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RISK FACTOR BASED INVESTING –

CASE: MSCI RISK FACTOR INDICES

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The aim of this thesis is to study risk factor based investing and test how well MSCI constructs their risk factor based indices. Risk factor based investing has gained a lot of media exposure in the recent years and “Smart Beta” products are becoming more popular. Blackrock estimated that there are more than 700 exchange traded products available and they have over $529 billion in assets under management. Risk factor investing aims to harvest the risk premia associated with factors like size, momentum and value.

I tested whether MSCI is able to provide higher Sharpe ratios for higher risk exposure indices and how much they deviated from the parent index of MSCI World. I used the Ledoit & Wolf bootstrap inference test to find out whether the Sharpe ratios of high exposure and high capacity indices differ from each other. Furthermore, I tested how well the Fama & French Three Factor-model with the addition of Carhart momentum factor could explain the returns of MSCI’s risk factor indices. I also constructed different risk factor portfolios using risk-parity methods to see whether it is possible to enhance the returns of risk factor indices by combining them.

The main results and conclusions of this thesis were that risk factor investing can provide excess returns. These excess returns are readily available by investing in MSCI’s risk factor indices. Another key finding was that by utilizing risk-parity methods an investor can achieve excess returns over an equally weighted risk factor portfolio and over the MSCI’s own Diversified Mix index. Furthermore, even though MSCI is the world leader in index creation, their way of creating indices doesn’t seem to be very efficient and it would be beneficial to analyse other index providers, too.

The data used in this thesis were gathered from “MSCI’s end of day index data search”. The data consists of six risk factor indices from developed countries. The price data ranged from November 1998 to August 2015. For the Ledoit & Wolf test I gathered four high capacity indices and four high exposure indices from the same time period. The proxies for academic factors were provided by Kenneth French on his website.
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1 INTRODUCTION

Traditional market-cap-weighted funds provide exposure to market risk, also known as beta. Pure index investors encourage us to simply “own the market” with plain-vanilla cap-weighted funds. But finance researchers have identified other sources of risk and return over the years. The Fama & French (1993) three-factor model suggests that a bias toward smaller firms and toward the value side of the style spectrum could improve performance. The Carhart (1997) model adds momentum as a fourth factor.

1.1 Background

These risk factors are widely acknowledged amongst the finance research industry and more factors are discovered every year. My thesis will look into “Morgan Stanley Capital International” (MSCI) factor indices and test if high exposure indices provide higher risk-adjusted returns than high capacity indices. I will also conduct a test between different portfolio optimization methods and test how well these most well-known factors can explain the performance of these factor-index portfolios. Furthermore I will construct simple portfolios to represent each single factors and I will test how much of the single factor portfolios return can be explained by the Fama & French-Carhart model.

Andrew Ang and Thierry Roncalli have inspired me with their papers most. They have found that factors do exist and they do offer high returns in the long run. There is only quite little academic research conducted in last years but there is a plethora of industry papers and I have been able to use the industry papers to motivate my thesis. My data is from MSCI and I have found MSCI’s research papers very useful when trying to understand their way of creating factor tilts. Factor investing has been a hot topic since 2010 and it is becoming more and more popular. According to Blackrock, in December 2014 there were more than 700 smart beta exchange traded products comprising of $529 billion in assets under management (Shores, 2015). Funds and ETF’s exploiting risk factors are popping up weekly and the industry is educating the investors to use these premiums. It has been argued by Ang (2013) that the hype around factor investing has already made the size-factor disappear.
1.2 Data and Results

I have gathered monthly returns data since November 1998 until September 2015 from MSCI database. This data spans across the most well-known factors of size, value, momentum, quality, high dividend yield and low volatility. I have both high capacity and high exposure counterparts for value, quality, minimum volatility and momentum factors.

The main results and conclusions of this thesis were that risk factor investing can provide excess returns. These excess returns are readily available by investing in MSCI’s risk factor indices. Another key finding was that by utilizing risk-parity methods an investor can achieve excess returns over an equally weighted risk factor portfolio and over the MSCI’s own Diversified Mix index. Furthermore, even though MSCI is the world leader in index creation, their way of creating indices doesn’t seem to be very efficient and it would be wise to analyse other index providers too.

1.3 Relationship with prior research

Risk factors have been said to come and go. Andrew Ang (2013) implied in his paper that for example the risk factor premium associated with size has been diminished from the market. My thesis will test if size has still had significant loadings in explaining the returns of international stock returns.

In addition to Ang’s findings about the size premium, Fama and French (2012) also found that size had no explanatory power in their sample period of international returns. Their sample period was from November 1989 to March 2011. However, my sample period starts and ends later so the results might differ. Fama and French also indicated that there are significant premiums for value and momentum factors.

Thierry Roncalli (2014) indicated that the value factor has been able to provide positive relative returns in developed markets. Also the size factor has been producing excess returns in the US but not in other developed countries.
Even the results of academic researchers differ from each other. This is mainly due to differences in data. My data is also different from any prior research and I will test how well these most well known risk factors can explain my data.

1.4 Structure of the thesis

In chapter two I will go through the brief history of portfolio management and focus on the main theories and the differences between active and passive portfolio management. Then, in chapter three I will explain the basics of factor investing and familiarise you with the most well-known factors. In chapter four I will concentrate on MSCI’s way of creating high capacity and high exposure risk factor indices. Chapter five delivers the methodology and the theories behind the testing phase and also the main risk-parity methods used. I will also explain the data gathering and manipulation in more detail. Chapter six will highlight the most important results divided in three sections based on the testing methods. Finally chapter seven concludes.
2 PORTFOLIO MANAGEMENT

Portfolio management industry can be divided in two categories. Active portfolio management aims to achieve higher returns than its benchmark index. In other words it tries to beat the market in its own investment universe. The other category is passive portfolio management that aims to capture the returns of benchmark indices as closely as possible. Today a third category has been said to have emerged called “smart beta” or risk factor based investing. Risk factor based investing aims to capture rewards for taking the risks associated with known risk factors. However, they aim to do this systematically to reduce the costs of active management. In a sense smart beta category aims to capture the best sides of both active and passive portfolio management.

2.1 Brief history

Hannu Kahra (2015) has presented the short history of portfolio management in his report to Finnish Centre for Pensions. He has followed Mark Rubinstein’s’ (2006) example by dividing the development of finance theory in three stages:

1. Era of antique: before 1950’s,
2. Era of classical theory: 1950’s until 1980 and

Before year 1950, the practice and theory of finance were only a compilation of investment related anecdotes. Harry Markowitz’s’ (1952) doctoral thesis about portfolio selection is considered as the corner stone of systematic finance theory. He offers a normative advice regarding the optimal portfolio construction when the investor is interested only about the expected return and variance of the portfolio.

The era of classical theory began with theories such as capital asset pricing model (CAPM), random walk-theory and the efficient market hypothesis (EMH). The classical theory has its foundations in stating that market prices reflect all the relevant information about its fundamental factors. It is intuitively clear that information is efficiently gathered and used because information is valuable. The efficient market
hypothesis remains a cornerstone of the modern finance theory. John Cochrane (2007) implies that the theory of efficient markets launched the classical era and formed the investment discussion into a recognized science. The origin of finance shifted from accounting to economics.

Cochrane (2011) states that the efficiency of the markets gets a new interpretation in modern finance theory, but the efficient markets mark the constraints that all investors should appreciate. There is no free lunch because information gathering is highly competed in the investment markets. Cochrane’s article “new facts in finance” (1999) expands our view of the mechanism through which the markets offer compensation for accepting the risks and understanding the mechanism of the risk factors behind premiums.

In the classical era theory the CAPM offers a good measure for risk and also a good explanation to the question why different asset classes (equities, bonds, mutual funds and different strategies) offer higher average returns than others. In the model the risk premium offered by the market portfolio is the only source of risk and beta indicates the exposure to this risk. This implies that an asset class can achieve higher returns only by having higher beta or in other words higher risk. The CAPM was soon followed by Arbitrage Pricing Theory (APT). The APT applies more risk factors in addition to the market risk and states that investors get higher returns by accepting the risk that is implicitly related to risk factors. Fama and French (1993) apply additional factors to this model. They use SMB (small minus big) and HML (high minus low) factors which take advantage of the size premium and value premium. Later Carhart (1997) added the momentum factor to complement the model.
2.2 Active and Passive Management

The debate between active and passive management styles has been ongoing since the inception of John Bogle’s first index investment trust. The Vanguard 500 Index Fund was the first passive investment device that mimics the Standard and Poor's 500 index. Active management style has been the dominant style for ages but passive is winning grounds to date.

Prior research by French (2008) showed that active management is a zero-sum-game, meaning that the aggregate of active fund returns equals the market return. When the active fund charges its fees it results in an underperformance of the aggregate active funds by the amount of fees charged. Even though, it has been shown that an average active fund manager earns positive alpha before costs but he’s alpha cannot quite cover the costs of active management.

The efficiency of the markets is in the core of active versus passive debate. Grossman and Stiglitz (1980) argued that, in a world of costly information, informed traders must earn an excess return or they will have no incentive to gather and analyze information to make prices more efficient. If we lived in a world of semi-strong form of efficiency all investors would choose passive over active management. These two findings imply that markets need to be “mostly, but not completely efficient.” Even though active management is a zero-sum-game, active management as a whole is definitely not. By making markets more efficient, active management improves capital allocation, and thereby economic efficiency and growth, resulting in greater aggregate wealth for society as a whole.

Burton Malkiel (2003) wrote a defense for indexing after multiple papers had attacked the efficient market hypothesis. He indicated in his paper that indexing can be justified even if markets are less than fully efficient. Indexing is a sensible strategy because our security markets appear to be remarkably efficient in digesting and adjusting to new information. When information arises about individual stocks or about the market as a whole, that information is generally reflected in market prices without delay. (Malkiel 2003:1) This is the essence of EMH. Malkiel also referred to active management as a zero-sum game: if one investor achieves above average returns there is bound to be
another investor who receives below average returns. He indicated that after costs and expenses active management as aggregate produces negative excess returns. He also noted that passive management has other benefits than the ones explained above. Passive management tends to minimize taxes and turnover. By minimizing turnover trading costs like brokerage costs and ask-bid spread costs are also minimized. When it comes to the statistical findings of prior research, Malkiel noted that the Vanguard Index Fund has beaten 71% of all US equity mutual funds after expenses (1991-2001). Even during the US stock market crash of 2001, the index fund outperformed more than 50% of the active funds. Furthermore, similar findings from bonds are also recorded. Even though research on active management and asset pricing suggests that asset prices can be predictable and certain anomalies exist, professional active management industry hasn’t been able to achieve abnormal risk-adjusted returns persistently. Over long periods, passive management outperforms active management.

William Sharpe (1991) introduced an arithmetic formula in his paper against active management. Based on simple rules of arithmetic’s he could prove that passive outperforms active at all times. His two assertions stated that before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar. Thus after costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar. Intuitively the weighted average of passive portfolio returns equals market returns because passive portfolios replicate market portfolios. From this follows that if active and passive portfolios combined result in a market portfolio, then active portfolio must also generate market return.

His second assertion can be proved by the fact that active management requires higher fees and costs to function than passive management and thus active net returns are inferior to passive net returns. Why then do sensible investment professionals continue to make statements pro active management? Sharpe finds three main reasons.

Firstly the passive managers in question may not be truly passive, as some index fund managers “sample” the market of choice, rather than hold all the stocks. Secondly, active managers may not actually be that active. Closet indexers and certain buy and hold strategies are closer to passive than active. Also, in research only professional or
institutional managers are taken into consideration and this can distort the results. Thirdly, the summary statistics for active managers may not truly represent the performance of the average actively managed dollar. In research the average percentage performance of managers is taken into consideration. To calculate the dollar-returns, researchers should calculate the beginning of period assets under management (AUM) and compare performance to that.

Sharpe also noted that there is a problem with comparisons in the research in general. Comparisons are usually made to a benchmark index that may not fully represent the active manager’s ideas. The benchmark should be identified in advance and it should be a feasible alternative.

2.3 The Cost of Active Investing

Kenneth French’s paper “The Cost of Active Investing” discusses the costs of active investing. His paper answers how active management differs from passive in regard of costs, risk profiles and portfolio diversification. The average active investor has spent 0.67% P.A. by chasing excess returns in the period of 1980-2006. This percentage is used in fees paid to the active investment fund, to hedge funds and fund-of-funds and to the stock exchanges that make investing possible. French focuses on the money expenses but he also points out that the average investor could achieve diversification benefits and risk reduction if he would switch to passive management.

Today factor investing applies dynamic factors that can be seen as combinations of active and passive management. Factor indices are constructed with an active mind set but they only charge similar fees to passive management. Maybe factor investing is the next generation of investing.
3 FACTOR INVESTING

Factors have their roots in academic literature and the question of what drives stock returns has been a constant discussion in modern finance. The most well-known and oldest model of stock returns is the Capital Asset Pricing Model, which became a foundation of modern financial theory. The CAPM was introduced by Jack Treynor (1961, 1962), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) independently. They built on the earlier work of Harry Markowitz on diversification and modern portfolio theory. Consequently, Sharpe, Markowitz and Merton Miller jointly received the 1990 Nobel Memorial Prize in Economics for their contributions to the field of financial economics. They stated that in CAPM, securities have only two main drivers: systematic risk and company-specific risk. Systematic risk is the risk that comes from exposure to the market and is captured by beta, the sensitivity of a security’s return to the market. Since systematic risk is something that cannot be diversified away, investors are compensated with returns for bearing this risk. So the expected return to any stock could be viewed as a function of its beta to the market.

Later, Ross (1976) proposed a different theory of what drives stock returns. According to Ross’ “arbitrage pricing theory” (APT) the expected return of a financial asset can be modeled as a function of various macroeconomic factors or theoretical market indices. Ross has popularized the term “factor” as the models he uses are called “multi-factor models”. Importantly, APT, unlike the CAPM, did not explicitly state what these factors should be. Instead, the number and nature of these factor models became, and continues to be, essentially empirical in nature.

Bender, Briand, Melas and Subramanian (2013a) explain factors as follows; “a factor can be thought of as any characteristic relating a group of securities that is important in explaining their returns and risks”. As noted in the early CAPM-related literature, the market can be viewed as the first and most important equity factor. Beyond the market factor, researchers generally look for factors that are persistent over time and have strong explanatory power over a broad range of stocks. Bender et. al. also discussed three key statistical criteria for factors: persistence over time, “large enough” variability in returns relative to individual stock volatility, and application to a “broad enough” subset of stocks within the defined universe. Since, unlike stock returns,
factors cannot be directly observed. Instead there remains a vigorous debate about how to define and estimate them. Factor returns can be constructed by building factor portfolios that mimic the target factor (as in Fama & French approach). Factor returns can alternatively be estimated through cross-sectional regression (as in the Barra approach). There are three main categories of factors today; macroeconomic, statistical, and fundamental. Macroeconomic factors include measures such as surprises in inflation, in GNP, or in the yield curve, and other measures of the macro economy. Statistical models identify factors using statistical techniques such as principal components analysis (PCA) where the factors are not pre-specified in advance.

Bender et. al. (2013a) further stated that the most widely used factors are fundamental factors. They captured stock characteristics, e.g. in which industry the stock belongs to, what country it belongs to, valuation ratios like P/E, B/M and many different technical indicators. They argued that the most popular factors today are value, quality, size and momentum. In addition to these factors I will focus on minimum volatility and high dividend yield in this thesis. These factors have been studied, tested and proved in academic research. The latest research has provided all kinds of factors. Few of the most unorthodox factors utilize for example the number of “Google” hits a company receives or the number of times the company is mentioned in mainstream media.

Andrew Ang (2013) stated that there is a lot of academic literature that shows how certain classes of equity, debt and derivative securities have higher payoffs than the broad market index. He showed how stocks with low Book-to-Market (value stocks) ratios beat stocks with high Book-to-Market (growth stocks) ratios over long periods. This phenomena is called value-growth premium. He also proved that stocks with past high returns (winners) beat stocks with lower negative past returns (losers). This phenomena is called Momentum.

These phenomena can be combined in portfolios having long positions in value stocks and winners and short positions in growth stocks and losers. By combining long value with short growth one can collect the value-growth premium with minimal market exposure.
This kind of investment strategy can’t be achieved passively because the strategy involves time-varying positions in securities which fluctuate over time. These are called dynamic factors and the factor premiums don’t come for free. Ang (2013) showed that while dynamic factors may beat the market over long periods of time, they can grossly underperform the broad market index in bad times. He contemplated that the factor risk premiums are persistent because they reward investors for bearing high losses during bad times. This implies that factors are not appropriate for all investors because they are risky.

Ang (2013) stressed that it is very important to notice that dynamic factors remove market exposure. Optimally constructed value-growth portfolio removes the market exposure and is only exposed to the returns of value stocks less the returns of growth stocks. This applies to momentum and size factors also. In practice it is important that factor portfolios are constructed with an equal number of stocks or equal dollars in offsetting long and short positions. The less the short positions, the greater the correlation of the factors with the broad market index. For example, one can find multiple of investment products utilizing the value factor but most of these products are constrained and can’t use shorting. This results in the fact that the main driver of returns in these funds is the market portfolio. If shorting is applied more and more of the market movements will be removed and the factor portfolio will end up reflecting the difference between value and growth stocks.

The investment industry often uses the terms smart beta, alternative beta, or exotic beta for dynamic factors. Ang uses the term “factors” because, in asset pricing theory, beta has the strict meaning of measuring exposure to a risk factor. These risk factors actually have a beta of one with respect to themselves. Ang pointed out that beta measures the magnitude of the exposure to a risk factor and investors invest in factors, not betas.

The recent popularity of Smart Beta as a defined asset class is a result of multiple trends currently impacting the investment management industry. First, advances in technology and communications have made fundamental analysis more easily available. Many insights that have required subjective investment analysis can now be captured in a more systematic way. Second, the investment industry has witnessed a
decade long rise in passive investing as investors seek transparency, consistency and low fees offered by indexation. Third, the underfunded status of multiple personal retirement accounts and pension funds has drawn investors to the benefits of passive investing but they are not ready to give up on the allure of excess returns marketed by active managers (Shores, 2015).

3.1 What is a factor

Factor investing is new to the market and it is in boom right now. New factors pop up all the time and they are easy to sell under the umbrella of “smart beta”. Today there are more than 300 factors described but only a handful has been widely accepted by the academy. Ang (2013) stated that the four most important features of a risk factor are;

1) Factors must be justified by academic research.

Factors should be based on an intellectual ground and only those factors that have the strongest support from the academy should be accepted as benchmarks. Research ought to exhibit compelling rational logic or behavioural stories or both in explaining the existence of these risk premiums.

2) Factors ought to have exhibited significant persistent premiums.

It is important to understand why these factors have generated premiums and we should have rational ground in believing that these premiums will persist also in the future.

3) Factors should have historical returns data for bad times also.

These factor risk premiums mainly exist because they provide rewards for the willingness to suffer significant losses during bad times. It is important that the data has some data points to measure the “worst-case” scenarios for the assessment of risk-return trade-offs and risk management. It is also important to have a reasonably long data set from the point of view of statistical significance.
4) It should be possible to implement the factor strategy in liquid and easily tradable instruments.

This fourth feature takes theory into practice by giving investability constraints. It is important that it is possible to invest in a factor cheaply and that the investment is liquid. It is also very important to large investors that it is possible to scale the investment. Factor strategies involve leverage and they work best when leverage is applied. Long-short approach is also important from the point of view of nulling the market exposure. However it has been shown by Israel and Moskowitz (2013) that factors still work without shorting.

3.2 Known factors

In this chapter, I will describe the most common factors in use today in detail and the ideas behind them.

The market (MKT) factor represents the exposure to a broad market index. It is plain vanilla cap-weighted factor that comes from owning the market. The MKT factor is not a dynamic factor. It is simply the reward of bearing market risk, for example by going long in a broad market index.

Ang (2013) stated that factors come and go and may even disappear. He implied that the size effect has worked well in the past but doesn’t work anymore. Banz (1981) discovered in his paper that small stocks outperform large stocks and the size premium was acknowledged by the industry soon after. Banz and many other scholars found that small stocks outperform large stocks for multiple reasons. Smaller stocks tend to be more illiquid, less followed by analysts and they operate in riskier segments of the economy. However, since the mid-1980’s the size premium has disappeared after adjusting for market risk, i.e. smaller stocks still have higher returns than large stocks but not after debiting out their exposure to the market factor. Ang suggested that the size premium has disappeared because of the creation of small stock mutual funds. They made it possible for ordinary investors to bear size-related risks. Even though Ang suggested that size-premium doesn’t exist anymore I will test it in this thesis. I believe that size can still explain some of the returns of multifactor portfolios.
The next five factors were described by Bender et. al. (2013a). High minus low factor uses the spread in returns between value and growth stocks. HML factor argues that companies with high book-to-market ratios (value stocks) outperform those with low ratios (growth stocks). It aims to capture excess returns to stocks that have low prices relative to their fundamental value. The risk premia is commonly captured by book to price, earnings to price, book value, sales, earnings, cash earning, net profit, dividends and cash flow ratios.

The momentum factor reflects excess returns to stocks with stronger past performance. WML factor is usually captured by relative returns historical alpha. It can be captured with different time intervals with the most common being 3, 6 and 12 month intervals.

Quality (QUAL) factor aims to capture excess returns to stocks that are characterized by stable earnings growth, low debt and other “quality” metrics. It is commonly captured by return-on-equity, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals and cash flows.

Minimum volatility (MVOL) factor aims to capture excess returns to stocks with lower than average volatility, beta and/or idiosyncratic risk. It is commonly captured by standard deviation (1-3-yrs), downside standard deviation, standard deviation of idiosyncratic returns and beta.

High dividend yield (HDY) aims to capture the excess returns of stocks that have higher than average dividend yields and it is commonly captured by dividend yield and dividend growth.

Another interesting factor introduced by Pástor & Stambaugh (2013) is the liquidity factor. MSCI does not use it in their methodology yet, but I believe it is an important driver behind the differences of high exposure and high capacity indices. Furthermore, it could be a useful factor to add into the Fama, French & Carhart model. It may be able to explain some of the alpha and also some of the momentum factor.
Fama and French offer a benchmark for these factors on Kenneth French's website. These benchmark portfolios offered by Fama and French are commonly used in academic research. There are also a plethora of other factors but they are out of scope of this thesis.
4 HIGH EXPOSURE VS. HIGH CAPACITY

This chapter explains MSCI’s way of creating indices. By testing these indices I will gain a clear view of the quality of MSCI’s work. I will clarify how much MSCI tilts their indices or does the market still explain most of the returns. I will also test whether the Sharpe of high exposure vs. high capacity indices are statistically significant by utilizing the Ledoit & Wolff bootstrap test.

![Factor pyramid diagram](image)

The most investable index, by definition, is the one whose weights are proportional to free float-adjusted market capitalization, the bottom of the pyramid. The factors at the top (e.g., the Fama & French or Barra factors) are the theoretical or pure factors that the institutional investors may wish to capture, but that are research oriented rather than investability oriented. The closest factor indices to market capitalization weighted indices are High Capacity Factor Indices. These indices hold all the stocks in the parent...
index but tilt the market cap weights toward the desired factor. As one moves up the pyramid, high exposure indices hold a subset of the constituents in the parent index and can employ more aggressive weighting mechanisms. The investor who seeks to control active country or industry weights or exposures to other style factors can use high exposure indices that employ optimization or systematic stock screening. High exposure indices suits also those investors who want to limit turnover, tracking error, or concentration. Further up the pyramid, Long/Short Factor Indices add leverage (e.g., 150/50, 130/30) primarily to hedge out residual exposure to other factors. Finally Market-Neutral Factor Indices are pure long/short zero investment indices that have zero market exposure. These leveraged index categories typically employ optimization methods.

4.1 Factor exposure

What does factor exposure actually mean? MSCI explains that factor exposure captures the amount how much the index has the pure “non-investable” factor. They suggest that for measuring the factor exposure investors could use different factor models like the Fama, French & Carhart model that I use in this thesis. Alternatively one could use the Barra factor model which incorporates over 40 data metrics including: earnings growth, share turnover and senior debt rating to name a few. Factor exposure is most commonly expressed as standard deviations away from the cap-weighted average of the market. It is worth noting that these factor models typically employ linear exposures and regressions so the exposure of an index to a factor is the weighted average of the exposure of the constituents. Factor exposure can alternatively be called signal strength (Bender et. al. 2013b).

Bender et. al. (2013b) also noted that it is important to control for incidental bets to other factors. If the control fails one might get unintended exposure to other factors and the returns might not scale up when exposure is increased.
4.2 Investability

According to Bender et. al. (2013b) investability can be measured by liquidity and tradability of the index. Investability also refers to the scalability of the allocation to an investment product that replicates the risk factor index. It can also be measured by turnover, cost of replication and capacity. Tradability/liquidity quantifies how tradable the portfolio is and how liquid the constituents are in the index replicating portfolio. The metrics include days to trade a certain portion of the portfolio and days to trade individual constituents at rebalancing and during initial construction. Turnover/cost of replication aims to measure the turnover of the index at rebalancing which directly affects the trading costs. The higher the turnover is, the higher the costs usually are. Active managers commonly use measures that show how much they deviate from the index. Few of these measures are active share and maximum strategy. Finally the capacity measure indicates the percentage of a stocks’s free float the portfolio would own. Investability is a combined measure of many different metrics as can be seen from picture 2. below.

![Diagram of Investability](image-url)

*Picture 2. Dimensions for Investability (adapted from Brender et. al. 2013b).*
4.3 Investability vs. exposure

There is an unavoidable trade-off between investability and exposure. Indices nearer the top of the pyramid in picture 1. have higher exposures to the desired indices but lower investability. Institutional investors must then decide what their preferences are and where they want to be on the pyramid. For institutions it is usually important to have low tracking error. However, when investors move up the pyramid in chase of higher returns, tracking error usually increases at the same time. If the institution has tracking error limits it must also limit its investments to the lower end of the pyramid.

According to Bender et al. (2013b) higher capacity indices typically hold exposure to a broad set of risk-factors and they are weighted with investability preferences in focus. High exposure indices aim to mainly hold exposures to the desired factor only. This being said the high exposure indices tend to be more concentrated and have lower investability.

One additional insight for institutional investors is that by combining these risk factor indices, it is possible to reduce trading costs by leveraging the benefits of natural crossing. Reducing the trading costs can be achieved by optimization methods during the construction of the portfolio and at each rebalancing stage. Take for example a stock whose price has fallen over time. As the price falls, it may drop out of momentum index but incidentally the lower price might push the stock into a value index. Now instead of selling the stock from the momentum portfolio and buying it in the value portfolio, the investor can just let the natural crossing reduce the trading costs. The aim of the MSCI Diversified Mix Index is to take advantage of this phenomena.
4.4 Pástor & Stambaugh liquidity factor

Liquidity has been an elusive and wide concept that denotes the ability to buy or sell large amounts quickly, at low cost and without having an effect on the price. Pástor & Stambaugh (2013) implied that liquidity could be an important factor for asset pricing theory. They stated that liquidity is a priced state variable and it can be used to predict expected returns. In their minds it seems reasonable that investors require higher expected returns on assets whose returns are more sensitive to aggregate liquidity. They argue that portfolios that have more sensitivity to aggregate liquidity are more likely to face margin calls and liquidations when aggregate liquidity is low. Then if the liquidity is already low it is difficult to liquidate the portfolio in order to meet the margin call. They concluded that adding their liquidity factor to a mean-variance frontier constructed of the MKT, SMB, HML, MOM and risk free cash position, they were able to increase the Sharpe ratio significantly.

As the investability decreases when moving closer to the pure academic factors, I suspect that the liquidity also decreases. This implies that the Pástor & Stambaugh liquidity factor might be able to predict or explain the return differences in high exposure and high capacity indices. I will contemplate on this more in results and conclusions.

4.5 MSCI as an index provider

MSCI is the leading index provider in the world and it has devised its own methodology for creating these indices. I will find out if their way of creating these risk factor indices is good by testing does higher exposure to the risk factors create higher risk-adjusted returns compared to the high capacity indices. I will also test if MSCI’s risk factor indices are able to create excess returns over the Fama & French model with the addition of Carhart momentum factor. My hypothesis for this study are below.
My first hypothesis is as follows:

\[ H_0: \text{High exposure indices provide higher and statistically significant risk-adjusted returns than high capacity indices.} \]

\[ H_1: \text{High exposure indices don’t provide higher and statistically significant risk-adjusted returns than high capacity indices.} \]

The second hypothesis is as below:

\[ H_0: \text{MSCI risk factor indices provide statistically significant excess returns.} \]

\[ H_1: \text{MSCI risk factor indices don’t provide statistically significant excess returns.} \]

In the next chapter I will go through the methods used for testing my hypothesis.
5 METHODOLOGY

I will conduct a series of different tests to answer at least the following questions:

1. I will test for the high exposure and high capacity indices and find out if high exposure indices provide higher risk-adjusted returns over high capacity indices.
2. I will utilize the Fama & French three-factor model with the addition of Carhart momentum factor. I will run a time-series regression on my data of monthly prices to see how well this model can explain the returns of MSCI’s individual risk factor indices.
3. I will also explain the risk-factor indices’ returns with the parent index, MSCI World. This will explain how much MSCI tilts their risk-factor indices away from the parent index.
4. I will construct different risk factor-based portfolios using risk parity methods and try to beat the MSCI Diversified Factor Mix index.

5.1 Ledoit & Wolf time-series bootstrap confidence interval

Ledoit & Wolf (Ledoit & Wolf, 2008) have designed a robust method for testing time-series related Sharpe ratios. They imply that performance hypothesis testing with the Sharpe ratio is not valid when returns have tails heavier than the normal distribution or are of time series nature. Instead they use a robust inference method by constructing a studentized time series bootstrap confidence interval for the difference of Sharpe ratios. Then they can declare that the two Sharpe ratios are different if zero is not included in the confidence interval.

I have collected price data of 8 different indices from MSCI for the purpose of testing high exposure and high capacity performance. The data ranges from November 1998 to September 2015. My data has both high exposure and capacity counterparts for the quality, minimum volatility, momentum and value factors. I will calculate the excess mean returns, volatilities and Sharpe ratios for these indices and finally I will test if
the Sharpe ratios are statistically different from each other. This way I will be able to demonstrate that is it worth it to move up in the pyramid towards the pure factor exposures.

5.2 Fama & French three-factor model and Carhart momentum factor

Capital asset pricing-model has been a widely used and accepted model to interpret portfolio returns in the past. After CAPM’s first introduction (Treynor 1961) to markets there has been a lot of academic research regarding the sources of returns or premiums. Research has shown that many anomalies question the use of CAPM as a model that predicts future market returns. These anomalies suggest that certain investment styles are persistently in contradiction with the expected return forecasts provided by the CAPM. In practice investors can achieve premium (excess market return) by investing in certain style of equities. For example if a portfolio manager invests in these premium offering equities he can achieve higher returns than the funds benchmark index but the excess return may not be due to alpha. CAPM can’t capture the portfolio managers’ skill nor the active returns but suggest only that the excess returns are due to high alpha. This is why we need models that measure exposure to these anomalies. The answer to this problem is using multifactor-models that measure, in addition to the market portfolio the portfolios returns correlation to certain returns generated by these anomalies.

The best known multifactor-model is the Fama & French three factor-model (Fama & French 1993) that measures the returns correlation with the market premium and small-cap stock premium and the value stock premium. The Fama & French three factor model can be phrased as follows:

$$r_p = \alpha_p + \beta_pM + \beta_pSMB \cdot SMB + \beta_pHML \cdot HML + \varepsilon_p,$$

where \(r_p\) = portfolio p’s excess return, \(\alpha_p\) = portfolio p’s alpha as the models constant term, \(\beta_pM\), \(\beta_pSMB\), \(\beta_pHML\) = portfolio p’s beta coefficients, that measure the portfolios exposure to different factors, \(rM\) = excess return on market, \(SMB\) = small cap stock premium that exceeds large cap stock returns (Small Minus Big), \(HML\) = high book-
to-market-ratio stock returns that exceeds low book-to-market stock returns (High Minus Low) and $\epsilon_p =$ residual as the unexpected return of the portfolio.

Fama and French (1992) studied corporate specific financial ratios effect on price changes and they noticed that portfolios constructed of small companies and high book-to-market companies can explain the variations of the prices. Small companies’ premium also known as the size premium is based on a finding by Banz (1981). He stated that companies of smaller market-cap produce higher risk-adjusted returns than larger market-cap companies. This study utilized the CAPM as its methodology.

Rosenberg, Reid and Lanstein (1985) noticed the same phenomena on stocks which book-to-market-ratio is larger than average. Fama and French (1993) continue to refine these findings to factors that they use together with the market factor to explain the variations in returns. They find that these factors can explain the variations of the returns quite well and in addition they don’t have high correlation with each other. Fama and French (1996) present their three factor model in its most recognized form and state that these factors explain remarkably well the anomalies found in CAPM.

\[
R_i - R_f = \alpha_i + b_i (R_M - R_f) + s_i SMB + h_i HML + \epsilon_i
\]  

Fama and French (1996) also find that the three factor model has some caveats. It does not fully explain the persistence of returns on a short time period. This is why the model might need more factors to function better. The finding that positive returns are followed by positive returns and negative returns followed by negative returns was first done by Jagadeesh and Titman (1993). They also noticed that a strategy that buys stocks that have performed well in the past and sell stocks that have performed poorly in the past produces significant abnormal returns. In other words returns that exceed the expected return forecasted by CAPM. This phenomena is called momentum. Carhart (1997) studied the persistence in mutual fund performance and adds the momentum factor to Fama & French three factor-model. Momentum-factor measures the portfolios returns exposure to the premium associated with this anomaly. Carhart finds that momentum explains a considerable portion of the alpha of some mutual funds. This model is also called Carhart four factor model and in can be presented as follows:

\[
r_p = \alpha_p + \beta_p R_M + \beta_p SMB + \beta_p HML + \beta_p WML + \epsilon_p
\]  

Fama and French (1996) also find that the three factor model has some caveats. It does not fully explain the persistence of returns on a short time period. This is why the model might need more factors to function better. The finding that positive returns are followed by positive returns and negative returns followed by negative returns was first done by Jagadeesh and Titman (1993). They also noticed that a strategy that buys stocks that have performed well in the past and sell stocks that have performed poorly in the past produces significant abnormal returns. In other words returns that exceed the expected return forecasted by CAPM. This phenomena is called momentum. Carhart (1997) studied the persistence in mutual fund performance and adds the momentum factor to Fama & French three factor-model. Momentum-factor measures the portfolios returns exposure to the premium associated with this anomaly. Carhart finds that momentum explains a considerable portion of the alpha of some mutual funds. This model is also called Carhart four factor model and in can be presented as follows:
in this model the coefficients and constant terms are the same as in equation (1) but we have added another factor $\beta_{pWML}WML$, in which $\beta_{pWML}$ is a beta-coefficient that represents the exposure to the momentum-premium and WML (Winners Minus Losers) is the return of the momentum portfolio.

Even though there are many different multifactor models that are based on regression analysis, these afore mentioned three and four factor models are widely used amongst academics and also industry specialists. These models are used to measure returns and to explain the source of the returns and of course measure the alpha of the portfolio. I will use the Carhart four factor model to measure the price data that I have gathered from MSCI database.

The proxies for worldwide factor portfolios were available at Kenneth French’s homepage. These international factors have been used in “Size, Value, and Momentum in International Stock Returns” by Fama and French (2012).

The global factors and portfolios include all 23 countries in the four regions: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, Sweden, United Kingdom and United States. The proxies are quoted in U.S. dollars, including dividends and capital gains. The market factor is the return on a region’s value-weighted market portfolio minus the U.S. one month T-bill rate. For the SMB and HML factors Fama and French sorted stocks in all four regions to two market cap and three book-to-market equity (B/M) groups. Big stocks were those in the top 90 decile and small stocks in the bottom 10 decile. For the B/M breakpoints they used 30th and 70th percentiles.

The 2x3 sorts on size and lagged momentum to construct WML were similar, but the size-momentum portfolios were formed monthly. For portfolios formed at the end of month $t-1$, the lagged momentum return is a stock's cumulative return for month $t-12$ to month $t-2$. The momentum breakpoints for a region are the 30th and 70th percentiles of the lagged momentum returns of the big stocks of the region.
SMB is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios.

\[ SMB = \frac{1}{3} (Small \ Value + Small \ Neutral + Small \ Growth) - \frac{1}{3} (Big \ Value + Big \ Neutral + Big \ Growth). \]

HML is the equal-weight average of the returns for the two high B/M portfolios for a region minus the average of the returns for the two low B/M portfolios.

\[ HML = \frac{1}{2} (Small \ Value + Big \ Value) - \frac{1}{2} (Small \ Growth + Big \ Growth). \]

WML is the equal-weight average of the returns for the two winner portfolios for a region minus the average of the returns for the two loser portfolios.

\[ WML = \frac{1}{2} (Small \ High + Big \ High) - \frac{1}{2} (Small \ Low + Big \ Low). \]

Now it is important to notice that these factor proxies are long-short portfolios. They are supposed to have close to zero market exposure. This is the pitfall of academic factors. They are great for academic studies but very difficult to achieve in the industry. Furthermore the long-short factors might not be able to explain the returns of long-only MSCI factor-indices.

By utilizing the Fama & French three factor model with the addition of Carhart momentum factor I will be able to estimate the quality of MSCI risk-factor indices. I will also test how much MSCI actually tilts their risk-factor indices away from the MSCI World parent index by running the time-series regression with MSCI World as the explaining factor. This way I will gain valuable information about the true nature of MSCI factor indices.

I have divided the time-series testing in three phases. In the first phase I will test MSCI’s individual risk factor indices with the Fama & French factor model with the addition of Carhart Momentum factor. Then I will test how much the MSCI World index returns can explain the individual risk factor indices returns. This way I will find out how much the MSCI risk factor indices provide exposure to the four academic
factors and how much have they been tilted away from the parent index. In the third phase I have constructed different portfolios from the risk factor indices by utilizing risk parity methods. I will test whether it is possible to beat the MSCI Diversified Factor Mix index that has equal weights in all the six risk factor indices. I will also test how well the Fama, French & Carhart model can explain the returns of these portfolios. These tests will further enlighten me about the quality of MSCI risk factor indices.

The Fama, French & Carhart model is extremely used in the industry and it rests on a solid theoretical base. Being one of the earliest multifactor model it has rooted itself in the research. I believe that in this study it could have been useful to add more factors to this model. One especially interesting factor is the Pástor & Stambaugh liquidity factor. It may have been able to explain the differences in high capacity and high exposure indices and also in the risk parity portfolios. Are the benefits of higher exposure to a risk factor only compensation of lower liquidity?

5.3 Risk parity based portfolio construction

I will run multiple risk-parity based optimization methods on my data and I will figure out which methods provide the best results. I will test portfolios created by minimum variance (MV), 1/N, equal risk contribution (ERC) and systematic risk parity (SRP). With these portfolios I will try to beat MSCI’s own Diversified Factor Mix index. MSCI utilizes the 1/N method in constructing the Diversified Mix index (Bender, 2013b).

Maillard et.al. (2008) have good introduction to portfolio optimization methods. They first introduced the minimum variance portfolio, which is a simple portfolio on the Markowitz’s efficient frontier. It is also the only mean-variance frontier portfolio that is presumed to be robust as it does not require expected returns to compute. Unfortunately, minimum variance portfolios suffer from portfolio concentration. A step up from minimum variance portfolios is the 1/N portfolio, which gives equal weights to all components. It has been shown that 1/N portfolios are efficient out-of-sample. These two above methods are simple and widely used in the industry due to their good implementation properties. Next they introduced the ERC method, which allocates weights so that every constituent has equal contribution to the overall risk of
the portfolio. The risk contribution of stock X for example is the share of total portfolio risk that is attributable to that stock. It is computed as the product of the allocation in stock X with its marginal contribution to risk. Marginal contribution to risk is calculated as the change in total risk of the portfolio induced by an infinitesimal increase in holdings of stock X. They also showed that ERC portfolios tend to lie between minimum variance and 1/N portfolios in terms of returns. An extension of the ERC-method was introduced by Kahra (2015). This extension is called Systematic Risk Parity (SRP) and it allocates risk budget to each portfolio component in proportion to its systematic risk.

I have formed 5 different portfolios from the before mentioned six factor indices by utilizing different portfolio construction methods. The methods are chosen based on the plausibility of the weights they offer after shorting-, leverage-, and turnover constraints. Most common and easy to construct is the 1/N method. It simply gives equal weights to each component in the portfolio. This naive method will also serve as a control for the risk-parity methods. I have also constructed the minimum variance portfolio introduced by Markowitz. Furthermore I have chosen two different risk-parity methods from a group of 7 methods. Equal risk contribution (ERC) and systematic risk parity (SRP) gave suitable weights, keeping in mind the investability of the methods. When I conducted portfolio optimization for inverse volatility (IV), inverse variance (IV2), alpha risk parity (ARP), maximum diversification (MD) and diversified risk parity (DRP) I got weights that utilized high leverage and shorting. After giving constraints these methods gave zero weights to multiple factors and unproportional weights to only few factors, namely minimum volatility.
5.4 Data collection

I have collected my data from the “MSCI end of day” data search. I chose MSCI as my data source because it was readily available and a large group of different investment products use MSCI indices as their benchmarks. MSCI is widely known reliable and respected index provider. I have monthly price data from November 1998 to September 2015. The indices that I have chosen are quoted in USD and they represent the developed world markets. MSCI has created indices that provide factor exposures. My data comprises of six different indices giving exposure to the size (SMB), value (HML), momentum (WML), high dividend yield (HDY), minimum volatility (MVOL) and quality (QUAL) factors. The risk free rate is represented by 1-month Libor rate. From the HML, QUAL, MVOL and WML factors, I will conduct a study of comparing Sharpe ratios between high exposure and high capacity indices. Furthermore I will test if the Sharpe ratios are statistically different from each other by conducting a Ledoit-Wolf-test.

The MSCI World Equal Weighted Index represents an alternative weighting scheme to its market cap weighted parent index, the MSCI World Index. The index includes the same constituents as its parent large and mid-cap securities from 23 Developed Markets (DM) countries. However, at each quarterly rebalance date, all index constituents are weighted equally, effectively removing the influence of each constituent’s current price (high or low). Between rebalances, index constituent weightings will fluctuate due to price performance. This index gives proportionally higher weights to small size companies and aims to give exposure to the size-factor.

The MSCI World Value Index captures large and mid-cap securities exhibiting overall value style characteristics across 23 DM countries. The value investment style characteristics for index construction are defined using three variables: book value to price, 12-month forward earnings to price and dividend yield. With 850 constituents, the index targets 50% coverage of the free float-adjusted market capitalization of the MSCI World Index.

The MSCI World Momentum Index is based on MSCI World, its parent index, which includes large and mid-cap stocks across 23 DM countries. It is designed to reflect the
performance of an equity momentum strategy by emphasizing stocks with high price momentum, while maintaining reasonably high trading liquidity, investment capacity and moderate index turnover.

The MSCI World High Dividend Yield Index is based on the MSCI World Index, its parent index, and includes large and mid-cap stocks across 23 DM countries. The index is designed to reflect the performance of equities in the parent index (excluding REITs) with higher dividend income and quality characteristics than average dividend yields that are both sustainable and persistent. The index also applies quality screens and reviews 12-month past performance to omit stocks with potentially deteriorating fundamentals that could force them to cut or reduce dividends.

The MSCI World Minimum Volatility Index aims to reflect the performance characteristics of a minimum variance strategy applied to the MSCI large and mid-cap equity universe across 23 DM countries. The index is calculated by optimizing the MSCI World Index, its parent index, for the lowest absolute risk (within a given set of constraints). Historically, the index has shown lower beta and volatility characteristics relative to the MSCI World Index.

The MSCI World Quality Index is based on MSCI World, its parent index, which includes large and mid-cap stocks across 23 DM countries. The index aims to capture the performance of quality growth stocks by identifying stocks with high quality scores based on three main fundamental variables: high return on equity (ROE), stable year-over-year earnings growth and low financial leverage.

I have manipulated the monthly price level data in R-Studio to form monthly returns data. Then I have also made sure that all the data variables are measured in the same currency, at the same time of the month and at the same precision. At first I had the 1-month Euribor rate as the risk free rate, but I changed it to be the 1-month libor because it is quoted in USD.

It is worth noting that all of these indices are formed by tilting weights away from MSCI world index. Furthermore, all the risk factor indices are long only, while the
Fama, French & Carhart model has long-short factors. This indicates that all of the factor indices should have high exposure to the market factor.
6 RESULTS

In this chapter I will go through the results from the testing phase of my thesis. I will first report the results of high exposure and high capacity Sharpe ratio differences and then go on to the Fama & French regression results.

6.1 High exposure vs. high capacity risk-factor indices

Moving from high capacity indices to high exposure gives the investor higher exposures to the desired factors. At the same time, the investability gets lower and the volatilities and expected returns increase. As we can see from the graph 1. below, high exposure indices have reached higher end values in the sample period from 1998 to 2015. In each category the high exposure counterpart has been able to beat the high capacity counterpart in terms of returns.

![Graph 1. End values of high exposure and high capacity risk factor indices in the sample period.](image)

How about the volatilities then? When we look at tables 1 and 2 it is clear that when adding exposure, the mean returns and volatilities have risen but not hand in hand. While returns have risen significantly, volatilities have risen only slightly. This can be concurred in the Sharpe Ratios. The Sharpe Ratios have grown by 44 % (0,117 → 0,169) in Quality to 208 % (0,103 → 0,317) in Value factors. By looking at the
volatilities measures in tables 1 and 2 we can also draw the conclusion that Value factor has the highest risk while Minimum Volatility has the lowest risk associated.

<table>
<thead>
<tr>
<th>High Exposure</th>
<th>Value</th>
<th>Momentum</th>
<th>Quality</th>
<th>Min Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Excess return</td>
<td>5,681</td>
<td>4,234</td>
<td>2,348</td>
<td>2,007</td>
</tr>
<tr>
<td>Volatility</td>
<td>17,910</td>
<td>16,210</td>
<td>13,890</td>
<td>11,030</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0,317</td>
<td>0,261</td>
<td>0,169</td>
<td>0,182</td>
</tr>
</tbody>
</table>

*Table 1. High exposure mean excess returns, volatilities and Sharpe ratios.*

By comparing the Sharpe ratios in tables 1 and 2 one can also notice that increasing risk factor exposure has been most beneficial in value factor and least beneficial in quality factor. The Sharpe ratio of value factor has increased by 0,214 while for quality factor it has increased only by 0,052.

<table>
<thead>
<tr>
<th>High Capacity</th>
<th>Value</th>
<th>Momentum</th>
<th>Quality</th>
<th>Min Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Excess return</td>
<td>1,704</td>
<td>2,332</td>
<td>1,755</td>
<td>1,318</td>
</tr>
<tr>
<td>Volatility</td>
<td>16,520</td>
<td>15,350</td>
<td>15,000</td>
<td>13,310</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0,103</td>
<td>0,152</td>
<td>0,117</td>
<td>0,099</td>
</tr>
</tbody>
</table>

*Table 2. High capacity mean excess returns, volatilities and Sharpe ratios.*

Next I will address my first hypothesis. The results of Ledoit & Wolf time-series bootstrap test are reported in table 3. below.

H₀: High exposure indices provide higher and statistically significant risk-adjusted returns than high capacity indices.

<table>
<thead>
<tr>
<th>Standard errors</th>
<th>Value</th>
<th>Momentum</th>
<th>Quality</th>
<th>Min Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>HAC</td>
<td>0,018</td>
<td>0,022</td>
<td>0,014</td>
<td>0,022</td>
</tr>
<tr>
<td>HAC,pw</td>
<td>0,018</td>
<td>0,022</td>
<td>0,014</td>
<td>0,022</td>
</tr>
<tr>
<td>P-values</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HAC</td>
<td>0,001</td>
<td>0,153</td>
<td>0,298</td>
<td>0,272</td>
</tr>
<tr>
<td>HAC,pw</td>
<td>0,001</td>
<td>0,157</td>
<td>0,274</td>
<td>0,272</td>
</tr>
<tr>
<td>Difference in SR</td>
<td>0,214</td>
<td>0,109</td>
<td>0,052</td>
<td>0,083</td>
</tr>
</tbody>
</table>

*Table 3. Ledoit & Wolf inference bootstrap results.*
To interpret the Ledoit-Wolf results it is important to revise their testing methods. Their null-hypothesis is that the two Sharpe ratios are equal. This can be rephrased so that the difference of Sharpe ratios is equal to zero. We can reject the null-hypothesis if the HAC.pw P-value is below 0.05. This indicates that the Sharpe ratios of high exposure and high capacity indices are different only for the value factor. It seems that MSCI risk factor indices can’t produce statistically significant and higher risk-adjusted returns by increasing the exposure of the risk factor. The value factor seems to be an exception to the rule. So we can reject the null hypothesis for momentum, quality and minimum volatility indices. However, for value factor we can’t reject the null hypothesis and we conclude that higher exposure to value factor provides higher and statistically significant risk-adjusted returns.

This may be due to the fact that value factor has the highest difference in Sharpe ratios. The differences for momentum, quality and minimum volatility factors are between 0.052 and 0.109 so it is highly unlikely to get confidence intervals that don’t include zero. For all risk factor indices it is beneficial to gain higher exposure but we can’t conclude that it is statistically so.

### 6.2 Fama & French regressions

For the Fama & French regressions, I have divided the testing in three stages. In the first phase I will test MSCI’s individual risk factor indices with the Fama & French factor model with the addition of Carhart Momentum factor. Then I will test how much the MSCI World index returns can explain the individual risk factor indices returns. This way I will find out how much the MSCI risk factor indices provide exposure to the four academic factors and how much have they been tilted away from the parent index. In the third phase I have constructed different portfolios from the risk factor indices by utilizing risk parity methods. I will test whether it is possible to beat the MSCI Diversified Factor Mix index that has equal weights in all the six risk factor indices. I will also test how well the Fama, French & Carhart model can explain the returns of these portfolios. Next I will address my second hypothesis shown below.

**H₀: MSCI factor indices provide statistically significant excess returns.**
From the first phase of testing I learned that the risk factor indices provide monthly excess return of 0.3 – 0.7 %, which would give 3.6 – 8.4 % annually. This can be seen from table 4. below. The excess return is statistically significant for value, size, momentum and minimum volatility factors. These findings are in line with Fama and Frenchs findings in their paper about international stock returns (2012). My results contradict with Roncalli’s (2014) findings about the value factor producing significant premiums in developed countries. In my sample the value factor had only negative loadings which indicates that growth strategies have performed better than value strategies.

When it comes to my second hypothesis the excess returns over the Fama, French & Carhart model indicate that we can reject the null hypothesis for high dividend yield and quality factors. For the other factors the null hypothesis can’t be rejected.

The factor loadings are presented as βMKT for market factor, βSMB for the size factor, βHML for the value factor and βWML for the momentum factor. These betas indicate how much the factor can explain of the movements of the current individual factor index. The R-Squared value gives an indication about the fit of the model. Even with low R-Squared values it is possible to draw conclusions of the sample. However, it is more important to understand why the R-Squared value is so low. This is probably due to the fact that the risk factor indices that I try to explain are long only factors, while the explaining factors of the model are long-short factors. Another fact affecting the R-Squared value is the amount of constituents used in MSCI World Index and the risk factor indices associated. MSCI World has about 1 650 constituents and the risk factor indices have less. Then the academic factors that are used in the model can have up to 10 000 constituents (Ang, 2013).
For the factor loadings it is interesting to see that the market factor can explain only a small part of the returns of these long only risk factors. I expected that the market factor would have a lot higher values. Interestingly it is not even significant for momentum, high dividend yield and quality factors. This is odd since the investing universe is constructed of the same 23 developed countries in all of these factors. It must be so that MSCI has a much more concentrated factors and don’t use as many constituents as Fama & French model.

From table 4. we can see that the size factor has no explanatory power in this sample, which is odd especially for the size risk factor index. However, this concurs the findings of Fama, French (2012) and Ang (2013). When it comes to the value factor it is significant only in momentum index and quality index. Value factor has negative loadings in all risk factor indices which might indicate that growth stocks could have some explanatory power for MSCI’s risk factor indices. Finally the momentum factor seems to have statistically significant loadings in value and size indices and all the signs are negative. This may indicate that the inverse of momentum strategy could have some explanatory power for value and size indices.

### Table 4. Fama, French & Carhart model results on individual risk factor indices.

<table>
<thead>
<tr>
<th>Index</th>
<th>$\alpha$</th>
<th>$\beta_{MKT}$</th>
<th>$\beta_{SMB}$</th>
<th>$\beta_{HML}$</th>
<th>$\beta_{WML}$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Value</strong></td>
<td>0.007</td>
<td>0.173</td>
<td>0.139</td>
<td>-0.054</td>
<td>-0.159</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Size</strong></td>
<td>0.006</td>
<td>0.133</td>
<td>0.085</td>
<td>-0.125</td>
<td>-0.152</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Momentum</strong></td>
<td>0.006</td>
<td>0.099</td>
<td>0.109</td>
<td>-0.304</td>
<td>-0.055</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High Dividend Yield</strong></td>
<td>0.003</td>
<td>0.095</td>
<td>0.142</td>
<td>-0.080</td>
<td>-0.114</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Quality</strong></td>
<td>0.005</td>
<td>0.042</td>
<td>0.083</td>
<td>-0.206</td>
<td>-0.073</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Minimum Volatility</strong></td>
<td>0.004</td>
<td>0.085</td>
<td>0.076</td>
<td>-0.135</td>
<td>-0.090</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(*)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(.)Significant at 5%; *Signf. at 1%; **Signf. at 0.1%; ***Signf. at 0%
In the second phase I tested how much the MSCI World index returns can explain the individual risk factor indices returns. I found out that the World index can explain over half of the returns for all the individual indices. We can see from table 5. that for the value factor, the world index can explain as much as 95,3 %. Furthermore, we can also see that minimum volatility factor tilts the most away from the parent index and delivers the lowest excess return of 12 % annually. It is quite perplexing to see that by tilting only 4,7 % away from the parent index for value factor one can achieve a staggering 20,4 % annual excess return over the World index. The R-Squared value is also a lot higher than previously which is expected. I am using the parent index to explain the returns of risk factor indices that have been created by tilting away from the parent index. From these results we can also conclude that MSCI does not tilt away much from the parent index. This is especially true for the value index. We can draw the conclusion that MSCI does not do such a good job as “active management” in the sense that by tilting more from the parent index does not yield higher active returns. This can be seen from the minimum volatility index, which deviates almost by half from the parent index but provides the lowest excess return.

These results indicate that it is very useful to utilize MSCI’s factor indices, especially if the alternative investment would be MSCI World Index. However, the case might not hold if the alternative investment could be chosen from a group of passive index providers.
### 6.3 Risk-parity portfolios

I constructed different risk factor portfolios by utilizing risk-parity methods and I will next report the results and claim that have I been able to beat MSCI’s own Diversified Factor Mix index.

I used 1/N and minimum variance as control portfolios. I also constructed 7 different risk-parity portfolios. I will report only 2 of these risk-parity portfolios because the other 5 methods gave unproportional weights to only few risk factor indices. In graph number 2, we can see the out of sample excess returns of MSCI World Index, 1/N, ERC, SRP and Diversified Mix portfolios. It is clear that all the portfolios that utilized risk factors had better results than the world index.

---

<table>
<thead>
<tr>
<th>Individual Factor Indices explained by MSCI World Index</th>
<th>α</th>
<th>β</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Value</strong></td>
<td>0.017</td>
<td>0.953</td>
<td>0.784</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
<tr>
<td><strong>Size</strong></td>
<td>0.015</td>
<td>0.917</td>
<td>0.828</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
<tr>
<td><strong>Momentum</strong></td>
<td>0.014</td>
<td>0.789</td>
<td>0.658</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
<tr>
<td><strong>High Dividend Yield</strong></td>
<td>0.011</td>
<td>0.813</td>
<td>0.767</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
<tr>
<td><strong>Quality</strong></td>
<td>0.012</td>
<td>0.769</td>
<td>0.853</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
<tr>
<td><strong>Minimum Volatility</strong></td>
<td>0.010</td>
<td>0.564</td>
<td>0.732</td>
</tr>
<tr>
<td></td>
<td>(***)</td>
<td>(***)</td>
<td></td>
</tr>
</tbody>
</table>

*Significant at 10 %; **Signf. at 5%; ***Signf. at 1%

*Table 5. Individual Factor Indices explained by MSCI World Index.*
From table 6. below one can see that the plain vanilla world index has had the worst performance out of sample. The out of sample period was from June 2010 to August 2015 and I constructed the portfolios in sample between November 1998 and May 2010. The Systematic Risk Parity method had the best results with annualized returns of 7.44 %. It was the only method that was able to beat the MSCI’s Diversified Mix. The SRP-method had only 0.03 % excess return over the index. It is important to notice that by utilizing risk-parity methods one could achieve over 1.19 % annual excess returns over the MSCI World index. This is a substantial benefit in the long run.
Table 6. End values of different portfolios out of sample.

<table>
<thead>
<tr>
<th></th>
<th>WORLD</th>
<th>EW</th>
<th>ERC</th>
<th>MIX</th>
<th>SRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>End value</td>
<td>32,79%</td>
<td>36,46%</td>
<td>37,41%</td>
<td>38,91%</td>
<td>39,07%</td>
</tr>
<tr>
<td>Annualized</td>
<td>6,25%</td>
<td>6,94%</td>
<td>7,13%</td>
<td>7,41%</td>
<td>7,44%</td>
</tr>
</tbody>
</table>

Even though the MSCI’s Diversified Mix index has been created by equally weighting the risk factor indices it has been able to beat the 1/N portfolio that I created. This must be due to the fact that I didn’t use rebalancing in the sample period (Bender, 2013b).

From table 7. we can notice that all portfolios have very similar results. This is due to the fact that the weights of these portfolios do not differ from each other significantly, which can be seen in graph 3. We can also notice that value and size factors have the highest contributions to risk while minimum volatility has the lowest. Systematic Risk Parity has the highest weight in minimum volatility and the lowest weight in value factor. With these alterations to weights it has been able to achieve higher risk-adjusted returns than the other portfolios. Even these small alterations can achieve 0,5 % annualized excess returns over the equally weighted portfolio. The most important finding is that all of these portfolios can achieve statistically significant excess returns over the Fama, French & Carhart model. The excess returns are same in all portfolios, 1 % monthly or 12 % annually.

If I would have added the Pástor & Stambaugh liquidity factor to the Fama, French & Carhart model, I believe that the excess return on these portfolios had been lower. However, the time limitations of this thesis process were tight and it would be a good idea to add this factor to further studies in the future.

The factor loadings in this regression are quite interesting. The market factor has a significant negative loading of -0,174 – -0,178 for ERC and BRP portfolios. This indicates that these portfolios move in the opposite direction compared to the market.
The size factor seems to have the highest explanatory power and it can explain over 50\% of the returns of my portfolios. All the loadings are statistically significant and which indicates that the size factor is the main driver behind these returns. These findings contradict Fama & French (2012) findings about international stock returns.

Value and momentum factors did not get significant loadings and so no conclusions can be drawn from them.

If you compare the regression results of individual indices and risk factor portfolios constructed from the individual indices, you might notice that the market beta and value beta have changed their signs. This is simply because the sample is of different
length. The individual indices are tested over a period of 1998 to 2015 when the risk factor portfolios are tested out of sample over 2009 to 2015. This is the primary reason for differences in results between tables 4. and 7.

These results concur that risk factor investing can be profitable. I was able to beat the MSCI’s Diversified Mix index and anyone could beat the MSCI World Index by investing in MSCI’s own risk factor indices. These risk factor indices are widely available and for example Blackrock already provides ETF’s that track these risk factor indices.
7 CONCLUSION

The purpose of this thesis was to test academically how well MSCI constructs their risk factor indices. I tested whether MSCI is able to provide higher risk-adjusted returns by adding risk factor exposure. Then I also tested academically how well can the Fama & French three factor-model with the addition of Carhart momentum factor explain the returns of MSCI’s risk factor indices. Finally I tested whether it was possible to beat MSCI’s own Diversified Mix index that invests in all six risk factors. I constructed different portfolios with risk-parity methods and tested their performance against the Diversified Mix index. The main conclusions of this study are opened below.

High exposure indices had higher returns than their high capacity counterparts in the sample period. Volatilities also increased when proceeding to high exposure indices but not as much as expected. The Sharpe ratios of high exposure indices were higher for all four counterparts but after testing the difference with Ledoit & Wolf inference method, we could conclude that only value factor had statistically significant and higher risk-adjusted returns than its high capacity counterpart. So we can reject the null hypothesis for momentum, quality and minimum volatility indices but not for value index. I also found out that from these four risk factors, value is the riskiest factor and minimum volatility has the lowest risk associated.

In the time-series regression tests, I found out that all the individual risk factor indices provide excess returns over the Fama, French & Carhart model. The excess returns are statistically significant for value, size, momentum and minimum volatility indices. So we can conclude that the null hypothesis holds true for value, size, momentum and minimum volatility but we can reject it for high dividend yield and quality indices. An interesting finding about the betas in this test was that the market factor does not have statistically significant explanatory power for momentum, high dividend yield and quality factors. I expected that the market factor would have high explanatory powers because it is the only factor that is long only like the MSCI’s risk factor indices.

I also found out that MSCI does not tilt away from the parent index that much. For the value risk factor index, the parent index MSCI World can explain 95.3% of the returns.
However, for minimum volatility the explanatory power is only 56.4%. This is partly due to the fact that minimum volatility has higher concentrations in low volatility stocks and has higher active risk compared to value index. For the other four factor indices, the MSCI World can explain over three quarters of the returns. This thesis has provided new information about the explanatory power of the parent index in MSCI’s risk factor indices. This is meaningful information when comparing index providers. High betas indicate low deviation from the parent index which can be seen negatively, when the idea of building different indices is to create something different from the parent index.

The individual index tests supported the finding by Ang (2013) that the size factor has disappeared. However, these results are overruled by the risk-parity portfolio tests where the size factor was the only factor that had significant positive loadings. The findings of Roncalli (2014) about the value factor were also contradicted in my results. Fama & French (2012) paper about international stock returns had a lot of similarities with my thesis. Their findings about size factor was concurred in my results. They found significant premiums for the value factor while I found none.

Even with the low R-Squared values one can generalize the results to two key points: Risk factor investing is able to provide excess returns over MSCI’s World index and risk-parity methods are able to provide excess returns over equally weighted risk factor indices.

The testing has been done with robust estimators and the sample size is large enough. It is also important to notice that the data has been collected with high precision. The investment universe for all indices and factors is the same 23 developed countries, they are all quoted in USD and the risk free rate is also quoted in USD. The restrictions that I utilized in the portfolio construction phase regarding shorting and leverage are common in industry research. It is important to test these phenomena so that normal investors can also gain access to the investment portfolios. Because of these restrictions anyone who reads this thesis could beat the MSCI World Index by investing in MSCI’s risk factor indices with equal weights.
I gained a broad understanding about factor investing through this thesis process and I found ideas for further research behind every corner. It would be very easy to conduct a similar study with different data gathered from other index providers like Russell or FTSE. Even more valuable study would be to go to the constituent level and try to beat the index providers with the researchers own portfolio construction methods.
REFERENCES


TABLES AND FIGURES

Picture 1. presents the unavoidable trade-off between investability and risk factor exposure.

Picture 2. presents the dimensions of investability.

Graph 1. presents the end values of high exposure and high capacity risk factor indices in the sample period.

Graph 2. presents the out of sample excess returns of different portfolio construction methods.

Graph 3. presents the marginal risk contributions and weights of test portfolios.

Table 1. presents the high exposure mean excess returns, volatilities and Sharpe ratios

Table 2. presents the high capacity mean excess returns, volatilities and Sharpe ratios.

Table 3. presents the Ledoit & Wolf inference bootstrap results

Table 4. presents the Fama, French & Carhart model results on individual risk factor indices.

Table 5. presents the individual factor indices explained by MSCI World Index.

Table 6. presents the end values of different portfolios out of sample.

Table 7. presents the Risk-parity portfolios explained by Fama, French & Carhart model.