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Beta dispersion and market timing

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Non-technical summary

Research Question

The beta dispersion, which is the spread of betas on a stock market, can be interpreted as a measure of market vulnerability. If this idea can be confirmed, then the level of beta dispersion can indicate the ability of a market to cope with systematic shocks. Based on the empirical beta dispersion observed in the US equity market, this study attempts to develop a reasonable measure of beta dispersion.

Contribution

The study contributes by being the first to introduce and analyze the beta dispersion as vulnerability measure of the market. An economic justification for this phenomenon as well as a comprehensive in-sample and out-of-sample analysis are provided. It is shown that beta dispersion is able to complement well-known predictors of the market risk premium. In addition, the study contributes toward the improvement of timing strategies by introducing distributional regressions to the implementation of portfolio strategies. This new approach leads to a strong reduction in the return volatility of the resulting timing strategies.

Results

The applicability of beta dispersion as vulnerability measure of the market can be confirmed broadly predominately with the help of predictive regressions and out-of-sample R^2. A high beta dispersion can indicate a distinct market downturn. Further, a focused analysis of the cascading effect supports the economic idea in more detail. Multiple predictive regressions approve that beta dispersion extends the already known predictors of the market risk premium. Hence, it can be stated that beta dispersion improves the forecasting accuracy of the future market return. In addition, distributional regressions are applied successfully to implement timing strategies. This approach improves the risk-return characteristics of the strategies clearly, especially by reducing the return volatility.

Nichttechnische Zusammenfassung

Fragestellung

Die Beta-Dispersion, also die Ausdehnung der Betafaktoren an einem Aktienmarkt, kann als Verletzlichkeitsmaß des Marktes interpretiert werden. Insofern diese Annahme zutrifft, gibt die Höhe der Beta-Dispersion Auskunft darüber, wie gut ein Markt einen systematischen Schock verkraften kann. Die vorliegende Studie versucht mit Daten des US-Aktienmarktes ein aussagekräftiges Maß für die Beta-Dispersion zu entwickeln.

Beitrag

Die Studie beschreibt und analysiert erstmalig die Beta-Dispersion als Verletzlichkeitsmaß des Marktes. Es wird eine ökonomische Begründung für dieses Phänomen entwickelt und eine umfassende "in-sample" und "out-of-sample" Untersuchung durchgeführt. Es zeigt sich, dass die Beta-Dispersion bekannte Maße zur Vorhersage der Marktrisikoprämie komplementieren kann. Zusätzlich trägt die Studie dazu bei, sog. "Timingstrategien" wirksamer zu implementieren, indem diese auf Wahrscheinlichkeitsverteilungen, die aus Verteilungsregressionen geschätzt wurden, basiert werden. Dieser neue Ansatz führt zu einer deutlichen Verringerung der Volatilität der hieraus resultierenden Strategien.

Ergebnisse

Die Eignung der Beta-Dispersion als Verletzlichkeitsmaß eines Marktes kann weitestgehend bestätigt werden. Eine hohe Beta-Dispersion kann auf einen erheblichen Markteinbruch hindeuten. Eine zielgerichtete Analyse des Kaskadeneffekts unterstützt darüber hinaus die ökonomische Idee hinter der Beta-Dispersion. Multiple Regressionen zur Bestimmung der Prognosegüte bestätigen zudem, dass die Beta-Dispersion bereits bekannte Maße zur Vorhersage der Marktrisikoprämie ergänzt. Die Beta-Dispersion trägt damit zu einer höheren Vorhersagegenauigkeit der Marktrisikoprämie bei. Schließlich kann gezeigt werden, dass Verteilungsregressionen erfolgreich beim Aufsetzen von Timingstrategien eingesetzt werden können. Dieser Ansatz verbessert deutlich die Risiko-Rendite-Eigenschaften der Strategien, insbesondere da die Volatilität reduziert werden kann.

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Beta Dispersion and Market Timing*

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Abstract

The beta dispersion, which is the spread of betas on a stock market, can be interpreted as a measure of market vulnerability. This study examines the economic idea of the beta dispersion and its application as a market return predictor. Based on the empirical beta dispersion observed in the US equity market, the study develops measures to predict future market returns. These dispersion measures have substantial predictive power for future market movements. Moreover, I show that the informational content of beta dispersion can be successfully exploited by market timing strategies with the help of distributional regressions. This is an innovative application of this novel way of modeling the relationship between multiple variables and appears to be quite useful for timing strategies.

Keywords: beta dispersion, market return predictability, systematic risk, predictice regression, distributional regression, market timing, investment strategies

JEL classification: G10, G11, G17.

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1 Introduction

The prediction of the market risk premium has been receiving considerable attention from both academics and investors. Over the past decades, a growing number of studies have developed macroeconomic and technical indicators that can forecast the market risk premium, at least to a certain extent (e.g., Ang and Bekaert (2007); Campbell and Thompson (2008); Rapach and Zhou (2013); Neely, Rapach, Tu, and Zhou (2014)). The precise prediction of future returns is almost impossible, but even reliable predictions of the sign of the future return can be very valuable to different stakeholders. It helps investors to allocate their assets, it allows for the cost of capital calculation in business valuation, and it can support supervisors in monitoring the financial stability of markets. This study introduces beta dispersion as a novel and successful predictor of the market return and provides a coherent economic explanation on this measure. The study also presents an innovative empirical implementation of a market timing strategy to show that the predictions are useful to investors. Besides this investment perspective, the introduced beta dispersion captures a facet of the systemic risk, which may contribute toward the quantification of financial stability by supervisors.

The beta dispersion, which is defined as the time-varying spread of stock betas, can be interpreted as a vulnerability measure of a market, particularly, measuring the magnitude of a downturn. The more the betas are dispersed, that is, the more the number of stocks with extremely high and low betas that are traded in a market, the more inhomogeneously the stocks will be affected by and react to a systematic shock. These market-wide shocks are inherently precarious for companies with high betas because such companies are hit seriously. Consequently, these shocks cause a sharp decline in the fundamentals of companies (e.g., sales and profit, among others), thereby increasing insolvency risks. Moreover, the collapse of these companies might trigger contagion effects for comparable and interconnected companies (e.g., suppliers), and this scenario might lead to an increase in the level of financial distress risk in the whole market. This can be inferred to as an endogenous shock caused by an initial exogenous shock and can be interpreted as the subsequent systematic shock. In comparison, a market with a narrow beta dispersion would be more likely to experience only the initial systematic shock. Therefore, beta dispersion should provide a measure for a market's vulnerability to systematic shocks. It must indicate the probability and severity of the expected market decline, and, consequently, should be able to predict future market returns. In this sense, beta dispersion can be linked to financial stability. If beta dispersion is a valuable predictor of the severeness of market downturns, then the level of beta dispersion can indicate the ability of a market to cope with systematic shocks. Therefore, beta dispersion can also serve as a measure for systemic risks and the stability of the financial market.

The study contributes by being the first to introduce and analyze the beta dispersion as vulnerability measure of the market. An economic justification for this phenomenon as well as an in-depth analysis are provided. Besides, a reasonable measure for beta dispersion as an indicator of the vulnerability of a market is derived.

This measure is studied and quantified empirically in a comprehensive way. Predictive regressions confirm the ability of beta dispersion to predict the future market return. The results can be verified by controlling for other well-known market return predictors, such as the cay factor, dividend yield, and short rate. Importantly, beta dispersion is also a valuable predictor of market return out-of-sample. It can clearly compete with and extend the already known predictors of the market risk premium. Hence, it can be stated that beta dispersion improves the forecasting accuracy of the future market return.

The study also contributes toward the improvement of timing strategies by introducing distributional regressions to the implementation of portfolio strategies. Beta dispersion is used as conditional information to estimate the distribution of the future market return. The probability that the market return will be positive is used as a decision criterion whether to invest in the market. This approach leads to a strong reduction in the return volatility of the resulting timing strategies and beats the benchmarks in terms of return per unit of risk. The study shows that investors can profit from the predictive relationship between beta dispersion and market return. It is demonstrated that the concept of distributional regressions is promising in the financial context and can be modified to other models of prediction for enhancing timing strategies.

First, this study is related to the literature on the prediction of market returns and the equity premium (among others Lettau and Ludvigson (2001); Goyal and Welch (2003); Lewellen (2004); Avramov and Chordia (2006); Ang and Bekaert (2007); Spiegel (2008); Cochrane (2008); Campbell and Thompson (2008); Kellard, Nankervis, and Papadimitriou (2010); Pollet and Wilson (2010); Rapach, Strauss, and Zhou (2010); Faria and Verona (2018)). Welch and Goyal (2008) provide a comprehensive overview of the most common macroeconomic predictors of the market return. They conclude that most predictors perform poorly out-of-sample and would not help an investor to profit from forecasts. Their analysis concludes that the historical mean of the market return seems to be the most stringent and successful predictor. Neely et al. (2014) as well as Baetje and Menkhoff (2016) compare macroeconomic predictors to technical indicators typically used by practitioners and reason that the latter perform just as well as macroeconomic predictors in- and out-of-sample. My study adds to the literature by demonstrating that beta dispersion contains unregarded information about future market returns and can successfully predict the market return in- and out-of-sample. Additionally, the study adds beta dispersion to the existing range of predictors of market return increasing the predictive accuracy of the market return.

As the definition of beta dispersion is inspired by the concept of return dispersion, this study is related to the literature on return dispersion. The return dispersion is a measure of the cross-sectional variability in stock returns at a certain point in time. A high return dispersion occurs in an economic recession and is positively related to the volatility level of the market and the momentum factor (Bekaert and Harvey, 2000; Christie and Huang, 1995; Connolly and Stivers, 2003; Stivers, 2003; Connolly and Stivers, 2006; Jiang, 2010). Maio (2016) explicitly studies return dispersion as the predictor of the future market return and confirms this connection. Contrarily, this study focuses on the cross-sectional standard deviation of betas, which resembles return dispersion, but explicitly focuses on systematic risk. Additionally, the interpretation of beta dispersion as a market return predictor differs from that of return dispersion. The beta dispersion is constructed to be a measure of systemic imbalances in the market, and, therefore, predicts stumbles of the market, while return dispersion is an alternative measure of volatility. My study shows that beta dispersion and return dispersion complement each other and can co-exist in predictive analyses.

Finally, this study is related to market timing strategies and their performance evaluation, which have been extensively discussed in the literature (Jeffrey, 1984; Pfeifer, 1985; Bauer Jr and Dahlquist, 2001; Kostakis, Panigirtzoglou, and Skiadopoulos, 2011; Neuhierl and Schlusche, 2011; Hallerbach, 2014; Dichtl, Drobetz, and Kryzanowski, 2016). To determine the allocation between stock and money market, technical, macroeconomic, and sentiment indicators have been introduced and tested for their ability to time the market (Brock, Lakonishok, and LeBaron, 1992; Shen, 2003; Chen, 2009; Feldman, Jung, and Klein, 2015). Unlike stock selection strategies, market timing strategies try to achieve an outperformance only by driving investment in the market portfolio during market upturns and prevent investments during market downturns without any selection of single assets (Sharpe, 1975). This study introduces a new possibility of differentiating between upturns and downturns with the help of distributional regression and chooses a careful investment approach that also considers the probability of a positive market return. The introduced strategies outperform the benchmark, even when the performance is accounted for general shortcomings of market timing strategies (Zakamulin, 2014).

The remainder of this paper is structured as follows. In Section 2, the economic idea why beta dispersion is a measure of market vulnerability is developed and the methodology how to measure the beta dispersion is described. Section 3 presents the data. Section 4 displays the empirical results, consisting of descriptive statistics, statistical analyses, and market timing strategies and their performance. Section 5 concludes the paper.

2 Beta Dispersion as a Measure of Market Vulnerability

2.1 Economic Idea

The spread between high betas and low betas on a market is defined as beta dispersion. In other words, beta dispersion refers to the deviation of the betas' distribution from its mean at a particular point in time. By definition, the market beta equals one and, accordingly, betas of all stocks in that market have to group around this weighted mean. Until now, not much attention has been paid to how widespread or concentrated the individual betas are and whether this has any impact on the stability of the market and, consequently, on the market return.

To illustrate the economic idea behind the beta dispersion as a measure for market vulnerability, two markets that are completely identical, except for their specific beta dispersion, can be considered. On market A, the beta dispersion is narrow, that is, the betas of all the stocks are clotted closely around one. Contrarily, on market B, the beta dispersion is large, and the betas are widespread, meaning that some stocks have beta values close to zero and some have extremely high betas. Now, both markets experience an identical systematic exogenous shock. All the stocks in market A should react very similarly because the companies are affected rather alike by the shock. Hence, this should be reflected in the stock prices as the shock hits all the stocks nearly equally strongly owing to their more or less equal betas. On market B, stocks with a low beta, close to zero, hardly react to the systematic shock, because the companies are hardly affected in their business operations by the shock. Contrarily, stocks with a high beta react intensely, indicating that for such companies the systematic shock might threaten their businesses in a way which jeopardizes their economic survival. This increases the risk of financial distress in market B. Since most of the firms in a market are interconnected, the collapse of endangered high-beta firms might spill over to those firms that are strongly connected to them. The spillover spreads via all possible transmission channels. This includes physical, legal, and intangible ways, such as loss of confidence. These contagion effects trigger an endogenous second round systematic shock (the risen level of distress risk) on market B and can lead to an overall market downturn if this spillover, or better yet, cascading effect proceeds. This makes beta dispersion an indicator of the vulnerability of the market and represents systemic risk characteristics of the market.

The larger the beta dispersion of a specific market, the higher the likelihood of a subsequent second-round shock following an initial exogenous shock. Therefore, a market with a high beta dispersion is more likely to be financially unstable compared to a market with a relatively narrower beta dispersion. If the beta dispersion is high, the market is especially endangered towards systematic shocks. With a high beta dispersion, the probability rises that a moderate systematic shock evolves and leads to a severe market decline due to the cascading effect. For example, during the subprime crisis, the financial institutions often exhibited extremely high betas. Even a moderate market shock can cause serious problems for such high-beta firms and affect the entire financial system because of the interconnectedness of financial institutions. Large beta dispersion and the concentration of high-beta companies within a specific industrial sector eventually lead to a severe overall market downturn when compared to a market with a more moderate beta dispersion. In this context, the beta dispersion can be considered a measure for the vulnerability of the market stability. Contrarily, such a strong downturn would be less likely if there were no stocks with extremely high betas or the high-beta stocks were less industrially concentrated and interconnected. This would make the cascading effect less pronounced. If this conclusion applies, then the beta dispersion would not only be a measure for the vulnerability of a market and a predictor of the magnitude of future market downturns but also a promising approach of extending systemic risk measures.

The beta dispersion can and should be clearly differentiated from the return dispersion in two ways. First, the beta dispersion is suitable as an explicit measure for market vulnerability and it focuses on the systematic component of stocks. The return dispersion can be understood as a model-free measure of market volatility. Angelidis, Sakkas, and Tessaromatis (2015) show that return dispersion can predict the expected market return as it is an alternative specification of market risk. The beta dispersion has a different economic idea and should explicitly predict the extent of market downturns. The heterogeneous behavior of companies and their business operations is accompanied with different sensitivities to systematic shocks, which is highlighted by this definition. The beta dispersion is better suited to measure this heterogeneity in stock returns because the beta standardizes the diverse return movements and makes them comparable in terms of sensitivity toward systematic risk. It must be noted that a large return dispersion can be caused by idiosyncratic risk and, thus, can be much less informative about market vulnerability, which is of special interest in this study. The idea that a cascading effect pushes the market into a crisis seems to be more straightforward when reducing the source of risk to systematic shocks.

2.2 Measures of Beta Dispersion

Based on the economic explanation, for the subsequent analysis, it is crucial to reflect how the beta dispersion can be measured to depict the economic idea and not waste any information. The first notion to measure the spread between high and low betas on the market is to compare the tails of the beta distribution in terms of extreme quantiles. Besides this, a reasonable definition of beta dispersion can be derived based on the return dispersion, which is, as described, the cross-sectional deviation of stock returns from their value-weighted mean. It quantifies the heterogeneity of stock returns at a certain point in time. In this sense, a beta dispersion will be represented by the cross-sectional deviation of betas from their mean and capture how heterogeneous the betas are at a certain point in time. Both definitions of beta dispersion combine a cross-sectional and a time dimension of market properties and aggregate them into a single measure of market vulnerability. Each measure emphasizes a specific feature of beta dispersion. While the first approach concentrates on the stocks that are most endangered following the economic idea of the beta dispersion, the second approach considers all the stocks in a market and, therefore, all possible information. Hence, both measures are defined and studied.

Both measures of beta dispersion are calculated based on the estimated betas of all stocks. The first approach measures the current difference between the mean beta of the high-beta quantile $\bar{\beta}_t^{High}$ (90%-quantile) and the mean beta of the low-beta quantile $\bar{\beta}_t^{Low}$ (10%-quantile) of all constituent stocks of the market ranked by their beta (compare Equation 1):

$$QBD_t = \bar{\beta}_t^{High} - \bar{\beta}_t^{Low}. \tag{1}$$

The second approach measures the value-weighted as well as the equal-weighted square root squared deviation of all betas from their mean, which is formally defined in Equation 2:

$$BD_t = \sqrt{\sum_{i=1}^{n} \left(w_{i,t} \cdot \beta_{i,t} - \sum_{i=1}^{n} (w_{i,t} \cdot \beta_{i,t}) \right)^2}. \tag{2}$$

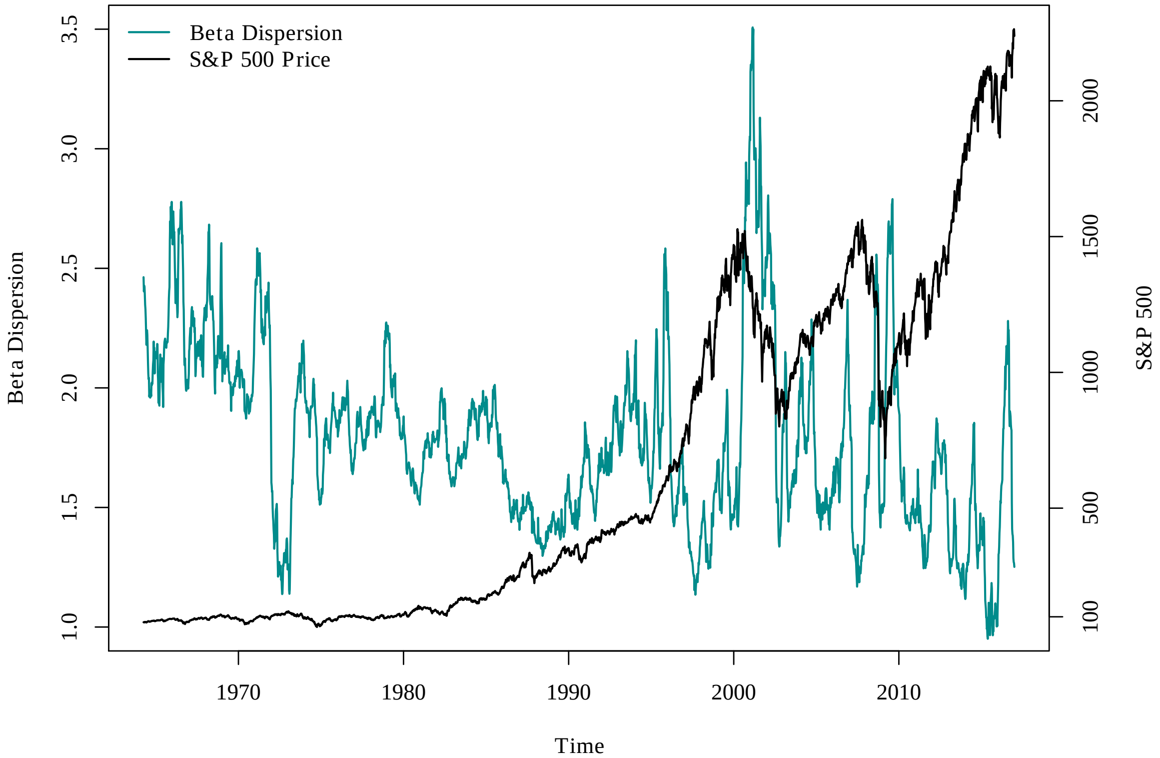
In this analysis $\beta_{i,t}$ is the estimated beta of stock i and $w_{i,t}$ is the value- or equal-weighted share of stock i in the market. The value-weighted version gives additional impact to the large stocks in the market. However, large firm-size does not automatically indicate that the company is highly interconnected with other firms, which is vital to the idea of beta dispersion. The equal-weighted version of the Equation 2 only focuses on the extent to which the betas are widespread, independently of other firm characteristics.

3 Data

The empirical analyses on beta dispersion are based on daily stock prices and market values of the S&P 500 Index and its constituents from April 1964 to December 2016. The data source for the stock data is the Wharton Research Data Service (WRDS), and the period is constrained by the availability of detailed information on the constituents of the S&P 500. In addition, the industry of each stock in the S&P 500 Index is needed. To classify the stocks, the S&P standard sector definition is used to ensure that the stocks are allocated to ten different, broad sectors including consumer discretionary, consumer staples, energy, financials, healthcare, industrials, materials, real estate, technology, and utilities. The focus on 500 highly liquid stocks is advantageous as it ensures the availability of the daily price data, which, in turn, ensures an appropriate beta estimation. Moreover, the availability of highly liquid exchange-traded funds (ETFs) on the S&P 500 Index facilitate easy trading the market, which will be crucial to the market timing strategy at a later stage. This also ensures the implementation of the timing strategies at relatively low transaction costs. As the 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), which is obtained from Martin Lettau's website, dividend yield of the S&P 500 Index (from WRDS), and volatility index (VIX) (accessed via Datastream) are needed. Further the aligned sentiment index (Huang, Jiang, Tu, and Zhou, 2015) used is provided by Guofu Zhou's website. Additional variables are calculated based on the described data.[1]

[1] A precise description of the additional variables and their calculation can be found in Appendix A.1.

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



Note: This figure shows the time series of beta dispersion and the level of the S&P 500 Index from the period April 1964 to December 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.

Betas are estimated with different rolling windows from daily returns over 3, 6, 12, and 36 months. These window lengths ensure that sufficient observations are available to estimate reliable betas. The estimates are calculated at the end of each month starting in April 1964 and ending in December 2016. These betas are used to calculate the different approaches to measure the beta dispersion as described in the previous section.

4 Empirical Implementation and Results

4.1 Empirical Description of the Beta Dispersion

A visual analysis of beta dispersion and market performance can give a basic understanding of the underlying predictive relationship. In order to visualize the economic idea, Figure 1 shows the price development of the S&P 500 Index, representing the market in this study, and the beta dispersion in this market.

In this figure, the beta dispersion is calculated with the quantile approach, following Equation 1. This figure supports the hypothesis that beta dispersion can be interpreted as a vulnerability measure and the economic idea seems to hold. The beta dispersion had been on an exceptionally high level on previous occasions of major market downturns. This was particularly noticeable around the dotcom bubble in 2000 and was less pronounced from 2008 onwards. The examination of separate time series of the 90% quantile and the 10% quantile of beta distribution leads to the conclusion that the variation of the beta dispersion is mainly caused by variations in the high-beta quantile. The variation of the 10% quantile (low-beta quantile) is relatively narrow and stable over the sampled period. Contrarily, the variability of the 90% quantile (high-beta quantile) is remarkable. This corresponds to the economic idea that the cascading effect is caused by the stumbling of the high-beta companies.

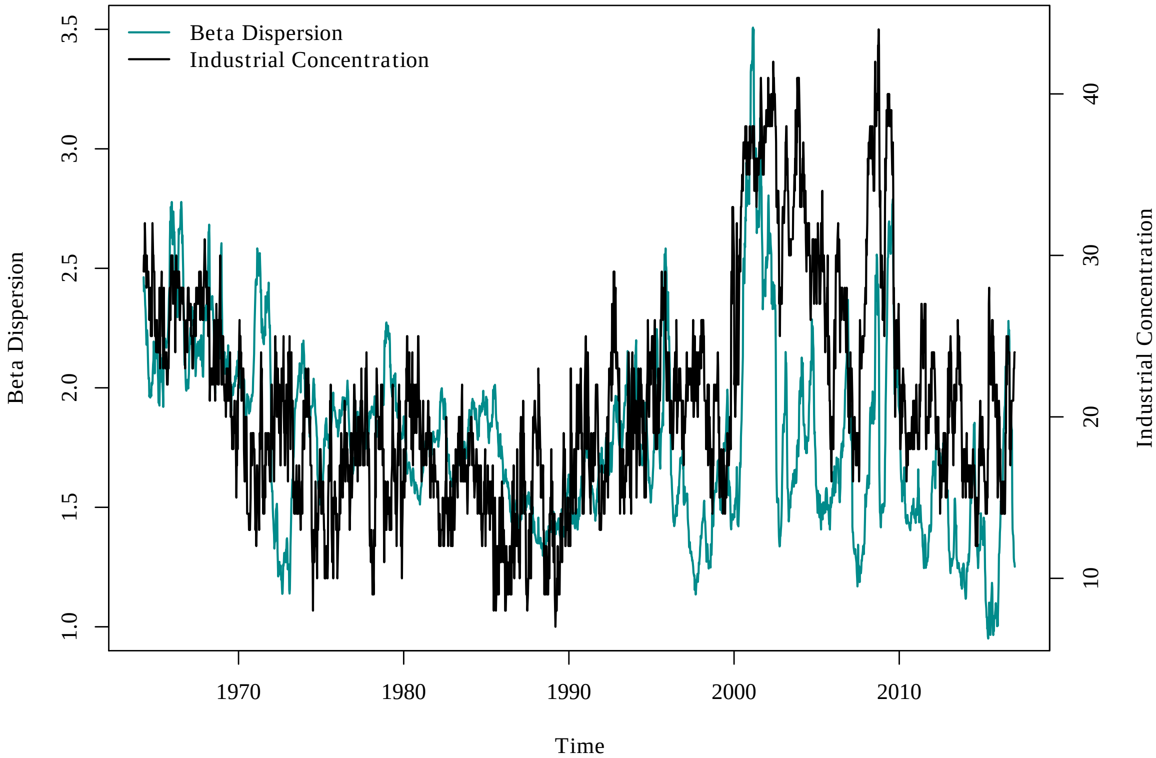
The effect of a second endogenous shock should be more pronounced if most of the stocks with high betas are operating within the same industrial sector. A closer look is now taken at the high-beta stocks. If the industry-specific concentration in the high-beta quantile coincides with a high beta dispersion, then the cascading effect on other companies in different industrial sectors would be intensified as there will be an increase in the bankruptcy risk of not only one company but of the whole sector. Figure 2 shows that the industry-specific concentration of high-beta stocks increases prior to market downturns and also slightly in advance of increases in the beta dispersion. This can be seen in the dotcom bubble of 2000 and the subprime crisis of 2008. The concentration is measured as the maximum absolute number of stocks from the same sector included in the high-beta quantile at a certain point in time.

In 2001, a maximum of 45 out of 50 stocks belonged to the same industrial sector. The sectors in which the stocks were concentrated were those that were hit by the crisis first. Contrary to the high-beta quantile, the industrial concentration of stocks in all other quantiles is rather stable and, by far, not as highly concentrated as in the high-beta quantile. The imbalance was due to the technology stocks before the dotcom bubble and financial sector stocks before the subprime crisis. These findings corroborate the hypothesis why the second endogenous shock is extensive if an initial systematic exogenous shock simultaneously and strongly hits a whole industrial sector. A high beta dispersion combined with a high industrial concentration seems to be a strong measure for the vulnerability of a market. This means systematic shocks cannot be absorbed easily by this market.

4.2 Predicting Market Returns – In-sample Evaluation

Predictive regressions are typically conducted to investigate and quantify an assumed predictive relationship. The dependent variable, here the log excess return of the market $R_{M,t}$, is regressed on a lagged explanatory or better predictive variable P_{t-1}. The general form of this linear regression is shown in Equation 3 below:

Figure 2: Beta Dispersion and the Concentration of Stocks in One Sector



Note: This figure shows the time series of beta dispersion and the concentration of the stocks in one specific sector in the high-beta decile from April 1964 to December 2016. The concentration comprises the absolute amount of stocks in the quantile that stem from the same sector. The S&P standard sector definition is used for this classification to ensure that the stocks are allocated to 10 different sectors (consumer discretionary, consumer staples, energy, financials, healthcare, industrials, materials, real estate, technology, and utilities). The maximum concentration is 50 stocks due to the construction of deciles.

$$R_{M,t} = \alpha + \sum \beta_{P_i} P_{i,t-1} + \varepsilon_t, \tag{3}$$

with β_{P_i} is the coefficient of predictive variable i, and ε_t being the disturbance term of the regression. This form of analysis is also referred to as in-sample prediction because the whole data sample is used to estimate the regression parameters. Predictive regressions face statistical particularities that have to be respected. If the dependent and predictive variables are both calculated from the same data (e.g., asset prices), then the autocorrelation in the ε_t can be induced because the data point at the split between $t-1$ and t is included in the calculation of both variables (Stambaugh, 1999). Another potential source of artificial autocorrelation and, thus, biased estimators, is a dependent variable calculated over more than one period. These problems can be solved by bootstrapping and simulation of critical test statistics (Bollerslev, Tauchen, and Zhou, 2009; Bollerslev, Marrone, Xu, and Zhou, 2014) and by following the correction proposed by Britten-Jones, Neuberger, and Nolte (2011). To address the first mentioned source of artificial autocorrelation, it is ensured that there is no overlap between the data used to calculate the dependent and the predictive variables. In addition, by a transformation of the explanatory variables matrix, the autocorrelation in the error terms, which is caused by overlapping periods, can be removed. This correction for artificial autocorrelation of Britten-Jones et al. (2011) is used for all the following regressions.

To test whether the beta dispersion is informative for future market movements, predictive regressions are run to explain the log excess return of the market ($R_{M,t}$) at time t for the next 3, 6, and 12 months. To begin with, the lagged measure of the beta dispersion QBD_{t-1}, respectively, the value-weighted and equal-weighted BD_{t-1}, as defined in Equation 1 and in Equation 2, respectively, is the only explanatory variable. The predictive regression follows the below-mentioned form:

$$R_{M,t} = \alpha + \beta \cdot (Q)BD_{t-1} + \varepsilon_t. \tag{4}$$

The results of these predictive regressions with the equal-weighted beta dispersion (BD_{EW}) as explanatory variable for the log excess return of the market are given in Table 1.[2] Panel A presents the results for the 3-month market return, Panel B for the 6-month market return, and Panel C for the 12-month market return.

All specifications of the beta dispersion generate significant results at least at a 10% level, which is generally much higher. All coefficients have a negative sign, as expected, following the idea of beta dispersion as a vulnerability measure. It shows that a very high beta dispersion in the estimation period tends to be associated with a negative market return in the following period. The shorter the estimation period of the betas, the more significant the coefficient in the predictive regression. The in-sample R^2_{adj} are the highest in the estimation of beta, with 6 months of daily data.

[2]The results of the predictive regression with the value-weighted beta dispersion (BD_{VW}) and the beta dispersion based on quantiles (QBD) are given in Appendix A.2, because they hardly give any additional insights.

Table 1: Linear Predictive Regressions with BD_{EW}

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0539**	**0.0590**	**0.0585**	**0.0607**
	(0.0000)	(0.0001)	(0.0002)	(0.0007)
Beta Dispersion	**-0.0838**	**-0.1248**	**-0.1467**	**-0.1868**
	(0.0033)	(0.0049)	(0.0068)	(0.0159)
R^2_{adj}	0.0228	0.0234	0.0230	0.0210

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0943**	**0.1055**	**0.1010**	**0.1019**
	(0.0000)	(0.0000)	(0.0003)	(0.0016)
Beta Dispersion	**-0.1468**	**-0.2266**	**-0.2518**	**-0.3066**
	(0.0014)	(0.0019)	(0.0120)	(0.0279)
R^2_{adj}	0.0237	0.0252	0.0231	0.0198

Panel C: 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.1547**	**0.1706**	**0.1677**	**0.1623**
	(0.0000)	(0.0003)	(0.0010)	(0.0068)
Beta Dispersion	**-0.2216**	**-0.3390**	**-0.3898**	**-0.4424**
	(0.0001)	(0.0107)	(0.0248)	(0.0841)
R^2_{adj}	0.0204	0.0214	0.0204	0.0164

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, and Panel C) as the dependent variable. BD is the cross-sectional equal-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

For this estimation period, the calculated betas are relatively stable as around 125 data points are used for the estimation, and hence short-term disturbances disappear during this period. All conclusions drawn from Table 1 are applicable for the other two measures (BD_{VW} and QBD). Nevertheless, the BD_{EW} slightly outperform BD_{VW} and QBD for the long-horizon prediction. This finding is not surprising as the BD_{EW}, on the one hand, neglects firm characteristics (e.g. size) and, on the other hand, includes information of all the stocks in the market, while the QBD measure only focuses on the tails of the beta distribution. Owing to the similarity in results, only the results of the equal-weighted BD measure are reported in the following section.[3]

The rationale of the beta dispersion is based on the ability of the beta dispersion to predict especially the magnitude of a market downturn due to the cascading effect, but not be the trigger. Hence, a dummy will be included in the regression capturing this cascading effect. The dummy measures whether the market has been already hit by a systematic shock, observable through negative market returns in the month prior to the estimation of the beta dispersion. The regression looks as follows:

$$R_{M,t} = \alpha + \beta_1 \cdot D_{t-2} \cdot BD_{t-1} + \beta_2 \cdot BD_{t-1} + \varepsilon_t, \tag{5}$$

where all variables correspond to Equation 4 extended by the dummy D_{t-2} times the beta dispersion. The dummy becomes one if the market return in $t-2$ is negative and becomes zero if it is positive. This explicitly measures the predictive efficiency of beta dispersion after the market experiences a systematic shock and specifically quantifies the described cascading effect. Table 2 shows the results.

The results reveal that the product of dummy and beta dispersion is meaningful. The sign of the regression coefficient of this variable is negative in all cases and mostly significant. This means that the beta dispersion in combination with a market decline can help to evaluate how hard a market will be hit by a shock. The results show that the shorter the estimation period of the betas, the more informative would be the beta dispersion. Nevertheless, the actual level of the beta dispersion still plays a role and its coefficients are still significantly negative. Therefore, the idea of the cascading effect caused by a high beta dispersion intensifying a systematic shock seems applicable.

Previous research has shown that the predictive efficiency of a variable can heavily depend on the market regime (Baltas and Karyampas, 2018) and that predictive power is higher in bad times (Garcia, 2013; Cujean and Hasler, 2017). In addition, Tu (2010) introduces a bayesian switching approach to distinguish between market regimes and shows how important it is for portfolio decisions to differentiate reliably between regimes. To account for this, in a next step the univariate predictive regression is performed for a good and a bad market regime separately. Two issues are arising to implement this analyses. First, how should good and bad regimes be

[3] All analyses also apply for the value-weighted BD and the QBD measure. As they do not deliver additional insights, the results are not displayed in this study, but are available upon request.

Table 2: Predictive Regressions with Dummy for Negative Market Returns

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
$D_{t-2} \cdot BD_{t-1}$	**-0.0278**	**-0.0327**	−0.0273	−0.0257
	(0.0319)	(0.0524)	(0.1016)	(0.1376)
Beta Dispersion	**-0.0736**	**-0.1094**	**-0.1324**	**-0.1679**
	(0.0057)	(0.0180)	(0.0182)	(0.0250)
R^2_{adj}	0.0253	0.0251	0.0231	0.0205

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
$D_{t-2} \cdot BD_{t-1}$	**-0.0470**	**-0.0513**	**-0.0450**	−0.0441
	(0.0177)	(0.0377)	(0.0748)	(0.1131)
Beta Dispersion	**-0.1300**	**-0.2029**	**-0.2282**	**-0.2748**
	(0.0014)	(0.0024)	(0.0098)	(0.0380)
R^2_{adj}	0.0270	0.0272	0.0237	0.0200

Panel C: 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
$D_{t-2} \cdot BD_{t-1}$	**-0.0626**	**-0.0666**	−0.0594	−0.0536
	(0.0415)	(0.0668)	(0.1057)	(0.1494)
Beta Dispersion	**-0.1989**	**-0.3081**	**-0.3590**	**-0.4050**
	(0.0074)	(0.0083)	(0.0160)	(0.0847)
R^2_{adj}	0.0219	0.0220	0.0203	0.0163

Note: This table shows the results of the predictive regressions comparable to Table 1, with an additional dummy D_{t-2} controlling for the market return of the period prior to the estimation of the beta dispersion. The dummy variable should indicate a systematic shock in the prior period and focus on the ability of the beta dispersion to predict how pronounced will be the evolution of a market downturn, given a high beta dispersion. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table and the p-value is given in parenthesis for every variable. The calculations use the Britten-Jones et al. (2011) correction for overlapping periods in the dependent variable and use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. Coefficients that are significant at least at a 10% level are printed in boldface.

determined and second, is beta dispersion able to predict the market return in both regimes equally well. To distinguish between good and bad regime the dummy from the preceding regression is used as a basic differentiation. For a more sophisticated determination, the market regimes are identified with a markov switching model. The results of the split regressions are reported in Table 3 and Table 4.[4]

The results align with the findings in the literature. The beta dispersion seems to be a valuable predictor for future market return in bad regimes, but looses its power in good regimes. The coefficients of beta dispersion in the bad regime are all negative and significant at 5% level. This finding is not too surprising, since the economic explanation of the beta dispersion is targeting at market downturns and the presence of a previous systematic shock. Therefore, the predictor should be especially accurate in bad regimes.

As beta dispersion, on a stand-alone basis, is a promising predictor of the market return, it is tested whether the measure maintains its explanatory power if further variables that have been found to be successful predictors in previous studies are added to the Equation 4. Particularly, the dividend yield of the S&P 500 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) and the average variance and average correlation (in the estimation period) of all constituents of the market from Pollet and Wilson (2010) are used. Whaley (2009) shows the predictive characteristics of the VIX in terms of a fear index for market developments; thus, this index is also included. In addition, the return dispersion (Maio, 2016) is included to control for redundant information in the two dispersion measures. The aligned investor sentiment index by Huang et al. (2015) is included to cover a different facet of successful predictors. Finally, three technical indicators each in its most successful specification according to Neely et al. (2014) are included: the moving average of the market return as the difference between the 2-month and 12-month moving average, the 12-month momentum and the difference between the 1-month and 12-month moving average of on-balance volume. Only one of these technical predictor is included in the regression at a time to prevent these predictors to interfere with each other. Table 5 shows the results of the multiple predictive regressions with the moving average as technical indicator.[5]

All coefficients of the beta dispersion measure retain their signs. For the 3-month and the 6-month market return (Panel A and B), the beta dispersion adds value, especially when it is estimated over a longer horizon. Concerning prediction for the 12-month market returns (Panel C), beta dispersion is considered one of the most valuable contributors to the prediction accuracy, besides the VIX and the return dispersion. The multiple prediction has a much higher predictive accuracy than the simple regression, and the R^2_{adj} are comparable to prior research. Nevertheless, the beta dispersion captures specific information that cannot be covered by other

[4] The results from the alternative differentiation of regimes are comparable to the basic differentiation. Hence, these results are only displayed in Appendix A.3

[5] The regression outputs with momentum and moving average of on-balance volume can be found in Appendix A.4 and Appendix A.5. The results are comparable to the here described.

Table 3: Linear Predictive Regressions with BD_{EW} in Good Market Regimes

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0087**	**0.0082**	**0.0085**	**0.0067**
	(0.0009)	(0.0032)	(0.0020)	(0.0031)
Beta Dispersion	0.0083	0.0133	0.0137	0.0318
	(0.5502)	(0.5031)	(0.5244)	(0.1916)
R^2_{adj}	−0.0002	0.0004	−0.0001	0.0033

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0163**	**0.0165**	**0.0173**	**0.0134**
	(0.0001)	(0.0002)	(0.0002)	(0.0026)
Beta Dispersion	0.0204	0.0257	0.0255	0.0633
	(0.3608)	(0.4396)	(0.5025)	(0.1827)
R^2_{adj}	0.0027	0.0021	0.0009	0.0079

Panel C: 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0321**	**0.0322**	**0.0331**	**0.0266**
	(0.0000)	(0.0000)	(0.0001)	(0.0006)
Beta Dispersion	0.0433	0.0565	0.0613	0.1288
	(0.2526)	(0.2939)	(0.3531)	(0.1148)
R^2_{adj}	0.0076	0.0070	0.0055	0.0174

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, and Panel C) as the dependent variable during a good market regime. BD is the cross-sectional equal-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The differentiation between a good and a bad market regime is based on a negative market return of the period prior to the estimation of the beta dispersion. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 4: Linear Predictive Regressions with BD_{EW} in Bad Market Regimes

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0212**	**0.0219**	**0.0216**	**0.0213**
	(0.0003)	(0.0001)	(0.0001)	(0.0004)
Beta Dispersion	**-0.0346**	**-0.0486**	**-0.0552**	**-0.0616**
	(0.0343)	(0.0169)	(0.0203)	(0.0678)
R^2_{adj}	0.0092	0.0117	0.0110	0.0089

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0425**	**0.0436**	**0.0424**	**0.0415**
	(0.0002)	(0.0001)	(0.0005)	(0.0005)
Beta Dispersion	**-0.0710**	**-0.0979**	**-0.1040**	**-0.1140**
	(0.0041)	(0.0027)	(0.0050)	(0.0219)
R^2_{adj}	0.0197	0.0237	0.0195	0.0152

Panel C: 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0800**	**0.0813**	**0.0798**	**0.0769**
	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Beta Dispersion	**-0.1177**	**-0.1586**	**-0.1714**	**-0.1729**
	(0.0030)	(0.0028)	(0.0037)	(0.0226)
R^2_{adj}	0.0272	0.0311	0.0266	0.0175

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, and Panel C) as the dependent variable during a bad market regime. BD is the cross-sectional equal-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The differentiation between a good and a bad market regime is based on a negative market return of the period prior to the estimation of the beta dispersion. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

Table 5: Predictive Regressions with Additional Explanatory Variables

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	0.0176	0.0225	0.0447	0.0778
	(0.8048)	(0.7518)	(0.4716)	(0.1679)
Beta Dispersion	−0.0025	−0.0145	**-0.0690**	**-0.1629**
	(0.9588)	(0.8222)	(0.0958)	(0.0880)
DivY	−0.0008	−0.0013	−0.0039	−0.0108
	(0.9519)	(0.9303)	(0.7714)	(0.4160)
SR	0.0374	0.0355	0.0257	−0.0066
	(0.5770)	(0.6091)	(0.6996)	(0.9190)
CAY	−0.7653	−0.7569	−0.7650	−0.6429
	(0.3723)	(0.3705)	(0.3639)	(0.4609)
AV	**-0.6217**	**-0.6077**	**-0.5870**	**-0.6190**
	(0.0004)	(0.0064)	(0.0108)	(0.0187)
AC	0.1356	0.1252	0.1071	0.1422
	(0.3495)	(0.3869)	(0.4315)	(0.2989)
RD	**-1.5903**	**-1.5645**	**-1.5415**	−1.2666
	(0.0655)	(0.0692)	(0.0745)	(0.1277)
VIX	**0.0037**	**0.0037**	**0.0037**	**0.0036**
	(0.0010)	(0.0012)	(0.0009)	(0.0014)
Sentiment	**-0.0190**	−0.0181	−0.0129	−0.0109
	(0.0802)	(0.1495)	(0.2555)	(0.3113)
MA (2,12)	−0.0029	−0.0029	−0.0030	**-0.0034**
	(0.1696)	(0.1662)	(0.1512)	(0.0900)
R_{adj}^2	0.0649	0.0654	0.0734	0.0842

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	0.0969	0.1147	0.1285	0.2026
	(0.5876)	(0.5161)	(0.4415)	(0.1742)
Beta Dispersion	−0.0860	−0.1575	**-0.1992**	**-0.4142**
	(0.4192)	(0.3471)	(0.0740)	(0.0079)
DivY	−0.0013	−0.0046	−0.0082	−0.0245
	(0.9717)	(0.8969)	(0.8246)	(0.4851)
SR	−0.0175	−0.0258	−0.0336	−0.1117
	(0.9215)	(0.8884)	(0.8501)	(0.5133)
CAY	−0.2749	−0.2898	−0.4139	−0.1052
	(0.8423)	(0.8306)	(0.7753)	(0.9462)
AV	−0.2128	−0.2134	−0.3142	−0.4097
	(0.5681)	(0.6200)	(0.4738)	(0.3812)
AC	0.0639	0.0369	0.0945	0.1949
	(0.8232)	(0.8991)	(0.7131)	(0.4371)
RD	**-2.7248**	**-2.5486**	**-2.7210**	−2.0401
	(0.0717)	(0.0775)	(0.0820)	(0.2092)
VIX	**0.0040**	**0.0042**	**0.0045**	**0.0044**
	(0.0097)	(0.0037)	(0.0020)	(0.0017)
Sentiment	−0.0374	−0.0317	−0.0248	−0.0218
	(0.1031)	(0.2652)	(0.2601)	(0.1867)
MA(2,12)	−0.0039	−0.0039	−0.0044	−0.0053
	(0.2714)	(0.2585)	(0.2461)	(0.1606)
R_{adj}^2	0.0513	0.0556	0.0604	0.0746

Panel C: 12-Month Market Returns

	BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{3M}_{EW}
Intercept	0.2360	0.2455	0.2653	0.3558
	(0.1825)	(0.1587)	(0.1176)	(0.0529)
Beta Dispersion	**-0.2058**	**-0.3011**	**-0.3649**	**-0.6390**
	(0.0276)	(0.0225)	(0.0179)	(0.0074)
DivY	0.0214	0.0160	0.0099	−0.0127
	(0.4157)	(0.5384)	(0.7221)	(0.6450)
SR	−0.2142	−0.2207	−0.2329	−0.3431
	(0.3816)	(0.3820)	(0.3418)	(0.1477)
CAY	1.8984	1.7968	1.5583	2.0307
	(0.3435)	(0.3496)	(0.4153)	(0.4027)
AV	0.3223	0.2158	0.0136	−0.1679
	(0.5746)	(0.7062)	(0.9825)	(0.7897)
AC	−0.2472	−0.2399	−0.1223	0.0593
	(0.6984)	(0.7095)	(0.8411)	(0.9256)
RD	**-4.9268**	**-4.6614**	**-5.0034**	−3.9972
	(0.0218)	(0.0279)	(0.0315)	(0.1627)
VIX	0.0035	**0.0041**	**0.0047**	**0.0045**
	(0.1479)	(0.0882)	(0.0483)	(0.0555)
Sentiment	−0.0535	−0.0451	−0.0334	−0.0340
	(0.1174)	(0.2037)	(0.3211)	(0.2949)
MA(2,12)	−0.0041	−0.0041	−0.0051	−0.0064
	(0.4281)	(0.4203)	(0.3352)	(0.2978)
R^2_{adj}	0.0645	0.0760	0.0796	0.0818

Note: This table shows the results of the predictive regressions with ten independent variables and 3-, 6-, and 12-month log excess return of the S&P 500 Index as dependent variables (Panel A, Panel B, and Panel C). The regression equation has the following independent variables: beta dispersion, dividend yield, short rate, cay factor, average variance, average correlation, VIX, return dispersion, aligned sentiment, and moving average. Dividend yield, average variance, average correlation, moving average, and return dispersion refer to the S&P 500 Index, and short rate is the 1-month T-bill rate. Additionally, the cay factor is provided by Lettau's database and the aligned sentiment index by Zhou's website, respectively. The beta dispersion is calculated based on 3, 6, 12, and 36 months. The in-sample, adjusted R^2_{adj}, of the predictive regressions is given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations of the significance levels use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals and the p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

predictors. The results and the interpretation also hold for the two alternative technical predictors, momentum and moving average of on-balance volume.

4.3 Predicting Market Returns – Out-of-sample Evaluation

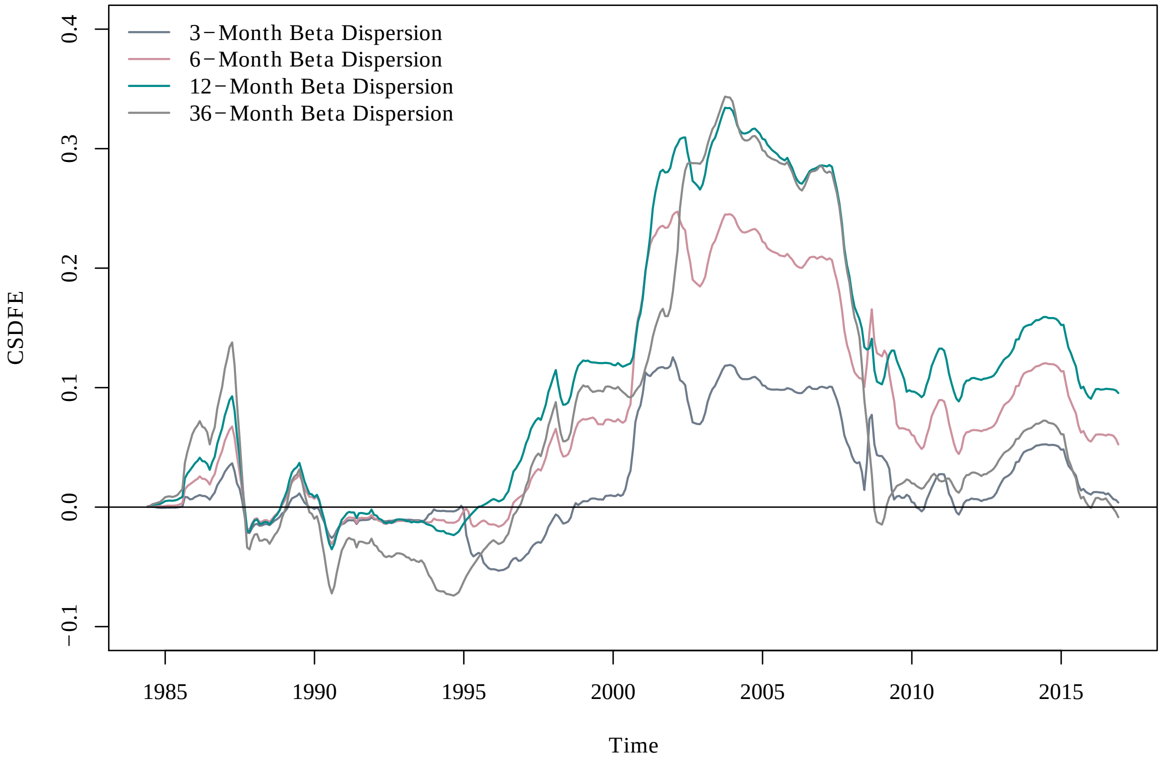
The in-sample evaluation of beta dispersion suggests that its level can be used, to a certain extent, to predict future market returns and the extent of the market downturn. The economic concept would gain much more strength if the results also hold in the out-of-sample evaluation. Two commonly used out-of-sample approaches are performed. The cumulative sum of differences in the squared forecast errors (CSDFE), on the one hand, evaluates the superior prediction out-of-sample graphically over time and the out-of-sample R^2_{OS}, on the other hand, aggregates the evaluation in one figure.

The CSDFE is a useful tool for out-of sample investigation (Goyal and Welch, 2003; Welch and Goyal, 2008). The resulting time series can be studied graphically and is calculated as presented in Equation 6:

$$\text{CSDFE}_T = \sum\nolimits_{t=1}^{T}((R_{M,t} - \bar{R}_{M,t})^2 - (R_{M,t} - \hat{R}_{M,t})^2). \tag{6}$$

where $R_{M,t}$ is the actual observed market return in t, $\hat{R}_{M,t}$ is the predicted market return by the beta dispersion, and $\bar{R}_{M,t}$ is the benchmark prediction. The CSDFE shows the dynamics of the predictive performance over time and helps to distinguish between periods where the beta dispersion is a more accurate predictor compared to the benchmark prediction. Typically, the historical mean of the market return, which is commonly seen as the most stringent benchmark for equity premium predictors (Goyal and Welch, 2003; Welch and Goyal, 2008), is used. If the CSDFE_T is positive, then the beta dispersion would be considered a superior predictor compared to the benchmark and vice versa. To calculate the predictions, the data sample is divided into two subsamples to estimate predictive regressions in the first and calculate the return predictions and the R^2_{OS} in the second. The choice of the split point is based on the argumentation in Neely et al. (2014). The first subsample should be long enough to estimate stable regression coefficients, but at the same time the second subsample (i.e., the evaluation sample) should be large enough to have sufficient data for the evaluation. This is because the power of the forecast tests increases with this size (also see Hansen and Timmermann (2012)). I use the first 20 years as the first subsample to determine the initial regression coefficients and extend this window monthly. At the end of every month, a predictive regression with all available information at that point is performed to estimate the regression coefficients. Together with the currently observed beta dispersion, the forecast of the market return is calculated (also see Campbell and Thompson (2008)). This forecast is compared to the prediction of the benchmark $\bar{R}_t$, calculated over the same period as the regression coefficients, with Equation 6. The benchmark is the mean of the market return and is estimated with data prior to the actual observed

Figure 3: Cumulative Sum of Differences in the Squared Forecast Errors



Note: This figure shows the time series of the CSDFE, following Goyal and Welch (2003) and Welch and Goyal (2008), over the period April 1984 to December 2016. This period is shorter than the total sampled period because the first 20 years of the sample are used to estimate the initial regression coefficients. It shows the dynamic predictive performance over time and helps to distinguish between periods where the beta dispersion is a superior predictor of future market return when compared to the historical market risk premium and where the beta dispersion is an inferior predictor. If the CSDFE are positive, it would indicate a superior performance of the beta dispersion when compared to the historical market risk premium.

market return. In Figure 3, the time series of CSDFE for the 6-month market return prediction is displayed.[6]

Figure 3 shows that the beta dispersion has been effectively predicting the market return more recently, since the late 1990s. Especially, before market crises in 1987, 2001, and 2008, the beta dispersion seemed valuable.

A second way of analyzing the out-of-sample predictive efficiency of beta dispersion is to examine the out-of-sample R^2_{OS}. The calculation of this figure follows an established approach (Campbell and Thompson, 2008; Neely et al., 2014). This measure compares the forecast of a predictor to the forecast of a benchmark. The

[6]The time series of CSDFE based on other specifications of the beta dispersion do not vary noticeably from Figure 3.

Table 6: Results of the Out-of-sample R^2_{OS} for BD_{EW}

Panel A: 20-year Initial Estimation, Historical Mean of S&P 500

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	0.0003	0.0074*	0.0178**	0.0110**
	6 Months	0.0133**	0.0301***	0.0425***	0.0244**
	12 Months	0.0215***	0.0515***	0.0545***	0.0104***

Panel C: 20-year Initial Estimation, Fix Market Risk Premium of 5.1%

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	0.0099**	0.0170**	0.0273***	0.0205**
	6 Months	0.0270***	0.0436***	0.0558***	0.0380***
	12 Months	0.0387***	0.0682***	0.0711***	0.0278***

Note: This table shows the out-of-sample R^2_{OS} for the prediction of the beta dispersion in comparison to the benchmark prediction for 3-, 6-, and 12-month log excess market return ($R_{M,t}$). The out-of-sample R^2_{OS} is calculated via Equation 7. The forecasts are estimated by using the predictive regression coefficients from a dynamically enlarged time series of beta dispersion and market return, which includes the whole period prior to the currently observed dispersion. The forecasts, taken from the monthly adjusted regression, are set in relation to different benchmark forecasts of the market risk premium. These benchmarks are historical mean of the S&P 500 excess returns and a commonly used constant of 5.1%. A positive out-of-sample R^2_{OS} indicates a superior forecasting performance of the beta dispersion. The significance level of the R^2_{OS} is estimated based on the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis that the benchmark forecast estimation error is less than or equal to the beta dispersion forecast error. Significance level: *** 0.01, ** 0.05, and * 0.1.

out-of-sample R^2_{OS} is calculated as shown in Equation 7:

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(R_{M,t} - \hat{R}_{M,t})^2}{\sum_{t=1}^{T}(R_{M,t} - \bar{R}_{M,t})^2}. \tag{7}$$

The value of the R^2_{OS} ranges between $(-\infty, 1]$. A positive out-of-sample R^2_{OS} indicates a superior forecasting performance of the tested measure against the benchmark. In contrast to the CSDFE calculation, an alternative benchmark is included in the analysis. More recent research argues that the historical mean of the market risk premium is not the most appropriate benchmark (Constantinides, 2002; Ibbotson and Chen, 2003; Donaldson, Kamstra, and Kramer, 2010). Therefore, an additional benchmark suggested in current literature is included. This benchmark is a fixed market risk premium of 5.1% (Avdis and Wachter, 2017). The results of the R^2_{OS} calculation are shown in Table 6.

The R^2_{OS} confirms the predictive dominance of the beta dispersion for mid- and long-term predictions. This is represented by positive R^2_{OS}. This out-of-sample predictive efficiency applies for the two different benchmarks. This is remarkable because other predictors often lack out-of-sample predictive efficiency. The significance test of R^2_{OS} is estimated based on Clark and West (2007)'s MSFE-adjusted (mean square forecast error) statistic for testing the null hypothesis that the benchmark forecast estimation error is less than or equal to the competing forecast error. Convincingly, the R^2_{OS} are not only positive but also significant. This confirms the conclusion that the beta dispersion is a reliable predictor of the market return, even in an out-of-sample framework.

To strengthen this finding, two enhancements to the R^2_{OS} calculation are studied. First, constraints are applied to the predictive model before calculating the out-of-sample R^2_{OS}. Recent studies show that applying constraints to predictive regressions (Campbell and Thompson, 2008; Pettenuzzo, Timmermann, and Valkanov, 2014) can help to improve the prediction results. Following Campbell and Thompson (2008), in a first step the sign of the regression coefficients of the beta dispersion is restricted to the expected sign and in a second step the prediction of the market return is restricted to positive values solely.

Campbell and Thompson (2008) show that forecasts and out-of-sample evaluation can be improved if it is ensured that the regression coefficient has the expected sign derived from the economic intuition of the relationship between predictor and market return. For the beta dispersion the coefficient should be negative as a high beta dispersion corresponds to a possible market downturn and, hence, supports the economic idea why beta dispersion can contribute to the prediction of the market return. This constraint is fulfilled for the whole sample for all combinations of beta dispersion and market return. Therefore, no additional table with results is provided, the results from Table 6 contain already these constrained results.

The second constraint, restricting the forecast of the market return to positive values, is based on the fact that investors would never expect a negative market risk premium. Out of this follows that the prediction made with the help of the estimated regression coefficients and the currently observed beta dispersion should not indicate a following negative market return. This constraint is, in general, a reasonable assumption and can improve the predictive power as shown by Campbell and Thompson (2008). To calculate the R^2_{OS} with this constraint, the prediction of the beta dispersion is set to zero if it indicates a following negative market return. The R^2_{OS} with constraint is shown in Table 7.

With this constraint the beta dispersion is still able to beat the two benchmarks in majority. All positive R^2_{OS} are also significant. The beta dispersion is still predominantly superior to the benchmark of a fixed market risk premium of 5.1%. Compared to the historical mean of the market return the beta dispersion looses its dominance partly. Especially the 36-month beta dispersion seems to provide no additional information to the benchmark. All in all, the R^2_{OS} are slightly lower than for the unconstrained version. This finding is less surprising: The beta dispersion as vulnerability measure of a market aims especially at downturns of a market. By restricting the predictions to a positive market return, the initial idea of the predictive power of the beta dispersion is partially counteracted.

Table 7: Results of the Out-of-sample R^2_{OS} for BD_{EW} with Constraints: Positive Market Risk Premium

Panel A: 20-year Initial Estimation, Historical Mean of S&P 500

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	−0.0054	−0.0006	0.0079*	−0.0059
	6 Months	0.0044*	0.0197***	0.0308***	−0.0031
	12 Months	0.0132***	0.0307***	0.0283***	−0.0191

Panel C: 20-year Initial Estimation, Fix Market Risk Premium of 5.1%

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	0.0043*	0.0090**	0.0175***	0.0038*
	6 Months	0.0183***	0.0333***	0.0442***	0.0109***
	12 Months	0.0305***	0.0477***	0.0454***	−0.0012

Note: This table shows the out-of-sample R^2_{OS} for the prediction of the beta dispersion in comparison to the benchmark prediction for 3-, 6-, and 12-month log excess market return ($R_{M,t}$). The out-of-sample R^2_{OS} is calculated via Equation 7. The forecasts are estimated by using the predictive regression coefficients from a dynamically enlarged time series of beta dispersion and market return, which includes the whole period prior to the currently observed dispersion. The forecasts, taken from the monthly adjusted regression, are set in relation to different benchmark forecasts of the market risk premium. Forecasts indicating a negative market risk premium are set to zero, following Campbell and Thompson (2008). The benchmarks are historical mean of the S&P 500 excess returns and a commonly used constant of 5.1%. A positive out-of-sample R^2_{OS} indicates a superior forecasting performance of the beta dispersion. The significance level of the R^2_{OS} is estimated based on the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis that the benchmark forecast estimation error is less than or equal to the beta dispersion forecast error. Significance level: *** 0.01, ** 0.05, and * 0.1.

Table 8: Results of the Out-of-sample R^2_{OS} for BD_{EW} in Good and Bad Market Regimes

Panel A: 20-year Initial Estimation, Good Market Regime

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	0.0103***	−0.0123***	0.0095***	−0.0024
	6 Months	0.0009	−0.0089***	0.0327***	0.0405***
	12 Months	0.0104***	0.0104***	0.0533***	0.0405***

Panel B: 20-year Initial Estimation, Bad Market Regime

		BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{36M}_{EW}
R_M	3 Months	0.0295***	0.0700***	0.0770***	0.0316***
	6 Months	0.0205***	0.0636***	0.0799***	−0.0013
	12 Months	−0.0078	−0.0122*	−0.0108*	−0.0124*

Note: This table shows the out-of-sample R^2_{OS} for the prediction of the beta dispersion in comparison to the benchmark prediction for 3-, 6-, and 12-month log excess market return ($R_{M,t}$) in a good and a bad market regime. The differentiation between a good and a bad market regimes is based on a negative market return of the period prior to the estimation of the beta dispersion. The out-of-sample R^2_{OS} is calculated via Equation 7. The forecasts are estimated by using the predictive regression coefficients from a dynamically enlarged time series of beta dispersion and market return, which includes the whole period prior to the currently observed dispersion. The forecasts, taken from the monthly adjusted regression, are set in relation to different benchmark forecasts of the market risk premium. Forecasts indicating an negative market risk premium are set to zero, following Campbell and Thompson (2008). The benchmarks are historical mean of the S&P 500 excess returns. A positive out-of-sample R^2_{OS} indicates a superior forecasting performance of the beta dispersion. The significance level of the R^2_{OS} is estimated based on the Clark and West (2007) MSFE-adjusted statistic for testing the null hypothesis that the benchmark forecast estimation error is less than or equal to the beta dispersion forecast error. Significance level: *** 0.01, ** 0.05, and * 0.1.

The second enhancement in the out-of sample evaluation is to calculate the out-of-sample R^2_{OS} in good and bad market regime separately analogously to the in-sample evaluation. The result of this calculation can be found in Table Table 8.

In good regimes the R^2_{OS} are mostly positive and significant. Consequently, the forecast based on the beta dispersion seems to be more accurate than the forecast of the benchmark in a good market regime. For the bad regime, the beta dispersion is still the superior predictor for the mid-term market return (three and six month). Surprisingly, for the 12-month market, the prediction of beta dispersion is worse than the benchmark. Nevertheless, these figures are not significant and the effect might be due to the much smaller sample. In general, the R^2_{OS} are higher compared to the results in Table 7.

Putting together the in-sample and out-of-sample evaluation of the beta dispersion, the empirical results highlight the appropriateness of the economic idea of beta dispersion. The BD measure, which takes all stocks into account, delivers slightly more reliable and stronger results than the QBD measure, which is explicitly based on the extreme tails of the beta distribution. In the initial predictive regression analyses, it is accounted for the overlapping periods in two different ways that lead to identical results. By including a dummy variable in the regression to study the applicability of the cascading effect, it can be seen that the beta dispersion is especially important in helping to determine the magnitude of a market downturn. The analysis of the predictive behavior of beta dispersion in good and bad market regimes shows, that beta dispersion is particularly valuable in bad regimes. The R^2_{OS} calculated for good and bad regimes fit into these conclusions. The multiple regressions show that the proposed measures contain additional information compared to already studied predictors. In addition, the time series analysis of the predictive efficiency of beta dispersion confirms that the beta dispersion has been apparently superior to its benchmark since the late 1990s. The computed out-of-sample R^2_{OS} confirm that the dispersion measure is valuable even when comparing the beta dispersion to stringent benchmarks. The CSDFE enhances the results of the out-of-sample R^2_{OS} because the worse performance seems to be caused by earlier observations from the late 1980s to the late 1990s. Also, applying constraints in the R^2_{OS} calculation weakens the predictive efficiency of the beta dispersion only slightly. The predictor suggested in this study clearly complements and mostly outperforms already examined predictors in the literature. This emphasizes the relevance of the beta dispersion being a measure of market vulnerability.

4.4 Market Timing Strategies Using Beta Dispersion

To evaluate the usefulness of the beta dispersion for an investor and to show further economic significance of the beta dispersion, market timing strategies based on this measure are implemented to obtain a comprehensive view. Furthermore, this section introduces distributional regressions to finance and shows their beneficial contribution toward market timing strategies. Distributional regressions comprise a new modeling approach for determining the probability distribution function of a variable, conditional on another observable variable (Silbersdorff, 2017).[7] The market timing strategies use the probability distribution to trigger the investment decision. If the probability that the market return will be positive, conditional on the observed beta dispersion, is greater than 50%, the strategies would drive investments in the market portfolio. Two versions of implementing such a strategy are explored. The first version involves the usual approach and shifts wealth between money and stock market. This serves as reference point to evaluate the advanced second market timing strategy. This second version makes a shift between short and long position in the market with a fraction of the wealth, dependent on the aforementioned probability. The possibility to be long and short in the market at considerably low transaction costs is ensured by having highly liquid ETFs and short ETFs on the S&P 500.

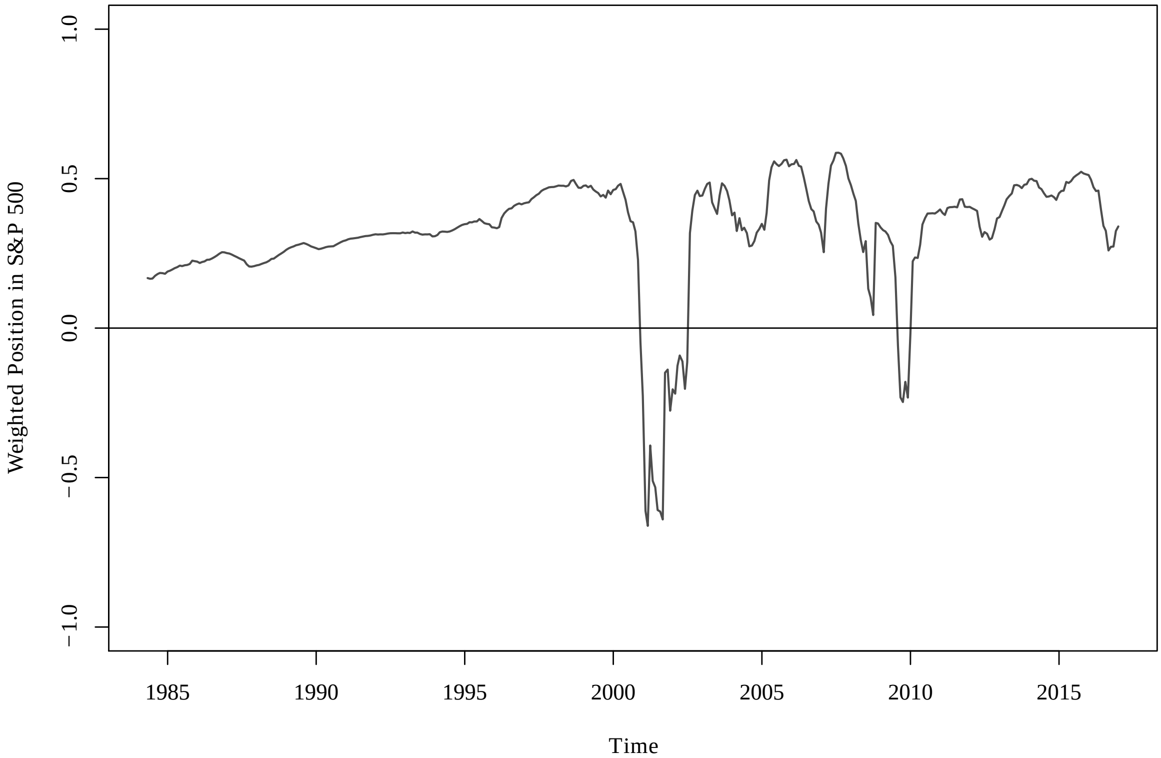
[7]Further information on the estimation of distributional regressions is provided in Appendix A.6.

Distributional regressions use the data sample to model a distribution of the dependent variable, conditional on the explanatory variable. In this way, the empirical distribution of the market return, conditional on the currently observed beta dispersion, can be determined. This approach has two major advantages compared to other approaches for modeling joint distributions (e.g., bivariate distributions or modeling a relation with copulas). First, it is not necessary to assume that the explanatory variable (here: beta dispersion) must have a specific distribution, and the distribution of the dependent variable (here: market return) can be flexibly tailored to the empirical observations. Second, the effective direction of the predictive relationship is studied in detail in the previous sections — the beta dispersion can to some extent predict market returns. This information can be used and empowers the modeling of the market return distribution via distributional regression. Beta is calculated based on backward-looking information, and the market return is estimated with forward-looking information. Therefore, it is reasonable to observe the beta dispersion and indicate the market return, and not the other way around. The alternative ways of bivariate modeling make no assumptions about the effective direction of a relationship between the variables, and this information is lost in these approaches.

The conditional probability p of a positive market return can be determined by $p \mid BD = 1 - F(0)$, where $F(0)$ is the cumulative distribution function of the conditional distribution of the market return. As mentioned, two different market timing strategies, using this probability as an investment trigger or better timing indicator, are introduced and studied. A probability higher than 50% for a positive market return in the next period indicates that the market will rise. First, a basic approach representing common market timing strategies is adopted from literature. Therefore, this strategy invests 100% in the market if the timing indicator signals rising markets. Otherwise, an investment in the money market is made. Second, a weighted long-short strategy is adopted, which invests in a weighted market position proportional to the conditional probability of a positive market return. Formally, the weighted strategy holds a position of $X_M = 2(p \mid BD - 0.5)$ in the market and a position of $X_R = 1 - 2(p \mid BD - 0.5)$ in the money market. The transformation of the conditional probability for the weighed strategy ensures that the maximum investment that can be done in the market is 1 or 100% of the wealth and the minimum investment is -1, which corresponds to a 100% short position in the market. Both strategies start with an initial standardized wealth of 1. This setting makes it easy to compare the market timing strategies with an appropriate benchmark.

The analyses in the previous subsection showed that BD, based on beta dispersion estimated for 6, 12, and 36 months, is most valuable for long-term prediction (6- and 12-month market return). So only these combination are used for more clarity of the timing strategies. Every month, these specifications of the BD are used to estimate distributional regressions over an extending window including all months prior to the month in which the portfolio is set up. It is assured that none of the strategies uses any in-sample information. The first conditional distribution can be determined in April 1984 to include a sufficient number of observations for the

Figure 4: Weights of Market Timing Strategy



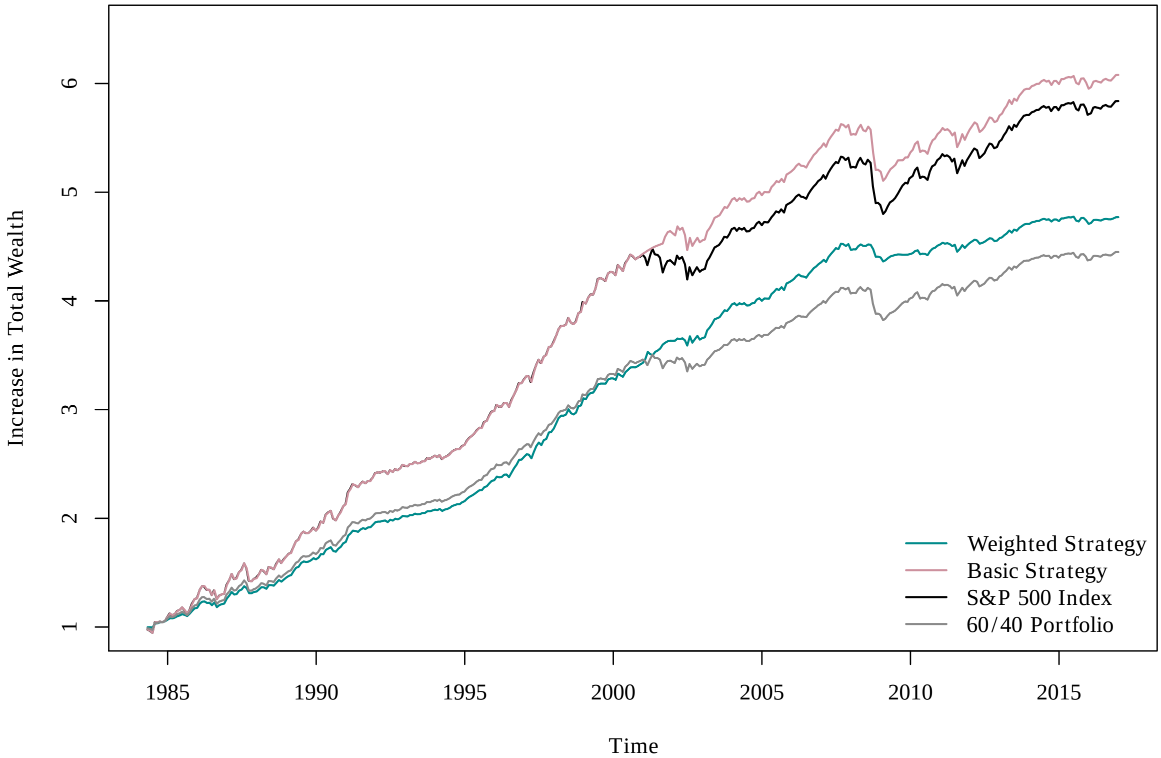
Note: This figure shows the time series of the weights of the position held in the market (S&P 500 Index) over the period April 1984 to December 2016. This period is shorter than the total sampled period because the first 20 years of the sample are used to have sufficient observations even for the first distributional regression. The weights are derived from the probability that the subsequent market return will be positive, calculated with distributional regressions. This probability is standardized between -1 and 1, with $X_M = 2(p \,|\, M - 0.5)$. A weight of 1 means a 100% long position in the market and a weight of -1 implies a 100% short position in the market. The weights are based on the regression of the 12-month beta dispersion on the yearly market return.

estimation.[8] Depending on the forecasting horizon of the market return, the first market timing strategy is set up in October 1984 (6-month market return) and April 1985 (12-month market return). Irrespective of the prediction horizon, the position held in the market is rebalanced every month to adjust the weight in the market portfolio to the most current information.

Figure 4 shows the development of the weights for the S&P 500 Index, based on the distribution of the 12-month market return, conditional on the 12-month BD. The level of the weights is important only for the weighted strategy. The basic strategy is fully invested in the market when the weight is positive, and investments are done in the money market, when the weight is negative. Notably, the conditional

[8]Compare the argumentation for the calculated out-of-sample R^2_{OS} in Section 4.3.

Figure 5: Increase in Total Wealth Resulting from Timing Strategies



Note: This figure shows an increase in the total wealth for the market timing strategies, based on the 12-month BD measure and a passive buy-and-hold strategy of the S&P 500 and a 60/40 portfolio as benchmarks. The period from April 1984 to December 2016 is displayed. This period is shorter than the total sampled period because the first 20 years of the sample are used to have sufficient observations even for the first distributional regression. An increase in the total wealth comprises the currently earned return from the timing strategy as well as all previously earned returns accrued at the risk-free rate.

weight is only negative[9] twice, namely, for the two most recent market downturns in the sample. After the results of Section 4.1 and Section 4.2, this new perspective emphasizes the capability of the beta dispersion to serve as a measure of market vulnerability.

Figure 5 compares the time series of the increase in the total wealth of the two market timing approaches and corresponds to the weights shown in the Figure 4. The increase in total wealth is calculated by adjusting the weight held in the market portfolio every month and saving all earned returns in a money market account until the end of the sampled period in December 2016.

The basic strategy imitates the market until around 2001. This is the first time that

[9] A negative weight in the market corresponds to holding a short position in the market portfolio for the weighted timing strategy.

the timing indicator foreshadows a market downturn. The basic strategy shifts the wealth from the market portfolio to a money market account, which is clearly visible in Figure 5. The second market downturn is much less anticipated by this strategy, and hence there is a decline in the performance. The weighted strategy falls short in terms of an absolute increase in wealth, compared to the buy-and-hold strategy and the basic timing strategy. The strength of the weighted strategy is seen in the lasting reduction of return volatility in combination with only a slight decrease in return performance. Compared to the more appropriate 60/40 benchmark[10], the weighted strategy is preferable. This is because the two large market downturns lead to much less performance loss than for the 60/40 portfolio. Taking all together, the beta dispersion can successfully discriminate between market up- and downturns, and, therefore, it leads to a superior performance of timing strategies compared to the two chosen benchmarks, either in terms of absolute wealth or volatility reduction.

The described results shown in Figure 5 hold for all implemented variations of the market timing strategies, which can be seen in Table 9.

Table 9 reports the average return, standard deviation, Sharpe ratio, and maximum drawdown (MDD) of all strategies. Irrespective of the strategy, all the average returns are positive. The basic strategy does not seem preferable compared to the buy-and-hold benchmark, although the average return and standard deviation are slightly better and there is an improvement in the Sharpe ratio. Taking the costs for implementing and monitoring this strategy into account, the additional work does not seem to pay off. Contrarily, the weighted strategy has lower average returns, but the return volatility reduces sharply, and hence the Sharpe ratio is the most favorable. Even when comparing all described strategies to the 60/40 benchmark, instead of the buy-and-hold benchmark, the weighted strategy provides the most interesting risk-return characteristics.

The drawdown is calculated as the relative difference between the backward-looking highest value of the total value to the current value at any point in time. In Table 9 the value MDD, which is the highest value in the time series of drawdowns, is presented for the entire investigation period of every strategy. The MDD can confirm the preferable characteristics of the weighted market timing strategy. The MDD of this strategy does not exceed its yearly average return, and this emphasizes that the weighted market timing strategy is relatively less risky.

Overall, the most striking result of the market timing strategies is that, owing to the distributional regression approach, the weighted strategy reduces the standard deviation of the returns.[11] This leads to outstanding Sharpe ratios, which are considerably higher than the Sharpe ratios of the benchmarks (buy-and-hold and 60/40). With risk reduction as a reasonable target of investment strategies, the results of the

[10] Compared to the buy-and-hold benchmark, this benchmark is more appropriate because the weighted strategy rarely invests 100% of the wealth in the market portfolio. The 60/40 benchmark matches more or less with the mean investment of the weighted strategy in the market portfolio and, therefore, reflects the risk characteristics of the weighted strategy.

[11] Reduction of the standard deviation refers to the comparison of the standard deviation of the weighted strategy with the standard deviation of the benchmarks (buy-and-hold and 60/40).

Table 9: Performance of Market Timing Strategies

	Distributional Regression R_M	BD	Av. Return	SD	SR	MDD
Basic Strategy	6 Months	6 Months	0.1002	0.1348	0.5511	−0.1043
	6 Months	12 Months	0.1060	0.1318	0.6080	−0.1043
	6 Months	36 Months	0.1107	0.1301	0.6512	−0.1043
	12 Months	6 Months	0.1017	0.1346	0.5629	−0.1043
	12 Months	12 Months	0.1060	0.1318	0.6080	−0.1043
	12 Months	36 Months	0.1096	0.1303	0.6420	−0.1043
Weighted Strategy	6 Months	6 Months	0.0551	0.0469	0.6216	−0.0364
	6 Months	12 Months	0.0610	0.0494	0.7125	−0.0332
	6 Months	36 Months	0.0674	0.0547	0.7620	−0.0376
	12 Months	6 Months	0.0708	0.0670	0.6711	−0.0385
	12 Months	12 Months	0.0799	0.0721	0.7510	−0.0466
	12 Months	36 Months	0.0853	0.0769	0.7754	−0.0723
	Buy-and-hold Benchmark		0.1000	0.1373	0.5386	−0.1043
	60/40 Benchmark		0.0705	0.0827	0.5386	−0.0737

Note: This table shows the average returns, standard deviations (SD), Sharpe ratios (SR), and the maximum drawdown (MDD) of the basic and weighted market timing strategies. In the last two rows, the figures of the two benchmark strategies (buy-and-hold and 60/40 portfolio split) are presented. All values are annualized. The SR is calculated on the excess return of every strategy. The drawdown represents the relative difference between the backward-looking highest value of the total value compared to the current value at any point in time. The maximum drawdown presented in the table is the maximum of this quantity.

weighted market timing strategy should be highlighted as it reduces the standard deviation by up to 65% compared to the buy-and-hold benchmark and up to 20% compared to the 60/40 benchmark. The use of the probability from the distributional regression as timing indicator is an innovative and successful way of improving the risk and return characteristics of market timing strategies. [12] There seems to be a clear advantage in performance that arises from calculating the weights from the conditional distribution and adjusting this for the newest information of the beta dispersion by monthly rebalancing[13].

Nevertheless, market timing strategies face some shortcomings that should be addressed. As per Zakamulin (2014), most market timing strategies lose their superior performance when realistic frictions are employed to the strategies. The most fundamental friction are liquidity, transaction costs, and prediction accuracy. The introduced strategies are based on investments in the S&P 500 Index, which represents a very actively traded market segment. Concerning this index, highly liquid ETFs exist that facilitate the easy implementation of the strategies; hence, concerns about liquidity are seemingly inapplicable in this case. Likewise, transaction costs can be expected to be low. As trading frequency also influences the cost of trading, the number of transactions for the basic strategy can be determined easily. The weight (compare Figure 4) changes two times in 32 years from positive to negative and the other way around. This means that the investor has to sell and rebuy in the market only twice, which seems justifiable. For the weighted market timing strategy, further analysis is necessary because this strategy has to be rebalanced every month. Therefore, the performance decline in terms of the Sharpe ratio is measured when the weights of the strategy are only rebalanced when the weight change exceeds specific limits, and hence the rebalancing frequency is reduced. Tests are conducted to examine how rarely the weight can be changed without the Sharpe ratio of the weighted strategy dropping below 0.60, which is still clearly above both benchmarks' Sharpe ratio (buy-and-hold and 60/40). Until the weight is only rebalanced when the absolute change is greater than 25 percentage points, the Sharpe ratio stays above 0.60, but the trading activities drop to 15 to 30 times (compared to 390 times), depending on the exact specification of the distributional regression. This is less than once a year. It illustrates that the transaction costs can be reduced considerably without much decrease in performance and, especially, by not increasing the return volatility. The third shortcoming of timing strategies — predictive accuracy — is captured by the combination of the distributional regression and the weighted strategy. A complete wealth shift between stock and money market is of limited suitability, since the investor has to ensure that his prediction is sufficiently accurate (Sharpe, 1975; Jeffrey, 1984; Bauer Jr and Dahlquist, 2001; Neuhierl and Schlusche, 2011; Hallerbach, 2014). The weighted strategy can be considered as

[12] Unreported results show, that the idea of the weighted market timing strategy can be also successfully implemented based on the earlier described additional predictors of the market return. As the focus of this paper is on the beta dispersion and its applicability, the results are not presented, but are available upon request.

[13] Other rebalancing frequencies are tested, which lead to comparable results. Nevertheless, the presented findings for the monthly rebalancing are the most striking.

relying on less predictive accuracy. It is because this strategy decreases the weight in the market portfolio only gradually when the likelihood of a market downturn rises and vice versa. The more uncertain the prediction about the future market return, the lesser the total weight that is invested in the market. This ensures that if the indicator points in the wrong direction, the consequences (negative returns of the timing strategy) would be as small as possible. Hence, predictions that do not turn out to be true are not as harmful as strategies that involve a total wealth shift. The weighted strategy overcomes this shortcoming and benefits from its more careful investment approach.

5 Conclusion

This study introduces the beta dispersion as a measure of market vulnerability. A high heterogeneity between betas in a market reduces the ability of that market to cope with systematic shocks. A high beta dispersion makes the market highly vulnerable, and the crash of high-beta companies is more likely to spill over to other firms, thereby increasing the overall financial distress risk, which can be interpreted as a second-round endogenous shock. Hence, the beta dispersion measures the probability and extent of a severe market decline. The economic and statistical significance show the suitability of this economic idea. In addition, the beta dispersion complements well-known predictor of the market return and adds to the accuracy of the prediction. By conducting comprehensive empirical analyses, it is confirmed that the economic idea and argumentation of the beta dispersion seems to be applicable. Furthermore, the study presents an innovative way of setting up market timing strategies by conducting distributional regressions to determine the timing indicator. This way of modeling is newly introduced to finance and seems to be convincing, based on the performance of the market timing strategies. The careful investment approach of the weighted market timing strategy delivers a promising risk and return characteristics that coincide with addressing usual shortcoming of market timing strategies.

The comprehensive findings of the study can be valuable for different stakeholders. For investors, the improved accuracy of market risk premium prediction and the introduction of distributional regression to timing strategies can be worthwhile. Both can enhance the implementation and performance of market timing strategies. Particularly, the distributional regression approach can be extended to other predictors (macroeconomic as well as technical) to enhance the performance of such strategies. For supervisors monitoring the financial stability of a market, the beta dispersion might serve as an additional indicator for measuring the market's vulnerability. It can complement and extend the possibilities of measuring and quantifying systemic risk in the stock market.

While it is intuitive that a group of stocks with extremely large betas can indicate a higher likelihood of systemic problems in the following periods, we certainly need a better understanding of why the beta dispersion carries information about future market movements and how this information is processed in the market. Especially, an in-depth analysis of the cascading effect should be conducted along with a specific focus on the spillovers and contagion of high-beta stocks during a systematic shock. A link of the beta dispersion to systemic risk measures and financial stability can give interesting insights about market characteristics that favor crisis-prone developments.

A Appendix

A.1 Calculated Variables

Some variables for the predictive regressions are calculated based on the price information of the S&P 500 and all its constituents:

- Log return of the market for 1, 3, 6, and 12 months:
  $R_{M,t} = ln(\frac{P_{t+s}}{P_t})$,
  where P is the price of the market index at time t and s is 1, 3, 6, and 12 months.

- Average variance following Pollet and Wilson (2010):
  $AV_t = \sum_{j=1}^{N} w_{j,t}\hat{\sigma}_{j,t}^2$,
  where N is the number of stocks traded at the market, w is the weight of the stock j at time t, and $\hat{\sigma}_j^2$ is the estimated volatility of stock j.

- Average correlation following Pollet and Wilson (2010):
  $AC_t = \sum_{j=1}^{N} \sum_{j \neq k} w_{j,t}w_{k,t}\hat{\rho}_{jk,t}$,
  where N is the number of stocks traded at a market, w is the weight of the stock j or k, respectively, at time t, and $\hat{\rho}_{jk}$ is the correlation coefficient between stock j and stock k.

- Moving average following Neely et al. (2014):
  $MA(2, 12) = MA_{2,t} - MA_{12,t}$ where $MA_{T,t} = (\frac{1}{s}) \sum_{i=0}^{s-1} P_{t-i}$ for $T = 2, 12$,
  where s is the number of trading days in the following T months for which the average is calculated and P is the price of the market index at time t.

- Momentum following Neely et al. (2014):
  $MOM(12) = P_t - P_{t-m}$ where P is the price of the market index at time t and m equals 12.

- Moving average of on-balance volume following Neely et al. (2014):
  $MA^{OBV}(1, 12) = MA_{1,t}^{OBV} - MA_{12,t}^{OBV}$ where $MA_{T,t}^{OBV} = (\frac{1}{s}) \sum_{i=0}^{s-1} OBV_{t-i}$ for $T = 1, 12$,
  where s is the number of trading days in the following T months for which the average is calculated and OBV is the on-balance volume of market index at time t. This volume is calculated as $OBV_t = \sum_{k=1}^{t} VOL_k D_k$ with VOL_k is a measure of the trading volume during period k and D_k has the value of 1 if $P_k - P_{k-1} \geq 0$ and -1 otherwise.

- Return dispersion following Maio (2016):
  $RD_t = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (R_{i,t} - \bar{R}_{M,t})^2}$,
  where N is the number of stocks traded at a market, R_i is the discrete return of stock i, and $\bar{R}_{M,t}$ is the weighted mean of the returns of all stock at the market.

A.2 Linear Predictive Regressions with BD_{VW} and $QBD_{10\%}$

Linear Predictive Regressions with BD_{VW}

Panel A: 3-Month Market Returns

	BD_{VW}^{3M}	BD_{VW}^{6M}	BD_{VW}^{12M}	BD_{VW}^{36M}
Intercept	**0.0533**	**0.0582**	**0.0603**	**0.0623**
	(0.0000)	(0.0001)	(0.0002)	(0.0008)
Beta Dispersion	**-0.0688**	**-0.0979**	**-0.1189**	**-0.1420**
	(0.0067)	(0.0067)	(0.0075)	(0.0175)
R^2_{adj}	0.0200	0.0197	0.0199	0.0190

Panel B: 6-Month Market Returns

	BD_{VW}^{3M}	BD_{VW}^{6M}	BD_{VW}^{12M}	BD_{VW}^{36M}
Intercept	**0.0932**	**0.1072**	**0.1085**	**0.1087**
	(0.0000)	(0.0000)	(0.0001)	(0.0010)
Beta Dispersion	**-0.1205**	**-0.1860**	**-0.2174**	**-0.2475**
	(0.0038)	(0.0027)	(0.0041)	(0.0202)
R^2_{adj}	0.0207	0.0216	0.0209	0.0189

Panel C: 12-Month Market Returns

	BD_{VW}^{3M}	BD_{VW}^{6M}	BD_{VW}^{12M}	BD_{VW}^{36M}
Intercept	**0.1597**	**0.1832**	**0.1880**	**0.1816**
	(0.0001)	(0.0001)	(0.0005)	(0.0051)
Beta Dispersion	**-0.1962**	**-0.3044**	**-0.3626**	**-0.3897**
	(0.0049)	(0.0049)	(0.0129)	(0.0601)
R^2_{adj}	0.0193	0.0201	0.0195	0.0166

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 1-, 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, Panel C, and Panel D) as the dependent variable. BD is the cross-sectional value-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

Linear Predictive Regressions with $QBD_{10\%}$

Panel A: 3-Month Market Returns

	$QBD^{3M}_{10\%}$	$QBD^{6M}_{10\%}$	$QBD^{12M}_{10\%}$	$QBD^{36M}_{10\%}$
Intercept	**0.0977**	**0.1005**	**0.0981**	**0.0862**
	(0.0004)	(0.0016)	(0.0018)	(0.0193)
Beta Dispersion	**-0.0380**	**-0.0425**	**-0.0467**	**-0.0569**
	(0.0062)	(0.0129)	(0.0135)	(0.0722)
R^2_{adj}	0.0234	0.0221	0.0213	0.0171

Panel B: 6-Month Market Returns

	$QBD^{3M}_{10\%}$	$QBD^{6M}_{10\%}$	$QBD^{12M}_{10\%}$	$QBD^{36M}_{10\%}$
Intercept	**0.1649**	**0.1790**	**0.1573**	**0.1401**
	(0.0002)	(0.0006)	(0.0048)	(0.0294)
Beta Dispersion	**-0.0635**	**-0.0795**	**-0.0731**	−0.0673
	(0.0033)	(0.0061)	(0.0291)	(0.1018)
R^2_{adj}	0.0232	0.0235	0.0197	0.0160

Panel C: 12-Month Market Returns

	$QBD^{3M}_{10\%}$	$QBD^{6M}_{10\%}$	$QBD^{12M}_{10\%}$	$QBD^{36M}_{10\%}$
Intercept	**0.2302**	**0.2364**	**0.2080**	0.1949
	(0.0045)	(0.0124)	(0.0382)	(0.1078)
Beta Dispersion	**-0.0943**	**-0.1618**	−0.0850	−0.0826
	(0.0375)	(0.0695)	(0.1517)	(0.2819)
R^2_{adj}	0.0175	0.0169	0.0149	0.0132

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 1-, 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, Panel C, and Panel D) as the dependent variable. BD is the difference between the mean beta of the high-beta quantile and the low-beta quantile (compare Equation 1). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

A.3 Linear Predictive Regressions with BD_{EW} in Good and Bad Market Regimes: Alternative Specification of Regimes

Panel A: Good Regime - 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0181**	**0.0172**	**0.0177**	**0.0143**
	(0.0002)	(0.0013)	(0.0010)	(0.0022)
Beta Dispersion	0.0112	0.0184	0.0194	0.0450
	(0.4681)	(0.4224)	(0.4814)	(0.1456)
R^2_{adj}	0.0009	0.0019	0.0011	0.0072

Panel B: Good Regime - 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0300**	**0.0279**	**0.0294**	**0.0243**
	(0.0022)	(0.0160)	(0.0092)	(0.0147)
Beta Dispersion	0.0177	0.0318	0.0305	0.0683
	(0.5789)	(0.5434)	(0.6010)	(0.3421)
R^2_{adj}	0.0013	0.0034	0.0015	0.0080

Panel C: Good Regime - 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0537**	**0.0506**	**0.0502**	**0.0420**
	(0.0081)	(0.0119)	(0.0097)	(0.0210)
Beta Dispersion	0.0213	0.0411	0.0510	0.1122
	(0.7214)	(0.6076)	(0.5789)	(0.3363)
R^2_{adj}	0.0001	0.0017	0.0019	0.0086

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, and Panel C) as the dependent variable during a positive market regime. BD is the cross-sectional equal-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The differentiation between a good and a bad market regime is based on a negative market return of the period prior to the estimation of the beta dispersion. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

Panel A: Bad Regime - 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	0.0010	0.0007	0.0002	0.0001
	(0.5193)	(0.5993)	(0.8889)	(0.9366)
Beta Dispersion	**-0.0873**	**-0.1014**	**-0.1087**	**-0.1245**
	(0.0209)	(0.0059)	(0.0023)	(0.0008)
R^2_{adj}	0.0461	0.0382	0.0274	0.0169

Panel B: Bad Regime - 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	0.0047	0.0052	0.0039	0.0029
	(0.1253)	(0.1116)	(0.2950)	(0.4624)
Beta Dispersion	**-0.1152**	**-0.1465**	**-0.1466**	−0.1488
	(0.0719)	(0.0563)	(0.0965)	(0.1812)
R^2_{adj}	0.0249	0.0327	0.0130	0.0324

Panel C: Bad Regime - 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	**0.0092**	**0.0100**	0.0091	0.0061
	(0.0367)	(0.0337)	(0.1090)	(0.2060)
Beta Dispersion	**-0.1064**	**-0.1423**	−0.1483	−0.1107
	(0.0986)	(0.0588)	(0.1251)	(0.3485)
R^2_{adj}	0.0269	0.0353	0.0273	0.0128

Note: This table shows the results of the predictive regressions, with the beta dispersion as independent variable and the 3-, 6-, and 12-month log excess return of the S&P 500 Index (Panel A, Panel B, and Panel C) as the dependent variable during a positive market regime. BD is the cross-sectional equal-weighted standard deviation of the individual stocks' betas (compare Equation 2). Beta is estimated from daily returns over a period of 3, 6, 12, and 36 months. The differentiation between a good and a bad market regime is based on a negative market return of the period prior to the estimation of the beta dispersion. The adjusted R^2_{adj} of the predictive regressions are given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations also use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals. The p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

A.4 Regression with Additional Explanatory Variables - Alternative Technical Predictors: Momentum

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	−0.0311	−0.0230	0.0013	0.0299
	(0.6873)	(0.7755)	(0.9834)	(0.7134)
Beta Dispersion	−0.0091	−0.0259	**-0.0808**	**-0.1723**
	(0.8872)	(0.7509)	(0.0768)	(0.0836)
DivY	0.0065	0.0052	0.0015	−0.0055
	(0.7309)	(0.8077)	(0.9395)	(0.7959)
SR	0.0669	0.0661	0.0625	0.0370
	(0.4442)	(0.4840)	(0.5119)	(0.7246)
CAY	0.1218	0.1104	0.1071	0.3232
	(0.7182)	(0.7590)	(0.7616)	(0.4396)
AV	**-0.6465**	**-0.6574**	**-0.7076**	**-0.7952**
	(0.0523)	(0.0947)	(0.0526)	(0.0075)
AC	0.0519	0.0402	0.0227	0.0535
	(0.7403)	(0.8023)	(0.8900)	(0.7381)
RD	**-1.7202**	**-1.6998**	**-1.7440**	−1.5103
	(0.0887)	(0.0995)	(0.0912)	(0.1747)
VIX	**0.0036**	**0.0037**	**0.0038**	**0.0037**
	(0.0058)	(0.0056)	(0.0044)	(0.0034)
Sentiment	−0.0213	−0.0201	−0.0151	−0.0142
	(0.1368)	(0.2244)	(0.2429)	(0.2597)
MOM(12)	0.0000	0.0000	0.0000	0.0000
	(0.8687)	(0.7612)	(0.5926)	(0.5448)
R^2_{adj}	0.0618	0.0628	0.0709	0.0785

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	−0.0067	0.0233	0.0206	0.0761
	(0.9578)	(0.8605)	(0.8116)	(0.5598)
Beta Dispersion	−0.0713	−0.1444	**-0.1662**	**-0.3461**
	(0.5573)	(0.4106)	(0.0489)	(0.0873)
DivY	0.0156	0.0099	0.0086	−0.0051
	(0.5712)	(0.7268)	(0.7440)	(0.8736)
SR	0.0083	0.0067	0.0068	−0.0442
	(0.9592)	(0.9666)	(0.9671)	(0.7999)
CAY	**1.0637**	**0.9937**	**1.0168**	**1.4515**
	(0.0656)	(0.0926)	(0.0549)	(0.0300)
AV	−0.0424	−0.1282	−0.2312	−0.4048
	(0.9164)	(0.7627)	(0.5654)	(0.3791)
AC	−0.0150	−0.0510	−0.0019	0.0620
	(0.9630)	(0.8716)	(0.9947)	(0.8237)
RD	−2.7461	−2.6488	−2.8371	−2.3668
	(0.1089)	(0.1130)	(0.1200)	(0.2619)
VIX	**0.0039**	**0.0041**	**0.0044**	**0.0043**
	(0.0251)	(0.0077)	(0.0034)	(0.0018)
Sentiment	−0.0408	−0.0355	−0.0311	−0.0297
	(0.1077)	(0.2479)	(0.1235)	(0.0485)
MOM(12)	0.0001	0.0000	0.0000	0.0000
	(0.4541)	(0.6687)	(0.7703)	(0.9530)
R^2_{adj}	0.0573	0.0676	0.0671	0.0801

Panel C: 12-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{3M}
Intercept	0.0712	0.0872	0.0810	0.1233
	(0.5187)	(0.4265)	(0.3995)	(0.4064)
Beta Dispersion	**-0.1543**	**-0.2277**	**-0.2581**	**-0.4261**
	(0.0923)	(0.0768)	(0.0861)	(0.0929)
DivY	0.0495	0.0430	0.0413	0.0282
	(0.1493)	(0.2227)	(0.2942)	(0.5815)
SR	−0.2091	−0.2057	−0.2053	−0.2644
	(0.3189)	(0.3263)	(0.3067)	(0.1298)
CAY	**3.4930**	**3.3695**	**3.4066**	**3.9494**
	(0.0001)	(0.0001)	(0.0000)	(0.0003)
AV	0.8113	0.6260	0.4660	0.2855
	(0.1769)	(0.3260)	(0.4972)	(0.7063)
AC	−0.2760	−0.2745	−0.1951	−0.0888
	(0.6850)	(0.6808)	(0.7598)	(0.8890)
RD	**-4.7117**	**-4.5918**	**-4.8879**	−4.2980
	(0.0196)	(0.0243)	(0.0267)	(0.1109)
VIX	0.0031	**0.0037**	**0.0041**	**0.0040**
	(0.1560)	(0.0910)	(0.0524)	(0.0524)
Sentiment	**-0.0574**	−0.0516	−0.0449	**-0.0476**
	(0.0714)	(0.1088)	(0.1225)	(0.0718)
MOM(12)	0.0002	0.0002	0.0002	0.0002
	(0.1170)	(0.1870)	(0.2304)	(0.4109)
R^2_{adj}	0.0645	0.0782	0.0770	0.0787

Note: This table shows the results of the predictive regressions with ten independent variables and 3-, 6-, and 12-month log excess return of the S&P 500 Index as dependent variables (Panel A, Panel B, and Panel C). The regression equation has the following independent variables: beta dispersion, dividend yield, short rate, cay factor, average variance, average correlation, VIX, return dispersion, aligned sentiment, and momentum. Dividend yield, average variance, average correlation, return dispersion, and momentum refer to the S&P 500 Index, and short rate is the 1-month T-bill rate. Additionally, the cay factor is provided by Lettau's database and the aligned sentiment index by Zhou's website, respectively. The beta dispersion is calculated based on 3, 6, 12, and 36 months. The in-sample, adjusted R^2_{adj}, of the predictive regressions is given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations of the significance levels use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals and the p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

A.5 Regression with Additional Explanatory Variables - Alternative Technical Predictors: Average of On-Balance Volume

Panel A: 3-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	−0.0376	−0.0343	−0.0195	−0.0017
	(0.6122)	(0.6674)	(0.7271)	(0.9759)
Beta Dispersion	−0.0103	−0.0215	**-0.0652**	**-0.1335**
	(0.8733)	(0.8109)	(0.0724)	(0.0934)
DivY	0.0074	0.0069	0.0050	0.0006
	(0.6601)	(0.7120)	(0.7614)	(0.9684)
SR	0.0710	0.0695	0.0633	0.0415
	(0.3812)	(0.4194)	(0.4682)	(0.6584)
CAY	0.1398	0.1392	0.1660	0.3540
	(0.6599)	(0.6643)	(0.5999)	(0.3685)
AV	**-0.6473**	**-0.6437**	**-0.6373**	**-0.6716**
	(0.0165)	(0.0566)	(0.0854)	(0.0737)
AC	0.0756	0.0700	0.0582	0.0849
	(0.6238)	(0.6418)	(0.6975)	(0.5663)
RD	**-1.6613**	**-1.6344**	−1.6325	−1.4240
	(0.0817)	(0.0972)	(0.1034)	(0.1662)
VIX	**0.0036**	**0.0037**	**0.0037**	**0.0036**
	(0.0045)	(0.0043)	(0.0023)	(0.0023)
Sentiment	−0.0200	−0.0191	−0.0148	−0.0142
	(0.1341)	(0.2394)	(0.2465)	(0.2068)
VOL(1,12)	0.0001	0.0001	0.0001	**0.0001**
	(0.1070)	(0.1135)	(0.1006)	(0.0790)
R_{adj}^2	0.0667	0.0674	0.0739	0.0796

Panel B: 6-Month Market Returns

	BD_{EW}^{3M}	BD_{EW}^{6M}	BD_{EW}^{12M}	BD_{EW}^{36M}
Intercept	0.0244	0.0409	0.0382	0.0809
	(0.8570)	(0.7915)	(0.7384)	(0.4293)
Beta Dipersion	−0.0931	−0.1638	**-0.1891**	**-0.3592**
	(0.4382)	(0.3705)	(0.0693)	(0.0355)
DivY	0.0098	0.0064	0.0049	−0.0064
	(0.7413)	(0.8468)	(0.8729)	(0.8213)
SR	0.0226	0.0147	0.0148	−0.0418
	(0.8905)	(0.9337)	(0.9327)	(0.8155)
CAY	**0.9511**	0.9295	0.9551	**1.4530**
	(0.0895)	(0.1072)	(0.1020)	(0.0497)
AV	−0.2261	−0.2354	−0.3533	−0.4530
	(0.5110)	(0.5396)	(0.3841)	(0.3011)
AC	−0.0375	−0.0608	−0.0056	0.0727
	(0.9197)	(0.8727)	(0.9864)	(0.8188)
RD	**-2.8636**	**-2.6870**	−2.9015	−2.3508
	(0.0805)	(0.0974)	(0.1018)	(0.2317)
VIX	**0.0040**	**0.0042**	**0.0045**	**0.0044**
	(0.0211)	(0.0132)	(0.0065)	(0.0052)
Sentiment	**-0.0400**	−0.0343	−0.0292	**-0.0287**
	(0.0710)	(0.2159)	(0.1442)	(0.0627)
VOL(1,12)	0.0000	0.0000	0.0000	0.0000
	(0.6944)	(0.7366)	(0.7220)	(0.6504)
R_{adj}^2	0.0523	0.0665	0.0660	0.0805

Panel C: 12-Month Market Returns

	BD^{3M}_{EW}	BD^{6M}_{EW}	BD^{12M}_{EW}	BD^{3M}_{EW}
Intercept	0.1574	0.1634	**0.1574**	**0.2068**
	(0.2098)	(0.1252)	(0.0619)	(0.0336)
Beta Dispersion	**-0.2176**	**-0.3113**	**-0.3573**	**-0.5800**
	(0.0507)	(0.0262)	(0.0149)	(0.0324)
DivY	0.0330	0.0278	0.0251	0.0089
	(0.2813)	(0.3702)	(0.4383)	(0.8108)
SR	−0.1656	−0.1714	−0.1709	−0.2544
	(0.4032)	(0.3938)	(0.3767)	(0.1510)
CAY	**3.1784**	**3.0909**	**3.1384**	**3.9121**
	(0.0001)	(0.0002)	(0.0001)	(0.0004)
AV	0.2814	0.1629	−0.0625	−0.2519
	(0.5866)	(0.7582)	(0.9114)	(0.6566)
AC	−0.3276	−0.3189	−0.2128	−0.0618
	(0.6536)	(0.6440)	(0.7496)	(0.9318)
RD	**-5.0179**	**-4.7607**	**-5.1700**	−4.3197
	(0.0228)	(0.0228)	(0.0267)	(0.1389)
VIX	0.0034	**0.0041**	**0.0047**	**0.0045**
	(0.1471)	(0.0761)	(0.0442)	(0.0484)
Sentiment	−0.0546	−0.0465	−0.0370	**-0.0408**
	(0.1016)	(0.1487)	(0.1904)	(0.0970)
VOL(1,12)	0.0002	0.0002	0.0002	0.0002
	(0.3503)	(0.3587)	(0.3203)	(0.3006)
R^2_{adj}	0.0676	0.0783	0.0768	0.0714

Note: This table shows the results of the predictive regressions with ten independent variables and 3-, 6-, and 12-month log excess return of the S&P 500 Index as dependent variables (Panel A, Panel B, and Panel C). The regression equation has the following independent variables: beta dispersion, dividend yield, short rate, cay factor, average variance, average correlation, VIX, return dispersion, aligned sentiment, and moving average of on-balance volume. Dividend yield, average variance, average correlation, return dispersion, and moving average of on-balance volume refer to the S&P 500 Index, and short rate is the 1-month T-bill rate. Additionally, the cay factor is provided by Lettau's database and the aligned sentiment index by Zhou's website, respectively. The beta dispersion is calculated based on 3, 6, 12, and 36 months. The in-sample, adjusted R^2_{adj}, of the predictive regressions is given in the last row of the table. Overlapping periods of the dependent variable are addressed by using the correction proposed by Britten-Jones et al. (2011). The calculations of the significance levels use the Newey–West estimator with corresponding lags to account for heteroscedasticity and autocorrelation in the residuals and the p-value is given in parenthesis for every coefficient. Coefficients that are significant at least at a 10% level are printed in boldface.

A.6 Distributional Regressions

The idea of structured additive distributional regressions is to aim explicitly at the complete distribution of the dependent variable and not only on the expected value of the dependent variable (Klein, Kneib, Lang, and Sohn, 2015; Silbersdorff, 2017). Conditional on the explanatory variable, a conventional linear regression model focuses on the description of the dependent variable by its expectation. Therefore, information about the dependent variable is lost. The structured additive distributional regression estimates all parameters of the conditional distribution of the dependent variable and, therefore, describes the relationship between dependent and explanatory variable in detail. Unlike quantile regressions, which are distribution-free, distributional regressions are a parametric yet flexible way of modeling a relationship. The assumption of the distribution of the dependent variable survives, and all parameters of its distribution are estimated regarding the covariates of the regression. Applied to this study, the assumption of a normal distribution for the log market return (y_i) seems a reasonable starting point, thus $y_i \sim N(\mu_i, \sigma_i)$. In a conventional regression, only the expected value of the market return, conditional on the observed beta dispersion (x_i), is estimated. Here, in addition, the variance of the market return, conditional on the observed beta dispersion, is estimated as well. Both parameters are estimated simultaneously via a back-fitting algorithm (Rigby and Stasinopoulos, 2005; Stasinopoulos, Rigby, et al., 2007). This algorithm uses penalized likelihood estimation to obtain unbiased estimates of the expected value and the standard deviation of the normal distribution that characterizes the market return. First, for each instance i, the distribution parameters are described with the following equations:

$$\mu_i = \beta_0^\mu + \beta_1^\mu x_i \tag{8}$$

$$\sigma_i = \beta_0^\sigma + \beta_1^\sigma x_i. \tag{9}$$

Equation 8 represents the mean of the conditional normal distribution of y_i, and Equation 9 represents the standard deviation of this distribution. The intention is to identify β_0^μ, β_1^μ, β_0^σ and β_1^σ such that the likelihood of obtaining the y_i is maximized. To this end, these two equations are used to replace μ_i and σ_i in the density function of the normal distribution for each instance i:

$$f_{y_i}(y) = \frac{1}{\sqrt{2\pi(\beta_0^\sigma + \beta_1^\sigma x_i)}} e^{-\frac{1}{2}\left(\frac{y-\beta_0^\mu+\beta_1^\mu x_i}{\beta_0^\sigma+\beta_1^\sigma x_i}\right)^2}. \tag{10}$$

Subsequently, the algorithm estimates the beta coefficients via penalized maximum likelihood in such a manner that, under the joint distribution, the observed market returns (y_i) are the most likely outcomes. To ensure that the standard deviation is positive, σ_i is replaced by $log(\sigma_i)$ in the Equation 9. The estimation procedure leads to a response function of y_i with the parameters μ_i and σ_i, which depend on the observed beta dispersion (x_i) and the corresponding estimated coefficients (β_0^μ, β_1^μ,

β_0^σ, and β_1^σ). Subsequently, the distribution of the market return can be expressed by $y_i \sim N(\beta_0^\mu + \beta_1^\mu x_i, exp(\beta_0^\sigma + \beta_1^\sigma x_i))$. This distribution can be used to estimate the probability of the market return being positive, conditional on the observed beta dispersion, which is used as a trigger for the market timing strategies.

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