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Systematic Risk and the Applicability of the CAPM across Digital Economy Sub-industries: An Empirical Study

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Abstract

This research employs 75 stocks from China A-share market from Shanghai and Shenzhen's digital economy stock markets as a typical example. Utilizing monthly figures spanning January 2015 to December 2024, the Capital Asset Pricing Model (CAPM) is applied in an unbalanced sampling approach to evaluate the systematic risk and relevance of the model in five distinct digital economy sectors. The results show that the average beta coefficients of all sub-industries are greater than 1, indicating that the digital economy sector as a whole has relatively high market sensitivity. Although there is some divergence in beta across sub-industries, the inter-group differences do not reach statistical significance. Simultaneously, discrepancies are noted in the sub-industries concerning R^2 and the proportion of significant alpha coefficients, indicating an inconsistency in the explanatory power of the CAPM among these sub-industries. Additional portfolio-level regressions based on beta sorting further show that beta coefficients increase monotonically from the low-beta portfolio to the high-beta portfolio, while all portfolio betas are significantly positive and no significant abnormal returns are observed. Generally, the risk attributes in the digital economy sector vary, implying that within China's capital market, the single-factor CAPM continues to have limitations in accounting for return changes in the digital economy sector.

Keywords

Digital Economy; CAPM; Systematic Risk; Model Applicability; Sub-industry Differences.

1. Introduction

Recently, the digital economy has played a pivotal role in propelling China's economic growth and industrial progress, propelled by the rapid advancement of emerging information technologies such as big data, cloud computing, artificial intelligence, and mobile internet [1]. At the same time, the capital market performance of related listed firms has attracted increasing attention. Compared with traditional industries, digital economy firms are generally characterized by high growth, high R&D investment, and high volatility [2]. Their stock prices are influenced not only by operating performance, but also more easily affected by technological iteration, policy changes, and fluctuations in market sentiment. Meanwhile, different sub-industries within the digital economy differ in terms of business models, degree of technological dependence, and earnings stability. As a result, their levels of systematic risk and return formation mechanisms may also differ.

In contemporary finance, the Capital Asset Pricing Model (CAPM) stands as a traditional model for asset valuation. The essence is in employing the beta coefficient to assess how asset returns respond to market return variations [3]. Although the CAPM has been widely applied, its explanatory power differs across markets and industries. In particular, for the digital economy

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industry, which is characterized by high growth and high volatility, whether the CAPM still has strong applicability deserves further examination.

Within this framework, the research concentrates on 75 chosen shares from the digital economy sector of the Shanghai and Shenzhen A-share markets. According to the Statistical Classification of the Digital Economy and Its Core Industries by the National Bureau of Statistics, these stocks are divided into five separate sub-sectors: digital product manufacturing, digital product services, digital technology application, digital factor-driven industry, and digital efficiency improvement industry, each comprising 15 stocks. Using monthly data from January 2015 to December 2024, this paper applies the CAPM under an unbalanced sample framework to compare differences among the five sub-industries in terms of systematic risk and model applicability. In addition, this study constructs beta-sorted portfolios to further examine whether market risk can explain return variation at the portfolio level.

2. Literature Review and Research Methodology

2.1. Analysis of Literature

The Capital Asset Pricing Model (CAPM) by Sharpe (1964) is a key component in modern asset pricing theories [3]. Fama and MacBeth (1973) provided concrete support for the CAPM [4], while Roll argued that its practical verification is intrinsically limited by the theoretical market portfolio's invisibility [5]. Additionally, Fama and French (1992, 1993) demonstrated that elements like the size of the firm and the book-to-market ratio might account for stock return variances [6][7], indicating the limited explanatory capacity of the single-factor CAPM.

There has been considerable discussion regarding the role of the CAPM within the Chinese market. Chen Xiaoyue and Sun Aijun (2000) argued that beta does not sufficiently explain the average stock market returns in China [8]. Jin Yunhui and Liu Lin (2001) highlighted the absence of a consistent linear correlation between stock returns and beta [9]. Guo Duozuo and Xu Zhandong (2002) argued that the relationship between beta and returns may be conditional [10]. Overall, although the CAPM has theoretical value in the Chinese market, its empirical explanatory power remains relatively limited.

Regarding the digital economy, Bukht and Heeks (2017) conducted a thorough examination of the digital economy's concept and metrics [1], while Wu Fei et al. (2021) found that corporate digital transformation can significantly improve stock liquidity [11]. Existing studies suggest that digital economy firms are generally characterized by high growth, high R&D intensity, and high volatility, and that their risk-return relationship may differ from that of traditional industries. Furthermore, digital product manufacturing, digital product services, digital technology application, digital factor-driven industry, and digital efficiency improvement industry differ in terms of profit model, technological dependence, and market environment. Therefore, their systematic risk and the applicability of the CAPM may not be the same. Existing research lacks a systematic comparison in this respect, and this paper carries out the analysis accordingly.

2.2. Approach to Research

The primary methodologies employed in this paper include literature review, empirical analysis, comparative analysis, portfolio analysis, and robustness testing. First, the paper provides theoretical support for the empirical analysis by reviewing current research on the CAPM and the digital economy. Second, the CAPM is used to conduct time-series regressions on the sample stocks. Third, by comparing beta, the proportion of significant alpha coefficients, and R^2 across sub-industries, the paper analyzes differences among the five digital economy sub-industries in terms of systematic risk and model applicability. Fourth, beta-sorted portfolios are constructed to further examine the explanatory power of the CAPM at the

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portfolio level. Finally, the robustness of the conclusions is examined by replacing the market return indicator.

3. Hypotheses and Foundations in Theory and Research

3.1. Theoretical Foundation of the CAPM

CAPM, a traditional theory in contemporary finance, posits that an asset's anticipated yield depends on its risk-free rate and susceptibility to systematic risk, where risk premiums stem solely from fixed risks associated with overall market variations [3]. The fundamental structure of the CAPM is outlined below:

$$E(R_i) - R_f = \beta_i[E(R_m) - R_f]$$

where $E(R_i)$ represents the anticipated yield on asset i, R_f signifies the risk-free rate, $E(R_m)$ the market portfolio's expected return, and β_i the systematic risk coefficient for asset i. Beta is used to measure the sensitivity of an individual stock's return to fluctuations in market returns [3]. When $\beta_i > 1$, the stock has higher systematic risk than the market; when $\beta_i < 1$, its market sensitivity is relatively low.

Empirical studies typically examine the CAPM through the lens of excess returns, specifically by considering the additional return on a single stock as the dependent factor and the surplus market return as the primary explanatory factor [4]. The corresponding time-series regression model can be written as:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}$$

In this context, $R_{i,t} - R_{f,t}$ symbolizes the excess return of stock i during period t, $R_{m,t} - R_{f,t}$ denotes the market's additional return in that identical period, α_i is the intercept factor, β_i is the stock's systematic risk coefficient, and $\varepsilon_{i,t}$ is the term for random disturbance. If α_i is not statistically significant, it indicates that after controlling for market risk, the stock does not exhibit significant abnormal returns, and the CAPM has relatively strong explanatory power for its returns. If α_i is statistically significant, it suggests that, in addition to market systematic risk, stock returns may also be affected by other factors. In addition, the regression R^2 can be used to measure the extent to which market excess returns explain fluctuations in individual stock excess returns [8]. A higher R^2 indicates relatively stronger applicability of the CAPM.

Therefore, in the subsequent analysis, this paper uses beta as the main indicator of systematic risk, and takes the significance of alpha and R^2 as important criteria for evaluating the applicability of the CAPM. In addition to individual-stock regressions, portfolio-level regressions can reduce firm-specific noise and provide further evidence on the relationship between systematic risk and expected returns.

3.2. Traits and Evaluating Risks in the Digital Economy Sector

Supported by advancements in digital technology, data components, and information networks, the digital economy sector is frequently marked by its innovative nature, expansion, and instability. Compared with traditional industries, digital economy firms often have higher growth expectations, greater R&D investment, and a higher proportion of intangible assets. Their market valuation depends more heavily on future expectations, and therefore their stock returns are more easily affected by technological iteration, policy changes, and fluctuations in market sentiment.

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At the same time, different sub-industries within the digital economy differ in terms of business models, technological dependence, and earnings stability. Digital product manufacturing is more oriented toward hardware production, and its risk characteristics are relatively clear. By contrast, digital product services, digital technology application, and digital factor-driven industry rely more on software, platforms, data, and network effects, making them more sensitive to market changes. Digital efficiency improvement industry, in turn, more strongly reflects the characteristics of the digital transformation of traditional industries. Accordingly, the levels of systematic risk and the applicability of the CAPM may not be the same across sub-industries. On this basis, this paper conducts a comparative analysis of the five digital economy sub-industries from three dimensions: the beta coefficient, the significance of alpha, and R^2.

3.3. Research Hypotheses

Drawing from CAPM theory, digital economy industry traits, and this study's variable structure, the paper suggests two-dimensional research hypotheses: systemic risk and the applicability of the model.

3.3.1. Hypothesis on Differences in Systematic Risk across Sub-industries

Within the CAPM framework, beta is the core parameter for measuring the systematic risk of individual stocks. Since the five digital economy sub-industries differ significantly in terms of growth, degree of technological dependence, profit model, and market competition environment, the sensitivity of stocks in different sub-industries to fluctuations in market excess returns may not be the same. Therefore, the beta coefficients of each sub-industry may show certain differences in terms of mean, distribution, and dispersion.

Accordingly, this paper proposes Hypothesis 1:

H1:Beta coefficients show significant variation across the digital economy's five subsectors, suggesting a disparity in systematic risk levels among these subsectors.

3.3.2. Hypothesis on Differences in CAPM Applicability

In the empirical design of this paper, the applicability of the CAPM is mainly assessed through the significance of alpha and R^2. If, within a given sub-industry, the alpha coefficients of most stocks are not statistically significant and the overall R^2 is relatively high, this indicates that market excess returns can better explain fluctuations in the excess returns of individual stocks in that sub-industry, and that the CAPM has relatively strong applicability. Conversely, if the proportion of significant alpha coefficients is high and R^2 is low, this suggests that stock returns may be more strongly affected by other factors, and that the explanatory power of the CAPM is relatively limited.

Considering that different digital economy sub-industries vary in policy sensitivity, speed of technological upgrading, and dependence on market expectations, the applicability of the CAPM may also differ across sub-industries.

Accordingly, this paper proposes Hypothesis 2:

H2: Differences in the applicability of the CAPM are evident among the digital economy's five subsectors, as indicated by the differing ratios of statistically significant alpha coefficients and the R-squared value.

To conclude, following the methodology outlined in Chapter 4, this study conducts CAPM time-series regression analyses on the sampled stocks across five sub-industries of the digital economy, aiming to validate the previously mentioned hypotheses.

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4. Research Design

4.1. Sample Selection and Data Sources

The study takes 75 A-share listed companies in the digital economy of Shanghai and Shenzhen as a sample. According to the Statistical Classification of the Digital Economy and its Core Industries (2021) released by the National Bureau of Statistics (NBS) [12], sample firms are grouped into five sub-sectors: Digital Product Manufacturing, Digital Product Services, Digital Technology Applications, Digital Factor-Driven Industries, and digital efficiency improvement industry, with 15 shares in each sub-sector on the list [1]. The study was conducted between January 2015 and December 2024, with monthly data utilized for analysis.

Considering that some digital economy firms were listed relatively late, this study adopts an unbalanced sample approach, whereby the actual regression period for each stock is determined according to its listing date and data availability. To maintain the fundamental steadiness of the regression outcomes, it's mandatory for every sample stock to possess a minimum of 34 successive months' worth of valid monthly data [4]. Under this criterion, all 75 sample stocks are included in the regression analysis.

The variables used in this study mainly include individual stock monthly returns, market monthly returns, and the risk-free rate. In the benchmark regression, the value-weighted average monthly market return based on free-float market capitalization is adopted as the proxy for the market return [8]. In the robustness test, this measure is replaced by the value-weighted average monthly market return based on total market capitalization.

4.2. Variables and Model

This research focuses on the excess return per share, calculated as the difference between the individual stock return and the risk-free rate during that interval. The primary variable explaining this is the market excess return, calculated as the difference between the market return and the risk-free interest rate during the identical timeframe. The CAPM regression model is specified as follows [3]:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}$$

For the portfolio-level analysis, the model is similarly specified as:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + \varepsilon_{p,t}$$

Where $R_{p,t} - R_{f,t}$ denotes the excess return of portfolio p in period t , and β_p measures the portfolio's sensitivity to market excess returns.

Among them, $R_{i,t} - R_{f,t}$ is the return of stock i in period t, $R_{m,t} - R_{f,t}$ is the market excess return over the same period, α_i is the intercept term, reflecting whether an individual stock exhibits significant abnormal returns; β_i is the stock's systematic risk coefficient, used to measure the sensitivity of the stock's returns to fluctuations in market returns; $\varepsilon_{i,t}$ is the random disturbance term; R^2 is used to measure the model's explanatory power regarding fluctuations in individual stock returns [8].

4.3. Testing Methods

This study first conducts CAPM time-series regressions for each of the 75 sample stocks and obtains the corresponding estimates of α,β and R^2 [4]. It then summarizes and compares the beta coefficients, the proportion of significant alpha coefficients, and the average R^2 across the five sub-industries.

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To test differences in systematic risk, this study employs one-way analysis of variance (ANOVA) and the Kruskal–Wallis nonparametric test to compare the beta coefficients across the five sub-industries. For the comparison of CAPM applicability, if a given sub-industry contains a relatively large number of stocks with significant beta coefficients, a relatively low proportion of significant alpha coefficients, and a relatively high average R^2, the CAPM is considered to have relatively stronger applicability in that sub-industry. The statistical significance of both α and β is assessed at the 5% significance level.

In addition, this study conducts portfolio-level CAPM regressions based on beta sorting. Specifically, sample stocks are sorted according to their estimated historical beta coefficients and divided into five portfolios, from the low-beta portfolio to the high-beta portfolio. The monthly excess return of each portfolio is then regressed on the market excess return. This procedure is used to examine whether the CAPM has stronger explanatory power at the portfolio level after reducing firm-specific noise [5].

5. Empirical Results and Analysis

5.1. CAPM Regression Results for Individual Stocks

This study conducts CAPM regression analysis under an unbalanced sample framework using 75 sample stocks drawn from five digital economy sub-industries. Each sub-industry contains 15 sample stocks. The sample distribution is therefore relatively balanced and provides good cross-sectional comparability.

Table 1. Comparison of CAPM Regression Results across the Five Sub-industries

Sub-industry	Mean β	Standard Deviation of β	Mean R^2	Proportion of Significant α	Sample Size
Digital product manufacturing	1.130	0.363	0.246	6.67%	15
Digital product services	1.121	0.349	0.281	0.00%	15
Digital technology application	1.152	0.261	0.304	0.00%	15
Digital factor-driven industry	1.324	0.340	0.326	0.00%	15
Digital efficiency improvement industry	1.187	0.316	0.300	0.00%	15

From the overall regression results, the mean beta coefficients of all five digital economy sub-industries are greater than 1, indicating that stocks in the digital economy sector as a whole exhibit relatively high market sensitivity, with return fluctuations generally exceeding the market average. This is consistent with the characteristics of digital economy firms, which are typically marked by high growth and expectation-driven valuation, suggesting that they are more susceptible to macroeconomic fluctuations, capital market sentiment, and changes in industry conditions.

Furthermore, the alpha components of the majority of stocks fail to meet the statistical significance criteria, suggesting that once market risk is accounted for, the sampled stocks collectively fail to show consistent abnormal returns. This suggests that the CAPM still retains a certain degree of explanatory power for the return formation of digital economy stocks. However, in terms of goodness of fit, there are substantial differences across individual stocks, implying that market excess returns have strong explanatory power for the return fluctuations of some stocks, but relatively limited explanatory power for others. Therefore, assessing the

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applicability of the CAPM only at the aggregate level is not sufficient, and it remains necessary to further examine the differences in its performance across sub-industries.

5.2. Comparison of Systematic Risk across the Five Sub-industries

The average beta values across the five sub-sectors stand at: 1.130 in digital product production, 1.121 in digital product services, 1.152 in digital technology implementation, 1.324 in industries driven by digital factors, and 1.187 in enhancing digital efficiency. Overall, the mean beta coefficients of all sub-industries are greater than 1. Among them, the digital factor-driven industry has the highest mean beta, while digital product services and digital product manufacturing show relatively lower values, suggesting a certain degree of divergence in systematic risk within the digital economy sector.

In terms of the standard deviation of beta, the values are 0.363 for digital product manufacturing, 0.349 for digital product services, 0.261 for digital technology application, 0.340 for digital factor-driven industries, and 0.316 for digital efficiency improvement. This indicates that there is also some dispersion in systematic risk among individual stocks within each sub-industry.

To further examine whether the intergroup differences are statistically significant, this study employs both one-way analysis of variance (ANOVA) and the Kruskal–Wallis test. Findings indicate that the ANOVA produces an F-statistic of 1.95 and a p-value of 0.1113, in contrast to the Kruskal–Wallis test, which generates a chi-square statistic of 8.533 and a p-value of 0.0739. The results of both examinations reveal that the variance in beta coefficients among the five sub-industries lacks statistical significance at a 5% level. This suggests that although there is some economically meaningful variation in systematic risk across sub-industries, such variation does not constitute a statistically significant difference. Therefore, Hypothesis 1 receives only limited support.

Table 2. Test Results for Differences in Beta Coefficients across the Five Sub-industries

Test Method	Statistic	p-value	Conclusion
One-way analysis of variance (ANOVA)	F=1.95	0.1113	Not significant
Kruskal–Wallis test	$\chi 2=8.533$	0.0739	Not significant at the 5% level

5.3. Comparison of CAPM Applicability across the Five Sub-industries

To further examine the explanatory performance of the CAPM across different digital economy sub-industries, this study compares CAPM applicability among the five sub-industries on the basis of mean R^2 and the proportion of significant alpha coefficients. The results are reported in Table 3.

Table 3. Comparison of CAPM Applicability across the Five Sub-industries

Sub-industry	Mean R^2	Proportion of Significant α	Assessment of CAPM Applicability
Digital product manufacturing	0.246	6.67%	Relatively weak applicability
Digital product services	0.281	0.00%	Moderate applicability
Digital technology application	0.304	0.00%	Relatively strong applicability
Digital factor-driven industries	0.326	0.00%	Relatively strong applicability
Digital efficiency improvement	0.300	0.00%	Relatively strong applicability

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The results show that the mean R^2 of digital product manufacturing is 0.246, with a significant alpha ratio of 6.67%; for digital product services, the mean R^2 is 0.281 and the significant alpha ratio is 0; for digital technology application, the mean R^2 is 0.304 and the significant alpha ratio is 0; for digital factor-driven industries, the mean R^2 is 0.326 and the significant alpha ratio is 0; and for digital efficiency improvement, the mean R^2 is 0.300 and the significant alpha ratio is 0.

Viewed from this angle, the industry propelled by digital factors holds the top position, succeeded by the application of digital technology and enhancements in digital efficiency, whereas the production of digital products is at the bottom. This indicates that the explanatory power of market excess returns for stock return fluctuations differs across sub-industries. In terms of the proportion of significant alpha coefficients, no significant alpha is observed in the other four sub-industries except digital product manufacturing, suggesting that, for most stocks in these sub-industries, no significant abnormal returns exist after controlling for market risk.

Considering the average R^2 and the ratio of notable alpha coefficients, the research deduces that the CAPM is notably applicable in the digital factor-driven sector, applications of digital technology, and enhancements in digital efficiency; moderately applicable in digital product services; and somewhat limited in the production of digital products. Therefore, Hypothesis 2 is supported by the sample results.

5.4. Portfolio-level CAPM Regression Results Based on Beta Sorting

To further examine the explanatory power of the CAPM at the portfolio level, this study constructs five stock portfolios based on estimated historical beta coefficients. Specifically, the sample stocks are sorted by beta values and divided into five groups, where P1 represents the low-beta portfolio and P5 represents the high-beta portfolio. The monthly excess return of each portfolio is then used as the dependent variable, while the market excess return is used as the explanatory variable. The regression results are reported in Table 4.

Table 4. CAPM Regression Results for Beta-sorted Portfolios

Portfolio	Alpha	Beta	R^2	N
P1 Low-beta portfolio	0.0064 (1.0104)	0.6453*** (12.2483)	0.5618	119
P2	0.0059 (1.2229)	0.8151*** (20.3602)	0.7799	119
P3	-0.0001 (-0.0167)	0.9084*** (29.3951)	0.8807	119
P4	-0.0029 (-0.6356)	1.0158*** (26.5700)	0.8578	119
P5 High-beta portfolio	0.0098 (1.2252)	1.1693*** (17.5386)	0.7244	119

Notes: t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

As shown in Table 4, the beta coefficients of the five portfolios are 0.6453, 0.8151, 0.9084, 1.0158, and 1.1693, respectively. The beta coefficient generally increases from the low-beta portfolio to the high-beta portfolio, indicating that the beta-sorting procedure effectively distinguishes portfolios with different levels of systematic risk. In particular, P1 has the lowest market sensitivity, while P5 has the highest market sensitivity

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In terms of statistical significance, the beta coefficients of all five portfolios are significantly positive at the 1% level. This suggests that market excess returns have strong explanatory power for the excess returns of beta-sorted portfolios. The result is consistent with the basic prediction of the CAPM that portfolios with higher systematic risk should exhibit stronger sensitivity to market movements.

With respect to the alpha coefficients, none of the five portfolios has a statistically significant alpha. This indicates that after controlling for market risk, the beta-sorted portfolios do not generate significant abnormal returns. Therefore, the portfolio-level evidence suggests that the CAPM can explain a substantial part of return variation across portfolios, although it does not provide evidence of significant abnormal performance.

The R^2 values range from 0.5618 to 0.8807, implying that the CAPM has relatively strong explanatory power at the portfolio level. Compared with the individual-stock regressions reported earlier, the portfolio-level regressions show substantially higher R^2 values. This may be because portfolio construction reduces firm-specific noise and allows the market factor to explain a larger proportion of return variation. Overall, the beta-sorted portfolio results further support the relevance of market risk in explaining stock returns in China's digital economy sector.

5.5. Robustness Check

To examine the robustness of the conclusions, this study replaces the float market capitalization-weighted average monthly market return used in the benchmark regression with the total market capitalization-weighted average monthly market return, and then re-estimates the regressions. The results show that the beta coefficients of the five sub-industries remain generally greater than 1, and the intergroup differences are still not statistically significant at the 5% significance level. In addition, the relative ranking of the sub-industries in terms of the proportion of significant alpha coefficients and the level of R^2 does not change materially. These results indicate that the main conclusions of this study are robust to alternative measures of market return.

6. Conclusion and Implications

This research uses 75 digital economy stocks from the Shanghai and Shenzhen A-share markets in China to examine systematic risk and CAPM applicability across five digital economy sub-industries, based on monthly data from January 2015 to December 2024. The results show that the mean beta coefficients of all five sub-industries are greater than 1, indicating that the digital economy sector as a whole has relatively high market sensitivity. Although beta values differ across sub-industries, the results of ANOVA and the Kruskal–Wallis test show that these differences are not statistically significant at the 5% level. Meanwhile, differences in R^2 and the proportion of significant alpha coefficients suggest that the explanatory power of the CAPM varies across sub-industries, with relatively stronger applicability in digital factor-driven industries, digital technology application, and digital efficiency improvement.

The beta-sorted portfolio regressions further show that beta coefficients increase from the low-beta portfolio to the high-beta portfolio, and all portfolio beta coefficients are significantly positive. This indicates that beta sorting effectively distinguishes systematic risk and that market excess returns have significant explanatory power for portfolio excess returns. However, the alpha coefficients of all portfolios are not statistically significant, suggesting no significant abnormal returns after controlling for market risk. Overall, the findings indicate that the single-factor CAPM can explain part of the return variation of digital economy stocks, especially at the portfolio level, but its explanatory power remains limited at the individual-

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stock and sub-industry levels. Future research may incorporate additional risk factors to better explain return fluctuations in the digital economy sector.

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