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Low-Beta Strategies

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Look deeper

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Low-beta Strategies

Abstract

This paper analyzes trading strategies designed to exploit the low-beta anomaly. Although the notion of buying low-beta stocks and selling high-beta stocks is natural, a choice is necessary with respect to the relative weighting of high-beta stocks and low-beta stocks in the portfolio. Our empirical results for US stocks show that this choice is very important for the risk-return characteristics of the resulting portfolios and their sensitivities to common risk factors. The weighting of stocks within the low-beta and high-beta portfolios and the chosen investment universe are essential design elements of low-beta strategies too. If smaller firms are excluded, risk-adjusted returns of low-beta strategies can even become insignificant.

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1. Introduction

The observation that returns of low-beta stocks are too high and returns of high-beta stocks are too low as compared to the predictions of the standard CAPM has long been documented in the literature (Black, Jensen, and Scholes, 1972; Haugen and Heins, 1975; Fama and French, 1992). This phenomenon, commonly referred to as the low-beta anomaly, also extends to the most recent period and is found in many different markets (Rouwenhorst, 1999; Baker and Haugen, 2012; Blitz, Pang, and van Vliet, 2013; Frazzini and Pedersen, 2014). From an investment perspective, the question arises how the low-beta anomaly could best be exploited via trading strategies,[1] and from an asset pricing perspective, one would like to know how the specific construction of a corresponding risk factor affects its return, risk and co-variation with other factors. It seems intuitive to exploit the low-beta anomaly by buying low-beta stocks, selling high-beta stocks, or both, however, there are many ways to do so. What is the universe of different stocks that should be considered from the outset? How should betas be estimated? How should low-beta stocks and high-beta stocks be weighted in a portfolio? How often should these portfolios be rebalanced? The question of how these design elements of low-beta strategies affect the properties of the resulting returns, for example, alpha or sensitivities to other risk factors, is important for investors and portfolio managers alike, because the idea of exploiting the low-beta anomaly must be made concrete and requires an understanding of the implications of specific choices. This paper is the first to study the effects of all these design elements systematically.

As the starting point of our analysis, we formally define low-beta strategies as zero-cost strategies, with zero ex ante market exposure, that are long in low-beta stocks and short in high-beta stocks. If investments in the market index and a risk-free asset are also available, this definition is fulfilled by a continuum of low-beta strategies

[1] Jank and Smajlbegovic (2016) show that trading based on the "betting against beta" factor proposed by Frazzini and Pedersen (2014) is common practice for institutional investors; that is, such strategies are widespread in practice. To what extent some low-beta strategies are more successful than others is an open issue, however.

that assign different weights to low-beta stocks and high-beta stocks. From this set of strategies, we select four basic ones covering the entire range of feasible weights. Implementation of these strategies requires specification of several additional design elements. We consider the choice of investment universe, the length of the time period used for beta estimation, the percentage of stocks included in the low-beta and high-beta portfolios, the weighting of individual stocks within these portfolios, and how often the portfolios are rebalanced.

Our empirical study focuses on the US stock market and shows that all design elements of low-beta strategies that we consider have an important impact on the return characteristics of the strategies. The specific design of low-beta strategies matters a great deal. This general finding is the main contribution of our study. In particular, we find that low-beta strategies that over-weight (buy) low-beta stocks differ substantially from strategies that over-weight (sell) high-beta stocks. Further, the weighting of single stocks within the low-beta and high-beta portfolios has a large impact on average returns and sensitivities to standard risk factors. When beta weighting and equal weighting of stocks is applied, portfolios that buy low-beta stocks perform very well. Value weighting, in contrast, leads to higher average returns for portfolios that sell high-beta stocks short. Another very important issue is the choice of investment universe. Within the universe of S&P 1500 stocks, we find strong low-beta effects, whereas within the S&P 500 universe, these effects disappear, showing the importance of the strategic decision to select a specific universe or benchmark.

Our paper relates to different strands of literature. First, it is naturally connected to work on the low-beta anomaly. Several analyses document the anomaly for varying time periods and markets (Rouwenhorst, 1999; Baker and Haugen, 2012; Blitz, Pang, and van Vliet, 2013; Frazzini and Pedersen, 2014; Auer and Schuhmacher, 2015), and several explanations for the appearance of the phenomenon and the related low-volatility anomaly have been suggested (Baker, Bradley, and Wurgler, 2011; Berrada and Hugonnier, 2013; Dutt and Humphery-Jenner, 2013; Blitz, 2014; Blitz, Falkenstein, and van Vliet, 2014; Frazzini and Pedersen, 2014; Christoffersen and

Simutin, 2015; Hong and Sraer, 2015; Jacobs, 2015; Jylhä, Suominen, and Tomunen, 2015; Bali, Brown, Murray, and Tang, 2016; Cederburg and O´Doherty, 2016; Jacobs, 2016; Schneider, Wagner, and Zechner, 2016). Our paper has a different focus, however, because we concentrate on the comparison of different strategies that try to exploit the low-beta anomaly. Most closely related to our paper is work that investigates zero-cost strategies using short positions in high-beta portfolios and long positions in low-beta portfolios. Black (1993) analyzes such a strategy, which he calls the beta factor.[2] Alternative strategies with different weighting schemes for low-beta stocks and high-beta stocks are used by Frazzini and Pedersen (2014) and Li, Sullivan, and Garcia-Feijoo (2014). However, none of these papers analyzes the effects of varying relative weights of high- and low-beta portfolios and how theses effects interact with a wide range of additional design specifications, the focus of our work.

Current work on factor investing and smart beta strategies is also related to our study. Important contributions to this literature investigate if and how the performance of value-weighted indexes can be improved via alternative weighting schemes, for example, by size, value, volatility, beta, dividend, or past return (Amenc, Goltz, and Lodh, 2012; Chow, Hsu, Kuo, and Li, 2014; Hsu, 2014; Jacobs and Levy, 2014; Malkiel, 2014; Amenc, Goltz, and Lodh, 2016). Our study is in the same spirit, as we investigate how different design elements, including the weighting within a portfolio, affect performance. In particular, we show that the weighting within a low-beta portfolio, for example, equal weighting versus value weighting, can make a large difference. In addition, our results provide information on other issues discussed in the literature on smart beta and factor investing. Amenc, Goltz, and Lodh (2016) conclude that it is important to analyze the properties of different smart beta strategies individually, and one must be careful with general statements. We come to the same conclusion for low-beta strategies. Blitz, Huij, Lansdorp, and van Vliet (2014) discuss whether a long-only approach for factor investing is

[2] The original idea goes back even to Black, Jensen, and Scholes (1972).

more efficient than a long-short approach. Likewise, we compare strategies based on buying low-beta stocks with strategies selling high-beta stocks and document important differences. In particular, we find that a long-only approach is able to capture the main effects of the low-beta anomaly. Amenc, Ducoulombier, Goltz, Lodh, and Sivasubramanian (2016) conduct a comparison of performance and risk of concentrated and diversified factor-tilted indices for six factor tilts. In our study, focusing on the "low-beta factor", we also analyze the effect of using more concentrated or more diversified low-beta and high-beta portfolios and find an important effect on both mean return and risk. Finally, factor investing is much concerned with the identification of factor exposures and factor attribution,[3] which motivates the design of our study. The low-beta strategies that we use have zero ex ante beta by construction and therefore no ex ante correlation with the market factor, meaning that we disentangle the low-beta premium from the market risk premium. Such a property can not be easily achieved for the low-volatility factor.[4] We therefore concentrate on low-beta strategies and do not consider low-volatility strategies.

This paper proceeds as follows. Section 2 provides a formal definition of low-beta strategies, introduces four basic strategies, and discusses additional design elements that need to be specified before implementation. The following Section 3 introduces the data and design of our study. Section 4 presents our empirical results on the return characteristics of the specified low-beta strategies. Section 5 sets forth our conclusions.

2. Characterizing Low-beta Strategies

2.1. Definition of Low-beta Strategies

For our investigation on the impact of different choices a portfolio manager can make when implementing a low-beta strategy we must state precisely what a low-beta

[3]For example, Blitz (2016) investigates the relation between the low-volatlity factor and the value factor.

[4]Seminal papers on the low-volatility anomaly are Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009).

strategy is. To define such a strategy, we suggest the fulfillment of four conditions. These conditions ensure that a strategy is in line with the intuitive notion of low-beta investing and that it puts different strategies on an equal footing, to make comparison meaningful.

In our setting, investors can form portfolios from a universe of N stocks. These N stocks constitute the "market", and betas of individual stocks are defined in relation to this market portfolio. We assume that an investment in the market portfolio is possible, via ETFs, futures, or by buying stocks directly. Moreover, there is also a risk-free investment (and financing) available. By definition, the beta of the market portfolio equals 1. It is therefore a natural requirement for a low-beta portfolio to have a beta below 1 and for a high-beta portfolio to have a beta above 1. Based on this notion of low-beta and high-beta portfolios, we define a *low-beta strategy* via the following conditions:

Condition (i): Denote the amount invested in a selected low-beta portfolio L by X_L and the amount invested in a selected high-beta portfolio H by X_H. Then, a low-beta strategy requires $X_L \geq 0$ and $X_H \leq 0$, with at least one of the conditions holding as a strict inequality.

Condition (i) states that a low-beta strategy is a long-short strategy that goes long a low-beta portfolio and short a high-beta portfolio. However, as it is a goal of this paper to investigate the roles of low-beta and high-beta portfolios in low-beta strategies, we also allow for the extreme cases that take only long positions in low-beta portfolios or only short positions in high-beta portfolios.

Condition (ii): The (ex ante) beta of a low-beta strategy is zero. Formally, this condition can be expressed as $X_L\beta_L + X_H\beta_H + X_M = 0$, where X_M denotes the amount invested in the market portfolio and β_L and β_H are the betas of the low-beta and high-beta portfolios, respectively.

The goal of low-beta strategies is to exploit the differential performance of high-beta and low-beta stocks. To concentrate on this differential, i.e., the "betting-against-beta factor", the returns of these strategies should be isolated as far as possible from the market factor. To achieve this, at least on an ex ante basis using estimated betas, the beta of the strategy should be zero, which is what condition (ii) states.

The next two conditions facilitate comparison between different low-beta strategies by ensuring homogeneity in specific aspects.

Condition (iii): A low-beta strategy has an initial value of zero. Formally, this condition reads $X_L + X_H + X_M + X_R = 0$*, where* X_R *denotes the amount invested in the risk-free asset.*

Condition (iv): The sum of the absolute amounts invested in the low-beta portfolio and the high-beta portfolio is the same for different low-beta strategies, i.e., $|X_{L,i}| + |X_{H,i}| = |X_{L,j}| + |X_{H,j}|$*, where* i *and* j *denote different low-beta strategies.*

Condition (iii) states that any low-beta strategy has the same initial amount invested, with zero as a natural choice.[5] Condition (iv) states that all low-beta strategies generate the same amount of total (dollar) trading volume (either long or short) in the low-beta and high-beta portfolios. We concentrate on the trading volume in the high-beta and low-beta portfolios because these portfolios usually consist of many different stocks and trading can generate significant transaction costs. In contrast, trading in the risk-free instrument and the market is much cheaper if appropriate derivatives (interest rate futures, index futures, ETFs) are available.

2.2. Basic Low-Beta Strategies

Our definition of low-beta strategies leaves substantial flexibility with respect to the portfolio weights assigned to the low-beta portfolio, the high-beta portfolio, the market index, and the risk-free instrument. For our empirical investigation, we consider a range of four basic low-beta strategies that cover natural reference points and extreme cases. In particular, they provide evidence on the performance

[5]Of course, other choices for the initial value, like a value of 1 dollar, could be considered. However, given that a strategy already fulfills conditions (i), (ii), and (iv), we could simply change the position in the risk-free asset to fulfill such a modified condition (iii).

contribution of the high-beta portfolio and the low-beta portfolio. The basic low-beta strategies are defined as follows:

Balanced (BL): A natural starting point is a strategy that invests 1 dollar in the low-beta portfolio and is short 1 dollar in the high-beta portfolio, i.e., $X_L = 1$ and $X_H = -1$. It follows from condition (ii) in the previous section that $X_M = \beta_H - \beta_L$, and condition (iii) finally implies that $X_R = \beta_L - \beta_H$.

Extreme Low (EL): A first extreme case takes a long position in the low-beta portfolio but no position in the high-beta portfolio. To fulfill condition (iv), in relation to the balanced strategy, we obtain $X_L = 2$ and $X_H = 0$. From conditions (ii) and (iii), the investments in the index and the risk-free instrument become $X_M = -2\beta_L$ and $X_R = 2\beta_L - 2$, respectively.

Extreme High (EH): The extreme high strategy is the mirror image of the extreme low strategy. It takes a short position in the high-beta portfolio and no position in the low-beta portfolio, i.e., $X_H = -2$ and $X_L = 0$. From conditions (ii) and (iii), the investments in the index and the risk-free instrument become $X_M = 2\beta_H$ and $X_R = -2\beta_H + 2$, respectively.

No Market Investment (NM): The weighting used in the fourth strategy is based on the idea described in Frazzini and Pedersen (2014) that no investment in the index is required, i.e., $X_M = 0$. The fulfillment of conditions (i), (ii), and (iv) then implies that $X_H = -2\beta_L/(\beta_H + \beta_L)$ and $X_L = 2\beta_H/(\beta_H + \beta_L)$. From condition (iii), we finally obtain $X_R = 2(\beta_L - \beta_H)/(\beta_H + \beta_L)$. For this strategy, the amounts invested in the low-beta and high-beta portfolios therefore depend on the magnitudes of the corresponding betas.

Table 1 provides an overview of the dollar amounts invested in various instruments according to the four basic strategies. Clearly, the four strategies give different weights to high-beta and low-beta portfolios. The low-beta portfolio is most important, in terms of absolute weights, for the EL strategy, followed by NM, BL, and EH. Also note that one has to take a long position in the market for both the EH and BL strategies, whereas the NM strategy uses a zero position in the market by construction and the EL strategy takes a short market position. All four low-beta strategies require risk-free borrowing.

[Insert Table 1 about here]

Concluding our introduction of the four basic strategies, we highlight how the NM strategy is related to the other strategies. For the NM strategy, the investments in the low-beta and high-beta portfolios depend on the relation of the corresponding betas, and it is instructive to examine some extreme parameter constellations. If β_L goes to zero or β_H goes to infinity, the NM strategy converges to the EL strategy.[6] As another extreme case, consider $\beta_L = \beta_H$. Under this parameter constellation, the NM strategy coincides with the BL strategy. We can therefore conclude that the NM strategy generally falls between the EL and BL strategies. The larger the deviation between β_L and β_H, the more the NM strategy behaves like the EL strategy, and the smaller the deviation, the more it behaves like the BL strategy.

2.3. Additional Design Elements of Low-Beta Strategies

In addition to the relative weighting of the low-beta and high-beta portfolios, choices on several other design elements affecting the actual set up of a strategy are required, for example, selection of the market, estimation periods, weighting schemes within the low-beta and high-beta portfolios, and the rebalancing frequency. Whereas selection of the market or investment universe is typically a strategic choice of the asset management firm or a particular client, the other choices mentioned above are usually made by the portfolio manager.

On the most general level, the market (*investment universe*) must be specified. In the literature, the low-beta anomaly is studied mainly for an investment universe that is as broad as possible; that is, studies for the US stock market use the CRSP

[6] If β_L even becomes negative, a strict implementation of the NM strategy would imply buying the high-beta portfolio, which is counter-intuitive and leads to a violation of condition (i). In our empirical analysis, we therefore use the EL strategy as an implementation of the NM strategy whenever β_L becomes negative.

universe.[7] Such a choice is reasonable if the anomaly itself is the focus of the investigation. However, our focus is on low-beta investment strategies. In this context, it makes sense to examine smaller universes consisting of more liquid stocks and with active markets for derivatives written on the universe. The benefits are lower transaction costs and a facilitated implementation of strategies. However, the anomaly may not be as strong in the smaller universe, potentially leading to smaller benefits from exploiting it.

To build low-beta and high-beta portfolios, all stocks must be ranked by their betas. This sorting is dependent on the estimated betas, and therefore on the estimation procedure used, in particular the *estimation period*. In the literature, betas are typically estimated from monthly data over the previous five years (60 observations).[8] If weekly or daily data are available, shorter estimation windows could lead to better estimates.

The *coverage* of the low-beta and high-beta portfolios, meaning the percentage of all stocks included in these two portfolios, must be determined next. This choice influences the betas and the diversification of low-beta and high-beta portfolios. Small coverage leads to more extreme betas and less diversified portfolios. Coverage also has an impact on trading costs, which are higher the more stocks are included in the portfolios. Usually decile portfolios are formed to exploit the low-beta anomaly.

For the *weighting* of single stocks within the low-beta and high-beta portfolios, an equal weighting of each stock within the corresponding portfolio would be a first, easily implementable choice. A natural alternative is value weighting, as single stocks are value-weighted in the market portfolio according to the CAPM. A third idea would be to weight individual stocks relative to their betas. This alternative emphasizes the anomaly that should be exploited, giving more weight to stocks

[7] A notable exception is Auer and Schuhmacher (2015), who study the low-beta effect for the 30 stocks included in Dow Jones Industrial Average (DJIA).

[8] Of course, there are also other estimation windows used in previous studies. For example, Frazzini and Pedersen (2014) use a mixed approach with different estimation windows for variances and correlations.

with very low betas in the low-beta portfolio and stocks with very high betas in the high-beta portfolio. Value weighting of portfolios is often chosen to investigate the low-beta anomaly, and equal weighting and beta weighting are rather unusual. As we know from the smart beta literature, however, special attention should be paid to the weighting scheme, as it can significantly change the risk-return trade-off of a strategy.

Commonly, monthly *rebalancing* of portfolios is applied in the literature. For the purpose of showing the existence of the low-beta anomaly, the rebalancing frequency is of minor concern. But from an investment perspective, it could be very important, because there is again a potential trade-off. More frequent rebalancing could be beneficial to exploit the anomaly using the most recent information; however, it would also lead to higher transaction costs.

3. Data and Design of the Empirical Study

Our empirical study uses the S&P 1500 Index and the S&P 500 Index as the investment universe. Concentrating on the 1500 (500) most significant US stocks has the advantage that investment strategies have relatively low transaction costs. Moreover, liquid derivatives contracts on the indexes are available, which ensures that the index investments required by our strategies are cheap and easy to implement. We use daily data for the period December 1991 to April 2016. The data source for the stock price data is Thomson Reuters Datastream. As the risk-free interest rate, we use the 1-month T-bill rate from Kenneth French's website. For performance analysis of the low-beta strategies, we additionally need the factors from the Carhart (1997) four-factor model. For evaluation of our strategies, we calculate factor returns that exactly match our holding periods, namely, monthly, and yearly, using the monthly data provided on Kenneth French's website.

As described, equal weighting, value weighting, and beta weighting are worthwhile alternatives for weighting within the low-beta and high-beta portfolios, so we use all three in our following investigation. Coverage of the high-beta and low-beta portfolios is set at 2%, 10%, or 20% of the entire market. For the S&P 1500 Index, the number of stocks in a portfolio is therefore 30, 150, or 300, respectively. For the S&P 500, we have either 10, 50, or 100 stocks. For the stocks considered in our study, daily returns are available. Betas are therefore estimated from daily stock returns and corresponding market returns over rolling estimation windows of 1, 3, and 12 months, respectively.[9] Beta estimates are obtained for each month in the investigation period between December 1994 and April 2015. These estimates refer to the last trading day of the particular month, which is also the day on which the strategies are set up or rebalanced. The first year of the data period is required to obtain the initial beta estimates and the last year of the data period is needed to obtain the strategies' realized returns after rebalancing for the last time. Finally, we consider monthly and yearly rebalancing for the strategies.

Our study of different low-beta strategies starts with an analysis of a base case in which we examine the performance of the four basic low-beta strategies. We then observe the influence of several specifications of the additional design elements on the performance of the strategies in comparison with the base case. We first consider the design elements usually determined by the investment manager (estimation period, portfolio coverage, weighting within portfolios, rebalancing frequency), then examine the impact of the investment universe.

The base case is defined as follows: We use the S&P 1500 as the investment universe, because we want to start with a universe that is closer to the one usually used in previous work in terms of the number of stocks included. We beta-weight the single stocks within the low-beta and high-beta portfolios to stress exploitation of the low-beta anomaly. Portfolio coverage is 10% of the investment universe, that is, 150 stocks per portfolio; this is the widely used standard approach. Beta is estimated over a period of three months with daily data, so that the number of observations (about 60) is comparable with previous studies. Finally, we use yearly rebalancing

[9] A longer estimation window of 36 months leads to very similar results as the 12 months window. Results are therefore not reported and are available upon request.

to keep transaction costs as low as possible. Table 2 gives an overview of the various design elements and the choices made for the base case.

[Insert Table 2 about here]

4. Empirical Results

4.1. Return and Risk Characteristics for the Base Case

Since the weights assigned to the instruments by the various strategies depend on the (estimated) ex ante betas of the low-beta and high-beta portfolios, we begin the discussion of our results with an indication of how these betas evolve over time. Figure 1 shows the corresponding values for the base case. Obviously, the beta of the high-beta portfolio is much more volatile over time than the beta of the low-beta portfolio. Early in the period, the beta of the low-beta portfolio is often close to zero or even negative, meaning that the NM and EL strategies coincide.

[Insert Figure 1 about here]

Figure 2 shows the performance, in terms of increase in total wealth for an investor, of the four basic low-beta strategies. The increase in total wealth is measured under the base-case specification of the strategies. At the end of each month of the investigation period, an investor sets up the respective low-beta strategy, which then runs for the following 12 months. At the end of the holding period, the returns of the strategy are transferred to a money market account, which earns the risk-free rate, or, in case of a negative balance, allows for risk-free borrowing. The figure shows how the balance of this account evolves over time. For comparison, the performance of a corresponding self-financing strategy that invests in the S&P 1500 Index and borrows at the risk-free rate is presented.

[Insert Figure 2 about here]

As Figure 2 shows, all (zero cost) low-beta strategies lead to a positive total wealth at the end of the sample period, which suggests the existence of a low-beta premium that can be exploited at least to some degree. This premium is also quantitatively quite substantial. The strategy based on the index investment essentially captures the market risk premium. Because all low-beta strategies lead to a higher total wealth at the end of the period, the low-beta premium seems to be at least as important as the market risk premium. Comparing the four basic low-beta strategies, we observe that the EL and NM strategies yield almost the same total wealth and their performance is closely related, as expected from the very small beta coefficients of the low-beta portfolio shown in Figure 1. Moreover, Figure 2 suggests that the EH strategy is more volatile than the EL and NM strategies, performing somehow better in up markets but much worse in down markets. The higher volatility is in line with the higher beta volatility of the high-beta portfolio, as compared to the low-beta portfolio. Over the entire data period, the performance of the EH strategy is clearly worse than the performance of the other three strategies.

Table 3 presents average yearly returns, standard deviations, Sharpe ratios, and certainty equivalent returns (CEV) of the four basic low-beta strategies (Panel A). The certainty equivalent return is calculated for an investor with constant absolute risk aversion (CARA) preferences and an absolute risk aversion of 1.[10] We include this measure because it depends on all moments of the return distribution, including higher order moments like skewness and kurtosis in addition to mean and standard deviation.[11] Because of the zero initial investment required by our low-beta strategies, the Sharpe ratio is simply the ratio of average return and standard deviation, and the reference point for the certainty equivalent return is zero.

[Insert Table 3 about here]

[10] Constant relative risk aversion (CRRA) preferences seem to be another natural candidate for such an analysis. However, because our low-beta strategies have discrete holding periods and contain short positions in stocks, terminal wealth cannot be guaranteed to be positive. CRRA investors would not invest in strategies that do not guarantee positive terminal wealth.

[11] The analysis in Schneider, Wagner, and Zechner (2016) shows that return skewness is a possible explanation for the low-beta anomaly.

The average returns in Panel A show a clear pattern. When moving from the EH strategy to the strategies that give a higher (absolute) weight to the low-beta portfolio (NM, EL), the average return clearly increases. This finding shows that which weighting scheme is employed can make a difference. The standard deviations of the four strategies also show a clear pattern; that is, the more high-beta stocks are over-weighted, the higher is the standard deviation. If we consider the Sharpe ratio and the certainty equivalent return as measures of investment performance, the best-performing strategies are those with a high weight in the low-beta portfolio, where it is remarkable that the NM strategy provides the best risk-return trade-off. Both measures lead to the same ranking of different strategies.

Since it is an important question how the observed patterns of average returns for different low-beta strategies can be explained, we address this question in Panel B. One idea is to ask to what extent the returns of individual low-beta strategies show different sensitivities to common risk factors. To investigate this issue, we use the Carhart (1997) four-factor model that augments the Fama and French (1993) three-factor model with a momentum factor. We regress the returns of the low-beta strategies on the returns of the four-factor portfolios (market, size, value, momentum) and obtain factor loadings for each of the four factors and each of the four low-beta strategies.

Panel B of Table 3 shows the alphas and the factor loadings for all four strategies. The observed pattern in average returns can be found again for the alphas. The more the low-beta stocks are over-weighted the higher is the alpha. Moreover, the alphas of the NM and the EL strategies are statistically significant, as it is evident from the p-values below 5%, whereas the EH and BL strategies yield no significant alphas. It is remarkable that the average risk-adjusted returns of the NM and EL strategies are slightly higher than the average raw return. For the EH and BL strategies, however, risk-adjusted returns are much lower. An explanation for this can be found in the market exposure, which is positive and highly significant for the EH and BL strategies. Market exposure decreases with the weight shifted to the low-beta stocks; for the NM and the EL strategies, it is negative but insignificant.

A reason for the higher market exposure of the EH strategy could be a higher estimation risk for high-beta stocks, which is in line with the strong variation of betas for the high-beta portfolio shown in Figure 1. If beta estimates contain a lot of noise, the beta of the high-beta portfolio is likely to be upward biased, due to a misclassification of stocks in the top beta decile. Due to such a bias, the long position in the market index would be too high and would cause an overall positive market exposure. The momentum exposure is negative and significant for all four strategies, with an increasing coefficient from the EH to the EL strategies. The negative exposure of the NM and the EL strategy with respect to the momentum factor could explain why the average risk-adjusted returns of these two strategies are slightly higher than the average raw returns.

From an investment perspective, it is important to know whether the alphas of the NM and EL strategies remain statistically and economically significant under transaction costs. To analyze this issue, we follow the approach of Grundy and Martin (2001) and calculate the implicit transaction costs that would still support significant positive alphas. Assuming an investment horizon of one year, which would require no rebalancing in our base case, we use a turnover of 200%, that is, all stocks are bought at the beginning of a 12-month period and sold at the end. For a 5%-significance level, the EL and NM strategies still yield significant alphas with very substantial transaction cost of up to 190 bps. The corresponding alphas are 10.04% and 9.88%, respectively. For a 10%-significance level, transaction costs can be as high as 270 bps. The corresponding alphas would be 8.44% for the EL strategy and 8.28% for the NM strategy.

From the analysis of the average returns, Sharpe ratios, alphas, and factor sensitivities, it is obvious that it makes a huge difference how the low-beta anomaly is exploited. Shifting weights from high-beta stocks to low-beta stocks leads to higher average returns, lower standard deviations, statistically and economically more significant alphas, and lower (absolute) factor sensitivities with respect to all four factors of the Carhart model, making a strong point for the use of the low-beta portfolio in an investment strategy. In particular, alpha seems to be generated predominantly by the long positions of low-beta stocks. This results is also good news for investors who are reluctant to follow long-short strategies, because the low-beta premium (alpha) can be very well exploited by a strategy (EL) that does not require any short sales of high beta stocks.

4.2. Effects of Additional Design Elements

4.2.1. Alternative Estimation Periods

As a first additional design element, we examine the period used to estimate beta. Table 4 shows that a shorter estimation period (1 month) results in both higher average returns, higher standard deviations and only small changes in Sharpe ratios and CEVs in comparison with the base case.

[Insert Table 4 about here]

Alphas show the same patterns as in the base case, meaning significantly positive alphas when over-weighting low-beta stocks in a strategy. The values are generally higher than in the base case. Remarkably, the BL strategy has a significant alpha, which is even higher than the average return, probably due to a strong negative momentum exposure that overcompensates the positive market exposure. Market exposure is again very large for the EH strategy, and momentum exposure is generally higher (more negative) than in the base case.

Enlarging the estimation period to 12 months leads to a decrease in average returns and standard deviations in line with lower Sharpe ratios and CEVs, as shown in Table 5. Hence, this variation in the design of a low-beta strategy does not seem to be favorable. Unreported results (available on request) show that this conclusion still holds true for an even longer estimation period of 36 months. The effects are qualitatively the same as for the 12 months period.

[Insert Table 5 about here]

According to Table 5, the alphas of the NM and EL strategies are still positive and significant. For the BL and EH strategies, the alphas are much lower, and in the extreme can even be negative. The market exposure is slightly below the level of the base case. A significant size exposure is observable for the EL and NM strategies with positive values. Momentum exposure vanishes gradually when the estimation period is enlarged.

In summary, we find that a shortening of the estimation period results in higher alphas. An enlargement of the period leads to less momentum exposure and significant size exposure for the NM and EL strategies, suggesting that over-weighting low-beta stocks while simultaneously enlarging the estimation period leads to increased investment in small stocks.

4.2.2. Varying Portfolio Coverage

Our next analysis considers the effects of varying portfolio coverage. Smaller coverage (30 stocks) results in higher average returns than in the base case, but also higher standard deviations. In terms of the risk-return trade-off, the latter effect overcompensates the former, leading to lower Sharpe ratios and CEVs in all but one case. The only (slight) improvement refers to the Sharpe ratio of the EH strategy. However, the EH strategy is still the worst of all strategies. As Table 6 shows, the relative ranking of different strategies is unchanged compared to the base case when using smaller portfolio coverage.

[Insert Table 6 about here]

Very similar patterns as in the base case are found for the alphas and factor sensitivities. There is one interesting difference, however. On the one hand, the values of the alphas and factor sensitivities are generally higher (in absolute terms) than in the base case. On the other hand, statistical significance declines, because returns become more noisy over time. In particular, the alphas of the various strategies are no longer statistically significant. This is very much in line with the increased average returns but lower Sharpe ratios as compared with the base case.

An increase in portfolio coverage (300 stocks) leads to slightly lower average returns and standard deviations than in the base case, as shown in Table 7. The consequences for the risk-return trade-off depend on the strategy and the criterion (Sharpe ratio or CEV). With respect to the Sharpe ratio, we observe somewhat higher values for the NM and EL strategies.

[Insert Table 7 about here]

The patterns in the alphas and the factor sensitivities are similar to the base case. One difference is that the momentum exposure is somewhat diminished and the EL strategy has a significant size exposure. With respect to alphas, we observe that their magnitude is going down, but the p-values for the NM and EL strategies are also lower. This finding suggests that there is a trade-off between realizing a higher alpha and being able to establish its statistical significance when changing the portfolio coverage. Smaller coverage, that is, concentrating on stocks with more extreme betas, seems to produce higher (raw and risk-adjusted) average returns, but also much higher (raw and idiosyncratic) return volatility. These general effects of portfolio coverage for the low-beta strategies are well in line with the results by Amenc, Ducoulombier, Goltz, Lodh, and Sivasubramanian (2016), who study the tilting of an index towards six different factors. Their study also concludes that a too narrow coverage does not achieve a satisfactory degree of diversification, leading to unnecessarily high risk levels.

4.2.3. Alternative Weighting Within Portfolios

As shown in Table 8, an equal weighting of the constituents of the low-beta and high-beta portfolios leads to similar results regarding risk and return characteristics as the beta weighting. Average returns are slightly lower and, at the same time, the standard deviations are slightly lower as well, leading to very similar Sharpe ratios and CEVs compared to Table 3.

[Insert Table 8 about here]

The alphas are somewhat lower compared to the base case, but again the NM and the EL strategies lead to significant, positive alphas and have no significant market exposure, whereas the EH and BL strategies show insignificant alphas and a significant positive market exposure. Again, no significant size or value factor loadings are observed for any strategy, but there are still significant negative momentum factor exposures, which become stronger the more high-beta stocks are over-weighted.

Value weighting within the portfolios leads to substantial differences in all observed patterns, as shown in Table 9. In this case, average returns are highest for the EH strategy and lowest for the EL strategy. The level of returns is comparable, but in reverse order. This finding suggests that larger stocks within the high-beta portfolio have higher returns than smaller stocks within this portfolio. For the low-beta portfolio, exactly the opposite is true. This result suggests that the good performance of the EL strategy in the base case relies on relatively small stocks within the low-beta portfolio. Standard deviations are in the same order as in the base case (lowest for the EL strategy), and generally even lower. Caused by this pattern, Sharpe ratios are more homogeneous among the different low-beta strategies. For the EH and BL strategies, the Sharpe ratio is clearly improved; for the NM and EL strategies, it is reduced. When judging the risk-return trade-off via the CEVs, we find the same ordering as for average returns.

[Insert Table 9 about here]

With value weighting, alphas are positive and significant for all strategies in descending order from EH to EL. In contrast to the base case, no significant market exposure remains, but the EH strategy shows a significant positive size exposure, that is, over-weighting high-beta stocks tends to select small stocks. Again the momentum factor exposure is negative for all four strategies but seems to be lower than in the base case for the EH and BL strategies.

Whereas an equal weighting leads to only small deviations from the base case results regarding the risk and return characteristics, value weighting within portfolios causes substantial differences. With respect to risk-adjusted returns, beta weighting should be preferred when over-weighting low-beta stocks. When over-weighting high-beta stocks, value weighting leads to better results.

In summary, the weighting of stocks is very important for the performance of low-beta strategies. We show that not only does the relative weighting of low-beta and high-beta stocks lead to substantial differences in average returns and risk characteristics of the resulting strategies, the weighting within the low-beta and high-beta portfolios does as well. This finding complements results on smart beta strategies using different weighting schemes within an investment universe. With respect to the base case results, we have learned that relatively small stocks within the low-beta portfolio contribute a lot to the good performance of the EL and NM strategies.

4.2.4. Alternative Rebalancing Frequencies

Another important aspect is whether more frequent rebalancing could further improve the low-beta strategies. This is generally not the case, as can be seen from Table 10, which show the results for monthly rebalancing. For the EH and BL strategies, Sharpe ratios and CEVs somehow improve, but are still lowest among the four strategies. For the NM and EL strategies, Sharpe ratios and CEVs even decrease.

[Insert Table 10 about here]

The alphas show a similar picture to the Sharpe ratios and the CEVs. They somehow increase for the EH and BL strategies, although these alphas remain statistically insignificant. The significant positive alphas of the NM and EL strategies, however, become smaller as compared to the base case. With respect to the other factors, we find that all factor loadings are now insignificant for all strategies. Overall, taking into account that more frequent rebalancing leads to higher transaction costs, our analysis suggests that there is no good reason to rebalance the portfolios more frequently than once per year.[12]

Summarizing our findings on the design variations that a portfolio manager could make, we observe that the most far-reaching impact on the performance of low-beta strategies is a change from a beta weighting or equal weighting of the stocks within the portfolios to a value weighting. All other design elements have an impact on the risk and return characteristics as well, but do not change the relative ranking of the basic strategies if we consider the NM and EL strategies as one group of strategies with very similar characteristics. Usually, these two strategies also have the best Sharpe ratios, CEVs, and alphas. It is nonetheless important to understand possible interdependencies between over-weighting low-beta stocks or high-beta stocks and other design elements. In the end, portfolio managers must know what kind of portfolio characteristics they are creating via the choices they make.

4.3. Using a Smaller Investment Universe

After analyzing the impact of various design variations for the S&P 1500 stocks, we repeat the whole analysis for a smaller investment universe, the S&P 500 Index. As argued in Section II.C, the decision on the investment universe or benchmark is typically made by the asset management firm or the client, not the portfolio manager. Our analysis has shown that for the S&P 1500 universe, the portfolio manager's decisions are very important for the characteristics of a low-beta strategy. It is an interesting question whether this is still the case for the smaller universe of 500 stocks. An advantage of the smaller universe is that only the most liquid stocks are considered, and therefore transaction costs should be smaller. However, the low-beta effects might be smaller as well and the portfolio manager's choice variables might not suffice to create value via low-beta strategies.

Table 11 shows the base case results for the S&P 500 universe. Average returns are generally smaller than for the larger stock universe, but there is no difference in

[12] This statement also applies for a medium frequent rebalancing of 3 months, which leads to very similar results as the monthly rebalancing. Results are therefore not reported and are available upon request.

the relative ranking of the four strategies. Still, NM is the most promising strategy, followed by EL, BL, and EH. The standard deviations are lower as well, but not enough to result in higher Sharpe ratios compared to the larger universe. The same statement applies to the CEV. Unreported results for variations in the various design elements show no advantage from more frequent rebalancing and decreasing average returns with the length of the estimation period.

[Insert Table 11 about here]

Risk-adjusted average returns (alphas) are even smaller than the average raw returns, and it is remarkable that this result holds for all four strategies. Moreover, there is no clear ranking among the strategies, because alpha is not statistically significant for any of them. This is a very striking difference compared to the results for the S&P 1500 universe. It seems that the opportunity to create excess returns through low-beta strategies depends on the availability of the 1000 smaller stocks within the S&P 1500 index.[13]

All strategies have a highly significant and positive market exposure. Despite setting up all portfolios as zero ex ante beta portfolios, the zero-beta condition holds for the beta estimates obtained from the estimation period returns, not necessarily for the realized betas over the holding period. This result is also in contrast to the results for the larger index, because a significant market exposure is observed only for the EH and BL strategies. For the S&P 500 universe, we also find some significant size and value exposures.[14] The size exposure is more negative and more significant the more high-beta stocks are over-weighted. Unreported results show that this finding also holds for different estimation periods and rebalancing frequencies. For the value

[13]At first sight this result seems to be at odds with Auer and Schuhmacher (2015), who find a low-beta effect even in the universe of DJIA stocks. However, Auer and Schuhmacher (2015) use a sample period from 1926 to 2013, but do not show alphas for the more recent sub-periods corresponding to our sample period.

[14]Blitz (2016) investigates the relation between the low-volatility effect and the value effect and concludes that the low-volatility effect is the more robust anomaly. It might therefore be misleading to "explain" the returns of a low-beta strategy by a value factor, because causality might well be the other way round.

exposure, the exact opposite occurs: the more low-beta stocks are over-weighted, the higher and more significant is the value factor loading of the corresponding strategies. Thus, high-beta stocks tend to be large stocks and low-beta stocks tend to be value stocks. Finally, the momentum factor loading is insignificant for all strategies. These findings are in clear contrast to the findings for the S&P 1500 universe.

The performance of the low-beta strategies for the smaller investment universe is driven mainly by sensitivities to common risk factors, such that none of the strategies is able to yield significant risk-adjusted returns, and the positive average returns of the strategies can be explained mainly by the risk factors. Nevertheless, even in this case, the results emphasize the importance of how an investment strategy actually tries to exploit the low-beta anomaly. As observed in the factor loadings, over-weighting high-beta stocks leads to a substantial size exposure, and over-weighting low-beta stocks results in an extensive value exposure. All of our results for both investment universes highlight that there is no low-beta strategy per se, but different strategies exist with quite different properties, which must be taken into account when designing a low-beta strategy.

5. Conclusions

This paper addresses the issue that different choices exist to exploit the low-beta anomaly via trading strategies. Our empirical results show that whether a low-beta strategy puts more weight on buying low-beta stocks or on selling high-beta stocks can make a significant difference. Likewise, it is important how the investment universe is defined. Only in a larger stock universe, such as the S&P 1500 Index, can significant alphas be achieved. Among a number of additional design elements, the weightings within the low-beta portfolio and the high-beta portfolio have the greatest impact on risk–return characteristics. Under equal weighting and beta weighting, over-weighting of low-beta stocks achieves higher average returns and lower risk. Under value weighting, however, putting more weight on selling high-beta stocks leads to higher average returns. We also find that a shorter estimation window leads to higher average returns, and a yearly rebalancing of the portfolios is sufficient.

In the smaller stock universe, consisting of the stocks included in the S&P 500 Index, we observe no significant alphas, but we emphasize that the return characteristics strongly depend on the design elements. Strategies that over-weight low-beta stocks deliver higher average returns and are very sensitive to the value factor, whereas strategies that over-weight high-beta stocks have no value exposure, but a higher size exposure. These results stress the importance of selecting a low-beta strategy that is in line with the desired portfolio characteristics and that does not take the investor or portfolio manager by surprise.

Our findings support the view that the low-beta anomaly is due to small, more illiquid stocks. A first reason is that significant risk-adjusted returns exist only for the larger investment universe. A second indication is that giving higher weights to small stocks within the low-beta portfolio (equal weighting instead of value weighting) improves performance. Moreover, risk-adjusted returns result primarily from a positive premium earned by low-beta stocks relative to the whole market and not from a negative premium of high-beta stocks. This is good news for investors who are reluctant to follow strategies requiring short positions, because the premium can very well be exploited by just buying low-beta stocks.

References

Amenc, Noël, Frédérik Ducoulombier, Felix Goltz, Ashish Lodh, and Sivagaminathan Sivasubramanian, 2016, Diversified or concentrated factor tilts, *The Journal of Portfolio Management* 42, 64–76.

Amenc, Noël, Felix Goltz, and Ashish Lodh, 2012, Choose your betas: Benchmarking alternative equity index strategies, *The Journal of Portfolio Management* 39, 88–111.

Amenc, Noël, Felix Goltz, and Ashish Lodh, 2016, Smart beta is not monkey business, *The Journal of Index Investing* 6, 12–29.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross section of volatility and expected returns, *Journal of Finance* 61, 259–299.

———, 2009, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 1–23.

Auer, Benjamin R., and Frank Schuhmacher, 2015, Liquid betting against beta in Dow Jones Industrial Average stocks, *Financial Analysts Journal* 76, 30–43.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40–54.

Baker, Nardin L., and Robert A. Haugen, 2012, Low risk stocks outperform within all observable markets of the world, Working Paper, Guggenheim Investments.

Bali, Turan G., Stephen Brown, Scott Murray, and Yi Tang, 2016, A lottery demand-based explanation of the beta anomaly, Working Paper, Georgtown University.

Berrada, T., and J. Hugonnier, 2013, Incomplete information, idiosyncratic volatility and stock returns, *Journal of Banking & Finance* 37, 448–462.

Black, Fischer, 1993, Beta and return, *The Journal of Portfolio Management* 20, 74–84.

———, Michael C. Jensen, and Myron. S. Scholes, 1972, The capital asset pricing model: Some empirical tests, *Studies in the Theory of Capital Markets, Michael C. Jensen (ed.), Praeger: New York,* pp. 79–121.

Blitz, David, 2014, Agency-based asset pricing and the beta anomaly, *European Financial Management* 20, 770–801.

———, 2016, The value of low volatility, *The Journal of Portfolio Management* 42, 94–100.

———, Eric G. Falkenstein, and Pim van Vliet, 2014, Explanations for the volatility effect: An overview based on the CAPM assumptions, *The Journal of Portfolio Management* 40, 61–76.

Blitz, David, Joop Huij, Simon D. Lansdorp, and Pim van Vliet, 2014, Factor investing: Long-only versus long-short, Working Paper, Erasmus University Rotterdam.

Blitz, David, Juan Pang, and Pim van Vliet, 2013, The volatility effect in emerging markets, *Emerging Markets Review* 16, 31–45.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cederburg, Scott, and Michael S. O´Doherty, 2016, Does it pay to bet against beta? On the conditional performance of the beta anomaly, *Journal of Finance* 71, 737–774.

Chow, Tzee-Man, Jason C. Hsu, Li-Lan Kuo, and Feifei Li, 2014, A study of low-volatility portfolio construction methods, *The Journal of Portfolio Management* 40, 89–105.

Christoffersen, Susan K., and Mikhail Simutin, 2015, On the demand for high-beta stocks: Evidence from mutual funds, Working Paper, University of Toronto.

Dutt, T., and M. Humphery-Jenner, 2013, Stock return volatility, operating performance and stock returns: International evidence on drivers of the low volatility anomaly, *Journal of Banking & Finance* 37, 999–1017.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Frazzini, Andrea, and Lasse H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Grundy, Bruce D., and J. Spencer M. Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29–78.

Haugen, Robert A., and A. James Heins, 1975, Risk and the rate of return on financial assets: Some old wine in new bottles, *Journal of Financial and Quantitative Analysis* 10, 775–784.

Hong, Harrison, and David Sraer, 2015, Speculative betas, Working Paper, Princeton University.

Hsu, Jason, 2014, Value investing: Smart beta vs. style indices, *Journal of Indexes* 5, 121–126.

Jacobs, Bruce I., and Kenneth N. Levy, 2014, Smart beta versus smart alpha, *The Journal of Portfolio Management* 40, 4–7.

Jacobs, Heiko, 2015, What explains the dynamics of 100 anomalies?, *Journal of Banking & Finance* 57, 65–85.

———, 2016, Beta and biased beliefs, Working Paper, University of Mannheim.

Jank, Stephan, and Esad Smajlbegovic, 2016, Dissecting short-sale performance: Evidence from large position disclosures, Working Paper, University of Mannheim.

Jylhä, Petri, Matti Suominen, and Tuomas Tomunen, 2015, Beta bubbles, Working Paper, Imperial College.

Li, Xi, Rodney N. Sullivan, and Luis Garcia-Feijoo, 2014, The limits to arbitrage and the low-volatility anomaly, *Financial Analysts Journal* 70, 52–63.

Malkiel, Burton G., 2014, Is smart beta really smart?, *The Journal of Portfolio Management* 40, 127–134.

Rouwenhorst, K. Geert, 1999, Local return factors and turnover in emerging stock markets, *Journal of Finance* 54, 1439–1464.

Schneider, Paul, Christian Wagner, and Josef Zechner, 2016, Low risk anomalies?, Working Paper, Swiss Finance Institute.

Figure 1: Time Series of Betas of the Low-Beta Portfolio and the High-Beta Portfolio

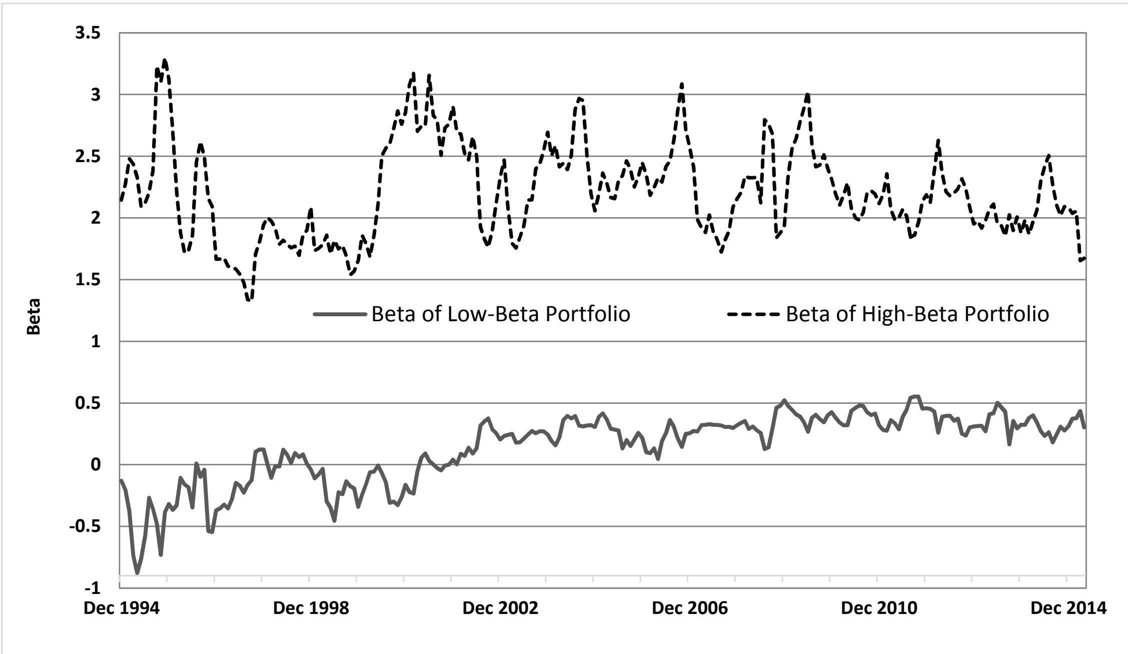

Figure 1 shows the betas of the high-beta portfolio (dashed line) and the low-beta portfolio (solid line) in the base case scenario (S&P 1500, beta weighting within the portfolios, 10% coverage, 3-month estimation window) over the period December 1994 to April 2015.

Figure 2: Increase in Total Wealth Resulting from Low-beta Strategies and an Index Strategy

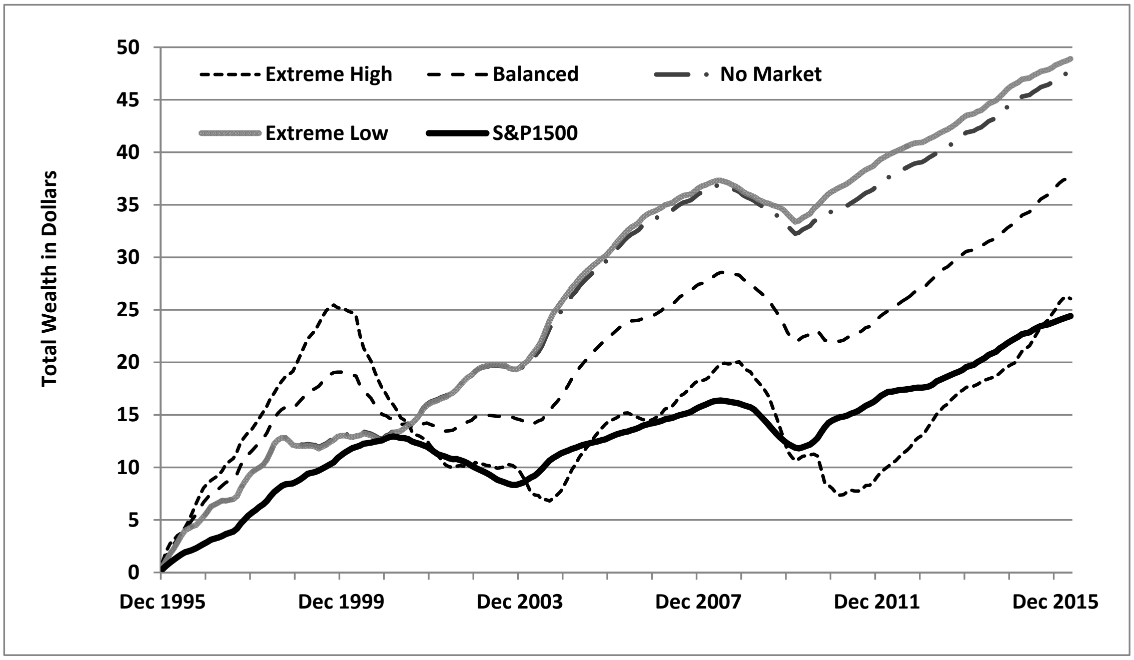

Figure 2 shows the increase in total wealth over the period December 1995 to April 2016 resulting from the four basic low-beta strategies and a corresponding index strategy that goes long in the S&P 1500 Index and short in the risk-free asset. The increase in total wealth is measured under the base-case specification of the strategies (S&P 1500, beta weighting within the portfolios, 10% coverage, 3-month estimation window, 12-month holding period). Investments are made every month over the investigation period, from December 1994 to April 2015, and proceeds are put into a money market account. The money market account pays the risk-free rate, or, in case of a negative balance, allows for risk-free borrowing. The figure shows the balance of the money market account over time.

Table 1: Dollar Amount Invested in Various Instruments when Following Basic Low-Beta Strategies

	Strategy			
Instrument	Balanced	Extreme Low	Extreme High	No Market
Low-Beta	1	2	-	$\frac{2\beta_H}{\beta_H+\beta_L}$
High-Beta	-1	-	-2	$\frac{-2\beta_L}{\beta_H+\beta_L}$
Market	$\beta_H - \beta_L$	$-2\beta_L$	$2\beta_H$	-
Risk-free	$\beta_L - \beta_H$	$2\beta_L - 2$	$-2\beta_H + 2$	$\frac{2(\beta_L-\beta_H)}{\beta_H+\beta_L}$

This table shows the dollar amounts invested in the low-beta portfolio (Low-Beta), the high-beta portfolio (High-Beta), the market index (Market), and the risk-free asset (Risk-free) for all four basic low-beta strategies (Balanced, Extreme Low, Extreme High, No Market Investment).

Table 2: Overview of Additional Design Elements of Low-Beta Strategies

Design Element	Considered Specifications
Investment universe	**S&P 1500**, S&P 500
Estimation period	1 month, **3 months**, 12 months
Portfolio coverage	lowest (highest) 2%, **lowest (highest) 10%**, lowest (highest) 20%
Weighting within portfolios	**beta weighting**, equal weighting, value weighting
Rebalancing frequency	monthly, **yearly**

This table gives an overview of all additional design elements of low-beta strategies that we consider in our empirical study. The highlighted bold specification is used as the base case.

Table 3: Base Case - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0861	0.4938	0.1744	−0.0536
BL	0.1090	0.3049	0.3576	0.0599
NM	0.1320	0.2355	0.5617	0.1046
EL	0.1319	0.2449	0.5386	0.1025

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0291	**1.0379**	0.6848	0.4206	**-0.5808**
	(0.8157)	(0.0008)	(0.5112)	(0.4678)	(0.0855)
BL	0.0841	**0.4548**	0.5468	0.2244	**-0.3862**
	(0.2767)	(0.0164)	(0.3890)	(0.4984)	(0.0396)
NM	**0.1352**	−0.0205	0.3868	0.0423	**-0.2270**
	(0.0364)	(0.9234)	(0.2532)	(0.8162)	(0.0629)
EL	**0.1390**	−0.1283	0.4089	0.0281	**-0.1916**
	(0.0444)	(0.5982)	(0.2212)	(0.8781)	(0.0915)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). The base case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are beta-weighted within the portfolios. The average return is the yearly return earned by each strategy, and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing the average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 4: Estimation Period: 1 Month - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.1453	0.5887	0.2469	−0.0366
BL	0.1751	0.4347	0.4029	0.0762
NM	0.2045	0.4087	0.5004	0.1216
EL	0.2050	0.4114	0.4981	0.1213

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.1182	**1.1335**	−0.0189	0.3244	**-0.8854**
	(0.3612)	(0.0012)	(0.9857)	(0.6193)	(0.0431)
BL	**0.1779**	**0.5270**	−0.1021	0.1115	**-0.6397**
	(0.0710)	(0.0581)	(0.8852)	(0.8056)	(0.0248)
NM	**0.2349**	−0.0373	−0.1980	−0.0892	**-0.3984**
	(0.0100)	(0.9087)	(0.6976)	(0.7790)	(0.0591)
EL	**0.2375**	−0.0794	−0.1853	−0.1015	**-0.3940**
	(0.0104)	(0.8141)	(0.7174)	(0.7551)	(0.0657)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 1 month, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are beta-weighted within the portfolios. Average return is the yearly return earned by each strategy and standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 5: Estimation Period: 12 Months - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0590	0.4480	0.1318	−0.0618
BL	0.0784	0.2713	0.2891	0.0382
NM	0.0945	0.1949	0.4848	0.0752
EL	0.0978	0.1979	0.4940	0.0783

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	−0.0140	**1.0249**	1.1043	0.5125	**-0.4993**
	(0.9074)	(0.0003)	(0.2576)	(0.3275)	(0.0370)
BL	0.0448	**0.3998**	0.9399	0.2163	**-0.3336**
	(0.5437)	(0.0166)	(0.1288)	(0.5161)	(0.0228)
NM	**0.0878**	−0.0305	**0.8085**	0.0215	**-0.2110**
	(0.0518)	(0.8398)	(0.0328)	(0.9291)	(0.0710)
EL	**0.1036**	−0.2253	**0.7755**	−0.0799	−0.1680
	(0.0266)	(0.2403)	(0.0364)	(0.7369)	(0.1052)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 12 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are beta-weighted within the portfolios. Average return is the yearly return earned by each strategy and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 6: Portfolio Coverage: 2% (30 stocks) - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.1521	0.7229	0.2105	−0.1482
BL	0.1580	0.4721	0.3347	0.0407
NM	0.1644	0.4018	0.4091	0.0889
EL	0.1638	0.4061	0.4035	0.0871

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0885	**1.4722**	0.5575	0.4302	**-0.8756**
	(0.6308)	(0.0002)	(0.7235)	(0.5913)	(0.0494)
BL	0.1286	**0.6939**	0.3426	0.3870	**-0.5593**
	(0.3346)	(0.0239)	(0.7513)	(0.5104)	(0.0307)
NM	0.1680	−0.0370	−0.1044	0.3445	−0.2598
	(0.1523)	(0.9300)	(0.8341)	(0.3780)	(0.1209)
EL	0.1688	−0.0844	0.1277	0.3437	−0.2429
	(0.1586)	(0.8510)	(0.7976)	(0.3970)	(0.1537)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 30 stocks, which are beta-weighted within the portfolios. The average return is the yearly return earned by each strategy and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 7: Portfolio Coverage: 20% (300 stocks) - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0534	0.3916	0.1365	−0.0300
BL	0.0893	0.2383	0.3748	0.0597
NM	0.1223	0.1987	0.6156	0.1025
EL	0.1252	0.2116	0.5914	0.1031

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0093	**0.8773**	0.3545	0.3654	−0.4730
	(0.9262)	(0.0007)	(0.6695)	(0.4355)	(0.1022)
BL	0.0686	**0.3638**	0.4383	0.1704	**-0.2902**
	(0.2760)	(0.0165)	(0.4007)	(0.5218)	(0.0491)
NM	**0.1180**	0.0014	0.4800	−0.0050	−0.1360
	(0.0197)	(0.9937)	(0.1207)	(0.9779)	(0.2437)
EL	**0.1279**	−0.1497	**0.5220**	−0.0246	−0.1073
	(0.0248)	(0.4821)	(0.0831)	(0.8917)	(0.3386)

This table shows, in Panel A, annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 300 stocks, which are beta-weighted within the portfolios. The average return is the yearly return earned by each strategy and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 8: Weighting within the portfolios: Equal Weighting - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0808	0.4671	0.1730	−0.0433
BL	0.1036	0.2844	0.3644	0.0610
NM	0.1282	0.2204	0.5815	0.1039
EL	0.1265	0.2290	0.5522	0.1007

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0260	**0.9823**	0.6701	0.4031	**-0.5450**
	(0.8216)	(0.0009)	(0.4803)	(0.4577)	(0.0895)
BL	0.0801	**0.4193**	0.5656	0.1922	**-0.3659**
	(0.2383)	(0.0144)	(0.3080)	(0.5061)	(0.0393)
NM	**0.1312**	−0.0251	0.4362	−0.0026	**-0.2230**
	(0.0181)	(0.8965)	(0.1620)	(0.9878)	(0.0631)
EL	**0.1343**	−0.1437	0.4611	−0.0187	**-0.1868**
	(0.0260)	(0.5171)	(0.1320)	(0.9099)	(0.0861)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are equal-weighted within the portfolios. The average return is the yearly return earned by each strategy, and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing the average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 9: Weighting within the portfolios: Value Weighting - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.1316	0.3246	0.4055	0.0781
BL	0.1059	0.2404	0.4405	0.0765
NM	0.0913	0.2210	0.4130	0.0670
EL	0.0802	0.2169	0.3696	0.0571

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	**0.1256**	0.1422	**1.1027**	−0.2509	**-0.3961**
	(0.0334)	(0.5270)	(0.0513)	(0.4642)	(0.0624)
BL	**0.1051**	0.1035	0.7240	−0.2286	**-0.2980**
	(0.0297)	(0.5377)	(0.1168)	(0.3156)	(0.0592)
NM	**0.0963**	0.0815	0.4052	−0.2317	−0.2403
	(0.0323)	(0.6200)	(0.2582)	(0.1235)	(0.1100)
EL	**0.0847**	0.0647	0.3454	−0.2063	−0.1999
	(0.0639)	(0.7135)	(0.3237)	(0.1540)	(0.1390)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are value-weighted within the portfolios. The average return is the yearly return earned by each strategy, and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 10: Rebalancing: Monthly - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0859	0.3899	0.2204	0.0048
BL	0.1068	0.2518	0.4240	0.0740
NM	0.1302	0.2458	0.5297	0.0996
EL	0.1276	0.2495	0.5115	0.0960

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0672	−0.0052	0.2538	0.3108	0.0576
	(0.4609)	(0.9769)	(0.2749)	(0.2120)	(0.6994)
BL	0.0936	0.0013	0.1776	0.2567	0.0147
	(0.1138)	(0.9908)	(0.2361)	(0.1102)	(0.8787)
NM	**0.1219**	0.0053	0.0996	0.2043	−0.0138
	(0.0360)	(0.9629)	(0.4968)	(0.1935)	(0.8834)
EL	**0.1200**	0.0079	0.1014	0.2026	−0.0282
	(0.0422)	(0.9455)	(0.4955)	(0.2037)	(0.7674)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 1500 stocks as the investment universe, an estimation period of 3 months, and a 1-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 150 stocks, which are beta-weighted within the portfolios. The average return is the annualized monthly return earned by each strategy and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value, and momentum effects, respectively. The calculations of the p-values (in parentheses) use the White estimator to account for heteroscedasticity. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 11: Investment Universe: Smaller Universe (S&P 500) - Return and Risk

Panel A: Average Returns, Standard Deviations, Sharpe Ratios and Certainty Equivalent Returns

Strategy	AvRet	SD	SR	CEV
EH	0.0338	0.4093	0.0825	−0.0622
BL	0.0622	0.2644	0.2352	0.0246
NM	0.0994	0.2178	0.4563	0.0756
EL	0.0906	0.2053	0.4414	0.0691

Panel B: Risk-adjusted Returns and Factor Sensitivities

Strategy	α	β_{Market}	β_{SMB}	β_{HML}	β_{MOM}
EH	0.0129	**0.6815**	**-2.0880**	0.4042	0.1334
	(0.8395)	(0.0005)	(0.0014)	(0.2890)	(0.6964)
BL	0.0232	**0.6208**	**-1.0127**	**0.5547**	0.0252
	(0.6036)	(0.0000)	(0.0212)	(0.0232)	(0.9182)
NM	0.0206	**0.6793**	−0.0836	**0.7703**	−0.0703
	(0.4340)	(0.0000)	(0.7576)	(0.0000)	(0.6508)
EL	0.0336	**0.5601**	0.0625	**0.7052**	−0.0831
	(0.2609)	(0.0000)	(0.8199)	(0.0000)	(0.5939)

This table shows, in Panel A, the annualized average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV), and in Panel B, the annualized risk-adjusted returns (alphas) and factor sensitivities in a Carhart (1997) 4-factor model for each of the four low-beta strategies (extreme high (EH), balanced (BL), no market investment (NM), extreme low (EL)). This case uses the S&P 500 stocks as the investment universe, an estimation period of 3 months, and a 12-month holding period. The strategies are set up at the end of each month for the period December 1994 to April 2015. Each low-beta and high-beta portfolio consists of 50 stocks, which are beta-weighted within the portfolios. The average return is the yearly return earned by each strategy, and the standard deviation is calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing average return by the standard deviation, and the certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. The multiple linear regressions underlying the results of Panel B use four independent variables (market excess return, SMB, HML, MOM) and read $R_t = \alpha + \beta_{Market} \cdot (R_{M,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy at time t and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The calculations of the p-values (in parentheses) use the Newey–West estimator with 11 lags to account for the overlapping periods. Coefficients that are significant at least at a 10% level are printed in boldface.

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