How Corporate Data Factor Utilization Shapes High-Quality Development: Evidence from China's A-Share Listed Firms

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Abstract. Based on data from A-share listed companies spanning the period 2009–2023, this paper empirically examines the impact of corporate data factor utilization levels on high-quality development and its underlying mechanisms. The findings reveal that, amidst the vigorous expansion of the digital economy, data, as a critical factor of production, profoundly influences corporate high-quality development. Regarding the mechanism, corporate data factor utilization primarily promotes high-quality development by mitigating information asymmetry and reducing agency costs. The results indicate that enterprises should enhance the systematic development and efficient utilization of data factors and improve data governance capabilities to foster high-quality development.

Keywords: Corporate Data Factor Utilization, High-Quality Development, Total Factor Productivity, Information Asymmetry, Agency Costs

1 Introduction

Propelled by the worldwide surge in the digital economy, the data factor is now widely regarded as a core factor of production, on par with established inputs like land, labor, capital, and technology. Extant literature generally acknowledges the strategic significance of data assets for corporate development. For instance, high-quality data can provide robust support for decision-making, aiding enterprises in identifying market trends and customer needs (Yeganeh et al., 2014). In-depth analysis of operational data can help identify efficiency bottlenecks and achieve cost optimization (Melville & Whisnant, 2014). Furthermore, data-driven approaches can foster the development of new products and services, thereby expanding corporate revenue streams (Battisti et al., 2014).

However, a significant gap persists between the strategic recognition of data and its effective utilization at the firm level. Evidence from a Malaysian manufacturing case underscores that this gap has measurable consequences: the lack of granular inventory data standards and real-time data interfaces led to poor visibility, while fragmented systems caused inconsistent data updates, resulting in concurrent overstocking and stock-outs. This operational breakdown contributed to inventory days 37% above the industry

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average and a 4.6-percentage-point decline in net profit margin. The translation of data potential into tangible value is often hampered by such widespread issues as data silos, inconsistent governance, and a failure to integrate analytics into key processes. Globally, these impediments systematically undermine performance, revealing a critical need to address the micro-foundations of data utilization.

While existing research predominantly focuses on macro-level descriptions or case studies, a systematic examination of how firm-level data factors influence high-quality development through micro-level mechanisms remains scarce. This theoretical gap impedes the effective advancement of corporate data governance practices.

Against this backdrop, this study empirically investigates the relationship between corporate data factor utilization and high-quality development by constructing quantitative measures for both, based on a panel dataset of China's A-share listed firms from 2009 to 2023. The analysis reveals that data utilization promotes high-quality development chiefly by alleviating information asymmetry and reducing agency costs, thereby strengthening internal governance and enhancing the efficiency of resource allocation. These findings enrich the understanding of the micro-foundations of high-quality development in the digital era and offer actionable insights for improving enterprise-level data governance and strategic decision-making.

2 Theoretical Analysis and Research Hypotheses

Data factors possess characteristics such as non-rivalry, partial excludability, increasing returns to scale, and network effects, enabling firms to acquire, process, and utilize massive amounts of information at very low marginal costs (Jackie Cheng, 2020). Their deep integration with various corporate functions such as R&D, production, management, and marketing can significantly enhance resource allocation efficiency, innovation capability, and overall governance quality, thereby promoting high-quality development[1][2].

Supporting evidence from corporate practice substantiates this logic. A representative case is Sany Group, a leading Chinese manufacturing company. Through its comprehensive digital transformation, Sany focused on key initiatives such as building "lighthouse factories," process digitization, and data governance. By integrating data across R&D, manufacturing, supply chain, and customer service, Sany achieved a 31% increase in manufacturing output per capita and a 47% reduction in labor costs. Notably, its Beijing pile machine plant was recognized as a "Global Lighthouse Factory" by the World Economic Forum, demonstrating how systematic data utilization can materially enhance production efficiency and product quality. This case illustrates the tangible pathways through which data factors drive high-quality development.

Data factors can also, through a "five-chain synergy" mechanism (industrial chain, data chain, innovation chain, capital chain, talent chain), deeply integrate with other factors and improve synergistic efficiency (OUYANG Rihui, 2024). Cross-departmental data integration and the application of machine learning can compress new product development cycles and improve patent output and new product market performance. The co-development of data factors and big data markets has become a key driver of corporate innovation[3].Furthermore, data application can promote organizational flattening, enhance business process transparency, and strengthen internal control and compliance management[4], thereby comprehensively improving corporate governance and market competitiveness, which is conducive to promoting high-quality development centered on quality and efficiency, rather than scale expansion. Based on this, Hypothesis 1 is proposed:

H1: An improvement in the level of corporate data factor utilization promotes high-quality development.

Digital data systems significantly reduce agency costs between shareholders and management (Jensen & Meckling, 1976) through real-time observable management behaviors and automated compliance checks. The real-time monitorability and verifiable characteristics of data factors also provide a technical foundation for reducing agency costs (Hanelt et al., 2021). Regarding real-time monitoring, IoT and ERP systems collect production, sales, and cash flow data in real-time, allowing the board of directors and major shareholders to monitor management behavior at low cost, reducing managerial slack and perk consumption, while also curbing earnings management and overinvestment (Banker et al., 2019). In terms of contract optimization, objective KPIs (e.g., customer retention rate, online defect rate) constructed based on big data make performance measurement more scientific, effectively linking management behavior to long-term corporate value (Lambert et al., 2007). Regarding reputational constraints, transparent data disclosure makes managerial opportunistic behavior more easily identified by the market, and the increased reputational cost further inhibits moral hazard (Armstrong et al., 2010). According to the sample results of Li et al. (2024), for every one standard deviation increase in the intensity of digital transformation, the administrative expense ratio decreases by 0.2 percentage points and TFP increases significantly, also verifying the mediating role of agency costs. Based on the above analysis, improving the level of corporate data factor utilization can reduce agency costs through real-time monitoring, contract optimization, and reputational constraints, thereby promoting high-quality development[5]. Based on this, Hypothesis 2 is proposed:

H2: Corporate data factor utilization promotes high-quality development by reducing agency costs.

High-level data factor utilization enables firms to capture and disclose information in a real-time, detailed, and multi-dimensional manner (Wu & Ren, 2022), thereby significantly reducing information asymmetry between insiders and external investors. When information asymmetry is weakened, capital and talent flow to their most efficient uses, and the monitoring costs for external investors also decrease, consequently enhancing Total Factor Productivity (TFP) – a core indicator of high-quality development (Li & Li, 2022). The empirical research of Francis et al. (2005) further indicates that improved information transparency, by narrowing bid-ask spreads and reducing equity financing costs, is ultimately translated into sustained growth in corporate value. Based on this, Hypothesis 3 is proposed:

H3: Corporate data factor utilization promotes high-quality development by reducing information asymmetry.

3 Research Design

3.1 Sample Selection and Data Sources

The initial sample comprises A-share listed companies from 2009 to 2023. The data were subjected to the following screening procedures: exclusion of ST and *ST firms, omission of financial companies, and removal of observations with missing values for key variables. Furthermore, all continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Data pertaining to corporate data factor utilization and high-quality development were manually collected from annual reports, whereas the remaining financial data were obtained from the CSMAR database.

3.2 Variable Definitions and Descriptions

Explained Variable. In existing literature, corporate high-quality development is frequently measured by Economic Value Added (EVA), multi-indicator comprehensive evaluation methods, and Total Factor Productivity (TFP). While EVA offers a financial perspective, it often fails to adequately capture non-financial aspects such as innovation. Similarly, multi-indicator approaches can be compromised by the subjectivity inherent in assigning weights. In contrast, TFP, which reflects the contributions of technological progress, managerial efficiency, and optimized resource allocation to output, offers a more congruent measure with the essence of high-quality development (Liu & Yu, 2025). Among prevalent TFP estimation techniques, the methods proposed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) are widely adopted for their ability to mitigate the limitations of OLS and fixed effects models. Consequently, this study employs the OP method as the primary metric and utilizes the LP method for robustness testing.

Explanatory Variable. A firm's proficiency in key technologies such as artificial intelligence, blockchain, cloud computing, and big data—encompassing their application—signifies its capacity to manage the entire data lifecycle, from collection and storage to analysis and utilization. Accordingly, drawing on the methodology of Wu et al. (2021), this study constructs a measure for the level of data factor input. This is achieved by tallying the frequency of disclosures related to these five technological domains in annual financial reports and aggregating the counts into a composite score.

Information Asymmetry: Amihud Illiquidity Ratio (ILL). This paper adopts the illiquidity ratio proposed by Amihud (2002) to measure the degree of information asymmetry. The basic rationale is that the lighter the adverse selection problem, the higher the stock liquidity, and the smaller the price change per unit trading volume. The calculation method is: where represents the stock return of firm i on the k-th trading day of year t, represents the daily trading volume, and represents the number of trading days in that year.

Agency Cost: Asset Turnover Ratio (ATO). Existing literature commonly employs metrics such as the operating expense ratio, management expense ratio, and asset turnover ratio to gauge agency costs. Among these, the asset turnover ratio is selected as the proxy in this study, following the established practice of Ang, Cole & Lin (2000) and Singh & Davidson (2003).Compared to the operating expense ratio and management expense ratio, the asset turnover ratio can reflect management's efficiency in generating revenue given inputs and is less affected by accounting policy choices and earnings management; a lower value indicates more severe asset idleness or over-investment, thus better capturing the agency problem emphasized by Jensen & Meckling (1976) wherein the agent fails to maximize asset use efficiency.

Control Variables. Following the practice of existing literature, this paper controls for the following variables: Firm Size, Solvency, Profitability, Current Ratio, Growth Ability, Whether Loss-Making, Board Size, Duality (CEO/Chairman), Cash Flow Ratio, Proportion of Independent Directors, Shareholding Balance, Audit Quality, and Book-to-Market Ratio. Industry and Year dummy variables are also introduced to control for their impact on corporate high-quality development.

3.3 Model Construction

To examine the relationship between corporate data factor utilization and high-quality development, Model (1) is constructed:

$$High_{i,t} = \alpha_1 + \alpha_2 De_{i,t} + Controls_{i,t} + \sum Ind + \sum Year + \mu_{i,t} \tag{1}$$

Where ‘High’ represents the level of corporate high-quality development, ‘De’ represents the level of corporate data factor utilization, ‘Control’ represents other control variables that may affect corporate high-quality development, and ‘Ind’ and ‘Year’ represent industry and year fixed effects, respectively.

To verify the pathway through which corporate data factor utilization affects high-quality development, a mediation effect model is constructed based on the above model:

$$Mid_{i,t} = \beta_1 + \beta_2 De_{i,t} + Controls_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t} \tag{2}$$

$$High_{i,t} = \theta_1 + \theta_2 De_{i,t} + \theta_3 Mid_{i,t} + Controls_{i,t} + \sum Ind + \sum Year + \pi_{i,t} \tag{3}$$

Where ‘Mid’ is the mediating variable, information asymmetry or agency costs, and the other variables are the same as in Model (1).

4 Empirical Results and Analysis

4.1 Descriptive Statistics

As presented in Table 1, the descriptive statistics outline the characteristics of the key variables. The mean of 'High' is 6.7687 with a standard deviation of 0.9058. This dispersion reflects a significant heterogeneity in the level of high-quality development among the sampled companies. Regarding the data factor utilization ('De'), its mean and median values are 1.3686 and 1.0986, respectively, which lie far below the maximum of 6.3008. The wide gap and zero minimum reflect low overall data utilization and significant firm-level variation.

Table 1. Descriptive Statistics

Variable	N	Mean	SD	Min	p50	Max
High	44171	6.7687	0.9058	2.6289	6.6597	11.4790
De	44171	1.3686	1.4087	0.0000	1.0986	6.3008
ATO	44171	0.6200	0.5133	0.0002	0.5141	12.1053
ILL	44171	0.5939	0.4094	0.1247	0.5135	3.8381
Size	44171	22.1238	1.2910	18.8283	21.9253	27.4677
Lev	44171	0.4170	0.2089	0.0274	0.4075	1.2624
ROA	44170	0.0346	0.0716	-0.7242	0.0376	0.3127
Growth	44037	0.3730	1.1793	-1.0006	0.1188	17.5937
CashFlow	44166	0.0459	0.0714	-0.2892	0.0455	0.3549
Board	44171	2.1198	0.1990	1.6094	2.1972	2.7726
Top1	44171	0.3369	0.1475	0.0743	0.3132	0.7584
AuditFee	43289	13.8024	0.6930	12.1007	13.7102	17.2167
ListAge	44170	2.0019	0.9440	0.0000	2.1972	3.4340

4.2 Baseline Regression Results

Table 2 presents baseline regressions of data factor utilization on high-quality development. The coefficient is positive and significant across both specifications, confirming that greater data utilization fosters high-quality development and supporting Hypothesis 1.

Table 2. Baseline Regression Results

Variable	High (1)	High (2)
De	0.0608***	0.0205***
	(9.19)	(3.95)
Size		0.3883***
		(29.94)
Lev		0.3246***
		(7.37)
ROA		1.5108***
		(19.51)
Growth		0.0056
		(1.32)
CashFlow		0.5871***
		(11.89)
Board		-0.0493
		(-1.54)
Top1		-0.0091
		(-0.11)
AuditFee		0.0509***
		(3.49)
ListAge		-0.0344***
		(-3.52)
_cons	6.1946***	-2.6745***
	(343.60)	(-9.94)
Year FE	Yes	Yes
Ind FE	Yes	Yes
R^2 (within)	0.2513	0.4428
N	44171	44171

Note: t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Same for the following tables.

4.3 Addressing Endogeneity and Robustness Checks

4.3.1 Propensity Score Matching (PSM). To mitigate potential self-selection bias, the study applies PSM. Propensity scores are estimated via a Logit model using control variables as covariates, followed by 1:1 nearest-neighbor matching with a 0.02 caliper. After matching, standardized biases fall below 5% and t-tests are insignificant, confirming good balance. Fixed-effects regression on the matched sample yields a coefficient of 0.0184, significant at the 1% level, as shown in Table 3, validating the robustness of the results.

Table 3. PSM Results

Variable	Coefficient
Ln (Data Factor Utilization)	0.0184*** (3.47)
_cons	-2.8665*** (-10.15)
Control Vars	Yes
Year FE	Yes
Ind FE	Yes
N	30,854
R^2 (within)	0.4778

4.3.2 Difference-in-Differences (DID). To identify the net effect of corporate data factor utilization on high-quality development, this paper constructs the following multi-period DID model:

$$TFP\_OP_{i,t} = \beta_0 + \delta(treat \times post)_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

Where 'treat' is a dynamic treatment variable indicating the period after an enterprise first reaches a 'high data factor utilization level', 'post' is a post-treatment dummy variable, $X_{i,t}$ represents the selected control variables, and μ_i, λ_t represent firm and year fixed effects, respectively. The results presented in Table 4 show that the coefficient of the interaction term 'treat×post' is 0.0057, significant at the 5% level. This indicates that after controlling for inherent firm characteristics and macro trends, digital transformation one year earlier leads to an average increase in firm TFP of 0.57%, verifying the positive causal effect of data factors on high-quality development.

Table 4. DID Results

Variable	Coefficient
treat×post	0.0057** (2.04)
Control Vars	Yes
Year FE	Yes
Ind FE	Yes
N	37,120
R^2 (within)	0.4721

4.3.3 Replacing the Explained Variable. As a robustness test, the main measure of high-quality development was replaced by TFP calculated using the LP method instead of the OP method. Re-estimation shows that a 1% increase in corporate data factor utilization raises LP-based TFP by 0.0299%, a result consistent in direction and stronger in magnitude than the baseline. This confirms that data factor utilization significantly enhances corporate productivity and alleviates concerns about indicator-driven bias.

4.4 Mechanism Tests

4.4.1 Test of the Mediating Effect of Agency Costs. The results in Table 5 support the mediating role of agency costs. Column (1) establishes the positive total effect of data factor utilization on high-quality development. Subsequently, Column (2) demonstrates that it significantly reduces agency costs, and Column (3) shows that including this mediator attenuates the direct effect of data utilization while the mediator itself remains significant, thereby confirming the hypothesized mediation path. Thus, Hypothesis 2 is supported.

Table 5. Agency Cost Channel Test

Variable	(1) Total Effect TFP_OP	(2) Mediator AC3	(3) With Mediator TFP_OP
Ln (Data Factor Util.)	0.0197*** (3.94)	0.0088*** (2.93)	0.0127*** (3.18)
AC3			0.800*** (15.38)
Control Vars	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes
_cons	-2.622*** (-9.71)	1.776*** (8.18)	-4.043*** (-17.13)
N	43,157	43,157	43,157
R^2 (within)	0.3095	0.6083	0.6076

Table 6. Information Asymmetry Channel Test

Variable	(1) Total Effect TFP_OP	(2) Mediator ILL	(3) With Mediator TFP_OP
Ln (Data Factor Util.)	0.0197*** (3.94)	–0.0136*** (-4.53)	0.0195*** (3.90)
ILL			–0.016*** (-2.67)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
_cons	-2.622*** (-9.71)	4.057*** (35.90)	-2.556*** (-9.40)
N	43,157	43,157	43,157
R^2 (within)	0.4758	0.3623	0.4759

4.4.2 Test of the Mediating Effect of Information Asymmetry. The three-step regression results in Table 6 show that corporate data factor utilization not only directly promotes high-quality development but also indirectly amplifies this effect by significantly reducing information asymmetry. When information asymmetry is included in the model, the direct coefficient slightly decreases, and its own negative coefficient on high-quality development indicates that the improvement of information transparency is a key channel for productivity leap.

Table 7. Heterogeneity Analysis

Grouping Dimension	Sub-sample	Coefficient	N	R^2(within)
Ownership	Non-SOE (SOE=0)	0.025*** (4.17)	28845	0.4760
	SOE (SOE=1)	0.010*** (1.11)	15312	0.4756
Industry Type	Information Technology	0.041*** (5.01)	8,901	0.5013
	Manufacturing	0.018*** (3.12)	20,112	0.4718
	Financial	0.025** (2.88)	2,345	0.4885
	Other Industries	0.012* (1.96)	10,813	0.4492

5 Heterogeneity Analysis

To further reveal the boundary conditions of the data factor utilization effect, this paper conducts grouped regressions from the dimensions of ownership nature and industry characteristics, with the results presented in Table 7. The analysis reveals that the coefficient for non-SOEs is markedly higher than that for SOEs, underscoring that more flexible ownership structures strengthen the catalytic role of data factors in fostering high-quality development, as non-state enterprises' market-oriented governance allows data to be more effectively embedded into production and decision-making, thereby yielding greater productivity dividends. Furthermore, the effect of data utilization exhibits substantial variation across sectors: it is most pronounced in the inherently data-driven Information Technology sector, remains strong in the Financial sector where data underpins risk management and operational efficiency, is moderate yet significant in Manufacturing through enhancing production processes and supply chains, and is weakest in Other Industries where data is less central to core operations. Overall, the promotive effect of data factor utilization is more salient among non-SOEs and data-intensive industries such as IT and finance, suggesting that policy measures should prioritize these groups while also advancing data governance reforms in state-owned enterprises and traditional sectors.

6 Conclusion

6.1 Main Findings

Given the rising prominence of the digital economy, data factors have become a key driver of high-quality corporate development. Using a comprehensive sample of China's A-share listed firms from 2009–2023, this study empirically examines the impact and mechanisms of data factor utilization. The results show that higher data utilization significantly enhances total factor productivity, thereby promoting high-quality development. Mechanism tests reveal two primary pathways: reducing agency costs through real-time monitoring and contractual discipline, and mitigating information asymmetry by improving transparency and innovation efficiency. The effect is more pronounced in non-state-owned, financially risky, and small or medium-sized firms, underscoring the moderating roles of institutional flexibility and governance needs.

This study contributes to the literature by clarifying how data translates into firm performance. By identifying micro-level transmission mechanisms, it fills a key research gap and provides new theoretical and empirical insights into the economic value of data factors.

6.2 Policy Implications

Based on the above findings, several policy implications can be drawn. Governments should enhance policy guidance and financial support for corporate data governance, particularly for SMEs and financially constrained firms, through digital transformation funds and tax incentives that promote broader data utilization and innovation. Meanwhile, standardizing the data factor market by establishing disclosure and valuation systems can reduce information asymmetry, improve resource allocation efficiency, and facilitate the flow of capital, talent, and technology to high-performing firms[6]. State-owned enterprises should also accelerate digital transformation and governance reform by adopting market-oriented data management mechanisms to enhance efficiency, innovation, and competitiveness[7]. In addition, financial institutions are encouraged to develop financing products and risk-control models based on data assets, broadening funding channels and supporting data-driven innovation, especially for high-growth and high-risk firms.

For business practitioners, the theoretical mechanisms identified in this study are powerfully illustrated by the earlier case of Sany Group. By advancing its "lighthouse factory" initiative and establishing a comprehensive data governance framework—encompassing process digitalization ("Four Modernizations"), industrial software integration (PLM, MOM, SCM, CRM), and centralized data platform development—Sany demonstrated that the pathway to high-quality development is paved by systematically leveraging data to enhance transparency and decision-making. Its experience offers three paramount insights for other firms: First, integrate core systems and build a unified data platform to dismantle information silos, which is the foundational step to reducing information asymmetry. Second, implement data-driven performance monitoring and management to create operational transparency, thereby directly curbing agency costs and improving efficiency. Third, proactively utilize data analytics to uncover new value propositions and drive innovation, transforming data from a supportive tool into a core driver of competitive advantage. Ultimately, treating data as a strategic asset and embedding it into the organizational fabric is indispensable for achieving sustainable, high-quality development[8].

6.3 Limitations and Future Research

Notwithstanding its contributions, this study has certain limitations that point to promising avenues for future research. First, the measurement of corporate data factor utilization primarily relies on text analysis of annual reports, which, while systematic, may not fully capture the depth and quality of data applications within firms. Future studies could develop more nuanced measures by incorporating micro-level data on actual IT investments, data infrastructure, data talent composition, and specific data application scenarios. Integrating these multidimensional indicators would provide a more comprehensive and accurate assessment of data factor utilization.

Second, although this study has employed methods including PSM and DID to mitigate endogeneity concerns, the potential for reverse causality and omitted variable bias cannot be entirely ruled out. Future research could leverage more advanced identification strategies, such as exploiting exogenous policy shocks or constructing instrumental variables based on regional digital infrastructure development, to establish more robust causal inferences.

Furthermore, future research could delve deeper into the heterogeneous effects of data factors across different technological contexts and industry ecosystems. Examining how data utilization interacts with emerging technologies like artificial intelligence[9] and blockchain, and how its value creation mechanism varies in different industrial clusters, would offer more targeted theoretical support and practical guidance for promoting high-quality development of Chinese enterprises in the digital era.

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