The Impact of Data Factors on Corporate Financial Resilience: Evidence from Shanghai and Shenzhen A-Share Listed Firms

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ABSTRACT

Business intelligence, data mining, cloud computing, and mobile Internet have reshaped how households behave and how firms operate. As digital and traditional economies converge, data factors have become central to firm survival and growth. Financial resilience, defined as a firm's ability to respond to a changing financial situation and to manage uncertainties, is a central indicator of financial management quality. This paper explores whether and how corporate data factor utilization affects financial resilience. Using a sample of Chinese A-share listed firms from 2015 to 2024, we measure data factor utilization through textual analysis of annual reports and employ instrumental-variable and Heckman two-stage estimations, supplemented by heterogeneity and mechanism analyses. The results show that: (1) data factor utilization positively impacts the financial resilience of firms, an effect that survives a battery of robustness checks; (2) the effect is channeled through two pathways, namely reducing financing constraints and agency costs, and holds for both SOEs and non-SOEs; (3) improved financial resilience raises firm value, with a stronger effect among firms that use data factors more intensively. The evidence clarifies how data factors relate to corporate financial resilience.

Keywords: Data factor; Financial resilience; Agency costs; Financing constraints

INTRODUCTION

The third industrial revolution ushered in the digital age. Business intelligence, data mining, and cloud computing have altered both household life and organizational production (Vial, 2019). The application of the data factor has, therefore, become crucial for survival and growth (Ren et al., 2024).

Research on the economic consequences of corporate digitalization has expanded rapidly, yet three gaps remain. Previous research mainly focuses on how corporate digitalization affects total factor productivity, innovations, and company performance or value (Zhai et al., 2022; Zhang & Dong, 2023). At the same time, how corporate digitalization impacts corporate financial resilience still requires further exploration. The few studies that address finance focus on isolated indicators such as cash flow, financing cost, or bankruptcy risk (Li et al., 2025), leaving the mechanisms through which data factors shape financial resilience largely untested.

This article examines whether and how corporate data factor utilization shapes financial resilience, and whether this channel contributes to higher-quality development.

This research offers three contributions. First, in contrast to previous studies focusing on one financial metric, we take financial resilience as the starting point. Second, we identify two mechanisms, the easing of financing constraints and the reduction of agency costs, through which data factor utilization improves financial resilience. Third, we expand our examination to the economic outcomes of whether financial resilience improvement ultimately leads to increased firm value.

The rest of this paper is structured as follows. Section 2 reviews the existing literature and formulates the research hypotheses. Section 3 describes the research methodology. Section 4 discusses the empirical findings. Section 5 discusses the implications and limitations of the study. Section 6 concludes the paper.

LITERATURE REVIEW

Data Factor Utilization: Antecedents and Consequences

The integration of digital and traditional economies is widely regarded as a driver of high-quality growth. Data factor utilization refers to the extent to which a firm collects and applies data resources in its production, operation, and decision-making processes (Ren et al., 2024). However, the literature is not conclusive about the nature, process, and impact of the data factor on the firm, as well as its contribution to firm value.

One strand of the literature argues that data factor utilization enhances firm value by stimulating innovation and R&D and by upgrading traditional industries. At the production level, data factors have become a key driver of total factor productivity and operational efficiency (Zhang & Dong, 2023). Ren et al. (2024) further show that effective data utilization significantly stimulates corporate total factor productivity by alleviating investment inefficiency and resource redundancy, and they find no evidence supporting the productivity paradox. Conversely, only a minority of firms achieve marked transformation success, as data factor utilization can substantially raise learning and management and R&D costs (Guo et al., 2023), eroding profit.

The different perspectives above can be aligned in the sense that the use of data factor should be considered as a way of exploration that involves the allocation of productive factors over space and time in order to reduce environmental uncertainties (Fu & Guo, 2025). Some specific examples are intelligent credit risk management, real-time supply chain management, and customer profiling for targeted marketing. These have been associated with increased efficiency, diversification of suppliers and customers, and greater financing capability (Chen et al., 2024). The implications of data factors for firms under these perspectives are basically financial.

Financial Resilience

Financial resilience can be defined as the ability of an organization to adjust to the ever-changing financial environment by managing the uncertainty in the environment (Denis, 2011), which plays a major role in firm performance and dividend policies and has a direct relationship with firm value (Rapp et al., 2014; Yung et al., 2015). It should be noted that financial resilience needs to be separated from the concept of financial flexibility, which is similar to the former. The latter includes the dimension of buffering resources, meaning the availability of cash and debt capacity that a company can use at any time when required (Denis, 2011; Arslan-Ayaydin et al., 2014), whereas financial resilience refers to the ability of an organization to adapt to the financial disruptions and restore normal operations, and flexibility is only one of the required features (DeAngelo et al., 2009).

Consistent with this view, Li et al. (2025) show that firm resilience not only enhances firm value but also mitigates risk, as resilient firms fortify internal controls and improve information transparency. The COVID-19 pandemic further underscored the critical importance of financial resilience for corporate survival, since firms with greater resilience were better able to withstand the crisis and recover quickly (Xia et al., 2022; Chen et al., 2024). Accordingly, a growing body of research has explored the determinants of corporate financial resilience, ranging from external information environments such as analyst coverage and ESG performance (Wu et al., 2024) to institutional factors such as data factor marketization (Song et al., 2025). However, whereas prior studies have predominantly focused on external drivers of financial resilience, the role of firm-level data factor utilization in shaping financial resilience remains largely unexplored, and this study seeks to fill that gap.

Research Gaps

Financial resilience is central to coping with uncertainty and to achieving high-quality development. Although recent studies have examined the determinants of financial resilience, they have predominantly focused on external factors such as institutional reforms and market development (Song et al., 2025) or on the resilience effects of digital transformation during crisis periods (Chen et al., 2024). Similarly, the emerging literature on data factor utilization has mainly documented its productivity consequences, such as higher total factor productivity and more efficient resource allocation (Ren et al., 2024), while evidence on how digital technologies reshape corporate financing and capital structure remains limited to specific contexts (Wu et al., 2025). Two gaps motivate this study: the link between data factor use and financial resilience remains underexamined, and the channels through which data factors act on resilience, specifically financing constraints and agency costs, have yet to be identified. This study discusses that relationship and its transmission channels, and examines the economic consequences, which helps to bridge the data factor literature and corporate finance research.

Hypothesis Development

Financial resilience represents the financial ability and capital structure of a company (Denis, 2011; Arslan-Ayaydin et al., 2014). It allows the firm to capture investment opportunities due to enhanced free cash flow management (Marchica & Mura, 2010).

H1. Data factor utilization is positively associated with corporate financial resilience.

Digitalization lowers market barriers and information asymmetry, curbs agency costs, widens financing sources, and reduces default risk (Li et al., 2025). Since greater earnings management leads to increased cash (enhanced cash flexibility) and decreased default rates result in easier debt financing (enhanced debt flexibility), data factor utilization is expected to increase financial resilience through cash and debt flexibility.

H2. Data factor utilization increases financial resilience by alleviating financing constraints.

In practice, information asymmetry and transaction costs raise financing costs (Hubbard, 1998), and constrained firms forgo valuable investments or slide into distress (Campello et al., 2010; Denis, 2011). Recent evidence confirms that this friction persists in the digital era, whereas digital transformation can speed up capital structure adjustment by alleviating financial constraints and information asymmetry, and digitalization eases financing constraints by improving the quality of information disclosure (Wu et al., 2025). Chinese listed firms commonly face financing constraints (Guariglia et al., 2011), so rational firms weigh the financing environment (Hadlock & Pierce, 2010). By signaling firm quality, data factor utilization reduces information asymmetry, improves access to external finance, raises the cash flow of constrained firms, and lowers financing costs, thereby strengthening financial resilience through the financing-constraint channel.

H3. Utilization of data factors enhances financial resilience through reduced agency costs.

METHODOLOGY

Sample Selection

The sample used in this research is Chinese A-share listed companies for the time frame 2015–2024. The main independent variable, the extent to which the data factor is being utilized, is measured by a Python-based textual analysis of annual reports that counts the frequency of data-factor-related keywords. Financial data are collected from China Stock Market & Accounting Research (CSMAR). To control for the effect of extreme cases or outliers, the following selection criteria have been adopted: (1) observations for the year in which the company went public are excluded; (2) observations with abnormal financial data are excluded;

and (3) observations with extensive missing data are excluded. The final sample size comprises 14,410 firm-year observations.

Variable Definitions

Dependent Variable: Financial resilience. We measure financial resilience along two dimensions: the capacity to deploy cash flow and the capacity to raise external finance. Following the DeAngelo et al. (2009), financial resilience is quantified as the sum of cash flexibility and debt flexibility. Cash flexibility is the difference between the cash holding ratio of the firm and that of the industry on average. Likewise, debt flexibility equals Max(0, industry-average debt ratio − firm's actual debt ratio), capturing the ability to obtain external financing.

Independent variable: Data factor utilization. Following Xie & Qi (2024), we adopt a textual-analysis approach by counting the frequencies of digitalization-related keywords in firms' annual reports to construct a firm-level data factor utilization index. Building on the original dictionaries of Xu & Li (2026) for measuring data factors, and grounded in digital technologies including big data, blockchain, artificial intelligence, and cloud computing, we extract and summarize keywords from data-factor-related reports to form the corpus shown in Figure 1.

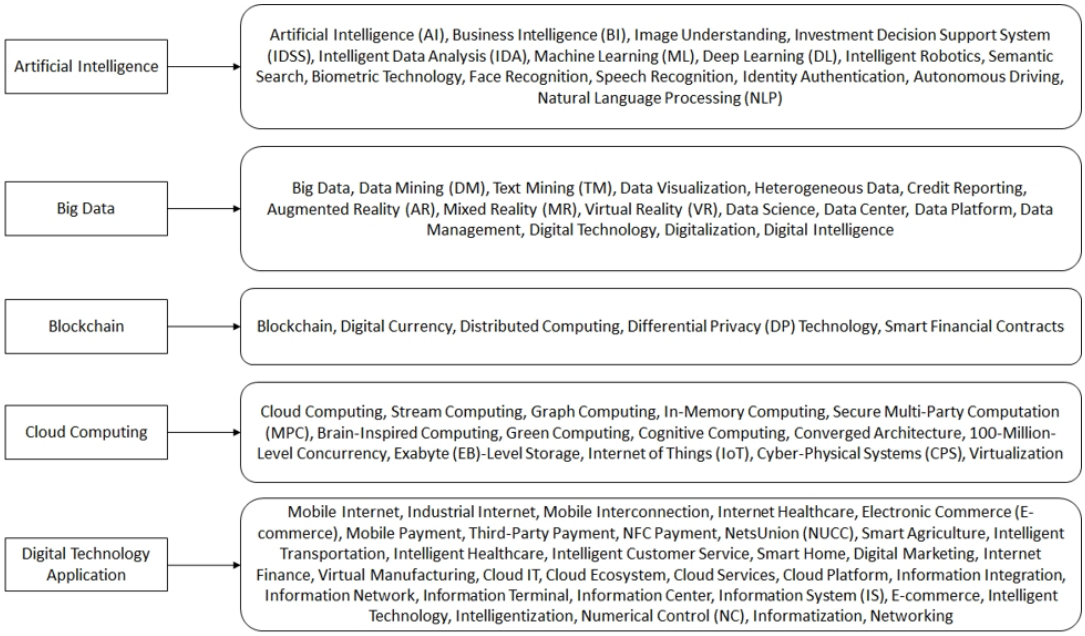


Figure 1: Keyword Map of Data Factor Utilization.

These keywords closely align with the concept of data factor utilization and capture the breadth and depth of a firm's application of data elements in production, operation, and decision-making, offering a broad proxy for the intensity of data factor utilization. Finally, we measure the degree of data factor utilization as the natural logarithm of one plus the total count of data-factor-related keywords in a firm's annual report. Although this text-based index effectively captures the breadth of firms' data factor engagement, it may partly reflect disclosed digital strategies rather than substantively implemented data utilization. We therefore interpret the index as the intensity of data factor utilization and disclosure, and revisit this measurement caveat in the Discussion.

Control variables. To mitigate firm-level omitted-variable bias, we include controls that may affect financial resilience. All variable definitions are summarized in Table 1.

Table 1: Variable Definitions

Variable	Symbol	Variable Name	Description
Dependent	*FR*	Financial Resilience	Sum of cash flexibility and debt flexibility

variable			
Independent variable	DF	Corporate Data Factor	Ln (total word count related to data factors in the company's annual financial report + 1)
Control variables	$Size$	Firm Size	Ln (Total Assets / 10,000)
	Lev	Leverage Ratio	Total Liabilities / Total Assets
	ROE	Return on Equity	Net Income / Shareholders' Equity
	Top	Ownership Concentration	Shareholding ratio of the largest shareholder
	$Dual$	CEO Duality	1 if chairman and CEO are the same person, 0 otherwise
	$TobinQ$	Tobin's Q	Market Value / Replacement Value
	Age	Firm Listing Age	Ln (Current Year - Listing Year + 1)
Mechanism variables	KZ	Financing Constraints	KZ index; a higher value indicates more severe financing constraints
	AC	Agency Costs	Other receivables / operating income; a higher ratio indicates higher agency costs
Outcome variable	MV	Market value	Market value / replacement capital

Empirical Model

To test our research hypotheses, we specify the following baseline model:

$$FR_{i,t} = \alpha_1 DF_{it} + \sum X_{it} + \sum Year + \sum Industry + \varepsilon_{it} \quad (1)$$

where $FR_{i,t}$ stands for the firm i's financial resilience in year t; $DF_{i,t}$ denotes the degree of data factor utilization; X_{it} is the vector of firm-level controls; ν_j and τ_t represent industry and year fixed effects, respectively, which we include to reduce omitted-variable bias; and $\varepsilon_{i,t}$ is the random error term. Robust standard errors are clustered at the firm level to account for within-firm serial correlation.

RESULTS

Descriptive Statistics and Correlation Analysis

Descriptive Statistics.

The descriptive statistics for the main variables are reported in Table 2. The average financial resilience is only 0.128, and some firms exhibit negative values, indicating that Chinese firms are, on average, only weakly resilient and have considerable scope for improvement. The standard deviation of data factor utilization is 1.231, indicating considerable cross-firm variation in the degree of data factor utilization.

Table 2: Descriptive Statistics of Main Variables

Variable	Variable Name	Mean	Std. Dev	Min	Max
FR	Financial Resilience	0.128	0.210	-0.402	1.148
DF	Data Factor	1.180	1.231	0	4.564
$Size$	Firm Size	22.097	1.164	20.036	25.659
Lev	Leverage Ratio	0.396	0.191	0.056	0.865
ROE	Return on Equity	0.065	0.116	-0.525	0.344
Top	Ownership Concentration	33.507	13.989	9	71.56
$Dual$	CEO Duality	0.303	0.459	0	1
$TobinQ$	Tobin's Q	2.123	1.304	0.878	8.344
Age	Firm Listing Age	1.8	0.632	0.693	2.944

Notes: N = 14,410 firm-year observations (2015-2024).

Correlation Analysis.

Table 3 reports the pairwise correlations. Data factor utilization is positively correlated with financial resilience, consistent with our hypothesis. The control variables are correlated with the dependent variable in plausible directions: firm size is negatively correlated with financial resilience (larger firms attach less weight to financial resilience); leverage is negatively correlated (higher leverage reduces debt flexibility); return on equity is positively correlated (stronger profitability yields more free cash, raising cash flexibility); ownership concentration and CEO duality are positively correlated (concentration of power facilitates financial resilience). Variance inflation factor (VIF) diagnostics reveal no severe multicollinearity.

Table 3: Correlation Matrix of Main Variables

	FR	*DF*	*Size*	*Lev*	*ROE*	*Top*	*Dual*
FR	1.000						
DF	0.075***	1.000					
Size	-0.295***	0.127***	1.000				
Lev	-0.698***	-0.001	0.527***	1.000			
ROE	0.154***	0.114***	0.134***	-0.143***	1.000		
Top	0.025***	-0.017	0.083***	0.017	0.101***	1.000	
Dual	0.080***	0.062***	-0.160***	-0.107***	0.035***	0.009	1.000

Notes: N = 14,410. *** p < 0.01, ** p < 0.05, * p < 0.1. Variables are defined in Table 1; VIF diagnostics indicate no serious multicollinearity.

Baseline Regression

Table 4 reports the baseline estimates from a sequential specification. The coefficient of the use of data factors is positive and statistically significant at the 1% level in columns (1)-(3). By including more control variables and considering industry and year fixed effects, the adjusted $\boldsymbol{R^2}$ rises from 0.0059 to 0.6108 as the specification gains explanatory power. These results support Hypothesis H1.

Table 4: Baseline Regression - Effect of Data Factor Utilization on Financial Resilience

Variable	**（1）**	**（2）**	**（3）**
	FR	*FR*	*FR*
DF	0.0133*** （7.2250）	0.0101*** （6.4032）	0.0138*** （7.8733）
Size		0.0261*** （11.7572）	0.0173*** （8.0799）
Lev		-0.8995*** （-63.6082）	-0.9474*** （-69.2453）
ROE		-0.0191 （-0.8569）	0.0138 （-0.6576）
Top		0.0002 （1.5077）	0.0061*** （3.5345）
Dual		0.0081** （1.9853）	0.0060 （1.6283）
TobinQ		-0.0050*** （-2.9290）	0.0061*** （3.5345）
Age		-0.0352*** （-9.2549）	-0.0401*** （-11.4765）
Constant	0.1135*** （38.0631）	-0.0428 （-0.9595）	0.1451*** （3.3604）
Industry FE	√	×	√
Year FE	√	×	√
Adj R^2	0.0059	0.5125	0.6108

F value	52.20	660.74	850.23

Notes: N = 14,410. Standard errors in parentheses. Significance levels as in Table 3. DF = ln(1 + keyword count), testing H1. FE = fixed effects.

Robustness Checks

Replacing Key Variables

First, we replace the continuous measure with a dummy that equals one for firms whose data factor utilization exceeds the annual industry median and zero otherwise. As shown in column (1) of Table 5, the coefficient on the data factor utilization dummy is significantly positive, consistent with the main results. Second, we replace the measure of financial resilience using equal-weighted and float-market-value-weighted constructions. Columns (2) and (3) of Table 5 show that the coefficients retain their sign and significance.

Table 5: Robustness Check - Replacing Key Variables of Data Factor Utilization

Variable	(1)	(2)	(3)
	FR	*FR_equal*	*FR_float*
DF_dum	0.0151*** (3.7978)		
DF		0.0124*** (7.2021)	0.0136*** (7.7562)
Controls	√	√	√
Industry FE	√	√	√
Year FE	√	√	√
Adj R^2	0.605	0.566	0.625
F value	845.6897	763.1968	903.0067

Instrumental Variable Approach.

To address potential reverse causality arising from the intertemporal interplay between data factor use and financial resilience, we adopt the instrumental-variable strategy of Lei and Wang (2023) and Li et al. (2025). Specifically, we use industry-year and province-year means of data factor utilization as instruments. Relevance holds because companies operating in the same province or industry face similar external, policy, and economic conditions that make their degree of data factor utilization correlated. Exogeneity is plausible because an individual firm's data factor use is unlikely to move the industry or province mean (Goldsmith-Pinkham et al., 2020). These results are presented in Table 6 where columns (1) and (3) include first-stage regression coefficients (0.9689*** and 0.8522***), and columns (2) and (4) include results of second-stage. Coefficients on data factor utilization in the second stage are 0.3052 and 0.6495 significant at the 5% and 1% level.

Table 6: Robustness Check - Instrumental Variables for Data Factor Utilization

Variable	Same industry		Same region	
	(1)	(2)	(3)	(4)
	DF	*FR*	*DF*	*FR*
DF_industry	0.9689*** (19.04)			
DF_region			0.8522*** (16.31)	
DF		0.3052** (2.0638)		0.6495*** (3.7153)
Controls	√	√	√	√
Industry FE	√	√	√	√

Year FE	√	√	√	√
$Adj\ R^2$	0.605	0.566	0.625	0.612
F value	845.6897	763.1968	903.0067	852.3413

The validity of the instruments rests on the exclusion restriction: industry-year and province-year averages of data factor utilization must affect a firm's financial resilience only through that firm's own data factor use.

This assumption is defensible because the instruments capture common technological and policy conditions shared by firms in the same industry or province, and an individual firm is too small to move these aggregates.

A possible threat is that common shocks to an industry or region, such as a demand boom or a local policy change, might affect firm resilience directly through channels other than data adoption. The first-stage estimates reported in Table 6 are strongly significant (t = 19.04 and 16.31 for the industry and province means, respectively), indicating that the instruments are indeed relevant.

Heckman Two-Stage Model

Because the adoption of data factors is not random, firms with stronger resources, better governance, or more favorable financing conditions are more likely to invest in data capabilities, and ordinary least squares estimates may therefore be contaminated by self-selection bias. We employ the Heckman two-stage correction to address this concern.

In the first stage, a Probit selection equation models the probability that a firm is a high data factor user, defined by whether its data factor utilization exceeds the annual industry median (DF_dum = 1). The identifying variable is the industry-year mean of data factor utilization: it predicts an individual firm's adoption decision because firms in the same industry and year face common technological and policy conditions, yet it does not directly determine any single firm's financial resilience except through that firm's own adoption. The selection equation also includes the full set of firm-level controls and fixed effects.

In the second stage, the estimated inverse Mills ratio is added to Model (1) as an additional regressor; its coefficient captures the magnitude of the selection effect and its statistical significance indicates whether self-selection is present. Table 7 reports the first-stage Probit estimates and the second-stage corrected regression. The coefficient on data factor utilization in the corrected model is 0.013 and significant at the 1% level, indicating that the baseline result is not driven by self-selection.

Table 7: Robustness Check-Heckman Two-Stage Correction

	First stage	**Second stage**
	DF_dum	FR
DF		0.013*** （0.0018）
IMR		0.195*** （0.023）
PLP	1.144* （0.588）	
Controls	√	√
Industry FE	√	√
Year FE	√	√
R^2	0.2046	0.6151
P value	0.0000	0.0000

Notes: N = 14,410. Probit first stage models the probability of high DF; the inverse Mills ratio is added in the second stage. Significance levels as in Table 3.

Firm Fixed Effects

Industry and year fixed effects absorb cross-industry and macro-level variation but leave time-invariant firm heterogeneity uncontrolled. To address this remaining source of omitted-variable bias, we re-estimate the baseline specification with firm fixed effects, which identify the effect from within-firm variation over time. Table 8 reports the results. The coefficient on data factor utilization is 0.0103 and significant at the 1% level (standard error = 0.0022), close to the baseline estimate of 0.0138. Control variables retain their expected signs, and the R-squared rises to 0.6821. The conclusion that data factor utilization strengthens financial resilience therefore does not depend on time-invariant firm characteristics.

Table 8: Robustness Check — Firm Fixed Effects

Variable	(1)	(2)
	Baseline	Firm FE
	FR	FR
Data factor utilization	0.0138*** （7.8733）	0.0103*** （4.7240）
Controls	√	√
Industry FE	√	√
Year FE	√	√
Firm FE	×	√
Observations	14,410	12,970
Adj R^2	0.6108	0.6821
F value	850.23	795.36

Heterogeneity Analysis

Table 9 reports the heterogeneity results. Columns (1) and (2) show regional heterogeneity. For firms located in the eastern coastal region, the coefficient of data factor utilization is 0.0155, which is significant at 1%. This indicates a significant contribution of data factor utilization to financial resilience. In other regions the coefficient is positive but statistically insignificant.

The reasons behind the differences could be: (i) better development of the eastern economy and high penetration of digital technologies leading to a favorable macroeconomic environment; (ii) higher competition among firms in the market leading to greater data factor utilization; and (iii) higher internationalization since the period of reform and opening up, which promotes innovation and technological support.

Columns (3) and (4) turn to ownership heterogeneity. The coefficient for the SOE group is 0.0156, which is significant at 1%, while for the non-SOE group, it is 0.0103, which is also significant at 1%. A coefficient-difference test between the two groups is not significant, suggesting that data factor utilization improves financial resilience for both the SOE and non-SOE firms, although the underlying channels differ: SOEs draw on abundant resources and state support, whereas non-SOEs respond more strongly to market incentives and technological opportunities.

Table 9: Heterogeneity in the Effect of Data Factor Utilization by Region and Ownership

	（1）	（2）	（3）	（4）
	Eastern	Other	SOEs	non-SOEs
DF	0.0155*** （0.0019）	0.0063 （0.0039）	0.0156*** （0.0024）	0.0103*** （0.0027）
Controls	√	√	√	√
Industry FE	√	√	√	√
Year FE	√	√	√	√
$Adj\ R^2$	0.6193	0.5862	0.6093	0.6098
F value	658.85	193.39	490.51	369.55

We further test whether the coefficients differ significantly across subsamples using a seemingly unrelated regressions (suest) framework with firm-clustered covariance. The regional gap is statistically significant: the coefficient for eastern firms exceeds that for other regions by 0.0092 (chi-squared = 4.50, p = 0.034). The ownership gap is not statistically distinguishable from zero (difference = 0.0053, chi-squared = 2.15, p = 0.143), supporting our reading that the effect operates in both state-owned and non-state-owned firms.

Table 10: Tests of Coefficient Differences Across Subsamples

Variable	(1) Eastern vs. other	(2) SOEs vs. non-SOEs
DF	0.0092** （0.0043）	0.0053 （0.0036）
chi-squared	4.50	2.15
p-value	0.034	0.143
Controls	√	√
Industry FE	√	√
Year FE	√	√

Mechanism Tests

We examine two transmission channels.

Table 11: Mechanism Tests of Data Factor Utilization - Financing Constraints and Agency Costs

	Financing Constraints			Agency Costs		
	（1）	（2）	（3）	（4）	（5）	（6）
	FR	KZ	FR	FR	AC	FR
DF	0.014*** （0.002）	-0.034** （0.015）	0.011*** （0.001）	0.014*** （0.002）	-0.007*** （0.001）	0.010*** （0.002）
KZ			-0.047*** （0.001）			
AC						-0.285*** （0.025）
Controls	√	√	√	√	√	√
Industry FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
$Adj\ R^2$	0.6108	0.5708	0.7251	0.6108	0.2942	0.6057
F value	167.19	223.80	246.77	167.19	124.13	88.04

The use of data factors could strengthen financial resilience by alleviating financing constraints. This research uses the KZ measure to measure the degree of financing constraints faced by firms and explores the mediation effect of "data factor usage → financing constraints → financial resilience." As shown in Table 11, the KZ coefficient in column (3) is -0.047 and it is significant at the 1% significance level, which shows that the financing constraints weaken financial resilience of firms. The coefficient of DF in column (2) is -0.034 and it is significant at the 1% significance level, which implies that the usage of data factors could significantly alleviate financing constraints. The coefficient of DF in column (3) is significantly positive, which confirms that firms' data factor usage strengthens the financial resilience of firms by alleviating financing constraints. A plausible explanation is that firms actively adopting data factors attract support and market recognition, which eases financing constraints and thereby strengthens resilience. Thus, Hypothesis H2 is supported. The measure of agency cost is taken as the proportion of other receivables to operating income, with the higher proportion indicating high agency cost. We then test the agency-cost channel. Data factor utilization significantly reduces agency costs, which in turn raise financial resilience, supporting Hypothesis H3.

To assess the statistical significance of the two channels more directly, we estimate the indirect effects with a bootstrap procedure. The indirect effect through financing constraints is 0.0016 (95% CI [0.0002, 0.0030]), and that through agency costs is 0.0020 (95% CI [0.0013, 0.0027]). Neither interval includes zero,

confirming that both channels transmit the effect of data factor utilization. The direct effect remains positive and significant after accounting for the mediators, indicating partial mediation.

Table 12: Bootstrap Tests of Indirect Effects

Path	Indirect effect	Bootstrap SE	95% CI
Financing constraints	0.0016	0.0007	[0.0002, 0.0030]
Agency costs	0.0020	0.0003	[0.0013, 0.0027]

Economic Consequences Analysis

Having established that data factors strengthen financial resilience, we ask whether this improvement generates economic value, and in particular whether it raises firm value. The sample is split by the median of the use of data factors into high- and low-data-factor-utilization sub-samples and Model (2) is estimated:

$$MV_{i,t} = \mu_0 + \mu_1 FR_{i,t} + \sum X + \varepsilon_{i,t} \qquad (2)$$

Table 13 shows the estimates. In the full sample (column 1), the coefficient on financial resilience is positive and significant, indicating that stronger resilience raises firm value. In columns (2) and (3), the coefficient is significantly positive only for the high-data-factor-utilization subsample but insignificant for the low-data-factor-utilization subsample, meaning that firms with higher degree of using data factors receive more value creation effect from financial resilience improvement. Taken together, data factor utilization enhances both financial resilience and firm value.

Table 13: Economic Consequences - Financial Resilience and Firm Value across Data Factor Utilization

Variable	(1)	(2)	(3)
	Full sample	High DF	Low DF
	MV	MV	MV
FR	0.414*** (0.107)	0.622*** (0.174)	0.143 (0.126)
Controls	√	√	√
Industry FE	√	√	√
Year FE	√	√	√
$Adj\ R^2$	0.3340	0.3182	0.3613
F value	141.86	68.95	80.50

DISCUSSION

This study finds that corporate data factor utilization significantly enhances financial resilience (H1), operating through two channels: it alleviates financing constraints by reducing information asymmetry and improving the financing environment (H2), and it lowers agency costs by strengthening internal control and information transparency (H3). The effect is stronger in China's eastern coastal region yet benefits both state-owned and non-state-owned enterprises.

Whereas prior studies link digitalization mainly to productivity, innovation, or isolated indicators such as cash flow and bankruptcy risk (Li et al., 2025; Zhai et al., 2022; Zhang & Dong, 2023), this paper adopts financial resilience—proxied by cash and debt flexibility (Denis, 2011; Arslan-Ayaydin et al., 2014)—as a holistic measure of financial management capability. The study thereby extends the data factor literature (Ren et al., 2024) into corporate finance.

A further limitation concerns the validity of the textual proxy. Because data factor utilization is inferred from the frequency of keywords in annual reports, the index may capture the disclosure of digital strategies rather than the substantive implementation of data systems. Firms with similar levels of actual digital investment may receive different scores simply because they describe their activities with different vocabularies, and firms may disclose ambitious plans that are not yet operational. Future research could validate the textual measure against observable digital inputs, and examine whether the results hold when the keyword index is replaced by these implementation-based indicators. Such validation would establish whether financial resilience responds to data capabilities themselves or mainly to their disclosure.

CONCLUSION

This study examines the relation between corporate data factor use and financial resilience. Data factor use significantly strengthens financial resilience through financing constraints and agency costs, with pronounced effects in the eastern coastal region and among both state-owned and non-state-owned firms. The result survives alternative variable construction, instrumental-variable estimation, and Heckman two-stage correction, and it extends to firm value.

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