

Economics and Business Review

Volume 12 (3) 2026

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Accounting-based CAPM: Symmetrical and downside risk approaches

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Abstract

The complexity of asset return variability justifies supplementing the standard Capital Asset Pricing Model (CAPM) formula with market risk measures based on firms' fundamental analysis. Moreover, a key area of investigation involves the approach to downside pricing. The main objective of this study is to test non-standard CAPM extensions that incorporate accounting information. The results for the Frankfurt Stock Exchange indicate that profitability ratios constitute a significant source of systematic risk and generate a positive premium related to a company's financial condition. Furthermore, in the case of large firms, sensitivity measures based on downside accounting betas demonstrate a clear advantage over their conventional counterparts.

Keywords

- CAPM
- profitability ratios
- accounting beta
- downside risk
- downside accounting beta

JEL codes: C1, C2, C5, F3, G1.

Article received 21 January 2026, accepted 10 September 2026.

Suggested citation: Markowski, L., Garsztka, P., Mizerka, J., & Rutkowska-Miczka, A. (2026). Accounting-based CAPM: Symmetrical and downside risk approaches. *Economics and Business Review*, 12(3), 101–132. <https://doi.org/10.18559/ebr.2026.3.2957>



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Introduction

The research presented in this paper is situated within the stream of studies on capital asset pricing that incorporate risk asymmetry and selected information derived from financial statements. Early contributions in this area include the works of Kim and Zumwalt (1979) and Kim and Ismail (1998), followed by more recent studies such as Konchitchki et al. (2016), Luo et al. (2021), W. Huang et al. (2022), and Rutkowska-Ziarko et al. (2024). These studies differ both in their approaches to modelling downside risk and in the types of financial statement information employed.

This paper makes a novel contribution to the literature on asset pricing and risk measurement in several crucial ways. Firstly, it advances the development of downside Capital Asset Pricing Model (CAPM) approaches by incorporating empirically observed features of financial returns, such as skewness and asymmetric volatility, which are often neglected in traditional models. This perspective aligns with behavioural finance insights and utility-based theories that emphasise loss aversion and asymmetric risk preferences (Kahneman & Tversky, 1979). Secondly, the study explores the viability of profitability-based measures as risk indicators, offering an alternative to purely market-derived metrics. The use of accounting betas constructed from firm-level profitability ratios serves as a practical and potentially more informative tool for capturing firm-specific exposure to systematic risk, especially in contexts where market data is limited or distorted. The integration of these two research streams provides the basis for the development of a Downside Accounting Capital Asset Pricing Model (DA-CAPM), in which the primary measure of systematic risk is the downside accounting beta (DAB). Motivated by the limitations inherent in traditional market-based approaches to risk assessment, this study investigates the incorporation of average profitability ratios and accounting-based betas as integral components in evaluating systematic risk. By embedding these accounting-derived metrics into the asset pricing framework, we aim to construct a more holistic representation of firm-specific risk exposures, particularly under heterogeneous financial conditions across listed firms. This novel integration addresses the shortcomings of conventional models grounded in symmetric variance, which often fail to capture the asymmetric behaviour of asset returns and the differential risk preferences exhibited by investors, especially in the presence of downside volatility.

The aim of this study is to examine the explanatory power of the classical Capital Asset Pricing Model (CAPM) with respect to stock returns and to assess the impact of incorporating accounting variables into the model framework. In particular, the study focuses on extending the standard CAPM specification by including corporate profitability indicators and accounting betas in order

to determine whether fundamental variables provide additional information relevant to risk pricing and the determination of expected stock returns.

Furthermore, the study investigates the importance of an asymmetric approach to risk by incorporating its downside dimension. In this context, it attempts to assess whether risk measures based solely on unfavourable return deviations are more effective in explaining the cross-sectional variation in stock returns than traditional measures based on total return variability. Therefore, the study seeks to determine whether the integration of accounting information and downside risk measures enhances the explanatory power of the extended CAPM framework.

The novelty of this study stems from the simultaneous incorporation of accounting profitability measures, accounting betas, and downside risk into the traditional CAPM framework. While prior studies have typically examined these factors separately, this research investigates their joint effect on explaining stock returns, thereby offering a more comprehensive approach to asset pricing and risk assessment.

A statistically significant pricing based on the DAB was obtained for assets listed on the New York Stock Exchange (NYSE) (Rutkowska-Ziarko et al., 2024). A key element in achieving this objective is the collection and analysis of quarterly financial statements. The choice of the Frankfurt Stock Exchange (FSE) is motivated by the availability of standardised quarterly financial reports, in contrast to other exchanges such as the London Stock Exchange (LSE), as well as by the fact that the German market is the largest market in the European Union in terms of national market capitalisation.

The literature provides a number of studies addressing asset pricing in the German market. Notably, significant cross-sectional regression analyses employing accounting data for firms listed on the German capital market, including financial factors, were conducted by Amel-Zadeh (2011) and Artmann et al. (2012). However, these studies do not incorporate a downside approach to risk, which is explicitly addressed in the present paper. The application of downside risk measures to accounting-based variables therefore constitutes a novel contribution to the existing literature, which has predominantly relied on symmetric measures in risk evaluation.

The methodological framework of our study incorporates accounting-based factors, such as profitability ratios and accounting beta coefficients. Moreover, these adaptations are tested under both symmetrical risk assumptions, which rely on the variance of returns, and under downside risk specifications, which account for return asymmetry and investors' heightened sensitivity to negative outcomes. Specifically, it employs lower partial moments (LPM), such as semi-variance, which are theoretically consistent with utility functions exhibiting decreasing absolute risk aversion (Bawa, 1975). Semi-variance captures deviations below the mean return and is widely recognized as a suitable metric for assessing systematic risk under asymmetry. Moreover, partial

moments in their general formulation (both lower and upper) exhibit lower estimation errors than the traditional mean–variance framework and should be considered a preferred initial choice of risk measures, particularly when return distributions deviate from normality (Nawrocki & Viole, 2024). Semi-covariance, an asymmetric co-LPM, has been employed in prior research to estimate downside betas (Ang et al., 2006; Bawa & Lindenberg, 1977; Harlow & Rao, 1989; Hogan & Warren, 1974; Levi & Welch, 2020).

The empirical methodology is inspired by the two-step Fama–MacBeth procedure. Owing to the limited time-series dimension of the quarterly data, a full implementation of the original approach was not feasible. Accordingly, the estimation strategy represents an adaptation of the Fama–MacBeth framework to the characteristics of the available sample. The empirical procedure corresponds more closely to that proposed by Black et al. (1972).

Our empirical evidence suggests that profitability ratios, along with accounting betas, most notably within the downside risk framework, constitute significant determinants of the cross-sectional variation in stock returns. In doing so, it extends the applicability of the CAPM through models that reflect both the distributional asymmetries of returns and the informational value embedded in firm-level accounting performance. The development of these extended CAPM variants represents a significant advancement toward a unified framework that blends accounting fundamentals with behavioural dimensions of risk perception. Our approach contributes to the existing literature by bridging the gap between market-driven and accounting-based perspectives on risk. Moreover, this synthesis offers a more nuanced and robust approach to asset pricing, with practical implications for both academic research and financial decision-making.

This paper is organised as follows. Section 1 briefly reviews the literature on testing the CAPM considering the downside framework to risk. Section 2 explains methodology as well as the hypotheses of cross-sectional standard and accounting regressions and Section 3 describes the dataset. Section 4 presents the research findings and discussion. The last section offers several conclusions and suggests areas for future research.

1. Literature review

The Capital Asset Pricing Model (CAPM) has a long and influential history, serving as a foundational framework for understanding the relationship between risk and expected return. Over time, researchers have proposed and rigorously tested numerous alternative pricing models, among which the Arbitrage Pricing Theory (APT) and the Fama–French multifactor models are

particularly prominent. Despite these advancements, the literature continues to report conflicting evidence. On one hand, several studies document persistent anomalies in risk pricing and return variability, but on the other, subsequent research has often challenged or even refuted these findings. Consequently, the question of how effectively asset pricing models explain the variation in returns remains both timely and relevant. In this context, Cho and Polk (2024) conducted an empirical investigation focusing on firms listed on the New York Stock Exchange (NYSE). Their study assessed the extent to which CAPM accounts for price-level variation associated with nine additional firm characteristics that are widely recognised as influencing the cross-sectional distribution of average returns. These characteristics include net issuance, investment, accruals, beta, size, momentum, and profitability. By integrating insights from asset pricing and corporate finance, their analysis revealed that portfolios constructed on the basis of adjusted value metrics incorporating market-to-book ratio, return on equity (ROE), and Sharpe beta exhibit substantial variation in abnormal pricing. These findings underscore the limitations of the traditional CAPM in capturing the complexity of return determinants and highlight the need for more comprehensive modelling approaches.

A growing body of literature suggests that economic fundamentals, particularly profitability indicators and accounting-based beta coefficients, can complement the traditional CAPM beta in estimating the cost of equity capital (Cohen et al., 2009; Nekrasov & Shroff, 2009). Barberis et al. (2021) show that firms with higher return on assets (ROA) tend to deliver higher returns in capital markets on average.

In addition to the risk associated with the firm's accounting profitability, the second major dimension of risk examined in this study relates to the downside risk framework. Unlike traditional risk measures such as variance or standard deviation that treat positive and negative return deviations from the mean as equally significant, the downside risk approach concentrates exclusively on returns that fall below a predetermined threshold, typically a benchmark or minimum acceptable return. This focus on negative tail outcomes is particularly pertinent in asset pricing models, as exemplified by the Downside Capital Asset Pricing Model (D-CAPM), which captures systematic risk by considering only negative market excess returns in its estimation (Nurjannah et al., 2012).

An associated methodological advancement is the two-beta market model, which facilitates the decomposition of asset return sensitivities under asymmetric market conditions, specifically during upward (upside) and downward (downside) market movements. This framework enables the downside accounting beta coefficients to be estimated, thereby allowing for a more targeted assessment of downside risk exposure. The conceptual distinction between positive and negative betas, originally introduced by Fabozzi and Francis (1977), was operationalised in empirical research by Kim and Ismail (1998),

who documented a positive and statistically significant pricing of downside risk for equities listed on the New York Stock Exchange (NYSE). These results are consistent with theoretical models of risk-averse investor behaviour, which posit that compensation is required for bearing downside volatility.

Nevertheless, despite robust empirical support for downside risk measures, a segment of the literature challenges their predictive efficacy relative to conventional risk metrics. For example, Levi and Welch (2020) argue that downside beta lacks superior explanatory power in cross-sectional return regressions when compared to the traditional CAPM beta. Their findings indicate that stocks with historically low downside betas do not systematically outperform during subsequent market downturns, calling into question the incremental value of downside beta in asset pricing applications.

It has been demonstrated by numerous studies that downside risk measures are more accurate reflections of investors' perceptions of equity risk, particularly in circumstances of market asymmetry (Ang et al., 2006; Menon et al., 2023). Traditional risk measures, such as variance and standard deviation, treat all deviations from the mean positive and negative as equally relevant. However, this assumption contradicts observed investor behaviour, which is predominantly risk-averse and more sensitive to losses than to equivalent gains. The downside risk framework addresses this limitation by focusing exclusively on returns that fall below a specified threshold, typically a risk-free rate or a minimum acceptable return. In this framework, positive deviations are viewed as desirable outcomes rather than sources of risk. This asymmetrical approach has gained wide acceptance in asset pricing and portfolio optimisation due to its conceptual alignment with investor preferences and its computational simplicity (Harlow, 1991).

Within this context, downside beta defined as the sensitivity of an asset's return to negative market movements has been increasingly employed as a refinement of traditional beta in Capital Asset Pricing Model (CAPM) extensions. Ang et al. (2006) provided empirical evidence that risk-averse investors demand a premium for bearing downside market risk, a relationship that is captured more effectively by downside beta than by its conventional counterpart. They found that stocks with higher downside betas tend to yield higher average returns, suggesting that investors seek compensation specifically for exposure to unfavourable market conditions. This finding aligns with broader theories of asymmetric risk pricing and has spurred a growing body of empirical research on the role of downside risk in asset valuation.

Further supporting this line of inquiry, positive and statistically significant premiums associated with downside beta have been observed in various asset pricing contexts. These premiums often appear in conjunction with other known risk factors such as co-skewness, illiquidity, and firm size. Estrada (2002, 2007) made a significant contribution to this literature by introducing a modified version of downside beta, which not only aligns more closely with inves-

tor loss aversion but also demonstrates superior explanatory power for return volatility. His work provides both a theoretical rationale and empirical validation for incorporating downside risk into mainstream asset pricing models.

The robustness of downside risk measures has also been tested across different market environments. For instance, empirical studies by Chen et al. (2009), Ali (2019), F. Huang (2019), and Atilgan et al. (2021) have all found a significant positive association between downside risk measures and expected returns in both developed and emerging markets. These findings suggest that the pricing of downside risk is a pervasive phenomenon not limited to specific geographies or market structures.

Despite this broad empirical support, the literature remains divided. Some researchers have challenged the predictive superiority of downside risk measures relative to conventional metrics. For example, Levi and Welch (2020) argue that downside beta does not consistently outperform the traditional CAPM beta in explaining cross-sectional variations in returns. Their analysis indicates that stocks with historically low downside betas do not necessarily deliver better performance during future market downturns. In turn, Atilgan et al. (2019) investigated the relationships between several downside risk measures such as lower partial moment, value-at-risk, expected shortfall, and subsequent returns, demonstrating that these relationships consistently exhibit a negative direction. This critique highlights the ongoing debate within the finance literature regarding the incremental value of downside risk metrics in asset pricing models.

In summary, while downside risk measures, particularly downside beta, have demonstrated substantial theoretical and empirical relevance in capturing investor preferences and return dynamics, their practical superiority over traditional risk metrics remains a topic of active research. Continued exploration is needed to reconcile these mixed findings and to refine models that more accurately reflect investor behaviour under asymmetric market conditions.

This study employs both accounting-based and market-based sensitivity measures to assess systematic risk. The accounting beta, first introduced by Hill and Stone (1980), quantifies the sensitivity of a firm's accounting returns such as return on assets (ROA) and return on equity ROE to changes in market or sector returns, following the one-factor Sharpe model (1964). In this research, accounting betas are calculated using accounting performance metrics (ROA and ROE), while market betas are derived from stock price data. Beyond these, other accounting measures, such as earnings, cash flow-based metrics (Kim & Ismail, 1998), return on sales (Rutkowska-Ziarko & Pyke, 2017), book value of equity and measures of the income statement (Sarmiento et al., 2021), have also been used to estimate accounting betas. For investors, accessing timely and reliable financial and non-financial information is essential. The comprehensive audit process plays a crucial role in this regard by significantly reducing the potential for inaccuracies in financial reporting.

A notable contribution demonstrating the use of earnings measures to explain stock returns is provided by Ellahie (2021). He finds that realised ROA and ROE betas are poor predictors of future returns, whereas earnings betas calculated as unexpected changes to earnings forecasts perform relatively well. In particular, Ellahie shows that earnings-based betas outperform the market beta, and that betas constructed from earnings changes exhibit superior performance relative to those based on earnings levels.

The present study centres on downside risk and, accordingly, utilises the downside accounting beta (DAB), a measure initially introduced by Rutkowska-Ziarko and Pyke (2017) and subsequently refined by Rutkowska-Ziarko (2023). This metric builds on the concept of risk asymmetry in accounting-based CAPM frameworks, originally advanced by Kim and Ismail (1998). They conceptualised risk asymmetry as a condition in which the accounting metric for the market portfolio in a given period declines relative to the previous period. In their approach, accounting betas based on earnings and cash flows were estimated using the arithmetic mean as a proxy for the market index, with up-market and down-market conditions delineated by whether the accounting variable (e.g., earnings or cash flows) increased or decreased compared to the prior quarter.

Importantly, this framework diverges from traditional downside risk metrics such as semi-variance or lower partial moments (LPM), as it leverages accounting information rather than market-based returns to characterise risk. Kim and Ismail (1998) found that accounting betas, whether based on earnings or cash flows, are significantly associated with return volatility, and that risk premiums vary substantially between rising and declining markets. Moreover, their findings suggest that the use of accounting data yields improved model performance compared to models relying solely on market prices, offering a compelling case for incorporating fundamental financial indicators into risk assessment models. Konchitchki et al. (2016) introduced a novel downside risk measure termed accounting-based downside risk (ABDR), which quantifies asymmetry in firm performance by calculating the ratio of the square root of the lower partial moments (LPM) of return on assets (ROA) to the square root of the upper partial moments (UPM) of ROA. Their findings provide empirical evidence supporting the linkage between accounting-based performance measures and asset pricing models, highlighting the potential of financial statement data in capturing downside risk.

Building on this framework, Alam et al. (2021) refined the ABDR metric by developing the cash flow downside risk (CFDR) measure, which applies a similar methodology using cash flow data instead of ROA. Their study revealed a positive relationship between CFDR and future credit spreads, suggesting that downside risk in cash flows may serve as a leading indicator of firms' creditworthiness. Separately, W. Huang et al. (2022) and Luo et al. (2021) applied the ABDR measure in the context of the Chinese equity market, demonstrating

a negative association between ABDR values and the likelihood of future stock price crashes, thus underlining its predictive utility for downside tail events.

It is important to note that the ABDR and CFDR approaches represent alternative methodologies for incorporating accounting data into downside risk assessment. These differ conceptually and methodologically from the downside accounting beta (DAB) framework employed in the present study, offering complementary perspectives on the use of financial statement information in risk modelling. While Alam et al. (2021) examine accounting-based downside risk measures primarily in the context of credit spreads, our work shifts the analytical lens toward the development and empirical testing of novel CAPM extensions that explicitly integrate accounting information with downside risk considerations. In particular, our approach emphasises the role of average profitability ratios and accounting betas as potential determinants of systematic risk, an area not addressed in Alam et al.'s framework. By incorporating these accounting-based proxies into both traditional and asymmetric CAPM specifications, our analysis offers a fundamentally different perspective on the pricing of risk in capital markets. Thus, our contribution lies in proposing an innovative fusion of accounting metrics and market-based factors to refine the asset pricing model, extending the literature beyond the scope of credit market dynamics and toward a more comprehensive understanding of equity valuation.

Similarly, the study by Luo et al. (2021) centres on the Chinese A-share stock market, with a specific emphasis on the pricing implications of accounting-based downside risk within that localised context. In contrast, our research extends the investigation of downside risk to a broader international setting, utilising data from the Frankfurt Stock Exchange. We develop and empirically test novel CAPM frameworks that are not constrained by regional market characteristics or the particular downside risk measures employed by Luo et al. Our models incorporate accounting-derived variables, specifically average profitability ratios and accounting betas, into both conventional and downside risk CAPM specifications, offering a more generalised and comprehensive framework for understanding systematic risk across diverse market environments. Moreover, while W. Huang et al. (2022) focus on the linkage between accounting-based downside risk and stock price crash risk in the Chinese market, our study adopts a fundamentally different angle. Rather than examining tail risk events in isolation, we integrate accounting information into asset pricing models to explore how such variables influence expected returns and the broader risk-return relationship. This approach moves beyond the domain of crash risk analysis, contributing to the literature by highlighting the role of downside risk in shaping asset prices more generally. By extending the scope of analysis beyond idiosyncratic crash risk to systematic pricing dynamics, our research offers a more holistic perspective on the integration of accounting variables into capital market valuation frameworks.

2. Downside and accounting CAPM

Conventional risk metrics like beta coefficient rely on the variance of returns as the primary indicator of the total risk associated with a given security. However, if risk is instead conceptualised as the deviation of returns falling below a specified threshold, then an alternative risk metric, the semi-variance of returns, becomes more appropriate. This measure belongs to the broader class of risk metrics known as lower partial moments (LPM). Specifically, semi-variance represents a lower partial moment of order 2. In general, lower partial moments can be defined as follows:

$$LPM_i^n = E\left[\min(R_{it} - \tau; 0)\right]^n, \quad (1)$$

where τ represents the threshold rate of return, which serves as the foundation for differentiating between various methodologies regarding the final formulation of downside sensitivity coefficients for securities' returns under adverse market conditions. In the classical framework, this threshold corresponds to the risk-free rate (Bawa & Lindenberg, 1977; Hogan & Warren, 1974). By contrast, the generalised LPM approach allows investors to adopt any chosen acceptable rate of return. One such alternative is to set the average rate of return as the threshold (Harlow & Rao, 1989). Under this formulation, the downside beta coefficient, as derived from the Harlow–Rao model, takes the following form:

$$\beta_i^{HR} = \frac{E\left[(R_{it} - E(R_i))\min(R_{Mt} - E(R_M); 0)\right]}{E\left[\min(R_{Mt} - E(R_M); 0)\right]^2} \quad (t = 1, 2, \dots, T). \quad (2)$$

where $E(R_i)$ denotes the expected return of the i -th security; $E(R_M)$ is the expected return of the market portfolio; T represents the length of the observed time series. In this study, systematic downside accounting risk will be defined by the above formula.

Based on the accounting data of individual entities and treating the financial condition of all analysed companies as a systematic source of return volatility, this study introduces a generalised measure of market (or sector) profitability. On this basis, accounting betas were constructed, which, alongside the average values of accounting ratios, serve as risk factors in non-standard versions of the CAPM model. The accounting beta for the i -th entity with respect to the return on assets indicator ($\beta_i(ROA)$) is determined using the formula proposed by Hill and Stone (1980):

$$\beta_i(ROA) = \frac{E\left[(ROA_{it} - \overline{ROA_i}) \cdot (ROA_{Mt} - \overline{ROA_M})\right]}{E\left[ROA_{Mt} - \overline{ROA_M}\right]^2}, \quad (3)$$

where ROA_{it} , $\overline{ROA}_i = \frac{1}{T} \sum_{t=1}^T ROA_{it}$ denote the return on assets for the entity in period t and its average level, respectively, while ROA_{Mt} , $\overline{ROA}_M = \frac{1}{T} \sum_{t=1}^T ROA_{Mt}$ represent the mean return on assets for the market (sector) in t period and its average long-term level. The values of ROA_{Mt} , which is the index (portfolio) of the market according to this return ratio, were determined as the weighted average market capitalisation of the return ratios of the entities included in this index, which is written as follows:

$$ROA_{Mt} = \sum_{i=1}^N ROA_{it} \cdot \frac{MV_i}{\sum_{i=1}^N MV_i}, \quad (4)$$

where MV_i is the market capitalisation value of the share capital of the i -th entity.

For the downside approach, the Harlow and Rao (1989) formula was used to determine the downside accounting beta (DAB) for ROA ($\beta_i^{HR}(ROA)$), as in equation (2), replacing the rates of return with the ROA values:

$$\beta_i^{HR}(ROA) = \frac{E\left[\left(ROA_{it} - \overline{ROA}_i\right) \cdot \min\left(ROA_{Mt} - \overline{ROA}_M; 0\right)\right]}{E\left[\min\left(ROA_{Mt} - \overline{ROA}_M; 0\right)^2\right]}. \quad (5)$$

The measures of profitability and risk related to return on equity (ROE) were determined using the methodology outlined above and defined by equations (3–5).

Following the classical procedure outlined by Fama and MacBeth (1973), the CAPM model is tested in two distinct stages. During the first stage, systematic risk measures, both market, and accounting, are estimated. Next, market or financial risk premiums are estimated. The standard and accounting CAPM cross-sectional regression equations in conventional and downside frameworks are presented in Table 1 as follows:

According to the equilibrium model, investors are rewarded for accepting systematic risk, expressed by the beta coefficient. Furthermore, profitable firms with high expected future profitability ratios ROA and ROE tend to exhibit faster dividend growth as a larger portion of earnings per book value share is efficiently utilised. Consequently, stocks that are low-priced yet remain profitable and financially stable are likely to be undervalued by the market (Cho & Polk, 2024).

In line with the main research question outlined above, the study examines whether profitability ratios and accounting-based beta coefficients generate a positive and statistically significant risk premium associated with

Table 1. The standard and accounting CAPM

Symmetrical	Downside
Standard versions of the CAPM	
$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \eta_i$	$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} + \eta_i$
Nonstandard (accounting) versions of the CAPM	
$\bar{R}_i = \lambda_0 + \lambda_1 \overline{ROA}_i + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \overline{ROE}_i + \eta_i$	–
Extended versions of the CAPM	
$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i (ROA) + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i (ROE) + \eta_i$	$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} (ROA) + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} (ROE) + \eta_i$
$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \lambda_2 \overline{ROA}_i + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \lambda_2 \overline{ROE}_i + \eta_i$	$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} + \lambda_2 \overline{ROA}_i + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} + \lambda_2 \overline{ROE}_i + \eta_i$
$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \lambda_2 \hat{\beta}_i (ROA) + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i + \lambda_2 \hat{\beta}_i (ROE) + \eta_i$	$\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} + \lambda_2 \hat{\beta}_i^{HR} (ROA) + \eta_i$ $\bar{R}_i = \lambda_0 + \lambda_1 \hat{\beta}_i^{HR} + \lambda_2 \hat{\beta}_i^{HR} (ROE) + \eta_i$

Note: $\bar{R}_i$ – the mean return of the i -th security or portfolio; $\hat{\beta}_i, \hat{\beta}_i^{HR}$ – estimates of conventional and downside beta coefficients; ROA_i, ROE_i – mean of ROA and ROE ratios; $\hat{\beta}_i(ROA), \hat{\beta}_i(ROE), \hat{\beta}_i^{HR}(ROA), \hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in conventional and downside framework; η_i – the random error term of the equation for ($i = 1, \dots, N$), where N is the number of securities or portfolios.

Source: own elaboration.

a firm’s financial condition. Formally, the expected values of the parameters for the standard and accounting-based specifications of the CAPM are presented in Table 2.

Table 2. Hypotheses for parameters of standard and accounting CAPM

Factors	The null hypothesis	The alternative hypothesis
Constant term	$H_0: E(\lambda_0) = 0$	$H_1: E(\lambda_0) \neq 0$
β_p, β_i^{HR} $\overline{ROA}_i, \overline{ROE}_i$ $\beta_i(ROA), \beta_i(ROE)$ $\beta_i^{HR}(ROA), \beta_i^{HR}(ROE)$	$H_0: E(\lambda_1) = 0$ $H_0: E(\lambda_2) = 0$	$H_1: E(\lambda_1) > 0$ $H_1: E(\lambda_1) > 0$

Source: own elaboration.

Positive relationships between expected returns and accounting-based risk factors should hold irrespective of the adopted risk approach (symmetrical or downside) and the number of variables included in the model.

3. Data

The empirical analysis was limited to companies listed on the stock exchange. This restriction arises from the fact that, for non-listed firms, it is not feasible to derive a reliable comparison between the accounting beta and the CAPM-based beta. In the absence of such a comparison, the proposed approach would lack a necessary benchmark against which its validity could be assessed. By focusing on publicly traded companies, the study ensures both the availability of consistent data and the methodological soundness required for evaluating the quality of the proposed framework. This study investigates a sample of firms listed on the Frankfurt Stock Exchange (Deutsche Börse), comprising constituents of the DAX40, MDAX, and SDAX indices. The CDAX index was employed as a proxy for the market portfolio. The research period spans ten years, from 2015 to 2024, selected as a balanced compromise between the availability of reliable financial and market data and the desirable length of the time series. The final sample includes 25 large-cap firms from the DAX40, 24 mid-cap firms from the MDAX, and 25 small-cap firms from the SDAX indices. Accordingly, the sole criterion for sample inclusion was the availability of complete data rather than the firm's continued existence, which substantially mitigates concerns regarding potential survivorship bias. The models proposed in this study were estimated for the full sample of 74 firms, as well as for three subsamples comprising companies included in the DAX 40, MDAX, and SDAX indices, in order to examine the models' sensitivity to firm size. Some studies suggest that firms exhibiting higher current profitability growth are expected to earn higher future returns; however, the positive relation between profitability growth and stock returns tends to diminish with firm size (Lim et al., 2024).

It should be noted that a distinctive feature of the German equity market is the substantial concentration of market capitalisation among large-cap firms included in the DAX 40 index. These firms account for approximately 82% of the aggregate market capitalisation of all companies included in the DAX 40, MDAX, and SDAX indices. In the present study, large-cap firms accounted for nearly 90% of the total market capitalisation of the 74 firms included in the sample. The firms included in the analysis, in aggregate, account for 66% of the total market capitalisation of the three selected indices. Additionally, Table 3 presents the distribution of the sample firms across economic sectors, together with their respective shares of total market capitalisation and their shares of the aggregate market capitalisation of the firms included in the study. The largest number of studied companies belongs to the Industrials and Materials sector. However, in terms of market capitalisation, companies from the Automotive & Transportation and Technology & Telecommunications sectors account for the largest share of the study.

Table 3. Distribution of the sample firms across economic sectors

Sector	Financials & real estate	Technology & telecommunications	Health-care & pharmaceuticals	Industrials & materials	Automotive & transportation	Energy, consumer & services
Number of companies	8	14	8	23	8	13
Share of the sample firms in total market capitalisation (%)	5	17	7	12	19	6
Share of the sample firms in the sample's total market capitalisation (%)	7	26	11	18	29	9

Source: based on information from Thomson Reuters Refinitiv Eikon database.

The dataset consists of daily closing stock prices and quarterly accounting-based profitability indicators, specifically return on assets (ROA) and return on equity (ROE). In constructing the accounting-based factors, particularly the accounting beta, lagged profitability ratios were incorporated, reflecting the notion that investors’ reactions are driven by previously released accounting information. All data were obtained from the Thomson Reuters Refinitiv Eikon database. The three-month rate of return was computed on the basis of daily price observations, while financial ratios were derived from quarterly financial statements.

In addition to individual securities, the study analyses equally weighted portfolios in which each constituent has an identical percentage share of the total, regardless of the firm’s market capitalisation and stock price. Securities were ranked in ascending order based on their average returns, and portfolios consisting of five securities each were constructed using a rolling window approach. This procedure, applied to the full set of 74 firms, resulted in 70 distinct portfolios.

Two methodologies were employed for estimating systematic risk (beta). The first follows the classical Sharpe model (1964), which defines risk in terms of return variance. The second applies the downside beta framework developed by Harlow and Rao (1989), which considers downside deviation as a more relevant risk measure in certain investment contexts.

4. Empirical results and discussion

The preliminary results section outlines the distribution parameters for systematic risk measures derived from both market and accounting data (Table 4). The findings suggest that across all companies, there is greater variability in risk metrics and profitability indicators compared to large firms alone, highlighting a higher heterogeneity in the broader market. Interestingly, certain ROE results deviate from this trend, with values being markedly higher in large companies, possibly reflecting their superior financial stability. Furthermore, the mean beta coefficients based on ROA substantially exceed those derived from ROE in both the conventional and downside frameworks. The pronounced skewness and kurtosis observed in the distributions of ROE-based coefficients, with the exception of small firms, suggest the presence of outliers and fat-tailed behaviour that deviate from the assumption of normality. It may imply that ROE captures risk dynamics more sensitively. Finally, the larger divergences between conventional and downside measures in the large-company group could point to structural differences in how these firms respond to downside risk relative to the overall sample.

The empirical analysis began with the standard specification of the CAPM. As indicated by the estimates for the full sample of firms presented in Table 5, asset pricing on the Frankfurt Stock Exchange (FSE) does not support the model's equilibrium assumptions. In particular, over the sample period, investors did not receive compensation in the form of a positive and statistically significant market risk premium, regardless of whether risk was measured using conventional beta or downside beta.

To examine the potential impact of firm size, the estimated models were evaluated across firms with different levels of market capitalisation. As a robustness criterion, both the classical CAPM and, subsequently, the accounting-based CAPM were estimated separately for different firm-size categories. The results based on individual securities are consistent with those obtained for the full sample. However, portfolio-level analysis revealed significant relationships for medium-sized and small firms. For medium-sized firms, the downside CAPM performed significantly better, whereas for small firms, the conventional CAPM provided a better fit. Nevertheless, these models appear insufficient to adequately explain return variations, underscoring the need to consider extended versions of asset pricing models.

Table 4. Descriptive statistics

Statistics	$\hat{\beta}_i$	$\hat{\beta}_i^{HR}$	ROA_i	ROE_i	$\hat{\beta}_i(ROA)$	$\hat{\beta}_i(ROE)$	$\hat{\beta}_i^{HR}(ROA)$	$\hat{\beta}_i^{HR}(ROE)$
All companies								
Minimum	0.045	-0.194	-1.173	-23.175	-1.728	-0.865	-2.777	-1.148
Maximum	2.551	2.221	5.937	37.907	4.424	7.130	6.104	8.067
Mean	1.021	1.007	1.065	10.619	1.036	0.675	1.092	0.670
Median	1.024	1.074	1.021	10.659	0.731	0.363	0.723	0.302
Stdev	0.460	0.473	1.061	10.611	1.167	1.262	1.554	1.422
Skewness	0.133	-0.316	1.900	-0.133	0.924	3.645	1.140	3.812
Kurtosis	0.357	-0.272	7.043	1.539	0.844	15.166	1.870	16.562
DAX40 companies								
Minimum	0.265	0.165	0.010	-8.551	-0.127	-0.047	-0.847	-0.792
Maximum	1.527	1.590	1.941	36.172	3.957	6.861	5.051	7.814
Mean	0.971	0.937	0.918	11.527	0.876	0.740	0.831	0.645
Median	1.025	1.059	0.910	13.067	0.648	0.221	0.418	0.163
Stdev	0.370	0.409	0.572	8.540	0.920	1.485	1.210	1.608
Skewness	-0.228	-0.352	0.148	0.372	1.698	3.230	1.905	3.749
Kurtosis	-1.187	-1.104	-0.842	1.847	3.227	10.116	4.090	14.218

Statistics	$\hat{\beta}_i$	$\hat{\beta}_i^{HR}$	ROA_i	ROE_i	$\hat{\beta}_i(ROA)$	$\hat{\beta}_i(ROE)$	$\hat{\beta}_i^{HR}(ROA)$	$\hat{\beta}_i^{HR}(ROE)$
MDAX companies								
Minimum	0.045	0.082	−0.609	−23.175	−1.729	−0.865	−2.777	−1.148
Maximum	1.598	1.737	5.937	33.201	4.425	7.130	5.504	8.067
Mean	1.022	1.057	1.281	12.237	1.019	0.780	1.145	0.862
Median	1.022	1.107	1.139	12.129	0.798	0.406	0.829	0.461
Stdev	0.418	0.421	1.279	13.042	1.217	1.569	1.688	1.846
Skewness	−0.481	−0.655	2.027	−0.687	0.727	2.951	0.551	2.761
Kurtosis	−0.562	−0.273	5.777	1.020	1.657	9.460	1.092	8.040
SDAX companies								
Minimum	0.052	−0.195	−1.173	−12.981	−0.773	−0.386	−1.071	−0.494
Maximum	2.551	2.221	4.985	37.907	3.801	1.411	6.104	1.413
Mean	1.071	1.029	1.003	8.158	1.211	0.508	1.302	0.510
Median	1.174	1.088	0.958	9.794	0.758	0.472	0.985	0.514
Stdev	0.578	0.578	1.207	9.838	1.349	0.484	1.742	0.487
Skewness	0.284	−0.230	1.302	0.492	0.596	0.092	1.148	−0.076
Kurtosis	0.076	−0.423	3.398	2.292	−0.740	−0.653	1.148	−0.608

Note: $\hat{\beta}_i, \hat{\beta}_i^{HR}$ – estimates of conventional and downside beta coefficients; ROA_i, ROE_i – ROA and ROE ratios; $\hat{\beta}_i(ROA), \hat{\beta}_i(ROE), \hat{\beta}_i^{HR}(ROA), \hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in conventional and downside framework.

Source: own elaboration.

Table 5. Estimates of standard CAPM in symmetrical and downside approaches.

Market	Variables	Estimate	t-Stat	R ²	Estimate	t-Stat	R ²
		individual securities			equally weighted portfolios		
All companies	Constant	0.0189**	2.368	0.006	0.0017	0.083	0.015
	$\hat{\beta}$	0.0045	0.639		0.0207	1.038	
	Constant	0.0207***	2.689	0.002	0.0116	0.631	0.005
	$\hat{\beta}^{HR}$	0.0028	0.396		0.0110	0.604	
DAX40 companies	Constant	0.0373**	2.391	0.038	0.0407	1.491	0.025
	$\hat{\beta}$	-0.0145	-0.960		-0.0195	-0.701	
	Constant	0.0362**	2.611	0.043	0.0376	1.390	0.018
	$\hat{\beta}^{HR}$	-0.0137	-1.012		-0.0166	-0.592	
MDAX companies	Constant	0.0229	1.683	0.001	0.0517	-0.882	0.112
	$\hat{\beta}$	-0.0014	-0.112		-0.0308	1.508	
	Constant	0.0177	1.275	0.004	-0.0861	-2.440	0.342
	$\hat{\beta}^{HR}$	0.0035	0.289		0.1020***	3.064	
SDAX companies	Constant	0.0097	0.711	0.071	-0.0325	-1.279	0.202
	$\hat{\beta}$	0.0150	1.327		0.0514**	2.196	
	Constant	0.0147	1.089	0.037	-0.0163	-0.645	0.113
	$\hat{\beta}^{HR}$	0.0107	0.935		0.0374	1.558	

Note: $\hat{\beta}_i$ – estimates of conventional beta coefficients, $\hat{\beta}_i^{HR}$ – estimates of downside beta coefficients. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

The analysis of the standard CAPM under the conventional approach was extended to incorporate measures reflecting firm profitability. The estimation results for both the full sample and the subsamples of firms of different sizes, presented in Tables 6, 7, 8, and 9, indicate that the accounting-based CAPM substantially outperforms the classical CAPM in explaining return variability. This advantage primarily pertains to models incorporating profitability ratios (ROA, ROE): both risk premia are positive and statistically significant at the 0.05 level, except in the case of ROE-based models for individual securities. Similar relationships were observed in the study by Rutkowska-Ziarko (2022). Notably, model fit reaches over 80% explanatory power for portfolio-level ROA models, which also yield the highest nominal premia.

Accounting betas based on both profitability measures generate statistically significant, yet unexpectedly negative, risk premia. However, in non-standard

Table 6. Estimates of symmetrical accounting CAPM (all companies)

Variables	Estimate	<i>t</i> -Stat	<i>R</i> ²	Estimate	<i>t</i> -Stat	<i>R</i> ²
	individual securities (<i>N</i> = 74)			equally weighted portfolios (<i>N</i> = 70)		
Constant	0.0138***	3.166	0.122	−0.0077	−1.521	0.390
$\overline{ROA}$	0.0092***	3.157		0.0289***	6.600	
Constant	0.0088	1.071	0.128	−0.0158	−0.967	0.393
$\hat{\beta}$	0.0049	0.726		0.0083	0.519	
$\overline{ROA}$	0.0092***	3.157		0.0286***	6.453	
Constant	0.0291	1.411	0.050	0.0438***	6.423	0.142
$\hat{\beta}$	−0.0053*	−1.948		−0.0209***	−3.357	
Constant	0.0236***	2.890	0.058	0.0266	1.296	0.152
$\hat{\beta}$	0.0055	0.786		0.0167	0.892	
$\hat{\beta}(\overline{ROA})$	−0.0055*	−1.992		−0.0205***	−3.286	
Constant	0.0171***	3.779	0.054	−0.0097	−1.654	0.343
$\overline{(ROE)}$	0.0006**	2.030		0.0031***	5.968	
Constant	0.0127	1.511	0.059	−0.0124	−0.732	0.344
$\hat{\beta}$	0.0043	0.615		0.0028	0.167	
$\hat{\beta}(\overline{ROE})$	0.0006**	2.010		0.0030***	5.791	
Constant	0.0261***	7.148	0.030	0.0303***	6.984	0.070
$\hat{\beta}(\overline{ROE})$	−0.0038	−1.489		−0.0121**	−2.266	
Constant	0.0195**	2.465	0.042	0.0105	0.522	0.084
$\hat{\beta}$	0.0068	0.953		0.0195	1.005	
$\hat{\beta}(\overline{ROE})$	−0.0043	−1.644		−0.0120**	−2.237	

Note: $\hat{\beta}_i$ – estimates of conventional beta coefficients; $\overline{(ROA)}_i$, $\overline{(ROE)}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i(\overline{ROA})$, $\hat{\beta}_i(\overline{ROE})$ – estimates of accounting beta coefficients in conventional framework; *N* – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

CAPM specifications, where the risk factor is an accounting beta derived from ROE, the risk premium turns positive, and in the extended model, remains significant at the 10% level. In summary, while ROA is a superior valuation metric in nominal terms, ROE offers better insights into financial sensitivity.

Unlike the results obtained for large and medium-sized firms, the accounting variables included in the extended CAPM specification were not statistically significant for small firms. One possible explanation is that accounting information is less informative in the valuation of smaller companies due to greater earnings volatility, lower reporting quality, and more pronounced information asymmetries. Furthermore, returns on small-cap stocks may be

driven primarily by factors such as liquidity constraints, firm-specific risk, and limited analyst coverage, which are not fully captured by accounting-based measures. The absence of significant accounting effects may also reflect the greater heterogeneity of small firms and the dominance of size-related risk factors in determining expected returns. Consequently, accounting indicators appear to provide limited incremental explanatory power beyond market risk in the case of small-cap companies.

These findings, particularly those regarding profitability ratios, align with recent advances in accounting-based and downside CAPM research. For in-

Table 7. Estimates of symmetrical accounting CAPM relationships (DAX40 companies)

Variables	Estimate	t-Stat	R ²	Estimate	t-Stat	R ²
	individual securities (N = 25)			equally weighted portfolios (N = 21)		
Constant	0.0024	0.252	0.230	−0.0244**	−2.744	0.607
$\overline{ROA}$	0.0228**	2.619		0.0509***	5.422	
Constant	0.0185	1.201	0.285	0.0233*	1.854	0.811
$\hat{\beta}$	−0.0175	−1.309		−0.0590***	−4.407	
$\overline{ROA}$	0.0237**	2.757		0.0616***	8.655	
Constant	0.0337***	4.749	0.162	0.0249***	3.189	0.011
$\hat{\beta}$	−0.0120**	−2.108		−0.0043	−0.465	
Constant	0.0421**	2.810	0.177	0.0423	1.215	0.025
$\hat{\beta}$	−0.0092	−0.637		−0.0220	−0.514	
$\hat{\beta}(\overline{ROA})$	−0.0112*	−1.924		−0.0011	0.077	
Constant	0.0125	1.376	0.087	0.0004	0.027	0.138
$(\overline{ROE})$	0.0009	1.480		0.0019*	1.741	
Constant	0.0272	1.642	0.131	0.0491**	2.117	0.344
$\hat{\beta}$	−0.0156	−1.062		−0.0727**	−2.462	
$\hat{\beta}(\overline{ROE})$	0.0010	1.534		0.0038***	2.962	
Constant	0.0235***	3.766	0.001	0.0175***	2.922	0.046
$\hat{\beta}(\overline{ROE})$	−0.0003	−0.076		0.0069	0.963	
Constant	0.0374**	2.343	0.042	0.0712**	2.384	0.196
$\hat{\beta}$	−0.0150	−0.947		−0.0620*	−1.832	
$\hat{\beta}(\overline{ROE})$	0.0005	0.138		0.0174*	1.958	

Note: $\hat{\beta}_i$ – estimates of conventional beta coefficients; $(\overline{ROA})_i, (\overline{ROE})_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i(\overline{ROA}), \hat{\beta}_i(\overline{ROE})$ – estimates of accounting beta coefficients in conventional framework; N – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

Table 8. Estimates of symmetrical accounting CAPM relationships (MDAX companies)

Variables	Estimate	<i>t</i> -Stat	<i>R</i> ²	Estimate	<i>t</i> -Stat	<i>R</i> ²
	individual securities (<i>N</i> = 24)			equally weighted portfolios (<i>N</i> = 20)		
Constant	0.0098	1.548	0.230	−0.0061	−1.232	0.684
$\overline{ROA}$	0.0091**	2.563		0.0222***	6.253	
Constant	0.0035	0.242	0.239	−0.0336	−1.656	0.717
$\hat{\beta}$	0.0057	0.0498		0.0283	1.396	
$\overline{ROA}$	0.0095**	2.565		0.0213***	6.030	
Constant	0.0227***	3.418	0.004	0.0344***	2.966	0.070
$\hat{\beta}$	−0.0012	−0.283		−0.0131	−1.167	
Constant	0.0243	1.645	0.004	−0.0151	−0.393	0.160
$\hat{\beta}$	−0.0016	−0.122		0.0467	1.346	
$\hat{\beta}(\overline{ROA})$	−0.0012	−0.282		−0.0109	−0.982	
Constant	0.0144**	2.163	0.097	−0.0150**	−2.708	0.736
$\overline{(ROE)}$	0.0006	1.536		0.0031***	7.091	
Constant	0.0128	0.861	0.098	−0.0567***	−3.347	0.810
$\hat{\beta}$	0.0015	0.123		0.0420**	2.570	
$\hat{\beta}(\overline{ROE})$	0.0006	1.502		0.0030***	7.905	
Constant	0.0262***	5.015	0.152	0.0354***	8.774	0.536
$\hat{\beta}(\overline{ROE})$	−0.0060*	−1.991		−0.0216***	−4.464	
Constant	0.0226*	1.767	0.156	0.0027	0.103	0.577
$\hat{\beta}$	0.0037	0.309		0.0316*	1.277	
$\hat{\beta}(\overline{ROE})$	−0.0062	−1.970		−0.0205***	−4.323	

Note: $\hat{\beta}_i$ – estimates of conventional beta coefficients; $\overline{(ROA)}_i$, $\overline{(ROE)}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i(\overline{ROA})$, $\hat{\beta}_i(\overline{ROE})$ – estimates of accounting beta coefficients in conventional framework; *N* – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

stance, Rutkowska-Ziarko et al. (2024) propose a conditional, non-standard CAPM that incorporates accounting betas and profitability ratios, concluding that the average values of profitability ratios and accounting betas proved to be significant sources of systematic risk.

The subsequent phase of the study examined non-standard extensions of the CAPM framework, integrating market-based and accounting-based variables under a downside risk perspective. This approach focuses on returns that fall below a specified target rate and, for financial ratios, values that are

Table 9. Estimates of symmetrical accounting CAPM relationships (SDAX companies)

Variables	Estimate	t-Stat	R ²	Estimate	t-Stat	R ²
	individual securities (N = 25)			equally weighted portfolios (N = 21)		
Constant	0.0187	2.229	0.068	0.0084	0.846	0.120
$\overline{ROA}$	0.0070	1.298		0.0150	1.613	
Constant	0.0050	0.354	0.125	−0.0382	−1.089	0.205
$\hat{\beta}$	0.0135	1.196		0.0602	1.384	
$\overline{ROA}$	0.0063	1.165		−0.0040	−0.241	
Constant	0.0330***	3.785	0.061	0.0481***	3.313	0.158
$\hat{\beta}$	−0.0060	−1.228		−0.0211*	−1.891	
Constant	0.0164	1.147	0.142	−0.0098	−0.411	0.417
$\hat{\beta}$	0.0160	1.439		0.0587	2.826	
$\hat{\beta}(\overline{ROA})$	−0.0064	−1.351		−0.0247	−2.575	
Constant	0.0210**	2.458	0.031	0.0134	1.408	0.063
$\overline{(ROE)}$	0.0006	0.855		0.0011	1.127	
Constant	0.0078	0.548	0.087	−0.0475	−1.471	0.228
$\hat{\beta}$	0.0136	1.161		0.0739*	1.961	
$\hat{\beta}(\overline{ROE})$	0.0004	0.616		−0.0011	−0.766	
Constant	0.0323***	3.384	0.037	0.0807***	4.764	0.400
$\hat{\beta}(\overline{ROE})$	−0.0128*	−0.935		−0.1138***	−3.557	
Constant	0.0141	1.034	0.161	0.0240	1.114	0.633
$\hat{\beta}$	0.0212	1.811		0.0554***	3.387	
$\hat{\beta}(\overline{ROE})$	−0.0215	−1.541		−0.1183***	−4.600	

Note: $\hat{\beta}_i$ – estimates of conventional beta coefficients; $\overline{(ROA)}_i$, $\overline{(ROE)}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i(\overline{ROA})$, $\hat{\beta}_i(\overline{ROE})$ – estimates of accounting beta coefficients in conventional framework; N – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

below their respective sample means. The extended versions of the CAPM, incorporating profitability and sensitivity measures, were also analysed within a downside risk framework (Tables 10, 11, 12, and 13). The results for the full sample of firms do not exhibit substantial deviations from those obtained under the conventional specification. Both downside beta coefficients and downside accounting betas generally emerge as statistically insignificant predictors, yielding negative risk premiums associated with firms’ sensitivity to shifts in the aggregate financial condition of the analysed securities. Nonetheless,

Table 10. Estimates of downside accounting CAPM (all companies)

Variables	Estimate	<i>t</i> -Stat	<i>R</i> ²	Estimate	<i>t</i> -Stat	<i>R</i> ²
	individual securities (<i>N</i> = 74)			equally weighted portfolios (<i>N</i> = 70)		
Constant	0.0111	1.411		−0.0036	−0.247	
$\hat{\beta}^{HR}$	0.0026	0.397	0.123	−0.0043	−0.299	0.391
$\overline{ROA}$	0.0092***	3.135		0.0291***	6.518	
Constant	0.0273***	6.957		0.0260***	4.479	
$\hat{\beta}^{HR}(ROA)$	−0.0034	−1.665	0.037	−0.0050	−0.663	0.006
Constant	0.0226***	2.939		0.0118	0.641	
$\hat{\beta}^{HR}$	0.0050	0.717	0.044	0.0153	0.808	0.016
$\hat{\beta}^{HR}(ROA)$	−0.0037*	−1.762		−0.0067	−0.853	
Constant	0.0146*	1.782		−0.0025	−0.167	
$\hat{\beta}^{HR}$	0.0025	0.365	0.056	−0.0077	−0.511	0.346
$\overline{ROE}$	0.0006**	2.011		0.0031***	5.911	
Constant	0.0254***	7.082		0.0268***	6.484	
$\hat{\beta}^{HR}(ROE)$	−0.0027	−1.184	0.019	−0.0067	−1.367	0.027
Constant	0.0200**	2.589		0.0165	0.881	
$\hat{\beta}^{HR}$	0.0058	0.795	0.028	0.0103	0.570	0.031
$\hat{\beta}^{HR}(ROE)$	−0.0033	−1.367		−0.0066	−1.344	

Note: $\hat{\beta}_i^{HR}$ – estimates of downside beta coefficients; $\overline{ROA}_i$, $\overline{ROE}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i^{HR}(ROA)$, $\hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in downside framework; *N* – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

these premiums are of lower absolute magnitude compared to their counterparts derived from the conventional model.

The absence of significant relationships between expected returns and accounting beta coefficients may be attributable to the inclusion of all firms in the analysis, irrespective of their heterogeneity in terms of market capitalisation. Firm size plays a critical role in risk perception and, consequently, affects the financial stability of a company. Smaller firms, although often more dynamic, tend to face greater challenges in capital acquisition, lower liquidity, and heightened susceptibility to market fluctuations, which may lead them to respond differently to changes in overall economic conditions. A similar observation regarding firm size in the German capital market is reported by Amel-Zadeh (2011). He identifies a number of differences in firm-specific variables between large and small companies. In this paper, it is partially supported by the results obtained for the subsample of large firms. For portfolio-level invest-

Table 11. Estimates of downside accounting CAPM (DAX40 companies)

Variables	Estimate	<i>t</i> -Stat	<i>R</i> ²	Estimate	<i>t</i> -Stat	<i>R</i> ²
	individual securities (<i>N</i> = 25)			equally weighted portfolios (<i>N</i> = 21)		
Constant	0.0160	1.118		0.0245**	2.121	
$\hat{\beta}^{HR}$	−0.0150	−1.246	0.280	−0.0637***	−4.937	0.833
$\overline{ROA}$	0.0232**	2.697		0.0640***	9.379	
Constant	0.0299***	4.722		0.0211***	3.499	
$\hat{\beta}^{HR}(ROA)$	−0.0080*	−1.833	0.127	0.0011	0.149	0.001
Constant	0.0373**	2.779		0.0522	1.557	
$\hat{\beta}^{HR}$	−0.0084	−0.622	0.142	−0.0367	−0.943	0.048
$\hat{\beta}^{HR}(ROA)$	−0.0073	−1.602		0.0076	0.754	
Constant	0.0259*	1.729		0.0414*	1.742	
$\hat{\beta}^{HR}$	−0.0148	−1.124	0.136	−0.0607*	−2.037	0.288
$\overline{ROE}$	0.0010	1.547		0.0033**	2.613	
Constant	0.0229***	3.815		0.0155***	3.294	
$\hat{\beta}^{HR}(ROE)$	0.0006	0.161	0.001	0.0130**	2.110	0.190
Constant	0.0377**	2.632		0.0738***	3.002	
$\hat{\beta}^{HR}$	−0.0168	−1.134	0.056	−0.0654**	−2.406	0.387
$\hat{\beta}^{HR}(ROE)$	0.0021	0.564		0.0216***	3.291	

Note: ; $\hat{\beta}_i^{HR}$ – estimates of downside beta coefficients; $\overline{ROA}_i$, $\overline{ROE}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i^{HR}(ROA)$, $\hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in downside framework; *N* – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

ments, accounting sensitivity measures based on the ROE indicator proved to be significant pricing factors. The associated risk premiums were significant at the 5% and 1% levels, depending on the model specification. In contrast, the downside beta based on ROA yielded premiums consistent in sign with expectations but statistically insignificant. Similar to the conventional framework, models incorporating profitability indicators showed greater explanatory power for return variability when based on ROA, whereas models employing accounting betas performed better in this regard when ROE was used.

Given the well-documented shortcomings of the traditional CAPM in adequately capturing return dynamics for Frankfurt Stock Exchange-listed equities, this study positions itself as both a critical reassessment and a forward-looking refinement of asset pricing frameworks. Our empirical results reinforce a growing body of literature questioning the CAPM’s empirical robustness, particularly its limited ability to generate statistically meaningful

Table 12. Estimates of downside accounting CAPM (MDAX companies)

Variables	Estimate	t-Stat	R ²	Estimate	t-Stat	R ²
	individual securities (N = 24)			equally weighted portfolios (N = 20)		
Constant	0.0014	0.099	0.247	−0.0484*	−1.994	0.734
$\hat{\beta}^{HR}$	0.0076	0.687		0.0438*	1.777	
$\overline{ROA}$	0.0094**	2.604		0.0191***	5.002	
Constant	0.0295***	3.676	0.044	0.0272***	2.966	0.025
$\hat{\beta}^{HR}(ROA)$	−0.0009	−0.312		−0.0050	−0.681	
Constant	0.0184	1.285	0.009	−0.0853**	−2.491	0.415
$\hat{\beta}^{HR}$	0.0041	0.322		0.1105***	3.365	
$\hat{\beta}^{HR}(ROA)$	−0.0011	−0.342		−0.0086	−1.447	
Constant	0.0074	0.497	0.108	−0.0791***	−4.793	0.864
$\hat{\beta}^{HR}$	0.0062	0.521		0.0650***	−4.009	
$\overline{ROE}$	0.0006	1.570		0.0027***	8.090	
Constant	0.0256***	4.892	0.130	0.0352***	8.391	0.506
$\hat{\beta}^{HR}(ROE)$	−0.0047	−1.816		−0.0189***	−4.295	
Constant	0.0151	1.153	0.160	−0.0448	−1.632	0.672
$\hat{\beta}^{HR}$	0.0104	0.866		0.0738***	2.937	
$\hat{\beta}^{HR}(ROE)$	−0.0054*	−1.979		−0.0158***	−4.136	

Note: $\hat{\beta}_i^{HR}$ – estimates of downside beta coefficients; $\overline{ROA}_i$, $\overline{ROE}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i^{HR}(ROA)$, $\hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in downside framework; N – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

risk premiums (see Markowski, 2024; Nurjannah et al., 2012; Vendrame et al., 2018). In this context, traditional models serve primarily as benchmarks, providing a reference point for evaluating the relative performance of more sophisticated alternatives.

A key contribution of this paper is the development of a non-standard, variant of the CAPM that integrates accounting-based betas and firm-level profitability metrics such as return on equity (ROE) and return on assets (ROA) with market risk coefficients. This enriched specification significantly enhances explanatory power relative to models relying solely on market betas. Of particular interest is the incorporation of the downside accounting beta. Our results confirm that this measure not only captures asymmetric risk more effectively in terms of explanatory power than measures based on the conventional approach, but also retains strong statistical relevance across more mature markets, suggesting a broader applicability beyond the confines of

Table 13. Estimates of downside accounting CAPM (SDAX companies)

Variables	Estimate	t-Stat	R ²	Estimate	t-Stat	R ²
	individual securities (N = 25)			equally weighted portfolios (N = 21)		
Constant	0.0091	0.646		−0.0028	−0.075	
$\hat{\beta}^{HR}$	0.0097	0.848	0.098	−0.0157	0.311	0.125
$\overline{ROA}$	0.0067	1.220		0.0097	0.492	
Constant	0.0307***	3.756		0.0307**	2.386	
$\hat{\beta}^{HR}(ROA)$	−0.0038	−0.994	0.041	−0.0062	−0.716	0.026
Constant	0.0181	1.324		−0.0117	−0.467	
$\hat{\beta}^{HR}$	0.0132	1.141	0.095	0.0479*	1.930	0.193
$\hat{\beta}^{HR}(ROA)$	−0.0046	−1.189		−0.0113	−1.335	
Constant	0.0121	0.853		−0.0239	−0.655	
$\hat{\beta}^{HR}$	0.0094	0.801	0.058	0.0491	1.059	0.118
$\overline{ROE}$	0.0005	0.710		−0.0005	−0.295	
Constant	0.0299***	3.100		0.0378	1.673	
$\hat{\beta}^{HR}(ROE)$	−0.0081	−0.587	0.015	−0.0292	−0.705	0.025
Constant	0.0152	1.146		0.0007	0.026	
$\hat{\beta}^{HR}$	0.0215	1.573	0.114	0.0643**	2.445	0.268
$\hat{\beta}^{HR}(ROE)$	−0.0226	−1.389		−0.0846*	−1.954	

Note: ; $\hat{\beta}_i^{HR}$ – estimates of downside beta coefficients; $\overline{ROA}_i$, $\overline{ROE}_i$ – mean of ROA and ROE ratios; $\hat{\beta}_i^{HR}(ROA)$, $\hat{\beta}_i^{HR}(ROE)$ – estimates of accounting beta coefficients in downside framework; N – Number of observations in the cross-sectional regression. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Source: own elaboration.

emerging market contexts (Rutkowska-Ziarko et al., 2024). The superior explanatory power of the downside accounting measures may reflect the substantially greater variation in downside accounting beta coefficients compared with their conventional counterparts, as shown in Table 4.

An alternative stream of literature explores the integration of financial statement information into asset pricing models through the development of novel risk measures. A notable example is the accounting-based downside risk (ABDR) framework introduced by Konchitchki et al. (2016). While ABDR contributes meaningfully to this domain, it diverges substantially from the DAB construct proposed in this study, both conceptually and methodologically. Fundamentally, DAB captures a firm’s downside sensitivity of accounting profitability relative to that of the broader market or sector, positioning it as a covariance-based risk metric. In contrast, ABDR does not reflect sensitivity per se, rather its magnitude is invariant to co-movements with market

or sector-level benchmarks. Methodologically, DAB leverages lower partial moments (LPMs) to isolate adverse performance realisations, focusing exclusively on the left tail of the profitability distribution. ABDR, by comparison, employs a ratio of the square root of the LPMs to the square root of the upper partial moments (UPMs), thereby providing a relative assessment of downside versus upside risk.

Empirical support for ABDR's relevance in explaining cross-sectional variation in returns has been documented by W. Huang et al. (2022) and Luo et al. (2021). However, the comparative structure of ABDR makes it inherently distinct from DAB, which emphasises direct downside co-movement, an aspect more aligned with systematic risk pricing in traditional asset pricing theory. Luo et al. demonstrate that market-level aggregated earnings downside risk, along with its constituent components, exhibits a significant positive relationship with subsequent stock market returns. Conversely, Huang et al. examine the relationship between accounting-based downside risk and stock price crash risk in the context of the Chinese market. They find that both earnings downside risk and its component, accruals downside risk, serve as negative predictors of future stock price crash risk. Instead of focusing on tail risk events, our study incorporates accounting information into asset pricing models to investigate how these variables affect expected returns and the overall risk–return trade-off. This approach shifts the emphasis away from crash risk analysis, offering new insights into the broader role of downside risk in asset pricing. By extending the analysis beyond firm-specific crash risk to encompass systematic pricing mechanisms, our research provides a more comprehensive perspective on how accounting variables can be integrated into capital market valuation models.

This study extends the downside CAPM by incorporating accounting profitability measures (ROA and ROE) and accounting beta coefficients. The proposed framework links firm fundamentals to the accounting risk premium and complements the existing asset pricing literature by moving beyond traditional variance-based models toward a downside risk perspective.

Conclusions

The empirical investigation conducted on the Frankfurt Stock Exchange (FSE) provides a novel approach to estimating the cost of equity by augmenting the classical CAPM framework with accounting information, specifically profitability ratios and risk measures such as accounting beta coefficients.

Over the analysis period from 2015 to 2024, the traditional Capital Asset Pricing Model (CAPM) failed to adequately explain the cross-section of re-

turns. However, incorporating additional explanatory variables into the form of accounting-based profitability ratios markedly enhanced model performance, yielding statistically significant parameter estimates and a higher degree of explanatory power. The most robust results were obtained when the return on assets (ROA) ratio was included in models for the large securities group.

The study also integrates downside risk measures into the analysis. Similar to the classical CAPM, the Downside CAPM when applied to market returns did not produce a satisfactory explanation of return behaviour on the FSE. Nevertheless, within the downside risk framework for large-cap firms, a negative downside market risk premium was identified in the Accounting-based CAPM when risk was measured using the DAB-downside accounting beta. Conversely, positive risk premiums were observed for downside accounting betas based on return on equity (ROE), particularly within equally weighted portfolios, suggesting an asymmetric and nuanced risk-return relationship. The empirical findings from the FSE indicate that enhancing asset pricing models with profitability ratios and accounting-based downside beta coefficients improves our understanding of return dynamics in this market. Furthermore, the downside risk approach appears to better capture observed market behaviour compared to symmetric risk modelling frameworks.

Two principal conclusions emerge from this research. Firstly, financial statements are a critical source of information for equity investors and should be disclosed at least quarterly to enable monitoring not only of profitability levels but also their temporal variability. Pricing model factors based on accounting information may serve as an alternative to beta coefficients derived solely from capital market data. This becomes particularly relevant for unlisted firms. Secondly, the inclusion of asymmetric risk measures in asset pricing models is essential, as such extensions can significantly improve the models' explanatory power.

The study presented focuses on firms listed in developed markets. It is important to note that these markets differ from emerging ones in several respects: they are characterised by higher market capitalisation, a longer history of more regulated capital trading mechanisms, and, at the same time, a generally slower pace of economic growth. Consequently, developed capital markets may offer lower expected returns compared to emerging markets, typically at the cost of reduced risk. Comparing the present findings with evidence from emerging economies would therefore be of particular interest, given the distinct asset class involved. Future research will thus be directed toward applying the proposed accounting-based risk measures to emerging markets. Moreover, it is essential to consider the sensitivity of CAPM results derived from accounting-based risk measures across different market conditions. This line of inquiry is particularly relevant for both investors' decision-making processes and for evaluating the extent to which these account-

ing measures behave in line with the traditional market-based risk measure, namely the beta coefficient.

Several limitations related to the data and empirical methodology should be acknowledged. Firstly, the comparability of accounting data across firms from different industries and of different sizes may be limited. Secondly, there is no market or sector-wide stock index that directly reflects firms' accounting profitability, constraining the construction of benchmark accounting returns. Finally, the estimates may be subject to potential measurement error in beta coefficients, as the original Fama–MacBeth procedure could not be fully implemented. Nevertheless, the use of portfolio formation based on stock returns helps mitigate measurement error in portfolio beta estimates.

Open Science Practices

The data collected during the study are publicly available at <https://doi.org/10.18150/6VQF3B>

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