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Minimum Volatility Indices

Free Lunch or Risk-Based Anomaly?

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Abstract

This thesis examines the relation between MSCI Minimum Volatility indices performance and underlying risk factors during the 2001-2011 period. The majority of minimum volatility indices outperforms its capitalization weighted benchmark in terms of Carhart four-factor risk-adjusted return. However, a large share of this outperformance is attributed to a bundle of risk sources. This implies the return premium on these indices is just a compensation for risk. The findings indicate minimum volatility portfolios are biased to low-beta stocks. Also, it is shown that concentration risk and absence of implied protection during extreme market events partly explain the Carhart four-factor outperformance. This study adds to existing literature by examining these risk sources into detail. After adjusting for all risk factors, the outperformance of the global minimum volatility portfolio compared to its capitalization weighted benchmark turns out to be statistically insignificant.

Contents

1. Introduction

“Matching the market is an inefficient investment strategy”
(Haugen & Baker, 1991, p.35)

Haugen and Baker (1991) can be seen as pioneers of a group of scholars that potentially initiated a paradigm shift in the asset management industry. In traditional finance, investors are assumed to be rational. The latter implies the utility level of investors is only determined by return and risk and hence funds should be invested in the portfolio with the highest Sharpe ratio. This portfolio is easy to identify if a set of assumptions holds. Namely, all investors agree about risk-return profiles of all securities (i); there are no short selling restrictions (ii); there are no taxes on investment return (iii) and the investment opportunity for all investors is equal to the securities in the cap weighted index (iv). In this ideal world, a market capitalization weighted (MCW) portfolio is Sharpe efficient (Haugen & Baker, 1991). However, as these conditions are very unlikely to be met, it is of great importance to identify a more efficient strategy.

1.1 Research problem

As mentioned, following Haugen and Baker (1991), many scholars attempted to identify an alternative for MCW portfolios. Among several alternatives for MCW, the minimum volatility (MV) weighting strategy is probably the most interesting option. The weights in a MV index are determined by minimizing ex-ante portfolio volatility. These portfolios historically outperformed MCW portfolios in terms of Sharpe ratio (Arnott, Kalesnik, Moghtader & Scholl, 2010; Baker, Bradley & Wurgler, 2011; Chow, Hsu, Kalesnik & Little, 2011; Clarke, Silva & Thorley, 2006; Geiger & Plagge, 2007; Melas, Briand & Urwin; 2011; Nielsen & Aylursubramanian, 2008; Scherer, 2010). The latter implies the excess return per unit of variance is higher than that of MCW portfolios. Most scholars found both a higher return and a lower variance for MV portfolios compared to MCW portfolios. The performance of MV portfolios relative to MCW portfolios is graphically presented in Figure 1. According to Markowitz (1952) portfolio theory, investors should invest in the risky asset portfolio that has the highest Sharpe ratio: the tangency portfolio. Subsequently investors should use leverage to arrive at the preferred level on the Capital Market Line (CML). According to traditional finance theory, rational investors should hold a combination of the MCW portfolio and the risk-free asset. However, empirical findings suggest a combination of the MV portfolio and the risk-free asset is more optimal.

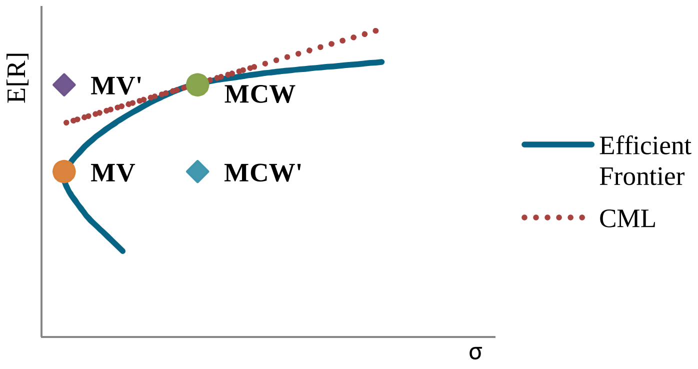

Figure 1: Risk-return profile of various portfolio. MV and MKT indicate the theoretical positions of the MV and MCW portfolio, whereas MV' and MCW' indicate the empirical positions. (Abbreviations: E[R] = expected return on the portfolio; σ = standard deviation of the portfolio returns; CML; Capital Market Line)

Previous research suggests the Sharpe ratio outperformance of MV portfolios is consistent over time and space. However, it is of great interest to find out whether this is an anomaly or whether there are other reasons that justify a 'CAPM-outperformance'. Arnot et al. (2010) argue the outperformance of a global MV portfolio is also present when adjusting for exposures to generally accepted risk based pricing anomalies, as identified by Fama and French (1992) and Carhart (1997). Chow et al. (2011) and Scherer (2010) disagree with this position. However, the approach they use to come to their stance can be criticized. Scherer only examined American stocks. Scholars who studied the returns on MV portfolios for a broader cross section of countries, showed the Sharpe ratio outperformance was larger in other regions than in the US (Geiger & Plagge, 2007). Therefore, the findings of Scherer (2010) cannot be generalized. Chow et al. (2011) created a global MV portfolio and found a positive, but statistically insignificant risk-adjusted return. Arnot et al. (2010) showed MV portfolios outperform MCW portfolios after adjusting for the four Carhart (1997) factors. Summarizing, findings are inconsistent and seem to depend on the region. The link between the extraordinary performance of MV portfolios and potential exposure to other risk factors, is an underexposed research area. This thesis will shed light on this subject.

MV investors aim to hold the equity portfolio with the lowest volatility. Hence, the optimal allocation is determined by the complete covariance matrix. Individual betas are calculated by dividing covariance with the market portfolio by the variance of the market portfolio (Hamilton, 1994). Hence, the information that is required for determining the allocation of MV portfolios is reflected in betas. As the goal is to minimize volatility, MV portfolios are expected to be dominated by low-beta stocks. The latter is confirmed by Scherer (2010), who showed MV portfolios indeed hold low-beta stocks. In an earlier study by Black, Jensen and Scholes (1972), the expected excess returns are not linearly related to beta. This finding has been used as a starting point by several scholars in the 2000s (Blitz & van Vliet, 2007; Baker, Bradley & Wurgler, 2011; Frazzini & Pedersen, 2010). They all found risk-adjusted returns on low-beta assets are significantly higher than those on high-beta assets. The betting against beta (BAB) factor, a portfolio that is long in low-beta and short in high-beta stocks and levered to a beta of one, captures the return difference. Frazzini and Pedersen (2010) argue the anomaly exists because some investors have leverage constraints or are limited by margin requirements. In short, leverage constrained investors who would like to buy market exposure can only implicitly lever up their portfolio. The market exposure that is obtained per euro investment, is highest for high-beta stocks. Therefore leverage constrained investors prefer high-beta assets over low-beta assets, which increases demand. As a result, these stocks became overvalued. If a stock is overvalued at present, risk-adjusted returns are lower in the future. Exactly the opposite holds for low-beta stocks. Hence, for investors that are not leverage constrained, the return premium on low-beta stocks seems to be a ‘free lunch’. However, there are reasons to assume the BAB factor actually captures a bundle of risk sources. To give an example, in a recent paper, Cowan and Wilderman (2011) claim the implied protection element in high-beta assets justifies a premium on low-beta assets. This will be discussed into detail in the next section.

Summarizing, MV portfolios outperformed their MCW benchmark in Sharpe ratio terms. Also, a possible relation exists between the beta anomaly and this outperformance. It is not clear yet whether MV portfolios also outperform when adjusted for a broader set of risk sources. The next paragraph clarifies which topics are studied.

1.2 Research aim

The aim of this thesis is to find out whether MV portfolios actually outperform on a risk-adjusted basis, or whether this is a compensation for other risk factors. The latter will be examined for the MSCI MV indices, which are a series of commercially successful MV indices. In order to gain a better understanding of these strategies and underlying risk factors, also other portfolios will be constructed and used as an identification tool. After measuring the Carhart (1997) four-factor outperformance, the relation between MV performance and BAB returns is clarified. Some potential risk sources, such as leverage constraints, are assumed to be completely captured by the BAB factor. As the link between the BAB factor and leverage constraints is well documented by Frazzini and Pedersen (2010), the current study will not elaborate on this. Underexposed risk sources that might affect MV portfolio returns either directly or through the BAB factor, are scrutinized. Besides the BAB risk, the other two risk factors that are studied are concentration risk and the absence of implied protection.

1.3 Relevance

This study on MV strategies addresses issues from both an academic as a practical point of view. Scherer (2010) links the performance of MV portfolios with the hypothesized bias to low-beta stocks, but solely American stocks are investigated. As previous studies showed the MV strategy has been even more profitable in other regions than in the US, it is relevant to investigate this topic from a global perspective. New insights, such as the implied protection in high-beta stocks (Cowan & Wilderman, 2011), have not been investigated in a MV context yet. Also an examination of the role of concentration risk, adds to existing literature.

This study is relevant for practitioners in the asset management industry as well. As stock markets have been extremely volatile during the recent decade, institutional investors such as pension funds became increasingly interested in equity strategies that generate less volatile returns. As MV strategies minimize volatility per definition, but also seem to be Sharpe efficient, a switch to a MV benchmark instead of a MCW benchmark seems appealing. Compared to MCW indices, the MV indices might be exposed to risk factors by different magnitudes. It is also possible that MV portfolios are exposed to different risk factors. This would have major implications for risk management. As MV portfolios in fact can only be protected by buying hedging instruments on MCW indices, a better understanding of underlying risk factors is key to risk managers.

1.4 Research question

This study addressed the following research question:

To what extent can the Sharpe ratio outperformance of MV indices be explained by exposure to risk factors?

1.5 Structure of the thesis

In order to answer the research question, the potential risk factors need to be identified first. Section 2 provides an overview of previous studies on MV portfolios. Also, risk factors that potentially provide an explanation for the outperformance of MV indices are included. In Section 3, the hypotheses that follow from the literature review are presented. An overview of the used data is given in Section 4. Subsequently, Section 5 deals with the methodology. Next, the findings are summarized in Section 6. Lastly, a conclusion, discussion and suggestions for future research are provided in Section 7 and Section 8.

2. Theoretical framework

In this section an overview of relevant literature is presented. First, traditional finance theory is discussed, as it is important to understand how portfolio performance is evaluated. As a side note, the advantages and disadvantages of MCW indices will be explained as it is important to understand why MCW indices became the standard benchmark in the investment industry. After this background information has been provided, in subsection 2.3 existing literature on MV indices is shown.

2.1 Portfolio performance evaluation

Traditional finance is based on the concepts of investor rationality (Miller & Modigliani, 1961) and market efficiency (Fama, 1970). If these concepts hold, this implies that a higher portfolio return can only be obtained by taking more systematic risk (Markowitz, 1952; 1959). Based on these theorems, the Capital Asset Pricing Model (CAPM) has been developed by Sharpe (1964), Lintner (1965) and Black (1972). According to the CAPM, the expected return on each security ($E[R_i]$) can be modeled in terms of expected market return ($E[R_m]$) and the risk-free rate (R_f). The beta coefficient (β_i) is an indicator of the sensitivity of the security excess returns to market excess returns.

$$E[R_i] = R_f + \beta_i \left(E[R_m] - R_f\right) \tag{1}$$

When allowing for an intercept term (α_i), Equation 1 can be rewritten as:

$$E[R_i] - R_f = \alpha_i + \beta_i \left(E[R_m] - R_f\right) \tag{2}$$

As all securities together form the market portfolio, the intercept term, or Jensen's alpha (1968), will be zero on average. According to the CAPM "the 'market portfolio' is mean variance optimal" (Arnott, Hsu & Moore, 2005, p.83). This implies rational investors should allocate their investment portfolio only to the market portfolio and the risk-free asset. They should determine their position on the CML (see Figure 1) in such a way that their preferences regarding return and risk are satisfied.

Although the CAPM is a respected cornerstone in finance, it is not difficult to create a portfolio that yields a positive alpha return. Fama and French (1992) showed that firms with a small market capitalization and those with a high book value compared to their market value, on average outperform the market in terms of risk-adjusted return in a CAPM setting. However, the higher return on these stocks is only a compensation for additional risk factors (Fama & French, 1993). Therefore, long-short portfolios that capture the return difference are introduced in the asset pricing model. These are respectively the small-minus-big (SMB) factor for the size effect and high-minus-low (HML) factor for the book-to-market effect. In another study, Carhart (1997) shows that markets overreact in the short run, after which correction follows. Stocks that did well in the recent past are expected to continue doing well in the near future. The same is true for stocks that underperform. A trading strategy that involves buying recent winners and selling recent losers, would contribute to generating a positive CAPM alpha. The factor that captures the return on this strategy is called the momentum (MOM) factor. Conducting a multi-factor regression analysis that includes the factors that are discussed above, results in an output that shows a more fair risk-adjusted return. The Carhart (1997) four-factor regression equation is presented below:

$$R_t^p - R_t^f = \alpha + \beta\left(R_t^{mkt} - R_t^f\right) + s * SMB_t + h * HML_t + m * MOM_t \tag{3}$$

Findings of studies investigating low-beta stocks (Frazzini & Pedersen, 2010) suggest this four-factor model should be extended with a fifth factor, namely the betting-against-beta (BAB) factor. The latter captures the beta weighted return difference between low-beta and high-beta assets. According to Scherer (2010), MV portfolios seek exposure to this pricing anomaly. This factor will be explained into more detail later.

To compare different investment alternatives in a way that is consistent with the arbitrage pricing theory (Ross, 1976), one could evaluate the return on a portfolio as the sum of compensations for different risk factors. In the CAPM, there is only one risk factor, market risk. If a portfolio has a beta of 0.7, then its expected excess return is 70% of the market excess return. Continuing this line of reasoning, an investor buys ‘factor exposures’ instead of underlying stocks. When evaluating whether low-beta assets or minimum volatility portfolios are a good alternative for a MCW portfolio, one should judge these after adjusting returns for factor exposures. This is reflected in alpha returns. Many institutional investors do not judge investments in this manner, but only look at return and volatility. However, when comparing portfolios in the current study, one should assume that an investor replaces a MCW portfolio by investing approximately $\frac{1}{\beta_{MV}}$ in the MV portfolio. Risk-adjusted returns that are obtained through regression analysis satisfy this prerequisite.

2.2 Market capitalization weighted indices

The finance industry has promoted the idea that MCW indices form a good proxy for the market portfolio for decades (Arnott, Hsu & Moore, 2005; Arnott et al., 2010). Many practitioners believe that MCW indices are mean variance efficient. One of the underlying reasons to stick to this belief, might be the fact that MCW offers several appealing advantages (Arnott, Hsu & Moore, 2005). As MCW is a passive investment strategy and portfolios are automatically rebalanced, little or no trading is required, which results in costs reduction. Furthermore, stocks with a larger market capitalization are often more liquid, which further reduces transaction costs. Also, a MCW investment strategy is a convenient way of diversifying across the equity market as the largest portfolio weights are automatically assigned to the largest companies. Lastly, scalability is another important advantage of MCW portfolio composition. In addition to this, Arnott et al. (2010) state that tax consequences of a MCW investment portfolio are low. As mentioned in the introduction, the MCW index is only efficient when four conditions are met. The fact that this is unlikely as well as the poor performance of MCW indices compared to MV indices, provides reasons to switch to a MV benchmark.

2.3 Minimum volatility indices

MV weighting is an optimization based strategy. As its name suggests, the strategy aims to minimize return volatility of an equity portfolio. In the subsequent sections, the construction methodology of these portfolios and findings of previous studies will be explained.

2.3.1 Construction

Expected stock returns and their covariance matrix (Σ_t) are difficult to estimate accurately, which is the main challenge when forming optimal portfolios. When creating a MV portfolio, weights (w_t) are chosen such that portfolio variance is minimized (DeMiguel, Garlappi, and Uppal, 2009, p.1924). Maximum combined portfolio weights are equal to one. This optimization problem is presented in Equation 4.

$$\min_{w_t}[\mathrm{w}_\mathrm{t}^\mathrm{T}\Sigma_\mathrm{t} w_t], \qquad s.t. 1_N' \, w_t = 1 \tag{4}$$

Contrasting other portfolio optimization methods, MV strategies do not require return estimates. The covariance matrix is the only determinant of the weights for MV portfolios, which stresses the importance of estimating future covariance accurately (Nielsen & Aylursubramanian, 2008). Chow et al. (2011) estimated the covariance matrix by applying a Bayesian shrinkage method (refer to Ledoit & Wolf, 2004) and using data of 60 months. Subsequently, portfolio weights for the next quarter or year are calculated by minimizing portfolio variance over the previous period. Haugen and Baker (1991) and Chow et al. (2011) composed such an index consisting of the largest thousand U.S. stocks by market capitalization. In both studies, maximum weights are constrained at industry and security level.

The MV portfolios that are developed by MSCI are among the most well known MV benchmarks. Nielsen and Aylursubramanian (2008) from index provider MSCI Barra, studied index returns of the MSCI MV World Index. MSCI Barra uses the Barra Global Equity Model covariance matrix as an input to determine the weights of MSCI MV indices. The Barra model is seen as the most successful commercial factor model that is used to predict variance of stock returns (Haugen & Baker, 1996). When applying this method, factor returns are used to create a covariance matrix that is more robust, as it takes errors into account that would arise from using pure return history (Nielsen & Aylursubramanian, 2008).

2.3.2 Performance

According to Markowitz (1952) portfolio theory, investors should invest in the risky asset portfolio that has the highest Sharpe ratio: the tangency portfolio. Subsequently investors should use leverage to arrive at the preferred level on the CML. Traditionally, MCW are assumed to be efficient, but scholars that studied the performance of MV portfolios found that they have a higher Sharpe ratio than a MCW benchmark (see Table 1).

Table 1 Literature Comparison: Sharpe Ratio MV Portfolios. Only studies which also presented the Sharpe Ratio of a market capitalization weighted benchmark are included.

Study	Period	Region	Sharpe Ratio	Benchmark
Arnott et al. (2010)	1993-2009	Global	0.52	0.18 (MCW index, 1000 stocks)
Baker, Bradley & Wurgler (2011)	1968-2008	US	0.47	Not mentioned
Chow et al. (2011)	1987-2009	World	0.39	0.22 (MSCI World)
Chow et al. (2011)	1964-2009	US	0.49	0.26 (S&P500)
Clarke, Silva, Thorley (2006)	1968-2005	US	0.54	0.36 (MCW index 1000 stocks)
Geiger & Plagge (2007)	2001-2007	Germany	0.34	0.06 (DAX)
Geiger & Plagge (2007)	2001-2007	France	0.40	0.05 (CAC40)
Geiger & Plagge (2007)	2001-2007	Japan	0.21	0.04 (Nikkei)
Geiger & Plagge (2007)	2001-2007	Switzerland	0.77	0.09 (SMI)
Geiger & Plagge (2007)	2001-2007	US	-0.10	-0.29 (S&P500)
Melas, Briand & Urwin (2011)	1988-2010	World	0.32	0.21 (MSCI World)
Nielsen & Aylursubramanian (2008)	1995-2007	World	0.67	0.45 (MSCI World)
Scherer (2010)	1999-2009	US	0.008	0.003 (MSCI US)

Even when investors are rational and markets are efficient, MV portfolios could ‘accidently’ be Sharpe efficient but then this portfolio should be equal to the market portfolio. It is more likely that there are other reasons for the outperformance of MV portfolios. These are discussed in the next paragraphs.

2.3.3 Traditional risk factors

Although some scholars provide empirical evidence as well as a theoretical explanation for the outperformance of MV portfolios, the previous section suggests that there are other factors that should be taken into account. First, the exposure of MV portfolios to generally ‘accepted’ risk based market anomalies is discussed.

Of the studies that are presented in Table 1, only few scholars conducted a Carhart (1997) four-factor regression to check whether minimum volatility portfolios also outperform when adjusted for exposure to the HML, SMB and MOM risk factors. Arnott et al. (2010) found a significantly positive four-factor alpha. Clarke, Silva and Thorley (2006) found similar results, but do not state whether the outperformance is statistically significant. Contrasting these scholars, Chow et al. (2011) did not find significantly positive Carhart (1997) four-factor alpha returns whereas Scherer (2010) did not find significantly positive Fama-French (1993) three-factor alpha returns. Findings and different methodologies are summarized in Table 2 that is presented on the next page.

Table 2 Overview of studies to MV portfolios that included multi-factor return regressions.

Study	Region	Period	Alpha	Factors	Universe	Rebalancing	Method
Chow et al. (2011)	US	1964-2009	0.30%	4 (MKT, SMB, HML, MOM)	CRSP largest 1000 by market capitalization	Annually	Covariance matrix from excess returns previous 60 months. Use shrinkage estimator as defined in Clarke, de Silva and Thorley (2006) *Weights restrictions*: Individual securities 0-5%
		1964-1969	0.54%				
		1970-1979	-0.10%				
		1980-1989	1.68%				
		1990-1999	-0.66%				
		2000-2009	1.46%				
Chow et al. (2011)	Global	1987-2009	1.25%	4 (MKT, SMB, HML, MOM)	Datastream largest 1000 By market capitalization	Annually	Covariance matrix from excess returns previous 60 months. Use shrinkage estimator as defined in Clarke, de Silva and Thorley (2006) *Weights restrictions*: Individual securities 0-5%
Arnott et al. (2010)	Global	1993-2009	1.81%*	4 (MKT, SMB, HML, MOM)	Proprietary (Lazard)	Quarterly	Covariance matrix based on proprietary Lazard Asset Management factor-model. *Weights restrictions:* Individual securities <1.5% Industries <20%.
Scherer (2010)	US	1999-2009	-0.00%	3 (MKT, SMB, HML). Regression of excess return MV portfolio w.r.t. cap weighted portfolio instead of risk-free rate.	MSCI Barra US Minimum Volatility Index (uses stocks from MSCI US)	Semi-annually	Covariance matrix based on proprietary MSCI Barra Global Equity factor-model. *Weights restrictions* (Nielsen & Aylursubramanian, 2007): • Individual securities: 0.05%-1.5% and maximum of twenty times weight of security in MSCI World. • Countries and GIC sectors: <5% deviation from benchmark. • Barra risk index exposures <.25SD from benchmark exposures. • One-way turnover <10%.

* significant on 95% confidence level

2.3.4 BAB factor

According to Scherer (2010), the performance of low-beta firms is an important source of risk for the MSCI US MV Portfolio. This type of risk is reflected in the BAB factor that has been introduced earlier. The BAB factor captures the empirical finding that low-beta assets outperform high-beta assets. The latter is presented Appendix A, Table 13 and Figure 10. Frazzini and Pedersen (2010, p.3) show that "BAB returns are consistent across countries, time, within deciles sorted by idiosyncratic risk and robust to a number of specifications". They argue this is caused by leverage constraints. However, possibly also other risk sources play a role. It is possible that the impact of some of these risk sources on the MV portfolios is only partially captured by the BAB factor. Therefore the direct impact of these particular risk sources will be studied as well. The potential sources of four-factor alpha are explained below.

Source 1 Leverage constraints

Both Blitz and Van Vliet (2007) and Frazzini and Pedersen (2010) argue real world investors face borrowing constraints and hence require a lower risk premium on high-beta stocks. The latter is explained in the example on the next page.

Example 1

Suppose the investment universe consists of three assets: Wal-Mart stocks ($\beta = 1$), Apple stocks ($\beta = 2$), and three month treasury bills. Assume the equity premium equals 6% and the risk-free rate is 2%. There are two investors: a pension fund and a hedge fund. The pension fund has two billion dollar to invest and requires a beta exposure of one. The hedge fund has 1 billion dollar to invest, requires a beta exposure of two and can borrow at 4%. The hedge fund manager can either:

- I. *Invest one billion dollar in Apple. Expected profit: 140 million dollar. (Implicitly levered portfolio)*
- II. *Borrow one billion at 4%. Invest two billion dollar in Wal-Mart. Expected profit: 120 million dollar. (Explicitly levered portfolio)*

The two alternatives imply similar market risks, but the first strategy generates a higher return, as it offers the opportunity to use implicit leverage against the risk-free rate. Hence, the hedge fund manager will choose alternative I. Now the options for the pension fund are evaluated. The pension fund can either:

- I. *Invest two billion dollar in Wal-Mart. Expected profit: 160 million dollar.*
- II. *Invest one billion dollar in Apple, and the remaining part in three month treasuries. Expected profit: 160 million dollar.*

As many leverage constrained investors face the same tradeoff as the hedge fund, demand for Apple increases after which expected returns on this asset go down. The price of Apple will continue to increase as long as alternative I is more attractive than alternative II. As this cannot be explained by the CAPM, this induces risk-adjusted returns (α) *to be negative. As a result, the low-beta stock will outperform. For the pension fund, alternative I will become relatively more attractive compared to alternative II.*

Hence, one would expect negative risk-adjusted returns on low-beta assets during periods with low liquidity because investors de-lever and compensate by buying high-beta assets. The TED spread proxies for tightness of the credit constraints (Frazzini & Pedersen, 2010). The TED spread is the premium on interbank loans over US treasury bills. As the TED spread turns out to be a predictor of BAB returns, leverage constraints are considered as one of the reasons that justify outperformance of low-beta assets. The relationship between leverage constraints and the BAB factor is well documented by Frazzini and Pedersen (2010). Please refer to their study for more information about this relation.

Source 2 Implied protection

Besides leverage, high-beta stocks offer protection during extreme circumstances, which might also justify lower returns. In short, high-beta stocks have less negative returns during extreme circumstances, than what their beta would predict. This relation between high-beta stock returns and market returns, implies that high-beta investors are to some extent protected during extreme market events (referred to as 'implied protection' from here onwards) (Cowan & Wilderman, 2011). As MV indices are expected to be biased to low-beta assets which do not have the implied protection feature, a premium is required. The idea behind this is illustrated in the example below, which is based on the idea of Cowan and Wilderman (2011).

Example 2

Although the arguments in Example 1 seem reasonable, the bank charges four percent on a loan to the hedge fund for other reasons than principal agent problems. The loan to the hedge fund has the same risk characteristics as a subordinated loan to Apple, as illustrated in Figure 2. The bank loan is referred to as 'equity owned by bank'. This Figure shows that the only difference between implicit and explicit leverage is the person who bears the risk. This becomes clear during extreme events. When markets decline by 50%, Wal-Mart shares ($\beta = 1$) *will drop by the same amount if the CAPM holds. The hedge fund can sell its shares and repay the bank. However, when equity markets drop by 70%, Wall-Mart would survive but the hedge fund will get a margin call and only be able to repay 60% of the loan. The problem is that the loan is valued by the CAPM as if it is* *risk-free. Note that in Figure 3, the debt/equity (D/E) ratio of Apple is higher than that of Wal-Mart. This often holds for high-beta firms relative to firms with a lower beta, but even equal D/E-ratios would not justify to ‘price implicit leverage at the risk-free rate’.*

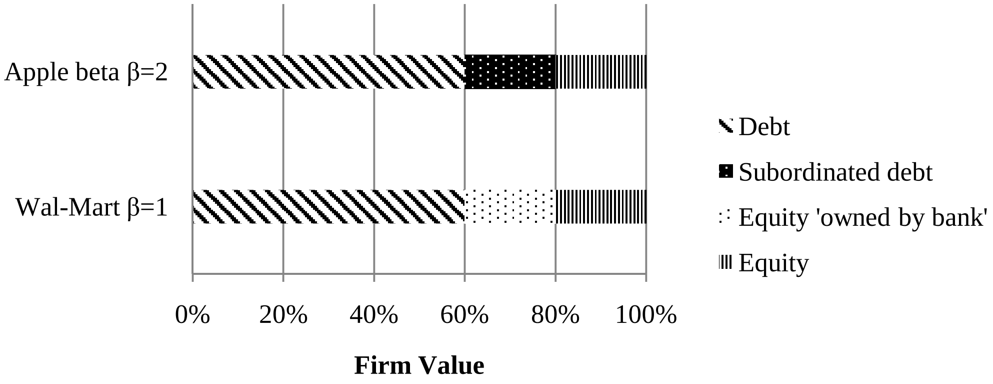

Figure 2 Hypothetical financing of low-beta versus high-beta stocks.

The extreme losses used in the example above only happen in extreme circumstances. Suppose one of the companies instantly becomes suspect of fraud and faces the threat of bankruptcy. If the pension fund chooses the second alternative (see Example 1), total loss is limited to one billion dollar compared to two billion dollar for the first alternative. In other words, investing in high-beta stocks is a safe way to buy market exposure, as a minimum investment per unit of beta is required. Hence, the maximum loss per unit of beta is also lower than for low-beta stocks. The implied protection feature of high-beta stocks becomes more appealing during extreme circumstances. As a consequence, demand for these stocks is expected to increase and the stock price diminishes by a lower amount than what their historical beta predicts. According to Merton (1974), equity can be seen as a call option on firm value. Continuing this line of reasoning high-beta stocks simply have a higher relative strike price. During bear markets, high-beta stocks get closer to the strike price in an early stage. This clarifies an implicitly levered investment has a similar upside potential, but less downside potential than an explicitly levered investment. Hypothetically, this feature is priced and therefore investors in low-beta stocks receive a premium that is reflected in alpha.

The alternative explanation for a premium on MV portfolios that is discussed above is in line with a paper written by Cowan and Wilderman (2011). When analyzing historical data, Cowan and Wilderman (2011) find that high-beta stock returns have a convex relation with market returns, whereas low-beta returns are a concave function of market returns. As a consequence, high-beta stocks have a lower beta during down-markets and a higher beta during up-markets, relative to their long term beta. Exactly the opposite is true for low-beta stocks. Hence, betas of low and high-beta stocks converge to one during extreme events (see Appendix A, Figure 11). In other words, when stock markets collapse, everything goes down irrespective of historical beta. This relation is very unfavorable for low-beta stocks. These characteristics justify the option approach as an explanation for positive risk-adjusted returns for low-beta stocks. In other words, the premium on low-beta stocks is a compensation for this asymmetric payoff structure (Cowan & Wilderman, 2011).

The above is graphically presented in Figure 3. Panel A shows the return on the low-beta portfolio. According to the CAPM, the slope of the return relation should be equal to beta. However, the beta depends on market conditions. As mentioned, returns on low-beta portfolios, and hence MV indices, are expected to be more negative than what its CAPM-beta suggests when market returns are very negative. As this return relation is unfavorable, investors are compensated by alpha. The opposite holds for high-beta assets (panel B). When no extreme events occur, this seems to be a risk free return. However, it is a compensation for risk. Suppose firm value of all companies in the world decreases by fifty percent today. Equity of both low-beta and high-beta stocks will be worth zero. However, low-beta investors need to hold a much larger equity portfolio than high-beta investors to obtain the same amount of beta exposure. Therefore these investors lose a higher amount per unit of beta.

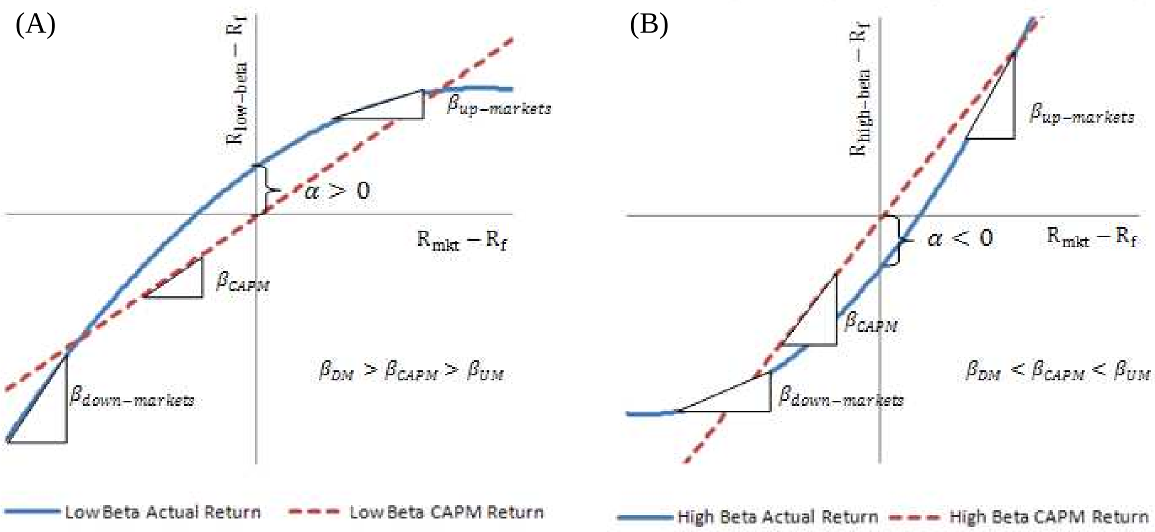

Figure 3 Asymmetric payoff. The payoff structure of the MV portfolio and low-beta stocks is presented in panel A. The payoff structure of high-beta assets is presented in panel B. The market return is presented on the horizontal axis whereas the portfolio return is presented on the vertical axis.

The type of risk that has been used in Example 2 is idiosyncratic, but it cannot be completely eliminated by diversifying through buying a portfolio of low-beta stocks. The consequences of extreme events per unit of beta exposure will be larger for low-beta stocks. Also, there will be some systematic tail risk for which the impact per unit of beta increases for low-beta portfolios. This is reinforced by the fact that low-beta portfolios are biased towards certain industries, such as utilities (Melas, Briand & Urwin, 2011). In an extreme event, such as the 2011 earthquake in

Japan, it is likely that an implicitly levered portfolio of Japanese stocks outperforms an explicitly levered portfolio of Japanese stocks (Rubing, 2012, as cited in De Vos, 2012).

Source 3 Concentration risk

As volatility varies over industries and MV indices minimize volatilities, it is likely that these indices are biased towards certain industries. Although MSCI imposes constraints on the maximum deviation from MCW industry weights for its MV portfolios, concentration risk most likely will not be eliminated completely. If a single industry outperforms on a risk-adjusted basis, this will probably not be eliminated by arbitrage as many financial market participants do not want to deviate from a MCW benchmark. Hypothetically, the Carhart (1997) four-factor outperformance of MV portfolios is partially obtained by investing a relatively large amount in industries that have exposures to risk factors that are not included in the model. The remaining risk might be industry specific and could have a negative impact on stock returns. Hence, a positive alpha return is required to compensate for this additional risk. The impact of industry concentration risk will be measured.

Source 4 Behavioral biases

Behavioral biases might cause private investors to show risk-seeking behavior and hence they overpay for high-beta stocks (Blitz & Van Vliet, 2007). Baker, Bradley and Wurgler (2011) mention preference for lotteries, representativeness and overconfidence as major reasons for the overvaluation of volatile stocks. The former induces investors to overpay stocks with lottery like characteristics (low probability, high possible gains). The second aspect causes investors to believe that extremely successful examples of stock picking (like participating in the IPO of Microsoft in the eighties) are representative for investments the whole section of startups and other volatile stocks. The latter, overconfidence, causes investors to overestimate their accuracy of estimating future stock prices. Logically, the resulting errors will be larger for volatile stocks and the range of all investors' estimations will also be larger. As optimistic people are more likely to participate in the stock market (Baker, Bradley & Wurgler, 2010), volatile stocks are overpaid. As it is impossible to measure the impact of the effect of behavioral biases, this will not be studied here.

Source 5 Fund manager incentives

Although it is clear that investors could have personal reasons to prefer volatile stocks over less volatile stocks (Source 4), it is not clear why price inconsistencies are not locked in by arbitrageurs. According to Baker, Bradley and Wurgler (2011) this is due to benchmarking. The latter is elaborated on in a report by Goldman Sachs (2010) in which it is stated that equity portfolio managers are evaluated based on relative performance compared to a benchmark. As a result, these portfolio managers treat deviations from benchmark weights as a "series of relative bets" (Goldman Sachs, 2010, p.2). The latter causes investment professionals to focus on relative performance instead of on their clients' needs. The fact that institutional investors became more dominant over the recent decades (Baker, Bradley & Wurgler, 2011) reinforces the consequences of limits to arbitrage for the size of the low volatility pricing anomaly. Further, a decentralized investment approach also creates incentives to invest in high-beta stocks as outperformance during bull markets is more attractive than outperformance during bear markets (Blitz & Van Vliet, 2007; Karceski, 2002). An example is presented below.

Example 3

Suppose the management team of mutual fund X receives five percent of the mutual fund return as a bonus on their yearly salary. Of course this bonus cannot be negative. This bonus structure does not provide incentives to limit losses whereas it pays to seek large gains. As a result, the demand for high-beta stocks increases, which causes prices to surge and subsequent period returns to decrease.

For similar reasons as for the fourth source, the role of this risk source is not tested. As mentioned, the fourth and fifth resource are probably at least partially captured by the BAB factor.

3. Hypotheses

Previous research showed MV indices outperform MCW portfolios in terms of Sharpe ratio. Other studies to MV indices lead to inconsistent conclusions regarding risk-adjusted performance in a Carhart (1997) four-factor regression. Therefore, this will be reexamined.

Proposition 1: Performance of MV portfolios

H_0^a*: MV portfolios do not outperform MCW portfolios in terms of Carhart (1997) risk-adjusted returns.*

H_1^a*: MV portfolios outperform MCW portfolios in terms of Carhart (1997) risk-adjusted returns.*

A positive Carhart (1997) alpha performance could possibly be explained by other risk factors. There is evidence that MV portfolios are biased to low-beta stocks (Scherer, 2010). Whereas Scherer only studies American stocks, this will also be examined for global and other regional portfolios in this thesis.

Proposition 2: BAB factor

H_0^b*: MV portfolios do not have a significant exposure to the BAB factor.*

H_1^b*: MV portfolios have a significant positive exposure to the BAB factor.*

If exposure to the BAB factor is detected, it is of great importance to study the underlying risk factors more closely. Frazzini and Pedersen (2010) state the anomaly exists because of leverage constraints. However, as mentioned in the previous section, there might also be other explanations for the outperformance of MV portfolios. These explanations, which are presented in Figure 4, are probably partially captured by the BAB factor.

Unfortunately, two sources are impossible to identify. These are ‘fund manager incentives’ and ‘behavioral biases’. As mentioned, the impact of leverage constraints has been well documented by Frazzini and Pedersen (2010). In this thesis, the two remaining sources, concentration risk and implied protection in high-beta will be studied more closely.

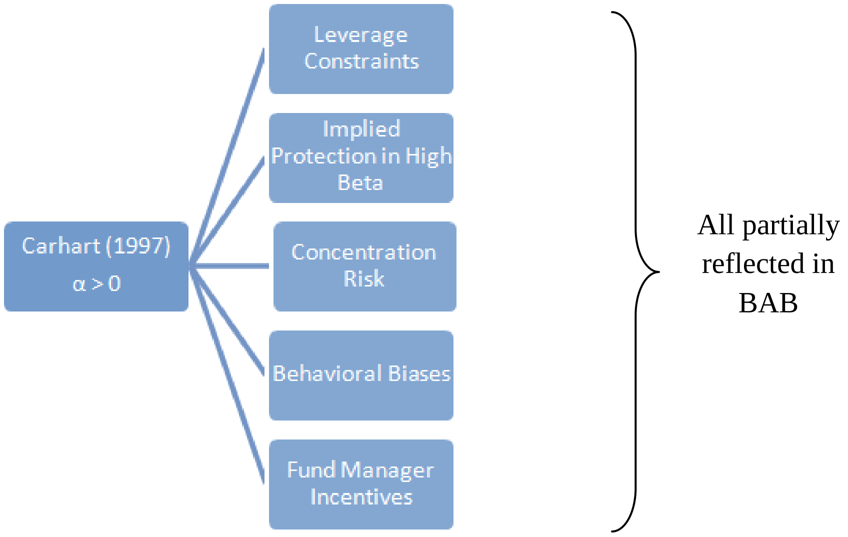

Figure 4 Potential sources of alpha for a MV portfolio

As MV portfolios may underweight or overweight certain industries within some constraints, it is possible that portfolios are biased towards industries with a relatively large share of risk that is captured by financial markets related factors.

Proposition 3: Concentration risk

H_0^c: *Adjustment for industry exposures does not reduce alpha return of MV portfolios.*

H_1^c: *Adjustment for industry exposures does reduce alpha return of MV portfolios.*

According to Cowan and Wilderman (2011), high-beta stocks offer implied protection. As MV portfolios are expected to be biased towards low-beta stocks, this protection is absent. As a result, MV portfolios are expected to perform relatively poor during extreme market conditions. Returns on low-beta portfolios, and hence MV indices, are expected to be more negative than what its CAPM-beta suggests when market returns are very negative. This implies MV returns are a concave function of MCW returns.

Proposition 4: Implied protection in high-beta

H_0^d: *The payoff structure of a MV portfolio compared to a MCW index is symmetric.*

H_1^d: *The payoff structure of a MV portfolio compared to a MCW index is concave.*

4. Data

In this section the data that is used is illustrated. First, an overview of the portfolio data is given. Then, the data that is required for evaluating portfolio performance is discussed and subsequently an overview which includes all data sources is presented.

4.1 Portfolios

Daily total return index (RI) data of the MSCI MV index is retrieved from the Thomson Datastream database. Total return data is favored over using normal return data as it also includes dividends. The dataset includes daily data from 3/12/2001 till 30/12/2011. Earlier daily data is not available. The base currency for optimization is US dollar. The following MSCI MV indices are studied:

- MSCI MV World $
- MSCI MV US $
- MSCI MV Europe $
- MSCI MV EAFE $
- MSCI MV Japan $
- MSCI MV Emerging Markets $

The performance of the global MSCI MV index is graphically presented in Figure 5.

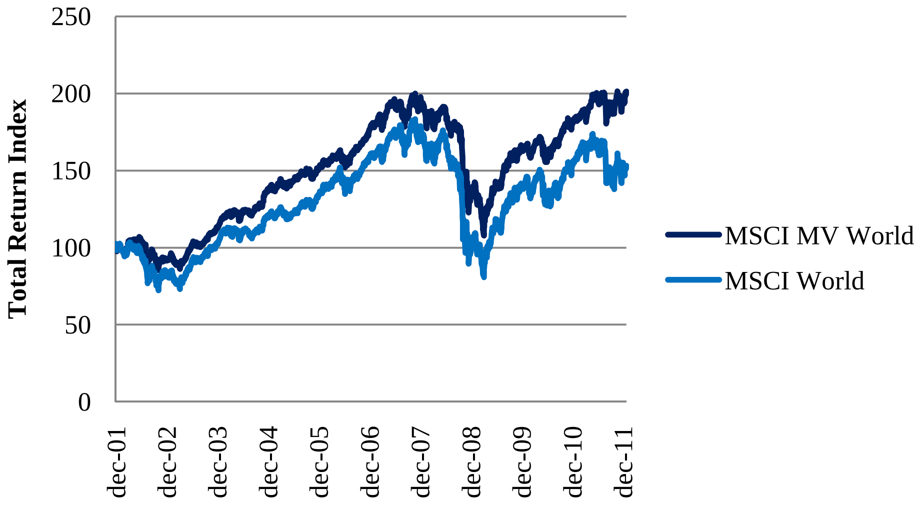

Figure 5 Performance MSCI MV World versus MCW benchmark.

When RI data is retrieved, logarithmic returns are calculated from this data as follows:

$$R_t^{MV} = \ln\left(\frac{RI_t^{MV}}{RI_{t-1}^{MV}}\right) \tag{5}$$

Unfortunately, data about the development of portfolio allocation is not available. In order to study the impact of weight constraints on portfolio performance, semi-annually rebalanced MV portfolios are created from American industry portfolios. Data for these portfolios is obtained from the website of Kenneth French. The dataset includes daily data from 20/12/1984 till 30/12/2011.

4.2 Factor data

For the assessment of the performance of MV portfolios, a benchmark is required. For each regional MSCI MV portfolio, the MCW counterpart will be used as the market return (MKT).

The other variables that are included in a Carhart (1997) four-factor regression model are discussed below.

- *Risk Free Rate* (R_f): the one-month US Treasury bills rate is used as the risk free rate.
- *Size Factor* (SMB): the excess return on firms with a small market capitalization over firms with a large market capitalization. This factor captures the empirical finding that small firms outperform large firms.
- *Growth Factor* (HML): the excess return on firms with a high book-to-market value over firms with a low book-to-market value. This factor captures the empirical finding that value firms outperform growth firms.
- *Momentum Factor* (MOM): the excess return on high prior return portfolios over low prior return portfolios.

This data is directly obtained from the website of Kenneth French. Unfortunately, daily data is only available for American factor data. Although the factors capture a certain amount of factor specific risk that is globally present, using custom made factors would have been more optimal. However, simple constructed regional long-short portfolios from respectively value and growth and small cap and large cap indices did not improve the model. Cremers, Petajisto and Sitzewitz (2010) found the Carhart four-factor model assigns nonzero alphas to passive benchmarks. Using factors that are constructed from traded benchmarks leads to different results. The latter implies the SMB and HML factor cannot easily be replicated from popular style benchmark portfolios such as MSCI Growth, MSCI Value, MSCI Smallcap and MSCI Largecap indices. In the academic literature it is common to use the original methodology to construct the SMB and HML factor. Frazzini and Pedersen (2010) also use American factors for equity portfolios of other countries. In order to make a sound comparison with other studies, using the American factors from the website of Kenneth French for all regressions is favored over using factors that are created from traded benchmarks.

Further, the BAB factor is used in a five-factor regression model. The returns on beta decile portfolios are used to construct the BAB factor. First, stocks are ranked on beta. Subsequently, stocks are grouped into ten portfolios. The returns on beta decile portfolios are obtained from the CRSP database that can be accessed via WRDS. The construction methodology will be discussed in the next section. Like the SMB, HML and MOM factor, the BAB factor is also calculated from American data. Frazini and Pedersen (2010) found the BAB factor four-factor alpha return in European countries, does not significantly differ from the worldwide average. It is assumed customized factors for all regions would have been of the same magnitude and would have captured the same risk sources in the sample period that is studied in this thesis, but this is not certain. MSCI World 'level 1' industry portfolio data is used to calculate industry excess returns. MSCI creates industry portfolios on different levels. On the top level, they make a distinction between ten broad industries. Return data for these indices is obtained from Datastream.

4.3 Overview

A complete overview of all data that is used is presented in Table 3.

Table 3 Data sources.

Type	Symbol	Frequency	Source
Total return index global and regional MSCI MV indices	$R_t^{MSCI\ MV}$	Daily	Thomson Datastream
Total return index global and regional MSCI MCW benchmarks	R_t^{MSCI}	Daily	Thomson Datastream
Returns on beta decile portfolios	R_t^{d}	Daily	CRSP / Wharton Research Data Services
One month treasury bill rate	Rf_t	Daily	Fama-French Factors / Wharton Research Data Services
American industry portfolio returns	R_t^{ind}	Daily	Website Kenneth French
MSCI World level 1 industry portfolio returns	$R_t^{msci\ ind}$	Daily	Thomson Datastream
SMB-factor	SMB_t	Daily	Fama-French Factors / Wharton Research Data Services
HML-factor	HML_t	Daily	Fama-French Factors / Wharton Research Data Services
Momentum factor	MOM_t	Daily	Fama-French Factors / Wharton Research Data Services

5. Methodology

In order to answer the research question, MSCI MV portfolios are studied. Unfortunately, for these indices only total return data is available. In order to analyze the development of portfolio allocations and the effect of changes in the construction methodology, a second type of MV portfolios is created. The construction methodology of both types of MV portfolios is discussed in subsection 5.1. Subsequently, the research question can be answered in two steps. First, the Carhart (1997) four-factor outperformance is measured. Second, additional risk factors are identified and measured if possible. The methods that are used are explained in subsection 5.2.

5.1 Portfolio construction

The construction methodology of the MSCI MV indices is elaborated on in subsection 5.1.1. The methodology that is used to construct self-created portfolios is discussed in subsection 5.1.2.

5.1.1 MSCI MV portfolios

As mentioned, the composition of a MV index is found by minimizing portfolio variance (see Equation 4). MSCI uses the proprietary Barra risk factor model to estimate covariance matrices. The investment universe that is considered includes all stocks that are included in the MSCI MCW parent index. Subsequently, certain constraints are imposed in order to ensure that the deviation from the MCW benchmark portfolio is limited. An overview of the methodology that is used to construct the MSCI MV indices is summarized in Table 4.

Contrasting MCW portfolios, MV portfolios are not automatically rebalanced in line with their objective. As a consequence, the allocation of the actual portfolio might differ from the optimal MV portfolio in between two review dates. For example, a stock that performed well recently, automatically receives a larger share in the index without taking its contribution to portfolio volatility into account. The latter is restored at each review. However, rebalancing on a frequent basis is expensive because of transaction costs. Therefore MSCI MV indices are rebalanced only twice a year.

The constraints that are imposed are not very restrictive. The ample constraints on industry and security level, allow a large deviation from the benchmark weights. Taking into account that only ten industry classes are considered, the average industry weight in a MCW index is ten percent. For an industry that has a weight of ten percent in the MCW index, the maximum deviation of five percent point implies the MV weight could be fifty percent higher or lower. The latter emphasizes that it is of great interest to examine the role of industry concentration risk. The maximum deviation for country weights compared to a MCW benchmark is also large. However, only indices that include stocks of more than one country can benefit from this. The maximum exposure to Barra risk factors may deviate 0.25 standard deviations from the exposure of the parent index. As a result, the MV portfolio may pick up risk based pricing anomalies that are not captured by the market factor. The latter is adjusted for by conducting multiple factor regressions. The many subjective constraints on the MV indices make it an active rather than a passive strategy (Blitz & van Vliet, 2011). The MSCI MV indices were launched on 14 April 2008. Data prior to the launch date is back-tested data (MSCI, 2012).

Table 4 Construction Methodology MSCI MV Indices.

Characteristic	
Rebalancing	Semi-annual
Covariance matrix	Barra risk factor model
Constraint	
Maximum weight index constituent	1.5% or 20 times weight of security in the parent index.
Minimum weight index constituent	0.05%
Maximum deviation country weight for countries with a weight larger than 2.5% in the parent index	+/-5% from weight in parent index
Maximum country weight for countries with a weight smaller than 2.5% in the parent index	3 times their weight in parent index
Maximum deviation industry weight	+/- 5% from weight in parent index (10 industries considered)
Exposure to Barra Risk factors other than the 'volatility risk factor'	+/- 0.25 standard deviations relative to parent index
Maximum one way turnover	10%

Source: MSCI Research (2012)

5.1.2 MV Portfolios from industry portfolios

The covariance matrix is calculated by taking the average of the true sample covariance matrix and the covariance matrix that is estimated by a factor model. This results in the following shrinkage estimator of the covariance matrix which looks similar to the one used in Ledoit and Wolf (2004):

$$\hat{\Sigma}_{\text{shrink}} = \hat{\delta}\text{F} + (1 - \hat{\delta})\text{S} \tag{6}$$

In this paper an empirical Bayes approach is used. The shrinkage constant $\hat{\delta}$ is assumed to be equal to 0.5. The latter implies that the investor interprets historical data (S) and the factor model (F) to be equally important (Wang, 2005). Wang (2005) argues this is a reasonable assumption when replicating methods that practitioners employ, as they often use the average of obtained estimates from various models. The factors that are used are the market, SMB, HML and MOM factor.

The optimal weights are calculated using portfolio return and factor return data over the previous years. The weights are chosen in such a way that the portfolio variance over the in-sample period is minimized. Subsequently, the out-of-sample performance of this portfolio is calculated by multiplying the weights vector by the industry portfolio returns.

In the next section, return characteristics and factor exposures of a standard minimum volatility (MV) portfolio and some portfolios that deviate from this standard portfolio are presented. The standard portfolio has the following characteristics:

- Data history: five years data history is used in order to estimate covariance matrices;
- Weights constraints: weights are set to the maximum of 2.5 percent deviation from the average weight, in a market capitalization weighted benchmark portfolio over the analyzed period; short selling is not allowed;
- Rebalancing: portfolios are rebalanced semi-annually;
- Weights in constituent portfolios: industry portfolios are market value weighted;
- Number of constituents: 49 industry portfolios are used to construct the portfolio.

In order to study how changes in the construction methodology affect the performance of MV indices, portfolios that slightly differ from the standard portfolio are constructed. For each alternative portfolio only one of the parameters that is listed above is adjusted, keeping all other factors constant. Also, a portfolio from ten industry portfolios which are comparable to the industry classes that MSCI considers, is constructed in order to study the development of portfolio allocation over time.

5.2 Performance measurement

In this subsection, the performance measurement is explained. The Sharpe ratio and Carhart (1997) four-factor model are presented in paragraph 5.2.1. In extended pricing models, the BAB factor is introduced. The five-factor model and construction methodology of the BAB factor is presented in paragraph 5.2.2. Lastly, the tests that are conducted in order to evaluate the role of concentration risk and implied protection in high-beta are discussed in paragraph 5.2.3.

5.2.1 Standard measures

First, MV portfolio performance is examined by calculating the Sharpe ratio (Sharpe, 1994):

$$Sharpe\ Ratio = \frac{E[R_p - R_f]}{\sqrt{var[R_p - R_f]}} \tag{7}$$

Next, Carhart (1997) four-factor regression analyses on alternative portfolio returns are conducted in order to calculate risk-adjusted returns and factor exposures.

$$R_t^{MSCI\ MV} - Rf_t = \alpha + \beta\left(R_t^{mkt} - Rf_t\right) + s * SMB_t + h * HML_t + m * MOM_t \tag{8}$$

5.2.2 BAB factor

In order test whether MSCI MV portfolios and the created portfolios are biased towards low-beta stocks, the BAB factor is constructed. This factor is calculated from beta decile portfolio returns. In order to calculate these returns, each year Scholes and Williams (1977) betas over the previous year are calculated for each NYSE/Amex security. Subsequently, stocks are ranked on its beta and grouped into equally weighted decile portfolios. This process is repeated each year. Beta decile portfolio returns are directly obtained from the CRSP database.

The approach that is used to calculate the return on a betting-against-beta (BAB) factor is almost similar to the one in Frazzini and Pedersen (2010). The only difference is that in this thesis the eighth and third decile portfolios are used as a proxy for respectively low and high-beta stocks. The use of these deciles is favored over the use of the most extreme deciles, as a low R^2 suggests the tenth decile portfolio contains stocks that are probably exposed to other factors than just the 'beta-risk' that is investigated in this thesis (see Appendix A, Table 13 and Figure 10). The beta of the eighth portfolio is almost equal to the beta of the MV portfolios. Like the BAB factor in Frazzini and Pedersen (2010), the factor is market neutral. The latter implies its beta is equal to zero. The return on the BAB factor is calculated as follows:

$$r_t^{BAB} = \frac{1}{\beta_{t-1}^{L}} \left(r_t^{Low} - r_t^{f} \right) - \frac{1}{\beta_{t-1}^{H}} \left(r_t^{High} - r_t^{f} \right) \tag{9}$$

Subsequently, the following return regression will be conducted:

$$\begin{aligned} R_t^{MSCI\,MV} - Rf_t \\ &= \alpha + \beta\left(R_t^{mkt} - Rf_t\right) + s * SMB_t + h * HML_t + m \\ &* MOM_t + b * BAB_t \end{aligned} \tag{10}$$

Equation 10 is a Carhart (1997) four-factor model extended with the BAB factor. The BAB factor indicates whether the independent variables are related to the excess return of low-beta stocks over high-beta stocks and allows to test hypothesis B. A *b* greater than zero indicates the portfolio is biased towards low-beta stocks. In order to test whether the model that includes the BAB factor significantly better fits the data, a t-test is conducted.

The next step is to define the role of concentration risk and implied protection in high-beta. These are partially captured by the BAB factor, but may also directly influence the performance of MV indices.

5.2.3 Concentration risk

First, the industries that possibly have been overrepresented in the MSCI MV portfolios during the last decade need to be identified. To this end, MV portfolios similar to the ones that were discussed in subsection 5.1.2 are used. The only difference is that the portfolio is constructed from just ten industry portfolios. Then, the development of the optimal portfolio allocation is plotted. Lastly, the excess returns on the most dominant industries are calculated.

$$r_t^i = r_t^{industry} - r_t^{mkt} \tag{11}$$

In order to calculate exposures to industry specific risks that are not captured by the BAB factor, the following return regression will be conducted:

$$\begin{aligned} R_t^{MSCI\,MV} - Rf_t \\ &= \alpha + \beta\left(R_t^{mkt} - Rf_t\right) + s * SMB_t + h * HML_t + m \\ &* MOM_t + b * BAB_t + \delta_i(R_t^i - R_t^{mkt}) \end{aligned} \tag{12}$$

A positive δ_i indicates a bias towards that particular industry. In order to test whether the δ_i variables are jointly significant, a heteroskedasticity-robust F test (Wald test) is conducted. Because of heteroskedastic standard errors, the Wald test is favored over a general F-test (Wooldridge, 2009).

5.2.4 Implied protection

The impact of extreme events on the performance of MV indices is difficult to measure, as these do not occur frequently. However, a study of the observations in the more extreme segments offers a good view on what could happen. Hypothetically, investors require an alpha return on MV portfolios, in order to compensate for the potential large loss in case of a catastrophe. Namely, the maximum loss per unit of beta is higher for MV portfolios than for MCW portfolios. If MV portfolios indeed underperform compared to MCW portfolios during extreme circumstances, a concave relation between MV returns and MCW benchmark returns exists. In order to check this, a regression on the excess market returns and squared excess market returns is conducted (see Equation 13).

$$R_t^{MSCI\,MV} - Rf_t = \alpha + \beta_{mkt}\left(R_t^{mkt} - Rf_t\right) + \beta_{mkt^2}\left(R_t^{mkt} - Rf_t\right)^2 \tag{13}$$

If the β_{mkt^2} coefficient is significantly negative, a concave relation exists. In this case, the CAPM-alpha return is indeed partially a compensation for the bad performance in case extreme events occur. Also, a one year rolling window CAPM regression will show what happened to the beta of MV indices during extreme circumstances. The events that are considered include bear markets during the last decade in general, the bankruptcy of Lehman Brothers and the earthquake in Japan.

Another way to detect whether alpha is indeed a compensation for a type of risk that has not been included in asset pricing model, the cumulative 'model outperformance' (CMO) is presented in a graph. At any point in time, the expected excess return on the MV World portfolio is calculated using the regression coefficient of Equation 12. This number at any point in time T is calculated as follows:

$$CMO = \sum_{t=0}^{T}((R_t^{MSCI\ MV} - Rf_t) - \ E[R_t^{MSCI\ MV} - Rf_t]) \tag{14}$$

By adding cumulative alpha in each period, a measure of realized alpha is obtained. The latter provides insight in when alpha returns are actually obtained.

5.3 Relative importance

Standard regression coefficients do not directly show the economic impact of each of the factors. In order to determine the relative importance, standardized beta coefficients are calculated. The latter allows to compare the impact of independent variables, irrespective of scale. Technically, standardized beta coefficients are calculated by replacing variables by their z-score and subsequently conducting a regression analysis (Wooldridge, 2009). These coefficients equal the original betas multiplied by the ratio of standard deviation of the independent variable (i) over the dependent variable (y), which is presented below.

$$\hat{b}_i = \left(\frac{\sigma_i}{\sigma_y}\right)\beta_i \tag{15}$$

Suppose the standardized beta coefficient of the SMB factor is 0.05. This implies that if the SMB variable increases by one standard deviation, the expected excess return on the MV portfolio is 0.05 standard deviation higher. Also, as a measure of 'unique' contribution to the asset pricing model, partial and semi-partial R^2 values are calculated for each independent variable. The semi-partial R^2 can be interpreted as the increase in R^2 from including a variable x_i in the model (Shedden, 2010). It simply is the difference between the R^2 of the complete model that is presented in Equation 12 extended by the squared excess market returns, R_C^2, and the R^2 of the restricted model, $R_{C-X_i}^2$. The restricted model is almost equal to the complete model, as only the variable for which the semi-partial R^2 is calculated is excluded.

$$R_C^2 - R_{c\,-\,x_i}^2 \tag{16}$$

The partial R^2 indicates what share of maximum improvement is obtained by including the variable (Shedden, 2010).

$$\frac{R_C^2 - R_{c\,-\,x_i}^2}{1 - R_{c\,-\,x_i}^2} \tag{17}$$

6. Results

Previous research showed MV indices consistently outperform MCW indices in Sharpe ratio terms. This serves as a starting point. As mentioned before, the goal of this thesis is to determine whether MV portfolios also outperform when adjusted for a comprehensive set of risk factors. In order to accomplish this goal, a series of commercially successful MV indices is studied. Namely, the MSCI MV indices. In order to give a complete view, return characteristics of all MSCI MV indices that have at least ten years of data availability are presented in Table 5. Not surprisingly, both the MSCI World MV and the regional MV portfolios outperformed their benchmark in terms of Sharpe Ratio over the last decade. Each MV portfolio had a lower volatility than its related benchmark. Remarkably, returns of all MV portfolios were higher as well. The latter stresses that during periods with extreme market conditions, such as the period under study, MV indices are an attractive investment alternative. Noteworthy, MV portfolios that invest outside the US have a relatively larger outperformance compared to their MCW benchmark. The positive CAPM alpha returns are statistically significant, except for the US and Japan. The findings stress that the conclusion of Scherer (2010) may not be generalizable to all regions.

Table 5 Summary statistics MSCI MV portfolios. The returns that are presented in this table are from 12/2001 till 12/2011. The complete dataset includes daily data from 12/1984 till 12/2011. Standard deviations, alpha returns and absolute returns are annualized based on 252 trading days a year.

MSCI MV	**Annual Return**	**SD**	**Sharpe Ratio**	**CAPM-α**
MSCI World MV $	6.94%	13.25%	0.34	3.48%*
MSCI US MV $	4.74%	18.09%	0.13	1.89%
MSCI Europe MV $	9.64%	18.89%	0.38	4.92%*
MSCI EAFE MV $	9.47%	14.11%	0.50	5.33%*
MSCI Japan MV $	4.40%	19.36%	0.10	2.55%
MSCI Emerging Markets MV $	16.00%	16.23%	0.83	6.39%*
Benchmark	**Annual Return**	**SD**	**Sharpe Ratio**	
MSCI World $	4.22%	18.50%	0.09	
MSCI US $	3.00%	22.02%	0.05	
MSCI Europe $	5.69%	24.46%	0.13	
MSCI EAFE $	5.34%	20.21%	0.14	
MSCI Japan $	1.87%	23.66%	0.00	
MSCI Emerging Markets $	12.51%	21.75%	0.49	

* alpha return significant at the 2.5% level (t-test)

The data confirms that MV indices indeed outperformed their MCW benchmark in Sharpe ratio terms. The next step is to determine whether the MV indices of interest also outperform their benchmark adjusted for other risk factors. First of all, the return adjusted for a limited number of risk factors is calculated. Besides the market factor, this set includes the SMB, HML and MOM factor. The latter capture (risk based) market anomalies that are well documented in the academic literature. The Carhart (1997) four-factor alpha that is obtained when these factors are included in the regression model, is of particular interest, as it is the risk-adjusted return. In Table 6 the results of regression analyses on MV portfolios are summarized. All MV indices, except those of Japan and the US, have a significantly positive four-factor alpha return. This is in line with hypothesis A, as the global portfolio is considered to be the most important one. Also these findings indicate the conclusion of Scherer (2010) should be treated with care. All MV indices except for the MSCI MV Emerging Markets index are significantly biased towards stocks with a large market capitalization. This is very remarkable, as putting too much emphasis on market capitalization was one of the major remarks on MCW indices. The bias to firms with a large market capitalization indicates this strategy could be applied on a larger scale as well. The exposure to the HML and MOM factor is inconsistent across regions.

The adjusted R^2 significantly increases when the pricing model is extended with the BAB factor. The latter confirms this factor indeed partially explains the variance of MV portfolio returns. All portfolios have a positive exposure to the BAB factor, which is in line with hypothesis B. The exposures are statistically significant at the 2.5% significance level. As the factor has a positive mean this automatically implies alpha returns decrease when adjusting for BAB risk. The loading on the BAB-factor is about the same size for the MSCI MV World, US, Europe and EAFE portfolio (between 0.073 and 0.088). For the MSCI MV World portfolio, the remaining alpha performance is not statistically significant. The alpha returns on MV portfolios for Europe, EAFE and emerging market stocks are still significantly positive. As a consequence of using American SMB, HML, MOM and BAB factors, the alpha returns for other regions are likely to be slightly overestimated.

It is unclear why alpha returns differ across regions. Possibly, the impact of risk sources that are not captured by the pricing model for stocks in MV portfolios compared to stocks in MCW portfolios differs across regions. For example, suppose companies that are presented in MV portfolios are more exposed to unobserved risk source X than companies in the MCW portfolio. If X has a larger impact in emerging markets than in the US, the required premium for these stocks is larger in emerging markets. This could be reflected in alpha. However, it should be stressed that this is just a hypothesis. Whether this risk source really exists or whether MV investors receive a risk free alpha return in those regions is not clear. A potential risk source could be that shareholder rights are less protected in emerging markets than in developed markets. As a consequence, investments that require a large investment per unit of market exposure, such as MV portfolios, might be priced at a discount.

Table 6 Regression analyses. The dataset includes daily data from 12/2001 to 12/2011. Alpha returns are annualized based on 252 trading days a year. The market portfolio that has been used as a benchmark in each regression is the general MSCI counterpart of the MV portfolio. For example, for the MSCI Europe MV, the MSCI Europe is used as a benchmark. Due to a lack of data availability, factor portfolios have only American constituents. T-values are presented in parentheses. The sample consists of 2539 observations.

Index	α	β_{mkt}	s_{smb}	h_{hml}	m_{mom}	b_{bab}	$adj. R^2$
MSCI World MV $	3.37%*	0.681	-0.035	0.083	0.016		0.921
	(2.87)	(154.84)	(-4.51)	(9.68)	(3.12)		
	1.96%	0.672	-0.023	0.077	-0.005	0.088	0.926
	(1.71)	(155.22)	(-2.96)	(9.21)	(-0.97)	(12.67)	
MSCI US MV $	1.88%	0.796	-0.062	0.114	0.028		0.950
	(1.48)	(194.80)	(-7.28)	(12.29)	(5.04)		
	0.71%	0.794	-0.052	0.108	0.012	0.073	0.952
	(0.56)	(197.19)	(-6.14)	(11.79)	(2.19)	(9.69)	
MSCI Europe MV $	4.76%*	0.757	-0.020	-0.051	0.055		0.947
	(3.48)	(205.11)	(-2.16)	(-5.10)	(-9.70)		
	3.47%*	0.749	-0.008	0.046	0.037	0.082	0.949
	(2.57)	(202.35)	(-0.94)	(4.61)	(6.25)	(9.82)	
MSCI EAFE MV $	5.24%*	0.668	-0.026	0.035	0.054		0.898
	(3.69)	(145.87)	(-2.72)	(3.35)	(9.25)		
	3.96%*	0.658	-0.015	0.029	0.036	0.081	0.902
	(2.82)	(142.13)	(-1.58)	(2.84)	(5.93)	(9.35)	
MSCI Japan MV $	2.64%	0.782	-0.025	-0.011	0.033		0.914
	(1.48)	(164.19)	(-2.06)	(-0.86)	(4.53)		
	2.12%	0.780	-0.020	-0.014	0.027	0.033	0.914
	(1.18)	(162.55)	(-1.70)	(-1.10)	(3.51)	(2.99)	
MSCI Emerging Markets MV $	6.40%*	0.730	-0.008	0.000	0.008		0.954
	(5.82)	(222.49)	(-1.09)	(0.00)	(1.75)		
	5.74%*	0.726	-0.002	-0.003	-0.001	0.043	0.955
	(5.24)	(219.27)	(-0.23)	(-0.37)	(-0.28)	(6.46)	

* alpha return significant at the 2.5% level (t-test)

Now the relation between MV portfolios and the BAB factor is clarified, underlying risk factors will be studied into detail in subsection 6.1.

6.1 Concentration risk

In order to identify whether adjustments in the construction methodology affect the performance of MV indices, six different MV portfolios have been constructed. Summary statistics for these portfolios are presented in Table 7. Clearly, adjusting weights constraints has a major impact on the performance of MV portfolios. The performance decreases when weight constraints are set tighter. Also, changing the number of included industries has a significant impact, as it reduces the possibility to shift to certain industries. The findings emphasize the importance of studying the effect of concentration risk closer.

Table 7 Summary statistics MV indices from US industry portfolios. The dataset includes daily data from 12/2001 till 12/2011. Alpha returns are annualized based on 252 trading days a year. The standard portfolio is created from 49 American industry portfolios. 2.5% benchmark deviation on the industry level is allowed. Covariance matrices are calculated using a shrinkage estimator. Five years data history is used and portfolios are rebalanced semi-annually. For the alternative portfolios, the methodology is adjusted to one specification at once.

Standard methodology	**Return**	**SD**	**Sharpe Ratio**
(1) Standard	8.10%	18.70%	0.33
Alternative specifications	**Return**	**SD**	
Weights constraints			
(2) Max. 5% BM deviation	8.41%	17.06%	0.39
(3) Max. 1% BM deviation	7.38%	20.56%	0.27
(4) No constraints	10.13%	15.21%	0.55
Rebalancing & covariance history			
(5) Monthly & Annually	7.65%	18.34%	0.31
Industry portfolios			
(6) 12 industry portfolios, 5% BM deviation	6.17%	20.08%	0.21

In Figure 6 the composition of a MV portfolio containing positions in ten different industries has been plotted. For the MV portfolio in Panel A, no weights constraints have been imposed as this offers the opportunity to examine what industry allocation would be optimal. The non-durable consumption goods, health care and utilities industry have been dominating the optimal MV portfolio. For the portfolio in Panel B, maximum weights have been set at twenty percent. It shows that the MV portfolio with weights constraints constantly allocates the maximum amount to utilities over the 1989-2011 period. The weights allocated to nondurable consumption goods and health care industry have been stable at about twenty percent during the last decade. Clearly, these industries are well represented in an optimal MV portfolio. The MSCI MV indices are constrained at the industry level, but since these constraints are not very tight, it is likely that concentration risk still plays an essential role. Hypothetically, the nondurable consumption goods, health care and utilities industry face industry specific risks. Examples include potential changes in government regulation or changes in patent protection. These unobserved risk factors might partially explain the outperformance of MV indices.

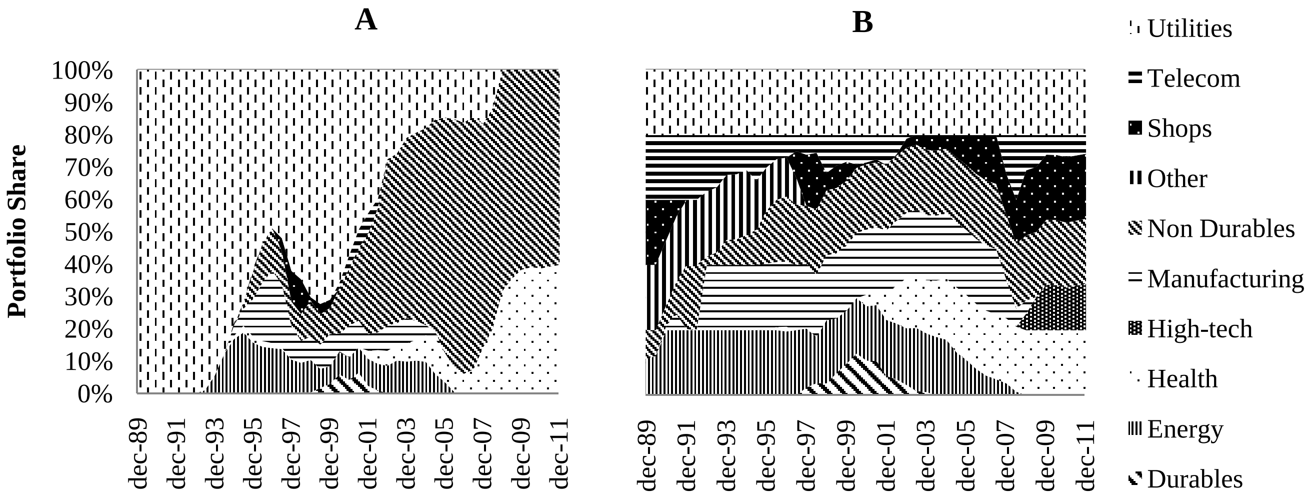

Figure 6 Development portfolio allocation. The dataset includes daily data from 12/1984 to 12/2011. The first five years of data are needed for calculating the covariance matrix that used for the first optimization. The American industry portfolios that are used are derived from the website of Kenneth French. The standard portfolio is created from 10 American industry portfolios. Covariance matrices are calculated using a shrinkage estimator. Five years data history is used and portfolios are rebalanced semi-annually. Panel A: no weights constraints. Panel B: maximum weights 20%

It is not a coincidence that these industries are overrepresented in the MV portfolios. Especially the health care and utilities industry have a relatively low R^2 when conducting a CAPM or Carhart (1997) four-factor regression (see Appendix B, Table 15). The low R^2 indicates a large share of industry specific risk could be present. For the nondurable consumption goods industry, a statistically significant positive alpha return is found.

The next step is to test whether a bias towards certain industries explains a part of the four-factor alpha performance. The four- and five-factor pricing model that have been used previously are therefore extended by three industry factors. These factors are simply the excess industry returns compared to a broad MCW benchmark. It is assumed these factors capture the industry specific risk that is mentioned above. Only the industries that proved to be overrepresented in MV portfolios are considered. The results are presented in Table 8. The four-factor alpha return is reduced to 2.06% from 3.37% when adjusting for industry exposures (see specification 1 and 3). Exposures to these industries are statistically significant on the 2.5% significance level. These findings are in line with hypothesis C. The bias towards certain industries is only partially captured by the BAB factor (see specification 2 and 4). When adjusting for both BAB risk and industry concentration risk, alpha performance is reduced to 1.61%.

Also, the exposure to the BAB factor is lower when adjusted for industry exposure. This indicates the BAB factor is biased. The latter is confirmed by comparing regression specifications 5 and 6. More than twelve percent of the variance of the BAB factor is explained by the excess return on the three industries. A Wald test indicates these variables are not jointly zero. A t-test shows the individual industry coefficients are also significant. However, the remaining risk-adjusted return on the BAB factor is still very large. Frazzini and Pedersen

(2010) showed a large share of volatility in BAB returns is related to liquidity. In Table 8 only the results for the MSCI MV World portfolio has been presented, but comparable effects have been found for other portfolios.

Table 8 Extended models. The dataset includes daily data from 12/2001 till 12/2011. Alpha returns are annualized based on 252 trading days a year. For the MSCI MV World portfolio, the MSCI World has been used as a benchmark. The excess industry returns are calculated using MSCI World level 1 industry portfolios which use a similar specification as Kenneth French. For the BAB factor, the market portfolio that is derived from the website of Kenneth French has been used as a benchmark. The excess industry returns are calculated using American industry returns that are derived from the website of Kenneth French. T-values are presented between parentheses. (Abbreviations: Utils = Utilities, HC = Health Care, ND = Nondurable Consumption Goods/Consumer Staples). Specifications 1 to 6 differ in the number of independent variables that have been taken into account, they do not refer to the portfolios in Table 7.

	MSCI World MV $				**BAB**	
Specification	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
α	3.37%* (2.87)	1.96% (1.71)	2.06%* (2.05)	1.61% (1.60)	15.99%* (4.88)	14.1%* (4.66)
β_{mkt}	0.681 (154.84)	0.672 (155.22)	0.786 (150.91)	0.777 (142.52)	0.042 (3.89	0.169 (12.90)
s_{smb}	-0.035 (-4.51)	-0.023 (-2.96)	-0.000 (-0.07)	0.002 (0.27)	-0.145 (-6.59)	-0.046 (-2.20)
h_{hml}	0.083 (9.68)	0.077 (9.21)	0.103 (13.55)	0.100 (13.19)	0.084 (3.48)	0.124 (5.18)
m_{mom}	0.016 (3.12)	-0.005 (-0.97)	-0.016 (-0.97)	-0.021 (-4.60)	0.216 (14.99)	0.140 (10.00)
b_{bab}		0.088 (12.67)		0.032 (4.95)		
δ_{Utils}			0.088 (11.58)	0.077 (9.77)		0.246 (15.43)
δ_{HC}			0.098 (12.00)	0.092 (11.28)		0.180 (8.37)
δ_{ND}			0.172 (16.06)	0.168 (15.76)		0.245 (15.43)
$adj.r^2$	0.921	0.926	0.942	0.943	0.090	0.218

* alpha return significant at the 2.5% level (t-test)

6.2 Implied protection

According to Cowan and Wilderman (2011) high-beta stocks offer implied protection. Empirical evidence shows beta and return are indeed positively related for high-beta stocks and negatively related for low-beta stocks (see Appendix A, Table 13). In the previous paragraphs it is shown that MV portfolios are biased towards low-beta stocks. Therefore MV investors do not profit from this favorable characteristic of high-beta stocks. In order to analyze the relationship between MV excess return and MCW excess return several regression analyses have been conducted. The CAPM-model is extended by the squared market excess returns. The results are summarized in Table 10. Note that if the relationship is linear, like the CAPM suggests, the β_{mkt^2} coefficient would be zero. In each geographic region, except for Europe, the coefficient for the squared excess returns is significantly negative at the 2.5% significance level. Hence, a concave relationship between MV and MCW excess returns exists, which implies hypothesis D is confirmed. Of course, extreme events do not happen for certain. The idea behind this theory, is that MV investors receive a constant return premium (alpha) and ‘pay the bill’ when the catastrophe occurs.

Table 9 Concavity. The dataset includes daily data from 12/2001 till 12/2011. The market portfolio that has been used as a benchmark in each regression is the general MSCI counterpart of the MV portfolio. Regression equation: $R_t^{MSCI\ MV} - Rf_t = \alpha + \beta_{mkt}(R_t^{mkt} - Rf_t) + \beta_{mkt^2}(R_t^{mkt} - Rf_t)^2$. The intercept term is not annualized. T-values are presented within parentheses.

Portfolio	α	β_{mkt}	β_{mkt^2}	$adj.r^2$
MSCI MV World $	0.021% (4.22)	0.684 (167.59	-0.531 (-4.60)	0.919
MSCI US MV $	0.012% (2.22)	0.799 (211.91)	-0.225 (-2.62)	0.947
MSCI Europe MV $	0.021% (3.56)	0.751 (208.95)	-0.055 (-0.68)	0.945
MSCI EAFE MV $	0.028% (4.69)	0.659 (146.16)	-0.447 (-3.63)	0.895
MSCI Japan MV $	0.015% (1.99)	0.782 (162.92)	-0.231 (-1.83)	0.913
MSCI Emerging Markets MV $	0.032% (7.17)	0.726 (226.36)	-0.701 (-5.09)	0.954

In order to clarify what this concave relationship implies, the daily excess return on the MSCI MV World portfolio has been plotted on its MCW benchmark excess return in Figure 14. The black line is the first regression equation of Table 10. Clearly, in the extreme negative events, the MV index loses more than what a linear beta would suggest. However, it should be noted that the effect is weak and not very reliable as only few observations in the extreme segment are available.

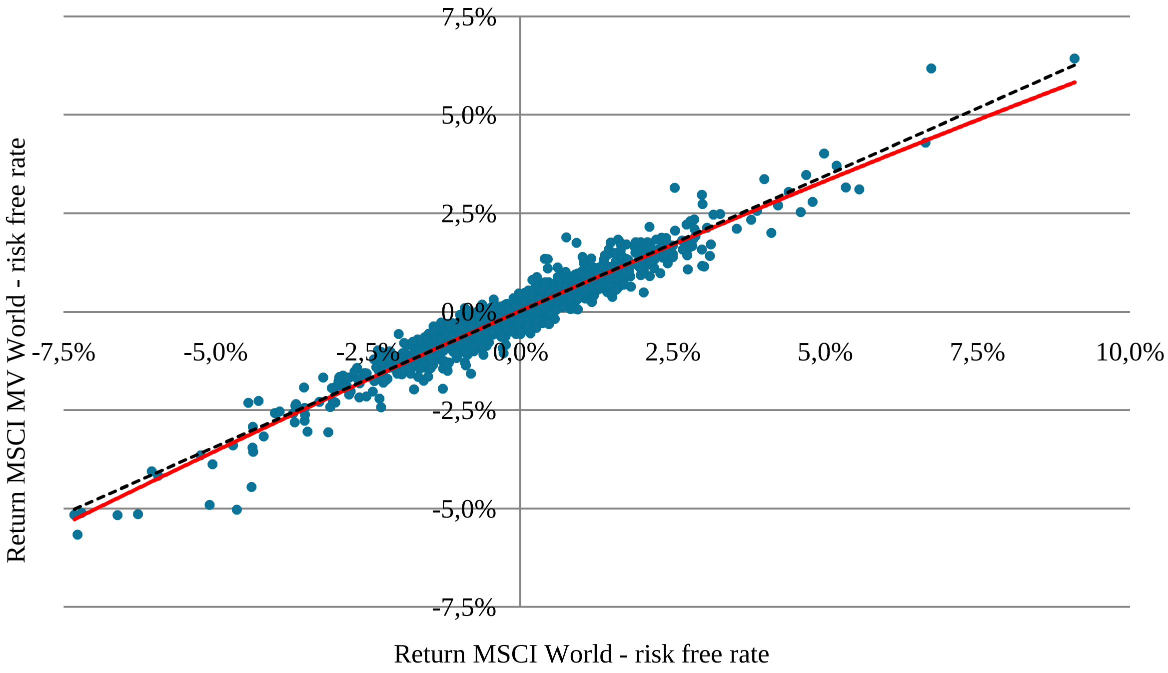

Figure 7 Scatter plot MSCI MV World on MSCI World. The dataset includes daily data from 12/2001 till 12/2011.The fitted value equation is equal to: $\boldsymbol{R_t^{MSCI\,MV} - Rf_t = 0.021\% + 0.684 * (R_t^{mkt} - Rf_t) - 0.531 * (R_t^{mkt} - Rf_t)^2}$. The latter is presented by the solid line. The dotted line represents the relation predicted by the CAPM.

The response of the stock markets on human and economic catastrophes such as the fall of Lehman Brothers and the earth quake in Japan is studied in order to hypothesize what would happen to the performance of MV in even more extreme events. Examples include a collapse of capitalism or an atomic war. The maximum loss on equity is the invested amount. Hence, in some sense high-beta stocks offer protection as the loss per unit of beta is limited. In other words, a lower investment in stocks is required to buy the same beta exposure and the remainder can be invested in gold, agricultural land or whatever asset class that performs well during catastrophes. The 252-days rolling window CAPM-beta is plotted in Figure 8. Clearly, the beta moves closer to one during extreme events. If these events are negative, this is an undesirable feature. Extrapolating this to even more extreme events, betas are expected to converge to one.

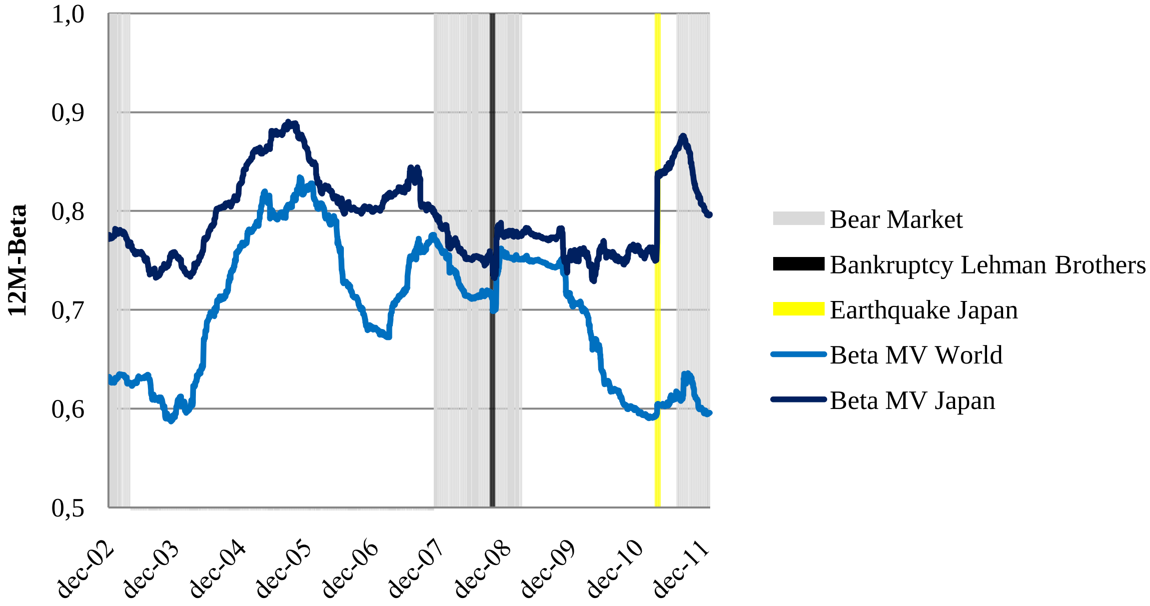

Figure 8 Rolling CAPM Regression. Rolling regression analysis of MV portfolio on its MSCI benchmark. A moving window of 252 days has been used. Bear market periods are shaded grey, these include the internet crisis (31/03/2000 - 31/03/2003), subprime crisis (31/10/2007 - 28/02/2009) and euro zone crisis (30-06-2011 - present). Window specifications are derived from Melas, Briand and Urwin (2011). The bankruptcy of Lehman Brothers (September 2008) and earthquake in Japan (March 2011) are indicated as well.

In Figure 9, the difference between the model predicted return and the actual return is presented (CMO). When the alpha return is added, this is an indicator of realized alpha return (CMO + alpha). The patterns in the CMO line suggest that alpha indeed depends on a type of risk. If the return would be risk-free, a more horizontal CMO line like in the pre-subprime crisis period would be expected. The impact of the high beta during extreme circumstances follows from the chart. During the subprime crisis the actual returns on the MV index were lower than the returns that were predicted by the model. The alpha return is clearly ‘realized’ when markets are stable. The credit crisis diminishes cumulative alpha return by about 7 percent of. Surprisingly, the MV index performed relatively well during the first part of the euro crisis. This suggests the performance of MV indices depends on the nature of the crisis. However, it should be noted that euro crisis did not have a global impact that is similar to that of the subprime crisis (see dotted line).

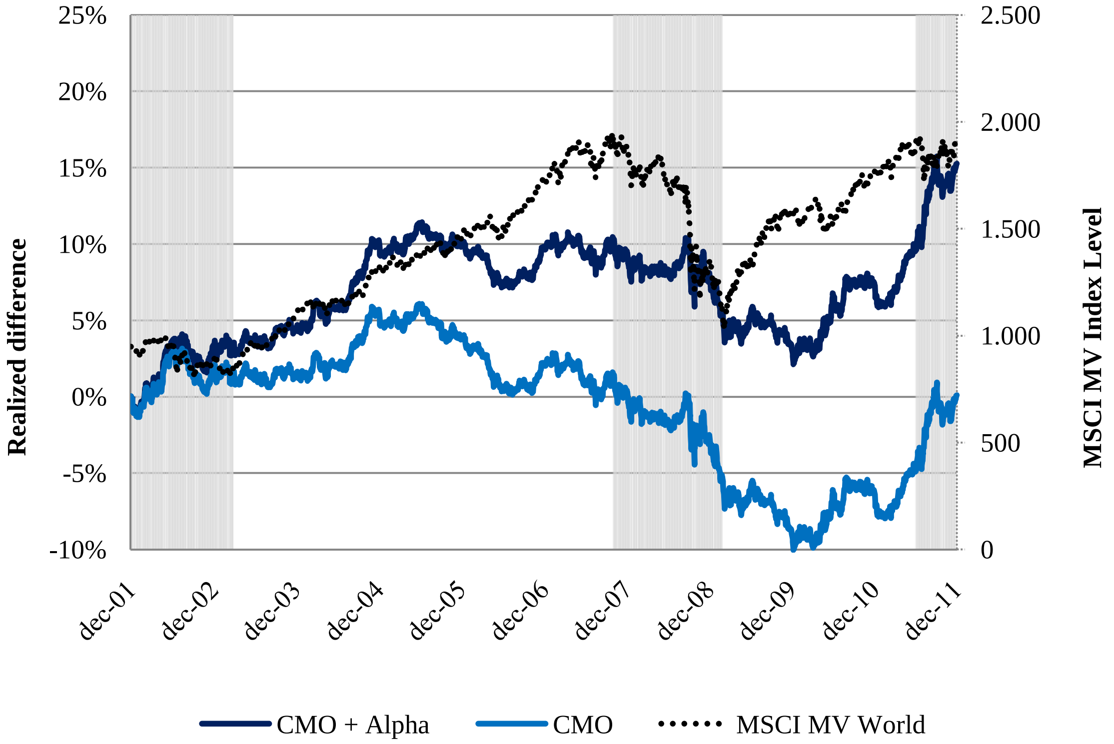

Figure 9 Difference predicted and actual returns. First model predicted returns are calculated using the model coefficients that are presented in Table 8, specification 5. Next, the difference between actual returns and predicted returns are calculated (CMO). Then, alpha's are added (CMO + alpha).

6.3 Relative importance

Standardized regression coefficients are calculated in order to compare the relative importance of several factors. After market risk, concentration risk has the largest standardized effect. To give an example, a one standard deviation increase in the excess return on the MSCI World Utilities industry on the broad MSCI World index, induces the expected excess return on the MSCI MV World index to increase by 0.061 standard deviations. HML-risk has a greater standardized effect than the remaining BAB-risk. The concave shape of MV returns compared to MCW returns did not have a very large impact during the last decade. However, the observations during the credit crisis suggest that the impact increases when more extreme events occur.

Table 10 Standardized Beta Coefficients MSCI MV World. These are the standardized beta coefficients of the Equation 12, extended with the squared market returns factor. Standardized beta coefficients are equal to regular beta coefficients multiplied by the ratio of the standard deviation of the independent variable over the standard deviation of the dependent variable.

	β_{mkt}	s_{smb}	h_{hml}	m_{mom}	b_{bab}	δ_{Utils}	δ_{HC}	δ_{ND}	β_{mkt^2}
Standardized Beta	1.084	0.001	0.069	-0.028	0.025	0.060	0.071	0.124	-0.015

As mentioned, it is measured how much a variable uniquely contributes to the regression model. This is done by calculating semi-partial R^2 and partial R^2. The results are presented in Table 11. When looking at the 5-factor model, the BAB factor seems to add significant value to the model, especially when compared to the SMB, HML and MOM factor. However, the BAB factor is correlated with the industry factors. The same analysis for the extended model gives a more clear view. The findings indicate in the same direction as the standardized beta coefficients. After market risk, biases to certain industries are combined the most important risk source. Also the bias to value stocks is an important risk source. The other factors only have a small contribution to the model.

Table 11 Unique contribution of factors. The semi-partial R^2 indicates the improvement in R^2 when the factor is added to a model that already includes all other considered factors. The partial R^2 indicates what share of maximum R^2 improvement is obtained by including the variable.

	Extended model		**5-Factor model**	
	Semi-partial R^2	**Partial R^2**	**Semi-partial R^2**	**Partial R^2**
$\boldsymbol{\beta_{mkt}}$	0.4543	88.90%	0.7037	90.48%
$\boldsymbol{s_{smb}}$	0.0000	0.00%	0.0003	0.40%
$\boldsymbol{h_{hml}}$	0.0038	6.28%	0.0025	3.27%
$\boldsymbol{m_{mom}}$	0.0005	0.87%	0.0001	0.13%
$\boldsymbol{b_{bab}}$	0.0005	0.87%	0.0048	6.09%
$\boldsymbol{\delta_{Utils}}$	0.0022	3.74%		
$\boldsymbol{\delta_{HC}}$	0.0029	4.87%		
$\boldsymbol{\delta_{ND}}$	0.0056	8.99%		
$\boldsymbol{\beta_{mkt^2}}$	0.0003	0.53%		

7. Conclusion

The MSCI MV indices that are studied outperformed MCW indices in Sharpe ratio terms, which is in line with earlier findings. Carhart (1997) four-factor regressions show that all MSCI MV indices, except those of Japan and the US, also outperform when adjusted for market, SMB, HML and MOM risk. Hence, the four-factor outperformance is not consistent across regions, but is present for the global MV portfolio. The aim of this thesis was to provide a complete picture of risk sources that affect the returns of MV portfolios. Therefore, also risk sources that are not present in the Carhart four-factor model were considered. The findings of Frazzini and Pedersen (2010) indicate that the pricing model should be extended by the BAB factor, which captures the return difference between high-beta and low-beta stocks. Low-beta stocks are assumed to outperform high-beta stocks in terms of four-factor alpha for a number of reasons. These include leverage constraints, concentration risk, absence of implied protection, behavioral biases and fund manager incentives. These affect the MV portfolio either through the BAB factor or directly. Five-factor regressions point out that inclusion of the BAB factor indeed significantly improves the pricing model and that all MV portfolios are biased to low-beta stocks. The five-factor risk-adjusted return of the MSCI MV World portfolio is statistically insignificant. The same holds for the MSCI MV Japan and US portfolio. The five-factor return for the MSCI MV Europe, EAFE and Emerging Markets portfolios is significantly positive.

Two risk factors that affect the returns on MV portfolios were studied into detail. First, concentration risk was examined. By creating MV indices from industry portfolios, insight into the development of MV portfolio allocation was obtained. MV portfolios have been biased to the health care, utilities and nondurable consumption goods industry over the past decade. The BAB factor is biased to the same industries, but does not capture concentration risk completely. Including factors that capture the outperformance of these industries compared to a broad MCW index, further reduces the risk-adjusted performance of the MSCI MV World index. Second, the absence of implied protection for MV portfolios compared to MCW portfolios was evaluated. A CAPM regression extended with the squared excess market variable factor, point out that the hypothesized concave relationship between MV returns and MCW returns is present indeed. However, the effect during ordinary market conditions is limited. A closer look at the response of the MSCI MV Japan index to the 2011 earthquake, indicates that during extreme negative shocks MV betas are likely to converge to one. Per unit of beta, a MV investor loses more in such a situation.

When adjusting for all these risk factors, the outperformance of the MSCI World MV portfolio is no longer statistically significant. Although the global MV portfolio is considered to be the most important one, it should be noted the risk-adjusted returns are not consistent across regions. Other risk factors than the ones that are examined might have an impact on MV portfolio returns. The impact of these risk sources might differ per region. Unfortunately, these factors have not been identified.

Although it is difficult to estimate the long impact of risk sources with the current dataset, an attempt to rank risk factors on relative importance was made. As mentioned, all MV portfolios are biased towards the BAB-factor, but concentration risk is a more important risk factor. The factor that seems least important under historical market conditions, is the absence of implied protection. Nevertheless, it is important to note that this aspect of equity portfolios might become increasingly important in the future.

The main message for investors is that the global MV portfolio is an attractive equity portfolio, but that the absolute outperformance is mainly a compensation for risk factors. In contrast to what its name suggests, MV portfolios do not completely offer the desired protection during extreme circumstances. Investors should be aware of finding that during those times, investments in MV portfolios are not the safest way to buy market exposure. Instead, investors are probably better off by investing a lower amount of money in MCW indices, and invest the remainder in safer asset classes.

8. Discussion

In this section, the limitations of this thesis are discussed. Furthermore, suggestions for future research are provided.

8.1 Limitations

As mentioned, daily SMB, HML, MOM and BAB factor data is only available for the American equity market. Creating global SMB and HML factors from traded benchmarks is not a good alternative (Cremers, Petajisto and Sitzewitz, 2010). Hence, American factors have been used for all portfolios. Due to this decision, estimated alpha returns are probably overestimated.

The MV outperformance is hypothetically caused by five sources. These sources are expected to be partially captured by the BAB factor. The impact of leverage constraints has been examined by Frazzini and Pedersen (2010). In this study, two other sources are examined, namely concentration risk and implied protection in high-beta. The two remaining sources, behavioral biases and fund manager incentives, are impossible to identify through this way of data analysis. These latter two sources are different from first three sources, as for an independent rational investor there is no real risk involved with these sources. Hence, the share of alpha return that can be explained by these reasons, could be seen as a risk-adjusted return. Unlike for example concentration risk, rational investors could benefit from these imperfections without risk. Therefore, it would be of great interest to measure the impact of these factors as well. As these cannot be detected in this study, it is impossible to state whether they are present, or whether they are offset by arbitrage.

Unfortunately, MSCI was not willing to cooperate by sharing their insight in the development of historical index compositions. Hence, an alternative method is used to find out how to detect industry biases. This method is not ideal, but was considered the best alternative. Also, in order to make a correct comparison between MV and MCW portfolios, a good estimation of transaction costs needs to be made. As turnover data was not available, it is not possible to do this.

A large part of the data on MSCI MV indices is back-tested data. This is an important limitation, as it implies that it is possible that the constraints have been optimized given the historical data.

Also, it is important to mention that the excellent performance over the past decade, is the main reason that MV strategies became popular. This is actually the reason that this strategy ‘survived’ and indirectly also the motivation that this topic is studied in this thesis. Therefore, investors should take into account that it is no guarantee that the MV strategy will be a winning strategy in the next decade as well. Performances are heavily influenced by a few major events.

Another limitation is that the window that is studied is relatively narrow. Unfortunately, earlier data was not available. As a consequence, the number of extreme events within this sample is limited. Also, the effect of a very extreme event is difficult to capture. The type of event that is mentioned before simply did not occur yet. Therefore, it is impossible to state which part of the alpha return is a compensation for the likelihood such an extreme event occurs. Also it is possible that the industries to which the MV portfolios are biased and contributed to the outperformance, will underperform in the future.

Lastly, the return that is adjusted for all considered risk factors is inconsistent across regions. As mentioned, it is possible that risk factors that are not captured by the pricing model influence MV returns. The impact of these risk factors might be different per region. Unfortunately, this hypothesis cannot be tested with the current dataset.

8.2 Suggestions

First of all, it would be interesting to generate a longer data history on MSCI MV indices using the same approach. To do this, cooperation of MSCI is required. When a broader window is studied, more extreme events are included, which could improve the quality of the estimates.

Further, it would be interesting to construct regional factor data using the same approach as Kenneth French and test whether this leads to different findings. This enables to make a solid comparison between regional portfolios. Due to time constraints and giving priorities to other tests, this was not feasible within this thesis project.

Whereas this study focused on MV equity portfolios, it would be interesting to execute the same type of research for other asset classes. This would be interesting from both an academic as a practical perspective. Frazzini and Pedersen (2010) looked at a broad universe of asset classes in their study on the relationship between beta and returns. This implies MV portfolios of other asset classes could be studied in a similar way using a BAB factor. Currently, investors are primarily focused on MV equity portfolios, but taking recent developments in sovereign debt markets into account, it would be interesting to examine whether these strategies are beneficial for those assets as well.

As mentioned, MV risk-adjusted returns differ substantially across regions. A study that examines why these differences are present would add to existing literature.

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Appendix A: BAB factor

In Table 12, summary statistics of beta decile portfolios are presented. Low-beta portfolios outperform high-beta portfolios in Sharpe ratio terms.

Table 12 Summary statistics beta decile portfolios. The dataset includes daily data from 12/2001 to 12/2011. The first decile includes stocks with the highest beta, whereas the tenth decile includes stocks with the lowest beta.

Decile portfolios of stocks sorted on beta	Return	SD	Sharpe ratio
Decile 1 (high beta)	19.29%	37.31%	0.45
Decile 2	15.83%	30.93%	0.43
Decile 3	15.62%	27.14%	0.48
Decile 4	13.24%	24.40%	0.44
Decile 5	14.63%	22.49%	0.54
Decile 6	15.50%	19.95%	0.65
Decile 7	15.41%	17.78%	0.73
Decile 8	14.11%	14.75%	0.79
Decile 9	10.80%	10.28%	0.81
Decile 10 (low beta)	18.93%	7.88%	2.09
BAB	16.10%	10.90%	1.25
Equally Weighted[1]	15.11%	20.11%	0.63
Value Weighted[1]	6.75%	21.64%	0.20

1. Equally and value weighted market portfolio data is retrieved from the CRSP database.

In Table 13 and Figure 10, the results of regressions of beta decile portfolios returns on factor returns are presented. Risk-adjusted returns are negatively related to beta. Furthermore, the adjusted R^2 of stocks with the lowest beta is only 0.288, which indicates these stocks are exposed to other risk factors than the ones incorporated in the multifactor model. The latter also validates using the eighth and third beta decile for constructing the BAB factor. The Carhart (1997) four-factor risk-adjusted return on the BAB factor is significantly positive. The BAB factor is biased towards large caps and value stocks. The factor captures a momentum effect.

Table 13 Regression on beta portfolio stock 12/2001 - 12/2011. The BAB factor is long in the eight decile leveraged to a CAPM beta of one, short in the third decile and deleveraged to a CAPM beta of one.

Portfolio	α	β_{mkt}	s_{smb}	h_{hml}	m_{mom}	$adj.R^2$
Decile 1 (high beta)	-5.917% (-2.27)	1.711 (170.66)	0.215 (11.75)	-0.016 (-0.82)	-0.189 (-16.38)	0.951
Decile 2	-5.884% (-3.79)	1.476 (247.32)	0.089 (8.21)	-0.004 (0.33)	-0.085 (-12.29)	0.975
Decile 3	-3.810% (-3.03)	1.306 (270.25)	0.079 (9.03)	-0.008 (-0.88)	-0.056 (-10.09)	0.979
Decile 4	-4.420% (-4.24)	1.200 (299.82)	0.012 (1.69)	-0.048 (-6.02)	-0.025 (-5.52)	0.982
Decile 5	-1.824% (-1.77)	1.125 (284.60)	0.012 (1.69)	-0.059 (-7.51)	0.011 (2.35)	0.979
Decile 6	0.539%	1.008	-0.040	-0.034	0.048	0.974

	(0.53)	(256.84)	(-5.61)	(-4.37)	(10.56)	
Decile 7	1.978% (1.79)	0.894 (211.04)	-0.082 (-9.35)	-0.012 (-1.45)	0.049 (10.09)	0.961
Decile 8	2.759% (2.05)	0.747 (144.46)	-0.116 (-12.26)	-0.003 (-0.26)	0.093 (15.60)	0.917
Decile 9	3.193% (1.83)	0.469 (69.94)	-0.129 (-10.52)	0.004 (0.32)	0.082 (10.57)	0.711
Decile 10 (low beta)	14.175% (6.47)	0.221 (27.42)	-0.033 (-2.27)	0.034 (4.57)	0.043 (4.57)	0.288
BAB	15.99% (4.88)	0.042 (3.89)	-0.145 (-6.59)	0.084 (3.48)	0.216 (14.99)	0.090

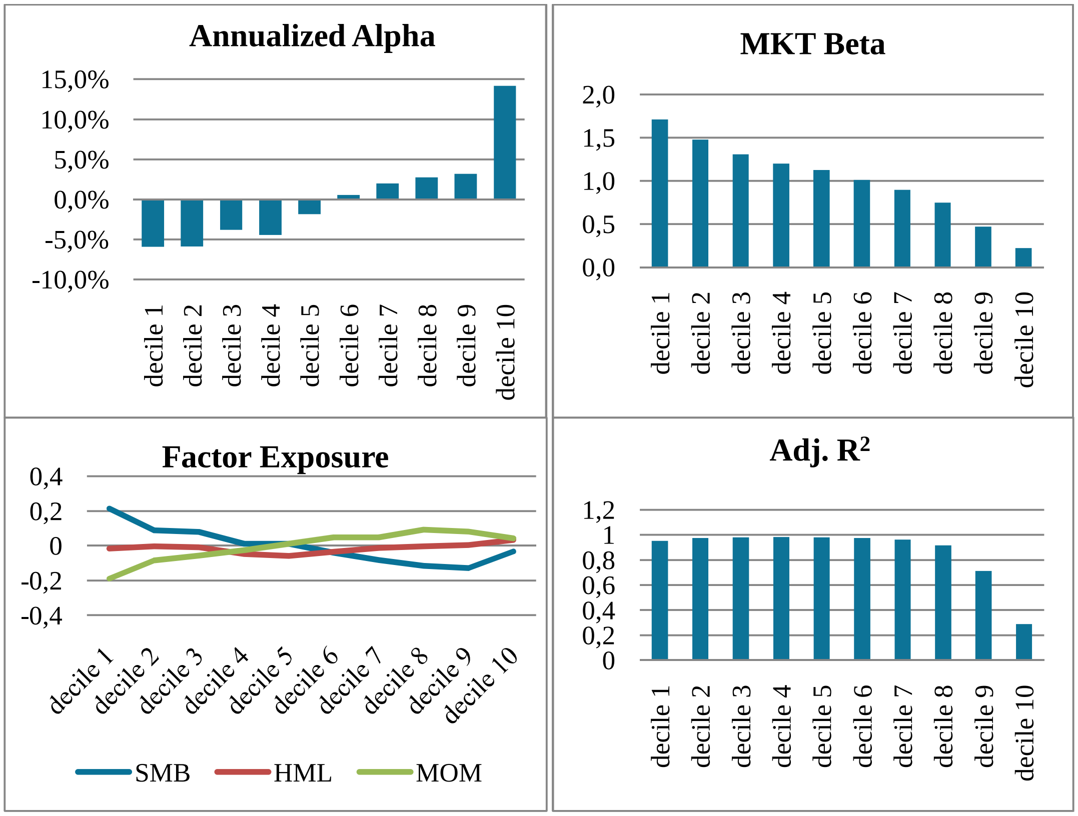

Figure 10 Beta decile portfolios. For each beta decile, a Carhart (1997) four-factor regression has been conducted. The dataset includes daily data from 12/2001 to 12/2011. Alpha returns are annualized based on 252 trading days a year. The market portfolio that has been used as a benchmark, is obtained from the website of Kenneth French.

The rolling window regression that is presented in Figure 11 indicates that betas are converging to one during extreme market circumstances (see September 2008).

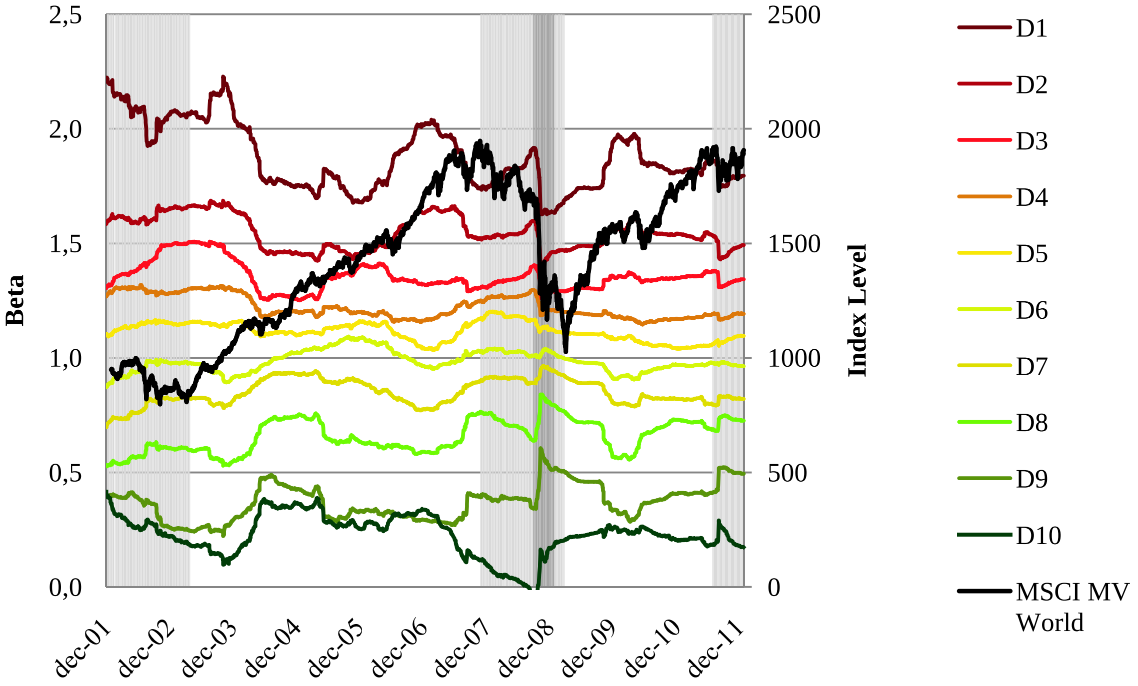

Figure 11 Rolling CAPM Regression. Rolling regression analysis of beta decile portfolios on a MCW benchmark. A moving window of 252 days has been used. Bear market periods are shaded grey, these include the internet crisis (31/03/2000 - 31/03/2003), subprime crisis (31/10/2007 - 28/02/2009) and euro zone crisis (30-06-2011 - present). Window specifications are derived from Melas, Briand and Urwin (2011). The bankruptcy of Lehman Brothers (September 2008) is indicated as well.

Appendix B: Industry portfolios

Simple CAPM and Carhart four-factor regressions have been conducted for ten industry portfolios. Obviously, the return regressions for the health care and utilities industries had relatively low levels of R^2. The latter indicates a large share of return variability for those industries is not explained by market related risk factors. The outperformance of nondurable consumption goods industry compared to the MSCI World is statistically significant.

Table 14 Performance industry portfolios. The dataset includes daily data from 12/2001 to 12/2011. Alpha returns are annualized based on 252 trading days a year. The market portfolio that has been used as a benchmark in each regression is the MSCI World portfolio. Due to a lack of data availability, factor portfolios have only American constituents. T-values are presented in parentheses. The sample consists of 2539 observations.

Industry	CAPM α	CAPM R^2	Carhart α	Carhart R^2
Durable consumption goods	-0.25% (-0.12)	0.87	-0.56% (-0.26)	0.87
Nondurable consumption goods	5.04% * (2.40)	0.74	5.25%* (2.57)	0.76
Energy	5.38% (1.34)	0.72	5.39% (1.32)	0.75
Financials	-4.75% (-1.70)	0.87	-5.45%* (-2.57)	0.93
Health Care	-0.18% (-0.07)	0.69	0.66% (0.25)	0.71
IT	-3.31% (-0.84)	0.72	-2.46% (-0.70)	0.77
Industrials	1.07% (0.61)	0.92	0.74% (0.43)	0.92
Materials	4.98% (1.31)	0.76	4.37% (1.19)	0.77
Utilities	3.98% (1.40)	0.70	4.11% (1.51)	0.72
Telecom/communication	-0.21% (-0.06)	0.71	0.83% (0.26)	0.72

* alpha return significant at the 2.5% level (t-test)