Beta Dispersion and Market-Timing

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Abstract

This paper examines the informational content of the beta dispersion and its time-variation for the subsequent market return. The dispersion of betas, which is the spread between highest and lowest betas on a market, can be interpreted as a risk measure for the likelihood of market crashes and therefore function as a predictor of following market downturns. Based on the beta dispersion and on the highest betas on a market, this paper develops indicators to predict the subsequent market return. These indicators have substantial predictive power for future market movements, even if controlled for other well-known predictors of the market return. Moreover, the informational content of the bet dispersion is exploited by market-timing strategies. A new and innovative idea of designing market-timing strategies based on the successful indicators is introduced. In contrast to usual market-timing strategies the new approach invest in the market portfolio with a weighted position on the currently observed indicator. The market-timing strategies are able to considerably enhance the risk-return characteristics compared to a buy and hold investment in the market, especially by reducing the return volatility dramatically.

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I Introduction

Commonly used models such as the capital asset pricing model (CAPM) assume a static sensitivity of stocks towards systematic market risk (beta), however a growing number of research shows that the beta coefficient is time-varying (e.g. Faff, Hillier, and Hillier (2000); Jostova and Philipov (2005); Reeves and Wu (2013); Hollstein and Prokopczuk (2016)). In a basic model, where the expected returns can be explained by a market factor and a manageable number of additional factors, a stochastic market beta coefficient has substantial impact on the expected returns of stocks and portfolios. In this paper a univariate specification of this model with the market factor solely is assumed. The covariance between beta and the market, given a stochastic beta, enlarges the calculation of the expected returns. This is used to show that the time-varying beta contains information about the market risk premium. The paper introduces a theoretical derivation of the relationship between beta dispersion and market downturns. It does not only aim at the empirical documentation and evaluation of this predictive relationship, but also at the exploitation of the predictive relation between stock betas and market returns by successful market-timing strategies.

This paper shows that the time-varying beta spread between high and low betas at a market is able to anticipate movements of the following market return. This beta dispersion can be interpreted as a risk measure for a subsequent market downturn, briefly: The higher is the beta dispersion on a market, meaning the more stocks with an extremely high beta are at this market, the more inhomogeneous stocks are hit by a systematic shock. Such shock is especially endangering the business model of high-beta companies. This might increase the level of financial distress risk at the market, which could lead to a second endogenous shock caused by the first one. In comparison, a market with a narrow beta dispersion would only experience the initial systematic shock. The first contribution of this paper is the well-grounded derivation of the beta dispersion as risk measure and its empirical quantification of this relationship. In addition, based on this indicators are developed that perform comparably well in predictive regressions for the subsequent market return even if controlling for other well-known predictors, such as the cay factor, dividend yield and short rate. The obvious difference between the just mentioned predictors and the new introduced, is, that it uses stock level data and not overall market data. By this, it is possible to get additional information the are lost otherwise when aggregate information to market-wide information.

The second contribution of this paper is to demonstrate, that the finding of the predictive power of the beta dispersion can be used to set up successful market-timing strategies. A bivariate normal distribution between beta indicator and subsequent market return is used to determine the probability that the following market return will be positive conditioning on the currently observed indicator. Three approaches are chosen. First a basic one, which only shifts the wealth between money market and stocks conditioning on the probability. Second an unweighted strategy, which shifts the wealth between a long and short position in the market. And third, a weighted timing strategy, which shifts the wealth again between long and short position, but weighted depending on the probability, which is translated in a weight between -1 and 1 specifying the position held in the market portfolio. Especially the last mentioned strategy is able to significantly reduce the return volatility, so that the Sharpe ratio is improved compared to a buy and hold strategy of the market portfolio for the whole investigation period.

This 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 (2016) compare different techniques to obtain option-implied betas and investigate the information content of alternative estimators and Hollstein and Prokopczuk (2016) provide a comprehensive analysis of beta estimators and their properties that considers both historical and implied betas. Furthermore this paper relates to literature about conditional estimation of beta where the variation of beta must be assumed (Jagannathan and Wang, 1996; Wang, 2003; Lewellen and Nagel, 2006). In contrast to this work, my paper concentrates on two specific aspects of beta dynamics, namely the dispersion of betas on a specific market over time and the joint distribution of betas and market returns, which has not been investigated in the literature so far.

Also this paper is related to literature on the prediction of market returns or the equity premium, where the prevalent view of the efficacy is not uncontroversial (Lettau and Ludvigson, 2001; Goyal and Welch, 2003; Lewellen, 2004; Avramov and Chordia, 2006; Spiegel, 2008; Cochrane, 2008; Campbell and Thompson, 2008; Rapach, Strauss, and Zhou, 2010). Ang and Bekaert (2007) show that the dividend yield, which is one of the most common predictors, in combination with the short rate is a reliable predictor of the return for short horizons. In addition, Welch and Goyal (2008) give an comprehensive overview of the most common macroeconomics predictors of the market return, they conclude that the most predictors perform poor out-of-sample and wouldn't help an investor to profit from forecasts. From their analysis can also be derived, taht teh historical mean of the market return seems to be the most successsful predictor. Neely, Rapach, Tu, and Zhou (2014) compare macroeconomic predictors to technical indicators typically used by practitioners and reason that the latter perform just as good as macroeconomic predictors in- and out-of sample. Baetje and Menkhoff (2016) support this finding by showing that technical indicators are able to stably forecast the market return as they repeat and expand the aforementioned study. Furthermore they introduce a standard investment strategy how an investor could profit from this knowledge. In addition, Pollet and Wilson (2010) successfully predict the market excess return with the average correlation, which they introduce as a new proxy for the aggregated market risk. This paper adds to the literature that it demonstrates that the magnitudes of current high betas and low betas in relation to historical averages contain important information on future market returns and can successfully predict the market return.

Lastly this paper is related to market timing and the evaluation of the performance which has been long discussed in literature (Sharpe, 1975; Jeffrey, 1984; Pfeifer, 1985; Bauer Jr and Dahlquist, 2001; Kostakis, Panigirtzoglou, and Skiadopoulos, 2011; Neuhierl and Schlusche, 2011; Hallerbach, 2014). To determine the shift between stocks and money technical, macroeconomical and sentiment indicators are introduced and tested on their ability to time the market by several papers (Brock, Lakonishok, and LeBaron, 1992; Shen, 2003; Chen, 2009; Feldman, Jung, and Klein, 2015). Besides to the identification of successful predictors, several work is engaged with the evaluation of market-timing strategies. Early measurement of market-timing performance goes back to Treynor and Mazuy (1966) and **?**, besides others. A more recent approach is proposed in Dichtl, Drobetz, and Kryzanowski (2016). They evaluate market-timing strategies by utility models instead of the usual risk and return measures to compare the strategies' performance to a benchmark. In addition, Zakamulin (2014) focuses on shortcomings of market-timing strategies as he investigates the real-life (out-of-sample) performance of strategies which implies also the consideration of transaction costs. Zakamulin (2014) concludes that market timing does not work in all financial markets and that the success of market timing is not equally distributed over time, so it might be hard for investors to profit from it. In addition to these shortcomings, it is often criticizes that the success of market-timing strategies depend heavily on the accuracy of the predictor, which is assumed to be correct abundantly clear 50%. In contrast to the usual principle of market-timing strategies which shifts the wealth between 100% market and 100% money account, this paper develops two versions of a long-short market-timing strategy, which successfully beat the benchmark and the weighted version even holds when considering the usual shortcomings of market-timing strategies.

The remainder of this paper is structured as follows: Section II shows in subsection A the derivation of the relation between ex ante beta and ex post market return and introduces formally the beta dispersion as risk measure in subsection B. Section III consists of five subsections: Subsection A describes the data and basic methodology, subsection B studies thes beta dispersion empirically, subsection C quantifies the decomposition of returns, subsection D shows the results of the predictive regressions and subsection E characterises the market-timing strategies and their performance. Section IV concludes the paper.

II Systematic Risk and Market Return

A Effects of Stochastic Beta

There is strong evidence in the empirical literature that betas are time varying and stochastic (Faff, Hillier, and Hillier, 2000; Andersen, Bollerslev, Diebold, and Wu, 2005; Jostova and Philipov, 2005; Reeves and Wu, 2013; Bali, Engle, and Tang, 2016; Hollstein and Prokopczuk, 2016). In addition, Korn and Kuntz (2015) show that even if portfolios are set up as zero ex-ante beta portfolio, they experience a non-zero market exposure in their holding period. Betas which are estimated with historical data before the stocks are bought and the portfolio is set up (ex ante betas) differ from the betas in the holding period of the according portfolio (ex post betas). This stochastic nature of beta has an impact on the performance of portfolios and their constituents via an additional component of expected returns that complements the common risk factors. To illustrate this assume that the returns of a portfolio ($\widetilde{R}_P$) are only driven by a market factor, according to

$$\widetilde{R}_P = \alpha + \tilde{\beta}_{ep}\widetilde{R}_M + \tilde{\epsilon}, \tag{1}$$

where $\tilde{\beta}_{ep}$ is a random variable that expresses the holding period beta of the portfolio, $\widetilde{R}_M$ is the market return in the holding period (ex post market return) and $\tilde{\epsilon}$ is a zero-mean residual term. Taking expectations on both sides of equation (1) delivers

$$E[\widetilde{R}_P] = \alpha + E[\tilde{\beta}_{ep}\widetilde{R}_M]. \tag{2}$$

Splitting up the expected value of the product of the ex post beta and the ex post market return in equation 2 results in

$$E[\widetilde{R}_P] = \alpha + E[\tilde{\beta}_{ep}]E[\widetilde{R}_M] + Cov[\tilde{\beta}_{ep}, \widetilde{R}_M]. \tag{3}$$

Equation (3) shows that a stochastic beta leads to the covariance term $Cov[\tilde{\beta}_{ep}, \widetilde{R}_M]$, which would not be present if betas were deterministic. This term is further decomposed by differentiating the holding period beta in the ex ante beta plus the change in beta from the estimation to the holding period. The outcome of this is

$$Cov[\tilde{\beta}_{ep}, \widetilde{R}_M] = \underbrace{Cov[\tilde{\beta}_{ep} - \tilde{\beta}_{ea}, \widetilde{R}_M]}_{natural-hedge\ component} + \underbrace{Cov[\tilde{\beta}_{ea}, \widetilde{R}_M]}_{market-timing\ component}, \tag{4}$$

where $\tilde{\beta}_{ea}$ denotes the ex-ante beta. The two covariances on the right-hand side of equation (4) have an intuitive economic interpretation. If the first covariance is positive, the ex post beta tends to be higher than the ex ante beta if markets are rising and it tends to be lower than the ex ante beta if markets are decrease. This return component is called a natural hedge because the portfolio will have a higher actual market exposure (holding period beta) than previously estimated (ex ante 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 ex ante beta will be associated with positive market returns in the holding period. If it is negative, high betas will be an indicator for falling markets. This covariance term is called the market-timing component of the total covariance between the holding period beta and the market return.

This decomposition of the expected returns applies to all assets and all portfolios in general if the corresponding beta varies over time. If it can be shown that the second component, the market-timing component, has a substantial value, this would be the starting point for further investigation of the informational content in the variation of beta and the predictive power of beta for the subsequent market return. To test this hypothesis, the market-timing component should be quantified for portfolios of stocks that strictly aim at this effect. The most intuitive notion would be a portfolio, that incorporates stocks with extreme values of beta, meaning stocks with a comparably low or high ex ante beta should be chosen. A systematic approach would be to sort the stocks on a market by their beta and investigate the value of the two described components for the top and bottom quantile of this sort. Furthermore, a portfolio consisting of a combination of such stocks could be a reasonable composition and should be included. At the same time, this combination would be a proxy for a beta dispersion as it measures the different behaviour of low beta stocks and high beta stock.

B Beta Dispersion as a Measure of Market Risk

Beta dispersion means the spread of the distribution of stock betas at a particular time, e. g. at the end of the month. By definition, the market beta is equal to 1 and accordingly betas of all stocks at the market have to group around this mean. The difference between the higher and the lower betas can be used as an estimate of the current beta dispersion. Until now not much attention has been paid to how wide-spread or concentrated the single betas are grouped at a market. A reasonable starting point for the empirical investigation of the connection between ex ante beta and subsequent market return are stock portfolio based on this beta dispersion, as it is described in the previous subsection A.

The beta dispersion can be interpreted as a risk measure for the market and its return. To illustrate this hypothesis, imagine two markets which are completely equal except the fact that the beta dispersion differs. On market A, the beta dispersion is narrow, meaning the betas of all stocks are grouped closely around one. On market B, in contrast, the beta dispersion is high and the betas are wide-spread, so that there are some stocks with a beta close to zero and some with an extremely high beta. Now both markets experience an identical systematic, exogenous shock. The stocks on market A should all react very alike, as the shock hits all stocks rather similarly due to their more or less equal betas. On market B, stocks with a low beta, close to zero, hardly react at all to the shock but in comparison stocks with a high beta react thoroughgoing. For those companies the systematic shock might trigger a business-endangering development, possibly in a way that the economic survival is questioned. This increases the risk of financial distress at market B. As most of the firms on a market are somehow interconnected, the tumbling of the endangered high beta firms might spill over to those firms that are strongly connected to them. The increase of financial distress risk can be interpreted as second systematic, endogenous shock on market B and could lead to a overall market downturn if this spill-over or better cascading effect proceeds.

Summarizing, only because of a larger beta dispersion, a market experiences a second systematic shock compared to market with a more narrow beta dispersion. To illustrate this, consider for example, the time of the subprime crisis when financial institutions often had extremely high betas. Even a moderate market shock could cause serious problems for such high-beta firms, leading to problems for the whole financial system because of the interconnections of the financial institutions. The high beta dispersion and the concentration of high beta companies to a specific industrial sector lead finally to an overall market downturn. In contrast, such a strong downturn would be less likely if no stocks with extremely high betas would exist or the high beta stock are not sectoral concentrated, so the cascading effect would not appear in such a range.

III Empirical Results

A Data and Methodology

The empirical study uses the S&P 500 index as the investment universe. The focus on 500 highly liquid stocks has the advantage that daily price data is available. Moreover, very liquid futures contracts on the S&P 500 index are available to easily trade the whole market, which will be important for the market-timing strategy designed later on to exploit the primal findings at relatively low transaction costs. The data source for the stock data is Thomson Reuters Datastream. As risk-free interest rate the 1-month T-bill rate from Kenneth French's website is used. For additional analysis, the Cay factor (Lettau and Ludvigson, 2001) and the dividend yield of the S&P 500 index are also needed. This data is obtained from Martin

Lettau's website, and from Datastream, respectively.

Betas are estimated with different rolling, historical time windows from the daily returns over one, three and twelve months, respectively. Beta estimates are obtained for each month in the investigation period, starting in September 1989 and ending in September 2016. They refer to the last trading day of the respective month. For each month, the beta estimates of the constituent stocks of the S&P 500 index are sorted in descending order and proxies for the high beta and the beta dispersion are calculated. These proxies are the mean beta of the top and bottom 5%- and 10 %-quantiles of all beta estimates, whereby the high beta is represented by the top quantile and the beta dispersion is the difference between the top and the bottom quantile. Discrete and continuous market returns are calculated for one, three and twelve months.

B Beta Dispersion

Figure 1 shows the price development of the S&P 500 index, representing the market, and the beta dispersion on this market to visualize and support the hypothesis of the beta dispersion as risk measure that is derived earlier.

[Insert Figure 1 about here]

The beta dispersion is calculated rather naive as difference between the 90% quantile and the 10% quantile of the beta distribution of all 500 constituent stocks of the S&P 500 index, whereby betas are estimated with historical daily data of three months. At first sight, this figure supports the hypothesis that the beta dispersion can be interpreted as a risk measure. Wherever there is a considerable increase in the beta dispersion the market tends to fall. This can be seen particularly around the dotcom bubble in 2000 and in eased form from 2008 onwards. The examination of the separate time series of the 90% quantile and the 10% quantiles of the beta distribution leads to the conclusion that the variation of the beta dispersion is mainly caused by shifts in the values of the high beta quantile. The variation of the 10%

quantile (low beta quantile) is relatively narrow and stable over the sample period, in contrast the variability of the 90% quantile (high beta quantile) is remarkable. Therefore not only the beta dispersion, but also the separate high beta will be included in the following empirical investigation of the informational content of the beta variation for the market return.

A requirement to support the idea that the beta dispersion is an indicator for following market movements is that the beta dispersion changes substantially over time in its characteristics, especially the level, so that high levels of beta expansion might be preparatory of a market downturn. Therefore the time series of the introduced beta dispersion and the 90% quantile are examined whether they stem each from two different distributions with clearly deviating means. This should be represented by a high beta dispersion regime and a moderate beta dispersion regime. Hence, the time series are tested whether they follow a Markov switching process with two regimes. Two different linear models are chosen: First, the beta dispersion time series is basically represented by a simple constant as the mean of the underlying distribution is the point of interest. And second, the time series is represented by an autoregressive process with one lag. Both analysis lead to the same result. No matter which underlying linear model is chosen, there seem to be structural breaks in the time series as soon as the beta dispersion starts noteworthy expanding respectively contracting. These significant structural break coincide clearly with changes in the market phase from upturn to downturn and vice versa. This should be seen as supportive evidence that the beta dispersion varies substantially over time and especially in advance to market downturns. This is complementary for the results of the previous visual analysis.

In a next step, to become more familiar with the properties of the beta dispersion, a closer look is taken on the constituents of the both extreme beta quantiles. As the rationale for the beta dispersion being a risk measure starts with the beta level of stocks in the high beta quantile, the effect of a second endogenous shock should be more pronounced if most of the stocks within the high beta quantile are operating in the same industrial sector. The more stocks with a high beta are from the same sector the more this hypothesis seems applicable and reliable. If the sector concentration in the high beta quantile coincide with a high beta dispersion the spillover effect (second shock) on other stocks in different industrial sectors is intensified as not only the bankruptcy risk of one company is risen, but of the whole sector. Figure 2 shows in addition to figure 1 that not only the beta dispersion increases in advance of the market downturn, but also the sectoral concentration of the high-beta stocks which initially caused the downturn. The analysis of the industrial sectors of the constituents of the extreme portfolios suggest that an expansion of the beta dispersion coincides with a concentration of the stock in specific sectors. There are two major market downturns included in the sample, the dotcom bubble of 2000 and the subprime crisis of 2008.

[Insert Figure 2 about here]

Remarkably, the sectoral concentration of stocks in the low-beta quantile experiences no abnormal behaviour prior to market downturns, i. e. changes in the concentration seem to be independent of the market phase and the concentration is always at a moderate level. In contrast, patterns can be found in the concentration of the high-beta quantile. Prior to market downturns and also slightly in advance of increases in the beta dispersion, the sectoral concentration in the high-beta quantile rises extremely, so that as a maximum 45 of the 50 stocks belong to the same industrial sector. This corroborates the introduced hypothesis, as the second, endogenous shock should be much more extensive, if a whole industrial sector is hit simultaneously and strong by the first, exogenous shock.

C Decomposition of Returns

After naively and visually proofing the connection between market return and beta variation, the market-timing and the natural-hedge component are quantified, following the idea and reasoning proposed in subsection II.A. In a first step, betas are estimated from historical data with estimation periods of one, three and twelve months. After ranking the betas in descending order, the quantiles and included stocks can be determined to form a beta dispersion portfolio and a high-beta portfolio. The portfolios are held for one, three and twelve months and the two components (natural hedge and market timing) can be calculated. Together with the two different portfolio sizes (5%- and 10%-quantile) this results in 36 realizations of the both components each.

[Insert Table 1 about here]

Table 1 shows the values of the natural-hedge and the market-timing component for the beta-dispersion portfolio (Panel A) and the high-beta portfolio (Panel B). The values for the one month and three months returns are annualized to make all covariances comparable and the calculation of the two components follows equation 4. Overall, the natural hedge effects are rather small and volatile for three and twelve months holding period, with values ranging from -0.43% to 2.68%. For the one month holding period of the portfolios this component seems to have substantial influence on the expected returns and helps to protect the portfolio in market downturns and supports the portfolio in market upturns, so additional expected returns are generated by this component. For the market-timing component negative values can be generally observed. This observation is far more stable in its size over the different estimation and holding periods with values up to -3.89%. The results verify that if the beta of a high-beta respectively beta-dispersion portfolio is very high in the formation period, the market tends to go down in the following holding period. Summarized, a large difference between the low and high betas indicates an forthcoming market downturn. If the betas are close together, the market tends to increase over the following holding period. In a nutshell, the natural-hedge component seems to immunize the portfolio in the short run against market downturns and the market-timing component supports the hypothesis that beta variation contains information about the subsequent market return.

Given the promising results of theadditional expected return components shown in Table 1, it is a natural next step to analyse the predictive power of beta for the market return more in-depth. Therefore, in the following several timing indicators based on the ex-ante high beta and beta dispersion are introduced and these indicators are investigated via predictive regressions. Afterwards subsection E defines and tests investment strategies based on these indicators, to show that the information in the beta dispersion can be actually exploited.

D Predicting Market Returns Using Beta Indicators

Based on the results of the previous section, two different indicators for the prediction of market returns based on high beta and beta dispersion are introduced. The first indicator (HB) measures whether the current beta of the high-beta quantile is large compared to the historical average beta of high-beta quantiles, as can be seen in equation 5. The second indicator (BD) measures the current difference between the betas of the low-beta quantile and the high-beta quantile compared to the historical average of this quantity (compare equation 6). In a last step the difference is put in relation to the historical mean of the quantity to standardise the indicator.

$$HB_t = \frac{\beta_t^{High} - \bar{\beta}}{\bar{\beta}}, \qquad with \;\; \bar{\beta} = \frac{1}{t} \cdot \sum_{i=1}^{t} \beta_i^{High} \tag{5}$$

$$BD_t = \frac{(\beta_t^{High} - \beta_t^{Low}) - \bar{\beta}}{\bar{\beta}}, \qquad with \;\; \bar{\beta} = \frac{1}{t} \cdot \sum_{i=1}^{t} (\beta_i^{High} - \beta_i^{Low}), \tag{6}$$

where β_t^{High} (β_t^{Low}) is the mean beta of the 5%- respectively 10%-top (bottom)-quantile of the beta distribution at time t. The betas are calculated for estimation periods of one, three, and twelve months leading to 12 indicator variables. The first twelve month of the sample are only used to calibrate the historical average of the described figure, so that at September 1990 the first value for the indicator is determined.

To test whether the indicators are informative for future market movements, predictive regressions are run for the excess log-return of the market ($R_{M,t}^{ex,c}$) over the next one (three, twelve) months to be explained. The lagged indicators (I_{t-1}) are initially the exclusive explanatory variables, following the below-mentioned form:

$$R_{M,t}^{ex,c} = \alpha + \beta \cdot I_{t-1} + \epsilon_t \tag{7}$$

It is always ensured that there is no overlapping between the explained and the explanatory variable. This means at every end of the month the indicator is estimated on backward-looking information only and the market return is calculated on forward-looking prices. In a next step multiple lagged factors are added to equation 7 as further predictors for the subsequent market return. This investigation is later referred to as in-sample prediction. The results of the univariate predictive regressions for the excess market log-returns are given in Table 2. Panel A presents the results for the one month market return, Panel B for the quarterly market return and Panel C for the yearly market return.

[Insert Table 2 about here]

The most striking result is that all specification of both indicators are significant on a 10% level at least, generally much higher and have a negative sign for the coefficient, as expected. This is in line with the results of Section C that a very high beta in the estimation period tends to be associated with a low or even negative market return in the holding period. The longer is the estimation period of the betas the more significant is the coefficient in the predictive regression. Same statement applies for comparing the in-sample R^2_{adj}: the longer are estimation and holding period, the higher is the in-sample R^2_{adj}.

In a second step it is tested whether the indicators maintain explanatory power if further variables that have been found to be successful predictors in previous studies are added. In particular, the dividend yield of the index and the short rate are used, as these variables jointly predict market returns according to Ang and Bekaert (2007). Moreover, the cay factor from Lettau and Ludvigson (2001) is used as well as the average variance and average correlation (in the estimation period) from Pollet and Wilson (2010). Table 3 shows the results of the multivariate predictive regressions.

[Insert Table 3 about here]

All beta indicators retain their signs and for the prediction of the twelve months market log-return all indicators are still significant (Panel C). For the prediction of the quarterly market return only the indicators based on the estimation with twelve month historical data seem valuable. When the level of the high-beta quantile or the beta dispersion is unusually high, they have still predictive power for the future market return even if other predictors are included. Remarkably the prediction of the one month ahead market return does not seem to work out at all in this sample. The results from this multivariate regression highlight that there is additional information included in the beta indicators compared to well-known other indicators. Depending on the horizon of prediction, the other included variables contribute also to the overall prediction of the market return. In the multivariate regressions in-sample R^2_{adj} of up to nearly 30% are attained. Furthermore, the beta indicators are better able to anticipate the mid-term market movements (twelve and partly three months) over short-term movements (one and partly three months). If the explanation of the beta dispersion as risk measure is applicable, this mid-term predictability is plausible as the appearance of the cascading effect and the second systematic shock does not emerge immediately and takes time to induce.

The in-sample evaluation of the beta indicators suggests that the level of the beta dispersion can be used to predict future market return. To support and corroborate the predictability of the indicator an out-of-sample evaluation is performed next. The procedure presented in this paper follows the established approach of calculating an out-of-sample R^2 (Campbell and Thompson, 2008; Neely, Rapach, Tu, and Zhou, 2014; Baetje and Menkhoff, 2016). This measure compares the forecast of a predictor to the one of the historical market return, which is commonly seen as the most stringent benchmark for equity premium predictors (Goyal and Welch, 2003; Welch and Goyal, 2008). The out-of-sample R^2 is calculated as shown in equation 8:

$$R^2_{OS} = 1 - \frac{\sum_{t=s}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=s}^{T}(r_t - \bar{r}_t)^2}, \tag{8}$$

where r_t is the actual observed market return in t, $\hat{r}_t$ is the predicted market return by the indicator and $\bar{r}_t$ is the historical mean market return estimated prior to s. For the prediction of the market return by the indicator, the sample is divided into two subsamples. The first subsample, here covering the first ten years, is used to estimate the predictive regression and the implied coefficients of this regression. The second subsample is used to calculate forecasts of the market return based on the estimated coefficients and the current observed indicator. The indicator's forecast is compared to the prediction of $\bar{r}_t$ via equation 8. The choice of the split point is based on the argumentation in Neely, Rapach, Tu, and Zhou (2014), the first subsample (estimation sample) should be large enough to estimate stable regression coefficients, but at the same time the second subsample (evaluation sample) should be large enough as the power of the forecast tests increases with the size (see also Hansen and Timmermann (2012)). The results are shown in table 4.

[Insert Table 4 about here]

The out-of-sample R^2 confirms the predicitve power of the indicators for mid-term prediction (three and twelve months), represented by a positive R^2. This is remarkable as numerous other well-known indicators often lack out-of-sample predictability. Even short-term predictability can be found in a weak form. As the results of this evaluation approach heavily rely on the chosen split point of the subsamples, a second possibility to calculate out-of-sample R^2 is applied. This approach estimates dynamically the regression coefficients every month, so that the estimation sample is an extending window. The advantage of this approach is that it uses all available information at a certain point in time and therefore accounts for the most updated information but still evaluates the prediction of the market return clearly without using in-sample information (Campbell and Thompson, 2008; Baetje and Menkhoff, 2016).

[Insert Table 5 about here]

Table 5 shows the out-of-sample results for the dynamic estimation of the regression parameters. This time all out-of-sample R^2 are positive showing a superior predictive performance of the indicators compared to the prediction of the historical average return. The size of the R^2 even seem to be even more stable. Notably, in some cases the dynamically computed out-of-sample R^2 exceeds the priorly estimated in-sample R^2.

Taking together the in-sample and out-of-sample evaluation of the HB and BD indicator, the results highlight the predictive power of the both indicators. On the one hand the multivariate regressions show that the proposed indicators contain additional information, especially in the prediction of the medium-term market log excess return. And on the other hand the computed out-of-sample R^2 show, that even if comparing the indicators to one of the most stringent benchmarks, the historical average of the market return. The new indicators suggested in this paper have definitively the right to exist and complement the already existing indicators in the literature. This corroborates the results from the decomposition of returns and emphasizes the relevance of the beta dispersion being a risk measure especially for future market downturns.

E Market-Timing Strategies Using Beta Indicators

The last section has shown that indicators based on the high-beta and low-beta quantile do carry information about future market movements. This section will focus on how to exploit this information from an investment perspective via market-timing strategies. Three different approaches are employed. The typical procedure for market-timing strategies is to shift the wealth between money and stock market. This paper introduces a new approach by developing and testing a shift of wealth between a short and a long position in the market on the one hand with 100% of the wealth and on the other hand with a weighted percentage of the wealth. The possibility to short the market at considerably low transaction costs is ensured by having highly liquid short ETFs respectively future contracts on the S&P 500. The question arises how to form portfolios based on the indicators. This new approach uses the indicators as conditioning information for the expected return and the return variance in the setting of a bivariate normal distribution.[1] If the market return $\widetilde{R}_M$ and the 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:

$$E[\widetilde{R}_M|I] = E[\widetilde{R}_M] + \frac{Cov[\widetilde{R}_M, \widetilde{I}]}{Var[\widetilde{I}]}(I - E[\widetilde{I}]), \tag{9}$$

$$Var[\widetilde{R}_M|I] = Var[\widetilde{R}_M]\Big(1 - Corr[\widetilde{R}_M, \widetilde{I}]^2\Big). \tag{10}$$

The conditional distribution with the moments from equations (9) and (10) also delivers the conditional probability (p) of a positive market return as $p \,|\, I = 1 - F(0)$, where $F(0)$ is the cumulative distribution function of the conditional distribution. Three different market-timing strategies are tested. First, a basic approach based on popular market-timing strategies in literature. This strategy invests 100% in the market, if the probability that the subsequent market return will be positive is greater than 50% conditioning on the current observed indicator. If the probability is lower than 50% percent no investment is made. Second an unweighted long-short market-timing strategy, which either has a full long position or a full short position in the market, conditioning on the probability. And third, a weighted long-short strategy, which invests weighted in the market proportional to the conditional probability of a positive market return. Formally, the weighted strategy holds a position of $X_M = 2(p \,|\, I - 0.5)$ in the market and $X_R = -2(p \,|\, I - 0.5)$ in the risk-free instrument. 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. All strategies are transformed to self-financing strategies with no initial costs by taking possibly necessary offsetting positions in the risk-free instrument.

[1] I 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.

This simplifies the comparison of the performance of the different approaches.

To implement the strategies, the current indicator variables I as described in the previous section is used, a total of 12 indicators, arising from the combination of the two indicators HB and BD, based on the 5%-quantiles[2], with different horizons of predicting the market return, namely one, three and twelve month as holding period. According to equations (9) and (10), we also need the (unconditional) expectations, variances and covariance of $\widetilde{R}_M$ and $\widetilde{I}$. These parameters are estimated from an extending window that precedes the months when the portfolio is set up. Therefore, the strategy does not use any in-sample information. The first conditional distribution is estimated in March 1991 to ensure a sufficient number of observations to reliably estimate this bivariate distribution. Depending on the holding period, the first market-timing strategy can be set up in April 1991 (1 month prediction period), respectively June 1991 (3 months prediction period) and April 1992 (12 months prediction period). Irrespective of the prediction horizon, which is used in estimating the conditional distribution, the market-timing strategy is rebalanced every month, to adjust the weight in the market portfolio to the most current information.

[Insert Figure 3 about here]

Figure 3 shows the development of the weights in the S&P 500 index based on the bivariate distribution of the twelve months BD indicator and the one, three, and twelve months prediction horizon for the market return. The level of the weights is only important for the weighted strategy, the other two just fully invest in the market depending on a positive weight. The weights for the market portfolio are the most distinctive for the twelve months prediction horizon, followed by horizons of three months and one month. Notably the conditional weight for the market is only negative[3] in exactly the two great market downturns in the sample. After the results of section C and D, this again emphasizes the capability of the high beta

[2]The predictive regressions show that the beta indicators based on the 5%-quantiles perform better than those based on the 10%-quantile in terms of significance and R^2_{adj} so that for the market-timing strategy only the smaller quantiles will be taken into account.

[3]A negative weight in the market corresponds in holding a short position in the market portfolio.

quantile and the beta dispersion of serving as a risk measure for a future market downturn.

[Insert Table 6 about here]

Table 6 reports the average return, the standard deviation, the Sharpe ratio, the Treynor-Mazuy coefficient and the Henriksson-Merton coefficient of all timing strategies. Irrespective of the strategy, all average returns are positive. The basic and the unweighted strategy (Panel A and B) seem to follow comparable patterns. The average returns are the highest for the HB indicator. The Sharpe ratio for the strategies based on this indicator are the highest, especially for the indicator that is estimated with twelve months of data. The standard deviation can be reduced by about 4 percentage points compared to the standard deviation of a naive investment in the market portfolio over the whole sample period. This results in higher Sharpe ratios and a risk-return improvement for the investor. The weighted strategy (Panel C) differs measurably from these two. The highest average returns arise for the strategies that use the BD, which is in line with our results from subsections C and D. Due to the most pronounced weight for the conditional distribution with a prediction horizon of twelve months, these strategies generate the highest average return. The Treynor-Mazuy coefficient is calculated by regressing the market-timing returns on the market excess return and its square, where the reported coefficient is the one corresponding to the squared term, following the work of Treynor and Mazuy (1966). A positive coefficient indicates market-timing ability. Taking this coefficient into account, the timing ability of the weighted strategy can be confirmed. For the basic and unweighted strategy based on the BD indicator the ability seems questionable. In contrast for the HB indicator the timing ability can be acknowledged. The last performance evaluation of the market-timing strategies is based on Henriksson and Merton (1981), where the timing ability is interpreted as an option payout. The returns of the market-timing strategy are regressed on a parametric model, which has the following form:

$$r_t^P - r_f = \beta_0 + \beta_{1,t}\gamma_{1,t} + \beta_{2,t}\gamma_{2,t} + \epsilon_t, \tag{11}$$

where $r_t^P - r_f$ is the excess return of the market-timing strategy, $\gamma_{1,t}$ is the maximum of $(0, r_t^{Market} - r_f)$ and $\gamma_{2,t}$ is the minimum $(0, r_t^{Market} - r_f)$. The reported difference between the two regression coefficients $(\beta_{1,t}, \beta_{0,t})$ of the parametric model confirms the timing ability of nearly all strategies. Overall the most striking result of the market-timing strategies is that all of these are able to clearly reduce the standard deviation of the returns[4]. This results in outstanding Sharpe ratios, which are considerably higher than the Sharpe ratio of the S&P 500 index, which is around 0.48. This reduction of the standard deviation is a clear advantage of the weighted market-timing strategy also in comparison of the other proposed strategies. As risk reduction is a reasonable target in investment strategies, the results of the weighted market-timing strategy should be highlighted.

In summary, the performance of the market-timing strategies is promising. There seems to be an advantage in performance arising from calculating the weights from the conditional distribution with twelve months prediction horizon and adapting the newest information in beta dispersion by monthly rebalancing. This supports the results from the previous sections, that beta is rather a medium-term than a short-term predictor. The weighted strategy seem favourable over the other two as this strategy clearly reduces the return volatility.

Figure 4 compares the time series of the increase in total wealth of the three market-timing approaches, based on the 12 months BD indicator. The increase in total wealth is calculated by rebalancing the market-timing strategy every month and the returns are paid on a money market account at the risk-free rate until the end of the investigation period.

[Insert Figure 4 about here]

The basic and the unweighted strategy just clone the market until around 2001. This

[4]Reduction of the standard deviation refers to the comparison with the standard deviation of the returns of a buy and hold strategy of the S&P 500 index

is the first time the indicator foreshadows a market downturn. The basic strategy therefore stops investing in stocks, which can be clearly seen in the chart. In contrast, the unweighted strategy takes a short position and is able to increase the total wealth for the investor. The second market downturn is much less anticipated by these two strategies, so that there is a distinct decrease in the performance. The weighted strategy falls short in terms of absolute increase in total wealth, but as already mentioned the strength of this strategy is the constant reduction of return volatility simultaneously with nearly no decrease in return performance. In a nutshell, the indicator is able to successfully discriminate between market up- and downturns and therefore leads to a superior performance than a passive buy and hold investment in the market portfolio.

After the overall successful performance evaluation of the market-timing strategies, the paper will now focus on the implementation of these strategies. As Zakamulin (2014) states, besides others, most market-timing strategies loose their superior performance, when realistic frictions are employed to the strategies. The most fundamental friction are transaction costs and liquidity. The introduced strategies are all based on investing in the S&P 500 index which represents a very actively traded market segment. For this index highly liquid ETFs and forwards contracts exist to implement the strategies at reasonable low transaction costs, so considerations about these market frictions can be held at a moderate level. In addition, for the basic and the weighted strategy the number of switches, where the weight changes from positive to negative and vice versa (compare figure 3), can be determined easily. This situation appears four times in 27 years, meaning, that the investor has to sell and rebuy the market twice, which seems justifiable.

Summarizing the comparison of three different approaches to time the market gives further insight in known shortcomings of market-timing strategies. A complete wealth shift between stock and money market is of limited suitability, as the investor has to ensure that his prediction is sufficient accurate (Sharpe, 1975; Jeffrey, 1984; Bauer Jr and Dahlquist, 2001; Neuhierl and Schlusche, 2011; Hallerbach, 2014). The results of the described market-timing strategies are likewise affected by this shortcoming. Nevertheless, the weighted long-short strategy is outstanding, as it substantially reduces the return volatility and thereby is able to achieve challenging portfolio characteristics for a naive buy-and-hold strategy. The weighted strategy can be of less predictive accuracy as it gradually increases the weight in the market portfolio the more likely a market upturn will be and vice versa. The more uncertain the prediction about the future market return is, the less total weight is invested in the market, so that if the indicator portend the wrong direction the consequences (negative returns of the timing-strategy) are as small as possible. By this, inapplicable predictions that not come out to be true are not as harmful as for the basic and the unweighted strategy which are fully invested and experience the complete magnitude of the wrong investment decision. In this is point the weighted strategy overcomes shortcomings from general market-timing strategies and can benefit from its more careful investment approach.

IV Conclusions

This paper addresses the impact of a time-varying beta coefficient and its implication for the market return. The beta dispersion can not only theoretically be derived and interpreted as a well-grounded risk measure for a following market downturn. Indicators based on this measure perform challenging well in predictive regressions for the subsequent market return, even if controlling for other well-known predictors. It can also been shown that this finding can be exploited by market-timing strategies including an innovative approach. The performance of those strategies and their risk-return profile are promising, although the weighted strategies overcomes the shortcomings of typical market-timing strategies the best. The weighted strategy reduces clearly the volatility of returns, so that the Sharpe ratio of this market-timing strategies clearly exceeds the Sharpe ratio of a buy and hold benchmark strategy.

While it is intuitive that a group of stocks with extremely large betas could indicate a higher likelihood of systemic problems in the following periods, we certainly need a better understanding of why the indicators carry information about future market movements. Especially the cascading effect should be studied in more depth, consistent with a focusing on the correlative behaviour and contagion of high beta stocks during a systematic shock. Another open issue is the development of market-timing strategies which combine the beta indicators with other predictors like the cay factor or the average correlation.

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Figure 1: Time Series of Beta Dispersion and S&P 500 Price

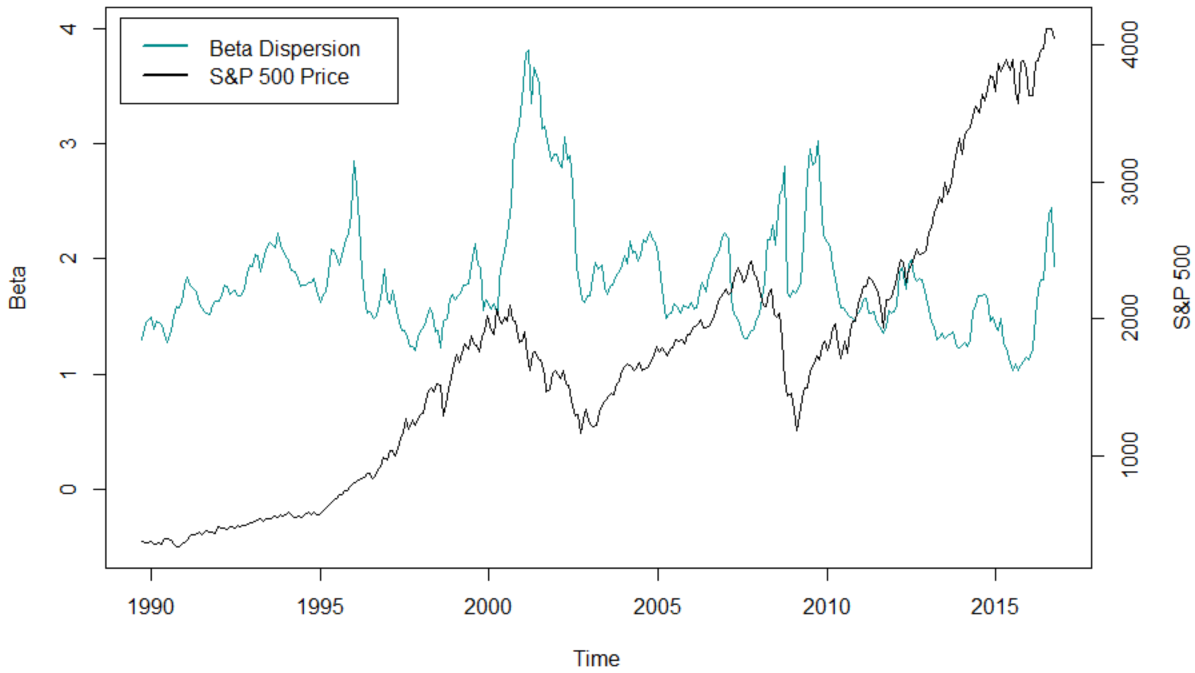

Figure 1 shows the time series of the beta dispersion and the total return developement of the S&P 500 index for the period September 1989 to September 2016. The beta dispersion is calculated as the difference between the 90%- and 10%-quantile of the beta-sorted constituents of the S&P 500 index.

Figure 2: Time Series of Beta Dispersion and the Concentration of the Stock in one Sector

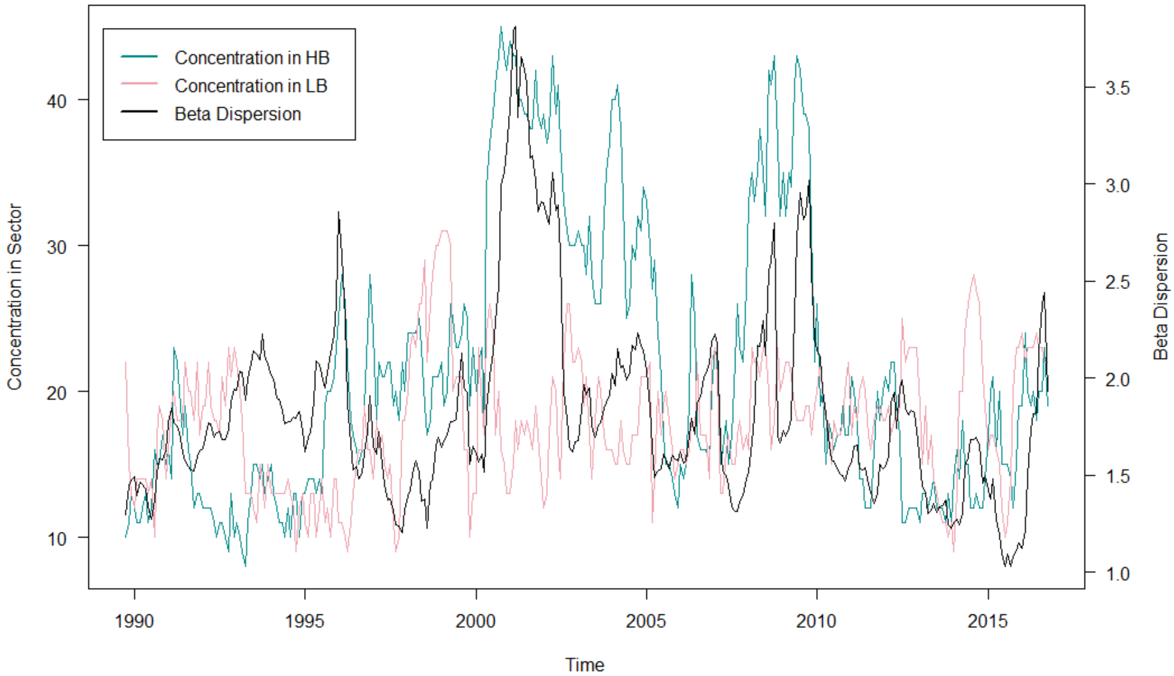

Figure 2 shows the time series of the beta dispersion and the concentration of the stocks in one specific sector in the high-beta quantile (HB) and the low-beta quantile (LB) from September 1989 to September 2016. The concentration is the absolute amount of stocks in the quantile that stem from the same sector. The S&P standard sector definition is used for this investigation, so that the stocks are allocated to 10 different sector (Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Materials, Real Estate, Technology, Utilities). The maximum concentration is 50 stocks as this is the maximum number of stocks in each quantile.

Figure 3: Weights of S&P 500 Index of Market-timing Strategy

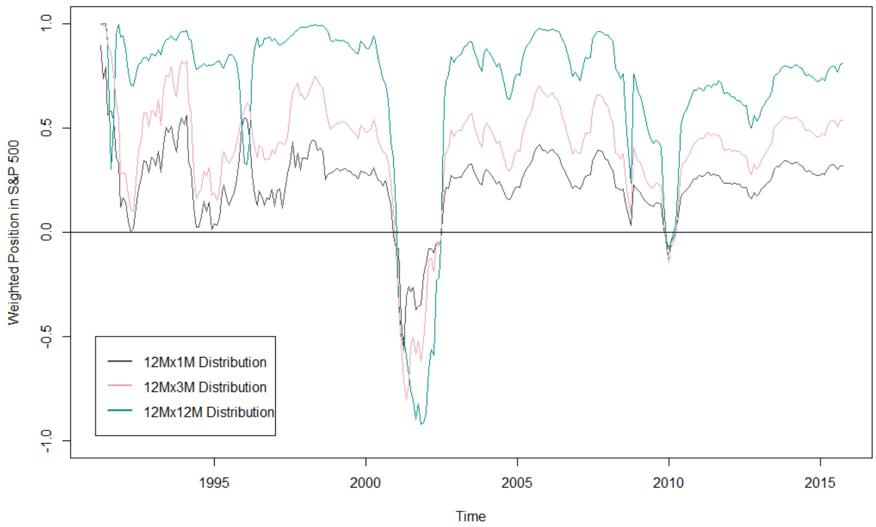

Figure 3 shows the time series of the weights of the position hold in the market (S&P 500 index) over the period September 1989 to September 2016. The weights are derived from the probability that the subsequent market return will be positive, calculated with the bivariate distribution of beta indicator and market return. This probability is standardized between -1 and 1 with $X_M = 2(p \,|\, I - 0.5)$. A weight of 1 means a 100% long position in the market and a weight of -1 is a 100% short position in the market.

Figure 4: Increase in Total Wealth for Market-timing Strategies

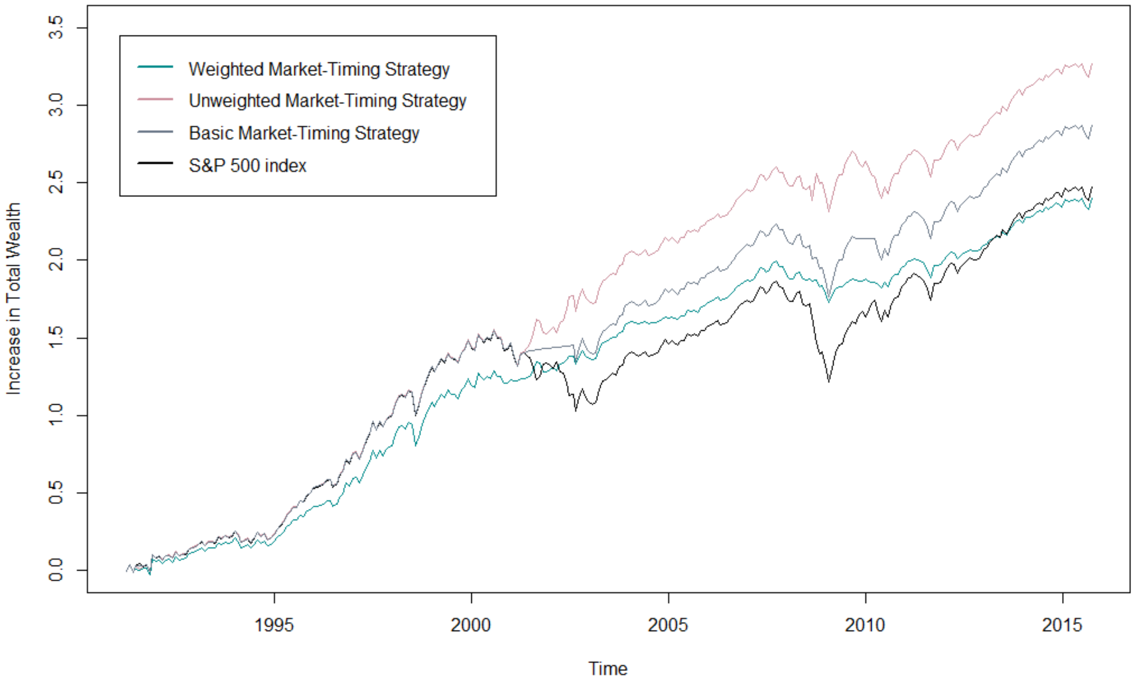

Figure 4 shows the increase in total wealth for the market-timing strategy based on the 12 months BD indicator and a passive buy and hold strategy of the S&P 500 as benchmark. The period from April 1992 to September 2016 is displayed. The increase in total wealth is the current earned return from the market timing strategy plus all previously earned returns accrued with the risk-free rate. The benchmark is a buy and hold strategy of the S&P 500 index. As all strategies are set up as self-financing strategies, the graphs start at zero. It should be pointed out that for the self-financing buy and hold strategy it is assumed that the initial amount invested in the S&P 500 is refunded at the risk-free rate on yearly basis.

Table 1: Decomposition of the Returns: Natural Hedge and Market Timing

Panel A: Beta Dispersion

		5 %-Quantile		**10 %-Quantile**	
ex ante Estimation	ex post Estimation	Market Timing	Natural Hedge	Market Timing	Natural Hedge
1 Month	1 Month	−0.0389	0.0892	−0.0332	0.0764
1 Month	3 Months	−0.0367	0.0238	−0.0294	0.0200
1 Month	12 Months	−0.0234	0.0037	−0.0193	0.0035
3 Months	1 Month	−0.0389	0.0283	−0.0311	0.0219
3 Months	3 Months	−0.0371	0.0268	−0.0301	0.0211
3 Months	12 Months	−0.0284	0.0000	−0.0242	0.0007
12 Months	1 Month	−0.0356	0.0097	−0.0298	0.0065
12 Months	3 Months	−0.0352	0.0071	−0.0298	0.0046
12 Months	12 Months	−0.0267	0.0001	−0.0238	0.0002

All values are annualized.

Panel B: High Beta

		5 %-Quantile		**10 %-Quantile**	
ex ante Estimation	ex post Estimation	Market Timing	Natural Hedge	Market Timing	Natural Hedge
1 Month	1 Month	−0.0348	0.0463	−0.0276	0.0401
1 Month	3 Months	−0.0316	0.0095	−0.0240	0.0084
1 Month	12 Months	−0.0211	0.0000	−0.0161	0.0005
3 Months	1 Month	−0.0349	0.0126	−0.0262	0.0084
3 Months	3 Months	−0.0320	0.0128	−0.0245	0.0094
3 Months	12 Months	−0.0240	−0.0034	−0.0190	−0.0020
12 Months	1 Month	−0.0301	0.0046	−0.0235	0.0010
12 Months	3 Months	−0.0293	0.0020	−0.0230	−0.0006
12 Months	12 Months	−0.0212	−0.0043	−0.0173	−0.0043

All values are annualized.

The table shows the contribution of the market-timing and the natural-hedge component to the one, three and twelve month returns of a corresponding portfolio (Panel A: beta-dispersion portfolio; Panel B: high-beta portfolio). Likewise, ex-ante betas are estimated for one, three and twelve months. The contributions are derived by decomposing the returns, following equation (4). Accordingly, the market-timing component is the covariance between the ex post market return and the estimated ex ante beta and the natural-hedge component is the covariance between the ex post market return and the difference between the estimated ex ante and realized ex post beta. The covariances are calculated from monthly data for the whole investigation period (September 1989 to September 2016).

Table 2: Results of Predictive Regressions

Panel A: 1 Month Market Returns

Beta Indicator		Intercept	P-Value	Coefficient	P-Value	R^2_{adj}
BD, 5 %	1 Month	0.0040	0.1169	−0.0161	0.0366	0.0075
	3 Months	0.0048	0.0527	−0.0231	0.0332	0.0174
	12 Months	0.0063	0.0078	−0.0244	0.0004	0.0209
BD, 10 %	1 Month	0.0041	0.1075	−0.0168	0.0344	0.0083
	3 Months	0.0051	0.0377	−0.0216	0.0361	0.0152
	12 Months	0.0065	0.0073	−0.0223	0.0005	0.0187
HB, 5 %	1 Month	0.0048	0.0576	−0.0256	0.0258	0.0137
	3 Months	0.0059	0.0121	−0.0324	0.0545	0.0216
	12 Months	0.0076	0.0005	−0.0376	0.0038	0.0237
HB, 10 %	1 Month	0.0049	0.0482	−0.0283	0.0298	0.0138
	3 Months	0.0061	0.0088	−0.0335	0.0646	0.0185
	12 Months	0.0075	0.0008	−0.0386	0.0037	0.0204

Panel B: 3 Month Market Returns

Beta Indicator		Intercept	P-Value	Coefficient	P-Value	R^2_{adj}
BD, 5 %	1 Month	0.0123	0.2720	−0.0471	0.0388	0.0256
	3 Months	0.0146	0.0749	−0.0683	0.0254	0.0536
	12 Months	0.0191	0.0107	−0.0722	0.0001	0.0637
BD, 10 %	1 Month	0.0127	0.2380	−0.0464	0.0422	0.0246
	3 Months	0.0154	0.0550	−0.0645	0.0306	0.0488
	12 Months	0.0196	0.0089	−0.0667	0.0001	0.0586
HB, 5 %	1 Month	0.0144	0.1461	−0.0722	0.0433	0.0393
	3 Months	0.0177	0.0185	−0.0921	0.0664	0.0603
	12 Months	0.0226	0.0020	−0.1099	0.0001	0.0694
HB, 10 %	1 Month	0.0149	0.1653	−0.0770	0.0632	0.0366
	3 Months	0.0183	0.0132	−0.0973	0.0833	0.0547
	12 Months	0.0225	0.0024	−0.1134	0.0003	0.0614

Panel C: 12 Month Market Returns

	Beta Indicator	Intercept	P-Value	Coefficient	P-Value	R^2_{adj}
BD, 5 %	1 Month	0.0541	0.2596	−0.1280	0.0594	0.0411
	3 Months	0.0601	0.1412	−0.2070	0.0688	0.1051
	12 Months	0.0734	0.1430	−0.2101	0.0393	0.1143
BD, 10 %	1 Month	0.0551	0.2597	−0.1272	0.0747	0.0401
	3 Months	0.0626	0.1207	−0.2012	0.0773	0.1019
	12 Months	0.0755	0.1537	−0.2032	0.0520	0.1159
HB, 5 %	1 Month	0.0599	0.1485	−0.1969	0.0396	0.0623
	3 Months	0.0692	0.0579	−0.2706	0.0702	0.1106
	12 Months	0.0823	0.0814	−0.3003	0.0313	0.1094
HB, 10 %	1 Month	0.0612	0.1534	−0.2084	0.0552	0.0573
	3 Months	0.0711	0.0530	−0.2904	0.0814	0.1038
	12 Months	0.0824	0.0981	−0.3167	0.0530	0.1014

The table shows the results of the predictive regressions with beta indicator as independent variable and the log-return of the S&P 500 index as dependent variable. Due to the calculation of the indicator, the regression incorporates 313 one, two and twelve month log-returns of the S&P 500 (Panel A, Panel B and Panel C). The indicator HB and BD are defined as the relative deviation of the current low respectively high-low beta from its mean, which is calculated over an extended window. Beta is estimated from daily returns over a formation period of one, three and twelve months and the indicator is based on the beta mean of the 5% and 10% quantile of the beta distribution. 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 corresponding lags to account for the overlapping periods.

Table 3: Results of Predictive Regressions with Additional Explanatory Variables

Panel A: 1 Month Market Returns

	Specification of Indicator	Intercept	Beta Indicator	DY	SR	CAY	AV	AC	$R^{2,iS}_{adj}$
BD, 5 %	1 Month	−0.0060	−0.0109	0.0054	0.0026	−0.0572	−0.1720	0.0375	0.0152
	3 Months	−0.0033	−0.0148	0.0045	0.0022	−0.0307	−0.1506	0.0291	0.0169
	12 Months	−0.0005	−0.0160	0.0030	0.0020	0.0101	−0.1595	0.0421	0.0192
BD, 10 %	1 Month	−0.0058	−0.0111	0.0053	0.0028	−0.0566	−0.1706	0.0379	0.0154
	3 Months	−0.0037	−0.0113	0.0042	0.0030	−0.0384	−0.1601	0.0393	0.0150
	12 Months	−0.0010	−0.0132	0.0028	0.0026	−0.0052	−0.1640	0.0486	0.0174
HB, 5 %	1 Month	−0.0060	−0.0163	0.0051	0.0023	−0.0558	−0.1581	0.0433	0.0174
	3 Months	−0.0031	−0.0203	0.0041	0.0015	−0.0346	−0.1437	0.0385	0.0191
	12 Months	0.0007	−0.0258	0.0027	0.0001	0.0056	−0.1554	0.0464	0.0219
HB, 10 %	1 Month	−0.0061	−0.0183	0.0051	0.0021	−0.0574	−0.1574	0.0442	0.0177
	3 Months	−0.0035	−0.0193	0.0041	0.0018	−0.0411	−0.1512	0.0446	0.0173
	12 Months	−0.0002	−0.0255	0.0029	0.0003	−0.0063	−0.1603	0.0515	0.0204

Panel B: 3 Month Market Returns

Specification of Indicator		Intercept	Beta Indicator	DY	SR	CAY	AV	AC	$R^{2,iS}_{adj}$
BD, 5 %	1 Month	−0.0201	−0.0310	0.0133	−0.0027	0.3299	−0.4681	0.1798	0.0642
	3 Months	−0.0102	−0.0507	0.0110	−0.0058	0.4231	−0.3787	0.1320	0.0744
	12 Months	0.0009	−0.0586***	0.0054	−0.0069	0.5795	−0.4004	0.1706	0.0866
BD, 10 %	1 Month	−0.0200	−0.0281	0.0127	−0.0015	0.3304	−0.4727	0.1905	0.0626
	3 Months	−0.0108	−0.0418	0.0100	−0.0036	0.4023	−0.4016	0.1592	0.0689
	12 Months	−0.0002	−0.0499**	0.0046	−0.0050	0.5305	−0.4125	0.1917	0.0806
HB, 5 %	1 Month	−0.0201	−0.0492	0.0126	−0.0042	0.3348	−0.4217	0.1917	0.0714
	3 Months	−0.0103	−0.0655	0.0096	−0.0072	0.4041	−0.3670	0.1708	0.0793
	12 Months	0.0036	−0.0889***	0.0048	−0.0129	0.5486	−0.3946	0.1913	0.0932
HB, 10 %	1 Month	−0.0204	−0.0518	0.0125	−0.0041	0.3293	−0.4272	0.1991	0.0703
	3 Months	−0.0112	−0.0659	0.0095	−0.0068	0.3870	−0.3818	0.1858	0.0757
	12 Months	0.0008	−0.0894**	0.0052	−0.0126	0.5104	−0.4097	0.2080	0.0884

Panel C: 12 Month Market Returns

Specification of Indicator		Intercept	Beta Indicator	DY	SR	CAY	AV	AC	$R^{2,iS}_{adj}$
BD, 5 %	1 Month	−0.0060	−0.1671***	0.0801*	−0.2761	3.0015***	−0.3632	−0.2032	0.2236
	3 Months	0.0510	−0.2886***	0.0680*	−0.2957	3.5350***	0.1691	−0.5032	0.2989
	12 Months	0.0843	−0.2603**	0.0424	−0.2880*	4.1021***	−0.1335	−0.1589	0.2992
BD, 10 %	1 Month	−0.0051	−0.1590***	0.0777	−0.2713	3.0069***	−0.3689	−0.1666	0.2187
	3 Months	0.0548	−0.2614***	0.0619	−0.2879	3.4632***	0.1198	−0.4114	0.2806
	12 Months	0.0848	−0.2334**	0.0376	−0.2817*	3.9317***	−0.1578	−0.0827	0.2853
HB, 5 %	1 Month	−0.0084	−0.2269***	0.0745*	−0.2773	3.0164***	−0.2076	−0.0784	0.2420
	3 Months	0.0395	−0.3168**	0.0609	−0.2938	3.3549**	0.0840	−0.1968	0.2873
	12 Months	0.0809	−0.3433**	0.0429	−0.3047*	3.8315***	−0.1953	−0.0204	0.2885
HB, 10 %	1 Month	−0.0101	−0.2389***	0.0743*	−0.2772	2.9911***	−0.2328	−0.0441	0.2371
	3 Months	0.0373	−0.3303**	0.0600	−0.2939	3.2835**	0.0407	−0.1392	0.2769
	12 Months	0.0723	−0.3534**	0.0440	−0.3050*	3.7011***	−0.2414	0.0384	0.2785

The table shows the results of the predictive regressions with six independent variables and the log-return of the S&P 500 index as dependent variable. The regression equation has the following independent variables: Beta indicator, 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 313 one, three and month log-returns of the S&P 500. The indicator HB and BD are defined as the relative deviation of the current low respectively high-low beta from its mean, which is calculated over an extended window. Beta is estimated from daily returns over a formation period of one, three and twelve months and the indicator is based on the beta mean of the 5% and 10% quantile of the beta distribution. The in-sample, 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 corresponding lags to account for the overlapping periods.
Significance level: *** 0.01, ** 0.05, * 0.1.

Table 4: Results of static out-of-sample R^2

Specification		1 Month	3 Months	12 Months
BD, 5 %	1 Month	−0.0107	−0.0252	−0.0551
	3 Months	−0.0319	0.0009	0.0411
	12 Months	0.0106	0.0596	0.0396
BD, 10 %	1 Month	−0.0073	−0.0208	−0.0617
	3 Months	0.0727	0.0119	0.0321
	12 Months	0.0139	0.0543	−0.1829
HB, 5 %	1 Month	−0.0074	−0.0194	0.0012
	3 Months	−0.0315	0.0035	0.0677
	12 Months	0.0062	0.0606	0.0979
HB, 10 %	1 Month	−0.0032	−0.0147	−0.0007
	3 Months	−0.0269	0.0106	0.0727
	12 Months	0.0059	0.0588	0.0616

This table shows out-of-sample R^2 for all introduced indicators for the one, three and twelve months log market excess return. The out-of-sample R^2 is calculated via equation 8. The forecasts are estimated by using the predictive regression coefficients from the first subsample period. A positive out-of-sample R^2 indicates a superior forecasting performance of the indicator compared to the historical mean of the market return, one of the most stringent benchmarks.

Table 5: Results of dynamic out-of-sample R^2

	Specification	1 Month	3 Months	12 Months
BD, 5 %	1 Month	0.0210	0.0212	0.0400
	3 Months	0.0349	0.0634	0.1085
	12 Months	0.0394	0.0629	0.1182
BD, 10 %	1 Month	0.0222	0.0233	0.0393
	3 Months	0.0357	0.0578	0.1049
	12 Months	0.0380	0.0638	0.1212
HB, 5 %	1 Month	0.0263	0.0347	0.0630
	3 Months	0.0383	0.0714	0.1130
	12 Months	0.0455	0.0744	0.1120
HB, 10 %	1 Month	0.0290	0.0362	0.0581
	3 Months	0.0389	0.0653	0.1067
	12 Months	0.0444	0.0703	0.1041

This table shows out-of-sample R^2 for all introduced indicators for the one, three and twelve months log market excess return. The out-of-sample R^2 is calculated via equation 8. The forecasts are estimated by using the predictive regression coefficients from an dynamically enlarged time series of indicator and market return, which includes the whole period prior to the current observed indicator. This means for every month the regression parameters are estimated based on all previous data. A positive out-of-sample R^2 indicates a superior forecasting performance of the indicator compared to the historical mean of the market return, one of the most stringent benchmarks.

Table 6: Average Returns, Standard Deviations and Sharpe Ratios of Market-Timing Strategies

Panel A: Basic Market-Timing Strategy

Specification		Av. Return	SD	SR	TM	HM
BD, 3M	1 Month	0.0779	0.1323	0.5890	1.3070***	0.1890***
	3 Months	0.0864	0.1322	0.6537	1.6496***	0.2653***
	12 Months	0.0706	0.1440	0.4902	−0.1353	−0.0318
BD, 12M	1 Month	0.0854	0.1351	0.6322	0.2908	0.1247**
	3 Months	0.0854	0.1351	0.6322	0.2909	0.1247**
	12 Months	0.0873	0.1352	0.6456	0.2758	0.1216**
HB, 3M	1 Month	0.0712	0.1294	0.5505	1.1622***	0.1660**
	3 Months	0.0880	0.1291	0.6815	1.4952***	0.2532***
	12 Months	0.0752	0.1366	0.5501	1.2781***	0.1529***
HB, 12M	1 Month	0.0898	0.1299	0.6915	1.8263***	0.3200***
	3 Months	0.0898	0.1299	0.6915	1.8263***	0.3200***
	12 Months	0.0877	0.1330	0.6592	1.6767***	0.2749***

Panel B: Unweighted Market-Timing Strategy

Specification		Av. Return	SD	SR	TM	HM
BD, 3M	1 Month	0.0818	0.1443	0.5666	2.6139***	0.3781***
	3 Months	0.0987	0.1434	0.6881	3.2992***	0.5306***
	12 Months	0.0671	0.1450	0.4629	−0.2707	−0.0636
BD, 12M	1 Month	0.0967	0.1436	0.6737	0.5817	0.2494**
	3 Months	0.0967	0.1436	0.6737	0.5818	0.2494**
	12 Months	0.1004	0.1433	0.7007	0.5517	0.2432**
HB, 3M	1 Month	0.0684	0.1449	0.4720	2.3243***	0.3321**
	3 Months	0.1019	0.1433	0.7114	2.9903***	0.5064***
	12 Months	0.0762	0.1446	0.5272	2.5562***	0.3058***
HB, 12M	1 Month	0.1056	0.1430	0.7381	3.6525***	0.6400***
	3 Months	0.1056	0.1430	0.7380	3.6527***	0.6401***
	12 Months	0.1013	0.1433	0.7066	3.3534***	0.5497***

Panel C: Weigthed Market-Timing Strategy

Specification		Av. Return	SD	SR	TM	HM
BD, 3M	1 Month	0.0217	0.0363	0.5971	0.5416***	0.0899***
	3 Months	0.0398	0.0613	0.6491	0.8672***	0.1610***
	12 Months	0.0661	0.1017	0.6501	1.1842***	0.2145***
BD, 12M	1 Month	0.0225	0.0381	0.5888	0.2308	0.0573
	3 Months	0.0432	0.0650	0.6648	0.4989*	0.1301**
	12 Months	0.0787	0.1070	0.7357	1.1886***	0.2864***
HB, 3M	1 Month	0.0212	0.0343	0.6203	0.7460***	0.1200***
	3 Months	0.0378	0.0563	0.6704	1.1036***	0.1894***
	12 Months	0.0630	0.0970	0.6494	1.4934***	0.2509**
HB, 12M	1 Month	0.0218	0.0365	0.5966	0.4430***	0.0905**
	3 Months	0.0416	0.0616	0.6753	0.8078***	0.1766***
	12 Months	0.0724	0.0990	0.7316	1.5047***	0.3118***

The table shows the average returns, standard deviations(SD), Sharpe ratios(SR), Treynor-Mazuy coefficient (TM) and the difference of the coefficients from the Henriksson-Merton market-timing test (HM) of the basic, unweighted and weighted market-timing strategies (accordingly Panel A, Panel B and Panel C). All values are annualized. Conditional on the current beta indicator(BD and HB, both estimated with three respectively 12 month), 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 beta indicator. All parameters of the bivariate normal distribution are calculated over an extending window preceding the investment date, so only out-of-sample information is used. The basic strategy invests in the market, if the probability that the subsequent market return will be positive is greater than 50%, otherwise it invests in the risk-free instrument. The unweighted strategy has a long position in the market, if the probability that the subsequent market return will be positive is greater than 50% and otherwise a short position in the market. For the weighted strategy the position in the market is not 100% percent of the wealth of the investor but a weighted short or long position, conditioning on the probability. Weights are standardized to fall in the range between -1 and 1. Irrespectively of the length for the calculation of the market return, the strategies rebalance the holdings every month to account for the most current information.