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The Impact of Data Assetization on the Cost of Equity Capital

Jianhong Tao, Xinyi Zhang*

School of Economics and Management, Shaanxi University of Science and Technology, Xi'an, China
Email: *m15037973421@163.com

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Abstract

With the advent of the digital economy era, data assetization has become an important driver of corporate value creation. Based on information asymmetry theory and dynamic capabilities theory, this paper examines the impact of data assetization on the cost of equity capital and its underlying mechanisms. Using data from listed companies in China from 2011 to 2023, this study employs a two-way fixed effects model for empirical testing. The findings reveal that data assetization significantly reduces the cost of equity capital by improving the corporate information environment and enhancing technological innovation. Moreover, the level of digital financial development in the region where the firm is located plays a significant positive moderating role. Further analysis shows that the inhibitory effect of data assetization on the cost of equity capital is more pronounced in non-state-owned enterprises and firms with high operating risk. Therefore, enterprises and the government should work together to promote data assetization by enhancing transparency and improving the market, thereby jointly reducing the cost of equity capital.

Keywords

Data Assetization, Cost of Equity Capital, Information Environment, Technological Innovation, Level of Digital Financial Development

1. Introduction

As digital technology becomes deeply integrated into various sectors of society, data has emerged as a new factor of production, permeating all aspects of the economy and society. This has given rise to numerous industry forms and business models driven primarily by data (Jones & Tonetti, 2020). By leveraging data, enterprises can fundamentally transform traditional production and management models, fully harnessing the multiplier effect of data resources in enhancing productivity (Brynjolfsson & McElheran, 2016). Consequently, as a key factor of production and core driving force, data represents an imperative for enterprises to build new competitive advantages and achieve transformation and upgrading, making its capitalization an inevitable trend (Farboodi & Veldkamp, 2023). On December 27, 2024, the Ministry of Finance issued the Pilot Program for the Whole-Process Management of Data Assets, which pilots the exploration of effective data asset management models and aims to improve the institutional standard system and operational mechanisms for data asset management. This initiative fully demonstrates the national emphasis on data assetization. Data assetization is the process of integrating data into product manufacturing workflows, facilitating the circulation and trading of data, and enabling its participation in value distribution (Cong, Xie, & Zhang, 2021). It is also the process of reflecting the true value of data and managing it scientifically by including it as an asset item in corporate financial statements. Therefore, data assetization not only participates in management decision-making and specific business operations to increase profits but also enables enterprises to create monetized value appreciation through market transactions. At the same time, sharing similarities with intangible assets, it can serve as collateralized credit assets to facilitate corporate financing (Haskel & Westlake, 2018). Equity financing is a crucial financing element for listed companies, and the cost of equity capital occupies a key position within the financing framework of listed companies, providing a vital reference for their financing activities. As a significant source of corporate financing, equity capital directly influences corporate investment decisions and value creation (Lambert, Leuz, & Verrecchia, 2007). Hence, conducting in-depth research on the impact of data assetization on the cost of equity capital for enterprises holds substantial significance.

The cost of equity capital represents the required rate of return for investors and comprehensively reflects a company's ability to acquire resources in the capital market (Botosan, 1997). Data assetization, through the effective use of data, accelerates information transmission and trading decisions in the stock market, leading to an effective reduction in the cost of equity capital for enterprises (Goldfarb & Tucker, 2019). Furthermore, studies indicate that data assetization can improve the information environment and promote technological innovation by constructing digital information platforms and optimizing the allocation of research and development resources. A favorable information environment reduces investor uncertainty regarding future risks, thereby lowering the cost of equity capital (Bhattacharya, Ecker, Olsson, & Schipper, 2012). Meanwhile, technological innovation helps enterprises maintain a long-term competitive advantage, making investors more optimistic about the company's future earnings, which in turn lowers the cost of equity capital (Elmawazini, Chkir, Mrad, & Rjiba, 2022). Therefore, whether data assetization affects corporate cost of equity capital through the information environment and technological innovation warrants further investigation.

As an emerging financial model, digital finance helps enterprises access more flexible and diversified financing methods and more comprehensive financial services through digital channels, thereby strongly driving corporate investment and exploration in innovation upgrading and quality optimization (Liu, Zhang, & Kuang, 2023). With its continuously expanding coverage and deepening usage, the development of digital finance not only effectively lowers the physical barriers to corporate financing but also enhances the pricing efficiency of the capital market by precisely aligning the risk-bearing willingness of both capital suppliers and demanders (Buchak, Matvos, Piskorski, & Seru, 2018). Therefore, does the level of a firm's digital finance development influence the relationship between data assetization and the cost of equity capital?

Based on this, this paper uses data from listed companies from 2011 to 2023 as a sample to investigate the impact and mechanism of data assetization on corporate cost of equity capital. The marginal contributions of this paper are as follows: First, it enriches research on data assetization at the micro level. Existing literature has studied the economic consequences of data assetization from perspectives such as financing constraints, trade credit financing, corporate growth, and capital market stability (Ouyang & Hu, 2024). However, few studies have examined the relationship between data assetization and corporate cost of equity capital. Therefore, exploring the impact of data assetization on corporate cost of equity capital in this paper helps to better leverage the role of data assetization in reducing equity financing pressure. Second, it expands research on the influencing factors of the cost of equity capital. Existing studies investigate the factors influencing the cost of equity capital from perspectives such as social credit system construction, corporate digital transformation, and ESG disclosure (Chen & Srinivasan, 2024). This paper examines the impact of data assetization on the cost of equity capital, analyzes the dual influence paths of the information environment and technological innovation based on information asymmetry theory and dynamic capability theory, and further deepens the research on the cost of equity capital by considering the moderating effect of regional digital finance development levels. Third, it refines the heterogeneous impacts of ownership structure and operational risk on the relationship between data assetization and the cost of equity capital from the perspectives of internal corporate characteristics and external environment, thereby providing better theoretical references for promoting data assetization and reducing the cost of equity capital.

2. Literature Review and Research Hypotheses

2.1. Direct Effect of Data Assetization on Corporate Cost of Equity Capital

Data assetization leverages the complete "Data chain" operational mechanism—from data collection, analysis, and processing to the formation of dynamic solutions—to bring about systematic changes in both internal and external environments (Veldkamp & Chung, 2024). It provides enterprises with professional information management solutions, enhances communication efficiency, and accelerates the flow of information resources. Consequently, through the production, analysis, and use of data, it increases trading velocity in the stock market and improves investment efficiency for investors in capital markets (Tambe, 2014), effectively reducing the corporate cost of equity capital.

Simultaneously, by utilizing data assets to comprehensively record production, sales, and other processes, enterprises can more accurately grasp market demand during product development and manufacturing stages, creating products that align with market trends (Xiao, Wang, & Li, 2025). This provides a scientific basis for production decisions and reduces potential operational risks. Furthermore, by applying disruptive information technology innovations to thoroughly reconstruct corporate operational processes, data assetization brings new opportunities for business growth and significantly enhances performance, thereby strengthening investor confidence in the enterprise's future development and lowering the cost of obtaining investment.

Moreover, advancing data assetization effectively prevents both underinvestment and overinvestment by enterprises, leading to increased investment returns. This effectively alleviates the risks faced by investors, thereby reducing the risk premium they demand (Zhu, 2019). As a result, the corporate cost of equity capital declines accordingly. Therefore, we propose the following hypothesis:

Hypothesis 1 (*H*1)*: Data assetization significantly reduces the corporate cost of equity capital.*

2.2. The Mediating Role of the Information Environment

By transforming data into a new type of asset characterized by high transparency and high value, and endowing it with a level of information flow superiority unmatched by other assets (Easley & O'Hara, 2004), data assetization can significantly improve a company's information environment. The full utilization of data enabled by data assetization promotes efficient information integration, facilitating real-time data linkage both internally and externally, as well as across internal functions. This process covers all stages from data collection and analysis to application (Francis, Nanda, & Olsson, 2008), thereby significantly optimizing the efficiency of information flow across production, R&D, management, and innovation processes, and enhancing the transparency of various business operations. This helps investors better understand the company's production and operational status, effectively mitigates information asymmetry between the firm and its investors, and improves the information environment. As the level of data assetization increases, management also tends to proactively convey true operational information to the capital market. This "information disclosure" improves the quality of information presented in annual reports of listed companies. Moreover, firms engaging in data assetization often attract more attention and coverage from financial media, which in turn communicates useful information about the firm's operations to investors. Data assetization also draws the attention of professional analysts, who continuously analyze the firm's status and improve earnings forecasts, providing specialized information to investors. Furthermore, auditors exercise greater vigilance and a higher degree of professional skepticism toward a firm's data assets, dedicating more audit resources to identify potential material misstatement risks and issuing more prudent and rigorous audit reports, which in turn enhances investors' ability to gain insight into the firm's actual operational condition. In summary, data assetization can effectively improve a company's information environment.

Based on information asymmetry theory, due to disparities in the information held by different parties, one party possesses information that the other does not have or does not fully possess, thereby creating information-advantaged and information-disadvantaged parties. In capital markets, this disparity manifests as information asymmetry both among investors and between investors and firms, which is a significant reason for the increase in corporate cost of equity capital. This is because, compared to the firm, investors do not have a full understanding of its operational status, making it difficult for them to accurately assess the value of the target investment company with insufficient information. Consequently, they face higher risks associated with holding the asset. To compensate for potential losses from such risks, investors demand a higher rate of return, which in turn increases the cost of equity capital. Additionally, stocks of firms with a poor information environment typically have higher transaction costs, contributing to a higher cost of equity capital. Conversely, if a firm has high information transparency, its cost of equity capital tends to be lower (Biddle & Hilary, 2006). Therefore, a poor information environment often results in uninformed investors having access to only limited information, thereby affecting expected returns and leading to an increase in the corporate cost of equity capital. Thus, improving the information environment is key to reducing the corporate cost of equity capital.

Based on this, this paper proposes hypothesis 2 as follows:

H2: *Data assetization reduces the corporate cost of equity capital by improving the quality of the information environment.*

2.3. The Mediating Role of Technological Innovation

Data assetization strongly promotes technological innovation in enterprises. On the one hand, benefiting from strong state support for the development of data technology, enterprises can actively engage in data assetization to obtain policy support and tax incentives, effectively reducing the costs associated with technological innovation and providing stable financial guarantees for their R&D investments, thereby significantly enhancing their motivation for technological innovation (Bloom, Jones, Van Reenen, & Webb, 2020). On the other hand, data assetization transforms traditional innovation models. Compared with conventional innovation approaches, data helps enterprises explore technological innovation paths at lower costs and significantly improves innovation quality (Cao & Ye, 2024). In terms of innovation resources, the unique advantages formed by data assetization enable faster and more effective discovery of innovation resources, as well as a more accurate understanding of target customer information and needs, allowing for more targeted innovation activities. Furthermore, the structural characteristics of digital technologies further strengthen innovation synergies and facilitate the flow of innovation factors. This open innovation environment not only broadens the innovation perspectives of enterprises but also creates conditions for the emergence of breakthrough technological innovations. Therefore, by building an open innovation system, enterprises can continuously improve innovation performance, ultimately achieving a virtuous cycle between technological innovation and business value.

Based on dynamic capability theory, enterprises need the ability to reconfigure internal and external resources to adapt to rapidly changing market environments (Teece, 2007). Consequently, enterprises must continuously enhance their competitiveness through technological innovation to achieve sustainable survival and development. Technological innovation injects strong growth momentum into enterprises, improves future earnings expectations, not only signals to the market that the enterprise has high growth potential but also facilitates accurate assessments of the firm's future cash flow situation, helping to ensure the stability of future earnings (Kogan, Papanikolaou, Seru, & Stoffman, 2017). From the perspective of investors, enterprises that form sustained competitive advantages through continuous technological innovation can significantly enhance market confidence in their long-term profitability. This not only makes investors more willing to invest capital in these enterprises, providing greater capital support, but also encourages the establishment of long-term, stable cooperative relationships with them. As the enterprise's reputation and recognition in the capital market continuously improve, investors perceive such enterprises as having lower risk and higher return potential, thus being willing to provide funds at a lower cost. This means that enterprises can secure favorable terms when financing and reduce the risk premium in the financing process. Innovation leads to cost reductions, efficiency improvements, and revenue growth for enterprises, optimizing their cash flow and enhancing their intrinsic value. Based on these changes, investors reassess the equity value of the enterprise. When the equity value rises, the enterprise can raise funds on more favorable terms when issuing stocks or engaging in other forms of equity financing, thereby reducing the cost of equity capital. Based on the above analysis, we propose research hypothesis 3:

H3: *Data assetization reduces the corporate cost of equity capital by enhancing the level of technological innovation.*

2.4. The Moderating Role of Digital Finance Development Level

Compared with traditional finance, digital finance leverages the deep integration of cutting-edge technology and financial services to expand the scope of traditional financial services, thereby accessing richer financial resources (Berg, Burg, Gombović, & Puri, 2020). By employing big data analytics, financial institutions can intelligently collect, accurately classify, deeply mine, and make scientific decisions based on massive amounts of data. This series of processes provides advanced technical support and diverse information supply for the development of enterprise data assetization, offering more sophisticated data collection, processing, and application capabilities. This lays a solid foundation for realizing the value of data assets (Philippon, 2019), breaks down information barriers between internal and external operations, upstream and downstream supply chain participants, and banks and enterprises, and integrates digital technology with inclusive finance. By leveraging the strengths of digital technology in information collection, processing, screening, and risk identification, it enables precise matching of supply and demand among different entities (Wang, Shan, & Zhang, 2026). On this basis, it allows for more effective assessment of enterprise risk profiles, enhances the accuracy of investor evaluations of corporate value, improves the scientific basis and rationality of investment decisions, and reduces the required rate of return demanded by investors. Furthermore, digital finance provides high-quality technological tools for enterprise information analysis. By utilizing these advanced tools, enterprises can better formulate scientifically sound, feasible production plans and technological innovation decisions, significantly boosting investor confidence in the firm. This increased confidence is reflected in the capital market, making enterprises more attractive when raising equity capital, thereby effectively reducing the cost of equity capital and strengthening the inhibitory effect on its increase. Therefore, we propose the following:

*H*4: *The level of digital finance development in the region where an enterprise is located positively moderates the impact of data assetization on the cost of equity capital.*

The research model is shown in **Figure 1**.

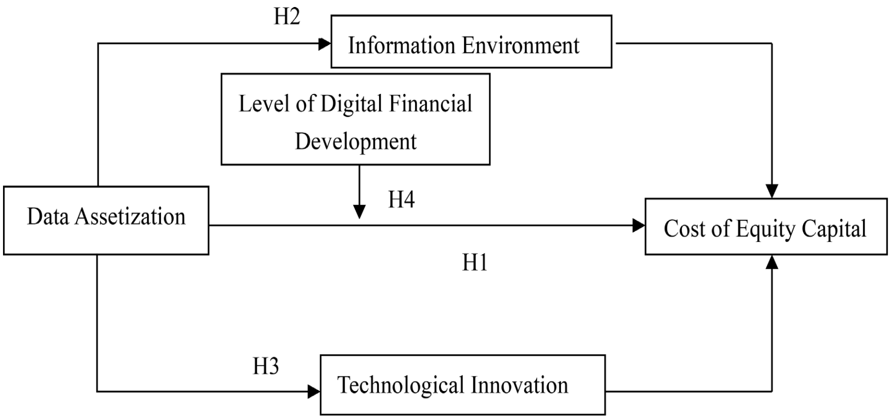

Figure 1. The research model.

3. Methods

3.1. Data Sources and Processing

This paper selects A-share listed companies in China from 2011 to 2023 as the research sample. In data processing, financial listed companies, companies with *ST, ST, and PT status, and those with missing key indicators are sequentially excluded. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles, ultimately resulting in 18,793 sample observations. The financial data of listed companies are obtained from the CSMAR database, while annual report data are sourced from CNINFO. The level of digital finance development is measured using the Digital Financial Inclusion Index, with data sourced from the Peking University Internet Finance Technology Center.

3.2. Variable Measurement

3.2.1. Dependent Variable

Enterprise Equity Capital Cost **(*Cost*)**

Following the approach of Cai (Cai, Zhang, & Xu, 2022), the equity capital cost is estimated using the MPEG model as specified in Equation (1)

$$\text{Cost} = \frac{dps_1}{p_0} + \sqrt{\left(\frac{dps_1}{p_0}\right)^2 + \frac{Eps_2 - Eps_1}{p_0}} \tag{1}$$

Eps_1 denotes the firm's earnings per share for the next fiscal year; Eps_2 denotes the firm's earnings per share for the second fiscal year; p_0 represents the stock closing price at the beginning of the year; and dps_1 denotes the dividend per share for the next period, calculated as $dps_1 = Eps_1 * K$, where K is the dividend payout ratio over the past three years.

3.2.2. Independent Variable

Enterprise Data Assetization **(*DA*)**

Following the approach of He (He, Chen, & Du, 2024), this study measures the degree of enterprise data assetization using a text analysis method based on corporate annual reports. By reviewing policy documents such as the 14th Five-Year Plan for Digital Economy Development and the Interim Provisions on Accounting Treatment of Enterprise Data Resources, and drawing on existing literature, this study selects four words highly associated with data assets—"information," "network," "digital," and "data"—as seed words. Second, corpus construction and word vector training. This study collects the full text of annual reports of all A-share listed companies from 2011 to 2023, uses Python's jieba word segmentation library to tokenize the report texts, and removes Chinese stop words. Subsequently, the Word2Vec neural network model (Skip-gram algorithm, with window size set to 5 and vector dimension set to 200) is employed to train the corpus, obtaining distributed vector representations for each word. Third, expansion and screening of similar words. The cosine similarity between all words in the corpus and the four seed words is computed, and the top 100 words with the highest similarity are selected as candidate words. After manual review, words unrelated to the concept of data assets or those carrying negative prefixes such as "not," "without," or "non-" (e.g., "nonlinear," "non-action") are excluded, ultimately retaining 32 words closely related to data assets to form the final feature lexicon. Fourth, indicator calculation and standardization. The frequency of occurrence of the feature lexicon words in each firm's annual report is counted (Raw_DA). To account for differences in report length, this study divides the raw frequency by the total number of pages in the annual report to obtain the average frequency per page, thereby mitigating measurement bias caused by report length. Finally, this study applies a logarithmic transformation to better capture the overall pattern of enterprise data assetization. It should be noted that the "data assetization" examined in this study, while somewhat related to the "enterprise digital transformation" discussed in existing literature, is fundamentally different in conceptual connotation. Digital transformation emphasizes the process by which enterprises utilize digital technologies (such as cloud computing, artificial intelligence, and blockchain) to reshape business processes and business models. In contrast, data assetization focuses more on the institutionalized process of recognizing data as measurable assets, enabling their participation in value creation and market transactions. In short, digital transformation highlights "using digital technologies," whereas data assetization highlights "turning data into assets." This distinction implies that data assetization involves not only the technological aspects of digitalization but also economic behaviors such as data rights confirmation, valuation, balance-sheet inclusion, and trading, and thus may have a more direct and far-reaching impact on firms' financing environment.

3.2.3. Mediating Variables

1) ***Information Environment* (*FDISP*)**

Following the approach of Pan (Pan, Sun, & Wang, 2025), this study measures the information environment using analyst forecast dispersion. The rationale is that when a firm's public information is insufficient or its information uncertainty is high, analysts have to rely more on non-public information in their forecasts. The diversity of such information sources tends to result in greater dispersion. Therefore, a larger analyst forecast dispersion indicates that the market has less access to firm-specific information, implying a poorer information environment. Following Chu, analyst forecast dispersion is calculated as shown in Equation (2):

$$\text{FDISP} = \text{SD (FEPS)/PRICE} \tag{2}$$

where SD (FEPS) is the standard deviation of the most recent earnings per share forecasts made by all analysts during the year, and PRICE is the firm's stock price at the beginning of the year.

2) ***Technological Innovation* (*ITI*)**

This study uses R&D investment to measure the input of the firm's technological innovation process. Technological Innovation Input = R&D Investment / Operating Revenue.

3.2.4. Moderating Variable

***Digital Finance Development Level* (*DFI*)**

Following Meng (Meng, Lv, & Li, 2025), this study measures the level of digital finance development using the logarithm of the regional digital finance index compiled by the Institute of Internet Finance at Peking University.

3.2.5. Control Variables

This study selects the firm size (Size), leverage ratio (Lev), return on total assets (ROA), return on equity (ROE), operating revenue growth rate (Growth), cash flow ratio (Cashflow), CEO duality (Dual), proportion of independent directors (Indep), and shareholding ratio of the top ten shareholders (Top10) as the control variables. All variable definitions and their corresponding measurements are summarized in Table 1.

Table 1. Variable definitions and measurements.

Variable Type	Variable Name	Variable Symbol	Variable Definition
Dependent Variable	Cost of Equity Capital	Cost	Cost of equity capital calculated using the MPEG model
Independent Variable	Data Assetization	DA	Logarithm of the frequency of data assetization-related words, as detailed above
Mediating Variables	Information Environment	FDISP	Analyst forecast dispersion, as detailed above
	Technological Innovation	ITI	R&D investment, as detailed above
Moderating Variable	Digital Finance Development Level	DFI	Logarithm of the regional digital finance index
Control Variables	Firm Size	Size	Natural logarithm of total assets
	Leverage Ratio	Lev	Year-end total liabilities/Year-end total assets
	Return on Total Assets	ROA	Net profit/Total assets
	Return on Equity	ROE	Net profit/Average shareholders' equity
	Operating Revenue Growth Rate	Growth	Current year operating revenue/Previous year operating revenue − 1
	Cash Flow Ratio	Cashflow	Net cash flow from operating activities/Total assets
	CEO Duality	Dual	Equals 1 if the CEO and chairman are the same person, otherwise 0
	Proportion of Independent Directors	Indep	Number of independent directors/Total number of board directors
	Equity Concentration	Top10	Shareholding ratio of the top ten shareholders

3.3. Model Specification

This paper constructs a two-way fixed effects model (3) to examine the direct impact of data assetization on corporate equity capital costs.

$$\text{Cost}_{i,t} = \alpha_0 + \alpha_1 \text{DA}_{i,t} + \alpha_2 \sum \text{Controls}_{i,t} + \sum \text{Industry} + \sum \text{Year} + \varepsilon_{i,t} \quad (3)$$

$\text{Cost}_{i,t}$ represents the cost of equity capital, $\text{DA}_{i,t}$ denotes data assetization, the subscript i refers to the firm, the subscript t refers to the year, $\sum \text{Industry}$ and $\sum \text{Year}$ represent industry and year fixed effects, and $\varepsilon_{i,t}$ is the random error term.

4. Analysis

4.1. Descriptive Statistics

As shown in Table 2, the mean value of enterprise data assetization (DA) is 3.3095, indicating that most enterprises have undertaken a certain degree of data assetization. The maximum value is 6.9791, while the minimum value is 0, suggesting significant variation in data assetization across firms. For enterprises with a data assetization value of 0, they have not engaged in data assetization, reflecting insufficient attention to this aspect. The mean value of the cost of equity capital (Cost) is 0.1329, with a maximum of 3.6440 and a minimum of 0.0029, indicating that the cost of equity capital varies considerably across different enterprises.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std	Min	Max
Cost	18,793	0.1329	0.073	0.0029	3.6440
DA	18,793	3.3095	0.7132	0	6.9791
Size	18,793	22.6355	1.3451	19.6286	26.4403
Lev	18,793	0.4126	0.1955	0.0319	0.9246
ROA	18,793	0.0617	0.0529	−0.3750	0.2539
ROE	18,793	0.1042	0.0865	−0.9616	0.4140
Growth	18,793	0.2031	0.3623	−0.6535	3.8082
Cashflow	18,793	0.0587	0.0685	−0.1994	0.2656
Dual	18,793	0.3014	0.4589	0	1
Indep	18,793	37.6665	5.4444	28.57	60
Top10	18,793	0.6067	0.1458	0.2086	0.9097
FDISP	18,793	0.0073	0.0090	0	0.0999
ITI	18,793	0.0469	0.0540	0	0.3059
DFI	18,793	5.5728	0.5658	2.7862	6.1609

4.2. Baseline Regression Results

The baseline regression results of the impact of data assetization on the cost of equity capital are presented in Table 3. Column (1) reports the univariate test results between enterprise data assetization and the cost of equity capital, showing that data assetization has a significant negative correlation with the cost of equity capital. Column (2) presents the impact of data assetization on the cost of equity capital after adding control variables, and the results also show a significant negative correlation. Column (3) further controls for year and industry fixed effects. The results indicate that the correlation coefficient between data assetization and the cost of equity capital is −0.0041, which is significant at the 1% level. Thus, data assetization significantly reduces the cost of equity capital.

Table 3. Baseline regression results.

Variable	(1) Cost	(2) Cost	(3) Cost
DA	−0.0059*** (0.001)	−0.0036*** (0.001)	−0.0041*** (0.001)
Size		0.0037*** (0.001)	0.0037*** (0.001)
Lev		0.0380*** (0.005)	0.0249*** (0.005)
ROA		0.0093 (0.033)	0.0316 (0.032)
ROE		0.0273 (0.018)	−0.0095 (0.018)
Growth		−0.0040*** (0.002)	−0.0005 (0.001)
Cashflow		−0.0079 (0.009)	0.0153* (0.009)
Dual		0.0041*** (0.001)	0.0021* (0.001)
Indep		0.0002* (0.000)	0.0002* (0.000)
Top10		−0.0048 (0.004)	−0.0154*** (0.004)
Constant	0.1545*** (0.003)	0.0404*** (0.011)	0.0526*** (0.015)
Year			Yes
Industry			Yes
Obs	18,793	18,793	18,793
adj R^2	0.00330	0.0257	0.117
F	63.26	50.57	26.06

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

4.3. Endogeneity Tests

4.3.1. Instrumental Variable Method

To address the issue of reverse causality, this study first employs the instrumental variable method. Since a firm's cost of equity capital is unlikely to be affected by other firms within the same province, this study follows the approach of Niu (Niu & Yu, 2024). By using the annual provincial mean of data assetization excluding the firm itself as the instrumental variable. The results are presented in **Table 4**.

The Kleibergen-Paap rk LM statistic is significant, indicating that the weak instrument test is passed. The Kleibergen-Paap rk Wald F statistic is also significant, suggesting that the instrumental variable passes the under-identification test. Column (2) of Table 3 reports the second-stage regression results of the instrumental variable method. The regression coefficient for enterprise data assetization remains significantly negative at the 1% level, confirming the robustness of the main findings. In the second stage, the coefficient for data assetization is significantly negative, further supporting Hypothesis 1.

Table 4. Endogeneity tests.

Variable	(1) DA	(2) Cost	(3) Cost
IV	0.2386*** (0.023)		
DA		−0.0481*** (0.011)	−0.0037*** (0.001)
Constant	2.5846*** (0.130)	0.1966*** (0.037)	
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Obs	18,564	18,564	10,159
adj R^2	0.455	0.0154	0.119
Kleibergen-Paap rk LM statistic	108.381***		
Kleibergen-Paap rk Wald F statistic	107.997		
Hansen J		0.000	

Note: Values in parentheses are t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (the same as in the following tables).

4.3.2. Propensity Score Matching

This paper groups enterprises based on the mean value of data assetization: those above the mean are assigned to the treatment group, and those below the mean to the control group. First, a Logit regression is performed using control variables as covariates, followed by 1:2 nearest neighbor matching. Second, a balance test is conducted. As shown in Table 5, the standardized biases of all variables are less than 10%, and the t-values indicate no systematic differences between the treatment and control groups, confirming that the balance test is passed.

Finally, after excluding the samples that did not match, the test was re-conducted, and the results are shown in column (3) of Table 4. The regression coefficients for corporate data assets are significantly negative at the 1% level. This further indicates that corporate data assets can reduce the cost of equity capital, supporting Hypothesis H1.

Table 5. Balance test.

Variable	Unmatched (U)/Matched (M)	Treated	Control	%bias	t-value	*p*-value
Size	U	22.578	22.686	−8.0	−5.49	0.000
	M	22.579	22.539	−1.1	−0.73	0.468
Lev	U	0.4733	0.41731	−5.1	−3.49	0.000
	M	0.4738	0.40807	−0.4	−0.24	0.811
ROA	U	0.5953	0.06358	−7.7	−5.25	0.000
	M	0.5959	0.05964	−0.1	−0.06	0.954
ROE	U	0.10008	0.10778	−8.9	−6.10	0.000
	M	0.10018	0.10054	−0.4	−0.28	0.776
Growth	U	0.22006	0.18803	8.8	6.05	0.000
	M	0.21885	0.21429	1.3	0.79	0.428
Cashflow	U	0.05421	0.0627	−12.4	−8.49	0.000
	M	0.05426	0.05366	0.9	0.58	0.564
Dual	U	0.32399	0.28126	9.3	6.38	0.000
	M	0.3238	0.33047	−1.5	−0.95	0.345
Indep	U	37.702	37.635	1.2	0.85	0.395
	M	37.7	37.567	2.4	1.64	0.101
Top10	U	0.60601	0.60734	−0.9	−0.62	0.534
	M	0.60602	0.60956	−2.4	−1.63	0.102

4.3.3. Robustness Tests

(1) High-Dimensional Fixed Effects

Considering the differences in economic development levels across regions where firms are located, this paper controls for provincial-level fixed effects based on the original model to test robustness. As shown in column (1) of Table 6, the results are significantly negative at the 1% level, supporting Hypothesis H1.

(2) Alternative Measure of the Dependent Variable

Following the approach of Chen (Chen et al., 2024), the OJ model (4) is used to estimate the firm's cost of equity capital.

$$\text{Cost} = A + \sqrt{A^2 + \frac{Eps_1}{p_0}\left(g_2 - g_p\right)} \tag{4}$$

where $A = \left(g_p + dps_1/p_0\right)/2$, *and* $g_2 = \left(Eps_2 - Eps_1\right)/Eps_1$; p_0 denotes the current stock price, Eps_2, Eps_1 represent analysts' forecasts of earnings per share for periods $t = 2$ and $t = 1$, respectively; dps_1 is the forecasted dividend per share for period $t = 1$, which is numerically equal to $k * Eps_1$ (where k is the average dividend payout ratio over the past three years); and g_p represents the constant growth rate of abnormal earnings.

The regression of data assetization on the cost of equity capital calculated using the OJ model is presented in column (3) of **Table 6**. The results show that data assetization is significantly negatively correlated with the cost of equity capital at the 1% level, further supporting Hypothesis H1.

Table 6. Robustness tests.

Variable	(1) Cost	(2) Cost	(3) Cost
DA	−0.0040*** (0.001)	−0.0047*** (0.001)	−0.0026*** (0.001)
Constant	0.0280* (0.016)		0.1440*** (0.008)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Obs	18,567	18,502	18,252
adj R^2	0.122	0.167	0.212
F	21.25	24.87	51.16

4.4. Mechanism Testing

4.4.1. Mediation Mechanism

Given that the traditional stepwise mediation approach may suffer from issues such as overuse and endogeneity bias, this paper adopts the method proposed by Jiang Ting (Jiang, 2022) to test the mediation mechanism. Based on the theoretical analysis above, an improved information environment can reduce the risks faced by investors, thereby lowering transaction costs and suppressing the cost of equity capital. Therefore, it is only necessary to test whether data assetization improves the information environment to verify the existence of the mediation effect. To this end, model (5) is constructed.

$$\mathrm{FDISP}_{i,t} = \beta_0 + \beta_1 DA_{i,t} + \beta_2 \sum \mathrm{Controls}_{i,t} + \sum \mathrm{Industry} + \sum \mathrm{Year} + \varepsilon_{i,t} \quad (5)$$

The specific results are shown in column (1) of **Table 7**, indicating that data assetization is significantly negatively correlated with analyst forecast dispersion at the 5% level. Since a smaller analyst forecast dispersion implies a better information environment for the firm, this suggests that data assetization helps improve the firm's information environment, supporting Hypothesis H2.

Based on the theoretical analysis above, technological innovation can broaden a firm's profit margins, improve earnings expectations, and convey positive signals that help strengthen the firm's market position. It enhances investor confidence, facilitating access to capital support and long-term cooperation, improving the firm's reputation in capital markets, and reducing the financing risk premium. Additionally, it can optimize cash flows, thereby affecting equity pricing and lowering the cost of equity capital. Following the approach of Jiang Ting (Jiang, 2022), it is only necessary to test whether data assetization promotes technological innovation to verify the existence of the mediation effect. To this end, model (6) is constructed.

$$\mathrm{ITI}_{i,t} = \lambda_0 + \lambda_1 \mathrm{DA}_{i,t} + \lambda_2 \sum \mathrm{Controls}_{i,t} + \sum \mathrm{Industry} + \sum \mathrm{Year} + \varepsilon_{i,t} \tag{6}$$

The specific results are shown in column (2) of Table 7. The regression coefficient between data assetization and R&D investment is 0.0093, which is significant at the 1% level. Since higher R&D investment indicates stronger technological innovation capability of the firm, this suggests that data assetization helps promote corporate technological innovation. Therefore, Hypothesis H3 is supported.

4.4.2. Moderating Mechanism

To examine the moderating role of the level of digital financial development, model (7) is constructed.

$$\begin{aligned}\mathrm{Cost}_{\mathrm{diff}_{i,t}} = {} & \theta_0 + \theta_1 \mathrm{DA}_{i,t} + \theta_2 \mathrm{DA}_{i,t} \times \mathrm{DFI}_{i,t} + \theta_3 \mathrm{DFI} + \theta_4 \sum \mathrm{Controls}_{i,t} \\ & + \sum \mathrm{Industry} + \sum \mathrm{Year} + \varepsilon_{i,t}\end{aligned} \tag{7}$$

The specific results are shown in column (3) of Table 7. The regression coefficient of the interaction term between data assetization and the level of digital financial development on the cost of equity capital is −0.0060, which is significant at the 1% level, indicating that a higher level of digital financial development strengthens the inhibitory effect of data assetization on the cost of equity capital. Thus, Hypothesis H4 is supported.

Table 7. Mechanism testing.

VARIABLES	(1) FDISP	(2) ITI	(3) Cost
DA	−0.0002**	0.0093***	−0.0038***
	(0.000)	(0.001)	(0.001)
DA*DFI			−0.0060***
			(0.002)
DFI			−0.0056
			(0.004)
Constant	−0.0140***	0.0691***	0.0715***
	(0.002)	(0.008)	(0.020)
Sample size	18,567	18,567	18,567
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
adj R^2	0.167	0.516	0.118
F	39.02	202.6	25.73

5. Heterogeneity Analysis

5.1. Nature of Property Rights

To examine the heterogeneity of property rights, this paper defines a variable, nature of property rights (SOE), which takes the value of 1 for state-owned enterprises and 0 otherwise, and conducts grouped regressions. In the grouped regression presented in Table 8, the observations with SOE = 1 (5362) and those with SOE = 0 (7375) sum to 12,737 observations. There is a gap of 6056 observations compared to the full sample (18,793). This is due to: 1) following industry practice, excluding listed companies in the financial and insurance sectors (approximately 3,800 observations); 2) excluding firms whose nature of ultimate controller could not be clearly determined (approximately 800 observations); and 3) excluding approximately 1456 observations due to missing values in the dependent variable or grouping variables.

As shown in columns (1) and (2) of Table 8, data assetization exerts a significant inhibitory effect on the cost of equity capital in non-state-owned enterprises, whereas this inhibitory effect is not significant in state-owned enterprises.

Table 8. Heterogeneity analysis by nature of property rights and operating risk.

VARIABLES	(1) SOE = 1	(2) SOE = 0	(3) High operating risk	(4) Low operating risk
DA	0.0005 (0.002)	−0.0074*** (0.002)	−0.0057*** (0.002)	−0.0015 (0.001)
Constant	−0.0508** (0.021)	0.0652* (0.036)	0.0575 (0.036)	0.0310 (0.021)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	5362	7375	6358	6379
adj R^2	0.214	0.104	0.101	0.177
F	16.27	9.285	7.423	14.03

5.2. Operating Risk

Since a firm's operating risk is related to earnings volatility, this paper follows the approach of Li (Li & Wang, 2025) and uses earnings volatility to measure operating risk. Specifically, the standard deviation of the rolling values of the earnings before interest, taxes, depreciation, and amortization (EBITDA) margin is used to measure the firm's operating risk. Firms with operating risk above the median are classified as the high operating risk group, while those below the median are classified as the low operating risk group.

The specific results are shown in columns (3) and (4) of Table 8. For firms with high operating risk, the regression coefficient of data assetization on the cost of equity capital is −0.0057, which is significant at the 1% level. For firms with low operating risk, the coefficient is not significant. This may be because firms with high operating risk typically face greater future uncertainty and unstable cash flows, and often suffer from resource misallocation, leading to lower investor confidence in future operations and a higher risk premium. In this context, data assetization plays a crucial role by providing timely support. Through digital technologies, it enables accurate prediction of various risks that the firm may face, reduces operational uncertainty, helps improve resource utilization efficiency, and significantly enhances investor confidence in the firm's future cash flows and operations. As a result, its effect on reducing the cost of equity capital is more pronounced. For firms with low operating risk, which already have stable cash flows, mature markets, sound operations, and relatively stable resource allocation, investors perceive limited risk. Although data assetization can improve operational efficiency, its impact on reducing the cost of equity capital is relatively small and unlikely to significantly affect the cost of equity capital.

6. Discussion

6.1. Research Findings

In the era of the digital economy, data has become an important resource for enterprises, and data assetization can have a significant impact on capital markets. This paper takes A-share listed companies from 2011 to 2023 as the research sample and empirically examines the impact of data assetization on the cost of equity capital and its underlying mechanisms. The results show that data assetization can directly reduce the cost of equity capital. Its influence path is that data assetization suppresses the cost of equity capital by improving the information environment and enhancing technological innovation. Moreover, the level of digital financial development in the region where the firm is located can strengthen the inhibitory effect of data assetization on the cost of equity capital. Furthermore, the effect of data assetization is more pronounced in non-state-owned enterprises and firms with high operating risk.

6.2. Theoretical Contributions and Practical Implications

This paper makes three contributions: It adds to micro-level data assetization research by linking it to equity cost—an overlooked angle compared to prior work on financing and growth; It broadens equity cost literature by identifying information environment and innovation as dual mechanisms, and by examining digital finance as a moderator; It unpacks heterogeneous effects by ownership and operational risk, providing actionable insights for policy and practice.

Based on the above conclusions, this paper proposes the following policy recommendations.

For enterprises, they should fully recognize the important role of data assetization in corporate development, actively explore paths to data assetization, and formulate relevant data assetization strategies by considering their own industry characteristics and business models while drawing on the experience of advanced enterprises. They should clarify the value of data assets, establish a foundational data management system, strengthen data security and compliance, and conduct regular data audits and optimization to improve data quality. Through data assetization, enterprises can build tools such as financial shared service centers and dynamic risk monitoring systems, disclose operational data in real time, enhance the quality of information disclosure, and leverage visualization technologies to make information more accessible. This enables investors to more intuitively assess profitability, thereby reducing the information risk premium. At the same time, data assetization can drive digital innovation, enabling enterprises to optimize product design through big data analytics and improve production efficiency through the Internet of Things, thereby strengthening market competitiveness and alleviating investor concerns about operational uncertainty. Additionally, enterprises should strengthen collaboration with digital financial platforms, leveraging technologies such as big data and cloud computing to enhance information transparency and bolster investor confidence, laying a solid foundation for reducing the cost of equity capital.

For the government, it should establish a special fund for data assetization and build a data asset trading platform to facilitate the circulation and sharing of data assets, thereby improving their market liquidity. At the same time, it should establish a data asset valuation and evaluation platform to provide professional references for data asset valuation, enhance market recognition of data assets, and facilitate corporate financing activities, thereby reducing the cost of equity capital. Furthermore, the government should improve policies and regulations by formulating laws and regulations related to data assets, clarifying the definition of ownership, transaction rules, and security standards. This will help regulate the market order for data assetization, provide legal guarantees for corporate data assetization, reduce risks and uncertainties in the process, stabilize investor expectations, and promote a reduction in the cost of equity capital.

6.3. Limitations and Future Research Directions

Although this paper analyzes the role of data assetization in reducing the cost of equity capital, the measurement indicators for data assetization are not yet fully standardized, and differences in data management capabilities across industries and firm sizes may affect the generalizability of the findings. Future research could conduct more in-depth and detailed discussions based on industry characteristics. Additionally, while this paper considers the moderating role of digital financial development, its moderating effect may be influenced by regional financial development levels. Therefore, future research could further conduct comparative analyses across sub-regions.

Author Contributions

Conceptualization, Jianhong Tao and Xinyi Zhang; methodology, Xinyi Zhang;

software, Xinyi Zhang; validation, Xinyi Zhang; formal analysis, Xinyi Zhang; investigation, Xinyi Zhang; resources, Xinyi Zhang; data curation, Xinyi Zhang; writing—original draft preparation, Xinyi Zhang; writing—review and editing, Xinyi Zhang; visualization, Xinyi Zhang; supervision, Xinyi Zhang; project administration, Xinyi Zhang; funding acquisition, Jianhong Tao. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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