

Article

Regional Digital–Real Integration and Enterprise Resilience: Evidence from Listed Manufacturing Firms

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Abstract

Regional digital–real integration (RDRI) refers to the deep integration of digital technologies into the real economy, through which digital technologies reshape industrial production, organizational processes, and value creation. Amid global industrial restructuring and increasing economic uncertainty, RDRI has become a key driver of high-quality economic development in China. Using A-share listed manufacturing firms, this study constructs a multidimensional index of enterprise resilience (ER) covering resistance, recovery, development, and innovation. It then applies the entropy weight method and the coupling coordination model to examine the impact of RDRI at the city level on ER. The results show that RDRI significantly improves ER, and the conclusion remains robust after endogeneity checks and robustness tests. Moreover, the results show that the positive effects of RDRI are stronger for firms in eastern China, capital-intensive firms, State-Owned Enterprises (SOEs), and high-tech firms. RDRI also enhances ER by optimizing resource allocation, improving firm productivity, and easing financing constraints. The paper provides theoretical insight and empirical evidence for deepening RDRI and strengthening ER.

Keywords: regional digital–real integration; enterprise resilience; resource allocation; firm productivity; financing constraints

1. Introduction

Against the backdrop of current global geopolitical tensions, sluggish economic recovery and frequent unforeseen events, the cumulative impact of external shocks poses a severe challenge to the stable operation of enterprises. Supply chain disruptions, sharp fluctuations in market demand and uncertainty regarding the prices of production factors have rendered the business environment increasingly complex [1]. In this highly uncertain environment, enterprises require not only the short-term survival capacity to withstand shocks, but also the comprehensive ability to recover rapidly from crises, adapt to new environments and achieve sustainable development. This capacity is defined in academic circles as enterprise resilience (ER) [2]. ER has become a strategic cornerstone at the micro level for ensuring the stability of industrial and supply chains and underpinning high-quality development.

The development of ER does not occur in isolation but is profoundly influenced by the external ecosystem in which the enterprise operates. In recent years, regional digital–real integration (RDRI) has involved the deep coupling and coordinated development of digital technologies and the real economy. It has been recognized as a key force in reshaping the



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operational logic of the real economy, providing enterprises with an entirely new external ecosystem [3]. By reshaping industrial logic, this ecosystem of convergence enables enterprises to become more resilient, adaptable and sustainable, whilst simultaneously strengthening industrial chains and supporting high-quality development [3]. At the macro level, it breaks down barriers across industries, improves resource allocation, and reconstructs industrial networks, thereby enhancing industrial resilience and recovery capacity. At the micro level, digital technologies such as the Internet of Things, artificial intelligence, and cloud computing enable end-to-end data flows and more informed decision-making. They narrow information gaps, reduce costs, improve supply-chain structures, and spread risk more effectively. As a result, firms become more agile and resilient [4].

However, most existing research has focused on the impact of enterprises' own digital transformation activities on their resilience [5,6], whilst few studies have examined the enabling effects on micro-level ER from the macro-level industrial ecosystem perspective of RDRI. More importantly, the analytical logic of digital transformation often centers on the application of digital technologies, whereas RDRI emphasizes the coupling and synergy between the digital and real economies. There are fundamental differences between the two in terms of theoretical mechanisms. How the integration ecosystem at the regional level is transmitted to firms' micro-level operational behavior, and the transmission pathways and boundary conditions involved, remain inadequately elucidated, constituting a key gap in current research.

Against this backdrop, several questions remain: does RDRI improve ER? Through which mechanisms? Does the effect vary across regions and firm types? Addressing these questions is both theoretically and practically important because it helps clarify the logic of firm survival and growth in the digital economy era and provides evidence for regional industrial policy and industrial-chain resilience. To address these issues, this study constructs an index system for RDRI that covers digital industrialization and industrial digitalization, capturing the penetration, integration, and reorganization of digital technologies across the real economy. Using city-level panel data, it also builds a comprehensive ER index spanning resistance, recovery, development, and innovation. Finally, the empirical analysis uses a two-way fixed-effects model to examine the impact of RDRI on ER. The study aims to provide theoretical insight and empirical evidence for deepening RDRI and strengthening ER.

Notably, the effect of RDRI on ER is not automatic but contingent on firms' internal absorptive capacity. Although RDRI provides external digital infrastructure and institutional support, its transformation into improved resilience depends on firms' digital adoption capability, organizational flexibility, and managerial cognition, consistent with the absorptive capacity and dynamic capability perspectives [7]. Accordingly, RDRI generates a conditional and non-linear enabling effect across firms. From this mechanism, significant heterogeneity is expected across firms with different resource endowments and capability structures. Firms with stronger digital foundations are more capable of internalizing external digital–real integration benefits, whereas weaker firms may face constraints in capability conversion. Consistent with this mechanism, this study focuses on A-share listed manufacturing firms, which generally possess stronger capital and technological bases, ensuring clearer identification of the enabling effect of RDRI. This setting also implies that the estimated effects are more representative of firms with established digital capabilities, while the impact may be weaker for small and less digitally mature firms, constituting an important boundary condition.

This paper makes two main contributions. First, in terms of research perspective, this study embeds urban RDRI into a unified framework, focusing on macro-level coupling and symbiosis rather than just firm-level digitalization or regional digital development. It

emphasizes the two-way structural, scale, and efficiency alignment between digital and real sectors, revealing how the external digital ecosystem empowers micro-level capacities for resistance, recovery, growth, and innovation. This overcomes the narrow focus on digitalization levels, offers a new angle on how integration improves real economy performance, and clarifies the underlying mechanisms. Second, in terms of mechanism identification, this paper empirically shows that RDRI strengthens ER through three channels: optimized resource allocation, improved firm productivity, and eased financing constraints. By linking these channels to factor endowments, productivity, and capital flows, the study sharpens mechanism discussions. It also conducts heterogeneity analyses by region, factor intensity, ownership, and industry, uncovering differentiated effects that inform targeted policies and enrich the literature on the economic consequences of digital–real integration.

The remainder of this paper is structured as follows: Section 2 develops the theoretical framework, reviews the relevant literature, and proposes the research hypotheses. Section 3 describes the research design, including model specification, variable definitions, and data sources. Section 4 presents the empirical results, covering baseline regressions, correlation analysis, robustness checks, and endogeneity tests. Section 5 conducts heterogeneity analysis and mechanism testing. Section 6 summarizes the main findings, offers policy recommendations, and discusses the study's limitations and directions for future research.

2. Theoretical Background and Hypothesis Development

2.1. Regional Digital–Real Integration and Enterprise Resilience

RDRI refers to the deep integration of digital technologies with the real economy through digital industrialization [8] and industrial digitalization [9]. Existing studies have demonstrated that RDRI promotes high-quality economic development [10], industrial upgrading [10], resource allocation efficiency [11], and green transformation at the regional level [12], while RDRI enhances firms' production efficiency [13], innovation capability [14], governance quality [15], and market responsiveness [16]. ER is defined as a firm's ability to resist, adapt to, and recover from external shocks while maintaining sustainable development [2], and has been widely linked to internal capabilities such as innovation [17], governance [18], and entrepreneurial resilience [19], as well as external institutional support [20]. However, existing studies have largely examined RDRI and ER separately, paying limited attention to how the regional digital ecosystem shapes ER. Moreover, RDRI is often conflated with firm-level digital transformation, despite the former emphasizing the coordinated development of digital and real economies rather than technology adoption by individual firms.

The resource-based view suggests that firms achieve sustainable competitive advantages by acquiring and utilizing valuable resources, whereas dynamic capability theory emphasizes firms' ability to integrate and reconfigure these resources in response to environmental changes. RDRI creates a favorable regional ecosystem by improving digital infrastructure, industrial Internet platforms, and data connectivity, enabling firms to access information, technologies, and complementary resources more efficiently [21]. Meanwhile, digital platforms facilitate knowledge spillovers, collaborative innovation, and real-time information sharing, allowing firms to sense environmental changes more rapidly, optimize resource allocation, and adjust production and supply-chain activities in response to external shocks [7]. Through the joint effects of resource enhancement and capability reconfiguration, RDRI strengthens firms' adaptive capacity under uncertainty.

Consequently, firms located in regions with a higher level of digital–real integration are better positioned to anticipate risks, absorb disruptions, and recover from crises, thereby improving ER. Based on the above analysis, the following hypothesis is proposed:

H1. RDRI positively enhances ER.

2.2. The Mediating Role of Resource Allocation

Efficient resource allocation is essential for ER because firms' ability to cope with external shocks depends not only on the quantity of resources they possess but also on how effectively these resources can be acquired, matched, and redeployed. Existing studies suggest that digital technologies improve resource allocation by facilitating information exchange, optimizing factor matching, and reducing resource misallocation [11]. However, most studies focus on the direct economic effects of digitalization, while little attention has been paid to how RDRI reshapes the regional factor allocation environment and consequently enhances ER.

RDRI promotes the integrated development of digital infrastructure, industrial networks, and data-sharing platforms, thereby improving the mobility and matching efficiency of production factors within regional industrial systems. As digital technologies become deeply embedded in the real economy, barriers to the circulation of information, technology, capital, and skilled labor are substantially reduced. This enables firms to identify complementary resources more efficiently and allocate production factors according to market demand rather than geographical or organizational constraints [14]. At the same time, digital connectivity strengthens coordination among upstream and downstream firms, allowing resources to be dynamically reallocated across supply chains and production networks in response to changing market conditions [22]. Such improvements reduce resource redundancy, alleviate factor mismatches, and enhance the overall efficiency of resource utilization.

More efficient resource allocation provides firms with greater operational flexibility and stronger adaptive capacity when facing external uncertainty. By rapidly mobilizing and reallocating critical resources, firms are better able to maintain production continuity, mitigate operational disruptions, and accelerate post-shock recovery. Therefore, resource allocation represents an important mechanism through which RDRI enhances ER. Based on the above analysis, the following hypothesis is proposed:

H2. Resource allocation mediates the relationship between RDRI and ER.

2.3. The Mediating Role of Firm Productivity

Firm productivity reflects a firm's ability to transform production inputs into economic outputs efficiently and constitutes an important foundation for ER. Existing studies suggest that digital technologies improve productivity by facilitating technological innovation, optimizing production processes, and enhancing operational efficiency [13]. At the regional level, digital–real integration promotes industrial collaboration and digital transformation, creating favorable conditions for productivity growth. However, the existing literature has mainly examined the direct productivity effects of digitalization, while the mediating role of firm productivity in linking RDRI to ER remains insufficiently explored.

RDRI improves firm productivity by reshaping regional production networks and facilitating knowledge diffusion across industries. The deep integration of digital technologies with the real economy promotes industrial collaboration through industrial Internet platforms, standardized data connectivity, and digital service platforms [8]. These developments enable firms to optimize production organization, reduce coordination costs, and improve operational efficiency. At the same time, enhanced data sharing and collaborative innovation accelerate the diffusion of digital technologies, managerial experience, and production knowledge across firms. Easier access to external knowledge lowers innovation costs, shortens technology commercialization cycles, and improves firms' capacity to absorb

and apply new technologies [17]. As firms continuously optimize production processes and strengthen innovation capability, productivity increases, providing stronger operational support for coping with external uncertainty.

Higher productivity enables firms to generate greater output with given resources, maintain stable operations under external shocks, and recover more rapidly from market disruptions. Consequently, improvements in firm productivity constitute an important mechanism through which RDRI enhances ER. Based on the above analysis, the following hypothesis is proposed:

H3. *Firm productivity mediates the relationship between RDRI and ER.*

2.4. The Mediating Role of Financing Constraints

Financing constraints are widely recognized as a major obstacle to ER because insufficient financial resources limit firms' capacity to invest in technological innovation, maintain stable operations, and respond to unexpected disruptions. Existing studies have shown that digital technologies and digital finance improve firms' access to external financing by enhancing information transparency, expanding financing channels, and reducing financing costs [23]. Nevertheless, previous research has primarily focused on the direct relationship between digital finance and corporate financing, while limited attention has been paid to whether RDRI alleviates financing constraints through improvements in the regional digital and financial ecosystem, thereby enhancing ER.

RDRI facilitates the deep integration of digital technologies with regional financial services, improving the efficiency of information transmission and financial resource allocation. Through digital infrastructure, industrial Internet platforms, and integrated data-sharing systems, firms generate more comprehensive and reliable operational information, enabling financial institutions to evaluate credit risk more accurately and reducing information frictions between borrowers and lenders [23]. Improved information transparency lowers financing uncertainty, broadens firms' access to formal financing channels, and reduces financing costs. Meanwhile, digital platforms simplify financing procedures and accelerate credit approval, allowing firms to obtain financial resources more efficiently. Greater financial accessibility enables firms to sustain investment in technological innovation, optimize production activities, and maintain operational stability during periods of economic uncertainty.

By alleviating financing constraints, firms are better equipped to absorb external shocks, recover from temporary disruptions, and pursue long-term development despite uncertain market conditions. Therefore, financing constraints constitute an important transmission mechanism through which RDRI enhances ER. Based on the above analysis, the following hypothesis is proposed:

H4. *Financing constraints mediate the relationship between RDRI and ER.*

3. Research Design

3.1. Model Specification

To examine the impact of RDRI on ER, this paper constructs Model (1) for the baseline regression:

$$ER_{it} = \alpha + \beta_1 RDRI_{it} + Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (1)$$

where the subscript i denotes industry and t denotes year; ER_{it} is the dependent variable; $RDRI_{it}$ is the core explanatory variable; β_1 is the estimated coefficient; $Control_{it}$ is the set of control variables; μ_i and σ_t denote the industry and year fixed effects, respectively; and ε_{it}

is the random error term. We use city-level clustering. Here, β_1 is the coefficient on the core explanatory variable of interest. If the coefficient of β_1 is positive, it indicates that RDRI can enhance ER, supporting the theoretical expectation of this paper [24].

In Model (1), industry and year fixed effects are included to control for unobservable heterogeneity across industries and common macroeconomic shocks over time, respectively. In addition, a comprehensive set of city-level economic characteristics is incorporated to account for observable regional differences and reduce potential omitted-variable bias. Since RDRI is measured at the city-year level, its identifying variation arises primarily from differences across cities and changes over time. Introducing city fixed effects would absorb most of the cross-sectional variation in RDRI, while firm fixed effects would substantially reduce the effective variation available for identification, given that firms are nested within cities. Therefore, following the identification strategy adopted in related regional-level studies, this paper employs industry and year fixed effects together with multidimensional control variables. This specification preserves sufficient identifying variation in the core explanatory variable while helping to mitigate omitted-variable bias, thereby ensuring the reliability of the estimation results. Nevertheless, to ensure the robustness of our findings, additional robustness tests are conducted using alternative model specifications.

3.2. Selection of Variables

3.2.1. Dependent Variable

ER refers to a firm's ability to withstand and recover from sudden shocks or chronic pressures while maintaining continuous growth and innovation. In this study, ER is defined as the capacity for resistance, recovery, development, and innovation demonstrated by a firm when facing crises. Drawing on existing literature [25], we construct a multidimensional evaluation framework for ER. First, resistance capacity captures a firm's ability to survive and maintain stable operations when confronted with risks or external shocks. Second, recovery capacity captures the ability to restore normal operations by adjusting long-term strategic goals and integrating resources after a shock. Third, development capacity reflects a firm's ability to expand its scale and strengthen market competitiveness after recovering from pressure. Finally, innovation capacity measures the ability to sustain innovation activities while withstanding shocks and resuming development.

The indicator system incorporates both financial and governance dimensions, as financial soundness provides the resources required to withstand disruptions, while effective governance enhances organizational adaptability and decision-making efficiency. Consistent with existing studies, liquidity and leverage indicators are included as key dimensions of financial resilience [26]. Innovation capability is measured by the number of authorized invention patents rather than research and development (R&D) expenditure or patent applications. Authorized invention patents represent innovation outputs that have undergone substantive examination and therefore better capture the quality of technological innovation. In contrast, R&D expenditure reflects innovation inputs, whereas patent applications may include low-quality patents and do not adequately reflect innovation efficiency [27]. Although this measure may not fully capture non-patent innovation activities, it provides a more reliable indicator of firms' effective innovation capability. Following previous studies, the entropy weight method is employed to determine the weights of individual indicators and construct the composite ER index [26]. The detailed indicator system is presented in Table 1.

Table 1. ER indicator system.

Primary Indicators	Secondary Indicators	Calculation Method	Attribute
Resilience capacity	Financial vitality	Current assets/Current liabilities	Positive
	Debt-to-equity ratio	Debt-to-equity ratio	Negative
	Potential resources	Cash and cash equivalents/(Total assets–Cash and cash equivalents)	Positive
Recovery capacity	Net operating profit margin	Net profit/Revenue	Positive
	Total asset turnover ratio	Revenue/Total assets at end of period	Positive
	Fixed asset turnover ratio	Revenue/Net fixed assets at end of period	Positive
	Quality of workforce	Number of employees with a bachelor's degree or higher/Total number of employees	Positive
Development capacity	Profit per employee	Net profit/Number of employees	Positive
	Governance structure	Equity balance: Shareholding ratio of the second to fifth largest shareholders/Shareholding ratio of the largest shareholder	Positive
Innovation capacity	Innovation quality	The number of invention patents granted during the year	Positive

ER is theoretically constructed from four dimensions, namely resilience, recovery, development, and innovation. As an objective weighting approach, the entropy weight method determines indicator weights according to the information provided by the sample data. Owing to the highly skewed distribution of authorized invention patents, the entropy weight method assigns a relatively lower weight to the innovation dimension. This reflects the statistical characteristics of the sample rather than the theoretical importance of innovation. To examine whether the relatively low weight assigned to the innovation dimension affects the empirical results, we reconstruct the ER index using an alternative measurement approach. The estimation results remain qualitatively unchanged.

3.2.2. Explanatory Variable

RDRI refers to the mutual promotion and coordination between the regional digital economy and the real economy to achieve deep integration. This paper uses the city-level degree of coordinated development between the digital economy and the real economy as the core explanatory variable to measure the extent of digital–real integration, thereby objectively reflecting cross-regional differences in integration levels. Drawing on Shen et al. [28], we construct a comprehensive index for digital economy development and a comprehensive index for real economy development. Specifically, the digital economy evaluation framework includes four dimensions: digital infra-structure, scale of digital business, digital application environment, and digital innovation environment, with a total of 11 secondary indicators. The real economy framework includes three dimensions: structure, scale, and benefits of the real economy, with a total of five secondary indicators (see Table 2). The digital economy subsystem is characterized by indicators of digital infrastructure and digital application capability, whereas the real economy subsystem captures the production foundation and development capacity of the regional economy. These variables constitute the necessary basis for assessing coordination between the two subsystems.

Table 2. RDRI indicator system.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Entropy-Weighted Method
Digital economy	Digital infrastructure	Internet broadband port density	0.0203
		Long-distance optical cable line density	0.0243
		Number of domain names	0.0470
		Number of IPv4 addresses	0.1080
	Scale of digital business	Per capita telecommunications service volume	0.1683
		Proportion of workforce in the information technology sector	0.0128
	Digital application environment	Internet broadband penetration rate	0.1278
		Mobile phone penetration rate	0.0301
		Per capita express delivery volume	0.0067
		Digital inclusive finance index	0.1196
	Digital innovation environment	Number of domestic patent applications	0.3351
Real economy	Structure of the real economy	Share of secondary industry value added in GDP	0.0332
		Share of value added by the tertiary sector in GDP	0.0425
	Scale of the real economy	Number of industrial enterprises above designated size	0.3524
		Total output value of industrial enterprises above designated size	0.1572
	Benefits to the real economy	Total retail sales of consumer goods	0.4147

Note: The weights are objectively determined using the entropy method; the weights within the two subsystems—the digital economy and the real economy—are each summed to give a total of 1.

In terms of methodology, we use the entropy weight method to standardize and weight the indicators within each dimension and derive separate development indices for the digital economy and real economy. On this basis, we introduce the coupling coordination model to measure city-level digital–real integration and construct the RDRI index. Rather than measuring digitalization in isolation, this model evaluates the extent to which the two subsystems evolve in a balanced and coordinated manner. The final integration index is determined by the coupling coordination degree rather than any single indicator [29]. The calculation is as follows:

$$RDRI = \sqrt{C \times (\alpha \cdot DE + \beta \cdot RE)} \quad (2)$$

$$C = \frac{DE \times RE}{\left(\frac{DE+RE}{2}\right)^2} \quad (3)$$

Here, *RDRI* represents the degree of integration between the digital and real economies; a higher value indicates a higher level of integration. *DE* and *RE* denote the levels of digital and real economic development, respectively. α and β are the weighting coefficients for digital and real economic development, respectively, and reflect their relative importance in the integration measure. Following prior research [28], this study assigns equal weights ($\alpha = \beta = 0.5$) to the digital economy and the real economy when constructing the RDRI index. This specification is consistent with the theoretical premise

of the coupling coordination model, which emphasizes the balanced and coordinated development of the two subsystems rather than their individual development levels. Equal weighting therefore provides a neutral benchmark for assessing their degree of integration. To ensure that the results are not sensitive to this specification, we further conduct robustness tests using alternative unequal weighting schemes, and the main findings remain qualitatively unchanged.

The construction of the composite indices may be subject to potential measurement errors arising from data normalization, entropy weighting, and the coupling coordination model. To mitigate these concerns, all variables are normalized after 1% winsorization, objective entropy weights are employed, and robustness tests using alternative dependent-variable measures and weighting schemes are conducted. The results remain qualitatively unchanged, indicating that the empirical findings are not sensitive to the measurement procedures.

3.2.3. Control Variables

Drawing on existing research [30], this paper selects the following control variables: firm size (Size, measured as the natural logarithm of annual total assets), return on equity (ROE, net profit/average annual equity), cash flow ratio (CashFlow, net cash flow/total assets), largest shareholder's stake (Top1, shares held by the largest shareholder/total shares), board size (Board, natural logarithm of the number of board members), per capita gross domestic product (PGDP, city GDP/city permanent resident population), revenue growth rate (Growth, current-year revenue/previous-year revenue $- 1$), years listed (Listage, $\ln(\text{current year} - \text{listing year} + 1)$), ownership type (SOE, 1 for state-controlled firms and 0 otherwise), debt-to-asset ratio (LEV, total liabilities/total assets), population (POP, total permanent resident population of the city), and industrial structure (IS, value added of the tertiary sector/value added of the secondary sector).

3.2.4. Institutional Variables

Resource allocation (reop). Following Crossland et al. [31], this paper measures strategic resource allocation adjustment and novelty using four indicators and the deviation of each from both the firm's own and industry averages, in order to capture whether resource allocation has improved. The four indicators are the advertising expenditure ratio (advertising expenditure/operating revenue), R&D expenditure ratio (R&D expenditure/operating revenue), equipment novelty (net fixed assets ratio), and capital investment intensity (fixed assets/number of employees). First, we calculate the absolute difference between the values of these four indicators in year t and year $t - 1$. We then take the logarithm, standardize the results, and sum them to obtain a single index. This index is compared with the mean of firms in the same year and industry, yielding the firm's resource-allocation index (reop). The index captures how a firm's resource allocation in a given year deviates from both its own prior-year allocation and the industry's prevailing allocation pattern.

Firm productivity (TFP_OP and TFP_LP). Existing research typically uses semiparametric methods, namely the OP and LP methods, to estimate total factor productivity. These methods effectively address the endogeneity and sample-selection problems associated with traditional econometric approaches. To better test whether RDRI enhances ER by improving firm productivity, this paper follows Levinsohn et al. [32] and uses TFP estimated by both the OP and LP methods as proxy variables for firm productivity.

Financing constraints (WW). Drawing on Whited et al. [33], this paper uses the WW index to measure firms' financing constraints. A higher index value indicates stronger financing constraints.

3.3. Data Sources

This study examines the impact of RDRI on ER and its underlying mechanisms using Chinese A-share listed manufacturing firms from 2011 to 2023 as the research sample. All data for the dependent, explanatory, and control variables are drawn from the China Stock Market & Accounting Research Database (CSMAR). To ensure accuracy and reduce the influence of outliers, we exclude ST, *ST, and PT firms during the sample period, remove observations from financial and insurance firms, and drop observations with missing or abnormal key variables. This study matches city-level RDRI to each firm using the registered address reported in CSMAR, following the standard practice in the literature. This provides a stable and legally defined geographic identifier for spatial matching. We also winsorize the core continuous variables at the 1% level on both tails. The final sample contains 20,800 valid observations.

4. Empirical Analysis

4.1. Descriptive Statistics

Table 3 reports the descriptive statistics of the main variables. The mean value of RDRI is 37.1491, with a standard deviation of 55.7077, indicating substantial heterogeneity across city-year observations. The relatively wide range of RDRI values is attributable to the nonlinear transformation embedded in the coupling coordination model, which amplifies differences in the coordinated development of the digital and real economy subsystems. The mean value of ER is 0.5127, with a standard deviation of 0.2229, ranging from 0.1310 to 0.9156, suggesting considerable heterogeneity among listed firms. Overall, the descriptive statistics demonstrate adequate variation in the main variables for subsequent regression analysis.

Table 3. Descriptive statistics.

Variable	Sample Size	Mean	Standard Deviation	Minimum	Median	Maximum
ER	20,800	0.5127	0.2229	0.1310	0.4875	0.9156
RDRI	20,800	37.1491	55.7077	0.0202	10.6540	223.2927
Size	20,800	22.1291	1.1711	20.0355	21.9547	25.7436
ROE	20,800	0.0544	0.1275	−0.6366	0.0654	0.3208
CashFlow	20,800	0.0506	0.0644	−0.1261	0.0479	0.2264
Top1	20,800	0.3296	0.1408	0.0863	0.3078	0.7132
Board	20,800	2.1030	0.1915	1.6094	2.1972	2.5649
PGDP	20,800	0.3776	0.0541	0.3333	0.3636	0.5714
Growth	20,800	0.1423	0.3159	−0.4782	0.0984	1.6620
Listage	20,800	2.0797	0.7866	0.6931	2.0794	3.3673
SOE	20,800	0.2817	0.4498	0.0000	0.0000	1.0000
LEV	20,800	0.3920	0.1903	0.0589	0.3833	0.8600
POP	20,800	1.8833	0.8949	1.0560	1.6197	6.6641
IS	20,800	0.0388	0.0611	−0.2009	0.0387	0.1902

4.2. Correlation Analysis

To assess potential information redundancy among the indicators, this study follows previous research [34] by examining the Pearson correlation matrix for the 16 underlying indicators. As shown in Table 4, only a few pairs of aggregate indicators exhibit correlation coefficients above 0.7, whereas the majority remain at low or moderate levels, indicating limited redundancy within the indicator system. In addition, the entropy weight method assigns weights according to the informational variation in each indicator rather than their covariance structure, making the weighting process less affected by moderate inter-

indicator correlations. Since the digital economy and real economy subsystem indices are constructed separately before calculating the coupling coordination index, moderate correlations among indicators within each subsystem do not compromise the validity of the composite indices. Overall, the results suggest that information redundancy and multicollinearity are unlikely to materially affect the measurement of RDRI.

Table 4. Pearson correlation coefficient matrix for individual indicators.

Indicators	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1.00															
2	0.27	1.00														
3	0.21	0.69	1.00													
4	0.30	0.62	0.52	1.00												
5	0.16	0.31	0.27	0.56	1.00											
6	0.77	0.22	0.18	0.37	0.23	1.00										
7	0.14	0.30	0.30	0.35	0.48	0.19	1.00									
8	0.48	0.19	0.15	0.28	0.21	0.64	0.20	1.00								
9	0.66	0.44	0.36	0.50	0.43	0.76	0.47	0.57	1.00							
10	0.27	0.48	0.41	0.72	0.77	0.34	0.59	0.30	0.60	1.00						
11	0.06	0.10	0.10	0.19	0.06	0.06	0.08	0.09	0.08	0.15	1.00					
12	−0.33	−0.09	−0.13	−0.17	−0.25	−0.44	−0.28	−0.33	−0.37	−0.22	−0.03	1.00				
13	0.52	0.41	0.37	0.40	0.44	0.61	0.47	0.48	0.70	0.51	0.07	−0.77	1.00			
14	0.22	0.47	0.34	0.59	0.46	0.24	0.35	0.22	0.56	0.75	0.08	−0.01	0.32	1.00		
15	0.54	0.50	0.41	0.49	0.40	0.52	0.37	0.35	0.67	0.59	0.09	0.03	0.41	0.52	1.00	
16	0.28	0.41	0.33	0.57	0.79	0.34	0.65	0.34	0.68	0.87	0.09	−0.28	0.58	0.71	0.56	1.00

Note: 1 = Internet broadband port density; 2 = long-distance optical cable line density; 3 = number of domain names; 4 = number of IPv4 addresses; 5 = per capita telecommunications service volume; 6 = proportion of workforce in the information technology sector; 7 = Internet broadband penetration rate; 8 = mobile phone penetration rate; 9 = per capita express delivery volume; 10 = digital inclusive finance index; 11 = number of domestic patent applications; 12 = share of secondary industry value added in GDP; 13 = share of value added by the tertiary sector in GDP; 14 = number of industrial enterprises above designated size; 15 = total output value of industrial enterprises above designated size; 16 = total retail sales of consumer goods.

4.3. Baseline Regression

Table 5 reports the baseline regression results. Columns (1) and (2) show that, before and after controlling for additional variables, the effect of RDRI on ER is significantly positive. This indicates that RDRI can significantly enhance ER. Hypothesis 1 is therefore supported.

Table 5. Baseline regression.

	(1) ER	(2) ER
RDRI	0.0102 ** (2.1638)	0.0095 ** (2.2702)
Size		1.0734 *** (11.0138)
ROE		1.5115 ** (2.1897)
CashFlow		−1.7995 *** (−2.7352)
Top1		−2.2090 *** (−41.7763)
Board		1.3164 *** (3.0965)
PGDP		4.3036 *** (2.7221)
Growth		0.2318 ** (2.3704)
Listage		−1.8669 *** (−17.0032)

Table 5. *Cont.*

	(1) ER	(2) ER
SOE		1.0528 *** (5.6979)
LEV		−6.2275 *** (−5.3515)
POP		0.4928 *** (3.2553)
IS		−0.9042 (−0.4568)
Constant term	9.5009 *** (60.0587)	−6.2299 ** (−2.4296)
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Sample size	20,800	20,800
R ²	0.132	0.466

Note: **, *** indicate significance at the 5% and 1% levels, respectively; figures in brackets are standard errors following clustering at the city level.

4.4. Robustness Tests

4.4.1. Heteroscedasticity Robustness Test

To examine the sensitivity of the RDRI index to alternative weighting schemes, the RDRI is reconstructed using two unequal weighting specifications ($\alpha:\beta = 0.6:0.4$ and $\alpha:\beta = 0.4:0.6$), and the resulting indices are re-estimated using the baseline regression model. As reported in Table 6, the estimated coefficients of RDRI remain positive and statistically significant at the 5% level under all three weighting schemes. These results indicate that the positive effect of RDRI on ER is robust to alternative weighting specifications.

Table 6. Regression results under different weighting schemes.

Weighting Settings ($\alpha:\beta$)	RDRI	t	R ²
0.5:0.5	0.0095 **	(2.2702)	0.466
0.6:0.4	0.0109 **	(2.2699)	0.466
0.4:0.6	0.0084 **	(2.2718)	0.466

Note: ** indicates significance at the 5% level; figures in brackets are standard errors following clustering at the city level.

4.4.2. Changing the Dependent Variable

To further test the robustness of the baseline results, following Zhou et al. [35], we construct an ER index based on two dimensions, bounce-back resilience and bounce-forward resilience, to capture a firm's risk-bearing capacity under uncertainty. This indicator system reduces interference from non-resilience factors associated with a firm's intrinsic characteristics and the external environment, and it covers the dynamic evolution of resilience more comprehensively. The results in column (1) of Table 7 show that the coefficients on the core explanatory variable remain significantly positive, confirming the robustness of the baseline findings.

Table 7. Robustness tests.

	(1) Replacing the Dependent Variable	(2) Clustering at the Firm-Year Level	(3) Excluding Samples from Municipalities Directly Under the Central Government	(4) Excluding 2020	(5) One-Period Lag
RDRI	0.0200 *** (3.8640)	0.0095 *** (6.1959)	0.0057 ** (1.9761)	0.0102 ** (2.3758)	0.0142 *** (3.2272)
Constant term	74.1279 *** (9.3302)	−6.2299 ** (−2.8502)	−4.1494 * (−1.7605)	−6.0628 ** (−2.3153)	−6.8202 ** (−2.4330)
Control variable	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Fixed effects for the year	Yes	Yes	Yes	Yes	Yes
Sample size	20,800	20,800	17,437	18,899	17,685
R ²	0.303	0.466	0.445	0.467	0.395

Note: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively; figures in brackets are standard errors following clustering at the city level.

4.4.3. Changing the Clustering Level

In empirical analysis, biased clustered standard errors may lead to incorrect judgments about statistical significance and thus distort the estimated impact of RDRI on ER. To address this possibility, we re-cluster standard errors at multiple levels, including the firm and year levels. This multi-level clustering approach reduces the risk of misjudgment caused by clustering bias and ensures robustness. The results in column (2) of Table 7 show that the coefficients on the core explanatory variable remain significantly positive, strengthening confidence in the findings.

4.4.4. Treatment of Special Samples

Municipalities directly under the central government have higher economic development, faster digitalization, and better human capital conditions than other cities during the digital–real integration process, which may introduce estimation bias in the core explanatory variable. Therefore, we exclude Beijing, Shanghai, Tianjin, and Chongqing from the sample and re-run the regression. The results in column (3) of Table 7 show that the coefficients on the core explanatory variable remain significantly positive, indicating that the findings are robust.

4.4.5. Adjustment for Sample Period

The COVID-19 pandemic affected all regions of China most severely in 2020. Business-operation data and regional economic development in that year deviated from normal conditions, making it difficult to identify the true effect of RDRI on ER. To avoid this external disturbance, we exclude the 2020 sample and re-run the regression. As shown in column (4) of Table 7, the coefficients on the core explanatory variable remain significantly positive, further confirming the robustness of the baseline results.

4.4.6. Explanatory Variables Lagged by One Period

RDRI is a complex and gradual process, and its economic effects do not materialize immediately but rather exhibit a lag. We therefore lag the explanatory variable by one period and re-run the regression. The results in column (5) of Table 7 show that the coefficients on the core explanatory variable remain significantly positive, indicating that RDRI can enhance ER.

The estimation results reported in Table 7 remain qualitatively consistent across a series of robustness checks. Excluding municipalities directly under the central government and omitting observations from the COVID-19 period produce coefficients that remain positive

and statistically significant, indicating that the baseline findings are not driven by regional heterogeneity or pandemic-related shocks. Similarly, replacing the dependent variable with an alternative measure of ER and introducing a one-period lag of the explanatory variable yield consistent estimation results. The variation in the estimated coefficients primarily reflects differences in sample composition and model specification rather than changes in the underlying relationship. Across all robustness checks, the estimated coefficients remain positive and statistically significant, confirming the stability of the positive association between RDRI and ER. Minor differences in coefficient magnitude are expected because alternative samples and model specifications capture different sources of variation in the data. Overall, these results provide strong evidence for the robustness of the baseline findings.

4.5. Endogeneity Tests

To address potential endogeneity, this study follows Zhao et al. [36] and employs the historical number of fixed-line telephones per 100 inhabitants as an instrumental variable (IV). Historical telephone penetration captures the initial level of regional telecommunications infrastructure, which laid the foundation for subsequent digital infrastructure development and is therefore strongly associated with current RDRI. At the same time, its direct influence on contemporary ER is unlikely after controlling for city-level characteristics, making the exclusion restriction plausible. Following previous studies, the 1984 telephone penetration rate is interacted with the number of Internet broadband access ports to construct a time-varying instrument for panel estimation.

Table 8 reports the IV estimation results. The Kleibergen–Paap rk Wald F-statistic is 65.619, well above the conventional critical value of 16.38, indicating that weak instruments are not a concern. The Kleibergen–Paap rk LM statistic rejects the null hypothesis of underidentification. The second-stage results show that the coefficient of RDRI remains positive and statistically significant at the 1% level, confirming the robustness of the baseline findings after accounting for potential endogeneity.

Table 8. Endogeneity tests.

	(1) RDRI Stage 1	(2) ER Stage 2
RDRI		0.0162 *** (0.0047)
IV	0.0039 *** (0.0005)	
IMR		
Control variable	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Sample size	20,800	20,800
Kleibergen–Paap rk LM statistic	4.597	
Kleibergen–Paap rk Wald F statistic	65.619	

Note: *** indicates significance at the 1% levels; figures in brackets are standard errors following clustering at the city level.

5. Heterogeneity Analysis and Mechanism Testing

5.1. Heterogeneity Analysis

5.1.1. Regional Geographical Heterogeneity

Eastern and central–western China differ in digital infrastructure, industrial structure, and institutional environment, so the effect of RDRI on ER may vary across regions. We divide China into eastern and central–western regions to test for geographic heterogeneity.

Columns (1) and (2) of Table 9 report the results. The effect of digital–real integration is stronger in eastern China than in central–western China. Specifically, RDRI enhances firms’ risk resilience and recovery capabilities more effectively in eastern China because its digital infrastructure is more advanced. In 2024, eastern China accounted for 51% of the nation’s telecommunications-service revenue, while central and western China accounted for 19.7% and 24.1%, respectively [37]. Eastern China also had the highest mobile Internet traffic, reaching 140.7 billion gigabytes, far exceeding the volumes in central and western China [37]. As a result, manufacturing firms in eastern China face lower costs and greater benefits when accessing digital information, making it easier to adopt digital technologies to optimize production and improve resource efficiency. In terms of industrial structure, RDRI also has a stronger effect in eastern China. By contrast, its enabling effect in central and western China remains limited. Eastern China hosts high-end manufacturing and modern service industries, with legal entities in the secondary and tertiary sectors accounting for more than 50% of the national total and a high rate of digital penetration [38]. In central and western China, resource-based industries and traditional services still dominate, and digitalization levels are lower. As a result, RDRI in eastern China can more quickly optimize production processes, supply chains, and early-warning systems. Finally, in terms of the institutional environment, RDRI is more effective in eastern China because the region has a more complete digital policy framework. This framework includes subsidies, pilot programs, and performance-based incentives. It also facilitates collaboration among government, firms, and universities in building digital platforms, promotes data and resource sharing, and helps establish risk early-warning systems. Together, these factors strengthen firms’ risk prevention and control capabilities [39].

Table 9. Heterogeneity analysis.

	(1) Eastern	(2) Central and Western Regions	(3) Capital- Intensive	(4) Labor- Intensive	(5) State- Owned	(6) Non-State- Owned	(7) High-Tech Industries	(8) Non-High- Tech Industries
RDRI	0.0098 *** (2.6785)	0.0093 * (1.8206)	0.0117 *** (2.8757)	0.0085 ** (2.0868)	0.0100 ** (2.2372)	0.0092 ** (2.4138)	0.0108 ** (2.1609)	0.0024 (1.3241)
Constant term	−7.9291 *** (−2.7110)	−1.9549 (−0.4749)	−5.4318 * (−1.7322)	−6.2749 ** (−2.1440)	−7.0918 ** (−2.1678)	−3.2432 (−1.0901)	−7.3637 ** (−2.5706)	−0.3427 (−0.1074)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects for the year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	13,825	6973	9446	11,352	5858	14,940	16,849	3946
R ²	0.485	0.448	0.477	0.474	0.447	0.499	0.450	0.504

Note: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively; figures in brackets are standard errors following clustering at the city level.

5.1.2. Heterogeneity in Enterprise Factor Density

Factor intensity differs across firms in terms of integration needs and resource inputs, so the effect of RDRI on ER may also vary by factor intensity. Following Qiao et al. [40], we use the natural logarithm of the ratio of a firm’s net fixed assets to its number of employees as the measure of factor intensity. Firms above the median are classified as capital-intensive, and those below the median are classified as labor-intensive. Columns (3) and (4) of Table 9 report the results for factor–intensity heterogeneity. Compared with labor-intensive firms, the effect is more significant for capital-intensive firms, suggesting that RDRI has a stronger impact on their resilience. In terms of integration demand, capital-intensive firms have a stronger need for digital transformation because they are concentrated in sectors such as

automobiles, electronics, information technology, and equipment manufacturing, where production processes are complex, precision requirements are high, and equipment is large-scale. Digital technologies can directly improve efficiency, quality, and equipment utilization. By contrast, labor-intensive firms, which are concentrated in clothing, light industry, and traditional processing, have a lower demand for transformation. Their many non-standardized production stages rely heavily on manual work, making digital technologies harder to replace at scale. In terms of resource investment, capital-intensive firms are better able to absorb the initial costs of RDRI because they have larger asset bases and more stable capital. They can fund industrial investment, technology upgrading, and digital industrial park construction more easily. They also usually have stronger digital foundations, more complete R&D teams, and more high-skilled talent, which supports the broad application of digital technology and improves intelligent production, management, and decision-making capabilities [40]. By contrast, labor-intensive firms often find digital–real integration more difficult because they have smaller asset bases and less stable financing. They face substantial fixed costs for hardware procurement, network upgrades, and data center construction. Combined with long investment cycles and uncertain short-term returns, these costs make large-scale, long-term upfront investment difficult. At the same time, these firms usually have weaker digital capabilities and a shortage of specialized digital and high-skilled talent.

5.1.3. Heterogeneity of Enterprise Ownership Structures

State-owned and non-state-owned firms differ in policy support and competitive pressure, so their resilience effects may also vary. At the policy level, the difference reflects policy positioning and resource support. State-owned firms are the main force in local government-led digital–real integration, and their performance is more directly linked to the achievements of their leaders, which gives them stronger execution capacity. Governments are also more likely to provide state-owned firms with financial, technical, and equipment support [41]. By contrast, non-state-owned firms mainly advance digital–real integration on their own according to development needs and receive less policy support. In market competition, SOEs often occupy monopolistic positions and face weaker competitive pressure, allowing them to concentrate resources on digital–real integration. Non-state-owned firms operate in highly competitive markets with many peers, so they emphasize short-term returns and have weaker risk-bearing capacity [42]. Columns (5) and (6) of Table 9 report the ownership-heterogeneity results. The coefficients are significantly positive for both types of firms at the 5% level, but the coefficient for SOEs is larger. This suggests that digital–real integration has a stronger effect on SOE resilience because the channels of influence differ. SOEs respond more rapidly through policy support and use their advantages in technology, capital, and talent to accelerate integration, improve efficiency and risk management, maintain supply-chain stability, and strengthen resilience. By contrast, market competition drives non-state-owned firms. They use digital–real integration to overcome resource constraints, optimize business models, and reduce operating costs, thereby compensating for weaker policy support and scale and ultimately improving resilience.

5.1.4. Industry Heterogeneity

There are substantial differences between high-tech and non-high-tech industries in the concentration of innovative factors and the synergy of industrial ecosystems, so the effect of RDRI on ER also varies by industry. Following Zheng et al. [43], we classify the sample into high-tech and non-high-tech firms. Columns (7) and (8) of Table 9 report the industry-heterogeneity results. The coefficient of digital–real integration is significantly

positive for high-tech firms but insignificant for non-high-tech firms, indicating that RDRI is more conducive to improving the resilience of high-tech firms. First, high-tech firms have a strong demand for innovative factors. Because they are often located in regions with dense innovation resources, digital–real integration is easier to realize. Such regions usually have many universities and research institutes, which support industry–academia–research collaboration. This collaboration promotes the integration of digital technologies into production, management, and decision-making, thereby improving the quality of digital–real integration [43]. These regions also attract digital-talent inflows, creating a virtuous cycle that strengthens innovation capacity and resilience. By contrast, non-high-tech firms usually rely on traditional operating models. They have lower demand for innovation factors and often locate near raw-material and labor markets, making it harder to attract technology, platforms, and high-end talent. As a result, factor aggregation is fragmented and digital transformation is slow. Second, RDRI is more effective for high-tech firms because they typically occupy a leading position within industrial clusters. They can use digital technology as a link to build collaborative ecosystems with upstream and downstream firms, break down information barriers, and improve resource-allocation efficiency. Non-high-tech firms, by contrast, remain constrained by the traditional division of labor and cooperation. They passively accept technical standards and rarely engage in data sharing or joint development of digital supply chains. Their collaboration is often short-term, offline, and weakly interconnected, making it difficult to build intelligent industrial collaboration systems.

5.2. Mechanism Testing

Theoretical analysis suggests that RDRI affects ER through three channels: optimizing resource allocation, improving firm productivity, and easing financing constraints. This section examines the effect of RDRI on these mechanism variables and estimates the following mechanism-testing model:

$$M_{it} = \alpha + \beta_1 RDRI_{it} + Control_{it} + \mu_i + \sigma_t + \varepsilon_{it} \quad (4)$$

Here, M_{it} represents the mechanism variable, while the remaining variables are consistent with the baseline regression model. This section considers three mechanism variables. Columns (1) and (2) of Table 10 present the results of the mediation tests for resource allocation. In column (1), the regression coefficient for the core explanatory variable RDRI is significantly positive. In column (2), the regression coefficients for both RDRI and resource allocation are significantly positive. This indicates that RDRI can optimize resource allocation, which validates the mechanism through which RDRI enhances ER through the optimization of resource allocation. Hypothesis 2 is therefore supported.

Columns (3), (4), (5) and (6) of Table 10 present the results of the mediation analysis for firm productivity. In columns (3) and (5), the regression coefficients for the core explanatory variable—RDRI—are significantly positive. In columns (4) and (6), the regression coefficients for both RDRI and firm productivity are significantly positive. This indicates that RDRI can enhance firm productivity, which validates the mechanism whereby RDRI boosts ER by improving firm productivity. Hypothesis 3 is thus confirmed.

Columns (7) and (8) of Table 10 present the results of the mediation analysis for financing constraints. In column (7), the regression coefficient for the core explanatory variable—RDRI—is significantly negative at the 1% level. In column (8), the regression coefficients for both RDRI and financing constraints are significantly negative. This indicates that RDRI helps alleviate firms' financing pressures, which validates the mechanism whereby RDRI enhances ER by easing financing constraints. Hypothesis 4 is supported.

Table 10. Mechanism analysis.

	(1) Resource Allocation	(2) ER	(3) Firm Productivity (OP)	(4) ER	(5) Firm Productivity (LP)	(6) ER	(7) Financing Constraints	(8) ER
RDRI	0.0005 *	0.0094 **	0.0008 **	0.0083 **	0.0007 ***	0.0089 **	−0.0024 ***	0.0089 **
Resource allocation	(1.7462)	(2.2712)	(2.2060)	(2.1826)	(3.7907)	(2.1295)	(−5.9959)	(2.1189)
Firm productivity (OP)		0.2390 ***		1.6059 ***				
		(8.7303)		(8.1214)				
Firm productivity (LP)						0.8220 ***		
						(5.6044)		
Financing constraints								−0.2499 ***
Constant term	−0.8023 *	−6.0382 **	−2.6163 ***	−2.0283	−5.1713 ***	−1.9791	−21.7954 ***	−11.6773 ***
	(−1.9372)	(−2.3881)	(−13.6301)	(−0.8227)	(−28.2506)	(−0.7451)	(−19.0671)	(−4.5219)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects for the year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	20,800	20,800	20,800	20,800	20,800	20,800	20,800	20,800
R ²	0.098	0.470	0.694	0.483	0.808	0.471	0.330	0.479

Note: *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively; figures in brackets are standard errors following clustering at the city level.

The estimated coefficients of the three mediating variables vary in magnitude, which may reflect differences in their measurement characteristics and underlying transmission processes. For example, the WW index is an indirect proxy for financing constraints and is more susceptible to measurement error than the other mediators, potentially leading to more conservative coefficient estimates. By contrast, resource allocation and firm productivity are more directly linked to firms' operational performance and therefore exhibit relatively stronger estimated relationships with ER. Nevertheless, differences in coefficient magnitude should not be interpreted as evidence of differences in the relative importance of the mediating mechanisms. Accordingly, this study emphasizes the existence and statistical significance of each mediation pathway rather than comparing their effect sizes.

6. Conclusions and Policy Recommendations

6.1. Conclusions

RDRI plays an important role in determining the quality and competitiveness of firm development. Against the backdrop of accelerated global industrial-chain restructuring, uncertainty has risen sharply, making it urgent to examine whether and how RDRI enhances ER. Using city-level macro data from 2011 to 2023 and micro data from A-share listed manufacturing firms, this paper constructs evaluation index systems for RDRI and ER. We measure city-level RDRI, build a two-way fixed-effects model, and examine the mechanisms through which RDRI affects ER. The results show that RDRI significantly enhances ER. We further examine heterogeneous effects from four perspectives: geographical location, factor intensity, ownership structure, and industry type. The results show that the positive effects of RDRI are stronger for firms in eastern China, capital-intensive firms, SOEs and high-tech firms. Mechanism analysis shows that RDRI enhances ER by optimizing resource allocation, improving firm productivity, and easing financing constraints.

6.2. Policy Recommendations

First, the government should improve resource allocation to strengthen the foundation of ER. It should expand digital infrastructure in small and medium-sized cities and remote areas of central and western China, and promote the industrial Internet, 5G, and big data centers. This will lower firms' barriers to accessing digital resources. The government

also needs to integrate industrial data and market information to break down silos and enable efficient resource matching. In addition, it should implement differentiated digital-transformation policies, supporting capital-intensive firms in building smart factories and digital workshops while providing low-cost digital tools for labor-intensive firms to reduce transformation costs.

Second, the government should focus on improving production efficiency, which is key to strengthening ER. It should promote digital–real integration within industrial clusters and build digital industrial clusters based on regional strengths. It should guide high-tech firms to increase R&D and digital-technology applications, and encourage non-high-tech firms to use digital tools to optimize production and reduce costs. These measures foster collaborative production and innovation across the chain and enhance cluster resilience. At the same time, the government should strengthen digital-talent development through training systems and university–industry collaboration. For example, Shenzhen offers up to 6 million yuan to outstanding talent, Hangzhou grants PhD graduates residency before employment, and digital start-ups can receive up to 5 million yuan in funding.

Third, the government should ease financing constraints to strengthen safeguards for ER. It should innovate financial-support models, guide financial institutions to build intelligent financing platforms that integrate firm information and credit data, and establish credit-evaluation systems. These measures reduce information asymmetry and lower financing thresholds. The government should also optimize credit management for SOEs to support their digital transformation and promote guaranteed digital-credit loans for non-SOEs. In addition, it should establish a special fund for digital–real integration and a financing risk-compensation mechanism that prioritizes digital projects and provides risk compensation for loans. This fund would encourage financial institutions to increase credit allocation and provide financial safeguards for ER.

6.3. Limitations and Future Directions

This study has several limitations that provide directions for future research. First, although ER is theoretically conceptualized as comprising four dimensions—resistance, recovery, development, and innovation—the entropy weight method assigns different weights to these dimensions according to the statistical characteristics of the data. Owing to the highly skewed distribution of authorized invention patents, the innovation dimension receives a relatively lower weight in the composite index. Consequently, the empirical analysis primarily captures firms’ survival-oriented resilience, whereas the development-oriented aspect of resilience may be underrepresented. Future research could distinguish between adaptive resilience (e.g., resistance and recovery) and transformative resilience (e.g., innovation and long-term development), thereby providing a more nuanced understanding of how RDRI influences different dimensions of ER.

Second, although resource allocation, firm productivity, and financing constraints are all identified as significant mediating mechanisms, this study does not quantify their relative contributions. Differences in measurement characteristics and identification strategies make direct comparisons of mediation effects inappropriate. Future studies could employ richer firm-level data or more advanced mediation techniques to further disentangle the relative importance of alternative transmission pathways.

Third, the empirical analysis is based on listed manufacturing firms in China, which may limit the generalizability of the findings. Listed firms typically possess stronger financial resources and digital capabilities than small and medium-sized enterprises, and manufacturing firms differ from service and agricultural firms in their digital transformation processes. Future research could extend the analysis to small and medium-sized

enterprises and other industries to assess whether the resilience-enhancing effects of RDRI vary across different organizational and industrial contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

RDRI	regional digital–real integration
ER	enterprise resilience
SOE	State-Owned Enterprise
R&D	Research and Development
IV	instrumental variable

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