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The Industry Beta as a Substitute for the Individual Stock Beta – An Empirical Analysis

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Abstract

The beta factor is often used to determine the systematic risk when calculating the cost of equity as part of the company valuation. This study examines whether it makes sense to use the industry beta instead of the beta factor of a listed company. Accordingly, an empirical test is performed to determine whether the assumption that the individual stock betas within a sector are homogeneous is justified. The study refers to the stocks included in the German DAX index, whereby 32 out of the 40 stocks could be taken into account, which were divided into six different sectors. The beta factors are calculated on the basis of the monthly stock and index returns over the past five years.
A multiple confidence interval comparison of all stocks included in a sector shows that there is no homogeneity of beta factors in four out of six sectors analyzed in this study, as significant differences in systematic risk could be detected in these sectors even with the very conservative Bonferroni method. The subsequent comparison of the individual beta confidence intervals with the respective industry beta shows that periods can be found for all sectors in which individual betas differ significantly from the industry beta. Consequently, the findings of this specific study suggest that when determining the cost of equity as part of an objective company valuation, the individual beta should not be replaced by an industry beta.

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1. Introduction

In practice, the discounted cash flow method is most frequently used to determine the value of a company (Hörler, Hauser and Gerig, 2019, Welfonder and Bensch, 2017). The weighted average cost of capital (WACC) plays a key role as the discount rate in this company valuation method (Bruns and Meyer-Bullerdiek, 2020). Of particular importance is the cost of equity, which is often determined using the Capital Asset Pricing Model (CAPM). According to this model, higher market risks are rewarded with higher expected stock returns. Accordingly, the cost of equity depends on the beta factor, which reflects the systematic risk (Sharpe, 1964, Lintner, 1965, and Mossin,1966).

Although often criticized, the CAPM continues to be a point of reference for new developments in the field of capital market models. An alternative model with better properties is currently not recognizable. In addition, capital market research is now also focusing more on empirical studies than on the development of new general models. Due to the lack of alternatives as well as the plausible structure and simple application of the basic model, it can be assumed that the CAPM will continue to be of great importance (Knoll, Lorenz and Wenger, 2018).

In the practical application of return estimation, the beta factor is often determined empirically using the single index model. For listed companies, the beta factors are estimated using a linear regression analysis of historical stock returns. However, many application issues have arisen in this regard, such as questions regarding the choice of index, the length of the return interval or the length of the entire estimation period. To date, no convincing parameter selection recommendation has been made in this regard (Ziemer, 2018).

If the beta of an unlisted company is to be determined, it is often recommended that the average beta of a (listed) peer group or all (listed) companies in a sector (industry beta) be used as a substitute when applying the CAPM. However, the use of such a substitute beta for listed companies is also discussed – despite the possibility of determining the company's own beta directly on the basis of stock returns – although there is no uniform assessment in the literature. In particular, the relatively few academic studies on this issue indicate that the use of peer group and industry betas in company valuation practice is viewed differently (Brüchle, Ehrhardt and Nowak, 2008, Zeugner, Göb and Knoll, 2013 and Rödl, 2024).

Against this background, the question arises as to whether an industry beta can generally be a useful substitute beta. The aim of this study is therefore to obtain an answer to this research question by means of a theoretical and empirical analysis for the German stock market. The study relates to the stocks included in the German DAX index on December 31, 2024. The stock prices from December 31, 2005 to December 31, 2024 are included in the analysis. The beta factors are calculated on the basis of the monthly stock and index returns over the past five years. The annual recalculation of the beta factors results in 15 overlapping five-year periods for which the suitability of the industry beta is tested for each of the sectors under consideration. In the empirical analysis, a multiple beta confidence interval

comparison and a confidence interval comparison with the respective industry beta are carried out for each industry.
The paper is organized as follows: Chapter 2 presents the beta from the single-index model and improvement approaches. Chapter 3 provides a comparison between the industry beta and the individual stock beta. Chapter 4 shows how the homogeneity of beta factors within an industry can be tested. In chapter 5, the procedure and the results of the empirical investigation are presented. In the last chapter, some concluding remarks and ideas for future research are given.

2. Beta from the single-index model and improvement approaches

The single index model, which is based on the assumption that the returns of individual investments develop in line with the movements of a (market) index, is often used in equity management theory and practice to forecast returns on equities. A regression analysis can be used to determine the excess return on a stock as follows (Fama, 1976, Brown and Warner, 1980 and Bruns and Meyer-Bullerdiek, 2020):

$$R_i(t) = \alpha_i + \beta_i \times R_M(t) + e_i(t) \tag{1}$$

where M is the market index, R_M is the market excess return, α_i is the intercept of the equation, $ß_i$ is the slope coefficient, i.e. the security's sensitivity to the index and e_i is the unexpected component of the return due to unexpected events that are relevant only to this security (firm-specific), e_i has a mean of zero and is also called "residual".
The beta factor or regression coefficient as an ordinary least squares estimator (OLS estimator) shows the extent of the influence of the market excess return on the stock excess return.
The problem with beta estimation using the single index model is that the requirements for the residual return (i.e. the difference between the actual excess stock return and its estimated value according to the regression equation) are often not met. It is assumed that the expected value of the residual return is zero, that the residual returns are uncorrelated and that the variance of the residual return is constant (Poddig, Brinkmann and Seiler, 2005). Accordingly, homoscedasticity is assumed. In addition, this form of beta estimation assumes intertemporal stability of the beta factor. However, the temporal instability of beta factors of individual stocks in successive, non-overlapping estimation periods has already been observed in earlier empirical studies (Rudolph and Zimmermann, 1998, Baele and Londono, 2013, Caporale, 2012, Yao, 2009 and Zimmermann, 1997). Meitner and Streitferdt (2015) also point out that the beta factor is not necessarily stable over time.
Other problems with beta estimation are related to the choice of market index, possible low liquidity in stocks, the intervalling effect (i.e. the systematic change in

the beta factor depending on the underlying return interval) or possible outliers in stock returns. Against this background, various research papers have been presented for improving the empirical estimation of the beta factor. These approaches can be categorized into three basic areas (Zeugner, Göb and Knoll, 2013):

(1) Adjustment of the beta factor resulting from the regression.
(2) Determination of a fundamental beta factor.
(3) Determination of a peer group beta or an industry beta.

To improve the forecasting quality of the equity beta ("raw beta"), methods have been developed that lead to an adjustment of the beta factor. Of these methods, the Blume beta and the Vasicek beta have attracted the most attention in literature and practice (Meyer-Bullerdiek, 2024).

According to Blume's method, it is assumed that the beta values move towards the market average over time, i.e. towards the value 1 for an all-encompassing market portfolio. In practice, the relationship determined by Blume has been modified somewhat, resulting in a so-called "adjusted beta". This adjusted beta can be criticized for not being conceptually in line with either the general understanding or the basic principles of company valuation and can regularly lead to significant misvaluations when betas are further away from one (Blume, 1971 Blume, 1975, Zimmermann, 1997 Spremann and Ernst, 2011 Scheld, 2013, Ziemer, 2018 and Meitner, 2021).

Another method for adjusting the beta that is also used in practice goes back to Vasicek. In contrast to Blume, the statistical quality of the regression is taken into account and a security-specific modification is made. A stronger beta adjustment is taken into account for companies with a relatively high beta standard error than for companies with a lower beta standard error. As a result, the beta value of the stock is changed more towards the mean value. Accordingly, the cross-sectional variance of ß (determined from the individual beta values of the respective stocks in the sample, the sector, a peer group or the entire market) is reduced by this adjustment procedure. This also applies to the Blume beta (Vasicek, 1973, Klemkosky and Martin, 1975, Zimmermann, 1997, Lally, 1998, Scheld, 2013, Gray, Hall, Diamond and Brooks, 2013 and Ziemer, 2018).

Fundamental beta factors are used to estimate the systematic risk of a company on the basis of quarterly or annual financial statements or other fundamental company data. A functional relationship between the fundamental data and the beta factor is assumed. Several empirical studies have examined the correlation between beta factors and fundamental company data. However, particularly for the German market, no improvement in forecast accuracy could be demonstrated through fundamental betas, nor could any stable and cross-period fundamental influences on the beta factor be identified. (Jähnchen, 2009, Scheld, 2013 and Ziemer, 2018).

The third approach to improve the empirical estimation of the beta factor refers to the determination of a peer group beta or an industry beta, which is used instead of the individual company beta. The peer group beta is determined from the beta factors of listed comparable companies that represent the peer group. In principle, the company to be valued and the peer group companies should be similar in terms of economic activities and markets. Selection criteria may include common operational characteristics such as industry sector, sales and procurement market, company size, capital structure, profitability, degree of diversification, company life cycle, competitive positioning, business strategy, etc. However, it should be noted that even a slight change in the peer group can result in significant changes in the beta factors to be estimated (Ziemer, 2018, Wollny, 2018, Scheld, 2013 and Ballwieser and Hachmeister, 2021).

If, on the other hand, the selection of comparable companies is based solely on the criterion of industry affiliation, this is referred to as industry beta, which is examined in more detail in the following section.

3. Comparing industry beta and individual stock beta

To determine the industry beta, a corresponding comparative portfolio must be compiled on the basis of industry affiliation. For example, the industry classification can be based on the homogeneity of the production materials and processes, the earnings and cost structure, the human capital or the sales markets. The basis for this can be a standardized classification methodology. However, the literature also points out that industry classification does not necessarily have to be tied to standards, but can also be based on the subjective judgment of the firm evaluater (Scheld, 2013).

If comparable structures exist, it can be assumed that companies belonging to the same sector have a comparable systematic risk. As a result, it should then be possible to determine the beta factor of a company by calculating the average beta of listed companies in the same sector weighted by their respective market capitalizations. If a sufficient number of peer companies are available, outliers and estimation errors can be reduced so that more reliable and stable beta estimates can be expected compared to the beta values of individual peer companies. In addition, the industry betas should be relatively constant over time. This approach can therefore be used to determine a representative beta factor for each sector in this way (Scheld, 2013, Lahmann, Brefo and Schwetzler, 2024 and Bruns and Meyer-Bullerdiek, 2020):

$$ß_{\text{Industry}} = \sum_{i=1}^{n} w_i \cdot ß_i \qquad \text{and} \qquad \sum_{i=1}^{n} w_i = 1 \tag{2}$$

where $ß_i$ is the beta factor of stock i, which is in the sector portfolio and w_i is the weight of stock i within the sector portfolio.

The industry beta takes into account the systematic risk of the entire sector, so that the effects of economic, technological or regulatory changes, for example, which have an impact on all companies in the same sector, are recorded. It is often assumed that a typical, relatively constant beta applies to certain sectors. For example, relatively low betas can be assumed for utility stocks. This means that market fluctuations only have a relatively small impact on the expected returns of these stocks. By contrast, a high beta can be assumed for technology stocks. This reflects a relatively high risk compared to the market as a whole (Zimmermann, 1997).

The use of an industry beta is problematic in cases where there are particular company-specific risks for individual (sector-specific) stocks, so that these companies differ from the sector average. For example, individual companies may have particular competitive disadvantages that do not apply to other stocks in the sector. This raises the question of whether the company in question actually correlates closely with the industry average. In addition, it can be problematic to assign companies to a specific industry, particularly in the case of a conglomerate.

It is sometimes pointed out that the indebtedness of the companies should be taken into account, so that the industry beta is calculated on the basis of the unlevered betas, which only reflect the operating risk of the individual companies. Once the (unlevered) industry beta has been determined, the debt of the company to be valued must be taken into account when calculating the company beta ("relevering") (Jähnchen, 2009, Koller, Goedhart and Wessels, 2020, Loßagk, 2014 and Bruns and Meyer-Bullerdiek, 2020).

As it has been observed that the standard error for the individual stock beta factor is higher than for an industry beta, it is recommended to use the industry beta in cases where the standard error can be significantly reduced as a result (Kruschwitz, Löffler and Essler, 2009).

However, it could be problematic if the beta values of relatively illiquid stocks are also included in the calculation of the sector beta. It can be assumed, however, that a value-based weighting of the beta factors, i.e., based on the market capitalization of the respective stock, will lead to a strong weighting of liquid stocks, which should have a positive effect on the sector beta. Nevertheless, an industry beta could possibly be dominated by a single stock with a relatively high market capitalization due to the weighting in terms of value. If, on the other hand, the individual beta factors are equally weighted when calculating the industry beta, unreliable estimates of the betas of illiquid stocks could possibly be given too high a weighting (Zimmermann, 1997).

In light of the aspects outlined in this section, it must be examined whether the assumption that the beta factor depends solely on the industry is justified. In the event that there is no homogeneity of beta factors within the industry, i.e. a strong dispersion is evident, the industry beta should not be used (Ziemer, 2018).

4. Testing the homogeneity of the beta factors of a sector

The comparability of beta factors for stocks within a sector can be checked using statistical methods (Zeugner, Göb and Knoll, 2013). It should be noted that these beta factors are not independent of each other within a given period. The usual comparative test methods are therefore not suitable. However, it is possible to compare the confidence intervals of the beta factors of all companies in a sector within a period. Statistically significant differences exist if at least two confidence intervals are disjoint, i.e. do not overlap. In principle, the respective confidence interval is obtained by converting the test statistic of the t-test to the null hypothesis ($\hat{ß}_i = 0$). The test thus checks whether there is a significant influence of the market return. Accordingly, the true beta factor of an individual company, which is estimated using linear regression, lies within the confidence interval at the 1-α level, whereby in a two-sided t-test the t-distribution is considered at 1-α/2 instead of 1-α. The confidence interval is then determined in this way (It should be noted here that t also – as usual – describes the running index over time) (Zeugner, Göb and Knoll, 2013 and Ziemer, 2018):

$$ß_i^{-+} = \hat{ß}_i - t_{1-\frac{\alpha}{2},T-2} \cdot \underbrace{\sqrt{\frac{\sum_{t=1}^{T}\left(r_{i,t} - \left(\hat{\alpha}_i + \hat{ß}_i \cdot r_{m,t}\right)\right)^2}{(T-2)\cdot\sum_{t=1}^{T}\left(r_{m,t} - \bar{r}_m\right)^2}}}_{S_{\hat{ß}_i}} ;$$

$$\hat{ß}_i + t_{1-\frac{\alpha}{2},T-2} \cdot \underbrace{\sqrt{\frac{\sum_{t=1}^{T}\left(r_{i,t} - \left(\hat{\alpha}_i + \hat{ß}_i \cdot r_{m,t}\right)\right)^2}{(T-2)\cdot\sum_{t=1}^{T}\left(r_{m,t} - \bar{r}_m\right)^2}}}_{S_{\hat{ß}_i}} \qquad (3)$$

where $\bar{r}_m$ ist he mean value of the market return r_m, $t_{1-\frac{\alpha}{2},T-2}$ is the quantile of the t-distribution for probability (1-α/2) and T-2 degrees of freedom and $S_{\hat{ß}_i}$ is the standard error of the regression coefficient $\hat{ß}_i$.

These confidence intervals can therefore be used to test the extent to which significant differences exist within an industry and the extent to which the industry beta is a useful substitute for the individual stock beta.

However, it should be noted in this context that a multiple confidence interval comparison must be carried out for such an approach, i.e. each beta factor of the individual companies is compared with all other beta factors within the sector. With multiple testing, however, there is an increase in the type 1 error (i.e. the probability that at least one of the null hypotheses is incorrectly rejected). To solve this problem, various correction methods have been developed to adjust the significance level of the individual tests in order to maintain the desired overall level. The Bonferroni method is considered to be very conservative. Here, all tests are performed at the level α/n ("adjusted significance level"), where n is the number of tests. For the

significance level α, this research paper uses the commonly required maximum permissible error probability of 5% (Hedderich and Sachs, 2020, Zeugner, Göb and Knoll, 2013, Poddig, Brinkmann and Seiler, 2005).
Since the betas of two companies are compared in each test, the number of tests can be determined using the binomial coefficient in the following way (Bourier, 2024, Henze, 2024, Bleymüller and Weißbach, 2015 and Zeugner, Göb and Knoll, 2013):

$$\binom{n}{k} = \frac{n!}{(n-k)! \cdot k!} \tag{4}$$

where n is the number of companies or betas included within the sector and k is the number of company betas that are compared with each other (here: 2).
Since the Bonferroni method is very conservative, it can be assumed that if the null hypothesis (the betas are the same) is rejected, there is a high probability that there are indeed differences between the beta factors.

5. Empirical Analysis

5.1 Research Design

An empirical analysis will be used to assess whether the use of an industry beta instead of the individual stock beta factor makes sense for the German stock market. Accordingly, it is to be examined whether there is homogeneity of beta factors within a sector.
The analysis relates to the stocks included in the German DAX index on 31 December 2024. It is based on the closing prices of these stocks and the DAX levels from 31 December 2005 to 31 December 2024, which were available at the end of each month. The stock prices used are taken from the ariva.de website and are adjusted for dividends, stock splits and subscription right proceeds. The monthly, discrete stock returns calculated on this basis are therefore comparable with the DAX as a performance index. The use of monthly returns means that price adjustment delays can be smoothed out. Accordingly, the beta factors should be more meaningful (Berner, Rojahn, Kiel, and Dreimann, 2005).
Excess returns are used to estimate the beta and determine the confidence intervals in accordance with the single index model, i.e. the respective risk-free (monthly) interest rates are deducted from the monthly stock and DAX returns. The respective 3-month Euribor rate for the previous month, broken down on a monthly basis, is used for this purpose. These interest rates are also taken from the ariva.de website and are divided by 12 in each case.
The respective beta factors are calculated in the analysis from the monthly excess returns of the past 60 months. So, the beta factors are determined for the first time on December 31, 2010 (on the basis of the monthly returns from January 31, 2006 to December 31, 2010). Subsequently, all beta factors are recalculated annually, resulting in a total of 15 overlapping five-year periods.

A total of 32 out of the 40 DAX stocks were included in the study. 8 stocks could not be included (3 stocks have only been listed on the stock exchange for too short a time, 1 stock could not be assigned to a sector, the market capitalization of 1 stock could not be fully surveyed and 3 stocks could not be included because the sector (mechanical engineering) would have comprised too few stocks). The remaining 32 stocks could be divided into 6 sectors (automotive – chemicals, pharmaceuticals, biotechnology and medical technology – finance – retail and consumer goods – technology – utilities, environment and infrastructure). Some stocks could only be included for certain periods because they were not listed on the stock exchange during all periods.

It should be noted that not all stocks included were always included in the DAX. This is not possible due to the increase in the number of DAX stocks from 30 to 40 on 20 September 2021. Nevertheless, in order to have a uniform basis, the DAX (as a representative of the German stock market and the most important sentiment barometer for the German financial market) is used as the benchmark index for calculating the beta for all periods.

The sector beta is calculated using formula (2), whereby the value weightings were calculated on the basis of the market capitalization of each stock at the time the beta was calculated. The market capitalization data was taken from the Index Composition Reports of Deutsche Börse and STOXX Ltd. However, as data could only be collected up to 31 December 2023, the market capitalization data as at 31 December 2024 was taken from the ariva.de website on 1 January 2025. If stocks in a sector were not yet listed, the industry beta resulted from correspondingly fewer stocks.

With regard to the test for homogeneity of the beta factors within a sector, the respective confidence intervals were calculated on the basis of formula (3) using excess returns instead of total returns. Thus, a two-sided test is carried out at the α level. The analysis includes both a multiple confidence interval comparison of all stocks included in an industry for each period under consideration and a comparison of the respective confidence interval with the industry beta (also for each period). For the multiple confidence interval comparison, the conservative Bonferroni method mentioned above is used with an α value of 5%. The number of tests was determined using formula (4).

In contrast, the Bonferroni correction is not necessary when comparing the confidence intervals with the sector beta, because in this case it is a separate test in each case, because a direct comparison is made with the industry beta for each confidence interval and each time period. This makes it possible to determine how many stock betas differ significantly from the industry beta (Zeugner, Göb and Knoll, 2013).

5.2 Results of the Empirical Analysis

5.2.1 Dispersion of the beta factors

First of all, the ranges of the beta factors are examined for each sector over all time periods. For this purpose, the results for each industry are presented below in graphical form using box-whisker plots, whereby in this study the quartiles are calculated including the median (Zeugner, Göb and Knoll, 2013, Hedderich and Sachs, 2020, Schuster and Liesen, 2017).
The box-whisker plot of the beta factors for the automotive sector are shown in Figure 1, with the time periods indicating the periods on which the beta calculation is based. The quartiles, whiskers and the median of the respective betas within the sector are shown. It should be noted that, unlike in English, a comma and not a point is placed after the integer in the beta values in accordance with the German notation.

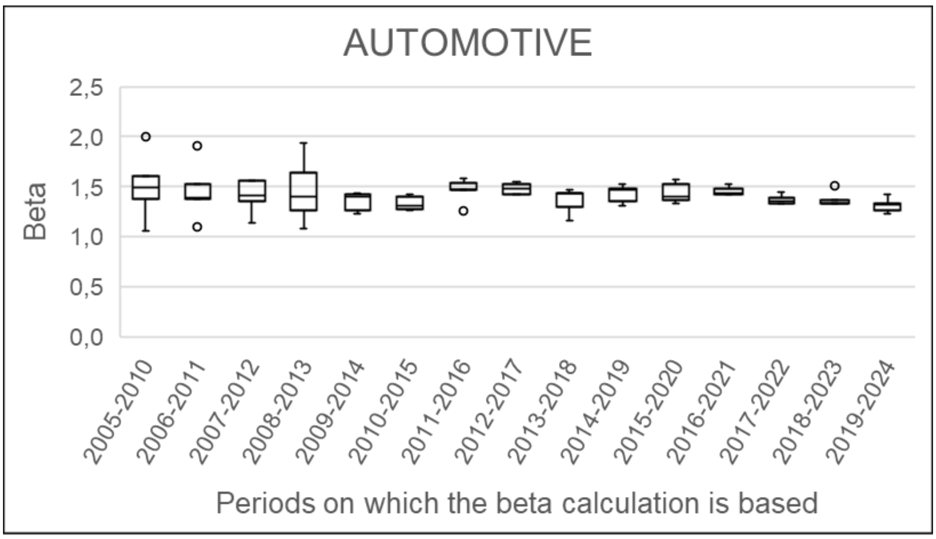

Figure 1: Box-whisker plot of the beta factors for the automotive sector

The median values for the automotive sector are relatively high in each period. Overall, all beta values in the respective periods are above 1, i.e. all shares in the automotive sector reacted more strongly than the DAX. The box-whisker plot also shows that the interquartile ranges are quite small. However, there are outliers in several periods, both upwards and downwards. There was also an outlier in the 2007-2012 period, which is unfortunately not shown in the chart. Overall, however, it can be stated that the range of beta factors in the respective years is relatively small. This relatively small range suggests that there are no particularly large deviations between the beta factors of the individual stocks in this sector and that they may not differ significantly from one another.
Figure 2 shows the box-whisker plot of the beta factors for the chemicals, pharmaceuticals, biotechnology and medical technology sector. It should be noted that stocks listed for the first time after 31 December 2005 were only included in

the analysis if past 60-month returns were available for the beta calculation. Compared to the automotive sector, the median betas for shares in the chemicals, pharmaceuticals, biotechnology and medical technology sectors are lower, but still quite close to one overall, although there are significant deviations, particularly on the downside. Figure 3 shows the corresponding results for the finance sector.

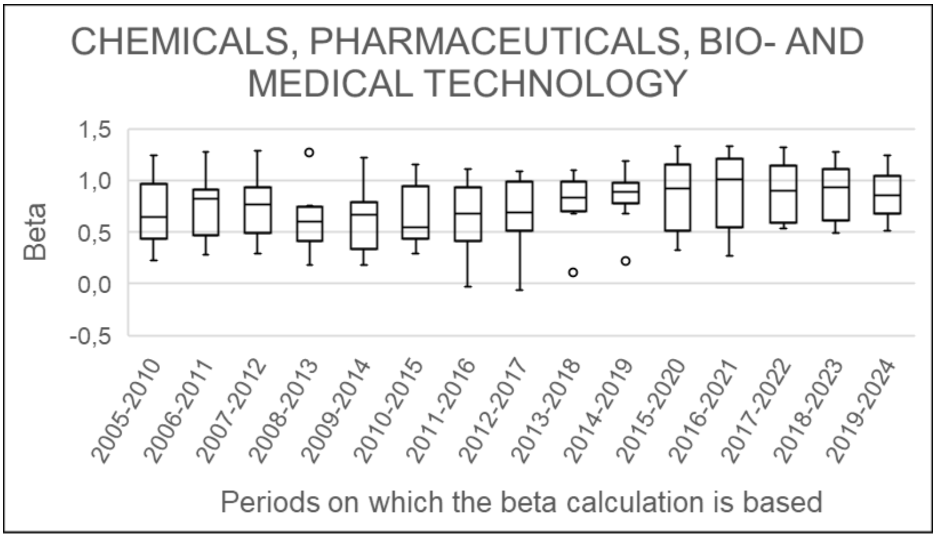

Figure 2: Box-whisker plot of the beta factors for the chemicals, pharmaceuticals, biotechnology and medical technology sector

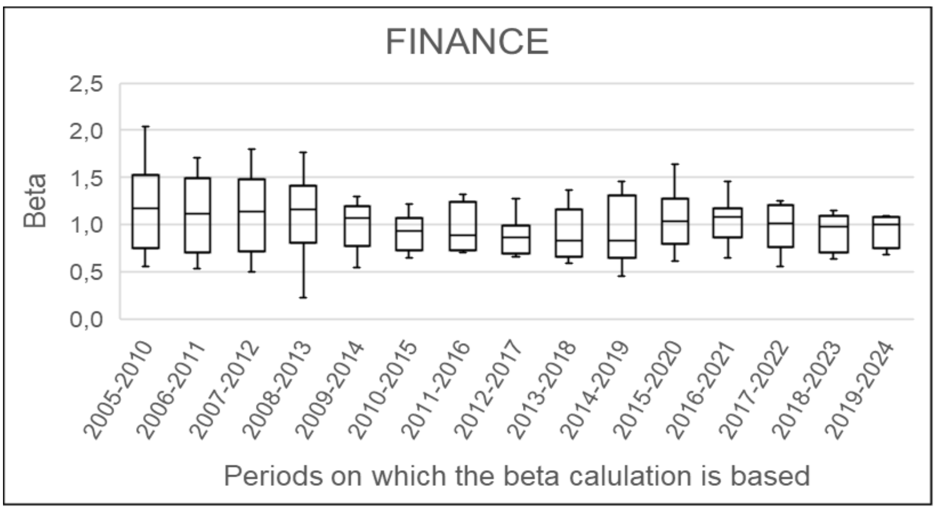

Figure 3: Box-whisker plot of the beta factors for the finance sector

The box-whisker plot for the finance sector shows that the respective median of the beta factors in the various periods is relatively close to one. The highest beta value was determined from the stock prices in the period from December 31, 2005 to December 31, 2010 (2.0451). The lowest beta value resulted from the stock prices of the period 2008-2013 (0.2272). It is noticeable that the fluctuation range of the

beta factors tends to decrease with the later periods. The relatively high beta values in the periods up to 2013 relate to the two bank stocks. However, these two stocks also almost always have the highest beta values in the subsequent periods.
Figure 4 shows the beta values for the retail and consumption sector.

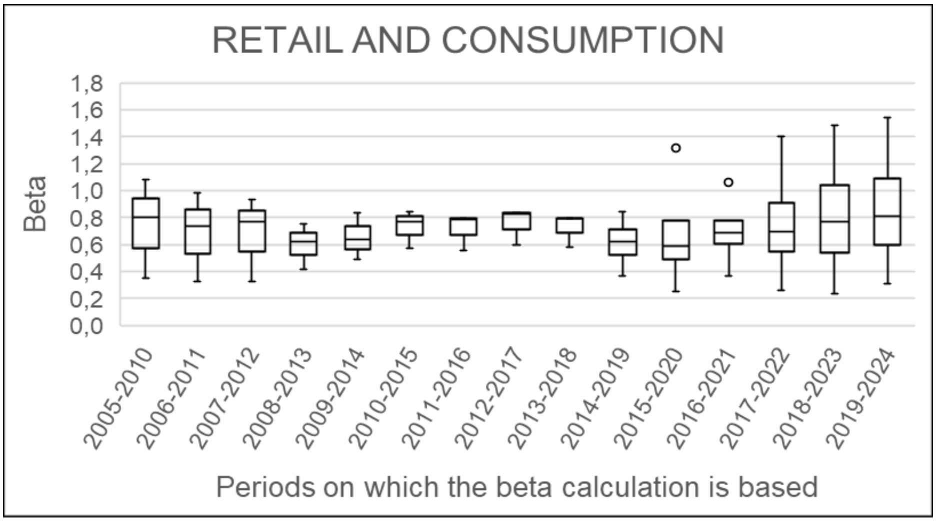

Figure 4: Box-whisker plot of the beta factors for the retail and consumption sector

It is remarkable that the beta factors in the retail and consumption sector were almost always less than one up to and including the 2014-2019 period, with the median being below one in all periods. Relatively high beta factors only occur in the periods from 2015-2020 onwards.
The corresponding figures for the technology sector can be seen in Figure 5.

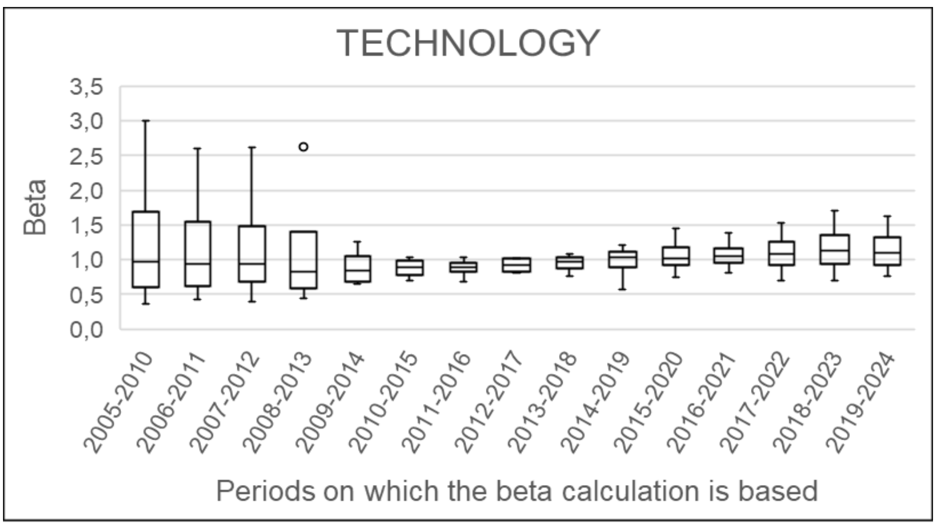

Figure 5: Box-whisker plot of the beta factors for the technology sector

Figure 5 shows that the median of the beta factors within the sector is relatively close to one in every period. This is due to the fact that in almost all periods the median is formed by two stocks, both of which have betas that tend to be close to one due to their high market capitalization (and thus their influence on the DAX). The beta values of the other stocks in this sector differ considerably from one another in the first few periods, as can be seen from the box plots and the long whiskers. Only after the financial and economic crisis of 2008 is no longer included in the beta calculation, do the beta values converge and extreme values no longer occur.
Finally, the box-whisker plot in Figure 6 shows the results for the utilities, environment and infrastructure sector.

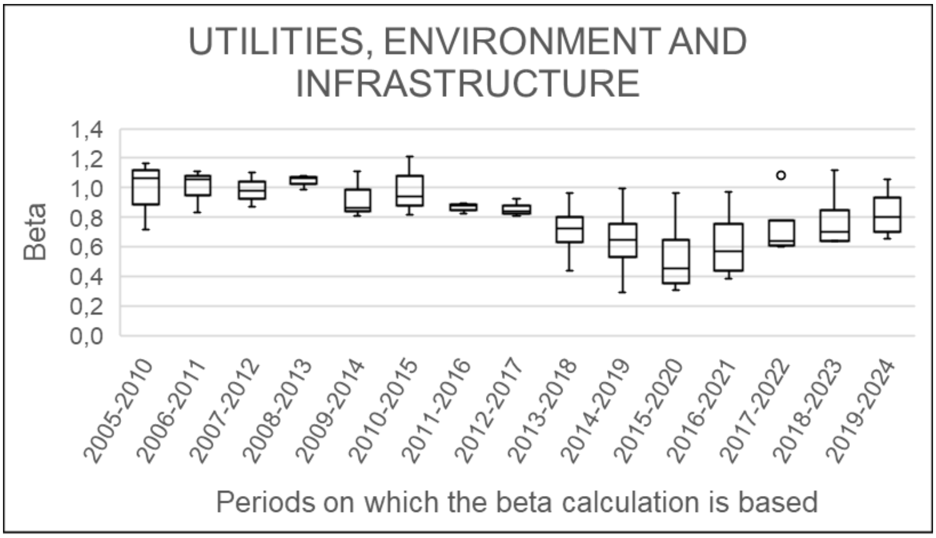

Figure 6: Box-whisker plot of the beta factors for the utilities, environment and infrastructure sector

Figure 6 shows that the beta factors in the periods 2005-2010 to 2012-2017 were relatively close to one with relatively small differences within the sector. In the subsequent periods, the median values are below one in each case. There is one outlier in the 2017-2022 period. This is due to the fact that the beta values of the other stocks in this period are between 0.6027 and 0.6737, the upper quartile is 0.7758, the interquartile range is 0.1675 and 1.5 times this range is therefore 0.2513. As a result, a value greater than 1.0272 is considered an outlier.
Now that the box-whisker plots have given an impression of the position and spread of the beta factors within an industry, the following two sections will examine in more detail whether the beta factors within an industry are actually comparable and whether it therefore makes sense to use an industry beta instead of the individual stock beta.

5.2.2 Comparison of the confidence intervals of the individual stock betas with all other betas within a sector

As explained above, the conservative Bonferroni method is used to test the extent to which the confidence intervals of the individual beta factors differ from one another. Taking into account the usually required significance level of 5%, an adjusted significance level of 0.05/n is used for this multiple confidence interval comparison, where n stands for the number of tests, which is determined according to formula (4). A detailed illustration will be provided using the finance sector. Table 1 shows the confidence intervals for each stock, whereby the respective upper and lower limits were determined using formula (3), i.e. a two-sided test is carried out at the 5% level. There is a significant difference between the beta confidence intervals of two stocks if either (1) the upper limit for one stock is lower than the lower limit for the other stock or (2) the lower limit for one stock is higher than the upper limit for the other stock (Zeugner, Göb and Knoll, 2013). These cases are marked accordingly with “yes” in the “Significance?” line.

Table 1: Multiple beta confidence interval comparison for the finance sector

		Allianz	**Commerz-bank**	**Deutsche Bank**	**Deutsche Börse**	**Hannover Rück**	**Münchener Rück**
2005-2010	Upper limit	1.6939	2.7504	2.1875	1.6609	1.0547	0.9294
	Lower limit	0.8416	1.3397	1.0485	0.5144	0.0593	0.3369
	Significance?		yes	yes		yes	yes
2006-2011	Upper limit	1.6353	2.4488	2.0879	1.4893	0.9666	0.8745
	Lower limit	0.8517	0.9765	1.0536	0.4792	0.0928	0.3465
	Significance?		yes	yes		yes	yes
2007-2012	Upper limit	1.6433	2.5573	2.0894	1.4205	0.9125	0.8775
	Lower limit	0.9161	1.0470	1.0052	0.5606	0.0868	0.3694
	Significance?	yes	yes	yes		yes	yes
2008-2013	Upper limit	1.5167	2.7168	2.1187	1.5245	0.6031	1.0092
	Lower limit	0.9450	0.8179	0.8355	0.6763	-0.1486	0.4246
	Significance?	yes	yes	yes	yes	yes	
2009-2014	Upper limit	1.5001	2.0578	1.8972	1.4285	0.8679	0.9960
	Lower limit	0.9393	0.2040	0.6953	0.5836	0.2132	0.3826
	Significance?	yes				yes	
2010-2015	Upper limit	1.3282	1.8431	1.7387	1.1825	0.9337	0.9570
	Lower limit	0.8515	0.2171	0.7026	0.5065	0.3687	0.4202
	Significance?						
2011-2016	Upper limit	1.3071	2.1782	2.0397	1.1408	1.0548	1.0335
	Lower limit	0.7432	0.4448	0.6127	0.3569	0.3976	0.3667
	Significance?						
2012-2017	Upper limit	1.2316	1.8826	2.0099	1.0530	1.1176	1.0089
	Lower limit	0.6652	0.1238	0.5419	0.2555	0.4430	0.3335
	Significance?						
2013-2018	Upper limit	1.1933	1.9344	2.0931	0.9957	1.0708	0.9281
	Lower limit	0.6338	0.5414	0.6332	0.1835	0.4445	0.3166
	Significance?						

Table 1: Multiple beta confidence interval comparison for the finance sector (*continued*)

		Allianz	**Commerz-bank**	**Deutsche Bank**	**Deutsche Börse**	**Hannover Rück**	**Münchener Rück**
2014-2019	Upper limit	1.1757	2.1357	2.1742	0.8597	1.0371	0.9198
	Lower limit	0.6527	0.7592	0.7474	0.0560	0.4361	0.3149
	Significance?						
2015-2020	Upper limit	1.4524	2.2872	2.0048	0.9819	1.0444	1.2232
	Lower limit	0.8819	0.9903	0.6119	0.2403	0.4573	0.6053
	Significance?		yes		yes		
2016-2021	Upper limit	1.4674	2.1634	1.8020	1.0082	1.1109	1.3570
	Lower limit	0.9108	0.7448	0.4328	0.2805	0.5052	0.7194
	Significance?						
2017-2022	Upper limit	1.4185	1.9539	1.8646	0.8939	1.0263	1.2452
	Lower limit	0.8148	0.5399	0.5979	0.2136	0.4135	0.5678
	Significance?						
2018-2023	Upper limit	1.3919	1.8284	1.7003	0.9752	0.9814	1.2192
	Lower limit	0.7647	0.4710	0.4860	0.2946	0.3215	0.5175
	Significance?						
2019-2024	Upper limit	1.4246	1.8105	1.6795	1.0081	1.0450	1.2999
	Lower limit	0.7694	0.3345	0.4757	0.3595	0.3262	0.5530
	Significance?						

For illustrative purposes, the values presented in Table 1 can also be presented in graphical form (Zeugner, Göb and Knoll, 2013), as shown in the following selected figures.

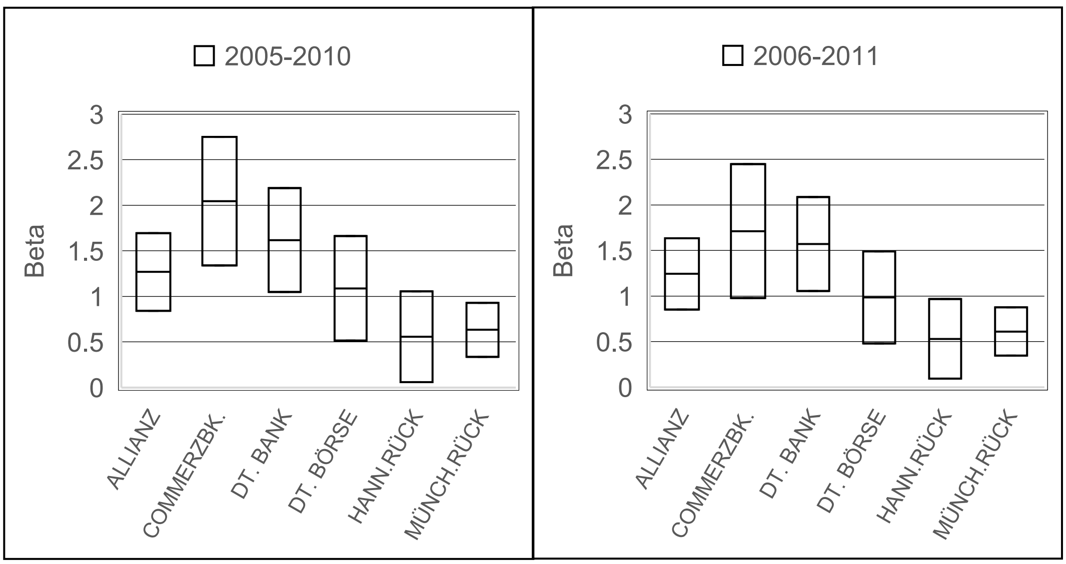

Figure 7: Multiple confidence interval comparison 2005-2010 and 2006-2011

The chart shows, for example, that the upper limit of the confidence interval for Münchener Rück (Munich Re) is below the lower limits of the confidence intervals for Commerzbank and Deutsche Bank in both periods. The beta factors are therefore significantly different in these two periods, meaning that there are no homogeneous beta factors within the finance sector. Moreover, the upper limit of the confidence interval for Hannover Rück (Hannover Re) in the period 2005-2010 (2006-2011) is also below the lower limit of the confidence interval for Commerzbank (Deutsche Bank). The following charts show the corresponding graphs for a few more selected periods.

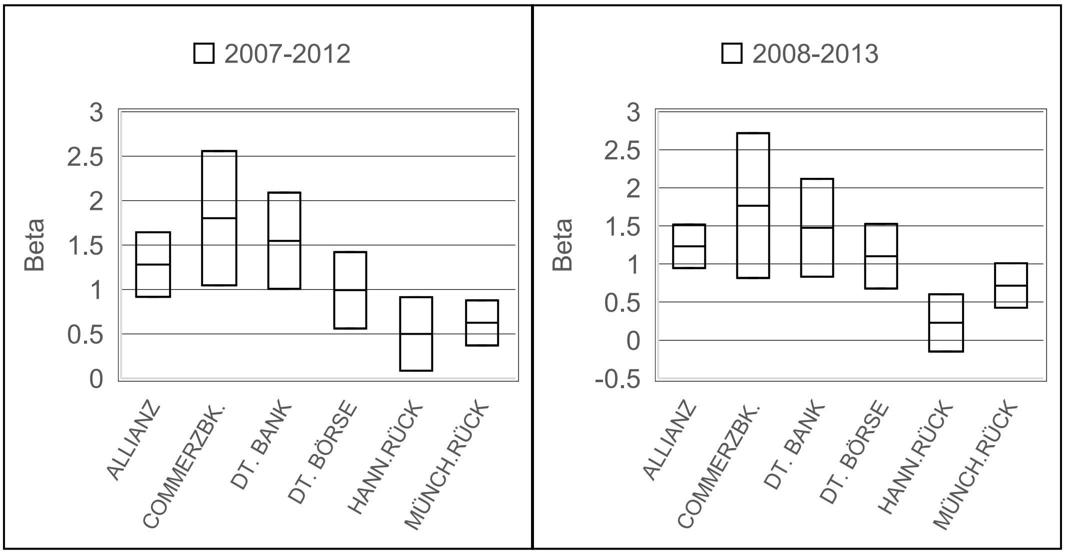

Figure 8: Multiple confidence interval comparison 2007-2012 and 2008-2013

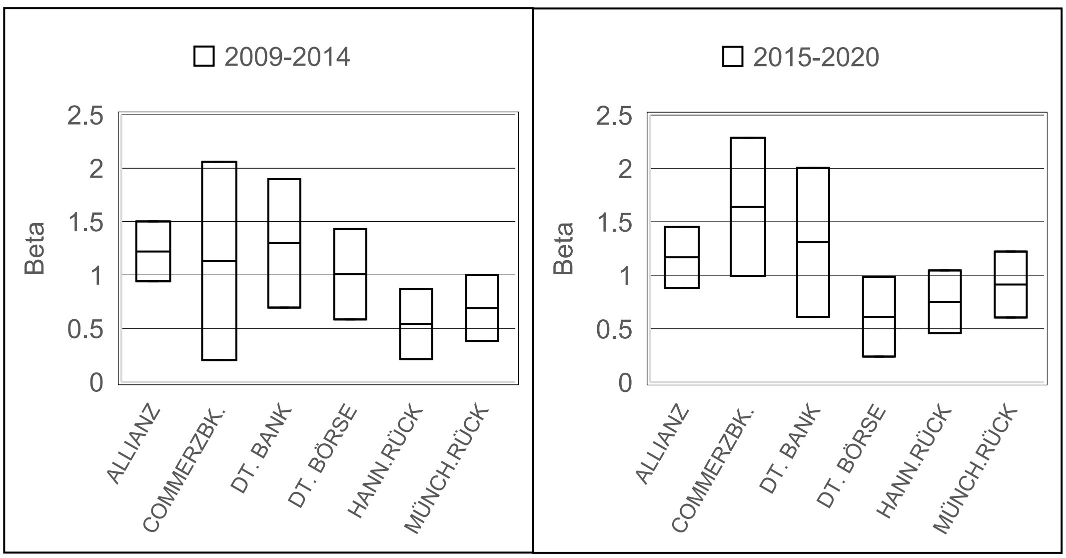

Figure 9: Multiple confidence interval comparison 2009-2014 and 2015-2020

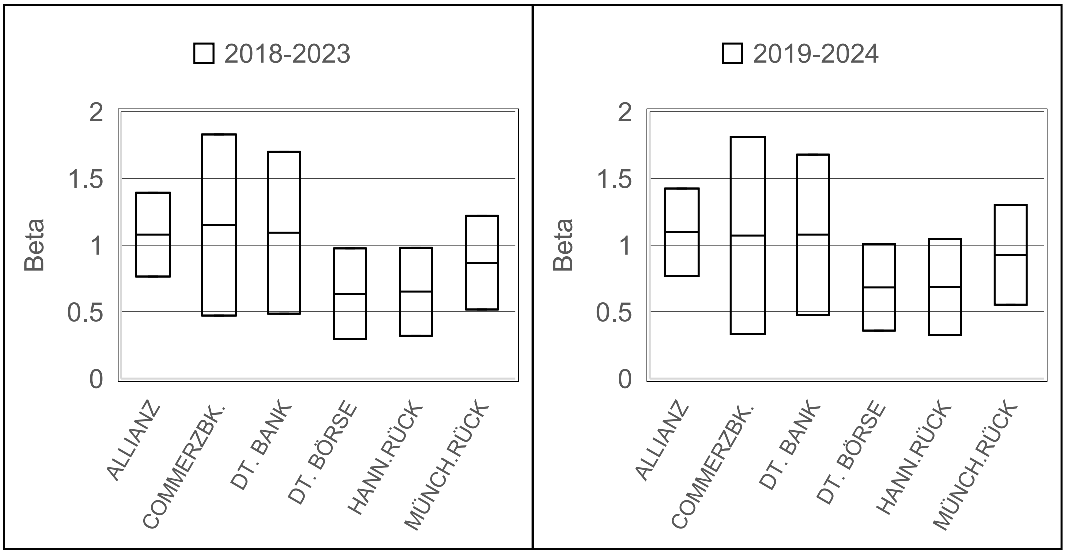

Figure 10: Multiple confidence interval comparison 2018-2023 and 2019-2024

As can be seen from Table 1 and also from Figures 7 to 10, using the very conservative test, there are significant differences between individual beta factors in the periods 2005-2010, 2006-2011, 2007-2012, 2008-2013, 2009-2014 and 2015-2020, i.e. in a total of 6 out of 15 periods (40%); because in these periods there are confidence intervals whose upper limit is lower than the lower limit of another confidence interval or whose lower limit is greater than the upper limit of another confidence interval.

The overall result across all sectors can be seen in Table 2. If significant differences between the beta factors could be determined in a period using multiple testing and taking into account the conservative correction according to Bonferroni, "yes" is indicated in each case.

Table 2: Cases of significant beta differences in the multiple confidence interval comparison

	Auto-motive	Chemicals, Pharmaceuticals, Bio- and Medical Technology	Finance	Retail and Consump-tion	Techno-logy	Utilities, Environment and Infrastructure
2005-2010		yes	yes	yes	yes	
2006-2011		yes	yes	yes	yes	
2007-2012		yes	yes	yes	yes	
2008-2013		yes	yes		yes	
2009-2014		yes	yes			
2010-2015		yes				

Table 2: Cases of significant beta differences in the multiple confidence interval comparison (*continued*)

	Auto-motive	Chemicals, Pharmaceuticals, Bio- and Medical Technology	Finance	Retail and Consump-tion	Techno-logy	Utilities, Environment and Infrastructure
2011-2016		yes				
2012-2017		yes				
2013-2018						
2014-2019						
2015-2020		yes	yes	yes	yes	
2016-2021		yes				
2017-2022		yes		yes	yes	
2018-2023				yes	yes	
2019-2024				yes	yes	
Total „yes“	**0**	**11**	**6**	**7**	**8**	**0**

As can be seen in Table 2, there are no significant differences between the beta factors in the automotive sector as well as in the utilities, environment and infrastructure sector. It can therefore be assumed that the systematic risk in these two sectors is comparable and that the individual stock beta could therefore be replaced by the industry beta. However, it should be noted that a very conservative test has been used. Even with this conservative test, however, significant beta differences arise quite frequently in the other sectors considered in this paper, so that the industry beta should not replace the individual beta in these sectors.
In the chemicals, pharmaceuticals, bio- and medical technology sector in particular, there were significant beta differences in 11 out of 16 periods although this sector has seen the strongest correction due to the majority of stocks. For example, a total of 8 companies were included in this sector in the period 2011-2016, which corresponds to 28 different tests according to formula (4):

$$\binom{8}{2} = \frac{8!}{(8-2)! \cdot 2!} = \frac{40.320}{720 \cdot 2} = 28$$

This results in an adjusted significance level of 0.1786% for this period according to the Bonferroni correction with 58 degrees of freedom (Zeugner, Göb and Knoll, 2013):

$$\alpha_{\text{adjusted}} = \frac{5\%}{28} = 0.1786\%$$

Since two-sided testing was used in this analysis, the t-distribution for 1-α/2 was considered instead of 1-α. The corresponding t-value, which is used in formula (3), is 3.275 in this case.

Thus, the beta differences suggest that the companies included in this industry do not appear to be very homogeneous.

In summary, the analysis of the DAX stocks has shown that the use of an industry beta for the automotive sector and the utilities, environment and infrastructure sector appears possible, although it should be noted that a very conservative test was used in this analysis. On the other hand, there is no homogeneity of beta factors in the other sectors considered here, as significant differences in systematic risk could be detected in these sectors even with the very conservative Bonferroni method. In these cases, it is therefore not advisable to use an industry beta. In the following, we will examine whether the comparison of the individual beta confidence intervals with the respective industry beta leads to the same results.

5.2.3 Comparison of the confidence intervals of the individual stock betas with the industry beta

In addition to the multiple confidence interval comparison, this paper also includes a comparison of the confidence intervals with the respective industry beta. Thus, for each stock in each period, the respective confidence interval of the stock beta according to formula (3) is compared directly with the industry beta, because if the respective stock beta is replaced, this is done by the specifically determined value of the industry beta. In this case, no correction of the significance level is necessary because it is not a multiple test, as a separate test is carried out for each individual beta (Zeugner, Göb and Knoll, 2013).

For this reason, the confidence intervals determined in section 5.2.2 differ from the intervals calculated in this section, i.e. the calculated intervals in this section are smaller, which is due to the lower t-value in formula (3). This value is 2.002 for a two-sided test, a significance level of 5% and 58 degrees of freedom.

These tests will also be presented in detail using the example of the finance sector. Table 3 shows the confidence intervals for each stock and the respective sector beta. There is a significant difference between the beta of a stock and the industry beta if the upper limit (lower limit) of the beta confidence interval is lower (higher) than the industry beta. These cases are marked accordingly with “yes” in the “Significance?” column. To illustrate this, the values presented in Table 3 can also be presented in graphical form, as shown in Figure 11 using the example of the first two periods. The dashed line shows the industry beta (Zeugner, Göb and Knoll, 2013).

Table 3 shows that there are significant differences between the beta factors of individual stocks and the industry beta in all periods, i.e. in these cases the industry beta lies outside the confidence interval of the individual beta.

Table 3: Comparison of the beta confidence intervals with the industry beta for the finance sector

		Allianz	Commerz-bank	Dt. Bank	Dt. Börse	Hannov. Rück	Münch. Rück	Industry beta
2005-2010	Upper limit	1.5464	2.5062	1.9903	1.4625	0.8824	0.8268	
	Lower limit	0.9891	1.5839	1.2457	0.7129	0.2316	0.4394	**1.2406**
	Significance?		yes	yes		yes	yes	
2006-2011	Upper limit	1.4996	2.1939	1.9088	1.3145	0.8154	0.7831	
	Lower limit	0.9873	1.2313	1.2326	0.6541	0.2441	0.4379	**1.2185**
	Significance?		yes	yes		yes	yes	
2007-2012	Upper limit	1.5174	2.2958	1.9017	1.2717	0.7695	0.7896	
	Lower limit	1.0419	1.3084	1.1929	0.7094	0.2297	0.4574	**1.2110**
	Significance?		yes			yes	yes	
2008-2013	Upper limit	1.4177	2.3881	1.8966	1.3777	0.4730	0.9080	
	Lower limit	1.0439	1.1466	1.0576	0.8231	-0.0185	0.5258	**1.2033**
	Significance?					yes	yes	
2009-2014	Upper limit	1.4030	1.7369	1.6892	1.2822	0.7546	0.8899	
	Lower limit	1.0364	0.5249	0.9034	0.7299	0.3265	0.4888	**1.1024**
	Significance?					yes	yes	
2010-2015	Upper limit	1.2457	1.5617	1.5594	1.0655	0.8359	0.8641	
	Lower limit	0.9340	0.4985	0.8819	0.6235	0.4665	0.5131	**1.0029**
	Significance?					yes	yes	
2011-2016	Upper limit	1.2095	1.8782	1.7927	1.0051	0.9411	0.9180	
	Lower limit	0.8408	0.7449	0.8597	0.4926	0.5114	0.4821	**0.9937**
	Significance?					yes	yes	
2012-2017	Upper limit	1.1336	1.5781	1.7558	0.9149	1.0009	0.8920	
	Lower limit	0.7632	0.4282	0.7960	0.3935	0.5598	0.4504	**0.9288**
	Significance?				yes		yes	
2013-2018	Upper limit	1.0965	1.6933	1.8404	0.8551	0.9624	0.8222	
	Lower limit	0.7306	0.7825	0.8859	0.3241	0.5529	0.4225	**0.8620**
	Significance?			yes	yes		yes	
2014-2019	Upper limit	1.0852	1.8974	1.9272	0.7206	0.9331	0.8151	
	Lower limit	0.7432	0.9974	0.9943	0.1951	0.5401	0.4196	**0.8389**
	Significance?		yes	yes	yes		yes	
2015-2020	Upper limit	1.3537	2.0627	1.7637	0.8536	0.9428	1.1162	
	Lower limit	0.9807	1.2148	0.8530	0.3687	0.5589	0.7123	**1.0456**
	Significance?		yes		yes	yes		
2016-2021	Upper limit	1.3711	1.9179	1.5650	0.8822	1.0060	1.2466	
	Lower limit	1.0072	0.9904	0.6698	0.4065	0.6100	0.8297	**1.0626**
	Significance?				yes	yes		
2017-2022	Upper limit	1.3140	1.7091	1.6453	0.7761	0.9202	1.1279	
	Lower limit	0.9193	0.7846	0.8171	0.3313	0.5195	0.6851	**0.9769**
	Significance?				yes	yes		
2018-2023	Upper limit	1.2833	1.5934	1.4901	0.8574	0.8672	1.0977	
	Lower limit	0.8733	0.7059	0.6962	0.4124	0.4357	0.6390	**0.9477**
	Significance?				yes	yes		
2019-2024	Upper limit	1.3112	1.5550	1.4711	0.8958	0.9206	1.1706	
	Lower limit	0.8828	0.5900	0.6841	0.4718	0.4506	0.6823	**0.9595**
	Significance?				yes	yes		

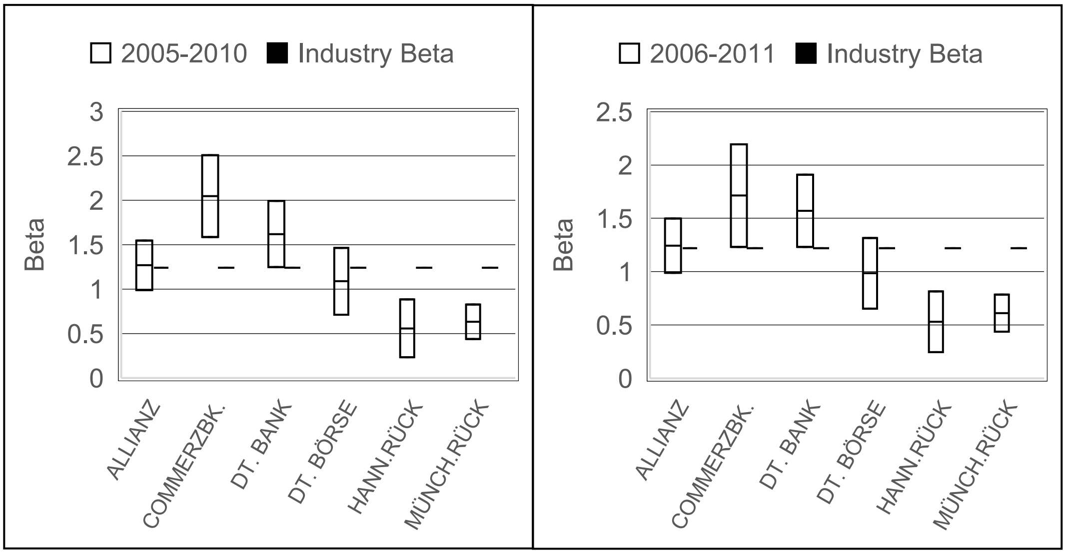

Figure 11: Confidence interval and industry beta 2005-2010 and 2006-2011

The overall result across all sectors is shown in Table 4. If there are significant differences between an individual beta and the respective industry beta, "yes" is indicated in each case.

Table 4: Cases of significant differences between an individual beta and the industry beta

	Auto-motive	Chemicals, Pharmaceuticals, Bio- and Medical Technology	Finance	Retail and Consump-tion	Techno-logy	Utilities, Environment and Infrastructure
2005-2010	yes	yes	yes	yes	yes	yes
2006-2011	yes	yes	yes	yes	yes	
2007-2012	yes	yes	yes	yes	yes	
2008-2013	yes	yes	yes	yes	yes	
2009-2014		yes	yes		yes	
2010-2015		yes	yes			
2011-2016		yes	yes			
2012-2017	yes	yes	yes			
2013-2018		yes	yes			yes
2014-2019		yes	yes		yes	yes
2015-2020		yes	yes	yes	yes	yes
2016-2021		yes	yes	yes	yes	yes
2017-2022		yes	yes	yes	yes	yes
2018-2023		yes	yes	yes	yes	yes
2019-2024		yes	yes	yes	yes	
Total „yes"	**5**	**15**	**15**	**9**	**11**	**7**

As Table 4 shows, there are periods in all sectors in which the industry beta lies outside the beta confidence interval for at least one company. In the chemicals, pharmaceuticals, bio- and medical technology sector and in the finance sector, this even applies to every period. In contrast to the multiple confidence interval comparison of the beta factors, the comparison with the industry beta also shows several periods in which the beta factors differ significantly from the industry beta in the automotive sector and in the utilities, environment and infrastructure sector. In this respect, significant differences in systematic risk can also be demonstrated for these sectors, although this was not possible using the very conservative Bonferroni method. Consequently, the use of an industry beta would not be recommended for these sectors either.
In order to provide a more precise statement, Table 5 shows for each period the percentage of companies for which the industry beta lies outside the beta confidence interval. The weighted average is determined by weighting by the number of companies included in the respective periods (Zeugner, Göb and Knoll, 2013). It can be seen that the greatest differences between the periods can be found in the technology sector. For example, the industry beta in the period 2006-2011 was outside all the beta confidence intervals included, while in other periods (e.g. 2010-2015) the industry beta was within the confidence intervals in each case. Consequently, the standard deviation of the percentage values is highest in this industry.

Table 5: Proportion of cases with an industry beta outside the individual beta confidence interval

	Auto-motive	Chemicals, Pharmaceuticals, Bio- and Medical Technology	Finance	Retail and Consump-tion	Techno-logy	Utilities, Environment and Infrastructure
2005-2010	40%	67%	67%	33%	75%	33%
2006-2011	40%	57%	67%	33%	100%	0%
2007-2012	40%	57%	50%	33%	50%	0%
2008-2013	40%	57%	33%	33%	75%	0%
2009-2014	0%	57%	33%	0%	25%	0%
2010-2015	0%	75%	33%	0%	0%	0%
2011-2016	0%	63%	33%	0%	0%	0%
2012-2017	20%	50%	33%	0%	0%	0%
2013-2018	0%	25%	50%	0%	0%	25%
2014-2019	0%	25%	67%	0%	25%	50%
2015-2020	0%	50%	50%	50%	50%	25%
2016-2021	0%	63%	33%	25%	25%	50%
2017-2022	0%	50%	33%	50%	50%	25%

Table 5: Proportion of cases with an industry beta outside the individual beta confidence interval (*continued*)

	Auto-motive	Chemicals, Pharmaceuticals, Bio- and Medical Technology	Finance	Retail and Consump-tion	Techno-logy	Utilities, Environment and Infrastructure
2018-2023	0%	44%	33%	50%	50%	25%
2019-2024	0%	22%	33%	50%	50%	0%
Mean value	**12.00%**	**50.79%**	**43.33%**	**23.89%**	**38.33%**	**15.56%**
Weighted Average	**12.00%**	**50.00%**	**43.33%**	**25.49%**	**38.33%**	**17.31%**
Standard deviation	**18.21%**	**15.73%**	**13.80%**	**21.56%**	**31.15%**	**18.86%**

If the weighted average (based on the number of companies) is calculated across all six sectors and periods, the result is a value of 34.01%. It should be noted that there were initially 6 companies in the chemical, pharmaceutical, bio- and medical technology sector and 9 in the last period.
Overall, it can be stated that there are significant deviations of beta factors from the industry beta for around a third of the companies, i.e. the (null) hypothesis that the beta factor corresponds to the industry beta must be rejected at the 5% level. At the same time, however, it must be noted that this does not mean that the null hypothesis applies to the remaining two thirds of the companies, as this statement can only be rejected at the 5% level. Accordingly, the hypothesis that the systematic risks within a sector are comparable cannot be upheld. Consequently, the findings of this specific study suggest that when determining the cost of equity as part of an objective company valuation, the individual stock beta should not be replaced by an industry beta (Zeugner, Göb and Knoll, 2013).

6. Conclusion

The beta factor is often used to determine the systematic risk when calculating the cost of equity as part of the company valuation. There is a debate as to whether it makes sense to replace a listed company's own beta factor with the industry beta. Against this background, following a theoretical discussion of the industry beta, this study uses various statistical methods to empirically test whether the assumption that the individual stock betas within a sector are homogeneous is justified. The study refers to the stocks included in the German DAX index on 31 December 2024, broken down – as far as possible – Into six sectors. In order to obtain meaningful results, the stock prices from 31 December 2005 to 31 December 2024 are included in the analysis. The beta factors are calculated on the basis of the monthly stock and index returns over the past five years. The annual recalculation of the beta factors results in 15 overlapping five-year periods for which the suitability of the industry

beta is tested for each of the sectors analyzed.
Overall, there are sometimes quite significant differences between the beta factors in the individual periods within each sector. This at least gives the impression that the use of an industry beta instead of the individual stock beta in the company valuation is at least questionable. A multiple confidence interval comparison of all stocks included in a sector shows that the use of an industry beta appears possible for the two sectors “Automotive” and “Utilities, Environment and Infrastructure”. On the other hand, there is no homogeneity of beta factors in the other four sectors analyzed here, as significant differences in systematic risk could be detected in these sectors even with the very conservative Bonferroni method. In these cases, it is therefore not advisable to use an industry beta. However, the subsequent comparison of the individual beta confidence intervals with the respective industry beta shows that periods can be found for all sectors in which beta factors differ significantly from the industry beta. Consequently, the findings of this specific study suggest that when determining the cost of equity as part of an objective company valuation, the individual stock beta should not be replaced by an industry beta.
For a more generally valid statement, however, further studies would be required that cover an even longer period of time, take a broader, also cross-national view of the industry and possibly also use overlapping monthly beta values. In this respect, the analyses carried out here on the use of an industry beta in the context of company valuation can serve as a basis for further research in this area.

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