positive returns across markets (across Europe: Rouwenhorst, 1998; worldwide: Chan et al., 2000; Griffin et al., 2003; Chui et al., 2010). Further, academics conduct studies explaining stock returns or GDP growth with multiple risk factors or portfolios across markets including HML and WML (Haugen and Baker, 1996; Liew and Vassalou, 2000).

[2] I present these studies in chapter 2.2.

Yet, either these studies examine value and momentum in isolation or they do not assess their correlation structure and joint effect. Asness et al. (2013) are first to study these two portfolios jointly and find strong negative correlation across markets.[3]

The negative correlation structure is astonishing because the momentum strategy is not well reconciled with the EMH since fundamentals do not explain it. In addition, Gerakos and Linnainmaa (2018) find that past negative changes in market value fully carry the HML factor, which strongly suggests a prior market overreaction to information. Hence, two seemingly independent behavioral effects of market inefficiency are strongly correlated.[4]

Aside from the behavioral puzzle, the negative correlation is a generally striking finding for financial investors. Every investor seeks diversification of her portfolio because it can dramatically improve one's risk-return profile. When there is no short selling constraint, both strong positive and negative correlation allow for substantial risk mitigation by combining two portfolios. When there is major positive correlation, an investor diversifies by buying the portfolio with the better risk-return profile and shorts the other. Given there is strong negative correlation, an investor may mitigate her risk exposure by longing both portfolios.

Asness et al. (2013) propose precisely this, given the negative correlation they find between value and momentum and their independently positive return. This is the investment strategy "Combo" they propose:

$$r_{COMBO} = {}^{1}/_{2} * r_{HML} + {}^{1}/_{2} * r_{WML} \tag{3}$$

The Combo portfolio is calculated by equal-weighting value and momentum return. In section 3.2, I describe the construction of the individual value and momentum portfolio.

2.4 Evaluation of Investment Performance

In this subsection, I present the assessment metrics for investment performance that I will use throughout this dissertation. I choose the measures most widely accepted and used among financial economists and practitioners.

The first important measure is the portfolio's mean of excess returns (holding period return above the risk-free rate).[5] Yet, evaluating a portfolio's performance solely on its excess return

[3] Asness et al. (2013) find these effects also across asset classes.
[4] Behavioral models do not assume such a correlation structure (see Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999).
[5] I address important issues like return log-normalization and currency adjustment in section 3.1.

does not take into account the underlying risk of the portfolio. Hence, I present widely used risk adjusted performance measures. First, I present the portfolio's standard deviation. Second, Sharpe (1994) proposes the Sharpe Ratio, which is widely used for comparing risk-adjusted returns:

$$Sharpe\ Ratio = \frac{(r_p - r_f)}{\sigma_p} \tag{4}$$

The Sharpe Ratio presents a portfolio's mean excess return relative to its associated risk. One deducts the risk-free rate r_f from the portfolio's return r_p to compute the excess return. Then, the excess return is divided by the portfolio's volatility represented by its standard deviation σ_p.

Further, an investor aims to create a portfolio that generates positive excess returns, which market returns and its associated variation do not explain. Jensen (1968) therefore presents the Jensen alpha as a metric for investment performance:

$$Jensen\ alpha{:}\ \alpha_p = r_p - r_f - \beta_p(r_M - r_f)] \tag{5}$$

The Jensen alpha α_p is computed in a linear time-series regression with the portfolio's excess returns $r_p - r_f$ as the dependent variable and the market excess returns $r_M - r_f$ as the independent variable. The market beta β_p of the regression presents the portfolio's co-movement with market returns. The Jensen alpha is the excess return of a portfolio that is not explained by exposure to market risk. Therefore, practitioners consider alphas a measure of skill. Given that Fama and French (1992, 1993) propose two additional risk factors in alignment with Ross's (1976) APT, frequently researchers present the FF3 alpha and market, value, size betas in a time-series regression:

$$FF3\ alpha{:}\ \alpha_p = r_p - r_f - \beta_{p,M}\left(r_M - r_f\right) - \beta_{p,V} r_{HML} - \beta_{p,S} r_{SMB} \tag{6}$$

The FF3 alpha presents the portfolio's excess return after controlling for these three types of common risk. Carhart (1997) and Fama and French (2012) use a four factor model including a momentum factor to explain actively managed investment funds' returns. Since momentum is a widely known market phenomenon, it is reasonable to control for it in such a setting because a private investor may just buy an exchange traded fund with a lower management fee tracking momentum on his behalf.

In my dissertation however, it is not adequate to control for either size, value, or momentum effects given the investment strategy I study and given my sample selection. First, I analyze a strategy that combines the value and momentum portfolio, hence value and momentum portfolios in a regression would fully explain its return. Second, since I only study the strategy with large capitalized stocks, a Combo return's explanation by a size factor would either be rationally explained as a spurious coincidence or would have a negative factor loading since small firms show higher returns than large capitalized stocks.

Prior presented measures reduce the risk-return profile to mean and variance. These assumptions are derived from Bachelier (1900) and Osborne (1959) that propose that logarithmic stock price changes, or log returns, are independent and identically distributed, hence follow a normal or Gaussian distribution (or Brownian motion). Mandelbrot (1963) and Fama (1965) find the data show strong leptokurtic (or fat-tailed) distributions and dismiss Osborne's (1959) findings.[6] Therefore, I also present the skewness, the third moment, and excess kurtosis, the fourth moment, of each portfolio. The skewness indicates the return distribution's degree and sign of asymmetry.[7] Positive skewness manifests in a fatter right tail, while negative skewness shows outliers in the left tail, which one associates with a higher frequency of negative outliers. A financial investor generally prefers positive skewness, since outlier events more frequently improve her returns. Moreover, the excess kurtosis indicates the distribution's frequency of extreme outlier event in both tails in comparison to the Gaussian normal distribution. An excess kurtosis below zero draws fewer outlier events than a Gaussian distribution and has flatter tails (referred to as platykurtic). A probability distribution with high positive excess kurtosis indicates a higher frequency of extreme events. All else equal, a risk averse investor prefers a portfolio with lower excess kurtosis.

Throughout the result sections of this dissertation, I will present an portfolio's mean excess return, standard deviation, Sharpe Ratio, and the Jensen alpha and market beta of a linear CAPM time-series regression.

[6] Anecdotal: the US stock market's daily log return on Black Monday (19 October 1987) was an event beyond 16 standard deviations with a probability far below 0,01% since the Big Bang (assuming trading had begun right away) according to the cumulative distribution function of the normal distribution.
[7] In the rare case where skewness is equal to zero, the distribution is symmetric.

3 Data and Methodology

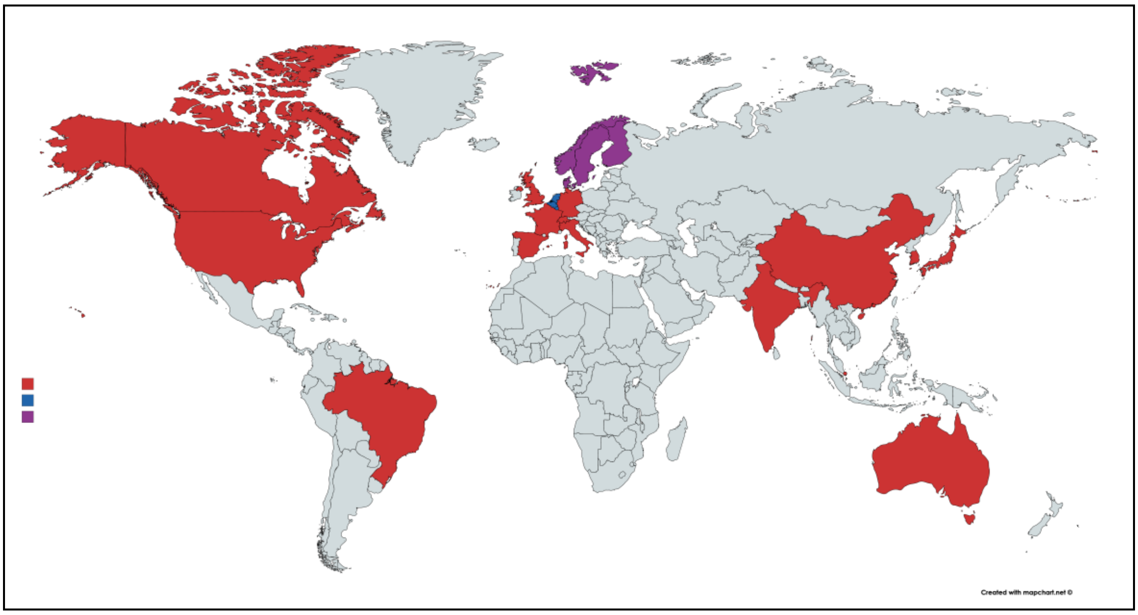
In this section, I present the stock market data I analyze. Then, I describe the portfolio construction methodology of the value and momentum portfolio. Across these steps, I mention several constraints in order to ensure conservative results, which rather under- than overstate the effects I find in my analysis.

3.1 Markets and Data

I conduct my analysis with a sample of 18 stock markets and regions: Australia, Benelux, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Scandinavia, Singapore, South Korea, Spain, Switzerland, United Kingdom, and the United States.

I study these markets because they are either in the top twenty of the world measured by GDP per capita or absolute GDP, according to the International Monetary Fund. Further, each particular stock market's Thomson Reuters Datastream sample contains at least 100 stocks in its constituent list. This is one portion of my approach to ensure a minimum level of diversification. The sample offers an insight whether Combo effects are evident in emerging markets, since I include India, Brazil, and China in my sample. Thus far, the Combo strategy is studied only in developed economies. Here, I show a map of the markets I study:

Figure 1: World map of studied markets highlighted



This figure shows the 16 markets I study marked in red (Australia, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Singapore, South Korea, Spain, Switzerland, United Kingdom and the United States). The regional markets Scandinavia and Benelux are marked in purple and blue.

The map illustrates that I study stock markets in many different regions in order to determine whether Combo effects are robust worldwide.

I retrieve the stock data from Thomson Reuters Datastream with the LTOTMK* country or region codes. The required data to construct the relevant portfolios are available since January, 1981. There is a trade-off between two constraining factors given by sample size (in terms of number of stocks) and sample period within each market.

My primary aim is to assess individual markets and to study the markets for long sample periods. However, the sample size within a few markets is small. I choose to analyze only markets with at least 100 stocks in its LTOTMK* constituent list. This is why I choose to aggregate the Benelux and Scandinavian countries into regional markets. I find this reasonable given that the Benelux countries form a special alliance atop their EU membership and the Scandinavian countries show strongly converging views in public and economic policy. Belgium, the Netherlands, and Luxembourg form the Benelux market. The Scandinavian market includes Denmark, Sweden, Norway, and Finland. The Datastream constituent lists reflect 75-80% of today's total market capitalization within the retrieved market. Some past large companies are not part of each market's sample (e.g. due to corporate consolidation, business failure, or bankruptcy) and newly founded businesses form part of the sample at a later entry date. To maintain a minimum level of diversification within the formed portfolios, I restrict the sample period within each market. I establish the rule that there are a minimum of 25 stocks with a value predictor and 25 stocks with momentum predictor. Once, a market clears the two restriction rules, I let their sample period begin at the beginning of the next 5 year increment. I study all markets until December, 2018. The following table describes the markets I analyze in this dissertation:

Table 1: Description of the 18 markets under investigation:

Market	Continent	High GDPPC	Sample Period	No. of Stocks	Mean Return	St.Dev.
France	Europe	Yes	1981-01 - 2018-12	250	6.08	21.13
Germany	Europe	Yes	1981-01 - 2018-12	247	4.81	20.60
Japan	Asia	Yes	1981-01 - 2018-12	997	2.27	20.50
United Kingdom	Europe	Yes	1981-01 - 2018-12	545	5.04	17.86
United States	North America	Yes	1981-01 - 2018-12	984	6.71	14.94
Canada	North America	Yes	1985-01 - 2018-12	247	5.46	18.32
Scandinavia	Europe	Yes	1985-01 - 2018-12	216	8.76	21.32
Australia	Oceania	Yes	1990-01 - 2018-12	159	5.96	20.34
Benelux	Europe	Yes	1990-01 - 2018-12	222	4.98	18.55
Italy	Europe	Yes	1990-01 - 2018-12	155	0.90	23.62
Switzerland	Europe	Yes	1990-01 - 2018-12	145	6.94	15.94
India	Asia	No	1995-01 - 2018-12	198	5.49	29.70
Singapore	Asia	Yes	1995-01 - 2018-12	98	2.90	22.75
South Korea	Asia	Yes	1995-01 - 2018-12	97	2.69	34.92
Spain	Europe	Yes	1995-01 - 2018-12	115	5.87	22.30
Brazil	South America	No	2000-01 - 2018-12	97	6.89	33.63
China	Asia	No	2000-01 - 2018-12	381	3.06	26.78
Hong Kong	Asia	Yes	2000-01 - 2018-12	130	4.20	20.37

The table describes the markets I study. It includes the market's name, its continent, a GDP per capita categorization, the market's sample period, its number of stocks (after data screening), its annualized mean log return, and standard deviation expressed in percent. All returns are currency-adjusted in USD. The returns are excess returns over the 30-day US T-Bill, serving as the risk-free rate. The table is ordered first by sample period beginning and second by alphabet. I maintain this order throughout.

The table shows the 18 markets I analyze and a set of summary statistics and descriptions. The market excess returns ranging from 0.90% to 8.76% indicate the conservatism of my sample choice. I study markets across multiple continents and also in emerging economies extending the scope of markets studied compared to Asness et al. (2013). Given the diversification requirement, the stock markets have varying sample periods.

I retrieve the following datatypes monthly from Datastream: unadjusted stock price, holding period return index, market value of equity, and common equity. In order to ensure comparability of the results across markets, I download all variables currency-adjusted to the US dollar. Hence, I conduct my analysis through the lens of a US investor.

The unadjusted price solely serves for control purposes. While LTOTMK* constituent lists are stated to be large market capitalized stocks, I ensure there are no stocks trading below $1 at the beginning of the month to mitigate volatility from jump returns due to penny stock effects.

With the holding period return index, I calculate monthly logarithmic, or continuously compounded, returns. The returns include cash flows from dividends. These returns serve to calculate the excess returns of each individual stock and are important to construct not only the momentum portfolio predictor, but also to compute the returns of the value and momentum portfolio.

I retrieve the common equity and market value of equity of each stock in order to calculate the book-to-market ratio as the signal for the value portfolio formation. The market value of equity is also essential to value-weight portfolios.

Many academics find an inverse relation between market value of equity and momentum and value return premiums (Hong et al., 2000; Grinblatt and Moskowitz, 2004; Fama and French, 2012; Israel and Moskowitz, 2012). Rouwenhorst (1998) and Griffin et al. (2003) show that market anomalies yield stronger returns in illiquid markets. Low market capitalized and illiquid equities show higher return premiums. I use only highly liquid, large market capitalized stocks. These steps align my replication study with Asness's et al. (2013) "Value and Momentum Everywhere" and ensure comparable results.

It is important to understand the data structures provided by Thomson Reuters Datastream. For example, Datastream provides return indices rounded to the second decimal point, whether currency-adjusted or not. Therefore, some extreme returns can arise from substantial market value loss over time reducing the return index from its initial 100 into the decimals. This, aside from incomplete data, is the major reason why currency-adjustment should be handled carefully and why data screening is very important. Given that the Korean Won, the Indian Rupee, and Japanese Yen trade highly above ten to the USD, I retrieve their constituents' return indices in their home currency and I currency-adjust the returns manually. Therefore, I divide the return indices by the currency exchange rate of the Federal Reserve Bank at noon on the particular date in question. I screen the stock data for missing and extreme data points, which do not reflect reality. I conclude to drop 85 stocks from the stocks market samples, mainly due to incomplete data. In the end, I analyze 5,286 stocks in 18 markets over periods ranging from 38 to 19 years depending on the market. I assess more than 5.5 million data points in my analysis.

To calculate market excess returns, I retrieve the holding period return indices of the TOTMK* codes for market model regression analyses. These codes constitute the value-weighted market portfolio of large capitalized stocks the particular market is comprised of.

From the Kenneth R. French Data Library, I download the US monthly risk-free rate (30-day US T-Bills). I log-normalize these returns and compute excess returns by deducting the risk-free return from each stock return. I retrieve all data into Excel spreadsheets and conduct my analyses in Python. I gladly share all my Python codes and Excel output files upon request.

3.2 Portfolio Construction

In alignment with Asness et al. (2013), I use the most standard methods to construct value and momentum. This ensures comparability of my results. It further mitigates possible effects of data snooping from excessive predictor optimization. For both measures, I calculate three portfolios with breakpoints at 30% and 70% according to each portfolio's predictor.

To construct the value portfolio, I measure the previous month's book-to-market ratio of all stocks (see Fama and French, 1992, 1993; Lakonishok et al., 1994) within a market. This is the most common and standard approach, although there are more predictive measures (Lakonishok et al., 1994; Piotroski, 2000). Here, I show the calculation of the predictor:

$$Value_{i,t} = {}^{Common\ Equity_{i,t-7}}\big/_{Market\ Value\ of\ Equity_{i,t-1}} \tag{7}$$

Hence, the value predictor for stock i within a market at time t is its book-to-market ratio at time t-1, where its book common equity value is lagged six months compared to the market capitalization to ensure data availability. The companies within the highest 30% measured by book-to-market ratio form the "high" value portfolio, while the 30% of stocks with the lowest ratios are part of the "low" value portfolio respectively.

I form the momentum portfolio according to the most common methodology by calculating the cumulative log return from the last twelve months. I skip the last month to avoid the one-month reversal of the returns (Jegadeesh and Titman, 1993; Fama and French, 1996; Grinblatt and Moskowitz, 2004). Empirical evidence suggests the effect is due to liquidity and microstructure issues (Jegadeesh, 1990; Lo and MacKinlay, 1990a; Boudoukh et al., 1994; Grinblatt and Moskowitz, 2004). I calculate the predictor in the following manner:

$$Momentum_{i,t} = \sum_{j=t-12}^{t-2} r_{i,j} \tag{8}$$

Hence, the momentum predictor for stock i within a market at time t is its cumulative return from time t-2 to t-12. While the 30% of stocks with the highest cumulative return form the "winner" momentum portfolio, I sort the 30% of stocks with the lowest cumulative return into the "loser" portfolio.

I value-weight the portfolios in alignment with Asness et al. (2013). Hence, I calculate the portfolio return like this:

$$r_{p,t} = \sum_{i=1}^{n} \frac{MV_{i,t-1} * r_{i,t}}{MV_{i,t-1}} \tag{9}$$

In the calculation, the portfolio's return at time *t* is the weighted average of the n stocks' returns by their prior month's market value of equity.

It is a common practice to value-weight portfolio returns. Fama and French (1992, 1993) construct their risk factor portfolios likewise and point out that it lowers return variance. It is also an alignment with the natural market portfolio construction. Further, in a comparison of US stock data between the most trusted security price database CRSP and Thomson Reuters Datastream, Ince and Porter (2006) show that equal-weighted market portfolios constructed with CRSP and Datastream data only correlate at 0.66, while the correlation of value-weighted market portfolios of the two databases is 0.998, which constitutes almost identical returns.

Therefore, I proceed with this established portfolio-weighting method. There are further methods like predictor or predictor rank weighting methods, which show increased returns. However, I prefer this method because it maintains conservative results. It also has the advantage that value-weighted portfolios can reduce transaction costs in practice, since the relative weight change between the portfolio constituents is reflected in the change of market value.

4 Replication Results

In this section, I present the results of my quantitative analysis of the Combo investment strategy presented by Asness et al. (2013). First, I show all relevant investment performance metrics. Second, I present the results of my correlation analysis where I show the correlation structure of the value and momentum portfolio separately across markets. I present the joint correlation structure of value and momentum and its variation over time using a three-year rolling window. Last, I assess the portfolio persistence of value and momentum in each particular market, which provide an insight into the accrued transaction costs of implementing the Combo strategy.

4.1 Combo Results across Stock Markets

In this subsection, I show the results of my Combo investment strategy application in the 18 stock markets presented in section 3.1. I report the results of the value and momentum portfolio and their three respective sub-portfolios as well as the Combo portfolio and the market portfolio for direct comparison. Hence, I show the result statistics of ten portfolios in each market. I present the following statistics: first, I show the annualized mean return, the standard deviation as a risk proxy and the Sharpe Ratio. Second, I show the annualized Jensen alpha and the market beta. Third, I show a portfolio's skewness and excess kurtosis. I present the extensive result table A.1 in appendix A. I clearly define all metrics in table A.1 and follow its conventions in all result tables, if I do not explicitly state otherwise.

A detailed look at the long-form table A.1 shows that the Combo investment strategy produces statistically significant mean returns in 13 of the 18 markets studied. On the contrary, market excess returns only produce significant returns in three markets, the US, Scandinavia, and Switzerland. A careful look into the Combo and market performance shows virtually equal Sharpe Ratios in the US, Scandinavia, and Switzerland. Yet, while the Combo strategy has a higher excess kurtosis and hence higher outlier risk compared to market excess returns in these three markets, the Combo investment has a higher and positive skewness. Combo's skewness is better than the market's skewness across all 18 stock markets studied.

A close assessment of the Combo investment's components shows that value and momentum separately perform worse than the Combo portfolio. Only in Italy and Australia is the momentum strategy performing better than Combo and only Singapore the value portfolio is superior to the equal-weighted Combo portfolio, in terms of Sharpe Ratio. It is important to note that the returns in Italy and Singapore are not statistically significant.

Further, when analyzing the value and momentum portfolio performance individually, I find that the value portfolio is superior to momentum in Asian markets, except India and Hong Kong. In European and American markets, except Brazil, the momentum portfolio outperforms HML. These findings are well-aligned with prior research (e.g. Fama and French, 1998; Chui et al., 2010).

When comparing value and momentum returns to the Combo investment strategy, I find that the Combo strategy heavily mitigates the return volatility. For example, in the United Kingdom the standard deviations of the value and momentum portfolios are 13.3% and 16.9% respectively, while the joint Combo portfolio has a volatility of 8.8%. This is due to negative correlation, which I study in detail in section 4.2.

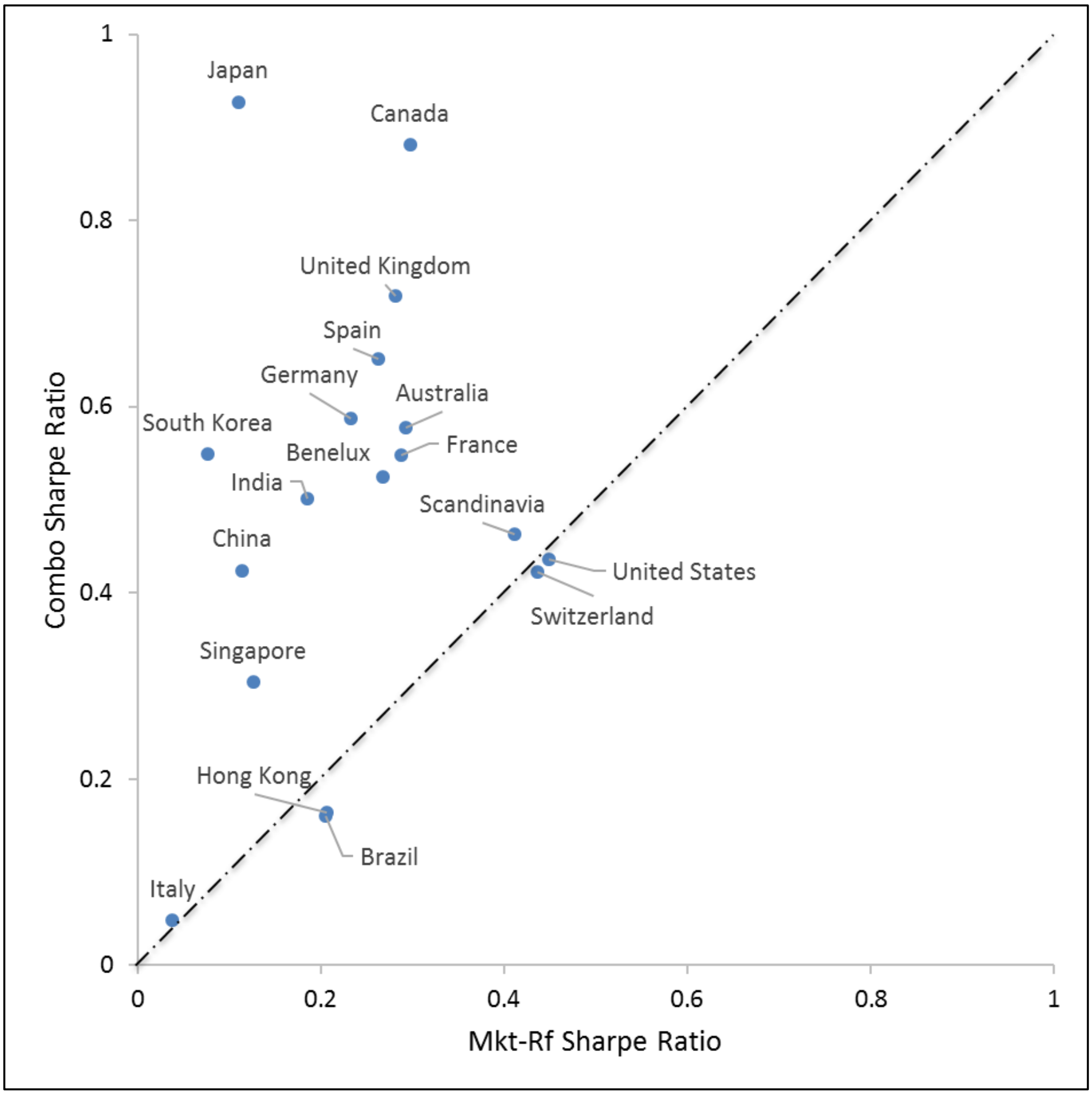
As elaborated in section 2.2, the SLB model predicts that if there is an investment strategy that produces positive returns, these returns are explained by exposure to market risk. Hence, I conduct market model regressions for all the portfolios presented in the table. I find statistically significant positive Jensen alphas in all 13 markets, which realize statistically significant returns. The other five markets also produce positive alphas, however they are not statistically significant. While I find statistically significant market betas in five of the 18 markets, there is no clear pattern detectable. Two of these betas are positive and three are negative. My takeaway is that the correlation structure of Combo and market return is very low. Market returns either do not explain Combo returns or, if they do, only with very low explanatory power.

I find it important to note that all investment portfolios presented are directly comparable to the others given that they are computed in US dollar and presented as excess returns over the 30-day US T-Bill. Hence, the statistics are all adjusted to the same base currency and can be viewed from a US investor's perspective. One finding is that a US investor can improve her investment performance substantially measured in terms of Sharpe Ratio by investing in Combo portfolios outside of the United States. In general, my findings are well-aligned with the results of Asness et al. (2013). I find the same effects across more stock markets and in emerging markets, in India.

A close look at the statistics in Spain show a very high level of kurtosis and skewness. This is due to the stock debacle of the bank Bankia S.A., which came close to failure. Concisely put, in May 2013 a very strong momentum return is generated from short selling Bankia, which at the time had a large market capitalization and therefore heavily affected the return. I find this case to be a good illustration of financial markets. Excluding Bankia S.A. in my analysis, I would consider an error.

For illustration of the performance of the Combo investment compared to market excess returns, I present a Sharpe Ratio mapping:

Figure 2: Sharpe Ratio mapping of Combo and market benchmark



The figure shows the Sharpe Ratios of the Combo investment strategy and market excess returns. The diagonal line serves solely for orientation and intuition. If a marker is above the diagonal, the Combo strategy is superior to the market portfolio in mean-variance terms.

If a country's or region's Sharpe Ratio is above the diagonal line, then the Combo strategy outperforms the market. The map shows that the Combo strategy produces higher Sharpe Ratios in 14 of the 18 markets studied in this dissertation. Especially in Asian markets, except Hong Kong, the Combo strategy is very successful. Generally, I find Combo effects worldwide.

4.2 The Correlation of Value and Momentum

In this subsection, I thoroughly analyze the correlation structure across markets for value and momentum separately as well as their joint co-movement.

Asness et al. (2013) claim substantial positive correlation of value portfolios and of momentum portfolios across different markets, however they do not show these results. Therefore, I compute the correlation matrices among value portfolios and among momentum portfolios separately in order to gain a clear picture of the correlation structures. I present the two correlation matrices of value portfolios and momentum portfolios in tables B.1 and B.2 in appendix B.

These correlation matrices generally confirm Asness's et al. (2013) claim that a country's momentum portfolio is positively correlated to other countries' momentum portfolios. Value portfolios show the same phenomenon.

Especially, momentum portfolios show substantial co-movement. Momentum portfolios show correlations between 0.3 and nearly 0.6. The correlation is stronger, if the markets are regionally related like the European markets. The three emerging markets studied, India, Brazil, and China, show lower correlation with the other countries' momentum portfolios.

Value portfolios are slightly less strongly correlated, but also show substantial co-movement. The correlations across these portfolios vary between 0.1 and 0.5. Here as well, the effect is stronger among regionally related markets and emerging markets show lower correlation.

Second, I analyze the correlation structure of value and momentum within the 18 single markets. I calculate the correlation over the entire sample period. I also compute the arithmetic mean of the correlation of a three-year rolling window and its standard deviation to determine whether I find variation in the value-momentum correlation structure.

Here, I present the table:

Table 2: Value-momentum correlation structure across markets

Market	Correlation	Sample Period		3Y-RW-Mean	3Y-RW-St.Dev.
France	-0.39	1981-01	2018-12	-0.41	0.27
Germany	-0.45	1981-01	2018-12	-0.41	0.30
Japan	-0.59	1981-01	2018-12	-0.47	0.34
United Kingdom	-0.34	1981-01	2018-12	-0.24	0.27
United States	-0.52	1981-01	2018-12	-0.45	0.32
Canada	-0.46	1985-01	2018-12	-0.44	0.21
Scandinavia	-0.24	1985-01	2018-12	-0.37	0.32
Australia	-0.27	1990-01	2018-12	-0.25	0.33
Benelux	-0.39	1990-01	2018-12	-0.41	0.27
Italy	-0.38	1990-01	2018-12	-0.41	0.25
Switzerland	-0.38	1990-01	2018-12	-0.35	0.22
India	-0.36	1995-01	2018-12	-0.30	0.49
Singapore	-0.27	1995-01	2018-12	-0.21	0.23
South Korea	-0.39	1995-01	2018-12	-0.41	0.29
Spain	0.02	1995-01	2018-12	-0.15	0.52
Brazil	-0.45	2000-01	2018-12	-0.45	0.29
China	-0.57	2000-01	2018-12	-0.51	0.28
Hong Kong	-0.53	2000-01	2018-12	-0.42	0.23

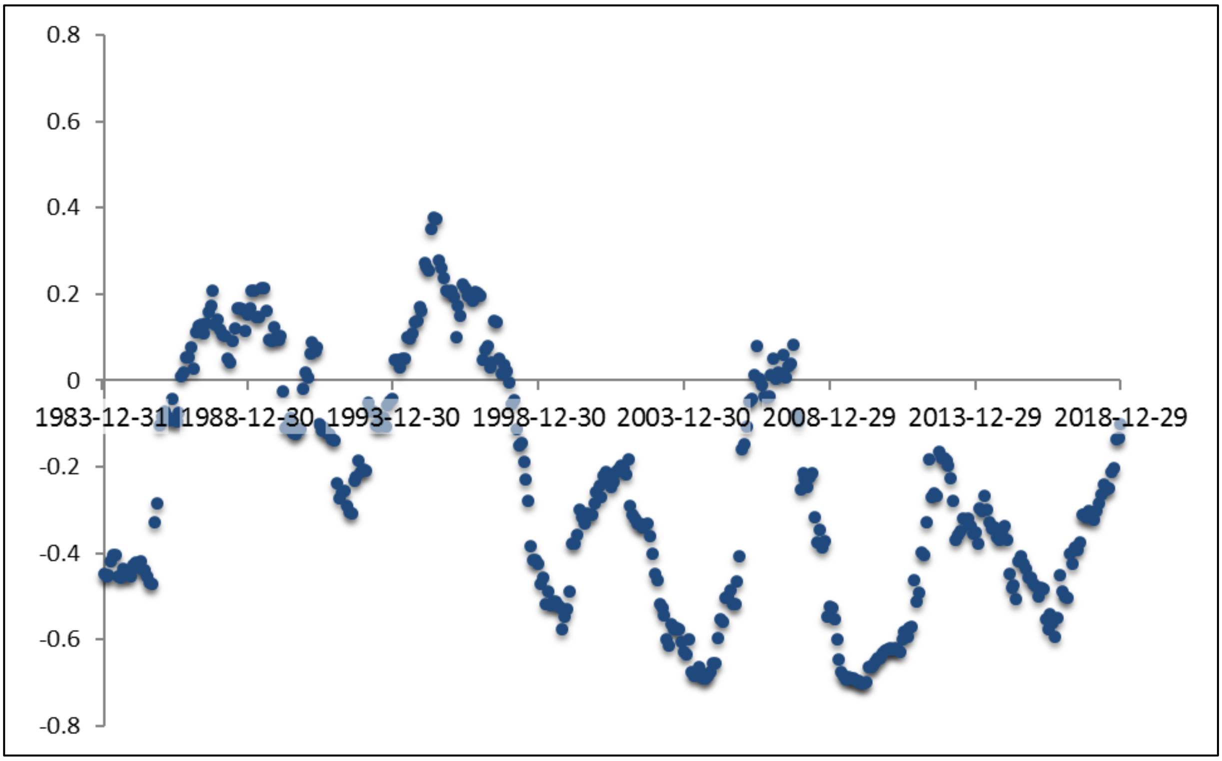
This table shows first the correlation of value and momentum across the entire sample period. Then, I show the arithmetic mean and standard deviation of the three-year rolling window correlation between value and momentum.

An assessment of the table shows strong negative correlation between the value and momentum portfolio across all markets ranging from -0.24 in Scandinavia to -0.59 in Japan over the full sample period. Only in Spain, there is no such correlation structure. There, the portfolios are independent.

The averages of the three-year rolling window assessment are almost equal to the overall correlations. Here, Spain shows slightly negative correlation. Yet, the rolling window analysis shows variation in the correlation structure. I find this variation substantial given the relatively high standard deviation in each market varying from at least 0.21 to 0.52.

In order to gain a better understanding of the correlation structure within a market, I show a scatter plot of the three-year rolling window in the United Kingdom as an example:

Figure 3: Scatter Plot of United Kingdom's three-year rolling window correlation



This figure shows a scatter plot of the three-year rolling window correlation of value and momentum in the United Kingdom over the period from January, 1984, to December, 2018.

The scatter plot does show a few substantial jumps in correlation, which rolling windows can cause, however the plot displays foremost a relatively fluidly changing co-movement structure. The correlation is negative over the majority of time and the rolling window correlation follows a strong autocorrelation instead of varying randomly. I find similar correlation structures as presented in table 2 and in figure 3 across varying rolling windows from one to five year, with more fluidity with increasing rolling window size. I find these phenomena across all markets.

I attempt to use the correlation structure to predict Combo returns. However, there is no correlation between Combo returns and the correlation structure of value and momentum.

Yet notably to take away, the value-momentum correlation structure as a whole strongly mitigates the volatility of the Combo investment strategy and allows for the successful investment in the first place. The negative correlation structure may also allow for dynamically shifting the weights between value and momentum portfolio to enhance the investment performance.

4.3 Portfolio Persistence

Like most academic studies, I focus on gross returns generated by the investment strategy I analyze. In this subsection however, I evaluate whether or not the composition of the longed and short-sold stocks of the value and momentum portfolio is persistent over time. I consider this a simplified proxy for transaction costs, given that when the portfolio composition is not subject to frequent change, it may be cheaper to implement.[8]

I calculate dropout rates as a proxy for the persistence of portfolio composition:

$$Dropout\ Rate_t = \frac{(Stocks\ in\ quantile_{t-1} \cap Not(Stock\ in\ quantile_t))}{Quantile\ size_t} \tag{10}$$

To compute the persistence, I sum the number of stocks that *a)* form part of the particular 30% quantile at time *t-1* and *b)* drop out at time *t* divided by the quantile size at time *t*.

In the following table, I show the dropout rates and their standard deviation for the shorted low value and loser stocks and the longed high value and winner stocks:

Table 3: Dropout rates and variation of value (HML) and momentum (WML) portfolios.

Market	**HML Low**		**HML High**		**WML Lose**		**WML Win**	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
France	5.84	4.35	6.75	4.57	19.28	6.35	19.65	6.46
Germany	6.14	4.64	5.65	4.36	19.22	6.96	18.82	6.08
Japan	7.21	2.78	8.03	2.98	22.19	4.85	20.75	5.01
United Kingdom	4.77	2.67	8.49	3.93	19.68	4.91	19.30	4.37
United States	5.78	2.50	6.73	2.87	20.29	4.41	20.45	4.13
Canada	7.00	4.23	7.37	4.43	19.06	6.63	18.56	6.06
Scandinavia	5.76	3.60	5.96	4.08	19.92	7.06	18.98	6.70
Australia	5.59	4.85	7.58	5.08	19.53	7.13	18.30	7.08
Benelux	5.41	3.52	6.57	3.99	18.03	5.56	18.18	5.65
Italy	6.15	4.97	8.65	7.27	21.37	9.02	19.66	8.92
Switzerland	4.69	3.43	4.54	3.78	19.05	6.83	18.68	6.52
India	5.38	3.27	7.58	4.39	20.00	5.98	18.72	5.85
Singapore	7.59	8.33	11.76	12.55	23.39	11.65	21.96	11.69
South Korea	7.28	5.43	8.16	5.35	21.81	7.90	20.00	8.50
Spain	5.62	5.29	7.89	5.58	19.06	7.74	18.78	7.60
Brazil	6.80	5.29	7.34	4.53	19.84	8.46	19.68	7.78
China	10.08	7.23	14.29	10.04	25.33	9.02	20.96	7.98
Hong Kong	7.05	6.58	7.37	7.73	22.52	10.09	20.40	9.73

This tables displays the dropout rates from the portfolios that as a long-short portfolio form the value (HML) and momentum (WML) portfolio. The first column of each portfolio shows the mean dropout rate, while the second column shows its standard deviation. The values are presented in percent and rounded to the second decimal point.

[8] There are more sophisticated methods to quantify transaction costs (Pontiff, 1996; Shleifer and Vishny, 1997).

The table shows that especially the composition of value portfolio is very stable. The mean of the dropout rates average between only 4.54-4.69% in Scandinavia and 10.08-14.29% in China, which even seems to be a slight outlier. However, the low variation in the composition indicates that transaction cost efforts to maintain the value portfolio are low.

There is more variation in the momentum portfolio composition across markets. The arithmetic mean of the dropout rates for the loser and winner portfolio composition vary from 18.03-18.13% in Benelux to 25.33-20.93% in China. Yet across all markets, less than half of the stocks on average need to be traded. Hence, also the transaction costs for momentum are moderate especially considering the sample selection. The all-over transaction costs necessary to invest in the Combo investment within a universe of large capitalized stocks I consider low to moderate, especially provided a large initial capital stock. Further, low capital investors can implement the strategy with ETFs at low fees, passively tracking the value and momentum portfolios.

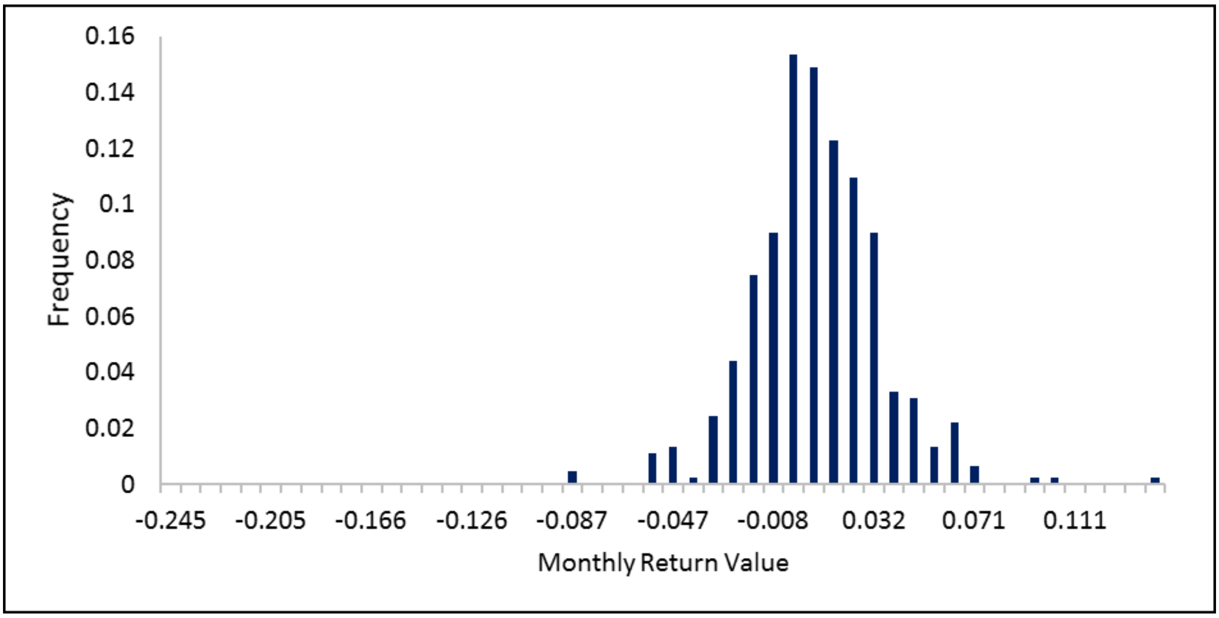
5 Bootstrap Analysis Combo vs. Market

In this section, I conduct pair-wise bootstrap simulations to assess within all 18 markets studied whether the Combo investment strategy is in fact probabilistically superior compared to market excess returns. First, it is important to note that the classic investment performance measures like Sharpe Ratio and regression analysis, as presented in section 4.1, assume that the return data under consideration are normally distributed.

Mandelbrot (1963) and Fama (1965) however find that returns, even when log-normalized, do not follow normal distributions. Of the 180 portfolios I display in table A.1 in appendix A, not a single portfolio's return distribution passed the Jarque-Bera test for normal distribution. I therefore agree with Mandelbrot and Fama.

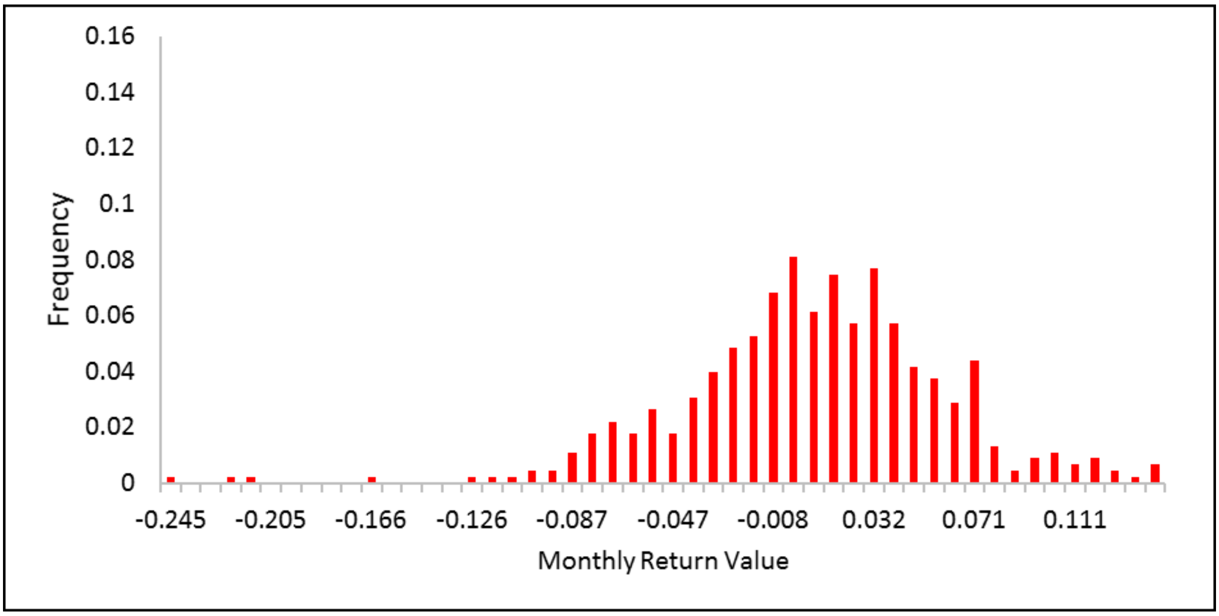
Further, the distributions of the Combo and market portfolio are not equal. Here, I show the histogram of the two portfolios in the United Kingdom to provide an example, which presents a common phenomenon across all markets studied.

Figure 4: UK Combo return histogram



This figure shows the normed return histogram of the Combo investment strategy in the United Kingdom. To allow for an accurate comparison with the market excess return histogram, I compute the minimum and maximum return of Combo and the market individually. Next, I select the respectively more extreme value to compute the range, which I use for both histograms. The histogram has 50 bins and a normed bin width. The frequencies sum to one. The following histogram of market excess returns adheres to the here set conventions.

Figure 5: UK Market excess return histogram



This figure shows the normed return histogram of market excess returns in the United Kingdom.

Comparing the two histograms, it is clear that the market portfolio suffers outlier returns more frequently, especially negative ones. The two histograms visualize my claim that the two portfolios do not follow the same probability distribution and that both portfolios do not follow the normal distribution. There is another issue the histograms do not address. The returns in these histograms are binned. Hence, there is no assessment possibility with regard to their timing and whether hidden correlates among the two portfolios exist. Classic investment assessment measures are linked to the normal distribution hypothesis and further do not link the two portfolios assessed, as opposed to pair-wise simulations. These metrics suffer from model simplification if they are not robust to non-parametric simulations.

Therefore, in order to increase the confidence in my findings, I conduct a bootstrap analysis comparing Combo’s investment performance measures against the market benchmark. My simulations are similar to Kosowski et al. (2006) and Fama and French (2010), who conduct bootstrap simulations to assess actively managed investment fund performance, but only in terms of their achieved alphas. I also assess Combo’s Sharpe Ratio, skewness, and excess kurtosis and compare it with the particular market portfolio. Further, I analyze achieved alphas.

Compared with a simulation like Monte Carlo,[9] the bootstrap analysis is non-parametric and does not assume that there is a particular model in place or that the data follow a particular probability distribution. To conduct a bootstrap analysis or simulation, one draws n bootstrap replicates of the size of the initial sample size. For example, in the United Kingdom, the initial sample runs 456 months and hence has 456 Combo and market return pairs. I assign a uniform probability distribution to each month in a sample. Hence, each month's Combo and market return pair, which is part of my sample for a particular market, is equally likely to be drawn. I randomly draw 10,000 bootstrap replicates consisting of return pairs with a market's initial sample size.[10]

It is therefore possible that a singled out bootstrap replicate does contain the Combo and market return pair of January, 2012, four times, while the return pairs of March and May, 2004, do not form part of the replicate. After I randomly draw the months of a particular bootstrap replicate, I select their respective Combo and market return pairs. The chance that a particular month's Combo and market return pair is not part of one bootstrap replicate is about 36.7%.[11] Then, I compute the Combo and market portfolios' Sharpe Ratio, skewness, and excess kurtosis. I run a market model regression to compute the Jensen alpha. I simulate 10,000 such bootstrap replicates in each market to conduct the bootstrap analysis. Since I study 18 markets, I calculate 180,000 values for each statistic for both Combo and market portfolio. Equally, I run 180,000 regressions to compute the bootstrapped alphas.

With the randomly drawn bootstrap replicates, I calculate probabilities for each investment performance measure. I sum the number of times when, for a bootstrap replicate, the Combo investment performs strictly better on the particular metric compared to the market portfolio. Next, I divide the sum by the number of bootstrap replicates (10,000). I call these probabilities "Combo superiority probabilities" and present them for the Sharpe Ratio, skewness and excess kurtosis.

In the following table, I present the averages of the 10,000 bootstrap replicates' investment performance measures and the Combo superiority probabilities for each given metric.

[9] A Monte Carlo simulation again imposes a normal distribution on the model.
[10] I present my Python code to conduct the pair-wise bootstrap simulation in Appendix C.
[11] The probability that a particular date, and hence return pair, is not drawn in the limit of the sample size at infinity is $\lim_{x\to\infty}(\frac{x-1}{x})^x = \frac{1}{e} = 36.788\%$. This limit is quickly approached. Hence, this number is a good approximate for the probability that a specific date's return pair will not form part of one bootstrap replicate.

Table 4: Bootstrapped Combo superiority probabilities by Sharpe Ratio, skewness and excess kurtosis

Market	Averaged Combo Metrics			Combo Superiority Probabilities		
	Sharpe Ratio	Skewness	Kurtosis	Sharpe Ratio	Skewness	Kurtosis
France*	0.16	0.73	6.70	87.36%	98.13%	3.60%
Germany*	0.17	1.24	7.02	92.43%	99.96%	0.64%
Japan*	0.27	0.27	2.46	99.94%	72.88%	0.30%
United Kingdom*	0.21	0.28	2.49	96.79%	96.36%	38.98%
United States*	0.13	0.63	3.71	47.18%	99.99%	36.86%
Canada*	0.25	0.27	1.67	98.88%	99.67%	92.58%
Scandinavia*	0.13	1.63	9.81	57.88%	99.89%	0.80%
Australia*	0.17	-0.09	2.54	86.82%	91.37%	46.01%
Benelux*	0.15	0.66	3.24	81.80%	99.99%	72.24%
Italy	0.01	-0.02	3.71	52.81%	67.69%	1.94%
Switzerland*	0.12	0.41	2.65	47.77%	99.90%	11.03%
India*	0.15	1.07	8.07	88.11%	94.83%	1.37%
Singapore	0.09	0.52	6.35	72.93%	90.54%	7.51%
South Korea*	0.16	0.24	3.17	94.72%	55.87%	56.55%
Spain*	0.20	4.77	57.16	93.84%	92.44%	1.79%
Brazil	0.05	-0.05	2.19	44.55%	87.47%	15.98%
China	0.12	-0.05	2.43	82.64%	76.11%	18.36%
Hong Kong	0.05	0.00	1.90	44.71%	95.12%	19.56%

This table shows the arithmetic means (averages) of investment performance measures of the 10,000 bootstrap replicates, namely Sharpe Ratio, skewness and excess kurtosis. I provide superiority probabilities comparing Combo with the market portfolio. A 90% value denotes that the Combo statistic is strictly better than the market upon 9,000 of the 10,000 generated return pair bootstrap replicates. This means either Combo has a higher Sharpe Ratio or skewness or lower kurtosis compared to the market portfolio. I add a star to the markets that generate statistically significant Combo returns and Sharpe Ratios in table A.1 in Appendix A.

Table 4 shows the following results: first, given the diverting third and fourth moment from the normal distribution, the averaged bootstrapped Sharpe Ratio of Combo plummets to some degree across all markets. Second, skewness and excess kurtosis remain fairly constant to their initial statistics, except in Spain. This is likely due to the 36.7% chance of each replicate that the extraordinary Combo outlier return, which I discussed in section 4.1, is not drawn.

Yet, the superiority probabilities show that the Combo investment performs very well compared to the market benchmark in terms of Sharpe Ratio. Only in six markets, the bootstrap analysis provides rather inconclusive results ranging between 44-58% whether Combo outperforms the market adjusted for risk. In Singapore, this probability is above 72% and in all other markets above 80%.

Combo's skewness superiority probabilities show even better results across markets. Compared with the market portfolio, Combo's return distribution has a higher likelihood that extreme outlier returns are positive. In South Korea, the probability is only about 56%. However, South Korea's Combo portfolio shows a high probability to have a better Sharpe Ratio than the market and also an inconclusive probability for excess kurtosis. Hence, also in South Korea the Combo investment is superior to the market accounting for the probabilities of all metrics. In terms of the frequency of outlier events measured with excess kurtosis, the Combo investment performs inferior to the market. In twelve markets, Combo's superiority probability to have lower kurtosis than the market is below 30%.

Due to the much better skewness however, the Combo investment strategy has a higher likelihood for outliers to be positive. Combo also yields lower volatility, as seen exemplified in the histogram comparison above, and a better risk-adjusted return profile shown by the Sharpe Ratio assessment. Therefore, I evaluate the Combo investment to be superior to the market portfolio across all markets studied. Only in Italy, I cannot draw a definite conclusion.

Further, I conduct market model regressions on the bootstrapped return pairs, like Kosowski et al. (2006) and Fama and French (2010) do similarly to assess mutual fund performance. The difference in assessing bootstrapped alphas compared with classic alphas is the following: in a linear regression on past returns, the regressed alpha has its significance level due to its linear regression's p-value, which indicates the probability that the estimator is non-zero. In a bootstrap analysis however, the p-value is computed differently, which I show in this formula.

$$pvalue = 1 - \frac{\sum_{i=1}^{n}(alpha_i > 0)}{n} \tag{11}$$

Here, i is a bootstrap replicate, n the size of the bootstrap simulation and $alpha_i$ a particular bootstrap replicate's alpha. The alpha is the intercept of a linear CAPM time-series regression with heteroscedasticity adjusted standard errors. In a bootstrap analysis with n bootstrap replicates, I conduct n regressions and sum all regressions where the bootstrap replicate i's alpha is larger than zero. Next, I calculate a fraction dividing the number by the bootstrap size n. Last, I subtract this fraction from one to calculate the bootstrapped *p-value*. Hence, this p-value is a one-sided test statistic providing a probability that the alpha is zero or negative. It is not equivalent to the non-zero p-value computed in a linear regression. They express probabilities of two different hypotheses. As prior in the analysis, I draw 10,000 bootstrap replicates of Combo and market return pairs and then run CAPM regressions explaining Combo returns with market returns.

In this table, I show the average annualized alphas of the 10,000 bootstrap replicates and their bootstrapped p-values.

Table 5: Bootstrapped alphas and p-values of the Combo strategy

Market	Annualized Bootstrapped Alpha	p-value
France*	5.63	0.001
Germany*	6.54	0.000
Japan*	7.76	0.000
United Kingdom*	6.52	0.000
United States*	3.71	0.002
Canada*	7.87	0.000
Scandinavia*	6.23	0.001
Australia*	5.01	0.003
Benelux*	6.23	0.003
Italy	0.50	0.414
Switzerland*	4.42	0.013
India*	7.36	0.007
Singapore	3.85	0.061
South Korea*	8.07	0.004
Spain*	13.65	0.000
Brazil	1.72	0.267
China	4.00	0.038
Hong Kong	1.70	0.243

This table shows the arithmetic mean of the Combo investment strategy's annualized Jensen alphas generated from the 10,000 bootstrap replicates. The p-values are bootstrapped and one-sided meaning they reflect the probability that the alpha is zero or smaller. This one-sided p-value does not assume a probability distribution and only follows the realized returns of the particular sample. This p-value is not comparable to a two-sided p-value from a linear regression, which provides the probability whether an estimator is non-zero.

The average of all bootstrap replicates' alphas in all markets studied are positive. I find that the bootstrapped alphas in 14 markets have a p-value below 0.05. Hence, the bootstrapped probability is below 5% that that the Jensen alpha is zero or negative given the resampled data from past realized return pairs.

Within the 14 markets with p-values below 0.05, the mean of annualized bootstrapped alphas varies between 3.7% in the United States and 13.65% in Spain. The bootstrap CAPM regression analysis confirms the findings from section 4.1. Combo returns produce statistically significant positive alphas and market returns do not explain them well.

The bootstrap analysis provides more empirical evidence that the performance of the Combo portfolio is in fact better than the market across all markets studied, with an inconclusive exception in Italy. Further, the bootstrap regression analysis adds additional robustness to the findings of section 4.1 given that non-parametric simulations confirm the results across markets.

6 Novel Strategies

In this section, I present the results of two novel strategies. First, I merge the 18 markets studied into one aggregate stock universe and study an international Combo strategy. Second, I investigate a strategy, in which I screen the particular market for value and momentum, and I only long stocks that are both high in value and past winners. Further, I short sell stocks, which are low in value and past losers. I call this strategy intersectional Combo.

6.1 International Combo

First, I present the international Combo strategy. Here, I unify the 18 stock markets I study throughout this dissertation into one aggregate stock market. Since all the data are currency-adjusted to the US dollar, I can conduct an aggregate global market analysis. Next, I follow the steps to compute the value, momentum, and Combo portfolio as previously. Within this aggregated market, I calculate the value and momentum predictor, sort the stocks into the particular portfolio, and compute the value-weighted return of each the value and the momentum portfolio. Then, I calculate the equal-weighted Combo portfolio.

In order to conduct market model regression analyses on the different portfolios, I calculate a value-weighted market portfolio of the 18 markets I study serving as the international market excess return portfolio of large capitalized stocks.

Here, I show the table of the international Combo with the statistics as presented in table A.1.

Table 6: International Combo strategy results broken down by value and momentum

Stock Market: Global		Sample Period:		1981-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	1.01	2.50	**6.15**	**5.14**	-2.36	2.39	5.02	**7.38**	**6.26**	4.51
p-value	*0.697*	*0.320*	*0.027*	*0.008*	*0.459*	*0.305*	*0.071*	*0.007*	*0.000*	*0.067*
St.Dev.	16.04	15.47	17.13	11.94	19.68	14.38	17.12	16.89	8.13	15.15
Sharpe	0.06	0.16	0.36	0.43	-0.12	0.17	0.29	0.44	0.77	0.30
Alpha	**-3.49**	**-1.92**	1.61	**5.10**	**-7.43**	**-1.70**	0.52	**7.94**	**6.52**	0.00
p-value	*0.000*	*0.008*	*0.214*	*0.011*	*0.000*	*0.013*	*0.700*	*0.004*	*0.000*	*1.000*
Mkt Beta	**1.00**	**0.98**	**1.01**	**0.01**	**1.12**	**0.91**	**1.00**	-0.12	-0.06	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.029*	*0.000*	*0.000*	*0.000*	*0.106*	*0.177*	*0.000*
Skewness	-0.65	-0.95	-0.92	0.31	-0.43	-0.86	-0.89	-0.20	0.53	-0.81
Kurtosis	1.71	3.22	4.66	2.60	3.57	2.95	2.20	2.10	11.07	2.29

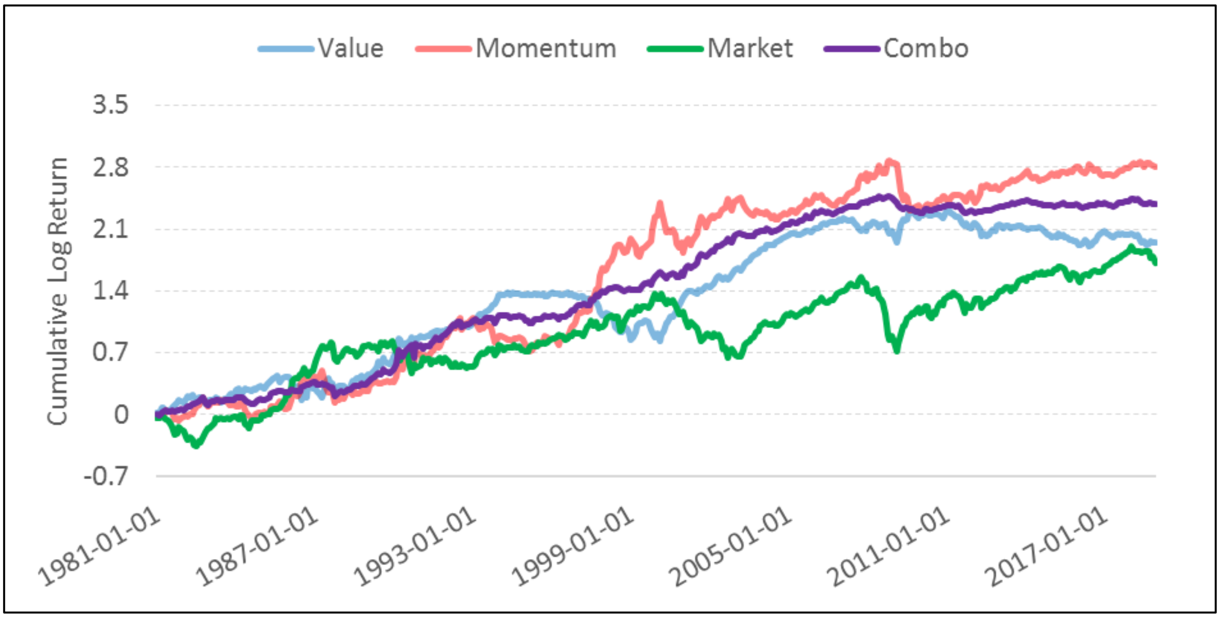
This table shows Combo investment strategy results of the aggregate global market comprised of the stocks of the 18 stock markets presented in section 3.1 and analyzed in section 4.1. I present the results broken down by value and momentum portfolio with their three sub-portfolios as well as the Combo investment strategy and market excess return. All statistics and values follow the conventions set in the extensive result table A.1 in Appendix A.

The international Combo strategy shows a strong performance over the 38-year sample period. With a Sharpe Ratio of 0.77, the strategy clearly outperforms the market, which does not produce statistically significant returns. The Combo returns are not explained by the market. While the Combo strategy's market beta is negative, it is not statistically significant. The Combo investment yields a statistically significant Jensen alpha of 6.52%.

The strategy yields a lower volatility than both the value and momentum portfolio individually due to a value-momentum correlation of -0.4.

To illustrate the risk-return profile of the international Combo investment strategy compared to the market and its components value and momentum, I plot their cumulative continuously compounded return over the sample period.

Figure 6: Cumulative returns of international Combo, its components, and the market[12]



This plot shows the cumulative log return of the international Combo portfolio and its components, value and momentum, over the sample period studied from January, 1981, to December, 2018.

The plot shows that the Combo investment yields substantially less volatile growth over time compared to both its components value and momentum. The market portfolio does not only generate a lower cumulative return, it also shows significant negative returns over short periods, which constitute strong negative outlier risk. Further, the international Combo strategy offers a US investor a significant improvement for her investments compared with the US market and

[12] For intuition, each continuously compounded return of roughly 0.7 (-0.7) constitutes a doubling (halving) of the initial investment. Presenting the cumulative return continuously compounded linearizes the result and is therefore more effective.

US Combo in mean-variance terms. Investing in the international Combo over the last 38 years increases the initial investment more than eleven times with a long-short neutral portfolio.

6.2 Intersectional Combo

In this subsection, I present a second novel strategy. The value and momentum portfolio are both screening one universe of stocks and then based on their predictor, boot-to-market ratio or cumulative return, sort the stocks into portfolios.

The idea of the intersectional Combo investment strategy is not to equal-weight these two portfolios, as the classic Combo strategy does, but to screen the universe of stocks jointly with both criteria. Hence, I conduct a positive and a negative screen. I check whether a stock is both high in value and a past winner in terms of momentum. Such stocks, I long in the intersectional Combo portfolio. I short stocks that are both low in value and recent losers. By construction, the portfolio is less diversified, yet I assess each stock on both criteria.

This strategy yields the following results, which I show in this table:

Table 7: Intersectional Combo results across markets

Market	France	Germany	Japan	United Kingdom	United States	Canada	Scandinavia	Australia	Benelux
Mean	**22.01**	**19.15**	**18.36**	**13.75**	**9.33**	**16.39**	7.40	**12.50**	**15.20**
p-value	0.000	0.000	0.000	0.000	0.003	0.001	0.151	0.009	0.006
St.Dev.	32.04	27.75	21.25	20.54	19.13	29.57	30.05	25.67	30.07
Sharpe	0.69	0.69	0.86	0.67	0.49	0.55	0.25	0.49	0.51
Alpha	**22.79**	**20.04**	**18.74**	**13.88**	**9.71**	**17.69**	8.39	**12.18**	**16.84**
p-value	0.000	0.000	0.000	0.000	0.002	0.001	0.127	0.013	0.004
Mkt Beta	-0.13	-0.19	**-0.17**	-0.03	-0.06	**-0.24**	-0.11	0.05	**-0.33**
p-value	0.310	0.059	0.006	0.773	0.502	0.013	0.282	0.473	0.025
Skewness	0.67	0.49	0.08	0.44	-0.05	0.48	0.77	-1.40	1.22
Kurtosis	4.40	2.96	1.37	3.02	3.43	3.26	3.56	12.46	4.75

Market	Italy	Switzerland	India	Singapore	South Korea	Spain	Brazil	China	Hong Kong
Mean	3.55	**15.46**	12.73	**12.34**	15.37	**28.87**	8.92	11.27	5.89
p-value	0.561	0.002	0.096	0.045	0.113	0.006	0.348	0.080	0.385
St.Dev.	32.83	27.14	37.44	30.11	47.47	50.95	41.44	28.09	29.55
Sharpe	0.11	0.57	0.34	0.41	0.32	0.57	0.22	0.40	0.20
Alpha	3.49	**17.06**	12.26	**12.66**	15.82	**30.82**	9.18	10.86	6.04
p-value	0.570	0.001	0.113	0.039	0.103	0.005	0.344	0.092	0.397
Mkt Beta	0.07	-0.23	0.08	-0.11	-0.17	-0.33	-0.04	0.13	-0.03
p-value	0.469	0.068	0.475	0.472	0.221	0.084	0.685	0.136	0.853
Skewness	-0.25	1.09	0.39	0.03	0.20	6.38	-2.32	0.47	-0.52
Kurtosis	2.40	5.87	2.42	3.78	2.93	67.42	21.07	1.49	2.22

This table shows the results of the intersectional Combo investment strategy. It longs only stocks, which form part of the top value and momentum quantile, and shorts stock that are in both the value and momentum bottom quantile. All statistics and values follow the conventions set in the result table A.1 in Appendix A.

The intersectional Combo strategy shows very strong performance in terms of its annualized mean return, but it also adds significantly more volatility compared to the regular Combo strategy. It is important to note that strategies can be scaled by increasing the net equity exposure, which is usually normed to be each 100% long and short. Thereby, the net equity exposure is 200% and a portfolio is long-short neutral. Scaling the net equity exposure increases the return and volatility equally, but skewness and excess kurtosis remain unaffected by design of the measures. Hence, it is careful to compare also the Sharpe Ratios of the regular Combo strategy to the intersectional Combo strategy rather than relying only on high annualized returns and alphas. Across markets, the intersectional Combo performs roughly equal to the regular Combo strategy in terms of Sharpe Ratio. In nine of the 18 markets, the intersectional Combo reaches a better result and vice versa. The intersectional Combo strategy offers a good risk-return profile comparable to the regular Combo and better than the market portfolio.

7 Conclusion

In this dissertation, I apply the Combo investment strategy proposed by Asness et al. (2013) in 18 stock markets. I find that the strategy generally performs better than the market across all countries and regions I study. I show that market returns are not significantly explaining Combo returns, which produces significant alphas in 13 of 18 markets. I add robustness to my findings by conducting a bootstrap analysis, which quantifies probabilities reflecting Combo's superiority over the market portfolio. Taking all bootstrapped metrics into account, my analysis shows that Combo returns outperform the market portfolio across all markets studied, except providing an inconclusive result in Italy.

To stay in the picture of Boudoukh's et al. (1994) schools of thought of loyalists, revisionists, and heretics, I like to take a side in my conclusion. I study a strategy that is a clear cut example of an investment, which cannot be reconciled to be a common risk factor for two reasons. First, given that the momentum market anomaly does not reflect a proxy for fundamental risk, it cannot be considered a common risk factor. Second, Gerakos and Linnainmaa (2018) provide evidence that also the value portfolio is fully explained by past changes in market value. In contrast to momentum, this phenomenon demonstrates a long-term overreaction to information, which is exploited by the value portfolio. Since the two individual components of the Combo portfolio are not grounded in fundamentals but predictable due to past price/market value changes, their joint portfolio can neither be considered a common risk factor in my view. Therefore, I view my results as empirical evidence of a market inefficiency based investment strategy clearly outperforming the market portfolio. Therefore, I do side with the heretics. I argue that there are market inefficiencies, which a skilled investor can exploit. Therefore, I answer the question of my dissertation in the affirmative. I claim financial investment is a matter of skill.

Intentionally, I choose to implement the strategy with strong conservatism. My sample selection, my constraint to study only large capitalized stocks, my choice to deny predictor and portfolio weighting enhancement, and penny stock exclusion allow me to clearly and unequivocally answer my research question. Given a different academic objective however, one may loosen these constraints in order to optimize the investment performance. One such approach may be to dynamically volatility-scale the strategy or to shift portfolio allocation between value and momentum. Taking a close look at the cumulative return plot (figure 6) in section 6.1, I am fairly certain that one can find a variable to time portfolio allocation between value and momentum portfolio.

In addition, Gerakos and Linnainmaa's (2018) finding draws a relevant opportunity for further academic scrutiny. If their finding is confirmed, then value and momentum are sheer asymmetric behavioral reactions to market information. The value premium is explained by a market overreaction to bad information and momentum by an underreaction to good information, which both can be exploited individually. Thus far, there is no scientific understanding why these two behavioral reactions show correlation, especially of such profound magnitude. In 17 of the 18 markets studied, I find negative and often strongly negative correlation between the two portfolios. It is this correlation structure, which strongly contributes to Combo's high risk-adjusted returns, since it substantially reduces its volatility. Understanding the origin of the correlation structure and providing a testable and empirically solid behavioral model explaining the effect are profound future research endeavors.

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Appendix A: Long-form Result Table

Table A.1: Combo investment strategy results broken down by value and momentum

Stock Market: France		Sample Period:		1981-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	3.03	3.40	5.68	2.65	-2.02	3.54	7.09	**9.11**	**5.88**	6.08
p-value	*0.384*	*0.331*	*0.203*	*0.385*	*0.633*	*0.302*	*0.063*	*0.005*	*0.001*	*0.076*
St.Dev.	21.49	21.57	27.51	18.77	26.05	21.16	23.49	20.12	10.72	21.13
Sharpe	0.14	0.16	0.21	0.14	-0.08	0.17	0.30	0.45	0.55	0.29
Alpha	-2.51	-2.47	-1.40	1.10	**-8.82**	-2.22	1.38	**10.21**	**5.66**	0.00
p-value	*0.104*	*0.033*	*0.489*	*0.705*	*0.000*	*0.048*	*0.512*	*0.002*	*0.001*	*1.000*
Mkt Beta	**0.91**	**0.97**	**1.16**	**0.25**	**1.12**	**0.95**	**0.94**	**-0.18**	0.04	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.003*	*0.285*	*0.000*
Skewness	-0.83	-0.72	-0.63	0.14	-0.96	-0.66	-1.63	-1.65	0.77	-0.72
Kurtosis	2.29	1.99	2.24	3.78	3.84	1.85	9.92	18.03	7.48	1.74

Stock Market: Germany		Sample Period:		1981-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	1.99	2.85	6.82	4.83	-1.65	3.39	5.55	**7.20**	**6.01**	4.81
p-value	*0.611*	*0.444*	*0.083*	*0.081*	*0.706*	*0.357*	*0.124*	*0.037*	*0.000*	*0.150*
St.Dev.	24.14	22.95	24.21	17.07	27.02	22.66	22.21	21.30	10.24	20.60
Sharpe	0.08	0.12	0.28	0.28	-0.06	0.15	0.25	0.34	0.59	0.23
Alpha	**-3.22**	**-2.29**	1.76	4.98	**-7.14**	-1.62	1.01	**8.15**	**6.56**	0.00
p-value	*0.034*	*0.034*	*0.328*	*0.079*	*0.001*	*0.183*	*0.566*	*0.019*	*0.000*	*1.000*
Mkt Beta	**1.08**	**1.07**	**1.05**	-0.03	**1.14**	**1.04**	**0.95**	**-0.20**	**-0.11**	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.575*	*0.000*	*0.000*	*0.000*	*0.020*	*0.006*	*0.000*
Skewness	-0.61	-0.76	-0.60	0.15	-0.90	-0.82	-0.49	0.08	1.35	-0.63
Kurtosis	2.12	2.80	2.62	2.87	5.89	2.51	1.76	7.68	7.95	1.53

Stock Market: Japan		Sample Period:		1981-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	-5.47	1.25	**7.80**	**13.27**	-1.75	-0.08	0.10	1.85	**7.56**	2.27
p-value	*0.133*	*0.696*	*0.021*	*0.000*	*0.642*	*0.981*	*0.978*	*0.559*	*0.000*	*0.495*
St.Dev.	22.42	19.81	20.83	15.95	23.24	19.53	22.31	19.52	8.16	20.50
Sharpe	-0.24	0.06	0.37	0.83	-0.08	0.00	0.00	0.09	0.93	0.11
Alpha	**-7.84**	-0.83	**5.86**	**13.70**	**-3.95**	**-2.14**	-2.15	1.80	**7.75**	0.00
p-value	*0.000*	*0.405*	*0.001*	*0.000*	*0.047*	*0.027*	*0.154*	*0.574*	*0.000*	*1.000*
Mkt Beta	**1.04**	**0.92**	**0.86**	**-0.19**	**0.97**	**0.91**	**0.99**	0.03	**-0.08**	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.666*	*0.001*	*0.000*
Skewness	-0.09	-0.03	0.24	0.23	0.16	-0.08	-0.12	-0.36	0.28	0.06
Kurtosis	1.84	1.42	1.05	4.95	1.60	1.02	1.47	3.11	2.58	0.98

The Table continues on the next page …

Stock Market: United Kingdom	Sample Period:	1981-01	to	2018-12						
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	3.63	1.89	**7.37**	3.74	-2.07	4.82	**6.84**	**8.90**	**6.32**	5.04
p-value	*0.209*	*0.554*	*0.027*	*0.083*	*0.579*	*0.100*	*0.029*	*0.001*	*0.000*	*0.082*
St.Dev.	17.83	19.74	20.53	13.29	22.98	18.08	19.25	16.93	8.79	17.86
Sharpe	0.20	0.10	0.36	0.28	-0.09	0.27	0.36	0.53	0.72	0.28
Alpha	-1.03	**-3.37**	2.26	3.29	**-7.76**	0.02	1.98	**9.73**	**6.52**	0.00
p-value	*0.343*	*0.002*	*0.168*	*0.137*	*0.000*	*0.982*	*0.170*	*0.001*	*0.000*	*1.000*
Mkt Beta	**0.93**	**1.05**	**1.01**	**0.09**	**1.13**	**0.95**	**0.96**	-0.17	-0.04	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.032*	*0.000*	*0.000*	*0.000*	*0.071*	*0.328*	*0.000*
Skewness	-0.35	-0.56	-0.58	0.15	-1.15	-0.50	-0.78	0.54	0.30	-0.60
Kurtosis	2.42	1.69	2.00	2.35	10.19	2.13	3.83	9.02	2.69	2.41

Stock Market: United States	Sample Period:	1981-01	to	2018-12						
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	4.74	4.61	**7.60**	2.85	3.17	**4.93**	**6.44**	3.28	**3.06**	**6.71**
p-value	*0.067*	*0.062*	*0.004*	*0.159*	*0.289*	*0.034*	*0.018*	*0.196*	*0.007*	*0.006*
St.Dev.	15.94	15.21	16.47	12.48	18.40	14.33	16.77	15.61	7.03	14.94
Sharpe	0.30	0.30	0.46	0.23	0.17	0.34	0.38	0.21	0.44	0.45
Alpha	**-2.04**	**-1.81**	1.33	3.38	**-3.84**	-1.13	-0.30	3.54	**3.46**	0.00
p-value	*0.017*	*0.041*	*0.390*	*0.117*	*0.025*	*0.166*	*0.812*	*0.187*	*0.005*	*1.000*
Mkt Beta	**1.01**	**0.96**	**0.93**	-0.08	**1.04**	**0.90**	**1.00**	-0.04	-0.06	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.186*	*0.000*	*0.000*	*0.000*	*0.638*	*0.065*	*0.000*
Skewness	-0.86	-0.99	-0.87	0.20	-0.45	-0.88	-0.95	-0.45	0.67	-0.92
Kurtosis	3.18	3.93	3.72	1.85	2.91	4.16	3.09	3.04	4.01	3.23

Stock Market: Canada	Sample Period:	1985-01	to	2018-12						
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	2.77	**6.23**	**7.42**	4.65	-2.57	**6.22**	**8.25**	**10.83**	**7.74**	5.46
p-value	*0.394*	*0.041*	*0.024*	*0.055*	*0.485*	*0.035*	*0.019*	*0.001*	*0.000*	*0.082*
St.Dev.	18.97	17.75	19.16	14.15	21.49	17.20	20.56	18.79	8.79	18.32
Sharpe	0.15	0.35	0.39	0.33	-0.12	0.36	0.40	0.58	0.88	0.30
Alpha	-2.39	1.40	2.56	**4.94**	**-7.87**	1.58	2.95	**10.81**	**7.88**	0.00
p-value	*0.084*	*0.294*	*0.145*	*0.045*	*0.000*	*0.233*	*0.105*	*0.001*	*0.000*	*1.000*
Mkt Beta	**0.94**	**0.88**	**0.89**	-0.05	**0.97**	**0.85**	**0.97**	0.00	-0.03	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.288*	*0.000*	*0.000*	*0.000*	*0.985*	*0.392*	*0.000*
Skewness	-1.23	-1.40	-0.46	0.09	-0.51	-1.11	-1.22	-0.47	0.28	-1.19
Kurtosis	4.65	7.71	2.35	1.34	3.36	6.17	4.51	3.27	1.79	5.36

Stock Market: Scandinavia	Sample Period:	1985-01	to	2018-12						
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	7.60	5.14	**9.57**	1.97	2.50	5.47	**11.70**	**9.21**	**5.59**	**8.76**
p-value	*0.064*	*0.172*	*0.020*	*0.520*	*0.574*	*0.149*	*0.003*	*0.011*	*0.007*	*0.017*
St.Dev.	23.94	21.95	24.08	17.82	25.90	22.09	22.98	21.05	12.06	21.32
Sharpe	0.32	0.23	0.40	0.11	0.10	0.25	0.51	0.44	0.46	0.41
Alpha	-1.49	-3.04	0.92	2.41	**-6.68**	-2.84	3.37	**10.06**	**6.24**	0.00
p-value	*0.371*	*0.070*	*0.657*	*0.454*	*0.004*	*0.071*	*0.077*	*0.007*	*0.005*	*1.000*
Mkt Beta	**1.04**	**0.93**	**0.99**	-0.05	**1.05**	**0.95**	**0.95**	-0.10	-0.07	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.441*	*0.000*	*0.000*	*0.000*	*0.151*	*0.088*	*0.000*
Skewness	-0.58	-0.86	-0.56	0.16	-0.65	-0.94	-0.56	0.18	1.75	-0.77
Kurtosis	1.83	3.98	2.48	3.23	2.44	3.62	2.09	1.79	10.69	2.63

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Stock Market: Australia		Sample Period:		1990-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	5.69	5.22	6.18	0.49	0.09	6.23	**10.38**	**10.29**	**5.39**	5.96
p-value	*0.141*	*0.194*	*0.147*	*0.856*	*0.983*	*0.110*	*0.013*	*0.001*	*0.002*	*0.115*
St.Dev.	20.80	21.61	22.96	14.53	22.42	21.02	22.52	16.37	9.35	20.34
Sharpe	0.27	0.24	0.27	0.03	0.00	0.30	0.46	0.63	0.58	0.29
Alpha	0.13	-0.88	0.05	-0.08	**-5.76**	0.32	**4.34**	**10.10**	**5.02**	0.00
p-value	*0.931*	*0.440*	*0.978*	*0.975*	*0.004*	*0.774*	*0.012*	*0.001*	*0.004*	*1.000*
Mkt Beta	**0.93**	**1.02**	**1.03**	**0.10**	**0.98**	**0.99**	**1.01**	0.03	**0.06**	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.031*	*0.000*	*0.000*	*0.000*	*0.643*	*0.029*	*0.000*
Skewness	-0.59	-0.74	-0.78	-0.28	-0.56	-0.65	-0.95	-0.39	-0.08	-0.76
Kurtosis	2.82	2.15	4.31	1.07	2.82	2.22	3.06	2.28	2.71	2.70

Stock Market: Benelux		Sample Period:		1990-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	3.83	1.91	5.17	1.33	-4.39	3.69	6.14	**10.53**	**5.93**	4.98
p-value	*0.248*	*0.664*	*0.269*	*0.714*	*0.399*	*0.273*	*0.101*	*0.008*	*0.005*	*0.148*
St.Dev.	17.85	23.62	25.17	19.55	28.03	18.12	20.18	21.26	11.32	18.55
Sharpe	0.21	0.08	0.21	0.07	-0.16	0.20	0.30	0.50	0.52	0.27
Alpha	-0.48	**-4.08**	-0.42	0.06	**-10.90**	-0.77	1.40	**12.30**	**6.18**	0.00
p-value	*0.766*	*0.008*	*0.882*	*0.987*	*0.000*	*0.605*	*0.467*	*0.001*	*0.007*	*1.000*
Mkt Beta	**0.87**	**1.20**	**1.12**	0.25	**1.31**	**0.89**	**0.95**	**-0.36**	-0.05	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.061*	*0.000*	*0.000*	*0.000*	*0.000*	*0.462*	*0.000*
Skewness	-0.80	-2.14	-1.51	-0.97	-1.66	-0.92	-1.75	0.09	0.70	-1.59
Kurtosis	1.89	12.34	9.65	6.44	9.77	1.97	10.08	2.44	3.50	7.77

Stock Market: Italy		Sample Period:		1990-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	0.06	-2.78	-5.45	-5.51	-6.64	-1.64	0.08	6.72	0.60	0.90
p-value	*0.988*	*0.531*	*0.360*	*0.152*	*0.240*	*0.722*	*0.987*	*0.128*	*0.794*	*0.837*
St.Dev.	23.08	23.93	32.04	20.70	30.42	24.72	26.02	23.77	12.44	23.62
Sharpe	0.00	-0.12	-0.17	-0.27	-0.22	-0.07	0.00	0.28	0.05	0.04
Alpha	-0.74	**-3.62**	**-6.54**	-5.80	**-7.66**	-2.51	-0.78	6.88	0.54	0.00
p-value	*0.673*	*0.046*	*0.016*	*0.108*	*0.006*	*0.161*	*0.746*	*0.117*	*0.816*	*1.000*
Mkt Beta	**0.89**	**0.93**	**1.21**	**0.32**	**1.12**	**0.96**	**0.95**	**-0.17**	**0.07**	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.030*	*0.034*	*0.000*
Skewness	-0.62	-0.45	-0.21	0.21	-0.57	-0.49	0.39	0.42	-0.06	-0.27
Kurtosis	1.57	0.81	1.02	2.40	1.72	1.12	2.68	2.69	4.13	0.62

Stock Market: Switzerland		Sample Period:		1990-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	**5.93**	6.10	**7.50**	1.57	-0.13	5.85	**6.75**	6.88	**4.22**	**6.94**
p-value	*0.043*	*0.121*	*0.048*	*0.539*	*0.977*	*0.065*	*0.049*	*0.073*	*0.023*	*0.019*
St.Dev.	15.75	21.18	20.42	13.78	24.45	17.07	18.50	20.64	10.01	15.94
Sharpe	0.38	0.29	0.37	0.11	-0.01	0.34	0.36	0.33	0.42	0.44
Alpha	-0.64	-2.30	0.02	0.66	**-8.52**	-1.00	-0.38	**8.15**	**4.40**	0.00
p-value	*0.466*	*0.164*	*0.993*	*0.805*	*0.005*	*0.436*	*0.824*	*0.049*	*0.028*	*1.000*
Mkt Beta	**0.95**	**1.21**	**1.08**	**0.13**	**1.21**	**0.99**	**1.03**	-0.18	-0.03	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.028*	*0.000*	*0.000*	*0.000*	*0.118*	*0.625*	*0.000*
Skewness	-0.66	-0.49	-0.74	0.01	-0.69	-0.44	-0.99	-0.09	0.44	-0.66
Kurtosis	1.18	1.93	2.12	1.31	6.03	1.11	3.13	8.10	2.88	1.31

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Stock Market: India			Sample Period:		1995-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	4.94	0.68	6.28	1.35	-0.90	1.25	**13.03**	**13.93**	**7.64**	5.49
p-value	*0.384*	*0.909*	*0.370*	*0.788*	*0.901*	*0.825*	*0.045*	*0.019*	*0.014*	*0.365*
St.Dev.	27.78	29.31	34.38	24.53	35.13	27.71	31.90	29.12	15.25	29.70
Sharpe	0.18	0.02	0.18	0.05	-0.03	0.05	0.41	0.48	0.50	0.18
Alpha	0.23	-4.36	0.60	0.36	-6.54	-3.50	**7.80**	**14.34**	**7.36**	0.00
p-value	*0.920*	*0.052*	*0.849*	*0.941*	*0.070*	*0.095*	*0.009*	*0.016*	*0.023*	*1.000*
Mkt Beta	**0.86**	**0.92**	**1.04**	**0.18**	**1.03**	**0.87**	**0.95**	-0.08	0.05	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.006*	*0.000*	*0.000*	*0.000*	*0.463*	*0.350*	*0.000*
Skewness	-0.72	-0.55	0.01	-0.29	-0.11	-0.32	-0.35	0.50	1.19	-0.39
Kurtosis	2.14	2.17	1.36	3.29	6.01	1.04	2.32	7.03	9.18	1.91

Stock Market: Singapore			Sample Period:		1995-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	-0.41	4.47	6.69	7.09	3.87	1.91	4.26	0.38	3.74	2.90
p-value	*0.928*	*0.401*	*0.226*	*0.086*	*0.530*	*0.693*	*0.399*	*0.926*	*0.137*	*0.533*
St.Dev.	22.21	26.05	27.07	20.25	30.23	23.77	24.74	20.39	12.31	22.75
Sharpe	-0.02	0.17	0.25	0.35	0.13	0.08	0.17	0.02	0.30	0.13
Alpha	-2.92	1.44	3.71	6.62	0.48	-0.89	1.48	1.00	3.82	0.00
p-value	*0.171*	*0.521*	*0.192*	*0.113*	*0.875*	*0.641*	*0.536*	*0.808*	*0.138*	*1.000*
Mkt Beta	**0.87**	**1.04**	**1.03**	0.16	**1.17**	**0.97**	**0.96**	**-0.21**	-0.02	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.119*	*0.000*	*0.000*	*0.000*	*0.027*	*0.600*	*0.000*
Skewness	-1.02	-0.75	-0.03	1.02	-0.45	-0.71	-0.54	-0.99	0.57	-0.52
Kurtosis	4.67	4.41	3.63	8.31	8.05	5.31	2.13	8.89	7.04	3.15

Stock Market: South Korea			Sample Period:		1995-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	-3.81	2.42	4.08	7.89	-4.81	0.92	3.51	8.32	**8.11**	2.69
p-value	*0.624*	*0.737*	*0.612*	*0.115*	*0.570*	*0.901*	*0.653*	*0.156*	*0.007*	*0.706*
St.Dev.	38.02	35.19	39.40	24.50	41.47	36.20	38.29	28.71	14.78	34.92
Sharpe	-0.10	0.07	0.10	0.32	-0.12	0.03	0.09	0.29	0.55	0.08
Alpha	**-6.53**	-0.16	1.31	7.82	-7.64	-1.74	0.79	8.44	**8.14**	0.00
p-value	*0.026*	*0.946*	*0.689*	*0.121*	*0.053*	*0.454*	*0.796*	*0.156*	*0.008*	*1.000*
Mkt Beta	**1.01**	**0.96**	**1.03**	0.02	**1.05**	**0.99**	**1.01**	-0.04	-0.01	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.685*	*0.000*	*0.000*	*0.000*	*0.587*	*0.797*	*0.000*
Skewness	0.03	0.18	0.51	0.04	0.10	-0.15	0.12	0.16	0.24	0.19
Kurtosis	6.14	3.85	5.25	2.81	3.79	3.32	5.99	3.24	3.38	3.85

Stock Market: Spain			Sample Period:		1995-01	to	2018-12			
	Value Portfolio				Momentum Portfolio					
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	2.42	2.87	9.88	7.45	-8.80	5.63	**9.21**	**18.01**	**12.73**	5.87
p-value	*0.639*	*0.553*	*0.061*	*0.095*	*0.243*	*0.229*	*0.050*	*0.006*	*0.001*	*0.197*
St.Dev.	25.32	23.74	25.78	21.85	36.93	22.90	22.98	32.00	19.55	22.30
Sharpe	0.10	0.12	0.38	0.34	-0.24	0.25	0.40	0.56	0.65	0.26
Alpha	-3.41	-3.01	4.01	7.42	**-15.83**	0.00	4.01	**19.82**	**13.62**	0.00
p-value	*0.199*	*0.069*	*0.143*	*0.113*	*0.006*	*0.999*	*0.105*	*0.004*	*0.002*	*1.000*
Mkt Beta	**0.99**	**1.00**	**1.00**	0.01	**1.20**	**0.96**	**0.89**	**-0.31**	**-0.15**	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.940*	*0.000*	*0.000*	*0.000*	*0.015*	*0.046*	*0.000*
Skewness	-0.93	-0.63	-0.62	0.55	-4.73	-0.54	-0.75	6.09	7.77	-0.51
Kurtosis	4.34	1.75	2.55	6.13	49.73	1.75	3.47	75.48	102.31	1.38

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Stock Market: Brazil		Sample Period:		2000-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	4.26	6.94	7.04	2.78	6.50	7.27	7.73	1.23	2.00	6.89
p-value	*0.559*	*0.413*	*0.471*	*0.603*	*0.489*	*0.375*	*0.314*	*0.824*	*0.480*	*0.372*
St.Dev.	31.85	36.98	42.56	23.24	40.95	35.71	33.46	24.07	12.37	33.63
Sharpe	0.13	0.19	0.17	0.12	0.16	0.20	0.23	0.05	0.16	0.20
Alpha	-1.87	-0.41	-1.03	0.83	-1.24	0.25	1.40	2.64	1.74	0.00
p-value	*0.467*	*0.845*	*0.785*	*0.867*	*0.739*	*0.916*	*0.637*	*0.625*	*0.543*	*1.000*
Mkt Beta	**0.89**	**1.07**	**1.17**	**0.28**	**1.12**	**1.02**	**0.92**	**-0.20**	0.04	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.002*	*0.206*	*0.000*
Skewness	-0.90	-0.58	-0.47	0.01	-0.23	-0.63	-0.59	-0.15	-0.05	-0.57
Kurtosis	2.79	1.63	1.80	1.06	1.47	1.86	1.47	0.18	2.45	1.23

Stock Market: China		Sample Period:		2000-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	-2.17	-2.72	4.48	6.65	-1.08	2.74	0.45	1.53	4.09	3.06
p-value	*0.740*	*0.682*	*0.494*	*0.169*	*0.877*	*0.667*	*0.945*	*0.742*	*0.064*	*0.618*
St.Dev.	28.61	28.95	28.50	21.06	30.26	27.73	28.76	20.28	9.64	26.78
Sharpe	-0.08	-0.09	0.16	0.32	-0.04	0.10	0.02	0.08	0.42	0.11
Alpha	-4.92	-5.84	1.38	6.30	-4.26	-0.29	-2.47	1.79	4.04	0.00
p-value	*0.172*	*0.009*	*0.506*	*0.190*	*0.117*	*0.881*	*0.417*	*0.701*	*0.068*	*1.000*
Mkt Beta	**0.90**	**1.02**	**1.01**	0.11	**1.04**	**0.99**	**0.95**	-0.09	0.01	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.076*	*0.000*	*0.000*	*0.000*	*0.208*	*0.603*	*0.000*
Skewness	-0.64	-0.57	-0.43	-0.02	-0.36	-0.68	-0.51	-0.24	-0.05	-0.41
Kurtosis	1.36	1.67	2.01	2.22	1.60	2.51	1.39	1.08	2.70	1.70

Stock Market: Hong Kong		Sample Period:		2000-01	to	2018-12			
	Value Portfolio				Momentum Portfolio				
	P1 (Low)	P2	P3 (High)	HML	P1 (Lose)	P2	P3 (Win)	WML	Combo	Mkt-Rf
Mean	5.34	0.66	5.07	-0.27	1.57	5.10	5.16	3.60	1.66	4.20
p-value	*0.316*	*0.885*	*0.365*	*0.949*	*0.768*	*0.269*	*0.355*	*0.498*	*0.479*	*0.369*
St.Dev.	23.21	20.00	24.41	18.32	23.16	20.08	24.32	23.16	10.25	20.37
Sharpe	0.23	0.03	0.21	-0.01	0.07	0.25	0.21	0.16	0.16	0.21
Alpha	0.97	-2.99	0.72	-0.24	-2.51	1.34	1.01	3.52	1.63	0.00
p-value	*0.661*	*0.174*	*0.800*	*0.954*	*0.376*	*0.495*	*0.747*	*0.512*	*0.499*	*1.000*
Mkt Beta	**1.04**	**0.87**	**1.04**	-0.01	**0.97**	**0.89**	**0.99**	0.02	0.01	**1.00**
p-value	*0.000*	*0.000*	*0.000*	*0.940*	*0.000*	*0.000*	*0.000*	*0.851*	*0.878*	*0.000*
Skewness	-0.57	-0.75	-0.30	-0.39	-0.26	-0.30	-0.47	0.68	0.04	-0.62
Kurtosis	0.57	3.12	0.89	4.57	1.32	1.01	2.59	5.10	2.10	1.23

This long-form table shows Combo investment strategy results of all the 18 stock markets studied in this dissertation. For each individual market, I present the results broken down by value and momentum portfolio with their three sub-portfolios. The HML (value) and WML (momentum) portfolio long their respective P3 and short their P1 portfolio. All returns are log-normalized and currency-adjusted to the US dollar. All portfolio returns are excess returns over the 30-day US T-bill rate. In the last double column, I present the results of the Combo investment strategy, an equal-weighted portfolio composed of value and momentum return and market excess returns. Both are formed of the same universe of large capitalized stocks. I provide the following statistics: first, I show each portfolio's annualized mean, standard deviation and Sharpe Ratio. I show the annualized Jensen alpha. The alpha is computed as the intercept of a linear CAPM time-series regression with heteroscedasticity adjusted standard errors according to MacKinnon and White (1985). Then, I show the market beta as well as skewness and excess kurtosis. By design, the annualized Sharpe Ratio, beta, skewness, and excess kurtosis are dimensionless. All other values are in percent to the US dollar. I mark values in bold, if they are statistically significant at the 5 percent level. All statistics are rounded to two decimals, except p-values to three. I follow the here set conventions in further tables ahead.

Appendix B: Value Correlation Matrix and Momentum Correlation Matrix

Table B.1: Correlation matrix of value (HML) portfolios

Value	**Sample Period**			**1981**		**1985**		**1990**				**1995**				**2000**		
Market	France	Germany	Japan	United Kingdom	United States	Canada	Scandinavia	Australia	Benelux	Italy	Switzerland	India	Singapore	South Korea	Spain	Brazil	China	Hong Kong
France	1.00																	
Germany	0.28	1.00																
Japan	0.13	0.18	1.00															
United Kingdom	0.21	0.17	0.09	1.00														
United States	0.36	0.32	0.25	0.18	1.00													
Canada	0.24	0.21	0.22	0.11	0.29	1.00												
Scandinavia	0.32	0.31	0.22	0.02	0.38	0.27	1.00											
Australia	0.35	0.11	0.16	0.15	0.33	0.34	0.28	1.00										
Benelux	0.47	0.44	0.18	0.36	0.40	0.14	0.30	0.26	1.00									
Italy	0.43	0.23	0.14	0.21	0.26	0.14	0.14	0.17	0.30	1.00								
Switzerland	0.41	0.23	0.08	0.34	0.30	0.11	0.19	0.23	0.46	0.26	1.00							
India	0.22	0.24	0.25	-0.01	0.39	0.25	0.25	0.12	0.25	0.14	0.13	1.00						
Singapore	0.11	0.29	0.24	0.12	0.21	0.16	0.10	0.05	0.13	0.15	0.14	0.15	1.00					
South Korea	0.23	0.22	0.29	0.06	0.24	0.19	0.26	0.12	0.21	0.13	0.11	0.09	0.04	1.00				
Spain	0.27	0.24	0.26	0.07	0.32	0.19	0.32	0.27	0.35	0.23	0.29	0.10	-0.07	0.26	1.00			
Brazil	0.19	0.06	0.17	0.18	0.17	0.20	0.19	0.18	0.17	0.13	0.15	0.22	0.04	0.16	0.09	1.00		
China	0.14	0.09	0.03	0.05	0.03	0.05	0.12	0.00	0.15	0.10	0.08	0.17	-0.03	0.07	0.10	0.03	1.00	
Hong Kong	0.35	0.22	0.31	-0.04	0.39	0.23	0.28	0.24	0.18	0.10	0.19	0.26	0.34	0.28	0.17	0.07	0.15	1.00

This table shows the correlation matrix of the 18 HML portfolios, computed in their respective market. The sample period assessed depends on the market with the shorter sample period. The sample periods start in January and end in December, 2018. Therefore, I add the orange, brown, purple, blue, and green lines for visual aid. The correlations are rounded to the second decimal. I follow the here set convention in table B.2 where I show the momentum correlation matrix.

Table B.2: Correlation matrix of momentum (WML) portfolios

Momentum	**Sample Period**			**1981**			**1985**			**1990**				**1995**			**2000**	
Market	France	Germany	Japan	United Kingdom	United States	Canada	Scandinavia	Australia	Benelux	Italy	Switzerland	India	Singapore	South Korea	Spain	Brazil	China	Hong Kong
France	1.00																	
Germany	0.40	1.00																
Japan	0.21	0.21	1.00															
United Kingdom	0.41	0.42	0.26	1.00														
United States	0.43	0.36	0.29	0.54	1.00													
Canada	0.39	0.26	0.23	0.42	0.55	1.00												
Scandinavia	0.43	0.38	0.23	0.42	0.47	0.42	1.00											
Australia	0.18	0.21	0.27	0.38	0.27	0.36	0.30	1.00										
Benelux	0.57	0.52	0.30	0.50	0.55	0.43	0.48	0.18	1.00									
Italy	0.57	0.38	0.27	0.45	0.47	0.45	0.38	0.12	0.43	1.00								
Switzerland	0.47	0.41	0.19	0.38	0.41	0.39	0.34	0.13	0.53	0.43	1.00							
India	0.25	0.21	0.27	0.25	0.36	0.31	0.31	0.16	0.29	0.29	0.27	1.00						
Singapore	0.11	0.15	0.09	0.18	0.22	0.04	0.14	0.11	0.15	0.06	0.07	0.22	1.00					
South Korea	0.17	0.10	0.20	0.12	0.15	0.13	0.14	0.02	0.18	0.12	0.07	0.11	0.20	1.00				
Spain	0.37	0.31	0.06	0.30	0.29	0.26	0.28	-0.01	0.31	0.29	0.34	0.16	0.02	0.03	1.00			
Brazil	0.23	0.18	0.10	0.19	0.28	0.28	0.22	0.21	0.30	0.18	0.29	0.25	0.09	0.05	0.17	1.00		
China	0.17	0.14	0.20	0.20	0.14	0.08	0.10	0.01	0.11	0.11	0.13	-0.01	0.02	0.07	0.16	-0.02	1.00	
Hong Kong	0.36	0.41	0.25	0.26	0.44	0.37	0.31	0.03	0.36	0.38	0.30	0.26	0.19	0.16	0.15	0.18	0.12	1.00

This table shows the correlation matrix of the 18 WML portfolios, computed in their respective market.

Appendix C: Bootstrap Analysis Python Code

```
import numpy as np
import pandas as pd
from scipy.stats import kurtosis
from scipy.stats import skew
import statsmodels.api as sm

np.random.seed(420)

# Define function for bootstrap analysis
def draw_pair_bootstrap(a, b, size=10000):
    """Perform pair bootstrap for comparing Sharpe Ratios, Skewness and Kurtosis of Combo and
Market Excess Returns and computing Combo alphas."""

    # Set up array of indices to sample from: inds
    inds = np.arange(len(a))

    # Initialize replicates as empty arrays
    sr_a = np.empty(size)
    sr_b = np.empty(size)
    skew_a = np.empty(size)
    skew_b = np.empty(size)
    kurt_a = np.empty(size)
    kurt_b = np.empty(size)
    alpha = np.empty(size)

    # Generate replicates over for loop
    for i in range(size):
        bs_inds = np.random.choice(inds, size=len(inds))
        bs_a, bs_b = a[bs_inds], b[bs_inds]
        sr_a[i] = np.mean(bs_a) / np.std(bs_a)
        sr_b[i] = np.mean(bs_b) / np.std(bs_b)
        skew_a[i] = skew(bs_a)
        skew_b[i] = skew(bs_b)
        kurt_a[i] = kurtosis(bs_a)
        kurt_b[i] = kurtosis(bs_b)
        y = bs_a.reshape(-1, 1)
        X = bs_b.reshape(-1, 1)
        X2 = sm.add_constant(X)
        result = sm.OLS(y, X2).fit(cov_type='HC3')
        alpha[i] = result.params[0]

    return sr_a, sr_b, skew_a, skew_b, kurt_a, kurt_b, alpha

# Load DataFrames for analysis
df_Combo = pd.read_excel('Combo_Results.xlsx', sheet_name=2, index_col=0, parse_dates=True)
df_MktRf = pd.read_excel('Combo_Results.xlsx', sheet_name=3, index_col=0, parse_dates=True)

# List of all markets studied
markets = ['AU', 'BD', 'BX', 'CN', 'FR', 'HK', 'IT', 'SC', 'SG', 'SW', 'UK', 'US', 'xJP',
        'ES', 'xKO', 'xIN', 'BR', 'CA']
```

```
# Shift to the correct sample period of the particular market
shift_c = [120, 12, 120, 60, 12, 240, 120, 60, 180, 120, 12, 12, 12, 180, 180, 180, 240, 240]

# Bootstrapping over for loop across all markets, calculating and printing all relevant values
for i in range(len(markets)):
    Combo = df_Combo.iloc[shift_c[i]:, i].values
    MktRf = df_MktRf.iloc[shift_c[i]:, i].values
    SR_Combo, SR_MktRf, Skew_Combo, Skew_MktRf, Kurt_Combo, Kurt_MktRf, alpha_Combo =
draw_pair_bootstrap(Combo, MktRf, size=10000)
    prob_SR = (np.sum(SR_Combo > SR_MktRf) / 10000) * 100
    SR_Combo_avg = np.mean(SR_Combo)
    SR_MktRf_avg = np.mean(SR_MktRf)
    prob_Skew = (np.sum(Skew_Combo > Skew_MktRf) / 10000) * 100
    Skew_Combo_avg = np.mean(Skew_Combo)
    Skew_MktRf_avg = np.mean(Skew_MktRf)
    prob_Kurt = (np.sum(Kurt_MktRf >= Kurt_Combo) / 10000) * 100
    Kurt_Combo_avg = np.mean(Kurt_Combo)
    Kurt_MktRf_avg = np.mean(Kurt_MktRf)
    prob_alpha = (np.sum(alpha_Combo > 0) / 10000) * 100
    alpha_avg = np.mean(alpha_Combo) * 12 * 100
    print('----------------------------------\n')
    print('The Non-parametric / Bootstrapped Probability that',
          'Combo achieves a better/higher Sharpe Ratio than MktRf in market ', markets[i], 'is', prob_SR,
'%')
    print('In ', markets[i], ', the average bootstrapped Sharpe Ratio of Combo is ', SR_Combo_avg,
          ' and of MktRf is', SR_MktRf_avg)
    print('----------------------------------\n')
    print('The Non-parametric / Bootstrapped Probability that',
          'Combo achieves a better/higher Skewness than MktRf in market ', markets[i], 'is', prob_Skew,
'%')
    print('In ', markets[i], ', the average bootstrapped Skewness of Combo is ', Skew_Combo_avg,
          ' and of MktRf is', Skew_MktRf_avg)
    print('----------------------------------\n')
    print('The Non-parametric / Bootstrapped Probability that',
          'Combo achieves a better/lower Kurtosis than MktRf in market ', markets[i], 'is', prob_Kurt, '%')
    print('In ', markets[i], ', the average bootstrapped Kurtosis of Combo is ', Kurt_Combo_avg,
          ' and of MktRf is', Kurt_MktRf_avg)
    print('----------------------------------\n')
    print('The Non-parametric / Bootstrapped Probability that',
          'Combo achieves a positive Alpha in', markets[i], 'is', prob_alpha, '%')
    print('In ', markets[i], ', the average bootstrapped annualized alpha of Combo is ', alpha_avg, '%')
```