

Article

Digitalization and Supply Chain Resilience: Evidence from Chinese Manufacturing Firms

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Abstract

This paper examines the relationship between supply chain digitalization and firm-level supply chain resilience using the staggered rollout of China's Supply Chain Innovation and Application Pilot Program as a quasi-natural experiment. Based on panel data for Chinese A-share listed manufacturing firms from 2012 to 2023, the difference-in-differences estimates indicate that policy exposure is associated with a statistically significant increase in supply chain resilience. The coefficient remains stable across parallel trends tests, placebo exercises, additional controls, high-dimensional fixed effects, and policy-selection diagnostics. Because pilot assignment followed an evaluation process, rather than randomization, the estimates remain subject to possible selection on unobserved characteristics. Subgroup regressions yield larger positive coefficients for firms in less marketized regions, non-state-owned enterprises, and mature firms. Sobel tests support the financing constraint pathway, whereas the information transparency pathway is only marginally significant. Asset turnover, the operating cycle, and inventory alignment are associated with resilience in the outcome equations, but the corresponding first-stage policy coefficients are not robust in the preferred firm- and year-fixed effect specifications. The findings document a positive quasi-experimental association between supply chain digitalization and resilience, while highlighting the institutional and firm-level conditions that shape the estimated relationship.

Keywords: supply chain digitalization; supply chain resilience; policy experiment; difference-in-differences (DID); heterogeneity analysis; mediation mechanisms

1. Introduction

In recent years, escalating geopolitical tensions, the resurgence of trade protectionism, and the unprecedented disruption caused by the COVID-19 pandemic have jointly accelerated profound transformations in the global economic landscape. Against this backdrop, ensuring the security and resilience of industrial and supply chains has emerged as a central policy priority for coping with heightened uncertainty and sustaining long-term economic growth. As the backbone of modern economies, complex supply chains enable specialization, facilitate customized inputs, and enhance productivity. However, supply chain disruptions can erode these efficiency gains and propagate substantial macroeconomic shocks [1]. At the firm level, strengthening supply chain resilience has become essential for maintaining operational continuity and mitigating external risks [2]. Despite sustained efforts, China continues to face technological bottlenecks and structural vulnerabilities in certain key supply chains, exposing insufficient resilience to adverse shocks.



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Reflecting these concerns, the report of the 20th National Congress of the Communist Party of China explicitly emphasized the need to “enhance the resilience and security of industrial and supply chains.” Similarly, the Third Plenary Session of the 20th CPC Central Committee highlighted the importance of “improving institutional mechanisms for strengthening industrial and supply chain resilience,” outlining strategic initiatives aimed at building autonomous, controllable, and reliable supply chain systems. Enhancing firm-level supply chain resilience is therefore integral to China’s pursuit of high-quality economic development and technological self-reliance, constituting a shared objective of both policymakers and enterprises.

The rapid advancement of next-generation digital technologies—such as artificial intelligence, the Internet of Things (IoT), and big data analytics—has fundamentally reshaped supply chain organization and governance. Chinese firms have increasingly embedded digital tools into supply chain management, rendering supply chain digitalization a critical lever for enhancing resilience. In October 2017, the General Office of the State Council issued the Guiding Opinions on Actively Promoting Supply Chain Innovation and Application, marking the transition toward “smart supply chains” characterized by deep integration with internet-based and IoT technologies. Subsequently, in April 2018, the Ministry of Commerce and other government agencies jointly launched the Supply Chain Innovation and Application Pilot Program, implementing a two-year pilot initiative at both the city and firm levels.

The city-level pilots aimed to establish supportive policy frameworks and institutional environments for supply chain innovation, while the firm-level pilots focused on promoting the adoption of digital technologies to reduce costs, improve efficiency, facilitate green development, and accelerate industrial upgrading. Following expert evaluation and public review, 55 pilot cities were selected from 114 applicants, alongside 266 pilot firms chosen from 1359 candidates. In April 2020, the Ministry of Commerce summarized the pilot outcomes and identified best practices, emphasizing the deep integration of supply chains with modern information technologies as a defining feature of the program’s success.

The question of how to build resilient supply chains has consequently attracted increasing attention from academics, practitioners, and policymakers. Existing studies provide valuable insights, but much of the literature relies on qualitative case studies, descriptive analyses, or analytical and simulation-based models. Large-sample evidence on firm-level supply chain resilience remains relatively scarce. In particular, the empirical relationship between supply chain digitalization and resilience, the conditions under which this relationship varies, and the candidate mechanisms underlying it remain open questions.

Supply chain digitalization refers to the construction of integrated, digitalized, and intelligent supply chain systems through the combined application of advanced information technologies, including artificial intelligence, big data, the Internet of Things, and blockchain, and modern management principles [3]. This study uses exposure to the Supply Chain Innovation and Application Pilot Program in a quasi-experimental DID design to estimate its relationship with supply chain resilience. Because pilot cities and firms were selected through evaluation, pre-policy balance diagnostics, high-dimensional fixed effect checks, and sensitivity analyses assess observable selection and specification dependence; they cannot eliminate selection on unobserved characteristics.

This paper makes three contributions. First, it develops an analytical framework that distinguishes hard structural mechanisms from soft relational mechanisms across operational efficiency, demand–supply matching, innovation capability, information transparency, financing constraints, and risk diversification. Second, it constructs a firm-level supply chain resilience index using the entropy method and five dimensions: resistance, recovery, operational stability, matching capacity, and renewal capability. Third, it provides

quasi-experimental evidence on the estimated relationship between digitalization policy exposure and supply chain resilience, while explicitly recognizing the identification limits created by non-random pilot selection.

2. Literature Review and Hypothesis Development

2.1. Supply Chain Digitalization and Firm-Level Supply Chain Resilience

A supply chain encompasses the full set of activities required to deliver products from raw materials to final customers, including procurement, manufacturing, warehousing, inventory management, order processing, distribution, delivery, and the information systems coordinating these processes [4]. The concept of resilience originates from materials science and refers to the ability of a system to return to its original state after deformation caused by external shocks without permanent damage [5]. Applied to supply chains, resilience captures the capability to anticipate, withstand, adapt to, and recover from disruptions while maintaining operational continuity and effective coordination [6,7].

Prior studies emphasize several core attributes of supply chain resilience. These include the speed of response and recovery following disruptive events [8], the adaptive capacity to absorb shocks and reconfigure operations under uncertainty [9], and organizational vigilance and responsiveness across supply chain nodes [10]. From a firm-level perspective, resilience reflects not only redundancy or buffers, but also the ability to dynamically adjust production, logistics, and coordination mechanisms when facing demand volatility or supply interruptions.

Supply chain digitalization fundamentally reshapes these capabilities. By embedding digital technologies, such as big data analytics, artificial intelligence, and the Internet of Things, into supply chain processes, firms enhance real-time coordination, improve decision accuracy, and strengthen inter-firm collaboration. Digitalization supports product quality improvement and diversification by empowering R&D, design, and production processes, facilitates collaborative innovation across supply chain nodes, and enables both incremental and breakthrough technological innovation [11–14]. These developments can strengthen firms' capacities to maintain competitiveness and operational stability under internal and external pressures [15–17].

Taken together, supply chain digitalization is expected to enhance firm-level supply chain resilience by improving coordination efficiency, adaptive flexibility, and risk response capability.

H1. *Supply chain digitalization enhances firm-level supply chain resilience.*

2.2. Soft Mechanism: Mitigating Financing Constraints

A firm's ability to withstand and recover from supply chain disruptions critically depends on the availability of financial resources. High-resilience strategies—such as maintaining redundant inventories, diversifying supplier networks, and implementing business continuity plans—often require substantial upfront investment and financial slack [10,18]. When firms face severe external financing constraints, their capacity to invest preventively or adjust operations during shocks is significantly weakened, thereby undermining supply chain resilience [19,20].

Supply chain digitalization can alleviate financing constraints by generating verifiable, transaction-level data through digitized orders, logistics tracking, and invoicing systems. These data improve transparency and credibility, reduce information asymmetry between firms and financial institutions, and facilitate access to external financing for both core firms and upstream or downstream partners. Enhanced financial flexibility allows firms to adopt capital-intensive resilience strategies with fewer trade-offs and to provide trade credit or

advance payments to key suppliers, thereby buffering risks at the network level [21,22]. Accordingly, supply chain digitalization is expected to strengthen supply chain resilience by easing firms' financing constraints.

H2a. *Supply chain digitalization enhances supply chain resilience by mitigating financing constraints.*

2.3. Soft Mechanism: Improving Information Transparency

Information transparency is a foundational element of supply chain resilience. Advanced digital technologies associated with Industry 4.0—such as artificial intelligence, IoT, and big data analytics—significantly improve the efficiency of data collection, transmission, and integration, enabling high levels of end-to-end visibility across supply chains [23]. Enhanced transparency facilitates early risk identification, accurate impact assessment, and coordinated responses to disruptions.

By reducing information asymmetry among supply chain partners, digitalization supports timely adjustments in production planning, inventory allocation, and logistics scheduling, thereby shortening response and recovery times. Policy-driven initiatives that promote integrated supply chain management platforms; combine operational, logistics, and financial data; and adopt IoT tracking and blockchain technologies further enhance data verifiability and reliability. These developments transform fragmented information into actionable insights and establish an information-driven resilience loop that strengthens adaptive capacity [24–26].

Thus, improved information transparency constitutes a key soft channel through which supply chain digitalization enhances resilience.

H2b. *Supply chain digitalization enhances supply chain resilience by improving information transparency.*

2.4. Hard Mechanism: Enhancing Asset Turnover

Beyond relational and informational factors, supply chain resilience also depends on the efficient utilization and reallocation of physical assets. Asset turnover captures how effectively firms convert assets into revenue and serves as a critical link between operational efficiency and risk-bearing capacity. Higher asset turnover reduces resource lock-in, facilitates rapid capacity adjustment, and improves delivery reliability and recovery speed following disruptions [27,28].

Supply chain digitalization promotes integrated asset management through digital platforms that leverage IoT, cloud computing, and data analytics. These systems improve asset visibility and utilization, release resources previously tied up in inefficient processes, and reduce sunk costs during demand or supply shocks. As a result, firms can allocate assets more flexibly and support resilience-enhancing adjustments.

H3a. *Supply chain digitalization enhances supply chain resilience by increasing asset turnover.*

2.5. Hard Mechanism: Reducing Operating Cycle

The operating cycle—defined as the time span from inventory acquisition to cash collection—links working capital management with liquidity and operational flexibility. Shorter operating cycles enhance firms' abilities to sustain critical supply relationships, accelerate procurement, and implement contingency measures under supply disruptions or demand fluctuations [29].

Digital transformation streamlines the procurement–production–sales–settlement process through electronic ordering, online settlement, intelligent warehousing, and smart transportation systems. These practices compress transaction and transit times, reduce dependence on excessive safety stock, and improve the monitoring of receivables and

payables. By freeing up liquidity and operational buffers, digitalization enables firms to respond more effectively to disruptions, thereby strengthening supply chain resilience.

H3b. *Supply chain digitalization enhances supply chain resilience by reducing the operating cycle.*

2.6. Hard Mechanism: Improving Inventory Turnover

Inventory management plays a central role in balancing efficiency and risk exposure within supply chains. Inventory turnover reflects how effectively firms manage inventory flows and is closely associated with profitability, liquidity, and operational continuity under uncertainty [30,31]. Higher turnover reduces holding costs, obsolescence, and stockout risks while improving cash flow and responsiveness.

Digital supply chain platforms that integrate order management, production planning, logistics, and financial data—supported by technologies such as barcodes, RFID, warehouse management systems, and intelligent replenishment—enable precise control over inventory allocation and timing. These capabilities allow firms to deploy inventory buffers more strategically at critical nodes without increasing total inventory levels, thereby enhancing resilience through efficiency, rather than redundancy.

H3c. *Supply chain digitalization enhances supply chain resilience by increasing inventory turnover.*

3. Research Design

3.1. Model Setting

To estimate changes in firm-level supply chain resilience associated with exposure to the digital supply chain transformation policy, this study adopts a difference-in-differences (DID) specification:

$$\text{Supplychain}_{i,t} = \alpha + \beta \text{DID}_{i,t} + \gamma \text{controls}_{i,t} + \delta \text{year}_t + \mu \text{firm}_i + \varepsilon_{i,t} \quad (1)$$

In Equation (1), $\text{Supplychain}_{i,t}$ is firm i 's supply chain resilience in year t . $\text{DID}_{i,t}$ is the policy-exposure indicator, equal to 1 for treated firms in and after implementation, and 0 otherwise. The coefficient β is the DID estimate of the treated–control differential change.

The vector $\text{controls}_{i,t}$ contains Size, Lev, Roa, Gro, Cash, and PRN. year_t and firm_i denote year and firm fixed effects, respectively, and $\varepsilon_{i,t}$ is the error term.

To examine candidate mechanisms underlying the estimated policy–resilience relationship, this study considers soft capabilities (information transparency and financing constraints) and hard capabilities (operational efficiency and inventory coordination). The mediation equations are specified as follows:

$$\text{Media}_{i,t} = \alpha + a \text{DID}_{i,t} + \gamma \text{controls}_{i,t} + \delta \text{year}_t + \mu \text{firm}_i + \varepsilon_{i,t} \quad (2)$$

$$\text{Supplychain}_{i,t} = \alpha + \beta \text{DID}_{i,t} + \kappa \text{Media}_{i,t} + \gamma \text{controls}_{i,t} + \delta \text{year}_t + \mu \text{firm}_i + \varepsilon_{i,t} \quad (3)$$

$$z_{\text{indirect}} = \frac{a\kappa}{\sqrt{\kappa^2 \text{SE}_a^2 + a^2 \text{SE}_\kappa^2}} \quad (4)$$

In Equation (2), $\text{Media}_{i,t}$ denotes Anal, Sa, TAT, OpCy, or InvSale, and a is the DID-to-mediator coefficient. Equation (3) includes both DID and the mediator, with κ denoting the mediator-to-Supplychain coefficient. Equation (4) gives the Sobel statistic, where SE_a and SE_κ are the corresponding standard errors.

A mediating pattern is statistically supported when DID predicts the mediator, the mediator enters the resilience equation in the expected direction, and the indirect effect $a\kappa$ differs from zero. The Sobel test evaluates this product term (Figure 1).



Figure 1. Research design flowchart.

3.2. Data

The primary data sources are the China Stock Market and Accounting Research (CSMAR) database, the China National Research Data Service (CNRDS) platform, and firms' annual reports. The sample consists of Chinese A-share listed manufacturing firms over the period of 2012–2023. The sample was constructed according to the following criteria: First, firms designated as ST or *ST, as well as financial institutions, were excluded. Second, firm–year observations with missing values for key variables or with negative operating revenue were removed. Third, to mitigate the influence of extreme observations, all continuous variables were winsorized at the 1st and 99th percentiles.

After applying these filters, the final sample comprised 18,962 firm–year observations. To reduce skewness and improve interpretability, several scale-related variables—such as firm size and firm age—were transformed using the natural logarithm. This transformation serves three purposes: First, it helps reduce the influence of extreme values and improves the robustness of the estimation results. Second, it facilitates elasticity-type interpretations of the estimated coefficients. Third, it ensures comparability across firms with heterogeneous scales. Definitions of all variables and their descriptive statistics are reported in Table 1.

Table 1. The definitions of variables.

Variable	Definition	Data Source
Supplychain	Supply chain resilience index constructed from resistance, recovery, operational stability, supply–demand matching, and renewal capability using the entropy method.	CSMAR, CNRDS, annual reports
DID	Treatment indicator for the Supply Chain Innovation and Application Pilot Program; equals 1 for treated firms in and after the policy year, and 0 otherwise.	National policy documents
Size	Natural logarithm of total assets.	CSMAR
Roa	Return on assets, measured as net profit divided by total assets.	CSMAR
Gro	Growth rate of operating revenue.	CSMAR
Cash	Cash holdings relative to total assets, capturing liquidity buffers.	CSMAR
Lev	Leverage ratio, measured as total liabilities divided by total assets.	CSMAR
PRN	Ownership indicator; equals 1 for state-owned enterprises and 0 for non-state-owned enterprises.	CSMAR
Sa	Financing constraints measured using the SA index following Hadlock and Pierce (2010) [32]; in the empirical sample, higher values indicate stronger financing constraints.	CSMAR
Anal	Information transparency, measured by the natural logarithm of analyst coverage plus one.	CSMAR

Table 1. Cont.

Variable	Definition	Data Source
TAT	Asset turnover, measured as operating revenue divided by total assets.	CSMAR
OpCy	Operating cycle, measured as inventory days plus accounts receivable days minus accounts payable days.	CSMAR
InvSale	Inventory-to-sales ratio, measured as inventories divided by operating revenue.	CSMAR and CNRDS

3.3. Variable Definitions

3.3.1. Explained Variable: Supply Chain Resilience (Supplychain)

The dependent variable is firm-level supply chain resilience (Supplychain). Following the literature on supply chain risk management and resilience [33,34], this paper constructs a composite index covering resistance capability, recovery capability, operational flexibility, demand–supply matching, and innovation capability. The firm–year index is calculated from CNRDS and annual report data using the entropy method, and is normalized to [0, 1]. Higher values indicate greater capacity to absorb shocks, adapt to disruptions, and restore supply chain operations.

3.3.2. Explanatory Variable: Supply Chain Digitalization Policy (DID)

The core explanatory variable is the policy exposure indicator DID. Based on official pilot lists issued by relevant ministries and local governments, firms located in pilot regions or explicitly included in pilot projects are classified as treated firms [34]. DID for firm i in year t equals 1 in and after the 2018 implementation year for treated firms, and 0 otherwise.

The DID coefficient estimates the differential change in supply chain resilience between treated and comparison firms after policy implementation, conditional on the parallel trends assumption and included controls. Given the non-random selection of pilot cities and firms, it is interpreted as a quasi-experimental association, rather than a definitive causal effect.

3.3.3. Mediating Variables

Guided by the theoretical framework, this paper examines both soft relational mechanisms and hard structural mechanisms through which supply chain digitalization may affect firm-level supply chain resilience.

Soft mechanisms: Two variables are employed to capture relational and informational capabilities. *Sa* measures firms' financing constraints using the SA index proposed by Hadlock and Pierce [32]. A higher value of *Sa* indicates stronger financing constraints in the empirical sample. *Anal* captures information transparency and is measured as the natural logarithm of one plus the number of financial analysts following firm i in year t [35]. A higher value of *Anal* reflects better information disclosure and stronger external monitoring.

Hard mechanisms: Three variables reflect operational efficiency and structural adjustment capacity. *TAT* denotes total asset turnover, calculated as operating revenue divided by total assets, capturing the efficiency of asset utilization [36]. *OpCy* represents the operating cycle, measured as inventory days plus accounts receivable days minus accounts payable days; a shorter operating cycle implies greater operational efficiency and flexibility [37]. *InvSale* is the inventory-to-sales ratio, defined as inventories divided by operating revenue, reflecting the firm's ability to align inventory management with product demand [38].

These mediating variables permit an assessment of whether the estimated policy–resilience relationship is consistent with financing, information, and operational channels.

3.3.4. Control Variables

Control variables are selected following prior studies on corporate digital transformation and supply chain resilience [39,40]. *Size* is measured as the natural logarithm of total assets and captures firm scale. *ROA* denotes return on assets and reflects profitability. *Gro* represents the sales growth rate and captures growth opportunities. *Cash* is measured as cash holdings relative to total assets, reflecting firms' liquidity buffers. *Lev* is the asset-liability ratio and proxies for leverage. *PRN* is a dummy variable indicating ownership type, equal to 1 for state-owned enterprises and 0 for non-state-owned enterprises.

In extended specifications, this paper further controls for regional and governance-related characteristics, including the provincial marketization index, per capita GDP, consumer price index (CPI), and indicators capturing executive duality and overseas experience of top management. All regressions include firm fixed effects and year fixed effects to control for time-invariant firm characteristics and common macroeconomic shocks, respectively.

Table 1 presents the definitions and data sources of the key variables employed in this study. The dependent variable, *Supplychain*, captures firms' supply chain resilience levels and is constructed using a comprehensive index encompassing resistance, recovery, operational stability, supply-demand matching, and renewal capability [41]. The core explanatory variable, *DID*, identifies firms affected by the digital supply chain transformation policy after the policy implementation year. Firm characteristics and control variables include *Size*, *Roa*, *Gro*, *Cash*, *Lev*, and *PRN*. The mediating variables include *Sa*, *Anal*, *TAT*, *OpCy*, and *InvSale*. All variables are primarily sourced from CSMAR, CNRDS, national policy documents, and firms' annual reports, providing a comprehensive foundation for evaluating the impact of supply chain digitalization on firm-level supply chain resilience.

4. Empirical Results

4.1. Descriptive Statistics Analysis

Table 2 reports the descriptive statistics for the main variables. The dependent variable, firm-level supply chain resilience (*Supplychain*), has a mean of 0.173 and a standard deviation of 0.043, with values ranging from 0.077 to 0.665. This indicates meaningful cross-firm variation in supply chain resilience, while remaining relatively concentrated for most observations.

Table 2. Descriptive Statistics.

VarName	Obs	Mean	SD	Min	Max
Supplychain	18,962	0.173	0.043	0.077	0.665
Size	18,962	22.154	1.160	20.011	25.673
Roa	18,962	0.040	0.062	−0.216	0.207
Gro	18,961	0.128	0.216	−0.268	1.135
Cash	18,962	17.983	11.852	1.875	59.102
Lev	18,962	39.395	19.017	5.659	86.701
PRN	18,962	0.287	0.452	0.000	1.000

Among the firm-level characteristics, *Size* has a mean of 22.154 and a standard deviation of 1.160, suggesting moderate dispersion in firm scale. *ROA* exhibits a mean of 0.040 and a standard deviation of 0.062, with negative values for some firms, reflecting the presence of loss-making observations. The growth rate (*Gro*) shows a mean of 0.128 and a standard deviation of 0.216, indicating substantial heterogeneity in firms' growth dynamics.

Liquidity and leverage also display notable variation. *Cash* has a mean of 17.983 and a standard deviation of 11.852, while *Lev* averages 39.395 with a standard deviation of 19.017,

reflecting heterogeneity in firms' financial positions and capital structures. Regarding ownership, the indicator *PRN* has a mean of 0.287, implying that approximately 28.7% of the sample firms are state-owned, with the remainder being privately controlled.

Overall, the summary statistics suggest sufficient variation in the key variables for empirical analysis, without evidence of extreme distributions that would unduly influence the regression results.

4.2. Baseline Regression

To estimate the relationship between supply chain digitalization and firm-level supply chain resilience, this paper reports the baseline DID specifications in Table 3. Across the specifications, the coefficient on DID is positive and statistically significant, indicating that policy exposure is associated with a larger post-policy increase in supply chain resilience.

Table 3. Benchmark regression table.

VARIABLE	(1) Supplychain	(2) Supplychain	(3) Supplychain
DID	0.012 *** (4.28)	0.011 ** (2.40)	0.012 *** (2.62)
Size	0.020 *** (76.21)		0.015 *** (15.09)
Roa	0.080 *** (16.08)		0.087 *** (17.13)
Gro	−0.002 * (−1.93)		−0.007 *** (−6.42)
Cash	0.000 *** (7.98)		0.000 (0.90)
Lev	−0.000 *** (−7.26)		−0.000 ** (−1.99)
PRN	0.004 *** (6.68)		−0.004 ** (−2.18)
Constant	−0.284 *** (−50.44)		
Observations	18,961	18,754	18,753
R-squared	0.322	0.739	0.759
Year fixed effect	No	Yes	Yes
Cluster	No	Firm	Firm
F	1284	5.763	79.96

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) presents the estimate without additional controls. After firm-level controls are included in column (2), the coefficient declines slightly, but remains statistically significant. Column (3) further absorbs firm and year fixed effects to account for time-invariant firm heterogeneity and common macroeconomic shocks. The DID coefficient remains positive and statistically significant, showing that the baseline estimate is stable across these specifications.

In terms of economic magnitude, the preferred DID coefficient of approximately 0.011 equals about 6.4% of the sample mean of the resilience index (0.173) and approximately 0.26 sample standard deviations (0.043). The estimated differential change is therefore economically nontrivial, as well as statistically significant.

Taken together, the baseline estimates show a positive and statistically significant relationship between pilot exposure and supply chain resilience and are consistent with Hypothesis H1.

4.3. Robustness Test

To evaluate the credibility and specification sensitivity of the baseline estimate, this paper conducts five sets of checks. It first applies an event study specification and a joint pre-treatment test, then conducts random-assignment placebo exercises, expands the controls and reweights the sample, accounts for contemporaneous digital economy policies, and examines observable policy selection using pre-policy balance, IPW-DID estimates, and province–year, city–year, and industry–year fixed effects.

4.3.1. Event-Study Evidence on Parallel Trends

A key identifying assumption of the DID approach is that treated and comparison firms would have followed parallel outcome trends before policy implementation. The event study specification estimates relative-time DID coefficients, taking 2018 as the implementation year and $t - 1$ as the omitted period. Because the available pre-policy window begins at the first observed sample year, the design cannot test trends before that date.

Figure 2 plots the event study coefficients. From $t - 6$ to $t - 2$, the estimates are close to zero and their confidence intervals include zero. A joint test also fails to reject that the pre-treatment coefficients equal zero ($F = 1.83, p = 0.120$). These results are consistent with parallel pre-policy trends within the observed sample window; they provide no information about trends before the first sample year.

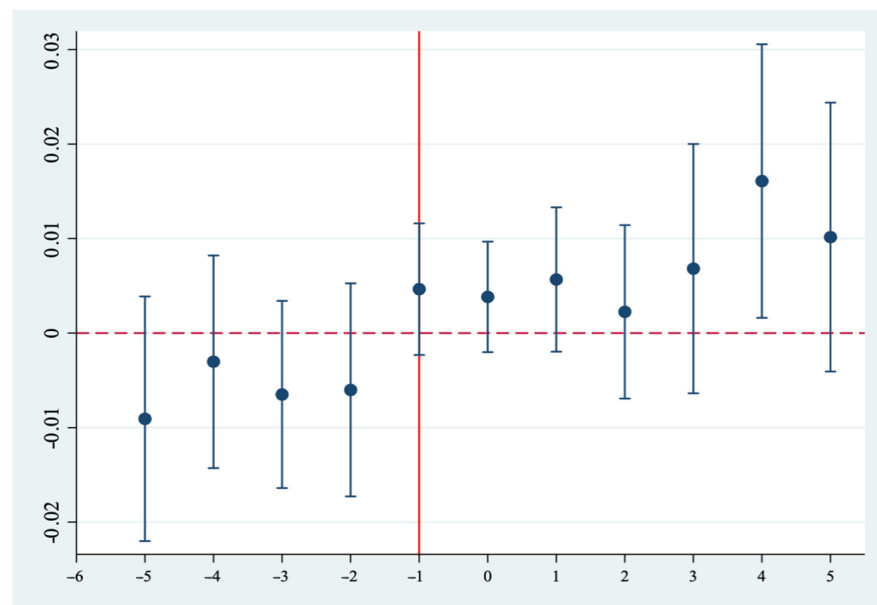


Figure 2. Parallel trends test.

After implementation, the relative-time coefficients become positive and generally increase, with larger estimates from $t + 3$ to $t + 5$. This pattern indicates that the treated–control difference in resilience emerges gradually over the observed post-policy period.

Together, the event study estimates and joint test support the parallel trends assumption within the observed pre-policy window.

4.3.2. Random-Assignment Placebo Exercise

The placebo exercise evaluates whether the baseline coefficient could arise mechanically from the sample structure or model specification. Firms are randomly assigned to pseudo-treatment groups while preserving the sample size, covariates, and regression structure, and the DID model is repeatedly re-estimated.

The placebo coefficients are centered around zero, while the baseline DID coefficient lies in the extreme tail of their distribution. Thus, coefficients of the observed magnitude rarely arise when treatment status is randomly reassigned.

Figure 3 illustrates the following aspects.

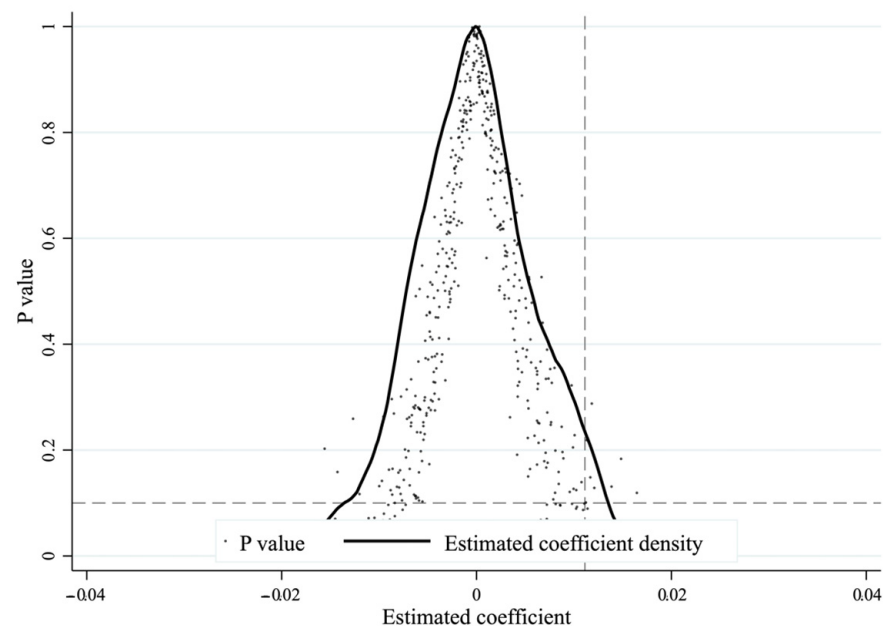


Figure 3. Placebo test. The vertical dashed line marks the baseline DID estimate, and the horizontal dashed line denotes $p = 0.10$.

First, the placebo coefficients are approximately symmetric and centered around zero, consistent with random sampling variation under pseudo-assignment.

Second, the baseline DID coefficient, marked by the dashed vertical line, lies in the extreme tail of the placebo distribution. The observed estimate is therefore closely tied to the actual assignment pattern, rather than to arbitrary reassignment.

Third, the p -values from the placebo regressions are broadly uniformly distributed, with no evident concentration around conventional significance thresholds. This further suggests that statistically significant results do not arise mechanically from the model specification or sample structure when treatment status is randomly assigned.

The placebo distribution provides no indication that the baseline significance is generated mechanically by the model or sample structure.

4.3.3. Control for Potential Omitted Variables and Kernel Propensity Score Weighting

This section evaluates the sensitivity of the baseline coefficient to additional controls and kernel propensity score weighting.

Column (1) adds regional macroeconomic controls, including per capita GDP (*pergdp*), foreign trade dependence (*Ftdr*), and the consumer price index (*Cpi*), together with executive concurrent positions (*Comp*) and managerial overseas experience (*Magback*). The DID coefficient remains positive and statistically significant (0.011, $p < 0.05$) and is similar in magnitude to the baseline estimate. The coefficient is therefore not sensitive to the inclusion of these observable regional and governance characteristics.

Column (2) applies kernel propensity score weighting to improve pre-policy comparability between treated and comparison firms. The weighted DID coefficient remains positive and statistically significant (0.012, $p < 0.01$), showing that the estimated association is stable under this alternative weighting scheme [42].

Overall, the positive association between policy exposure and supply chain resilience remains stable after expanding the controls and adjusting the sample weights (Table 4).

Table 4. Result of control for potential omitted variables and kernel propensity score weighting.

VARIABLE	(1) Supplychain	(2) Supplychain
DID	0.011 ** (2.51)	0.012 *** (2.61)
Size	0.015 *** (14.98)	0.015 *** (15.25)
Roa	0.085 *** (16.62)	0.087 *** (17.07)
Gro	−0.007 *** (−6.34)	−0.007 *** (−6.45)
Cash	0.000 (0.96)	0.000 (0.83)
Lev	−0.000 ** (−1.98)	−0.000 ** (−2.02)
PRN	−0.005 ** (−2.25)	−0.005 ** (−2.20)
pergdp	0.009 ** (2.32)	
indstru	−0.002 (−0.98)	
Ftdr	0.000 (0.13)	
Cpi	−0.000 (−0.15)	
Conp	0.001 (0.85)	
Magback	−0.000 (−0.00)	
Observations	18,319	18,747
R-squared	0.758	0.760
Year fixed effect	Yes	Yes
Cluster	Firm	Firm
F	42.13	80.55

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

4.3.4. Exclude the Interference of Other Policies

This section examines whether the baseline coefficient remains distinguishable after accounting for three contemporaneous national digitalization initiatives: the China Intelligent Manufacturing Pilot Program, the National Big Data Comprehensive Experimental Zones, and the Artificial Intelligence Innovation Development Pilot Zones.

Indicators for the three contemporaneous initiatives (DID2, DID3, and DID4) are added using the same controls, fixed effects, and clustered standard errors. The coefficient on the supply chain pilot remains positive and statistically significant across the specifications, reducing concern that it merely reflects exposure to these other digitalization policies.

The alternative policy specifications show that the positive resilience coefficient is not a mechanical reflection of the three broader digital economy initiatives considered here. Because digital policies overlap in location, timing, and objectives, this exercise does not resolve all policy-selection concerns (Table 5).

Table 5. Controls for alternative digitalization policies.

VARIABLE	(1) Supplychain	(2) Supplychain	(3) Supplychain
DID2	0.021 *** (4.82)		
DID3		0.005 *** (3.98)	
DID4			0.008 *** (6.91)
Size	0.020 *** (26.49)	0.020 *** (26.86)	0.020 *** (26.91)
Lev	−0.000 ** (−2.45)	−0.000 ** (−2.34)	−0.000 ** (−2.38)
Roa	0.087 *** (10.81)	0.089 *** (11.09)	0.089 *** (11.21)
Gro	−0.002 (−1.40)	−0.002 (−1.53)	−0.003 (−1.58)
Cash	0.000 *** (3.57)	0.000 *** (3.47)	0.000 *** (3.22)
PRN	0.007 *** (4.22)	0.007 *** (4.33)	0.007 *** (4.33)
Observations	18,961	18,961	18,961
R-squared	0.346	0.343	0.345
Year fixed effect	Yes	Yes	Yes
Cluster	Firm	Firm	Firm
F	153	149.4	153.6

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

4.3.5. Addressing Policy-Selection Concerns

Pilot cities and firms were selected through expert evaluation and public review from a larger applicant pool, and this process may be correlated with digital readiness, managerial quality, or growth prospects. To assess this selection channel, this study estimates a pre-policy selection model using firm-level averages before 2018 and examines covariate balance. Treated firms differ substantially from untreated firms before weighting, confirming that selection is empirically meaningful. After inverse-probability weighting, standardized differences are reduced for most covariates, although the common-support sample becomes much smaller.

The analysis then adds high-dimensional fixed effects to absorb time-varying local and industry shocks. The DID coefficient remains positive and statistically significant with province–year fixed effects, industry–year fixed effects, and both sets jointly. The city–year specification yields a smaller positive coefficient that is significant at the 10% level. The common-support IPW coefficient is positive but imprecise. Together, these estimates show that the positive association persists across several observable selection and fixed effect specifications, but they do not eliminate selection on unobserved characteristics (Table 6).

Table 6. Policy-selection endogeneity diagnostics.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	Supplychain	Supplychain	Supplychain	Supplychain	Supplychain	Supplychain
DID	0.010 ** (2.31)	0.004 (0.75)	0.011 ** (2.32)	0.008 * (1.76)	0.010 ** (2.30)	0.011 ** (2.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Cont.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	Supplychain	Supplychain	Supplychain	Supplychain	Supplychain	Supplychain
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying fixed effects	Year	Year	Province-year	City-year	Industry-year	Province-year + industry-year
IPW common-support sample	No	Yes	No	No	No	No
Observations	17,752	2939	17,749	17,010	17,739	17,736
R-squared	0.771	0.824	0.778	0.804	0.771	0.778

Notes: All specifications include firm-level controls. Baseline, IPW, and high-dimensional fixed effect models cluster standard errors at the firm level. The IPW specification uses pre-2018 covariates and the common-support sample. t-statistics in parentheses. ** $p < 0.05$, * $p < 0.1$.

4.4. Heterogeneity Test

The full-sample estimates show a positive relationship between pilot exposure and supply chain resilience. This section reports subgroup regressions by regional marketization, firm life cycle stage, and ownership structure to describe how the estimated coefficients vary across institutional and firm-level contexts.

4.4.1. Heterogeneity by Regional Marketization

Regional marketization is measured using the China Marketization Index developed by Fan Gang et al. The sample is divided at the annual median into high-marketization (HighMarket = 1) and low-marketization (HighMarket = 0) groups. Separate DID regressions describe the policy coefficients in the two institutional environments.

Table 7 reports the marketization subgroup estimates. The DID coefficients are positive, but below conventional significance thresholds in high-marketization regions, consistent with a smaller marginal association where market mechanisms and digital infrastructure are already more developed.

Table 7. Business environment heterogeneity.

VARIABLE	(1) Supplychain	(3) Supplychain	(4) Supplychain	(6) Supplychain
DID	0.005 (0.86)	0.003 (0.56)	0.010 * (1.79)	0.011 ** (2.01)
Size		0.014 *** (9.80)		0.017 *** (10.52)
Roa		0.084 *** (11.05)		0.083 *** (10.93)
Gro		−0.006 *** (−4.18)		−0.009 *** (−5.37)
Cash		0.000 (0.18)		0.000 (1.64)
Lev		−0.000 *** (−2.85)		−0.000 (−0.33)
PRN		−0.002 (−0.68)		−0.006 ** (−1.99)
Observations	9800	9800	8303	8302
R-squared	0.778	0.792	0.746	0.770

Table 7. Cont.

VARIABLE	(1) Supplychain	(3) Supplychain	(4) Supplychain	(6) Supplychain
Year fixed effect	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
F	0.732	35.62	3.206	38.84

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In low-marketization regions, the DID coefficients are positive and statistically significant. The larger coefficients are consistent with a compensating policy role in settings with weaker market mechanisms, greater information asymmetry, and lower digital governance capacity.

The marketization subgroup coefficients are larger in less marketized regions and smaller in more marketized regions, a pattern consistent with an environment-compensation interpretation.

4.4.2. Heterogeneity Across Firm Life-Cycle Stages

Firm life cycle subgroups are defined by firm age (AGE), following Li Ben and Wu Lihua: start-up firms (1–6 years), growth-stage firms (7–12 years), and mature firms (more than 12 years) [43]. The baseline DID model is estimated separately for each subgroup.

Table 8 reports the subgroup estimation results across firm life cycle stages. For start-up firms, the DID coefficients are positive, but do not pass conventional significance thresholds. This pattern is consistent with weaker policy transmission among firms whose supply chains, organizational routines, and digital foundations remain under development.

Table 8. Enterprise life cycle heterogeneity.

VARIABLE	(1) Supplychain	(2) Supplychain	(3) Supplychain	(4) Supplychain
DID	0.007 (0.77)	0.004 (0.51)	0.009 *** (2.62)	0.010 *** (2.84)
Size		0.017 *** (6.45)		0.015 *** (12.19)
Roa		0.092 *** (9.26)		0.095 *** (11.28)
Gro		−0.010 *** (−3.28)		−0.010 *** (−4.87)
Cash		0.000 (0.63)		0.000 (0.46)
Lev		0.000 (1.02)		−0.000 ** (−2.06)
PRN		−0.015 ** (−2.28)		0.002 (0.94)
Observations	2708	2708	6574	6574
R-squared	0.836	0.851	0.798	0.814
Year fixed effect	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
F	0.597	20.67	6.862	37.80

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

For growth-stage firms, the DID coefficients remain below conventional significance thresholds. Although these firms have achieved a certain scale, their digital investments

may be directed more toward production organization or market expansion than toward systematic supply chain restructuring.

For mature firms, the DID coefficients are positive and statistically significant at the 1% level and increase slightly after controls are added. More developed organizational structures, stronger resource access, and more complete digital infrastructure may help explain the larger coefficients in this subgroup.

Overall, the life cycle subgroup estimates are concentrated among mature firms. The results indicate that policy design should account for differences in organizational capability, digital infrastructure, and supply chain management maturity across firm development stages.

4.4.3. Ownership Heterogeneity

The ownership analysis estimates the baseline model separately for state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). Differences in external constraints, governance, and market incentives provide the basis for comparing the subgroup coefficients.

Columns (1)–(2) of Table 9 report the SOE estimates. With and without controls, the DID coefficients are positive, but below conventional significance thresholds. This pattern is consistent with lower marginal responsiveness among firms operating in relatively stable, policy-shielded supply chain systems.

Table 9. Ownership heterogeneity.

	(1)	(2)	(3)	(4)
VARIABLE	Supplychain	Supplychain	Supplychain	Supplychain
DID	0.007 (1.06)	0.010 (1.45)	0.009 *** (2.74)	0.008 ** (2.49)
Size		0.016 *** (7.24)		0.015 *** (13.82)
Roa		0.078 *** (6.67)		0.086 *** (15.42)
Gro		−0.012 *** (−4.76)		−0.007 *** (−5.59)
Cash		−0.000 (−0.33)		0.000 (0.68)
Lev		−0.000 (−0.13)		−0.000 (−1.56)
Observations	5400	5400	13,329	13,328
R-squared	0.769	0.785	0.716	0.739
Year fixed effect	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm
F	1.129	17.25	7.527	87.23

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$.

Columns (3)–(4) report the NSOE estimates. The DID coefficients are positive and statistically significant at the 1% level (0.009 and 0.008), whereas the corresponding SOE coefficients do not pass conventional significance thresholds. Stronger competitive pressure and harder budget constraints may contribute to the larger NSOE coefficients.

Overall, the ownership subgroup results are stronger for non-state-owned enterprises than for SOEs. This pattern is consistent with the role of market-oriented incentives and governance flexibility in shaping firms' responses to digitalization policies.

Tables 7–9 report different coefficient patterns across institutional and firm-level contexts. Resource constraints, development stage, and governance efficiency provide three possible interpretations of these descriptive differences.

First, the coefficients in Table 7 are larger in low-marketization regions. Weaker market mechanisms, greater information asymmetry, and tighter financing constraints may increase the marginal value of digital upgrading, whereas more mature institutions may leave less scope for additional gains.

Second, Table 8 reports statistically visible estimates, mainly among mature firms. Mature firms have stronger resource endowments and more complete organizational and digital infrastructures, whereas start-up and growth-stage firms face tighter constraints or competing expansion priorities. This pattern is consistent with life cycle theory, which links firm development stages to absorptive capacity and resource utilization efficiency [43].

Third, Table 9 reports larger positive coefficients for NSOEs. Stronger competitive pressure and harder budget constraints may make these firms more responsive to digitalization incentives, whereas more stable supply chain arrangements and weaker market-based incentives may reduce the corresponding SOE coefficients.

Overall, the subgroup estimates vary with regional marketization, firm development stage, and ownership structure, motivating differentiated implementation across regions and firm types.

4.5. Mediation Effect Test

After documenting the positive full-sample coefficient, this section evaluates candidate soft and hard pathways underlying the estimated policy–resilience relationship.

Soft mechanisms concern external relational and informational conditions, including financing constraints and information transparency. Digital information disclosure, data sharing, and credit verification may be reflected relatively quickly in financing conditions and external monitoring.

By contrast, hard mechanisms correspond to firms' internal structural and operational capabilities, including asset utilization efficiency, operating cycle coordination, and inventory alignment. Improvements in these dimensions typically rely on deeper organizational changes, such as production process reengineering, digital platform integration, and internal management restructuring. These adjustments involve substantial implementation costs and longer construction cycles, and their effects are subject to pronounced time lags. Moreover, many commonly used financial and operational indicators are outcome variables, which may not immediately reflect the underlying structural transformation induced by digitalization. The empirical analysis therefore distinguishes between cross-firm diagnostic responses and more stringent within-firm evidence after absorbing firm fixed effects.

Based on this distinction, Tables 10–12 test whether the estimated coefficients are consistent with soft or hard mediation patterns.

Table 10. Soft-mechanism mediation regressions and indirect effect tests.

VARIABLE	(1)	(2)	(3)	(4)
Dependent Variable	Sa	Supplychain	Anal	Supplychain
DID	−0.068 *** (−4.56)	0.007 * (1.73)	0.211 * (1.88)	0.010 ** (2.21)
Sa		−0.053 *** (−5.23)		
Anal				0.003 *** (10.61)
Indirect effect		0.003604 ***		0.000633 *

Table 10. Cont.

VARIABLE	(1)	(2)	(3)	(4)
Dependent Variable	Sa	Supplychain	Anal	Supplychain
Sobel z-statistic		3.44		1.85
Sobel <i>p</i> -value		0.001		0.064
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered SEs	Firm	Firm	Firm	Firm
Observations	12,861	12,861	12,861	13,198
R-squared	0.976	0.783	0.750	0.343

t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11. Hard-mechanism mediation regressions and indirect effect tests.

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	TAT	Supplychain	OpCy	Supplychain	InvSale	Supplychain
DID	0.015 (0.53)	0.010 ** (2.50)	−0.058 (−0.62)	0.013 (1.62)	−0.059 (−1.25)	0.010 (1.25)
TAT		0.005 ** (2.29)				
OpCy				0.004 *** (6.48)		
InvSale						−0.001 *** (−3.99)
Indirect effect		0.000075		−0.000232		0.000059
Sobel z-statistic		0.52		−0.62		1.19
Sobel <i>p</i> -value		0.606		0.537		0.233
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Firm	Firm	Firm	Firm	Firm	Firm
Observations	12,861	12,861	12,861	13,198	13,198	13,198
R-squared	0.824	0.781	0.901	0.348	0.006	0.338

t-statistics in parentheses. Indirect effect tests are paired by columns and reported under the corresponding resilience equation. *** $p < 0.01$, ** $p < 0.05$.

Table 12. Lagged hard-mechanism tests.

Specification/Mediator	(1) t	(2) t + 1	(3) t + 2
Panel A. Preferred firm and year fixed effects			
TAT	0.025 (1.01)	0.020 (0.73)	0.015 (0.45)
OpCy	3.263 (0.54)	6.642 (1.41)	4.454 (0.87)
InvSale	−0.032 (−0.64)	−0.047 (−0.83)	−0.007 (−0.37)

Table 12. Cont.

Specification/Mediator	(1) t	(2) t + 1	(3) t + 2
Panel B. Supplementary year fixed effects only			
TAT	0.134 (1.63)	0.144 * (1.69)	0.157 * (1.76)
OpCy	−28.065 *** (−3.90)	−27.639 *** (−4.46)	−25.999 *** (−4.13)
InvSale	−0.059 (−1.27)	−0.077 (−1.53)	−0.053 (−1.53)
Controls	Yes	Yes	Yes
Firm fixed effects	Panel A: Yes; Panel B: No	Panel A: Yes; Panel B: No	Panel A: Yes; Panel B: No
Year fixed effects	Yes	Yes	Yes
Firm-clustered SEs	Yes	Yes	Yes
Observations	12,237	8886	6824

t-statistics in parentheses. *** $p < 0.01$, * $p < 0.1$.

4.5.1. Mediation Effects of Soft Mechanisms

Table 10 presents the mediation regressions for financing constraints (Sa) and information transparency (Anal). In the Sa equation, DID is significantly negative; in the resilience equation, Sa is significantly negative. After Sa is included, the DID coefficient is smaller than the baseline estimate and remains marginally significant. These results are consistent with a financing constraint channel.

For the information transparency pathway, DID is positive in the Anal equation and significant at the 10% level. In the resilience equation, Anal is positively associated with Supplychain, while DID remains positive and significant. Because the Anal-to-resilience coefficient attenuates under a stricter firm-level two-way fixed effect re-estimation, this pathway is retained as supplementary evidence.

The lower panel of Table 10 reports Sobel tests for the soft-channel indirect effects. The Sa pathway is significant at the 1% level, whereas the Anal pathway is positive, but only marginally significant at the 10% level. The mechanism interpretation therefore places primary weight on financing constraints and treats information transparency as supplementary.

4.5.2. Mediating Effects of Hard Mechanisms

Table 11 evaluates asset turnover (TAT), the operating cycle (OpCy), and the inventory-to-sales ratio (InvSale) as candidate hard-mechanism variables related to operational efficiency, process coordination, and inventory alignment.

For operational efficiency, the DID coefficient in the TAT equation is positive, but does not pass conventional significance thresholds. In the resilience equation, TAT is positively associated with Supplychain, and the DID coefficient remains positive. Thus, asset turnover is related to resilience, but the policy-to-TAT path does not support a mediation interpretation.

For the operating cycle, the DID coefficient in the OpCy equation is negative, but below conventional significance thresholds. In the resilience equation, OpCy is significantly associated with Supplychain, whereas DID remains below conventional significance thresholds. These results do not support a policy-induced OpCy mediation path.

For inventory coordination, DID does not significantly affect the inventory-to-sales ratio. InvSale is negatively associated with Supplychain in the resilience equation. Since

the policy-to-InvSale path is not significant, the evidence does not support inventory coordination as a policy-induced mediation channel within the observed window.

TAT, OpCy, and InvSale are statistically associated with Supplychain in the outcome equations, but DID does not consistently predict these variables in the preferred first-stage specifications with firm and year fixed effects. Table 12 produces the same conclusion at t , $t + 1$, and $t + 2$. The year fixed effect-only estimates show shorter operating cycles and weak lagged increases in TAT, but these patterns do not persist after firm fixed effects are absorbed.

Taken together, the mechanism estimates support the financing constraint pathway. The information transparency indirect effect is marginal, whereas the hard mechanism first-stage and lagged coefficients do not pass conventional significance thresholds in the preferred specifications. TAT, OpCy, and InvSale remain associated with resilience in the outcome equations, but the current evidence does not identify them as policy-induced mediators.

5. Conclusions

Using a panel of Chinese A-share listed manufacturing firms from 2012 to 2023, this study applies a DID framework to the staggered rollout of supply chain digitalization pilots and estimates the relationship between policy exposure and firm-level supply chain resilience.

The DID coefficient is positive and statistically significant across the baseline specifications. Event study, placebo, extended control, weighting, high-dimensional fixed effect, and alternative policy checks show that the estimate is stable across specifications. These diagnostics strengthen the credibility of the comparison under observable selection and the maintained DID assumptions, but they do not eliminate selection on unobserved characteristics.

Subgroup regressions report larger positive coefficients for firms in low-marketization regions, NSOEs, and mature firms. These descriptive patterns are consistent with the roles of institutional frictions, market incentives, and organizational capability.

Sobel tests support the financing constraint pathway, while the information transparency indirect effect is only marginally significant. TAT, OpCy, and InvSale are associated with resilience in the outcome equations, but the preferred first-stage and lagged estimates do not identify them as policy-induced mediators within the sample period.

6. Research Limitations

This study has several limitations. First, the resilience index is constructed from financial and disclosure data; logistics records, transaction data, and supply chain network measures could provide more direct evidence. Second, pilot assignment followed expert evaluation and public review, rather than randomization. Pre-policy balance diagnostics, IPW sensitivity analysis, and high-dimensional fixed effects address observable selection, but unobserved differences in managerial quality, digital readiness, or growth prospects cannot be ruled out. Third, available variables may not capture process-level digital practices. Fourth, longer panels are needed to assess structural adjustment. Finally, the listed-firm sample limits generalizability to SMEs and other supply chain participants.

Future studies could examine the proposed mechanisms using order-level logistics records, supplier–customer transactions, warehouse and delivery data, or other operational indicators that capture process-level digital upgrading more directly than financial statements.

Overall, this study documents a positive quasi-experimental association between supply chain digitalization policy exposure and firm-level resilience and evaluates several

candidate pathways. The interpretation remains bounded by the non-random selection of pilot cities and firms.

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References

1. Acemoglu, D.; Tahbaz-Salehi, A. The Macroeconomics of Supply Chain Disruptions. *Rev. Econ. Stud.* **2025**, *92*, 656–695. [\[CrossRef\]](#)
2. Sheffi, Y.; Rice, J.B., Jr. A supply chain view of the resilient enterprise. *MIT Sloan Manag. Rev.* **2005**, *47*, 41–48. Available online: <https://sloanreview.mit.edu/article/a-supply-chain-view-of-the-resilient-enterprise/> (accessed on 18 July 2026).
3. Fatorachian, H.K.H. Impact of Industry 4.0 on supply chain performance. *Prod. Plan. Control* **2021**, *32*, 63–81. [\[CrossRef\]](#)
4. Lummus, R.R.; Vokurka, R.J. Defining Supply Chain Management: A Historical Perspective and Practical Guidelines. *Ind. Manag. Data Syst.* **1999**, *99*, 11–17. [\[CrossRef\]](#)
5. Caniato, F.F.A.; Rice, J. Building a secure and resilient supply chain. *Supply Chain Manag. Rev.* **2003**, *7*, 22–30.
6. Golgeci, I.; Kuivalainen, O. Does social capital matter for supply chain resilience? The role of absorptive capacity and marketing-supply chain management alignment. *Ind. Mark. Manag.* **2020**, *84*, 63–74. [\[CrossRef\]](#)
7. Zhao, N.; Hong, J.; Lau, K.H. Impact of supply chain digitalization on supply chain resilience and performance: A multi-mediation model. *Int. J. Prod. Econ.* **2023**, *259*, 108817. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Wieland, A.; Durach, C.F. Two perspectives on supply chain resilience. *J. Bus. Logist.* **2021**, *42*, 315–322. [\[CrossRef\]](#)
9. Yao, Y.; Fabbe-Costes, N. Can you measure resilience if you are unable to define it? The analysis of Supply Network Resilience (SNRES). *Supply Chain Forum* **2018**, *19*, 255–265. [\[CrossRef\]](#)
10. Ambulkar, S.; Blackhurst, J.; Grawe, S. Firm's resilience to supply chain disruptions: Scale development and empirical examination. *J. Oper. Manag.* **2015**, *33–34*, 111–122. [\[CrossRef\]](#)
11. Limnios, E.A.M.; Mazzarol, T.; Ghadouani, A.; Schilizzi, S.G. The Resilience Architecture Framework: Four organizational archetypes. *Eur. Manag. J.* **2014**, *32*, 104–116. [\[CrossRef\]](#)
12. Chu, Y.; Tian, X.; Wang, W. Corporate Innovation Along the Supply Chain. *Manag. Sci.* **2019**, *65*, 2445–2466. [\[CrossRef\]](#)
13. Sabahi, S.; Parast, M.M. Firm innovation and supply chain resilience: A dynamic capability perspective. *Int. J. Logist. Res. Appl.* **2020**, *23*, 254–269. [\[CrossRef\]](#)
14. Bustinza, O.F.; Vendrell-Herrero, F.; Perez-Arostegui, M.N.; Parry, G. Technological capabilities, resilience capabilities and organizational effectiveness. *Int. J. Hum. Resour. Manag.* **2019**, *30*, 1370–1392. [\[CrossRef\]](#)
15. Kamalahmadi, M.; Parast, M.M. An assessment of supply chain disruption mitigation strategies. *Int. J. Prod. Econ.* **2017**, *184*, 210–230. [\[CrossRef\]](#)
16. Todo, Y.; Nakajima, K.; Matous, P. How Do Supply Chain Networks Affect the Resilience of Firms to Natural Disasters? Evidence from the Great East Japan Earthquake. *J. Reg. Sci.* **2014**, *55*, 209–229. [\[CrossRef\]](#)
17. Wu, L.; Zhang, Z.; Huang, J.; Su, I.-H.; Tian, S. Digital Technologies and Supply Chain Resilience: A Resource-Action-Performance Perspective. *Inf. Syst. Front.* **2025**, *27*, 2137–2158. [\[CrossRef\]](#)
18. Pettit, T.J.; Fiksel, J.; Croxton, K.L. Ensuring supply chain resilience: Development of a conceptual framework. *J. Bus. Logist.* **2010**, *31*, 1–21. [\[CrossRef\]](#)
19. Fan, J.; Zhou, Y. Empirical Analysis of Financing Efficiency and Constraints Effects on the Green Innovation of Green Supply Chain Enterprises: A Case Study of China. *Sustainability* **2023**, *15*, 5300. [\[CrossRef\]](#)
20. Suanin, S.; Laphet, J.; Sanvises, D.; Tandamrong, D.; Ouansrimeang, S.; Kidrakarn, K. Digital Innovation Capability and Innovation-Driven Compliance for Supply Chain Resilience: Evidence from Thailand's Plastic Recycling Industry. *Sustainability* **2026**, *18*, 5799. [\[CrossRef\]](#)

21. Pettit, T.J.; Croxton, K.L.; Fiksel, J. Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool. *J. Bus. Logist.* **2013**, *34*, 46–76. [\[CrossRef\]](#)
22. Ersahin, N.; Giannetti, M.; Huang, R. Trade credit and the stability of supply chains. *J. Financ. Econ.* **2024**, *155*, 103830. [\[CrossRef\]](#)
23. Dolgui, A.; Ivanov, D.; Sokolov, B.V. Reconfigurable supply chain: The X-network. *Int. J. Prod. Res.* **2020**, *58*, 4138–4163. [\[CrossRef\]](#)
24. Scholten, K.; Schilder, S. The role of collaboration in supply chain resilience. *Supply Chain Manag.* **2015**, *20*, 471–484. [\[CrossRef\]](#)
25. Scholten, K.; Sharkey Scott, P.; Fynes, B. Building routines for non-routine events: Supply chain resilience learning mechanisms and their antecedents. *Supply Chain Manag.* **2019**, *24*, 430–442. [\[CrossRef\]](#)
26. Sheffi, Y. *The New (ab) Normal: Reshaping Business and Supply Chain Strategy Beyond COVID-19*; Mit Ctl Media: Cambridge, MA, USA, 2020.
27. Alkhatib, S.F.; Momani, R.A. Supply Chain Resilience and Operational Performance: The Role of Digital Technologies in Jordanian Manufacturing Firms. *Adm. Sci.* **2023**, *13*, 40. [\[CrossRef\]](#)
28. Stavropoulos, A.S.; Zounta, S. Cash Conversion Cycle and Profitability: Evidence from Greek Service Firms. *J. Risk Financ. Manag.* **2025**, *18*, 208. [\[CrossRef\]](#)
29. Wang, Y.; Ji, Y.; Chen, X.; Song, C. Inflation, operating cycle, and cash holdings. *China J. Account. Res.* **2014**, *7*, 263–276. [\[CrossRef\]](#)
30. Kiyamaz, H.; Haque, S.; Choudhury, A.A. Working capital management and firm performance: A comparative analysis of developed and emerging economies. *Borsa Istanbul. Rev.* **2024**, *24*, 634–642. [\[CrossRef\]](#)
31. Guo, Y.; Liu, F.; Song, J.S.; Wang, S. Supply chain resilience: A review from the inventory management perspective. *Fundam. Res.* **2025**, *5*, 450–463. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Hadlock, C.J.; Pierce, J.R. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Rev. Financ. Stud.* **2010**, *23*, 1909–1940. [\[CrossRef\]](#)
33. Ponomarov, S.Y.; Holcomb, M.C. Understanding the concept of supply chain resilience. *Int. J. Logist. Manag.* **2009**, *20*, 124–143. [\[CrossRef\]](#)
34. Tian, Y.; Cui, L. Supply chain resilience and digital transformation: Perspectives from a supply chain network. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 1738. [\[CrossRef\]](#)
35. Lang, M.H.; Lundholm, R.J. Corporate Disclosure Policy and Analyst Behavior. *Account. Rev.* **1996**, *71*, 467–492. Available online: <http://www.jstor.org/stable/248567> (accessed on 18 July 2026). [\[CrossRef\]](#)
36. Hu, C.; Li, Y.; Zheng, X. Data assets, information uses, and operational efficiency. *Appl. Econ.* **2022**, *54*, 6887–6900. [\[CrossRef\]](#)
37. Popa, V. The Financial Supply Chain Management: A New Solution for Supply Chain Resilience. *Amfiteatru Econ.* **2013**, *15*, 140–153. Available online: <https://www.econstor.eu/handle/10419/168782> (accessed on 18 July 2026). [\[CrossRef\]](#)
38. Zhen, Y.; Shang, L. The effect of enterprise digital transformation on supply chain efficiency and its transmission mechanism. *Sci. Rep.* **2025**, *15*, 38321. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Wang, H.; Chen, Y.; Xie, J.; Liu, C. Research on digital empowerment, innovation vitality and manufacturing supply chain resilience mechanism. *PLoS ONE* **2025**, *20*, e0316183. [\[CrossRef\]](#) [\[PubMed\]](#)
40. Lv, W.; Yang, Q.; Li, Y. Digital Empowerment and Supply Chain Resilience Reconstruction. *Sustainability* **2026**, *18*, 2261. [\[CrossRef\]](#)
41. Shushan, Z.; Cheng, G. Supply Chain Digitization and Supply Chain Resilience. *J. Financ. Econ.* **2024**, *50*, 21–34. [\[CrossRef\]](#)
42. Austin, P.C.; Stuart, E.A. Moving towards best practice when using inverse probability of treatment weighting (IPTW) using the propensity score to estimate causal treatment effects in observational studies. *Stat. Med.* **2015**, *34*. [\[CrossRef\]](#) [\[PubMed\]](#)
43. Li, B.; Wu, L. Resource Dependence or Innovation Success? On the Survival of Newly Founded Ventures Based on Organizational Imprinting Role. *Foreign Econ. Manag.* **2018**, *40*, 35–50. [\[CrossRef\]](#)

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