Low-Beta Investment Strategies

Olaf Korn[‡] and Laura-Chloé Kuntz[*]

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[‡]Olaf Korn, Chair of Finance, Georg-August-Universität Göttingen and Centre for Financial Research Cologne (CFR), Platz der Göttinger Sieben 3, D-37073 Göttingen, Germany, Phone +49 551 39 7265, Fax +49 551 39 7665, Email okorn@uni-goettingen.de

[*]Laura-Chloé Kuntz, Chair of Finance, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 3, D-37073 Göttingen, Germany, Phone +49 551 39 8305, Fax +49 551 39 7665, Email lkuntz@uni-goettingen.de

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Abstract

This paper investigates investment strategies that 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 investment portfolio. Our empirical results for US large-cap stocks show that this choice is very important for the risk-return characteristics of the resulting portfolios and their sensitivities to common risk factors. We also show that investment strategies based on betas have a natural-hedge component and a market-timing component due to the stochastic variation of betas. We construct indicators to exploit the market-timing component and show that they have substantial predictive power for future market returns. Corresponding market-timing strategies deliver large positive excess returns and high Sharpe ratios.

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I Introduction

The observation that returns of low-beta stocks are too high and returns of high-beta stocks 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 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 should be exploited via investment strategies. It is an intuitive notion to buy low-beta stocks and sell high-beta stocks, however, there are several ways to do so. How should low-beta stocks and high-beta stocks be weighted in a portfolio strategy and how does the specific way to construct low-beta investment strategies affect the properties of the resulting returns, for example, their sensitivities to specific risk factors? These are important questions for investors and portfolio managers alike because the idea of exploiting the low-beta anomaly has to be made concrete and requires an understanding of the implications of specific choices.

This paper formally defines low-beta investment 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 available we obtain a continuum of low-beta strategies that assign different weights to low-beta stocks and high-beta stocks. An empirical study for US large-cap stocks analyzes the properties of some representative strategies. This study is the first major contribution of the paper. We find that low-beta investment strategies that overweight low-beta stocks differ substantially from strategies that overweight high-beta stocks. The former show much higher average returns and a high sensitivity to the value factor, whereas the latter are more sensitive to the size factor.

The characteristics of investment strategies that use beta to determine portfolio composition are affected by the time-varying and stochastic nature of betas in different ways. First, the realized beta of a portfolio over its holding period can substantially deviate from the portfolio's ex-ante beta obtained from historical beta estimates, as we show in our empirical study. Second, there are specific components of a portfolio's return that relate to the comovement of its beta with the market return in the holding period. We identify two such components that can be interpreted as a natural-hedge component and a market-timing component and quantify them empirically. The natural-hedge component is rather small but the market-timing component can be substantial. To exploit this component for investment strategies, we construct indicators based on the current beta level of high-beta stocks and low-beta stocks and show that these indicators are valuable predictors of future market returns, even if we control for other predictors that have been used successfully in the literature. Market-timing strategies based on our indicators lead to substantial excess returns and high Sharpe ratios. The analysis of return components caused by the time variation of beta and the development of related market-timing strategies is the second major contribution of the paper.

Our paper is related to different strands of literature. First, it is naturally connected to work on the low-beta anomaly. Several analyses have documented the anomaly for varying time periods and markets (Rouwenhorst, 1999; Baker and Haugen, 2012; Blitz, Pang, and Van Vliet, 2013; Frazzini and Pedersen, 2014) and different explanations for the appearance of the phenomenon have been suggested (Baker, Bradley, and Wurgler, 2011; Blitz, Falkenstein, and Van Vliet, 2014; Frazzini and Pedersen, 2014; Christoffersen and Simutin, 2015; Hong and Sraer, 2015; Jylhä, Suominen, and Tomunen, 2015; Schneider, Wagner, and Zechner, 2015). Our paper has a different focus, however, because we concentrate on an analysis and comparison of different investment strategies that exploit information contained in a stock's beta. 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 an investment strategy, which he calls the beta factor.[1] Alternative strategies with different weighting schemes for high-beta and low-beta stocks

[1] The original idea goes even back to the work by Black, Jensen, and Scholes (1972).

are used by Frazzini and Pedersen (2014) and Li, Sullivan, and Garcia-Feijoo (2014). However, none of these papers compares the effects of different weighting schemes, which is a major contribution of our work.

Second, our paper is related to work on beta estimation and the dynamics of betas. Faff, Hillier, and Hillier (2000) provide an overview of different modeling and estimation techniques based on historical returns. Baule, Korn, and Saßning (2015) compare different techniques to obtain option-implied betas and investigate the information content of alternative estimators and Hollstein and Prokopczuk (2015) provide a comprehensive analysis of beta estimators and their properties that considers both historical and implied betas. In contrast to this work, our paper concentrates on a specific aspect of beta dynamics, namely the joint distribution of betas and market returns, which has not been investigated in the literature so far.

A third strand of related literature is work on the prediction of market returns (Lettau and Ludvigson, 2001; Ang and Bekaert, 2007; Pollet and Wilson, 2010) and market-timing strategies (Kostakis, Panigirtzoglou, and Skiadopoulos, 2011). The new aspect that our paper introduces into this literature is to demonstrate that the magnitudes of current betas of high-beta portfolios and low-beta portfolios in relation to historical averages contain important information on future market returns and can be exploited successfully in market-timing strategies.

The remainder of our paper is structured as follows: Section II provides a formal characterization of low-beta investment strategies. The following Section III introduces the data and design of our empirical study. Section IV presents the empirical results. In Subsections A and B we show risk and return characteristics of different investment strategies and look at the factor sensitivities with respect to common risk factors. Subsection C defines and quantifies the natural-hedge and market-timing return components of investment strategies and Subsections D and E investigate the information content of beta indicators for future market returns by means of predictive regressions and market-timing strategies. Section V concludes the paper.

II Characterizing Low-Beta Strategies

We consider a setting where 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, either via ETFs, futures or by buying the stocks directly. There is also a risk-free investment (and financing) available. By definition, the beta of the market portfolio equals one. It is therefore a natural requirement for a low-beta portfolio to have a beta below one and for a high-beta portfolio to have a beta above one.

To characterize a low-beta investment strategy, we suggest some conditions:

Condition (i): Denote the amount invested in a low-beta portfolio by X_L and the amount invested in a high-beta portfolio by X_H. Then a low-beta investment 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 investment strategy is a long-short strategy that goes long a low-beta portfolio and short a high-beta portfolio. However, as it is one of the goals of this paper to investigate the roles of low- 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 beta of a low-beta investment 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.

It is the idea of low-beta investment strategies to exploit the differential performance of high-beta and low-beta stocks. To concentrate on this differential, the returns of these strategies should be isolated as far as possible from market movements. To achieve this, at least on an ex-ante basis using estimated betas, the beta of the strategy should be zero, that is what condition (ii) states.

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

Condition (iii): A low-beta investment strategy has zero costs initially. 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 investment 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 investment strategy has the same initial amount invested, with an amount of zero being a natural choice. 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) are available.

The general characterization of low-beta investment strategies highlights that several choices have to be made to define a specific low-beta strategy. These choices include the selection of the market, the way betas are estimated, the way high-beta and low-beta portfolios are formed and how often the investment portfolio is rebalanced. An important aspect that we investigate specifically in this paper is the choice of the low-beta portfolio's relative weight in comparison the high-beta portfolio's weight. The next section outlines which choices we make for our empirical study of different low-beta investment strategies.

III Data and Implementation of Strategies

Our empirical study uses the S&P 500 index and its component stocks as the investment universe. The concentration on 500 relatively liquid stocks has the advantage that investment strategies have relatively low transaction costs. Moreover, very liquid futures contracts on the S&P 500 index are available to trade the whole market. We use daily data for the data period September 1988 to October 2014. The data source for the stock data is Thompson Reuters Datastream. As the risk-free interest rate we use the 1-month T-bill rate from Kenneth French's website. For additional analysis, we also need the factors from the Carhart (1997) four-factor model, the Cay factor (Lettau and Ludvigson, 2001) and the dividend yield of the S&P 500 index. These data are obtained from Kenneth French's website, Martin Lettau's website, and from Datastream, respectively.

We use different historical time windows for beta estimation. Betas are estimated from daily returns of the corresponding stocks and the index over rolling windows of one, three, six, and twelve months, respectively. Beta estimates are obtained for each month in the investigation period, starting in September 1989. They refer to the last trading day of the respective month. For each month, the 500 beta estimates of the component stocks are sorted. The 50 stocks with the highest betas build the high-beta portfolio and the 50 stocks with the lowest betas the low-beta portfolio. Individual stocks are equally weighted in the high-beta and low-beta portfolios.

With respect to the weighting of high-beta portfolios and low-beta portfolios we consider four different low-beta investment strategies:

Equal Weighting: It is a natural starting point to consider a strategy that is long one dollar in the low-beta portfolio and short one dollar in the high-beta portfolio, i.e., $X_L = 1$ and $X_H = -1$. From condition (ii) in the previous section follows that $X_M = \beta_H - \beta_L$ and condition (iii) finally implies that $X_R = \beta_L - \beta_H$.

Extreme Low: 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 equal weighting 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: 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.

Frazzini/Pedersen: The fourth strategy is the one used by Frazzini and Pedersen (2014).[2] It starts from the idea that no investment in the index is made, i.e., $X_M = 0$. The fulfillment of conditions (i), (ii), and (iv) then imply 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 $X_R = 2(\beta_L - \beta_H)/(\beta_H + \beta_L)$.

Clearly, the four different 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 extreme low strategy, followed by Frazzini/Pedersen, equal weighting and extreme high. For the importance of the high-beta portfolio, the ordering is reversed. Also note that one has to take a long position in the market for both the extreme high and equal weighting strategies, whereas Frazzini/Pedersen uses a zero position and extreme low a short position. All four low-beta investment strategies require risk-free borrowing.

The four different weighting schemes in combination with the four different estimation windows deliver 16 different low-beta strategies. We set up these strategies for each month in the investigation period and calculate the returns over the following three months and twelve months, respectively, i.e., we consider quarterly and yearly rebalancing. The returns of the resulting 32 strategies build the basis of our

[2]The reference to Frazzini and Pedersen (2014) is made with respect to the amounts invested in the high-beta portfolio, the low-beta portfolio, the market, and the risk-free asset. The strategy that Frazzini and Pedersen (2014) investigate differs, however, in other aspects. For example, they use a weighting that is proportional to a stock's beta to build the high-beta and low-beta portfolios.

investigation.

IV Empirical Results

A Returns and Risks of Low-Beta Strategies

Table 1 presents the average returns (Panel A), the standard deviations (Panel B), the Sharpe ratios (Panel C), and the certainty equivalent returns for all 16 strategies, referring to a quarterly holding period. A total of 290 returns is used in the calculations for each strategy. All numbers presented in the table are annualized values. The certainty equivalent return is calculated for an investor with constant absolute risk aversion (CARA) preferences and an absolute risk aversion of 1.[3] 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 the mean and standard deviation.[4] Because of the zero initial investment required by our low-beta strategies, the Sharpe ratio is just the ratio of average return and standard deviation and the reference point for the certainty equivalent return is zero and not the risk-free rate.

[Insert Table 1 about here]

The average returns in Panel A show a clear pattern. First, when moving from the extreme high strategy to the strategies that give a higher (absolute) weight to the low-beta portfolio (Frazzini/Pedersen, extreme low), the average return clearly increases. This finding holds for all four formation periods and clearly shows that it can make a difference which weighting scheme is employed. Second, average returns decrease with the length of the formation period, leading to large differences between

[3]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 which do not guarantee positive terminal wealth.

[4]The analysis by Schneider, Wagner, and Zechner (2015) shows that return skewness is a possible explanation for the low beta anomaly.

the average returns for a one-month formation period and a twelve-month formation period. This finding holds for all four strategies.

The standard deviations (Panel B) of the 16 strategies do not show such a clear pattern. But there seems to be a tendency that the standard deviation decreases with longer formation periods, at least for the Frazzini/Pedersen and extreme low strategies. It is a general result that the Frazzini/Pedersen and extreme low strategies have very similar return characteristics. If we consider the Sharpe ratio (Panel C) and the certainty equivalent return (Panel D) as measures of investment performance, the best performing strategies are the ones with a high weight in the low-beta portfolio and a short formation period. Both measures lead to the same ranking of different strategies.

[Insert Table 2 about here]

Table 2 reports the corresponding results for a yearly holding period. It confirms the patterns already observed for the quarterly period. The average return is increasing with the (absolute) weight of the low-beta portfolio and decreasing with the length of the formation period. The standard deviation decreases with the formation period. Again, the best performing strategies, according to both the Sharpe ratio and the certainty equivalent return, are the ones with a high weight in the low-beta portfolio and a short formation period.

In addition, it is an interesting observation that the portfolio performance is generally better for a yearly holding period as compared to a quarterly, mainly due to higher average returns. This is good news for investors because it does not pay to rebalance the portfolio quarterly instead of holding it unchanged for a whole year, even without transaction costs. With transaction costs, the outperformance would even be higher.

B Factor Sensitivities and Alphas

It is an important question how the observed patterns of average returns for different low-beta strategies can be explained. We address this question now and in the following section. A first idea is to ask in how far the returns of different low-beta investment 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 by a momentum factor. To be consistent with our definition of the market, we use the S&P 500 index to represent the market factor. All other factors (size, value, momentum) are taken from Kenneth French's website. We regress the returns of the low-beta strategies on the returns of the factor portfolios and obtain factor loadings for each of the four factors and each of the 16 low-beta strategies.

[Insert Table 3 about here]

Table 3 shows the factor loadings for the market factor. Panel A presents the results for the quarterly holding period and Panel B for the yearly holding period. We observe a very strong pattern. All factor sensitivities are positive and the sensitivities are higher for shorter formation periods. This pattern holds for all four low-beta strategies and for both holding periods in the same way. An explanation for this phenomenon is estimation risk. All portfolios are set up as such that their estimated beta is zero (see condition (ii)), i.e., they have no market exposure. However, the zero-beta condition holds for the beta estimates obtained from the formation period returns, not necessarily for the realized betas in the holding period. If high beta estimates in the formation period are more likely to overestimate the true beta and low estimates are more likely to underestimate the true beta, we would actually obtain positive market sensitivities of the low-beta portfolios in the investment period. Because low-beta strategies are short high-beta portfolios (that have overestimated betas) and long low-beta portfolios (that have underestimated betas), the ex-post beta of the strategies should be positive. This estimation error argument also explains why short formation periods lead to higher sensitivities. If the formation period is too short, there are too few observations to obtain precise beta estimates. In summary, it is a very important message to distinguish between the formation period betas the holding period betas and to recognize that low-beta portfolios can have (despite their construction as ex-ante zero-beta portfolios) very substantial market exposure.

[Insert Table 4 about here]

Table 4 presents the results for the size factor. Again, we have one panel (Panel A) for the quarterly returns and one panel (Panel B) for the yearly returns. The table shows strong differences between the low-beta strategies. Strategies with significant (short) positions in the high-beta portfolio (extreme high, equally weighted) show significant negative factor loadings, meaning that a relatively high beta of a stock is usually associated with a small firm size. When looking at the strategies with large positions in the low-beta portfolio (Frazzini/Pdersen, extreme low), we observe no clear pattern, indicating that low-beta stocks are not clearly related to firm size. These results basically hold for all formation periods and both holding periods. In summary, we can conclude from the table that the relative weight that a low-beta portfolio strategy assigns to high-beta portfolios and low-beta portfolios can be very important for the size exposure of the investment strategy.

[Insert Table 5 about here]

Table 5 shows the corresponding results for the value factor. For this factor we again find a pattern that is related to the relative weight of the high-beta and low-beta portfolios in an investment strategy. Whereas there is often no significant exposure to the value factor for the extreme high strategy, we find a strong positive exposure for the extreme low strategy. The latter finding suggests that low-beta stocks tend to be value stocks as well.

[Insert Table 6 about here]

The results for the momentum factor are shown in Table 6. The Frazzini/Pedersen and extreme low portfolios have no relation to momentum. For the extreme high strategy, the momentum effect depends on the holding period. Over the shorter horizon (three months) high-beta stocks seem to be predominantly past losers. Over the longer horizon (twelve months) such an effect is much smaller and insignificant.

[Insert Table 7 about here]

Finally, we look at the alphas of the different strategies that are presented in Table 7. We see that the alphas are generally much smaller than the average returns as presented in Tables 1 and 2. Given the various patterns in terms of factor sensitivities, this result is not surprising. In particular, the high average returns for the formation period of one month can be mainly attributed to the high sensitivity to the market factor.[5] In contrast to the average returns, we find that alphas tend to increase with the formation period and not to decrease. Moreover, we find that alphas are generally higher for a yearly holding period than for a quarterly period.

In summary, we observe important patterns with respect to factor sensitivities and alphas. These patterns show that the length of the formation period, the way a strategy is defined (relative weight of low-beta and high-beta portfolios), and the length of the holding period are all important for the characteristics of a strategy's return. In particular, short formation periods lead to a high market exposure, strategies that use high-beta stocks tend to be sensitive to firm size, strategies that use low-beta stocks tend to be exposed to value effects, and a shorter investment horizon can lead to a momentum exposure if high-beta stocks are used. In terms of a strategy's alpha, the results indicate that longer formation and holding periods are to be preferred. All these results highlight that there is no low-beta strategy per se but different strategies with quite different properties exist, which has to be taken into account by investors and portfolio managers when designing a low-beta investment strategy.

[5] If we consider a one-factor specification with the market factor only, the alphas are already much lower than the average returns of the strategies.

C Effects of Stochastic Betas

There is strong evidence in the literature that betas are time varying and stochastic (Ferson and Harvey, 1993; Faff, Hillier, and Hillier, 2000; Jostova and Philipov, 2005; Hollstein and Prokopczuk, 2015). This observation is also in line with our results from Section B on the market sensitivities of low-beta strategies. If betas are stochastic, betas in the formation period usually differ from those in the holding period and low-beta strategies have non-zero market exposure ex post. The stochastic nature of betas has an impact on the performance of investment strategies via additional components of expected returns that complement the common risk factors of the previous section. To illustrate this point assume that the returns of an investment strategy ($\widetilde{R}_S$) are driven by a market factor and a set of K additional risk factors $\tilde{F}_1, \ldots, \tilde{F}_K$, according to

$$\widetilde{R}_S = \alpha + \tilde{\beta}_{HP}\widetilde{R}_M + \sum_{i=1}^{K} \beta_{F_i}\widetilde{F}_i + \tilde{\epsilon}, \tag{1}$$

where $\tilde{\beta}_{HP}$ is a random variable that expresses the holding period beta of the investment strategy and $\tilde{\epsilon}$ is a zero-mean residual term. Taking expectations on both sides of equation (1) delivers

$$E[\widetilde{R}_S] = \alpha + E[\tilde{\beta}_{HP}]E[\widetilde{R}_M] + Cov[\tilde{\beta}_{HP}, \widetilde{R}_M] + \sum_{i=1}^{K} \beta_{F_i}E[\widetilde{F}_i]. \tag{2}$$

Equation (2) shows that a stochastic beta leads to the covariance term $Cov[\tilde{\beta}_{HP}, \widetilde{R}_M]$ that can be further decomposed by recognizing that the holding period beta equals the formation period beta plus the change in beta from the formation period to the holding period. We therefore obtain

$$Cov[\tilde{\beta}_{HP}, \widetilde{R}_M] = Cov[\tilde{\beta}_{HP} - \tilde{\beta}_{FP}, \widetilde{R}_M] + Cov[\tilde{\beta}_{FP}, \widetilde{R}_M], \tag{3}$$

where $\tilde{\beta}_{FP}$ denotes the beta in the formation period and $\widetilde{R}_M$ is generally the market return in the holding period. The two covariances on the right hand side of equation (3) have an intuitive economic interpretation. If the first covariance is positive, the holding period beta tends to be higher than the formation period beta if markets are rising and tends to be lower than the formation period beta if market markets are going down. We call this return component a natural hedge because the investor will have a higher actual market exposure (holding period beta) than previously estimated (formation period beta) if markets are rising and a lower exposure if markets are falling, thereby protecting the performance of the portfolio. The second covariance term is associated with information about future market movements. If it is positive, a high formation period beta will be associated with an increasing market in the holding period. If it is negative, high betas will be an indicator for falling markets. We call this covariance term the market timing component of the total covariance between the holding period beta and the market return.

The two covariances on the right hand side of equation (3) can be further decomposed by considering strategies that invest fixed dollar amounts X_L, X_H, X_M, and X_R in the low-beta portfolio, the high-beta portfolio, the market, and the risk-free investment, respectively. Because the risk-free instrument has a beta of zero and the market has a beta of one by definition the two covariance terms can be rewritten as

$$Cov[\tilde{\beta}_{HP} - \tilde{\beta}_{FP}, \widetilde{R}_M] = X_H Cov[\tilde{\beta}_{H,HP} - \tilde{\beta}_{H,FP}, \widetilde{R}_M] + X_L Cov[\tilde{\beta}_{L,HP} - \tilde{\beta}_{L,FP}, \widetilde{R}_M] \quad (4)$$

$$Cov[\tilde{\beta}_{FP}, \widetilde{R}_M] = X_H Cov[\tilde{\beta}_{H,FP}, \widetilde{R}_M] + X_L Cov[\tilde{\beta}_{L,FP}, \widetilde{R}_M], \quad (5)$$

where $\tilde{\beta}_{H,HP}$ and $\tilde{\beta}_{L,HP}$ are the holding period betas of a high-beta portfolio and a low-beta portfolio, respectively, and $\tilde{\beta}_{H,FP}$ and $\tilde{\beta}_{L,FP}$ are the corresponding quantities in the formation period. The formulation in equations (4) and (5) allows us to quantify the natural-hedge component and the market-timing component for different values of X_H and X_L. In line with our previous analysis, we consider the cases $X_H = -2$ and $X_L = 0$, $X_H = -1$ and $X_L = 1$, and $X_H = 0$ and $X_L = 2$. For these cases we estimate the natural-hedge component and the market-timing component from the corresponding portfolio returns over the whole investigation period.

[Insert Table 8 about here]

Table 8 shows the values of the natural-hedge component estimated from quarterly returns (Panel A) and yearly returns (Panel B). The values for the quarterly returns are annualized to make the two panels comparable. Overall, the natural hedging effects are rather small, with values ranging from 0.54% to -1.32%. Moreover, most values are negative, indicating that investment strategies taking short positions in high-beta portfolios and long positions in low-beta portfolios do not generate expected return via natural hedges but generate expected losses because market exposure tends to be higher than expected when markets go down.

[Insert Table 9 about here]

Table 9 gives the values for the market-timing component. It has also two panels for quarterly returns (Panel A) and yearly returns (Panel B). Here we observe generally positive values that can be substantial and reaches up to 4.45% for the yearly horizon and the investment strategy that goes short in the high-beta portfolio. The results show that if the beta of a high-beta portfolio is very high in the formation period, the market tends to go down in the following holding period. To a somehow lesser degree, we also see that a very low beta of the low-beta portfolio also tends to be associated with a bear market in the following holding period. Taken together, one can say that a large difference between the betas of a high-beta portfolio and a low-beta portfolio provide information on a market downturn. If the betas of high-beta portfolios and low beta-portfolios are close together, the market tends to increase over the following holding period.

It is important to note that the low-beta strategies that we analyze in Sections A and B do not exploit the market-timing component of expected returns. The reason is that due to condition (ii) the (estimated) formation period beta is generally set to zero and therefore has zero covariation with the holding period market return. Given the promising expected returns shown in Table 9, it is a natural next step to devise investment strategies that exploit the information in holding period betas for future market movements. We do so in two steps. Section D introduces some timing indicators based on the formation period betas of high-beta portfolios and low-beta portfolios and investigates these indicators via predictive regressions. Section E then defines and tests investment strategies based on these indicators.

D Predicting Market Returns Using Betas

We consider three different indicators for the prediction of market returns that are based on the betas of high-beta and low-beta portfolios. These indicators correspond to the three cases investigated in the previous section. The first indicator (HB) measures if the current beta of the high-beta portfolio is large compared to the historical average beta of high-beta portfolios. The second indicator (LB) measures whether the current beta of the low-beta portfolio is relatively high compared to the historical average beta of the low-beta portfolio, and the third indicator (LB-HB) measures how the current difference between the betas of the low-beta portfolio and the high-beta portfolio compares with the historical average of this quantity. Specifically, for each month in the investigation period, we calculate the relative difference between the formation period beta (or beta difference in the case of LB-HB) and the average formation period beta over all previous months in our investigation period. All three indicators are calculated for formation periods of one, three, six, and twelve months, leading to 16 indicator variables altogether.

To test whether the indicators are informative for future market movements, we run predictive regressions of the excess market return over the next three (twelve) months on the indicator variables. In a first step, we use the beta indicators as the only predictor. The results of these predictive regressions for the quarterly excess market returns are given in Table 10.

[Insert Table 10 about here]

The most striking result is that the HB and LB-HB indicators are all significant on a 1% level and have a negative sign. This is in line with the results of Section C that a very high beta of the high-beta portfolio in the formation period tends to be associated with a low market return in the holding period. What could be a rationale behind this relation? One explanation is that a situation where some firms have very high betas is particularly dangerous for an economy. Consider, for example, the time of the subprime crisis when financial institutions often had extremely high betas. Even a moderate market downturn could then cause serious problems for such high-beta firms, leading in turn to problems for the whole financial system and finally to an even stronger downturn of the market. In contrast, such a strong market downturn could be less likely if no stocks with extremely high betas exist.

[Insert Table 11 about here]

In a second step we check whether our indicators maintain explanatory power if we add further variables that have been found to be successful predictors in previous studies. In particular, we use the dividend yields of the index and the short rate. These variables jointly predict market returns according to Ang and Bekaert (2007). Moreover, we use the cay factor from Lettau and Ludvigson (2001) and the average variance and average correlation (in the formation period), as used by Pollet and Wilson (2010). Table 11 shows the results of the augmented predictive regressions. All our beta indicators retain their signs and the HB indicator also retains statistical significance. When betas of the high-beta portfolio are unusually high, they have still predictive power even if other predictors are included. From these other predictors, the cay factor, the average variance, and the average correlation show statistical significance.

Tables 12 and 13 provide the corresponding results for the prediction of yearly excess market returns. The results are even better than for the quarterly returns. Again, the indicators using betas of high-beta portfolios deliver the highest predictive power, with R^2s of up 15% for the univariate regressions.

[Insert Table 12 about here]

[Insert Table 13 about here]

In the multivariate regressions, R^2s of more than 30% are attained. All the beta indicators retain their statistical significance. Interestingly, from the set of remaining predictors, the short rate becomes significant and the average variance and average correlation loose significance. It is only the cay factor and our beta indicators that are clearly significant predictors for both the quarterly and yearly horizons.

E Market-Timing Strategies Using Betas

The last section has shown that our indicators based on the betas of high-beta and low-beta portfolios carry some information about future market movements. In this section, we want to exploit this information via market-timing strategies. The question arises how to form portfolios based on the indicators. Our approach uses the indicators as conditioning information for the expected return and the return variance in the setting of a bivariate normal distribution.[6] If the market return $\widetilde{R}_M$ and our indicator variable $\widetilde{I}$ are bivariate normally distributed, the conditional distribution of the market return, given a realization of the indicator variable, I, is normal with the following conditional expectation and variance:

$$E[\widetilde{R}_M|I] = E[\widetilde{R}_M] + \frac{Cov[\widetilde{R}_M,\widetilde{I}]}{Var[\widetilde{I}]}(I - E[\widetilde{I}]), \quad (6)$$

$$Var[\widetilde{R}_M|I] = Var[\widetilde{R}_M]\Big(1 - Corr[\widetilde{R}_M,\widetilde{I}]^2\Big). \quad (7)$$

The conditional distribution with the moments from equations (6) and (7) also delivers the conditional probability of a positive market return as $p\,|\,I = 1 - F(0)$, where F is the cumulative distribution function of the conditional distribution. We

[6]We do not claim that the market return and the indicator variable exactly follow a bivariate normal distribution but use this assumption as an approximation to obtain the conditional probability of a positive market return.

consider two strategies. The first one (unweighted strategy) invests one dollar in the market if the conditional probability is above 0.5 and goes short one dollar if the probability is below 0.5. The second one (weighted strategy) invests in the market proportional to the conditional probability of a positive market return. Both strategies use zero cost portfolios by taking offsetting positions in the risk-free instrument. Formally, the unweighted strategy uses $X_M = 1$ and $X_R = -1$ if $p \,|\, I > 0.5$ and $X_M = -1$ and $X_R = 1$ if $p \,|\, I < 0.5$. The weighted strategy uses $X_M = 2(p \,|\, I - 0.5)$ and $X_R = -2(p \,|\, I - 0.5)$. The transformation of the conditional probability in the weighed strategy ensures that the maximum investment in the market is 1 and the minimum investment is -1, as for the unweighted strategy.

To implement the strategies, we use the current indicator variables I as described in the previous section, a total of 16 indicators, arising from the combination of the three indicators HB, LB, and $LB - HB$ with the formation periods of one, three, six, and twelve months. According to equations (6) and (7), we also need the (unconditional) expectations, variances and covariance of $\widetilde{R}_M$ and $\widetilde{I}$. These parameters are estimated from a rolling window of 36 months that precedes the month when the portfolio is set up. Therefore, our strategy does not use any in-sample information. Because we require 36 months of data to obtain sufficiently accurate parameter estimates, September 1992 is the first month when a market-timing strategy is set up.

Table 14 reports the average return, the standard deviation, the Sharpe ratio, and the certainty equivalent return (CARA investor with absolute risk aversion of 1) of the timing strategies for a holding period of three months. The numbers refer to annualized values. Irrespective of the strategy, average returns are all positive. The highest average returns arise for the strategies that use the HB indicators, which is in line with our results from Sections C and D. In comparison with the unweighted strategy, the weighted strategy has both much lower average returns and standard deviations. That was to be expected because the (absolute) market exposure of the unweighted strategy is always one dollar whereas the market exposure of the weighted strategy has an upper limit of one and is usually much smaller. In terms of the Sharpe ratio, the weighted strategy leads to higher values, indicating that it pays to stay (essentially) out of the market if the conditional probability of a positive market return is close to 0.5. With respect the certainty equivalent return, the unweighted strategy is preferred by a CARA investors with absolute risk aversion of 1.[7]

[Insert Table 14 about here]

Table 15 presents the corresponding results for a holding period of one year. Again, all average returns are positive and highly significant. For the weighted strategy, the average returns are much higher than for the quarterly horizon but the standard deviations increase even more, leading to a generally lower Sharpe ratios. For the unweighted strategy, average returns are of the same order of magnitude as for the quarterly horizon, but the standard deviations are slightly higher. Accordingly, Sharpe ratios are reduced. Again, Sharpe ratios are higher for the weighted strategy and certainty equivalent returns for the unweighted strategy for the chosen level of risk aversion.

[Insert Table 15 about here]

In summary, the performance of the market-timing strategies is promising. There seems to be a slight advantage in performance arising from quarterly portfolio rebalancing instead of yearly rebalancing. However, this advantage has to be balanced against higher transaction costs due to more frequent portfolio revisions.

V Conclusions

This paper addresses the issue that different choices exist to exploit the low-beta anomaly via investment strategies. Very little has previously be known about the

[7] If the risk aversion is increased, the weighted strategy is eventually preferred to the unweighted strategy.

impact of these choices on a strategy's return characteristics. Our empirical results show that it can make a big difference whether a low-beta investment strategy puts more weight on buying low-beta stocks or on selling high-beta stocks. The former strategy delivers higher average returns and is very sensitive to the value factor, whereas the latter strategy has low value exposure but a high size exposure. These results stress the importance to select a low-beta investment strategy that is in line with the desired portfolio characteristics and does not take the investor or portfolio manager by surprise.

Our paper also shows that the stochastic movement of beta over time can have an important impact on investment strategies that use historical betas in the portfolio formation process. The most striking result is that the magnitude of the beta of a high-beta portfolio in comparison with its historical average is a strong predictor of future market returns. In particular, when the betas of high-beta portfolios are very large, the market tends to go down in the following period. The effect is still present if we control for other predictors from the literature and can be exploited via a market-timing strategy with promising risk-return profile. While it is intuitive that a group of stocks with extremely large betas could indicate a higher likelihood of systemic problems in the following period, we certainly need a better understanding of why our indicators carry information about future market movements. Another open issue is the development of market-timing strategies which combine our beta indicators with other predictors like the cay factor or the average correlation.

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Table 1: Average Return, Standard Deviation, Sharpe Ratio, and Certainty Equivalent Return of Different Low-Beta Strategies: 3 Month Holding Period

Panel A: Annualized Average Return

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.0892	0.1059	0.1269	0.1226
3 Months	0.0451	0.0579	0.0752	0.0707
6 Months	0.0227	0.0478	0.0723	0.0729
12 Months	0.0086	0.0329	0.0551	0.0571

Panel B: Annualized Standard Deviation

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.3637	0.2882	0.3192	0.3102
3 Months	0.3124	0.2255	0.2195	0.2281
6 Months	0.3345	0.2160	0.1826	0.1857
12 Months	0.3451	0.2259	0.1890	0.1886

Panel C: Annualized Sharpe Ratio

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.2451	0.3675	0.3975	0.3953
3 Months	0.1446	0.2569	0.3425	0.3099
6 Months	0.0679	0.2212	0.3962	0.3925
12 Months	0.0251	0.1455	0.2917	0.3026

Panel D: Annualized Certainty Equivalent Return

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.0037	0.0153	0.0184	0.0180
3 Months	−0.0018	0.0078	0.0126	0.0110
6 Months	−0.0099	0.0059	0.0139	0.0139
12 Months	−0.0144	0.0016	0.0093	0.0099

The table shows the average returns (Panel A), standard deviations (Panel B), Sharpe ratios (Panel C), and certainty equivalent returns (Panel D) of each of four low-beta strategies (extreme high, equal weighting, Frazzini/Pedersen, extreme low) for different formation periods (1, 3, 6 and 12 months) and a three month holding period. The portfolios are built at the end of each month beginning in September 1989 and ending in October 2013. All current constituents of the S&P 500 index are ranked in descending order by their ex-ante beta, which is estimated from daily returns. The topmost decile stocks build the high-beta portfolio and the lowermost decile stocks the low-beta portfolio, using equal weighting. This procedure leads to four high-beta and four low-beta portfolios each month, referring to the four different formation periods. Based on the betas of these portfolios, the weights of the different low-beta strategies are calculated and the portfolios are set up. The portfolios are held until the end of the three month holding period without rebalancing. The average return is the annualized return earned by each strategy. The standard deviation is also annualized and calculated from the returns for the whole investigation period. The Sharpe ratio is calculated by dividing the annualized average return by the annualized standard deviation. The annualized certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1.

Table 2: Average Return, Standard Deviation, Sharpe Ratio, and Certainty Equivalent Return of Different Low-Beta Strategies: 12 Month Holding Period

Panel A: Annualized Average Return

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.1058	0.1328	0.1603	0.1598
3 Months	0.0504	0.0756	0.0998	0.1007
6 Months	0.0390	0.0608	0.0799	0.0826
12 Months	0.0281	0.0488	0.0649	0.0695

Panel B: Annualized Standard Deviation

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.4225	0.3164	0.2983	0.2995
3 Months	0.3743	0.2488	0.2056	0.2122
6 Months	0.3647	0.2379	0.1978	0.2035
12 Months	0.3625	0.2310	0.1895	0.1946

Panel C: Annualized Sharpe Ratio

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.2451	0.4199	0.5374	0.5336
3 Months	0.1347	0.3037	0.4853	0.4748
6 Months	0.1071	0.2557	0.4042	0.4061
12 Months	0.0776	0.2310	0.3427	0.3570

Panel D: Annualized Certainty Equivalent Return

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.0123	0.0818	0.1160	0.1150
3 Months	−0.0276	0.0430	0.0783	0.0779
6 Months	−0.0396	0.0306	0.0601	0.0619
12 Months	−0.0497	0.0210	0.0473	0.0511

The table shows the average returns (Panel A), standard deviations (Panel B), Sharpe ratios (Panel C), and certainty equivalent returns (Panel D) of each of four low-beta strategies (extreme high, equal weighting, Frazzini/Pedersen, extreme low) for different formation periods (1, 3, 6 and 12 months) and a twelve month holding period. The portfolios are built at the end of each month beginning in September 1989 and ending in October 2013. All current constituents of the S&P 500 index are ranked in descending order by their ex-ante beta, which is estimated from daily returns. The topmost decile stocks build the high-beta portfolio and the lowermost decile stocks the low-beta portfolio, using equal weighting. This procedure leads to four high-beta and four low-beta portfolios each month, referring to the four different formation periods. Based on the betas of these portfolios, the weights of the different low-beta strategies are calculated and the portfolios are set up. The portfolios are held until the end of the twelve month holding period without rebalancing. The average return is the annualized return earned by each strategy, the standard deviation is calculated from the returns for the whole investigation period and the Sharpe ratio is calculated by dividing the average return by the standard deviation. The annualized certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1.

Table 3: Market Factor Sensitivity of Different Low-Beta Strategies in a 4-Factor-Model Regression

Panel A: Holding Period: 3 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	1.5869***	1.5144***	1.4547***	1.4419***
3 Months	0.8944**	0.8195***	0.7637***	0.7447***
6 Months	0.5352*	0.4687**	0.4232***	0.4022***
12 Months	0.2902	0.2378	0.2022*	0.1853*

Panel B: Holding Period: 12 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	1.3938***	−1.3653***	1.3054***	1.3368***
3 Months	0.7384***	0.6704***	0.5913***	0.6024***
6 Months	0.4103*	0.3652**	0.3048**	0.3201**
12 Months	0.1834	0.1960	0.1798	0.2087*

The table shows the factor loadings of the returns of the four low-beta strategies for the market factor over the investigation period from September 1989 to October 2013. The multiple linear regressions consist of four independent variables (market excess return, SMB, HML, MOM) and read $R_{S,t} = \alpha_{S,t} + \beta_{S,t} \cdot (R_{M,t} - R_{f,t}) + s_{S,t} \cdot SMB_t + h_{S,t} \cdot HML_t + p_{S,t} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy (the S&P 500) and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The originally monthly factors are adjusted to fit the holding period of the strategies (either three months or twelve months) and the regression is run with monthly data. The calculations of the significance levels use the Newey-West estimator with two lags (Panel A) and eleven lags (Panel B) to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 4: Size Factor Sensitivity of Different Low-Beta Strategies in a 4-Factor-Model Regression

Panel A: Holding Period: 3 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	−1.2233***	−0.4566**	0.3300	0.3102
3 Months	−1.0582***	−0.4266***	0.0519	0.2048
6 Months	−1.3560***	−0.6193***	−0.1137	0.1174
12 Months	−1.3993***	−0.6449***	−0.1633	0.1095

Panel B: Holding Period: 12 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	−1.9242***	−0.68742**	0.5543**	0.5758**
3 Months	−1.8992***	−0.8065**	0.0192	0.2862
6 Months	−1.7207***	−0.7590**	−0.1144	0.2027
12 Months	−1.5154**	−0.5825	−0.0035	0.3504*

The table shows the factor loadings of the returns of the four low-beta strategies for the size factor over the investigation period from September 1989 to October 2013. The multiple linear regressions consist of four independent variables (market excess return, SMB, HML, MOM) and read $R_{S,t} = \alpha_{S,t} + \beta_{S,t} \cdot (R_{M,t} - R_{f,t}) + s_{S,t} \cdot SMB_t + h_{S,t} \cdot HML_t + p_{S,t} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy (the S&P 500) and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The originally monthly factors are adjusted to fit the holding period of the strategies (either three months or twelve months) and the regression is run with monthly data. The calculations of the significance levels use the Newey-West estimator with two lags (Panel A) and eleven lags (Panel B) to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 5: Value Factor Sensitivity of Different Low-Beta Strategies in a 4-Factor-Model Regression

Panel A: Holding Period: 3 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.1487	0.2373	0.3574**	0.3560**
3 Months	0.3841	0.4804***	0.5688***	0.5767***
6 Months	0.4876**	0.5315***	0.5420***	0.5753***
12 Months	0.7018***	0.6976***	0.6725***	0.6933***

Panel B: Holding Period: 12 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.0727	0.3438*	0.6995***	0.6149***
3 Months	0.3038	0.5624**	0.7922***	0.8211***
6 Months	0.3002	0.5776***	0.7717***	0.8550***
12 Months	0.3447	0.5877***	0.7434***	0.8306***

The table shows the factor loadings of the returns of the four low-beta strategies for the value factor over the investigation period from September 1989 to October 2013. The multiple linear regressions consist of four independent variables (market excess return, SMB, HML, MOM) and read $R_{S,t} = \alpha_{S,t} + \beta_{S,t} \cdot (R_{M,t} - R_{f,t}) + s_{S,t} \cdot SMB_t + h_{S,t} \cdot HML_t + p_{S,t} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy (the S&P 500) and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The originally monthly factors are adjusted to fit the holding period of the strategies (either three months or twelve months) and the regression is run with monthly data. The calculations of the significance levels use the Newey-West estimator with two lags (Panel A) and eleven lags (Panel B) to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 6: Momentum Factor Sensitivity of Different Low-Beta Strategies in a 4-Factor-Model Regression

Panel A: Holding Period: 3 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.6772***	0.3084*	−0.0014	−0.0604
3 Months	0.5896***	0.2939	0.0837	−0.0019
6 Months	0.6593**	0.3322	0.1327	0.0050
12 Months	0.7201**	0.3250	0.0771	−0.0700

Panel B: Holding Period: 12 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.2279	0.1674	0.1826	0.1068
3 Months	0.1205	0.0677	0.0676	0.0148
6 Months	0.1696	0.0176	−0.0580	−0.1344
12 Months	0.1897	0.0262	−0.0634	−0.1372

The table shows the factor loadings of the returns of the four low-beta strategies for the momentum factor over the investigation period from September 1989 to October 2013. The multiple linear regressions consist of four independent variables (market excess return, SMB, HML, MOM) and read $R_{S,t} = \alpha_{S,t} + \beta_{S,t} \cdot (R_{M,t} - R_{f,t}) + s_{S,t} \cdot SMB_t + h_{S,t} \cdot HML_t + p_{S,t} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy (the S&P 500) and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The originally monthly factors are adjusted to fit the holding period of the strategies (either three months or twelve months) and the regression is run with monthly data. The calculations of the significance levels use the Newey-West estimator with two lags (Panel A) and eleven lags (Panel B) to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 7: Annualized Alpha of Different Low-Beta Strategies in a 4-Factor-Model Regression

Panel A: Holding Period: 3 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	−0.0486	−0.0207	0.0049	0.0073
3 Months	−0.0480	−0.0262	−0.0036	−0.0044
6 Months	−0.0461	−0.0112	0.0189	0.0238
12 Months	−0.0526	−0.0136	0.0187	0.0254

Panel B: Holding Period: 12 Months

Formation	Extreme High	Equal Weighting	Frazzini/Pedersen	Extreme Low
1 Month	0.0172	0.0141	0.0061	0.0109
3 Months	0.0136	0.0151	0.0196	0.0166
6 Months	0.0213	0.0269	0.0354	0.0324
12 Months	0.0212	0.0236	0.0294	0.0260

The table shows the annualized alpha of the four low-beta over the investigation period from September 1989 to October 2013. The multiple linear regressions consist of four independent variables (market excess return, SMB, HML, MOM) and read $R_{S,t} = \alpha_{S,t} + \beta_{S,t} \cdot (R_{M,t} - R_{f,t}) + s_{S,t} \cdot SMB_t + h_{S,t} \cdot HML_t + p_{S,t} \cdot MOM_t + \epsilon_t$, where $(R_{M,t} - R_{f,t})$ is the excess return of the market proxy (the S&P 500) and SMB_t, HML_t and MOM_t are the returns of the factor-mimicking portfolios for size, value and momentum effects, respectively. The originally monthly factors are adjusted to fit the holding period of the strategies (either three months or twelve months) and the regression is run with monthly data. The calculations of the significance levels use the Newey-West estimator with two lags (Panel A) and eleven lags (Panel B) to account for the overlapping periods. Significance level: *** 0.01, ** 0.05, * 0.1.

Table 8: Decomposition of the Returns of Different Low-Beta Strategies: Contribution of Natural Hedge

Panel A: Annualized Contribution for 3 Month Holding Period

Formation	Extreme High	Equal Weighting	Extreme Low
1 Month	−0.0089	−0.0107	−0.0125
3 Months	−0.0113	−0.0122	−0.0131
6 Months	−0.0075	−0.0070	−0.0065
12 Months	−0.0054	−0.0059	−0.0064

Panel B: Annualized Contribution for 12 Month Holding Period

Formation	Extreme High	Equal Weighting	Extreme Low
1 Month	0.0043	0.0001	−0.0042
3 Months	0.0001	−0.0027	−0.0056
6 Months	0.0009	−0.0021	−0.0051
12 Months	0.0055	0.0001	−0.0053

The table shows the contribution of the natural-hedge component to the three and twelve month returns of the three specified cases. These cases represent an extreme high (X_H = -2; X_L = 0), equal weighting (X_H = -1; X_L = 1) and extreme low (X_H = 0; X_L = 2) strategy. The contributions are derived by decomposing the returns, following equations (2) and (3). Accordingly, the natural-hedge component is the covariance between the market return and the difference between the estimated and realized beta of each strategy. The covariances are calculated from monthly data for the whole investigation period (September 1989 to October 2013). Annualized values are reported.

Table 9: Decomposition of the Returns of Different Low-Beta Strategies: Contribution of Market Timing

Panel A: Annualized Contribution for 3 Month Holding Period

Formation	Extreme High	Equal Weighting	Extreme Low
1 Month	0.0258	0.0157	0.0056
3 Months	0.0269	0.0166	0.0063
6 Months	0.0270	0.0165	0.0061
12 Months	0.0250	0.0161	0.0072

Panel B: Annualized Contribution for 12 Month Holding Period

Formation	Extreme High	Equal Weighting	Extreme Low
1 Month	0.0365	0.0222	0.0078
3 Months	0.0432	0.0276	0.0121
6 Months	0.0445	0.0294	0.0144
12 Months	0.0378	0.0261	0.0143

The table shows the contribution of the market-timing component to the three and twelve month returns of the three specified cases. These cases represent an extreme high (X_H = -2; X_L = 0), equal weighting (X_H = -1; X_L = 1) and extreme low (X_H = 0; X_L = 2) strategy. The contributions are derived by decomposing the returns, following equations (2) and (3). Accordingly, the market-timing component is the covariance between the market return and the estimated beta of each strategy. The covariances are calculated from monthly data for the whole investigation period (September 1989 to October 2013). Annualized values are reported.

Table 10: Results of Predictive Regressions with Timing Indicator I as Explanatory Variable for 3 Month Market Return

Formation	Intercept	Timing Indicator	R^2_{adj}
LB - 1 M	0.0256***	0.0001	0.0009
LB - 3 M	0.0238***	0.0083*	0.0082
LB - 6 M	0.0241***	0.0167*	0.0092
LB - 12 M	0.0243***	0.0298**	0.0179
HB - 1 M	0.0264***	−0.0851***	0.0386
HB - 3 M	0.0307***	−0.1032***	0.0559
HB - 6 M	0.0333***	−0.1178***	0.0682
HB - 12 M	0.0363***	−0.1312***	0.0729
LB-HB - 1 M	0.0239***	−0.0476***	0.0222
LB-HB - 3 M	0.0274***	−0.0658***	0.0457
LB-HB - 6 M	0.0297***	−0.0679***	0.0536
LB-HB - 12 M	0.0326***	−0.0736***	0.0630

The table shows the results of the predictive regressions with timing indicator I as independent variable and the return of the S&P 500 index as dependent variable. Due to the calculation of the indicator, the regression incorporates 290 three month returns of the S&P 500. The indicator LB (HB, LB-HB) is defined as the relative deviation of the current low (high, low-high) beta from its mean, which is calculated over an extended window. Beta is estimated from daily returns over a formation period of one, three, six and twelve months. The adjusted R^2's of the predictive regressions are given in the last column of the table. The calculations of the significance levels use the Newey-West estimator with two lags to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 11: Results of Predictive Regressions with Additional Independent Variables for 3 Month Market Return

Formation	Intercept	TI	DivY	SR	CAY	AV	AC	R^2_{adj}
LB - 1 M	−0.0011	0.0001	−0.0035	3.8330	0.7480**	−0.5612***	0.3390***	0.0624
LB - 3 M	−0.0004	0.0033	−0.0025	4.0858	0.7459**	−0.5329***	0.2993**	0.0576
LB - 6 M	0.0005	0.0083	−0.0034	4.2755	0.7805**	−0.5205***	0.2964***	0.0583
LB - 12 M	0.0071	0.0275*	−0.0064	4.7542	0.9362***	−0.4712***	0.2616**	0.0670
HB - 1 M	−0.0003	−0.0513*	0.0009	2.6924	0.6341*	−0.4474***	0.2588**	0.0687
HB - 3 M	0.0069	−0.0659**	−0.0003	2.2947	0.6319*	−0.3982***	0.2370**	0.0753
HB - 6 M	0.0126	−0.0826***	−0.0012	1.9044	0.6271*	−0.3809***	0.2258**	0.0851
HB - 12 M	0.0185	−0.1021***	−0.0024	1.3263	0.6929**	−0.3949***	0.2361**	0.0965
LB-HB - 1 M	0.0004	−0.0249	−0.0002	3.2200	0.6878**	−0.4975***	0.2627**	0.0613
LB-HB - 3 M	0.0075	−0.0417*	−0.0006	2.7978	0.6977**	−0.4159***	0.2141*	0.0693
LB-HB - 6 M	0.0113	−0.0458**	−0.0023	2.8501	0.7219**	−0.4015***	0.2180**	0.0755
LB-HB - 12 M	0.0177	−0.0571***	−0.0042	2.5524	0.8110**	−0.3947***	0.2219**	0.0888

The table shows the results of the predictive regressions with six independent variables and the return of the S&P 500 index as dependent variable. The regression equation has the following independent variables: Timing indicator (TI), dividend yield (DY), short rate (SR), cay factor (CAY), average variance (AV) and average correlation (AC). DY, AV and AC refer to the S&P 500 index, SR is the 1-month T-bill rate and the cay factor is the one provided by Lettau's database. Due to the calculation of the indicator, the regression incorporates 290 three month returns of the S&P 500. The indicator LB (HB, LB-HB) is defined as the relative deviation of the current low (high, low-high) beta from its mean, which is calculated by an extended window. Beta is estimated from daily returns over a formation period of one, three, six and twelve months. The adjusted R^2's of the predictive regressions are given in the last column of the table. The calculations of the significance levels use the Newey-West estimator with two lags to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 12: Results of Predictive Regressions with Timing Indicator I as Explanatory Variable for 12 Month Market Return

Formation	Intercept	Timing Indicator	R^2_{adj}
LB - 1 M	0.1116***	0.0001	−0.0027
LB - 3 M	0.1039***	0.0318***	0.0307
LB - 6 M	0.1037***	0.0792***	0.0532
LB - 12 M	0.1056***	0.1204***	0.0654
HB - 1 M	0.1136***	−0.2551***	0.0713
HB - 3 M	0.1277***	−0.3421***	0.1252
HB - 6 M	0.1368***	−0.3975***	0.1576
HB - 12 M	0.1441***	−0.4071***	0.1417
LB-HB - 1 M	0.1056***	−0.1411***	0.0411
LB-HB - 3 M	0.1172***	−0.2248***	0.1098
LB-HB - 6 M	0.1260***	−0.2495***	0.1484
LB-HB - 12 M	0.1342***	−0.2453***	0.1423

The table shows the results of the predictive regressions with timing indicator I as independent variable and the return of the S&P 500 index as dependent variable. Due to the calculation of the indicator, the regression incorporates 290 twelve month returns of the S&P 500. The indicator LB (HB, LB-HB) is defined as the relative deviation of the current low (high, low-high) beta from its mean, which is calculated over an extended window. Beta is estimated from daily returns over a formation period of one, three, six and twelve months. The adjusted R^2's of the predictive regressions are given in the last column of the table. The calculations of the significance levels use the Newey-West estimator with eleven lags to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 13: Results of Predictive Regressions with Additional Independent Variables for 12 Month Market Return

Formation	Intercept	TI	DivY	SR	CAY	AV	AC	R^2_{adj}
LB - 1 M	0.0840**	0.0001	0.0014	−9.3113	5.0263***	−0.9196***	0.5747***	0.1788
LB - 3 M	0.1269***	0.0533***	−0.0002	−7.3360	5.4574***	−0.5406*	0.0030	0.2252
LB - 6 M	0.1459***	0.1412***	−0.0147	−4.0103	6.0692***	−0.3115	−0.0736	0.2715
LB - 12 M	0.1642***	0.2211***	−0.0297**	−2.8850	6.7491***	−0.2346	−0.0125	0.3088
HB - 1 M	0.0964**	−0.2574***	0.0188	−15.5838**	4.5728***	−0.3700	0.1919	0.2372
HB - 3 M	0.1358***	−0.3529***	0.0134	−18.1438***	4.5335***	−0.0700	0.0496	0.2830
HB - 6 M	0.1585***	−0.4019***	0.0083	−19.2172***	4.5517***	−0.0630	0.0427	0.3104
HB - 12 M	0.1708***	−0.4190***	0.0026	−20.0197***	4.8902***	−0.2530	0.1672	0.3098
LB-HB - 1 M	0.1037**	−0.1699***	0.0186	−14.2922**	4.7893***	−0.5169*	0.0834	0.2197
LB-HB - 3 M	0.1549***	−0.2850***	0.0145	−17.1849***	4.8566***	0.0412	−0.2495	0.2942
LB-HB - 6 M	0.1735***	−0.2894***	0.0029	−16.2539***	5.0192***	0.0607	−0.1640	0.3257
LB-HB - 12 M	0.1840***	−0.2797***	−0.0065	−16.1198***	5.4497***	−0.1243	0.0195	0.3302

The table shows the results of the predictive regressions with six independent variables and the return of the S&P 500 index as dependent variable. The regression equation has the following independent variables: Timing indicator (TI), dividend yield (DY), short rate (SR), cay factor (CAY), average variance (AV) and average correlation (AC). DY, AV and AC refer to the S&P 500 index, SR is the 1-month T-bill rate and the cay factor is the one provided by Lettau's database. Due to the calculation of the indicator, the regression incorporates 290 twelve month returns of the S&P 500. The indicator LB (HB, LB-HB) is defined as the relative deviation of the current low (high, low-high) beta from its mean, which is calculated by an extended window. Beta is estimated from daily returns over a formation period of one, three, six and twelve months. The adjusted R^2's of the predictive regressions are given in the last column of the table. The calculations of the significance levels use the Newey-West estimator with eleven lags to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 14: Average Return, Standard Deviation, Sharpe Ratio, and Certainty Equivalent Return of Market-Timing Strategies: 3 Month Holding Period

	Weighted Strategy				Unweighted Strategy			
Indicator	AvRet	SD	SR	CEV	AvRet	SD	SR	CEV
LB - 1 M	0.0161	0.0188	0.8566	0.0160	0.0889	0.1541	0.5769	0.0770
LB - 3 M	0.0159	0.0188	0.8477	0.0158	0.0926	0.1536	0.6031	0.0808
LB - 6 M	0.0178	0.0198	0.8990	0.0176	0.0974	0.1528	0.6373	0.0857
LB - 12 M	0.0182	0.0209	0.8728	0.0180	0.0959	0.1531	0.6267	0.0842
HB - 1 M	0.0179	0.0189	0.9435	0.0177	0.1148	0.1498	0.7663	0.1036
HB - 3 M	0.0191	0.0242	0.7901	0.0188	0.1068	0.1512	0.7064	0.0954
HB - 6 M	0.0196	0.0231	0.8492	0.0194	0.1086	0.1509	0.7193	0.0972
HB - 12 M	0.0192	0.0227	0.8470	0.0190	0.1081	0.1510	0.7154	0.0967
LB-HB - 1 M	0.0165	0.0172	0.9631	0.0164	0.1114	0.1504	0.7402	0.1000
LB-HB - 3 M	0.0187	0.0225	0.8324	0.0185	0.1009	0.1523	0.6623	0.0893
LB-HB - 6 M	0.0192	0.0219	0.8801	0.0190	0.1114	0.1504	0.7402	0.1001
LB-HB - 12 M	0.0198	0.0227	0.8744	0.0196	0.1035	0.1518	0.6816	0.0920

The table shows the average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV) of the weighted and unweighted market-timing strategies for a holding period of three months. All values are annualized. The certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. Conditional on the current timing indicator, the probability that the subsequent market return will be positive is calculated monthly under the assumption of a bivariate normal distribution of the market return and the timing indicator. All parameters of the bivariate normal distribution are calculated over a window of 36 months preceding the investment date, so only out-of-sample information is used. The unweighted strategy invests 1 dollar in the S&P 500 if the probability that the subsequent return will be positive is greater than 0.5, financed with an offsetting position in the risk-free instrument. If the probability is lower than 0.5, the strategy holds an investment of -1 dollar in the S&P 500 and an investment of 1 dollar in the risk-free instrument. The amount invested in the S&P 500 for the weighted strategy depends on the calculated probability, the higher the probability, the higher the weight of the S&P 500, again financed with a offsetting psotion in the risk-free instrument. Weights are standardized to fall in the range between -1 and 1.

Table 15: Average Return, Standard Deviation, Sharpe Ratio, and Certainty Equivalent Return of Market-Timing Strategies: 12 Month Holding Period

	Weighted Strategy				Unweighted Strategy			
Indicator	AvRet	SD	SR	CEV	AvRet	SD	SR	CEV
LB - 1 M	0.0466	0.0638	0.7307	0.0446	0.0973	0.1726	0.5640	0.0818
LB - 3 M	0.0434	0.0632	0.6868	0.0414	0.0797	0.1814	0.4393	0.0625
LB - 6 M	0.0476	0.0666	0.7158	0.0455	0.0857	0.1787	0.4795	0.0689
LB - 12 M	0.0529	0.0670	0.7903	0.0507	0.1060	0.1674	0.6331	0.0911
HB - 1 M	0.0469	0.0604	0.7768	0.0451	0.1005	0.1707	0.5888	0.0854
HB - 3 M	0.0470	0.0608	0.7720	0.0452	0.0931	0.1749	0.5320	0.0771
HB - 6 M	0.0483	0.0625	0.7721	0.0464	0.0944	0.1742	0.5423	0.0785
HB - 12 M	0.0521	0.0616	0.8456	0.0502	0.1064	0.1671	0.6368	0.0918
LB-HB - 1 M	0.0460	0.0601	0.7657	0.0443	0.1000	0.1710	0.5850	0.0848
LB-HB - 3 M	0.0485	0.0630	0.7690	0.0465	0.0933	0.1748	0.5337	0.0772
LB-HB - 6 M	0.0510	0.0683	0.7464	0.0487	0.0931	0.1749	0.5321	0.0770
LB-HB - 12 M	0.0561	0.0689	0.8161	0.0538	0.1036	0.1688	0.6137	0.0886

The table shows the average returns (AvRet), standard deviations (SD), Sharpe ratios (SR), and certainty equivalent returns (CEV) of the weighted and unweighted market-timing strategies for a holding period of twelve months. All values are annualized. The certainty equivalent return is calculated for an investor with CARA utility function and absolute risk aversion of 1. Conditional on the current timing indicator, the probability that the subsequent market return will be positive is calculated monthly under the assumption of a bivariate normal distribution of the market return and the timing indicator. All parameters of the bivariate normal distribution are calculated over a window of 36 months preceding the investment date, so only out-of-sample information is used. The unweighted strategy invests 1 dollar in the S&P 500 if the probability that the subsequent return will be positive is greater than 0.5, financed with an offsetting position in the risk-free instrument. If the probability is lower than 0.5, the strategy holds an investment of -1 dollar in the S&P 500 and an investment of 1 dollar in the risk-free instrument. The amount invested in the S&P 500 for the weighted strategy depends on the calculated probability, the higher the probability, the higher the weight of the S&P 500, again financed with a offsetting position in the risk-free instrument. Weights are standardized to fall in the range between -1 and 1.