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Evaluating the Effectiveness of Accounting Beta in Explaining Stock Returns: An Extended CAPM Approach

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Abstract

The purpose of this study is to evaluate the effectiveness of accounting betas and downside risk–based accounting betas in explaining and pricing stock returns within the extended Capital Asset Pricing Model (CAPM). To this end, the performance of accounting betas based on Return on Assets (ROA), Return on Equity (ROE), and Return on Sales (ROS) is examined, both in their conventional and downside risk forms, alongside the classical market beta and control variables. The study's statistical population comprises large, index-forming firms listed on the Tehran Stock Exchange, and the final sample includes 25 non-financial companies over the period 2015–2024. Quarterly data are employed, and the empirical analysis is conducted using panel-data regression techniques in EViews. The results indicate that the classical CAPM alone lacks sufficient explanatory power to account for cross-sectional differences and average stock returns in the Iranian capital market. However, incorporating the accounting beta based on ROA, particularly in its downside risk form, significantly enhances the explanatory power of the extended CAPM. In contrast, accounting betas based on ROE and ROS, whether in conventional or downside risk forms, do not exhibit statistically significant explanatory power in most model specifications. Moreover, the findings suggest that downside accounting betas do not necessarily provide significant incremental information beyond their conventional counterparts. Overall, the findings indicate that the effectiveness of accounting betas in asset pricing models is selective, and only certain measures (most notably the downside accounting beta based on ROA) can provide a more comprehensive representation of the systematic risk affecting stock returns when used alongside the classical market beta.

Keywords: Accounting beta, Lower partial moment, Capital asset pricing model.

1 | Introduction

The primary objective of any investor in the capital market is to allocate resources to achieve the expected return while accepting a certain level of risk. Investors, by accepting risk, expect to receive a return commensurate with it [1]. In financial literature, risk is divided into two categories: systematic risk and unsystematic risk. Unsystematic risk arises from a company's or industry's specific characteristics. It can be reduced through diversification within an investment portfolio, whereas systematic risk stems from unpredictable changes in macroeconomic factors and general market conditions and is non-diversifiable [2].

Systematic risk, typically measured by the beta coefficient, indicates the sensitivity of a stock's return to market return changes. Beta represents the volatility of a security's return in response to market fluctuations; the higher its value, the greater the uncertainty regarding the expected return [3], [4]. Within this framework, the Capital Asset Pricing Model (CAPM), as one of the most fundamental financial models, elucidates the equilibrium relationship between systematic risk and expected return. It posits that only systematic risk is rewarded in the market [5]. Despite CAPM's pivotal position in the financial literature, empirical evidence suggests that the classic version of the model falls short of fully explaining cross-sectional differences in stock returns. Consequently, numerous extended versions of CAPM have been introduced, attempting to enhance the model's explanatory power by incorporating various dimensions of risk. Among these models are CCAPM, ICAPM, ACAPM, DCAPM, and MCAPM. In the Consumption-based Capital Asset Pricing Model (CCAPM), efforts have been made to improve the efficiency of the traditional CAPM by including economic variables related to consumption [6]. Additionally, the Intertemporal Capital Asset Pricing Model (ICAPM) predicts that asset returns depend not only on their covariance with the market portfolio but also on state variables that capture investment opportunities [7]. On the other hand, liquidity has been considered as one of the factors affecting expected stock returns within the framework of the Adjusted Capital Asset Pricing Model (ACAPM). This model incorporates liquidity risks in the pricing process [8]. The Multi-period Capital Asset Pricing Model (MCAPM) has also been developed to provide a dynamic, time-dependent model. However, one limitation is its lack of attention to multiple risk factors [9]. Furthermore, Estrada [10], by introducing the Downside Capital Asset Pricing Model (DCAPM), has emphasized the importance of

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downside and asymmetric market risk in estimating expected returns [11]. Despite these efforts, most extended versions of CAPM still rely on market price data and have paid less attention to companies' accounting information. While the economic value of companies arises from their operating, investing, and financing activities, it follows that accounting-based indicators should be used directly to measure systematic risk [12]. In this context, accounting beta, first proposed by Hill and Stone [13], has attracted attention as an alternative measure of systematic risk.

However, empirical research on the application of accounting beta in asset pricing has been limited, with scarce evidence regarding its use as a proxy for systematic risk, particularly in the Iranian capital market. Previous studies have indicated that downside accounting beta can serve as an advanced measure of systematic risk, and significant similarities have been observed between market and accounting betas across industries [14]. Nevertheless, no comprehensive study to date has examined simultaneously classic accounting betas and downside-risk-based accounting betas (such as the Lower Partial Moment (LPM) method within the extended CAPM framework) on the Tehran Stock Exchange. Therefore, the present research, focusing on large companies listed on the Tehran Stock Exchange, seeks to evaluate the efficiency of accounting beta in explaining stock returns. Specifically, this study investigates whether classic accounting betas and downside-risk-based accounting betas, alongside the classic market beta, can explain cross-sectional differences in average stock returns, and whether incorporating these accounting-based indicators can enhance the explanatory power of the extended CAPM relative to its classic version. This research also aims to determine whether downside-risk-based accounting betas provide significantly incremental information for explaining stock returns compared to conventional accounting betas, and to what extent the use of accounting performance-based measures such as ROA, Return on Equity (ROE), and ROS within the downside risk framework can lead to an improved explanatory power of the model.

2 | Theoretical Foundations and Research Background

Risk and return are considered fundamental concepts in financial and investment literature and have always been the focus of attention for investors, financial managers, and researchers. One of the most important theories explaining the relationship between risk and return is the CAPM, which posits that an asset's expected return is a function of its systematic risk, measured by its beta coefficient. In the classic CAPM, market beta is used as the primary measure of systematic risk. However, numerous studies have shown that market beta lacks temporal stability and sufficient explanatory power, and in many markets, especially emerging markets, it has limited explanatory power. In response to these limitations, researchers have developed adjusted and extended versions of the CAPM and introduced alternative measures of systematic risk. One such measure is accounting beta, which, rather than using market price-based data, uses companies' accounting information to gauge the sensitivity of their financial performance to macroeconomic or market changes. Due to its reliance on data on companies' profitability and operational performance, accounting beta can provide a more stable picture, less affected by short-term market fluctuations, and has thus been proposed in financial literature as a complement or alternative to market beta. On the other hand, the development of CAPM and the introduction of concepts such as downside betas, distress betas, and other adjusted forms of systematic risk indicate researchers' efforts to improve the explanatory power of asset pricing models, particularly in asymmetric market conditions and downturn periods. In this regard, examining the efficiency of accounting beta within the extended CAPM framework is particularly important, especially in the Iranian capital market, which exhibits characteristics of an emerging market.

In the domain of studies within Iran, several research works have explored various types of betas and their roles in explaining stock returns. Haddadzadeh and Abasian [15] in their study titled "using capital loss beta in managers' decision-making to form an optimal portfolio in the Tehran Stock Exchange" demonstrated that CDaR and ERoD betas possess higher temporal stability compared to standard beta. They also showed better performance in measuring risk and guiding investment decisions during market downturns and declines in the total index. The findings of this study suggest that using alternative betas can improve the quality of investment managers' decisions. Geraeeli Nezhad Foomeshi et al. [16] in a research titled "Evaluating the effect of systematic risk on the stock returns of Iranian listed companies using a hybrid model including the Raff set, regression, and arbitrage pricing theory" found that variables such as sales growth, net profit margin, and debt to equity ratio have a significant impact on systematic risk. At the same time, the interest rate does not show a significant effect on stock beta. Their results also indicate a significant positive relationship between systematic risk and stock returns.

Mehrali et al. [11], by comparing an adjusted and downside CAPM with the standard CAPM in explaining the cost of capital, concluded that extended versions of CAPM possess higher explanatory power and perform better than the classic model. These findings emphasize the need to reconsider the exclusive use of the standard CAPM. Abbasi and Kaviani [9], in a study titled "experimental test and evaluate the possibility of using traditional CAPM model and MCAPM in the Tehran Stock Exchange", showed that adding new variables to the traditional CAPM model increases its explanatory power in explaining stock returns. The results of this research also imply the superiority of extended models over the classic version. Furthermore, Khavari and Mirjalili [17] in a study titled "the interaction of systematic risk with stock returns in the Tehran Stock Exchange" found that stock returns have a significant relationship with their past returns. The findings indicated an inverse relationship between stock returns and indicators of systematic risk and information asymmetry. Conversely, there was a positive relationship between stock returns and earnings per share and between the ratio of operating cash flow to assets and stock returns. In this study, firm size and the book-to-market ratio did not show a significant impact on stock returns.

At the international level, numerous studies have also examined systematic risk, beta, and extended versions of asset-pricing models. Irawan et al. [18] in a research titled "the influence of asset growth and asset size on systematic risk (Beta) of banking stocks on the Indonesia Stock Exchange" demonstrated that asset growth has a positive and significant effect on stock beta. In contrast, asset size negatively and significantly influences systematic risk. These results suggest that larger banks are more stable and have lower systemic risk. El Mosallamy and Yasser [19] in a study titled "does downside beta matter in asset pricing? Evidence from the Egyptian Stock Exchange" showed that conventional asset pricing models, primarily designed for developed markets, are unable to account for the specific conditions of emerging markets. Their results indicate that downside beta performs better and is more stable than conventional beta in the Egyptian market. Usman [20], in a study titled "bank participation in the financial sector's systemic risk and expected returns", used data from large U.S. banks to show that even banks with a larger share in the financial system's systemic risk continue to benefit from higher expected returns and implicit government subsidies. Feng et al. [21] in a study on "systemic risk spillovers and their determinants in the stock markets of belt and road countries" found that cross-border investment and international trade are among the most important channels for systemic risk contagion. At the same time, economic freedom can be a driver of these spillovers. Finally, Zhang et al. [22] in a study titled "systemic risk of Chinese financial institutions and asset price bubbles" demonstrated that stock market bubbles and real estate bubbles have a significant positive correlation with systemic risk, and an increase in these bubbles can lead to the intensification of systemic risk in the financial system.

3 | Research Methodology

The present research aims to evaluate the efficiency of accounting beta in explaining company stock returns within the extended CAPM framework. In terms of objective, this research is applied, and in terms of nature and method, it is descriptive-analytical. It examines the relationships between the research variables with a quantitative approach based on historical data. The data used in this study were extracted from audited financial statements and trading information for companies listed on the Tehran Stock Exchange, and were analyzed quarterly. The statistical population of the research includes large and index-making companies on the Tehran Stock Exchange. In the first stage, 30 large companies from the exchange with the greatest impact on the total market index due to their high trading volume and market capitalization, were selected as the initial population for the study. Given the fundamental differences in activities, financial structures, and financial reporting methods among companies operating in the financial industry, these companies were excluded from the research sample. Finally, the final research sample consists of 24 non-financial index-making companies. The selection of index-making companies was based on their trading trends and price fluctuations, which play a decisive role in changes to the total market index. Therefore, examining the behavior of accounting betas in these companies can more accurately and significantly demonstrate their explanatory power for stock returns than other types of betas. Furthermore, focusing on large and influential market companies reduces biases caused by low liquidity and abnormal stock price fluctuations. The research period spans 10 years, from 2015 to 2024. The data were collected quarterly for each company, leading to an increase in the number of observations, greater statistical power of the tests, and more accurate estimates of model coefficients.

To test the research hypotheses and examine the relationship between accounting beta and stock returns, regression-based statistical methods have been employed. Stock returns have been treated as the dependent variable, and accounting beta as the main independent variable within the extended CAPM framework. Given the data structure, which combines cross-sectional company observations with time-series data, the analyses were performed using panel data methods. Before estimating the regression models, the necessary diagnostic tests were conducted to examine the classical assumptions of regression, including the normality of data distribution, the presence or absence of multicollinearity, heteroscedasticity, and autocorrelation. Additionally, to select the appropriate panel-data model, relevant diagnostic tests were used. All statistical calculations, model estimation, and hypothesis tests were performed using EViews.

Finally, the results from the regression analyses have been used to evaluate the explanatory power of accounting beta in predicting company stock returns within the extended CAPM framework, and they form the basis for accepting or rejecting the research hypotheses.

3.1 | Research Model

3.1.1 | Calculation of accounting and market beta

The classic measure of systematic risk is the beta coefficients (β_i), which are used in Sharpe's CAPM model and are typically calculated as follows:

$$\beta_i = \frac{cov_{iM}}{S_M^2}. \tag{1}$$

Eq. (1) represents beta, the value of which is obtained by dividing the covariance of the return rate of stock i and the market portfolio's return rates (cov_{iM}) by the variance of the market portfolio's return (S_M^2). In this approach, it is assumed that investors exhibit mean-variance behavior [10]. If investors consider risk as the possibility of loss or earning a return lower than a specified target point, then the appropriate measure for systematic risk should be downside beta (β_i^{LPM}), which is calculated as follows [23]:

$$\beta_i^{LPM} = \frac{CLPM_i^2}{dS_M^2(f)}, \tag{2}$$

where $CLPM_i^2$ is the second-order partial mixed moment of LPMs for companies accepted in the stock exchange, and $dS_M^2(f)$is the semi-variance of the market portfolio related to the risk-free rate of return. In this research, it is assumed that in the calculation of semi-variance and LPM, the reference point is equal to the risk-free rate of return (R_{ft}), such that the value of this rate changes from one period to another. The second-order asymmetric LPM is calculated as follows [23]:

$$CLPM_i^2 = \frac{1}{T-1}\sum_{T=1}^{T}(R_{it} - R_{ft}) * lpm_{Mt}, \tag{2}$$

where:

$$lpm_{Mt} = \begin{cases} 0, & \text{for } R_{Mt} \geq R_{ft}, \\ R_{Mt} - R_{ft}, & \text{for } R_{Mt} < R_{ft}. \end{cases} \tag{2}$$

R_{Mt} represents the market portfolio's return rate in period t. Similarly, the semi-variance of the market portfolio is calculated as follows:

$$dS_M^2(f) = \frac{\sum_{T=1}^{T} lpm_{Mt}}{T-1}. \tag{2}$$

Both types of beta can be considered "market beta" because the market return rate is used in the calculation of systematic risk. To calculate accounting beta, one of the profitability ratios can be used instead of the market return rate. The accounting beta coefficient for asset returns, $\beta_i(ROA)$, is calculated as follows [13]:

$$\beta_i(ROA) = \frac{cov_{iM}(ROA)}{S_M^2(ROA)}, \tag{2}$$

where, $cov_{iM}(ROA)$is the covariance of the profitability ratio of company. The market portfolio's profitability ratios (market indicators of profitability ratios); $S_M^2(ROA)$is the variance of the market's profitability ratios. In this way, accounting beta can be calculated for various profitability ratios, including ROA, ROE, ROS, as well as other accounting ratios. In this study, the methodology presented in the previous research by the authors has been used to calculate the downside accounting beta [14]. Below, the downside accounting beta for ROA is defined:

$$\beta_i^{LPM}(ROA) = \frac{CLPM_i^2(ROA)}{dS_M^2(\overline{ROA_M})}. \tag{6}$$

In this equation, $\overline{ROA_M} = \frac{1}{T}\sum_{T=1}^{T} ROA_{Mt}$ overline ROA is the average ROA level for all companies analyzed in the section. Also, $ROA_{Mt} = \sum_{i=1}^{k} W_i^* ROA_{it}$ and $W_i = MV_i/\sum_{i=1}^{k} MV_i$, where MV is the market value of company i. The expression $dS_M^2(\overline{ROA_M})$ represents the semi-variance of the market portfolio determined in relation to the average ROA level.

$$CLPM_i^2(ROA) = \frac{1}{T-1}\sum_{T=1}^{T}(ROA_{it} - \overline{ROA_M}) * lpm_{Mt}(ROA), \tag{7}$$

where,

$$lpm_{Mt}(ROA) = \begin{cases} 0, & \text{for } ROA_{Mt} \geq \overline{ROA_M}, \\ ROA_{Mt} - \overline{ROA_M}, & \text{for } ROA_{Mt} < \overline{ROA_M}. \end{cases} \tag{8}$$

Similarly, the method of calculating the semi-variance of ROA will be as follows:

$$dS_M^2(\overline{ROA_M}) = \frac{\sum_{T=1}^{T} lpm_{Mt}(ROA)}{T-1}. \tag{9}$$

The downside accounting beta for a profitability ratio can also be defined similarly.

4 | Evaluating Accounting Betas within the CAPM Framework

This research is based on the fundamental equilibrium relationship of the Sharpe-Linter-Mossin CAPM.

$$E(R_i) = R_f + RM_i[E(R_M) - R_f], \quad (9)$$

where RM_i is the systematic risk measure. $E(R_i)$ is the expected return of the asset, $E(R_M)$ is the expected market return, and R_f is the risk-free rate. The structure of this model is maintained when semi-variance and co-semi-variance replace their standard counterparts. In this case, the model is called the Downside CAPM (D-CAPM) [10]. The CAPM equations are tested using a classic two-stage procedure. In the first stage, conventional betas and accounting betas, within both the classic and downside frameworks, are estimated separately for each security, following the formulas provided in the previous section [24]. In the second stage, the cross-sectional average returns of securities are regressed on the estimated systematic risk to examine the significance of the linear regression (i.e., risk factor pricing). The cross-sectional estimation equations are written as follows [10], in the standard CAPM format and the extended CAPM version, where the regressions include a combination of conventional beta and accounting beta:

$$\begin{aligned} \bar{R}_i &= \lambda_0 + \lambda_1 \widehat{RM}_i + \varepsilon_i \\ \bar{R}_i &= \lambda_0 + \lambda_1 \widehat{RM_{i1}} + \lambda_2 \widehat{RM_{i2}} + \varepsilon_i \end{aligned} \quad (10)$$

where $\bar{R}_i$ represents the rate of return of security. $\widehat{RM}_i$ and $\widehat{RM_{i2}}$ are the estimated risk measures in formats such as $\beta_i\,(ROS), \beta_i\,(ROA), \beta_i\,(ROE),\ \beta_i\,, \beta_i^{LPM}(ROS), \beta_i^{LPM}(ROA), \beta_i^{LPM}(ROE)$; and λ_0, λ_1, λ_2 are the structural parameters of the model, and ε_i represents the random error term. Market betas were calculated based on quarterly rates of return. The rates of return were calculated as the relative price increase of the stock and according to the following formula:

$$R_{it} = (N_{i.t+s} - N_{it})/N_{it}\,.100\%, \quad (12)$$

where R_{it} is the rate of return of security i at time t; s is the investment period length, expressed in days; N_{it} is the trading value (closing price) of security i at time t; and $N_{i.t+s}$ is the trading value of security i after s days have passed since the beginning of the investment at time t.

5 | Research Findings

5.1 | Descriptive Statistics of Data

In descriptive methods, the aim is to describe the research data by presenting tables and using descriptive statistics tools such as measures of central tendency and dispersion, to help clarify the subject. The descriptive statistics for the research variables and the return data for different indices are presented in *Table 1*. According to the descriptive statistics, the above indices can be divided into measures of central tendency and dispersion, and other indices. Central tendency measures include the mean and median; dispersion measures include the standard deviation; and other indices include the minimum, maximum, skewness, and kurtosis.

Table 1. Descriptive statistics of research variables.

Variables	N	Mean	SD	Min	Max
Asset turnover	897	0.539	0.741	0.0003	6.836
Financial leverage	897	0.456	0.270	-0.504	1.805
ROA	897	0.145	0.174	-0.702	0.998
ROE	897	0.255	0.248	-0.932	0.920
Return on sales	897	0.353	0.686	-0.160	1.655
Stock return	897	0.035	0.274	-0.993	1.009
Market return	897	0.096	0.172	-0.12	0.519
Firm size	897	8.12	0.701	5.07	10.2

Table 1 presents the descriptive statistics for the research variables based on 897 observations. The average stock return is 0.035, and its standard deviation is 0.274. Alongside a minimum of -0.993 and a maximum of 1.009, this indicates high volatility and risk in stock returns within the quarterly data. In contrast, the index return, with an average of 0.096 and a lower standard deviation (0.172), shows greater stability compared to individual stocks. The ROA is reported at 0.145 with a standard deviation of 0.174, ranging from 0.702 to 0.998, indicating significant differences in companies' operational profitability across different quarterly periods. Similarly, the ROE has an average of 0.255 and a standard deviation of 0.248, with a range of -0.932 to 0.920, highlighting the role of financial leverage and fluctuations in shareholder profitability. The Return on Sales (ROS), with an average of 0.353 and a high standard deviation of 0.686, as well as asset turnover with averages of 0.539 and 0.456, and a maximum (up to 6.836), suggest considerable variation in the operational efficiency and business structure of companies across different quarters. Finally, company size, most likely measured as the logarithm of assets, has a mean of 8.12, a minimum of 5.07, and a maximum of 10.22, indicating a reasonable dispersion of company sizes. However, the wide range and relatively high standard deviation of some variables in the quarterly data highlight the need to account for outliers and to employ robust methods in subsequent analyses.

6 | Cross-Sectional Regressions of Average Returns and Various Betas

Table 2 presents the results of single-factor cross-sectional regressions of average stock returns on various types of betas within the extended CAPM framework. In these regressions, the intercept (λ_0) represents the adjusted risk-free return, and the coefficient λ_1 indicates the price of risk associated with each type of beta. The statistical significance of the coefficients can indicate whether the beta used is capable of explaining the cross-section of average stock returns

Table 2. Cross-sectional single-factor regressions of average returns and different types of betas.

Variable	λ_0	t-stat(λ_0)	λ_1	t-stat(λ_1)	R^2
β_i	0.0362	1.79	0.0224	1.14	0.0555
β_i (ROS)	0.0584	3.37***	-4.3E-05	-0.358	0.00581
β_i (ROA)	0.059	8.31***	-0.00798	-1.95*	0.148
β_i (ROE)	0.0562	7.31***	-0.00013	-0.884	0.0343
β_i^{LPM}	0.0573	6.81***	0.000354	0.997	0.00045
β_i^{LPM}(ROS)	0.0576	7.34***	3.1E-06	0.023	0.00002
β_i^{LPM}(ROA)	0.0652	8.67***	-0.0101	-2.39**	0.205
β_i^{LPM}(ROE)	0.0564	7.36***	-0.00013	-0.88	0.034

(*, **, ***= significance at the 10%, 5%, and 1% levels, respectively)

In the regression based on the conventional market beta (β_i), the coefficient λ_1 is 0.0224 and is not statistically significant. This result suggests that market beta alone has limited explanatory power for average stock returns in the sample studied, which aligns with the critiques of the classic CAPM and the motivation for developing alternative models in the reference paper. Regarding accounting betas based on ROS and ROE, although the intercept λ_0 is significant in both models, the λ_1 coefficients are not. This finding indicates that these two types of accounting betas, although they reflect aspects of companies' operational and financial performance, have limited ability to price systematic risk at the cross-sectional level.

In contrast, the results for the accounting beta based on Return On Assets (ROA) (β_i (ROA)) are different. The λ_1 coefficient in this model is negative and significant at the 10% level. This finding suggests that the ROA accounting beta is partially capable of explaining cross-sectional differences in average stock returns, although the negative sign of the coefficient indicates an inverse relationship between ROA-based accounting risk and expected return. In the section on downside risk betas (LPM), most λ_1 coefficients lack statistical significance, except for the model based on β_i^{LPM}(ROA). In this model, the λ_1 coefficient is -0.0101 and is significant at the 5% level. This result strongly supports the view that downside risk-based accounting betas, particularly when calculated based on ROA, have a greater ability to explain and price systematic risk. Overall, the results from *Table 3* show that classic market beta and some accounting betas are not capable of significantly explaining average stock returns, while the accounting beta based on ROA, especially within the LPM framework, performs better in cross-sectional regressions. *Table 3* presents the results of multiple cross-sectional regressions of average stock returns, simultaneously considering the classic market beta and accounting betas for individual assets. The purpose of this analysis is to evaluate the incremental explanatory power of accounting betas compared to market beta within the extended version of the framework. In *Model (1)*, where average stock return is estimated simultaneously based on market beta (β_i) and accounting beta based on ROS (β_i(ROS)), neither explanatory coefficient is statistically significant. The low F-statistic and limited R-squared (0.060) indicate that the combination of market beta and ROS beta is not capable of significantly explaining the cross-sectional variations in stock returns. This result suggests that the ROS-based beta does not provide added informational value for risk pricing, even in the presence of market beta.

In *Model (2)*, which includes market beta and accounting beta based on ROA (β_i(ROA)), relatively stronger results are observed. The λ_2 coefficient corresponding to the ROA beta is negative and significant at the 10% level, and the R-squared value increases to 0.185, showing a significant improvement compared to *Model (1)*. This finding indicates that the ROA accounting beta still has explanatory power even after controlling for the effect of market beta and can act as a complementary factor in explaining cross-sectional stock returns. This result is consistent with the findings of the reference paper, which identifies ROA as one of the most stable bases for deriving accounting beta. In *Model (3)*, where market beta is included along with accounting beta based on ROE, although the market beta coefficient approaches the 10% significance threshold, the ROE beta coefficient is not significant. Furthermore, the F-statistic and R-squared (0.157) indicate that this model has less explanatory power than *Model (2)*. This result confirms that the high volatility of ROE, mainly due to financial leverage, weakens the ability of ROE-based accounting beta to price risk. Overall, the results from *Table 3* suggest that among the examined accounting betas, only the ROA-based beta can significantly and incrementally explain average stock returns, in conjunction with the classic market beta. This finding emphasizes that accounting information based on ROA plays a more effective role in developed asset pricing models compared to indicators affected by ROE or ROS.

Table 3. Multiple cross-sectional regressions of average returns with classical and accounting betas for individual assets.

Model (1): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i\,(ROS) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0371	0.0222	-0.00004	0.0603	0.674
t-stat	1.78	1.10	-0.33		
Model (2): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i\,(ROA) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0413	0.0184	-0.00752	0.185	2.38
t-stat	2.12*	0.98	-1.83*		
Model (3): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i\,(ROE) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0196	0.0370	-0.00025	0.157	1.96
t-stat	0.88	1.75	-1.59		

Table 4 presents the results of multivariate cross-sectional regressions of average stock returns, focusing on downside accounting betas within the extended CAPM framework. The main objective of this analysis is to investigate the role of downside risk, based on accounting information, in explaining cross-sectional expected asset returns and to compare it with the classic market beta. In *Model (1)*, where the the average stock return is estimated simultaneously from market beta and downside accounting beta based on ROS, neither the risk coefficients λ_1 nor λ_2 are statistically significant. The very low R-squared (0.001) and F-statistic indicate that this model has virtually no explanatory power for cross-sectional stock returns. This result suggests that the downside beta based on ROS, even within the framework of asymmetric risk, cannot explain differences in investors' expected returns. In contrast, *Model (2)*, which includes market beta and downside accounting beta based on ROA, provides significant and meaningful results. The λ_2 coefficient corresponding to is negative and significant at the 5% level, while the market beta coefficient remains statistically insignificant. The R-squared value of 0.206 and the F-statistic of 2.72 indicate that this model has greater explanatory power than other models. This finding directly supports the viewpoint of the reference paper that downside risk-based accounting betas, particularly those calculated based on ROA, better reflect the systematic risk associated with potential losses than market beta.

Table 4. Multiple cross sectional regressions of average returns and accounting downside betas.

Model (1): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i^{LPM}(ROS) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	-0.0572	0.000419	0.000008	0.001	0.006
t-stat	6.26***	0.11	0.06		
Model (2): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i^{LPM}(ROA) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0657	-0.00038	-0.0102	0.206	2.72
t-stat	7.75***	-0.12	-2.33**		
Model (3): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i^{LPM}(ROE) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0558	0.000586	-0.00013	0.035	0.384
t-stat	6.45***	0.16	-0.87		

In *Model (3)*, where the downside accounting beta based on ROE is included in the regression alongside market beta, again, none of the risk coefficients are significant. The low R-squared and weak F-statistic indicate that this model also has limited explanatory power. This result confirms that the extreme volatility of ROE and the significant impact of financial leverage, even within the framework of downside risk, reduce the effectiveness of ROE-based accounting beta in asset pricing. Overall, the results in *Table 4* clearly show that among the downside accounting betas examined, only the ROA-based beta has incremental and significant explanatory power for average stock returns. This finding emphasizes the superiority of indicators based on operational performance and downside risk over the classic market beta in extended asset pricing models.

Table 5 presents the results of multivariate cross-sectional regressions of average stock returns, focusing on both conventional accounting betas and downside accounting betas for individual assets. The main objective of this analysis is to examine the relative and simultaneous explanatory power of symmetric and asymmetric accounting betas and to evaluate whether downside beta provides incremental information over the conventional accounting beta. In *Model (1)*, where the accounting beta based on ROS and its corresponding downside beta are included simultaneously in the regression, none of the λ_1 and λ_2 coefficients are statistically significant. The very low R-squared and F-statistic indicate that indicators based on ROS, whether in the form of conventional or downside beta, have little explanatory power for average stock returns. This result suggests that fluctuations in sales profit margins, even when focusing on downside risk, are not well-reflected in asset pricing. In *Model (2)*, where accounting betas based on ROA and their corresponding downside betas are employed, although none of the risk coefficients are statistically significant, this model offers the highest explanatory power among the three models, with an R-squared of 0.215 and an F-statistic of 2.88. The positive sign of the conventional ROA beta coefficient and the negative sign of the downside ROA beta coefficient indicate that downside risk based on operational performance can have an effect distinct from symmetric risk. However, this effect is not statistically reinforced when both variables are present simultaneously. This finding is consistent with the results of previous tables, which showed that the downside ROA beta becomes significant mainly when it is included in the model independently or alongside the market beta. In *Model (3)*, which includes the accounting beta based on ROE and its corresponding downside beta, none of the coefficients are significant, and the low R-squared indicates limited explanatory power for these indicators. This result confirms that extreme fluctuations in ROE and the high impact of financial leverage, whether in the context of symmetric or downside risk, prevent these betas from effectively explaining expected stock returns. Overall, the results of *Table 5* show that the simultaneous entry of conventional and downside accounting betas based on a single performance indicator does not lead to a significant improvement in explaining average stock returns. This indicates an informational overlap between these two types of betas and emphasizes that the main advantage of downside accounting betas becomes apparent when they are used as a substitute or complementary factor to market beta, rather than alongside the conventional version of the same beta.

Table 5. Multiple cross sectional regressions of average returns and accounting betas for individual assets.

Model (1): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i\,(ROS) + \lambda_2\beta_i^{LPM}(ROS) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0583	-0.000083	0.000056	0.012	0.123
t-stat	7.20***	-0.50	0.35		
Model (2): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i\,(ROA) + \lambda_2\beta_i^{LPM}(ROA) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0685	0.00562	-0.0158	0.215	2.88
t-stat	6.88***	0.52	-1.34		
Model (3): $\bar{R}_i = \lambda_0 + \lambda_1\beta_i\,(ROE) + \lambda_2\beta_i^{LPM}(ROE) + \varepsilon_i$					
Statistic	λ_0	λ_1	λ_2	R^2	F
Estimate	0.0556	-0.00071	0.00057	0.035	0.378
t-stat	5.61***	-0.13	0.10		

Based on the set of results obtained from *Tables 3-5*, several useful, consistent, and reliable conclusions can be drawn for the present research and financial literature, possessing both theoretical and practical aspects:

I. Firstly, the inefficiency of the classic market beta in explaining the cross-section of stock returns is confirmed. In most single-factor and multi-factor regressions, the risk premium coefficient of the market beta is either statistically insignificant or has very limited explanatory power. This finding suggests that the classic CAPM, on its own, is incapable of explaining cross-sectional differences in stock returns in the studied market and requires additional variables. Secondly, accounting betas based on ROA perform better than those based on other accounting indicators. Among the accounting betas (ROA, ROE, and ROS), only the ROA-based beta has consistently shown a significant coefficient and higher R-squared in both single-factor and multi-factor models. This result indicates that ROA, as an indicator of a company's true operational performance, provides a more suitable basis for estimating accounting systematic risk than indicators affected by capital structure or sales volatility. Thirdly, downside accounting risk significantly increases the model's explanatory power. The downside accounting beta based on ROA has yielded the strongest and most stable results, accounting for the highest R-squared values in some models. This finding confirms that investors are more sensitive to potential losses than to symmetric fluctuations, and models based on downside risk better reflect actual investor behavior.

II. Fourthly, betas based on ROE and ROS perform poorly at risk pricing. The results indicate that accounting betas based on ROE and ROS, whether in conventional or downside form, are predominantly statistically insignificant. This suggests that volatility arising from financial leverage (in ROE) and instability in revenues and costs (in ROS) diminishes the ability of these indicators to measure systematic risk. Fifthly, the simultaneous inclusion of conventional and downside accounting beta for a single index does not create additional value.The results from *Table 5* show that using both the conventional beta (β_i) and the downside beta (β_i^{LPM}) based on the same accounting variable does not lead to a significant improvement in the model's explanatory power. This implies an informational overlap between these two betas and suggests that the downside beta should be used as a substitute or complement to the market beta, rather than as the conventional version of the same beta. Finally, the key conclusion of the research is that the extended CAPM version based on accounting betas, particularly the downside ROA beta, provides a more suitable framework for asset pricing. These results indicate that integrating accounting information and asymmetric risk can improve the explanation of expected stock returns and havee important practical implications for investors, financial analysts, and capital market policymakersregardingf risk management and asset allocation.

6.1 | A Multi-Factor Model Controlling for Firm Size, Financial Leverage, and Asset Turnover

To investigate the explanatory power of accounting betas and market beta in determining average stock returns, multivariate regressions were estimated, controlling for variables such as firm size, financial leverage, and asset turnover. This analysis assesses the independent and relative effects of each type of beta on stock returns and examines the incremental role of the classic market beta alongside accounting betas. *Table 6* shows that in *Model (1)*, where only the downside ROA beta (DAB_ROA) is included along with the control variables, the coefficient for DAB_ROA is negative and near the significance level (t = -1.87), with an R-squared of 0.295. This finding suggests that DAB_ROA has a weak but meaningful effect on average returns. Upon adding the market beta to *Model (2)*, the coefficient for DAB_ROA decreases slightly and becomes statistically weaker (t = -1.72), while the market beta becomes significant (t = 2.14). Furthermore, financial leverage also reaches a significant level in the second model (t=2.33). Overall, the R-squared of the second model increases to 0.438, indicating a better explanatory power when combining DAB_ROA and market beta.

Table 6. Multiple regressions of average returns with and without market beta.

Variable	Model (1): DAB_ROA + Controls	Model (2): CAPM + DAB_ROA + Controls
λ_0	0.1443 (t=1.29)	0.1462 (t=1.42)
Beta_mkt	—	0.0413 (t=2.14) **
DAB_ROA	-0.0838 (t=-1.87) *	-0.0716 (t=-1.72)
Size	-0.1160 (t=-0.83)	-0.1730 (t=-1.31)
Lev	0.3970 (t=1.49)	0.6190 (t=2.33) **
AssetTurnover	-0.0300 (t=-0.30)	-0.1130 (t=-1.15)
R^2	0.295	0.438
F-statistic	1.99	2.80 **
Residual SE	0.0339 (df=19)	0.0311 (df=18)

Table 7 indicates that, in the regressions related to DAB_ROE, the coefficient for DAB_ROE is close to zero and not statistically significant in both models, suggesting a limited effect of this beta on average returns. Upon adding the market beta, the Beta_mkt coefficient becomes significant (t=2.54), and financial leverage also becomes significant in the second model. The R-squared increases from 0.166 to 0.386, demonstrating that combining market beta with control variables yields higher explanatory power than DAB_ROE alone.

Table 7. Multiple regressions of average returns with DAB_ROE.

Variable	Model (1): DAB_ROE + Controls	Model (2): CAPM + DAB_ROE + Controls
Intercept	0.1815 (t=1.51)	0.1799 (t=1.07)
Beta_mkt	—	0.0548 (t=2.54)**
DAB_ROE	-0.000021 (t=-0.13)	-0.000175 (t=-1.1)
Size	-0.1740 (t=-1.17)	-0.2370 (t=-1.77)
Lev	0.4840 (t=1.50)	0.6160 (t=2.13)**
AssetTurnover	-0.0288 (t=-0.27)	-0.1350 (t=-1.31)
R^2	0.166	0.386
F-statistic	0.94	2.26
Residual SE	0.0369 (df=19)	0.0325 (df=18)

Table 8 shows that for DAB_ROS, the beta coefficient in both models is close to zero and insignificant, and the R-squared for the models remains low. The addition of market beta in the second model leads to the significance of Beta_mkt (t=2.23) and financial leverage (t=2.64), but DAB_ROS continues to lack a significant effect. These results suggest that the downside beta based on ROS, either alone or even in the presence of the market beta, does not have the explanatory power for average returns.

Table 8. Multiple regressions of average returns with DAB_ROS.

Variable	Model (1): DAB_ROS + Controls	Model (2): CAPM + DAB_ROS + Controls
Intercept	0.1821 (t=1.49)	0.1805 (t=1.62)
Beta_mkt	—	0.0460 (t=2.23)**
DAB_ROS	-0.000006 (t=-0.05)	-0.000019 (t=-0.16)
Size	-0.1760 (t=-1.17)	-0.2310 (t=-1.66)
Lev	0.5030 (t=1.78)	0.7330 (t=2.64)**
AssetTurnover	-0.0303 (t=-0.28)	-0.1250 (t=-1.15)
R^2	0.165	0.346
F-statistic	0.94	1.09
Residual SE	0.0369 (df=19)	0.0336 (df=18)

The results from *Table 9* indicate that in the regressions related to AB_ROA, the accounting beta (AB) coefficient is negative and close to the significance level (t=-1.76). However, after adding the market beta, its effect weakens (t=-1.56). The market beta is significant (t=2.10), and financial leverage also reaches a significant level in the second model (t=2.58). The R-squared of the second model (0.423) is higher than the first, suggesting an incremental explanatory power from combining AB_ROA and market beta. *Table 10* shows that the coefficient for AB_ROE is close to zero and insignificant in both models. In the second model, the market beta is significant (t=2.55), and financial leverage also has a significant effect (t=2.13). The R-squared increases from 0.166 to 0.387, indicating that the effect of AB_ROE on average returns was limited, and adding the market beta and controls increases the explanatory power.

Table 9. Multiple regressions of average returns with AB_ROA.

Variable	Model (1): AB_ROA + Controls	Model (2): CAPM + AB_ROA + Controls
Intercept	0.1610 (t=1.44)	0.1610 (t=1.56)
Beta_mkt	—	0.0411 (t=2.01) **
AB_ROA	-0.0715 (t=-1.76)	-0.0592 (t=-1.56)
Size	-0.1460 (t=-1.05)	-0.1990 (t=-1.52)
Lev	0.4670 (t=1.77)	0.6790 (t=2.58) ***
AssetTurnover	-0.0348 (t=-0.35)	-0.1160 (t=-1.17)
R^2	0.282	0.423
F-statistic	1.86	2.63
Residual SE	0.0342 (df=19)	0.0315 (df=18)

Table 10. Multiple regressions of average returns with AB_ROE.

Variable	Model (1): AB_ROE + Controls	Model (2): CAPM + AB_ROE + Controls
Intercept	0.1817 (t=1.51)	0.1810 (t=1.71)
Beta_mkt	—	0.0550 (t=2.55) ***
AB_ROE	-0.000024 (t=-0.14)	-0.000180 (t=-1.12)
Size	-0.1750 (t=-1.17)	-0.2380 (t=-1.79)
Lev	0.4820 (t=1.49)	0.6150 (t=2.13) **
AssetTurnover	-0.0288 (t=-0.27)	-0.1360 (t=-1.32)
R^2	0.166	0.378
F-statistic	0.95	2.28
Residual SE	0.0369 (df=19)	0.0325 (df=18)

Table 11. Multiple regressions of average returns with AB_ROS.

Variable	Model (1): AB_ROS + Controls	Model (2): CAPM + AB_ROS + Controls
Intercept	0.1817 (t=1.52)	0.1780 (t=1.64)
Beta_mkt	—	0.0466 (t=2.27) **
AB_ROS	-0.000045 (t=-0.37)	-0.000062 (t=-0.55)
Size	-0.1740 (t=-1.17)	-0.2270 (t=-1.66)
Lev	0.5060 (t=1.79)	0.7390 (t=2.68) ***
AssetTurnover	-0.0394 (t=-0.36)	-0.1370 (t=-1.25)
R^2	0.171	0.356
F-statistic	0.98	1.99
Residual SE	0.0368 (df=19)	0.0333 (df=18)

The results in *Table 11* show that in the regressions for AB_ROS, both the accounting beta and the downside ROS beta are insignificant in both models. Upon adding the market beta, Beta_mkt becomes significant (t=2.27), and financial leverage also demonstrates a significant effect (t=2.68). The R-squared of the second model increased to 0.356, but AB_ROS remains a weak and unreliable predictor. The results from this set of regressions indicate that the classic market beta is generally significant in multivariate models and has incremental explanatory power. DAB_ROA and AB_ROA have a significant and incremental effect on returns. However, other accounting betas, on their own, show limited or insignificant effects. The control variable, financial leverage, has a significant effect in most models, and its importance in explaining average returns is confirmed. Betas based on ROS and ROE have limited explanatory power over time and in controlled models. This analysis suggests that combining ROA-based accounting beta with market beta and control variables provides a suitable framework for explaining average stock returns. In contrast, other accounting betas play a complementary or weaker role.

7 | Conclusion

This research aimed to investigate the role of accounting betas, particularly downside risk betas (LPM), in explaining and pricing stock returns within the extended CAPM framework. To this end, the performance of various accounting betas based on ROA, ROE, and ROS – in both conventional and downside risk forms – was empirically tested alongside the classic market beta and control variables for large companies on the Tehran Stock Exchange. The research findings clearly demonstrated that the classic CAPM alone is insufficient to explain the cross-sectional differences and average stock returns in the Iranian capital market. This result aligns with previous theoretical and empirical literature on the relative inefficiency of this model in emerging markets. However, the findings indicate that extending the CAPM by incorporating accounting variables improves the model's explanatory power only if these variables possess informational stability and appropriate economic content. The most significant finding of the research is that the accounting beta based on ROA, especially when modeled in its downside risk (LPM) form, has greater power to explain cross-sectional differences and average stock returns than other accounting betas. This variable, both as a complement to the market beta and in conjunction with control variables, enhances the explanatory power of the extended CAPM. This result suggests that asset utilization efficiency and a focus on potential losses arising from a decline in operational performance can reflect important dimensions of systematic risk that are not fully captured by symmetric market fluctuations and the classic beta.

In contrast, the results showed that accounting betas based on ROE and ROS, in both their conventional and downside-risk forms, do not significantly explain stock returns across most models. This finding suggests that indicators heavily influenced by capital structure, financial leverage, or short-term operational fluctuations lack the stability needed to measure systematic risk. Furthermore, the results of the fourth hypothesis indicated that downside risk-based accounting betas do not necessarily provide significant incremental information when directly compared simultaneously with their corresponding conventional versions, confirming an informational overlap between these two types of betas.

Overall, the research findings suggest that the effectiveness of accounting betas in asset pricing models is selective. The indiscriminate use of these variables not only fails to improve model performance but can also weaken its explanatory power. Among these, the downside ROA accounting beta was identified as the most effective indicator, which, alongside the classic market beta, can provide a more comprehensive picture of market, operational, and economic risks influencing stock returns. Finally, from a theoretical perspective, this research's results emphasize the necessity of considering downside risk and stable accounting information in developing advanced CAPM versions. From a practical standpoint, it offers valuable guidance to investors, portfolio managers, and capital market policymakers for improving risk assessment and estimating expected stock returns. However, the sample's restriction to large companies on the Tehran Stock Exchange and the use of linear frameworks limit the generalizability of the findings. Therefore, it is recommended that future research utilize multi-factor models, dynamic and non-linear approaches, and broader samples to investigate the role of downside risk based on accounting information in asset pricing with greater precision.

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