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Does the Movement in Total Market Risk Justify Unchanged and Sticky Cost of Capital Rates? A Financial-Statistical Analysis Using DAX-30 Data

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Abstract

Despite low interest rates, DAX-30 companies in Germany continue to set high WACC. In the period from 2004 to 2020, the risk-free interest rate computed by the yield of a long-term government bond consequently declined from 4.1% in 2004 to -0.19% in 2020. This paper aims to evaluate the total market risk extent as explanatory variable for an implicitly increased risk exposure. Therefore, we use the logarithmic volatility of daily stock returns of the DAX-30 price index and extract WACC rates from annual reports. Additionally, total market risk developments are exposed to the observable practically invariable cost of capital. We provide evidence, based on two hypotheses using financial-statistical methods. Based on the results of these methods, this paper indicates that there is no across-the-board increase in the overall market risk extent expressed by volatility for log daily DAX-30 return data.

Keywords: cost of capital, market risks, financial-statistics, value-based management, risk measurement
Jel codes: G30, G32

1. Introduction

The estimation of the cost of capital is crucial practice to ensure and evaluate positive corporate growth. Economic value creation, in absolute terms, requires both the implementation of value creation tasks and risk avoidance tasks. The cost of capital (CoC) rate is a performance metric for pricing risk and expected return of an investment. From an investor's perspective CoC quantifies the risk-adjusted minimum required return for providing equity capital. Both, for external investors and a company's senior management, reliable and realistic CoC estimates are ultimate decision parameter for capital expenditures that foster economic growth of a company. Financial practitioners widely use a weighted average cost of capital (WACC) which is calculated from the weighted cost of equity and the weighted cost of debt. To estimate the imputed cost of equity, the Capital Asset Pricing Model (CAPM) is the dominant method due to its non-manipulative nature (Castedello et al., 2018). Not only for the cost of debt computation but also for equity costs, the interest-rate controlled by central banks influences the level of cost of capital. The risk-free interest rate allows for low-cost debt financing. The yield on long-term, default-free government bonds, are used as a proxy for risk-free interest rate (IDW, 2016).

Evidence suggests, that the implementation of an investment project should be primarily made using the net present value (NPV) of particular projects (Berk and DeMarzo, 2011). The NPV is based on the accuracy of cashflow forecasts and the CoC. Intentional manipulation and deviating from broadly accepted financial methodologies can lead to overly optimistic cashflow forecasts, i. e. incorrect estimates and decisions (Brotherson et al., 2013). Explanations are provided by numerous past empirical studies, which observed systematic manipulation of the CoC principles (Zenner et al., 2014; Saleheen & Levina, 2017; Jagannathan et al., 2012). Increasingly, financial managers add a premium to the CoC which compensates for overly optimistic cashflow forecasts or incorrect CoC assumptions (Poterba and Summers, 1995).

Risk can be expressed as the degree of uncertainty that must be priced in order to determine the minimum rate of return required by an investor. Bearing this in mind, CoC is the sum of a risk-free interest rate and a risk premium. Using the CAPM, the risk premium refers to the product of beta and market risk premium. Because beta, risk-free interest rate and market risk premium are affected by the capital market situation, the market risk level should have considerable impact on the level of CoC (Bertram et al., 2015). In general, good diversification options are provided to investors to compensate for company-specific risks in the best possible way (Castedello et al., 2018).

If we examine the risk handling procedures from a corporate governance perspective, we migh refer to the Deutsche Corporate Governance Kodex (DCGK) as the leading catalog of requirements for good corporate governance (CG) practice in Germany. We conducted a machine-learning based, bibliometric analysis of 530 peer-reviewed CG publications and conclude that there is not only an excessive emphasis on risk avoidance but also that value-based management approaches are underprioritized (Frey et al., 2023, submitted).

The empirically given relevance of volatility in the context of high CoC on the one hand, and the observed risk avoidance orientation at the supervisory level on the other, provide rationale for examining the unchanged cost of capital in light of an implicitly increased risk premium. Among other things, an increase in market risk defined by volatility of returns, may cause the unchanged WACC. This study approaches the observable implicitly increased risk premium on the basis of the extent of total market risk. For this purpose, the following working hypotheses are addressed:

- *Hypothesis 1 (H1):* The extent of total market risk expressed by volatility has increased.
- *Hypothesis 2 (H2):* The ex-post analyses of historical volatility is good practice for measuring expected volatility.

In the next section, we describe the methodology used to address the above working hypotheses as well as the technical aspects to generate quantitative insights. The methods used, serve to prove an unchanged market risk as well as to confirm empirical values that support the deployment of classical capital market-based determination of the CoC. According to Gleißner (2014), "capital market orientation" results from the use of historical price returns as a basis to derive beta factors as risk parameter in the WACC model.

2. Data & Methodology

We use the programming language Python and in particular its scientific library "SciPy" to address the hypotheses by financial-statistical methods. In descriptive statistics, the mean value of a variable is interpreted as its expected value. Volatility is understood as the variation intensity of a variable over time. By nature, the range of variation is expressed as a percentage, based on logarithmic returns of a security. We compute it as follows:

$$s = \sqrt{\frac{1}{n-1}(\bar{x} - x_i)^2}$$

Equation 1. Volatility

In essence, the formula above represents the root square of the variance. We resort to variance to measure the average squared deviation of realized returns from expected returns (mean). Thus, squaring deviations ensures to obtain always positive values. For interpretational convenience, the variance is converted into the standard deviation by its root, expressing the volatility in relation to price returns.

The stock price data of the DAX-30 price index serves as data sample for this paper. The daily index price data was downloaded from Google Finance comprising 11.074 data points and 20 fiscal years: from 2000 to 2020. Lastly, the variance is computed using 21 trading days. The technical transformation process of daily index prices looks as it follows:

- Log computation of daily closing prices
- Calculation of daily index returns by differencing back-to-back index prices
- Calculation of the variance of daily index returns based on a 21-trading day rolling window
- Taking the root from the variance

We add natural log-transformation to the process of volatility computation because a logarithmic scale gives equal visual weight to equal relative changes and facilitates interpretation as multiplicative factors are depicted linearly (see figure 2).

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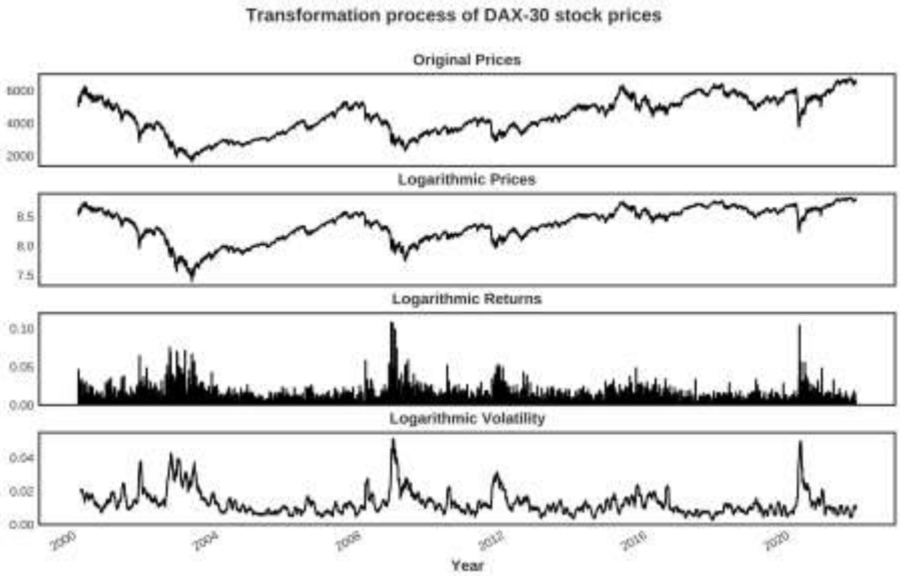

Figure 1. Transformation process of DAX-30 data

Source: https://www.boerse-frankfurt.de/index/dax-kursindex/kurshistorie/historische-kurse-und-umsaetze

2.1. Exploratory volatility analysis (addressing H1)

H1 is addressed by looking at the development of total market risk over time. For this purpose, computed volatilities are grouped year by year and visualized using Boxplot diagram. Boxplots are based on percentiles and allow quick visualization of the distribution of the data points. Using statistics like mean, interquartile range and the number of statistical outliers, we can visualize trends in the boxplots and put them in context with the CoC development. Additionally, we construct three linear regression lines for the following statistics:

1. Median (*Median*): The sum of all values divided by the number of values.
2. Interquartile Range (*IQR*): The difference between the 75th percentile and the 25th percentile
3. Total number of outliers per year: *(#-outliers*): Count of data values that are very different from most of the data

In a separate analysis, we exclude years of extreme detrimental price fluctuations such as 2008 and 2020, in order to illustrate the impact unexpected financial and societal events might have on the overall regression analysis. Historically, black swan events such as financial crisis 2008 are statistically not predictable (Taleb, 2010). Considering such events in machine learning models make them not generalize well and might have adverse effects on model quality (Wabartha, 2020). Moreover, we compute the compounded annual growth rate (CAGR) which gives an idea about how volatility would have grown / declined at the same year from 2000 to 2020.

2.2. Assessing robustness of historic volatility estimates (addressing H2)

With *H2*, we want to retrospectively replicate the results of volatility estimates from the perspective of financial practitioners. Analysts and investors often use historical capital market data to estimate expected values and anticipate future financial events. This is called ex-post analysis of market data. While extrapolating past data into future is certainly associated with uncertainty, we can identify patterns from the past and attempt to project into the future. Despite numerous critics, a predominant part of financial practitioner, deploy past-oriented observation to make estimates about expected developments (Castedello et al., 2018; Fernández, 2009). For example, in Germany the estimation of the market risk premium is built on past capital market data, which is regularly updated by the IDW (Institut der Wirtschaftsprüfer Deutschland e.V.) (Gleissner, 2014).

If we put ourselves in the position of an investor, we estimate the expected market risk (or market return) for a given $Year\ x$ by taking the historical average from a given period starting at $Year_{x-n}$ and ending at $Year_{x-1}$ where $5 \leq n \leq 10$. Our research question for *H2* pose the question of whether the historical volatilities, as a function of the investment period are good estimators of the expected (future) volatilities for a given $Year\ x$ where $2010 \leq x \leq 2020$. The framework for retrospective, ex-post analysis of volatility is shown graphically below (figure 2).

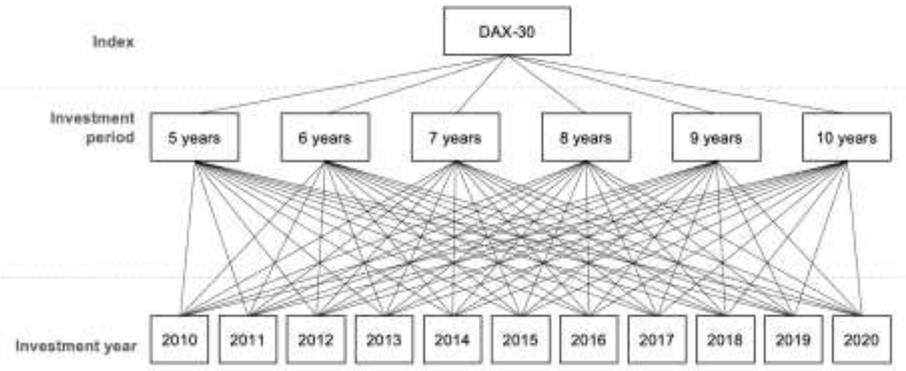

Figure 2. Framework to assess historic volatility as good estimator for expected volatility

Source: Own illustration

We use the already log-transformed pre-processed daily index returns and compute the historic volatility for six different investment periods (from 5 year- to 10 year-horizon). The evaluation of historic volatility as a good estimator depends on whether it is close to the expected (retrospectively: actually observed) volatility. This leads to a new volatility variable:

$$Volatility\ Buffer = Volatility_{investment\_period} - Volatility_{invstment\_year}$$

Equation 2. Computation of volatility buffer (VB)

The variable „Volatility Buffer Ratio" (VBR) computes the volatility buffer (VB) as percentage of volatility of the investment year:

$$Volatility\ Buffer\ Ratio = \frac{Volatility\ Buffer}{Volatility_{investment\_year}}$$

Equation 3. Computation of volatility buffer ratio (VBR)

Evidence suggests, the longer the time horizon the smaller the probability of an extreme risk of loss occurring. Therefore, Pearson's correlation coefficient (PCC) is applied to determine the relationship between VB and the length of the underlying investment period.

In the light of probability estimates, the question of *H2* is further analyzed using kernel density estimation (KDE). Finance professionals often deal with uncertain probability estimations of a financial event. The most common approaches use average occurrence of a particular event or approximate a sample distribution to normal distribution based on the central limit theorem (Gustin et al., 2020). In this study, VBs are classified as positive, negative and total. If the VB is negative, the investment year was more volatile than the historic volatility. Thus, forecasting models probably did not depict quantitatively well the market risk exposure which might have contributed to value stagnation or even value destruction. With a positive VB, there is implicitly a forgone loss of value creation potential, as investors behave too risk averse during investment decision making. Investors expected a higher market risk exposure and thus restrained in their investment decisions.

Once classified, this study expands to probability estimates. This method attaches on KDE, which allows practitioners to estimate non-parametrically the density function of a random variable. In essence, it leverages on the idea of histogram by smoothing the discrete buckets. To assess the risk of loss magnitude in the case of underestimated volatilities (negative VB) or underestimated value creation potential (positive VB), KDE allows to determine probabilities of occurrence for defined events. The following sample statement can be made which gives additional insights to *H2*: *"With a probability of x %, the positive/negative VB is ≤ y % for a given year z."*

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2.3. Data sampling and methods for CoC computation

The disclosed WACC of DAX-30 companies are extracted from annual reports and visualized over time. The years considered is determined by the availability of disclosed WACC data which is required for computations. For this study, we extract WACC rates from 2004 to 2020. Then, we assess the implicitly increased risk premium by looking at the risk parameters used in the CAPM. The opportunity cost of equity is determined using the CAPM. As equation 4 outlines, that beta factor and market risk premium guide risk exposure for a particular security. To compensate for the systematic risk, the risk premium is calculated by multiplying beta factor and market risk premium of the DAX price index.

$$CAPM = risk\ free\ interest\ rate + Beta\ \times\ (expected\ Market\ return - riskfree\ interst\ rate)$$

Equation 4. Computation of the Capital Asset Pricing Model (CAPM)

In our analyses, beta factor computation is based on weekly prices of the DAX-30 for a 5-year period. The risk-free interest rate included in the CAPM is represented by the year-end values of a ten-year German government bond. The expected market return is determined using an investment horizon of 15 years. The market risk premium and risk-free interest rate behave inversely (see equation 4). Thus, we focus on the development of beta factors in the period 2004 to 2020 to derive insights regarding an increase in risk premia. We plot beta factors using boxplots that capture distribution metrics and relate to volatility statistics using a correlation analyses. We consider distribution-related statistics such as standard deviation, variance, IQR, etc. Volatility statistics such as median, IQR and #-outliers are analyzed in the context of the computed beta factor, risk-free interest rate and CAPM. This last analysis is implemented using correlation matrices to analyze beta factor fluctuations and volatility statistics over time.

3. Results

3.1. Results for H1: development of volatility

The development of daily volatility, depicted as boxplots in figure 4, indicate a declining trend not only of the volatility range (length of box) but also of the median. Years of unexpected economic and societal events are reflected as wide boxplots surrounded by outliers. The chart that illustrates volatility distribution from 2000 to 2020 shows a decrease of the median from 0.014693 (2004) to 0.014304 (in 2020) which equals a relative decrease of the median of 2.65%. Note here, that the median in 2020 is off trend and the volatility distribution is skewed upward by outliers.

As mentioned, it is common practice to approximate non-parametric distributions to parametric distribution (e. g. normal distribution) because of the central limit theorem. Therefore, data cleaning procedures address removing (unexpected) downside risks and associated strong outliers to not be considered in ex-post analyses. Then, we can also look at the development excluding the years 2008 and 2020, which provides a more distinct picture (lower boxplots, figure 4). Excluding volatility data of 2020, a median reduction of -41.97% can be observed. The CAGR supports the picture of a declining median. The CAGR including 2020 totals -0.128%. excluding 2020 and 2008, the median decays at a more dynamic annual rate of -2.56%.

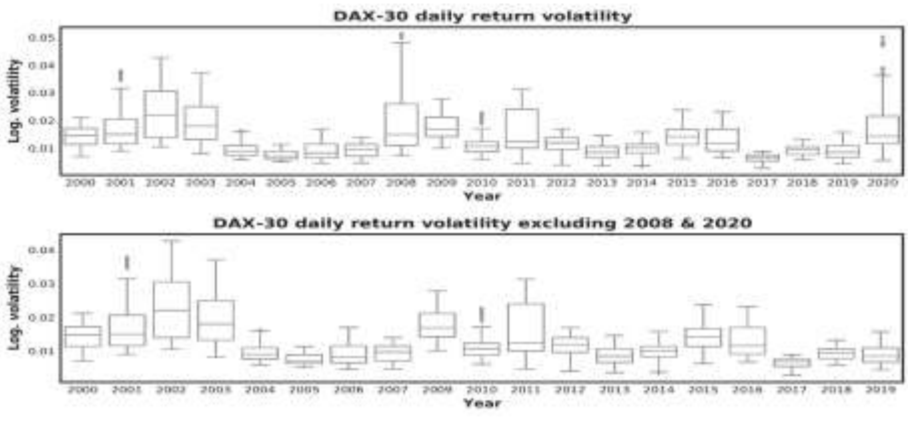

Figure 3. Boxplots of DAX-30 daily return volatility

Source: Own computations using DAX-30 data

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To attach on the insights above, we construct regression lines for median, IQR and #-outliers. Model quality is evaluated using the coefficient of determination or goodness of fit, called R^2. In Figure 4 regression lines for median and IQR are declining over time. The regression of #-outliers seems stable and regression gives slightly positive slope. This observation should be taken with caution in the context of the 18 outliers in 2020. Once, we remove the pandemic year 2020 from regression, its slope is also declining (see table 1).

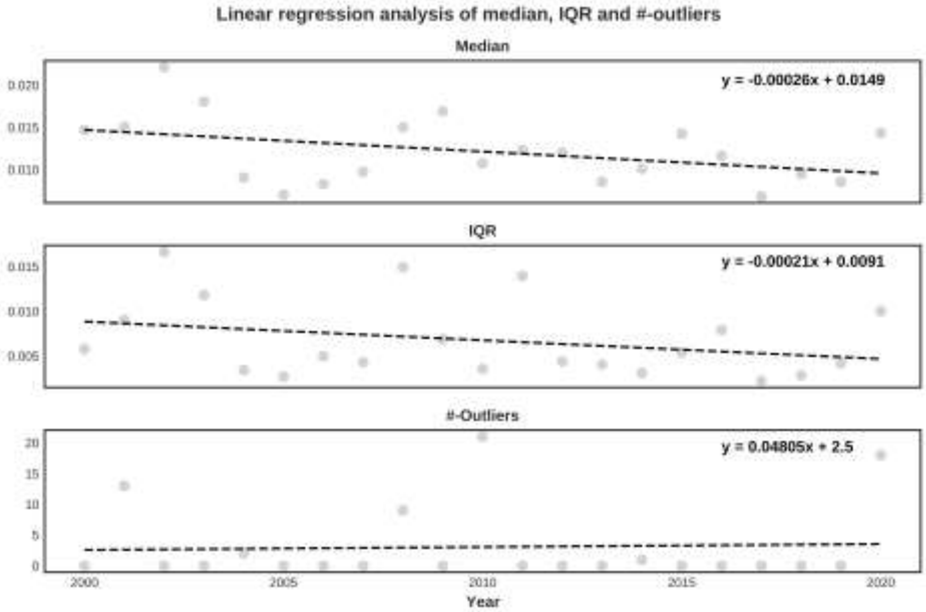

Figure 4. Linear regression analyses of median, IQR and #-outliers

Source: Own computations using DAX-30 data

Table 1. Model quality of regression analyses

Model Parameter	**Variable [unit]**	**Period 2000 to 2020**	**Period 2000 to 2019**
Slope of regression line	Median [log volatility]	-0.00026	-0.00033
	IQR [log. volatilty]	-0.00021	-0.00029
	#-Outliers [absolute]	0.048	-0.18
Goodness of fit (R^2)	Median [log volatility]	0.162	0.237
	IQR [log volatility]	0.089	0.156
	#-Outliers [absolute]	0.002	0.0037

Source: Own computations using DAX-30 data

As table 1 shows, the model quality slightly improves once 2020 is removed. The coefficient of determination describes how much variance of a given sample is detected by the slope of the linear regression line. Nonetheless, the best regression is given for the median. This observation is due to the median as a statistic measure being robust

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against outlier bias. However, model quality may be high enough to support an overall downward trend in volatility.

3.2. Results for H2: Assessing robustness of historic volatility estimates

For *H2*, the VB expresses the difference between historic and expected (retrospectively: actually occurred) volatility and thus provides a measure to quantitatively assess historic volatility as good estimate for expected volatility.

Figure 5 depicts positive VB across various investment periods. Columns in the positive y-axis range indicate a higher average historic volatility than the volatility was observed in the investment year. A Negative VB then indicates higher volatility in the investment year versus historic volatility.

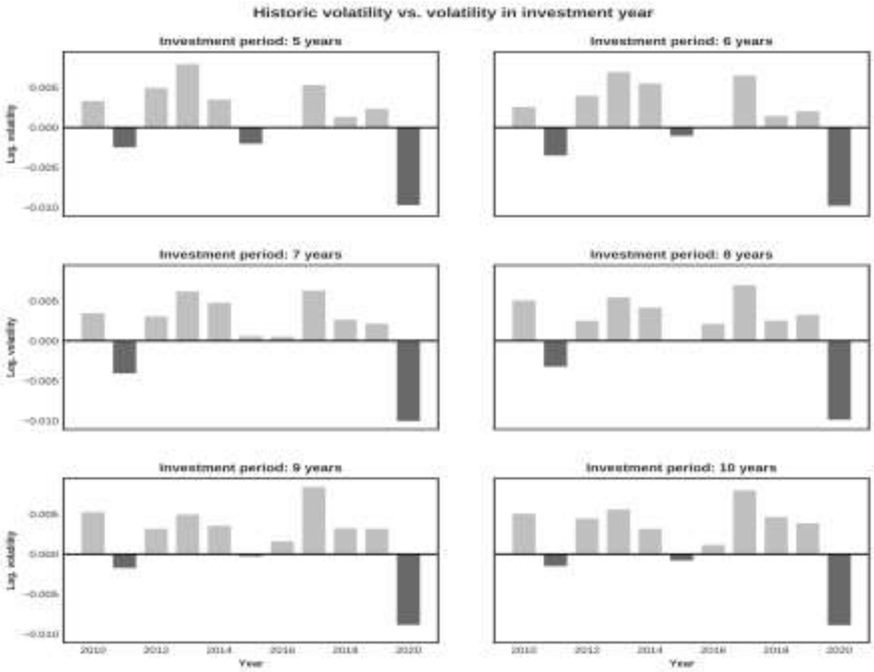

Figure 5. Visualization of VBs across various investment periods

Source: Own computations using DAX-30 data

In almost 3 out of 4 cases (74.5%), a VB is greater than zero. For investment periods ranging from 7 to 8 years, past volatility is in more than 4 out of 5 cases (82%) greater than zero and thus investors might be able to ensure the probability of loss risk is mitigated by a positive VB.

According to the (VBR) equation, we consider the VB in relation to the volatility in a respective investment year (table 2).

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Table 2: Volatility buffer ratios (VBR)

Investment period	**5 years**	**6 years**	**7 years**	**8 years**	**9 years**	**10 years**
Average investment year volatility	0.01234	0.01234	0.01234	0.01234	0.01234	0.01234
Average volatility buffer	0.00137	0.00136	0.00149	0.00179	0.00210	0.00230
Volatility buffer ratio (total) [%]	11.1	11.0	12.1	14.5	17.0	18.6
Volatility buffer ratio (only positive) [%]	36.1	43.3	31.8	34.2	41.8	44.9
Volatility buffer ratio (only negative) [%]	-27.0	-22.1	-36.7	-34.1	-20.7	-21.3

Source: Own computations using DAX-30 data

VBR is defined as the average VB divided by the average volatility in an investment year between 2010 and 2020. The positive and negative VB follow the same logic, except only taking years of positive/negative VB respectively into consideration. According to table 2, a strong positive correlation exists between the length of the investment period and the average VB. Since the trend of each parameter approximates to be linear, we obtain a value for the PCC of 0.9646 (investment period ~ average VB). The positive correlation affirms the strong argument of investing long-term.

The picture looks different, when we compute the PCC between the investment horizon and positive or negative VBs. The PCC of positive VB remains strong with 0.4176 (investment period ~ VB (only positive)). For the negative VB, we obtain a PCC of 0.2719 (investment period ~ VB (only negative)). Both PCCs indicate a positive linear relationship: the greater the time period that we consider for analyzing average volatility (ex-post), the greater the positive VB. If, we consider loss risk in terms of high negative VB, we observe, that the greater the investment period, the lower the average negative VBR.

Since the PCC of positive and negative VBs are very different, we enhance insights by creating KDE plots which are generated using a kernel density estimation. Figure 6 illustrates that the negative VBR entail a shift of the positive KDE-plot to towards zero. Whereas positive VBR reach their maximum value at around 60% and peak at 40%, the KDE-plot of the negative VBR looks more normally distributed (i.e. symmetric). Furthermore, the light grey KDE (negative buffer) is slightly right skewed indicating, that data is more likely of being in the negative 20% area than the negative 40% area. In general, using KDE-plots allows to find the probability that an event will occur. In our case, an event would be a VB of x % or $-x$%. The probability matrix provides an overview of the probability distribution for the positive and negative VB respectively.

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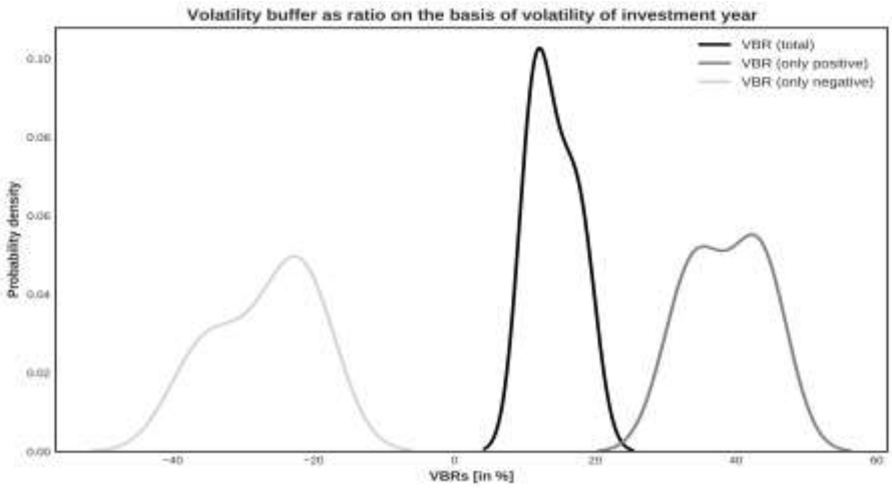

Figure 6. Visualization of VBs across various investment periods

Source: Own computations using DAX-30 data

The probability distribution of positive VBR is left skewed, which is evident from the swift increase (i. e. data density) of 16.5% to 74.2% (2 to 6). For example, if we measure a positive VBR, the probability is 50.0%, that the VBR is between 36.25% and 40.93%. The KDE of negative VBR shows an almost symmetric distribution of probability indicating a normally distributed dataset (Mondello, 2021). In case of negative VBRs (expected volatility is greater than historic volatility), the gap between historic and expected volatility is smaller compared to the case of positive VBRs. On average, historic volatility tend to be larger than expected volatility independent of investment period which diminish the chance of loss risk to be realized.

Table 3: Probability matrix of positive and negative VBR

Probability function steps	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Volatility buffer ratio (positive) [%]	31.8	33.3	34.7	36.2	37.7	39.1	40.5	42.0	43.4	44.9
Entry probability (positive buffer values) [%]	10.0	15.6	22.9	31.9	42.2	52.9	63.5	73.1	81.3	87.7
Volatility buffer ratio (negative) [%]	-36.7	-34.9	-33.1	-31.4	-29.6	-27.8	-26.0	-24.3	-22.5	-20.7
Entry probability (negative buffer values) [%]	8.1	12.6	18.7	26.4	35.4	45.3	55.4	65.3	74.3	81.7

Source: Own computations using DAX-30 data

The entry probability can be interpreted similar to a one-sided p-value, i. e. in case of a positive/negative volatility buffer scenario, the chance of observing a positive/negative buffer ratio that is equal or smaller than the given one (from function step 1 to step 10).

3.3. Results of CoC Analysis of DAX-30 companies

In figure 5, we see the WACC from 2004 to 2020 according to financial reports of DAX-30 companies. The disclosed WACC seems to be sticky over time despite the significant drop in the risk-free interest rate. Interest rates on a ten-year government bond have been following a steady downward trend, bottoming out at -0.19% in 2020. The growing spread between risk-free interest rate and WACC, it is questionable to what extent other risk-implicating parameters in the WACC model may have increased in real terms to the same extent as the risk-free interest rate has declined.

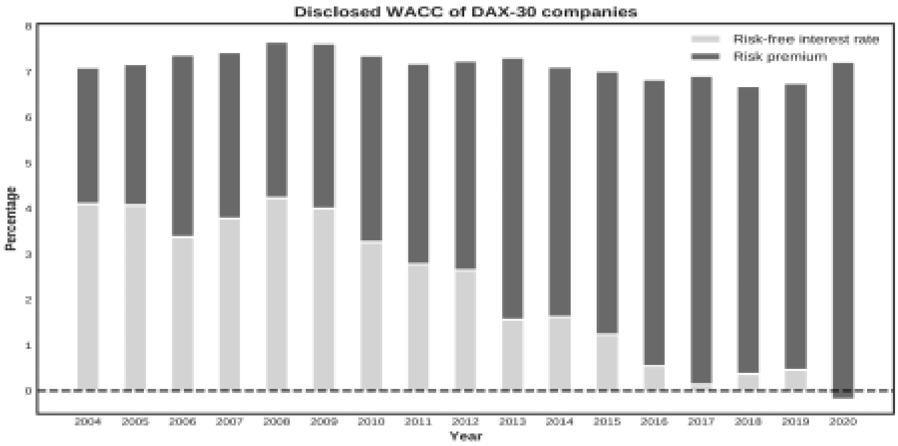

Figure 7. Disclosed WACC of DAX-30 companies

Source: Annual reports of DAX-30 companies from 2004 to 2020

Apart from a significant increase in equity capital and thus greater financing costs, the effect of the declined risk-free interest rate can only be explained by an implicitly increased risk premium. In the CAPM, risk exposure of the respective security is captured by the beta factor and market risk premium. Therefore, computing 5-year beta factors for each of the DAX-30 companies gives a similar declining trend as with the volatility. Median and mean do not provide valuable insights, therefore standard deviation and IQR developments are assessed. For the standard deviation, a decline of -27.90% has been observed. The IQR of beta factors declined by -39.30%, with a CAGR of -2.89%.

The observed values are consistent with the overall observation of volatility development, we made earlier in this study. Both, WACC development and volatility development are joined to harmonize conclusive statistical insights. Table 4 lists PCCs for WACC variables and especially beta factor statistics that might be driven by volatility conditions.

Table 4: PCCs for Volatility statistics and WACC-Variables

Volatility statistics	**WACC-Variables**			
	Disclosed WACC	Beta-STD	Beta-IQR	RfRoR
Median	0.458	-0.057	-0.100	0.140
Standard deviation	0.438	0.147	0.135	0.314
IQR	0.392	0.139	0.138	0.265
#-Outliers	0.295	0.110	-0.018	0.259

Source: Own computations using DAX-30 data

Notes: Beta- STD: standard deviation of beta factors; Beta-IQR: interquartile range of beta factors; RfRoR: Risk-free Rate of Return

4. Discussion and Conclusion

The analyses of this study revolve around the volatility of DAX-30 price index in the context of unchanged disclosed CoC (WACC rates) of German DAX-30 companies. We provided various methods that allow to graphically but also quantitatively clear the perception of an implicitly increased risk premium required from investors and considered when corporate financial practitioners prepare capital budgeting processes.

Looking back to the results that address *H1*, we find no resilient evidence based on financial-statistical methods. Median, IQR and number of outliers (datapoints outside IQR) of log. volatility declined over time and against common explanations for high CoC, volatility did not increase (table 1). With regard to *H2*, our analyses and volatility computations revealed, that ex-post analysis retains dominant position in the estimation of future expected values. The averaged historic volatility is greater than zero in most cases (77.5%). In the past investors might expected higher volatility than has occurred in reality assuming that investors predominantly use ex-post analyses. This can be perceived as a buffer that compensates for unintentional miscalculations, for example overoptimistic cashflow estimates or emerging (unexpected) black swan events.

With the methods used, we are not able to observe any significant, across the board, increase of volatility. Rather, based on statistics and ex-post analyses a significant decreasing trend in volatility measures was gauged. In practice, financial experts might see these results from two different perspectives. Form a risk management perspective, averaged historical volatility is only a good estimator if its value is greater than zero. From a value-based management perspective, the sweet spot of historic volatility being a good estimator must be close to zero. Therefore, the number of net present value positive investments could be maximized in order to fully exploit economic value creation potential (Rappaport, 1999).

References

Berk J., DeMarzo P. (2011) *Grundlagen der Finanzwirtschaft*, Pearson Studium.

Bertram I., Castedello M. & Tschöpel A. (2015). Überlegungen zur Marktrendite und zur Marktrisikoprämie. *Corporate Finance*, 6, 468-473.

Brotherson, W.T., Eades, K. M., Harrris, R. S., & Higgins, R. C. (2013). Best Practices in Estimating the Cost of Capital: An Update. *Journal of Applied Finance*, 23(1), 1-19. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2686738 [Accessed on October 2022].

Castedello, M., Jonas, M., Schieszl, S. & Lenckner, C. C. C. (2018). Die Marktrisikoprämie im Niedrigzinsumfeld: Hintergrund und Erläuterung der Empfehlung des FAUB. *WPg – Die Wirtschaftsprüfung*, 13, 806-825.

Da, Z., Guo, R.-J. & Jagannathan, R. (2012) „CAPM for estimating the cost of equity capital: Interpreting the empirical evidence“, *Journal of Financial Economics, Forthcoming*, 103(1), 204–220. Available at: https://www3.nd.edu/~zda/COC.pdf [Accessed on November 2022].

DAX-30 Unternehmen (2004-2020). Annual Reports. DAX-30 Unternehmen.

Deutsche Bundesbank (2021). Tägliche Renditen der jeweils jüngsten Bundeswertpapiere. Rendite der jeweils jüngsten Bundesanleihe mit einer vereinbarten Laufzeit von 10 Jahren. Deutsche Bundesbank. Available at: https://www.bundesbank.de/de/statistiken/geld-und-kapitalmaerkte/zinssaetze-und-renditen/taegliche-renditen-der-jeweils-juengsten-bundeswertpapiere-772218 [Accessed on November 2022].

Fernández, P. (2009). The Equity Premium in 150 Textbooks. *Working Paper*, WP-829, IESE Business School. Available at: https://media.iese.edu/research/pdfs/DI-0829-E.pdf [Accessed on November 2022].

Flossbach von Storch (2017). Die EZB irrt sich. Available at: https://www.flossbachvonstorch.de/de/news/die-ezb-irrt-sich/ [Accessed on October 2022].

Frank, M. & Shen, T. (2016). Investment and the weighted average cost of capital. *Journal of Financial Economics, Forthcoming*, 119(2), 300-315. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0304405X15001683 [Accessed on November 2022].

Frey S., Gleißner W., Heilmann H. (2023, submitted) Risikovermeidung und Wertmanagement in der Corporate Governance, *submitted to Der Aufsichtsrat 11/2022*.

Gleißner, W. (2014). Die Marktrisikoprämie: stabil oder zeitabhängig?. *WPg – Die Wirtschaftsprüfung*, 5, 258-264. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2888786 [Accessed on October 2022].

Gleißner, W. (2014). Kapitalmarktorientierte Unternehmensbewertung: Erkenntnisse der empirischen Kapitalmarktforschung und alternative Bewertungsmethoden. *Corporate Finance*. 4, 151-167.

Gustin et al. (2020). Deriving distributions from time series using Kernel Density Estimation. *Reafcin White Paper*, 2, Available at: https://www.reacfin.com/wp-content/uploads/2016/12/20200519-Kernel-Density-Estimation-with-an-application-to-estimate-the-volatile-Balance-of-NMD-Protected.pdf [Accessed on November 2022].

IDW Standard (2016). Grundsätze zur Durchführung von Unternehmensbewertungen (IDW S 1 i.d.F. 2008).

Mondello, E. (2021) *Finance: Angewandte Grundlagen*, SpringerGabler, Wiesbaden.

Poterba, J. M. & Summers, L. H. (1995). A CEO Survey of U.S. Companies' Time Horizons and Hurdle Rates, *Sloan Management Review*, 37(1), 43-54.

Rappaport A. (1999). *Creating shareholder value. A guide for managers and investors*. New York, Free Press.

Regierungskommission Deutscher Corporate Governance Kodex (2020). *Deutscher Corporate Governance Kodex*. Available at: https://www.dcgk.de//files/dcgk/usercontent/de/download/kodex/191216_Deutscher_Corporate_Governance_Kodex.pdf [Accessed on October 2022].

Saleheen, J. & Levina, I. (2017) The financial system and productive investment: new survey evidence, Bank of England, *Quarterly Bulletin Q1*. Available at: https://www.bankofengland.co.uk/quarterly-bulletin/2017/q1/the-financial-system-and-productive-investment-new-survey-evidence [Accessed on October 2022].

Taleb, N. N. (2010) *The black swan: The impact of the highly improbable*, Penguin Random house, UK.

Wabartha M. et al. (2020) Handling Black Swan Events in Deep Learning with Diverseley Extrapolated Neural Networks“, *Proceedings of the 29th International Joint Conference on Artifical Intelligence (pp. 2140-2147)* Vienna, Austria.

Zenner, M., Junek, E. & Chivukula, R. (2014) „Bridging the Gap between Interest Rates and Investments“, *Journal of Applied Corporate Finance*, 26(4), 75–80.