ISSN 1611-1699/eISSN 2029-4433

VILNIUS TECH
Vilnius Gediminas Technical University

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2026
Volume 27
Issue 3
Pages 633–655

https://doi.org/10.3846/jbem.2026.27916

TURNING UNCERTAINTY INTO ADVANTAGE: HOW POLICY-INDUCED DIGITALIZATION FUELS EXPORT COMPETITIVENESS

Jing SHAO[1]✉, Lingtong HUANG[1], Bowen SONG[2], Yuanhao TIAN[3], Yihang JIANG[1]

[1] *School of Business, Qingdao University, 266071 Qingdao, China*
[2] *Institute of International Relations, Yunnan University, 650091 Kunming, China*
[3] *Steven J. Green School of International and Public Affairs, Florida International University, 33199 Miami, USA*

Article History:
- received 24 September 2025
- accepted 16 April 2026

Abstract. We exploit China's 2018 Supply Chain Innovation and Application Pilot Program as a quasi-natural experiment to evaluate how supply chain digitalization shapes firm-level export competitiveness amidst rising global volatility. Using a difference-in-differences framework spanning 2010–2023, validated by a battery of robustness checks, we document a substantial export-promoting effect of policy-driven digital upgrading. This strategic advantage is structurally mediated through substantive innovation, equipping firms with core technological breakthroughs rather than mere operational efficiencies. Furthermore, we uncover a distinct asymmetry in risk mitigation: digitalization serves as an adaptive buffer against systemic industry-level shocks, yet it fails to mitigate idiosyncratic firm-level volatility. Finally, although positive spatial and industrial spillovers exist, the direct policy benefits remain overwhelmingly dominant and highly asymmetric, accruing predominantly to large, non-manufacturing, and digitally mature enterprises. These findings highlight a binding resource constraint, underscoring that supply chain digitalization functions as a contingent dynamic capability rather than a ubiquitous, universally accessible technological fix.

Keywords: supply chain digitalization, export competitiveness, substantive innovation, uncertainty, spillover effects, DID, double machine learning.

JEL Classification: C21, F14, L25, O33.

✉Corresponding author. E-mail: *shaojing2208@hotmail.com*

1. Introduction

In today's hyper-connected global economy, international trade is no longer merely an exchange of goods but a strategic arena shaped by systemic volatility. Heightened global competition and rising protectionism have severely challenged traditional cost-based export models. Major macroeconomic and geopolitical events have further intensified environmental uncertainty, exposing firms to systemic supply chain disruptions (Gereffi, 2020). Against this turbulent backdrop, supply chain digitalization has emerged as a transformative enabler (Spieske & Birkel, 2021). By deploying intelligent logistics, cross-border e-commerce integration, and data-driven coordination, multinational and exporting firms are fundamentally shifting digitalization from a competitive advantage to a survival necessity (Veit & Thatcher, 2023).

Yet, despite the widespread consensus on the necessity of digital transformation, the empirical literature leaves several critical gaps. Prior studies predominantly treat digitalization as an endogenous managerial choice, complicating causal inference, and tend to focus heavily on domestic integration or routine efficiency gains (Siems et al., 2023). Crucially, how exogenous digital policy shocks translate into sustained export competitiveness—particularly under the amplifying pressure of global turbulence—remains insufficiently understood. Furthermore, the structural mechanisms driving this "digital dividend," particularly the indispensable role of substantive innovation as a strategic conduit, are often treated as a black box (Usai et al., 2021).

This study bridges these gaps by exploiting China's 2018 Supply Chain Innovation and Application Pilot Program as a quasi-natural experiment (Tian & Cui, 2025). Using a comprehensive panel of A-share listed firms from 2010 to 2023, we employ a generalized Difference-in-Differences framework—supported by Double Machine Learning estimations, Propensity Score Matching, and event-study validations—to delineate the pathways from policy-induced digital upgrading to export competitiveness. We document a substantial and causal export-promoting effect of supply chain digitalization, demonstrating that policy-driven interventions successfully foster structural trade advantages.

The remainder of this paper is organized as follows: Section 2 reviews the literature and develops the research hypotheses. Section 3 details the research design, including the data sample, variables, and the empirical strategy used to evaluate the 2018 policy shock. Section 4 presents the main empirical results and robustness checks. Section 5 explores the underlying mechanisms and boundary conditions, focusing on substantive innovation and environmental uncertainty. Finally, Section 6 concludes and offers relevant policy implications.

2. Literature review and hypothesis development

2.1. Export competitiveness and supply chain digitalization

Export competitiveness serves as a critical macroeconomic barometer and a strategic firm-level benchmark. While classical trade theories emphasize cost efficiency and scale economies, deepening globalization and fragmented value chains have rendered these foundations fragile. Competing solely on cost is unsustainable amid shifting comparative advantages and geopolitical shocks. Consequently, scholars and policymakers increasingly seek new engines of export competitiveness grounded in dynamic, adaptive capabilities rather than static factor endowments (Verhoef et al., 2021).

In this search, supply chain digitalization has emerged as a transformative force. Digital technologies such as big data analytics, IoT-enabled monitoring, cloud-based platforms, and AI-driven logistics are rewriting the rules of cross-border commerce. By integrating data across previously fragmented nodes, these technologies reduce transaction frictions, enable predictive coordination, and enhance visibility across global networks (Dubey et al., 2021). Likewise, cross-border e-commerce and digital logistics platforms accelerate disintermediation, lowering market entry barriers and giving smaller firms direct access to international buyers. Extensive empirical evidence underscores this potential, indicating that digitalized supply chains substantially reduce trade costs, translating into measurable improvements in export intensity and market expansion (Brynjolfsson et al., 2019).

Yet the relationship between digitalization and export competitiveness is far from linear. Absorptive capacity matters. Kache and Seuring (2017) demonstrate that digital tools yield diminishing returns in firms lacking the literacy, governance agility, or organizational flexibility to absorb and operationalize them. Similarly, Eller et al. (2020) argue that SMEs often face financing bottlenecks and technological shortfalls, leaving them unable to capture the economies of scale embedded in digital platforms. Even at the industry level, digital dividends can vary sharply. These findings collectively suggest that digitalization is not a universal recipe for competitiveness but a contingent process shaped by firm resources, absorptive capacity, and institutional context.

While current literature extensively documents the efficiency-enhancing effects of digitalization, it remains limited in two key respects. First, the reliance on macro-level data complicates robust causal identification at the firm level. Second, existing studies primarily focus on "business as usual" environments, offering limited insights into how digitalization helps firms navigate export bottlenecks amid external turbulence like geopolitical friction or regulatory shocks (Ivanov & Dolgui, 2021; Sodhi & Tang, 2021). Consequently, the question of when, how, and under what conditions digital dividends materialize remains underexplored. Addressing this gap, our study links policy-driven supply chain digitalization to firm-level export performance, moving beyond efficiency narratives to examine digital transformation as a strategic lever under heightened global uncertainty.

2.2. Supply chain digitalization and substantive innovation

Substantive innovation—genuine, high-quality technological advancements that upgrade core competencies (Yang et al., 2025)—is crucial for sustained international competitiveness. Unlike superficial innovations pursued for subsidies or short-term operational tweaks, substantive innovation enables firms to transcend low-margin rivalry, capture premium segments, and secure long-term strategic advantages in global markets.

Research highlights supply chain digitalization as a key catalyst for substantive innovation (Appio et al., 2021). Digital technologies not only optimize routine processes but also create the informational and structural conditions necessary for genuine technological breakthroughs (Nambisan et al., 2019). Integrating cross-boundary data through cloud platforms and IoT networks grants firms real-time access to upstream demand signals and downstream operational feedback. This heightened connectivity fosters novel combinations of complex knowledge across organizational boundaries, increasing the likelihood of high-value, substantive discoveries. Furthermore, digital technologies enable precision in R&D strategy. Haefner et al. (2021) demonstrate that advanced analytics and AI-driven algorithms allow firms to map technological trajectories and identify critical bottlenecks in the global research landscape, optimizing resource allocation for core technological exploration. Additionally, digital infrastructures mitigate the extreme risks of high-quality R&D. Through digital twin simulations, firms can rapidly prototype complex designs and iterate at a lower cost, overcoming resource constraints that typically deter substantive innovation (Tao et al., 2019).

The strategic payoff of substantive innovation for export competitiveness is particularly pronounced. Firms committing to core technological upgrades escape the trap of competing solely on cost, leveraging product differentiation and high-tech premiums to command bargaining power in global value chains. For firms in emerging economies, substantive innovation provides a mechanism to break free from low-value, labor-intensive positions and capture high-margin niches (Kano et al., 2020). By integrating digital supply chain platforms with pioneering technological advancements, these firms successfully transition from passive participants to proactive competitors, rapidly building global competitiveness and ascending to higher value-added segments within international markets (Luo, 2021).

Despite these insights, existing literature primarily focuses on digitalization's routine efficiency gains, leaving its role in catalyzing substantive innovation underexplored. Empirical evidence linking supply chain digitalization, substantive innovation, and export performance remains limited (Y. Wang et al., 2024). By contextualizing this dynamic within emerging markets, our framework illuminates how digital empowerment drives fundamental upgrades in global competitiveness beyond mere cost advantages.

2.3. Policy-induced supply chain digitalization and export performance

Under China's "dual circulation" strategy, supply chain digitalization serves as a crucial mechanism for industrial modernization. Integrating information systems, logistics platforms, and cross-border data enables firms to overcome information asymmetries and coordinate value-adding activities across fragmented global networks (Peng et al., 2026). This systemic digital upgrading provides an ideal empirical context to examine its causal implications for export performance.

From the perspective of Resource Dependence Theory (Pfeffer & Salancik, 1978), exporters are particularly vulnerable to external constraints, relying heavily on foreign demand information, global logistics, and compliance with international technical standards. Such reliance exposes firms to significant transaction costs and strategic vulnerabilities. Supply chain digitalization mitigates these dependencies by lowering global input costs, improving transaction transparency, and enhancing structural autonomy in global markets (Daniel et al., 2026). Concurrently, Dynamic Capability Theory posits that firms must continuously sense, seize, and reconfigure resources in volatile environments (Teece et al., 1997). These imperatives are amplified in export markets, where uncertainties surrounding demand fluctuations, regulatory shifts, and geopolitical tensions are more acute than in domestic contexts. Digital tools—such as real-time analytics, IoT-enabled monitoring, and algorithm-driven coordination—equip firms with sharper sensing capabilities, greater agility in seizing opportunities, and stronger flexibility in resource reconfiguration (Dubey et al., 2023; Mohsin et al., 2025). Consequently, digitalization fortifies the dynamic capabilities critical for sustained international competitiveness. Synthesizing these perspectives, policy-induced digital upgrading simultaneously reduces external dependence and strengthens dynamic capabilities, thereby enhancing firms' export competitiveness. Based on this reasoning, we propose the following hypothesis:

H1: Policy-induced supply chain digitalization significantly improves firms' export performance.

2.4. The mediating role of substantive innovation

While efficiency gains provide immediate operational benefits, securing lasting international competitiveness requires firms to overcome low value-added positioning. This demands substantive innovation—the development of genuine, high-quality core technologies that fundamentally upgrade a firm's technological frontier—rather than incremental process improvements or superficial "strategic" patents pursued for short-term incentives (Jiang & Bai, 2022; Zhan et al., 2025). Supply chain digitalization acts as a powerful enabler of this deep technological transformation (Ai et al., 2025).

Drawing on Resource Dependence Theory, exporters rely heavily on transnational knowledge flows and collaborative research networks to overcome the capability barriers inherent in substantive innovation. Digital platforms drastically reduce these barriers by linking firms to global databases, patent pools, and cross-border partners, providing the scarce, high-value knowledge resources required to catalyze genuine breakthroughs (Luo et al., 2024). Concurrently, Dynamic Capability Theory emphasizes the ability to sense, seize, and reconfigure resources for sustained competitiveness. Within this framework, digitalization becomes critical for high-quality R&D: big-data analytics sharpen the sensing of technological bottlenecks, AI-driven simulations help firms seize new design opportunities, and digital twins accelerate reconfiguration through rapid prototyping, thereby mitigating the prohibitive costs and inherent risks traditionally associated with substantive exploration.

Synthesizing these theoretical perspectives, substantive innovation functions as the critical mechanism through which supply chain digitalization translates into sustainable international competitiveness. Based on this reasoning, we propose the following hypothesis:

H2: Substantive innovation mediates the relationship between supply chain digitalization and firms' export performance.

2.5. The moderating role of environmental uncertainty

Environmental uncertainty constitutes a fundamental condition of global competition (Li & Xiong, 2022), yet its strategic implications are far from uniform. For firms undergoing digital transformation, the nature of this uncertainty—whether systemic (industry-level) or idiosyncratic (firm-specific)—determines if digital tools function as strategic assets or remain underexploited technologies.

At the industry level, systemic uncertainty stems from macroeconomic volatility, regulatory realignments, or sector-wide demand shocks. High turbulence substantially increases the value of information processing and structural flexibility (Bloom, 2014). In this context, supply chain digitalization enhances organizational resilience by improving end-to-end visibility, enabling real-time coordination, and accelerating response speeds (Zouari et al., 2021). By leveraging digital infrastructures to capture and process market signals, firms can effectively mitigate collective shocks and convert external volatility into opportunities for competitive differentiation. Empirical evidence supports this view: firms operating in volatile industries such as energy or electronics consistently derive disproportionate strategic dividends from their digital investments (Mithas et al., 2013; Peng & Tao, 2022).

By contrast, firm-specific uncertainty reflects idiosyncratic instability, often manifesting through erratic operational cycles, unpredictable cash flows, or inconsistent strategies. Unlike systemic turbulence, which imposes shared external constraints, high internal volatility frequently indicates deficits in organizational design or resource orchestration (Irvine & Pontiff, 2009). Digital tools cannot inherently substitute for managerial coherence: without stable routines and sufficient absorptive capacity, fragmented organizations struggle to effectively operationalize digital resources into performance gains (Durman et al., 2025; Li et al., 2020). While some highly volatile firms may accelerate digital adoption as a reactive measure, internal instability often dilutes the structural benefits of digitalization. Due to these conflicting mechanisms, the moderating role of idiosyncratic uncertainty on the digitalization-performance nexus tends to be empirically inconclusive.

Synthesizing these distinctions, systemic shocks magnify the value of digitalization by rewarding coordination and agility, whereas idiosyncratic turbulence introduces organizational noise that makes the absorption of digital tools highly unpredictable. Thus, we propose:

H3a: Industry-level environmental uncertainty strengthens the positive effect of supply chain digitalization on export performance.

H3b: Firm-specific uncertainty does not exert a systematic moderating effect, as its influence is contingent and heterogeneous.

3. Research design

3.1. Sample selection and data sources

This study exploits the 2018 Supply Chain Innovation and Application Pilot Program as a quasi-natural experiment to examine how policy-driven digitalization shapes firm-level export performance (J. Ma et al., 2024). We construct a panel dataset of A-share listed firms from 2010 to 2023. To ensure reliability, we exclude "ST" or "*ST" firms, delisted firms, and observations with missing key values, yielding an unbalanced panel of 28,121 firm-year observations.

Financial and accounting data are obtained from CSMAR and CNRDS. Our primary data for firm export performance is derived from the "Geographical Segment Reporting" disclosed in the notes to audited financial statements, sourced from the CNINFO database. Pilot firms are identified based on official announcements by NDRC and MOFCOM, ensuring the credibility of treatment assignment.

3.2. Dependent variable

Export performance is defined as the natural logarithm of the total operating revenue from overseas regions disclosed in the geographical segment reporting. The log transformation normalizes skewed distributions and allows coefficients to be interpreted in percentage terms, a standard practice in empirical trade research (S. Wang et al., 2024).

Additionally, to assess the robustness of our findings, we employ Export Resilience and Export Intensity as alternative dependent variables. Export Intensity is defined as overseas revenue divided by total operating revenue (H. Ma et al., 2024). Export Resilience uses the 2008 Global Financial Crisis as a benchmark and measures a firm's export performance in year *t* relative to its 2008 level. Higher values indicate stronger post-crisis recovery and long-term export growth, reflecting greater resilience to external uncertainty (Zheng et al., 2023).

3.3. Independent variable

The key explanatory variable is supply chain digitalization, identified via the 2018 pilot program. Following the difference-in-differences framework, firms selected into the pilot form the treatment group ($Treat_i = 1$), while others serve as controls ($Treat_i = 0$). $Post_t = 1$ for years 2018 onward, 0 otherwise. The interaction term ($Treat_i \times Post_t$) captures the exogenous shock of policy-driven digitalization.

3.4. Mediating variables

Following Kong et al. (2017), we proxy Substantive Innovation (SI) using the annual number of independently applied invention patents. As invention patents require high R&D intensity and reflect genuine technological pioneering, independent applications serve as a highly credible indicator of a firm's autonomous innovation commitment and immediate response to digital upgrading. To reduce skewness, we apply a log transformation by adding one to the actual count:

$$SI = \ln\left(Independent\ Invention\ Applications + 1\right). \tag{1}$$

3.5. Moderating variables

The moderating variables are Environmental Uncertainty (*EU*) and Idiosyncratic Uncertainty (*IU*). Following Ghosh and Olsen (2009) and Shen et al. (2012), we first compute abnormal sales volatility for each firm over the past five years by removing firm-specific growth trends, and then use this detrended volatility as the base measure of uncertainty. *EU* captures common, industry-wide turbulence and is defined as the annual median abnormal sales volatility among all firms within the same industry. *IU* captures firm-specific instability beyond common industry shocks and is calculated as the ratio of a firm's abnormal sales volatility to the corresponding industry-level *EU* , thereby normalizing firm volatility by the industry benchmark. By distinguishing *EU* from *IU* , we examine how external turbulence versus internal instability conditions the effect of digitalization on export competitiveness.

3.6. Control variables

To mitigate omitted variable bias, we control for firm size (*Size*), profitability (*ROA*), financial leverage (*Lev*), firm age (*FirmAge*), ownership concentration (*Top*1), state ownership (*SOE*), operating cash flow (*CashFlow*), and firm value (*TobinQ*). All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers (Jiang et al., 2010). Detailed definitions of all variables are reported in Table 1.

Table 1. Main variables

Type	Variable	Symbol	Definition and Measurement
Dependent	Export Performance	ln(Export)	ln(*Total Overseas Operating Revenue* + 1)
Robustness	Export Resilience	Resilience	Deviation of export value in year *t* relative to the 2008 benchmark
	Export Intensity	Intensity	Overseas Operating Revenue/Total Operating Revenue
Independent	Supply Chain Digitalization	DID	Interaction term: *Treat*×*Post* (1 for pilot firms after implementation, 0 otherwise)
Mediator	Substantive Innovation	SI	ln(*Number of Invention Patent Applications* + 1)
Moderator	Env. Uncertainty	EU	Industry-level volatility: Median of abnormal sales volatility over past 5 years
	Idio. Uncertainty	IU	Firm-specific risk ratio: Firm's Abnormal Volatility/Industry EU
Controls	Firm Size	Size	ln(*Total Assets at Year-end*)
	Return on Assets	ROA	Net Income/Average Total Assets
	Leverage	Lev	Total Liabilities/Total Assets
	Firm Age	FirmAge	ln(*Current Year-Establishment Year* + 1)
	Ownership Conc.	Top1	Shareholding ratio of the largest shareholder
	State Ownership	SOE	Dummy: 1 if the ultimate controller is the government or SOE, 0 otherwise
	Cash Flow	CashFlow	Net Cash Flow from Operating Activities/Total Assets
	Tobin's Q	TobinQ	(Mkt Value of Equity+Book Value of Debt)/Total Assets

3.7. Model specification

To empirically examine the causal impact of supply chain digitalization on export performance, we exploit the 2018 "Supply Chain Innovation and Application Pilot Program" as a quasi-natural experiment. Based on a difference-in-differences framework (Angrist & Pischke, 2008), we estimate the following baseline specification:

$$\ln\left(Export_{i,t}\right) = \beta_0 + \beta_1 DID_{i,t} + \gamma Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}, \quad (2)$$

where the dependent variable, $\ln\left(Export_{i,t}\right)$, denotes the natural logarithm of firm i's export value in year t. The core independent variable, $DID_{i,t}$, is the interaction term $Treat_i \times Post_t$, which equals 1 if firm i is a pilot enterprise and year t falls in the post-implementation period (2018–2023), and 0 otherwise.

The coefficient β_1 is of central interest. We acknowledge that the pilot status is an administrative designation and may bundle multiple policy components. Accordingly, we interpret β_1 as the average treatment effect of exposure to a digitalization-oriented supply chain policy, rather than mechanically equating pilot selection with digitalization itself. This interpretation is grounded in two facts: First, the central directive of the program (State Council Doc. No. 84 (General Office of the State Council of the People's Republic of China, 2017)) places "enhancing digitalization and intelligence" among the key evaluation criteria, indicating that digital upgrading is a core policy component. Second, our manual review of pilot firms' disclosed projects confirms substantive digital initiatives, aligning with the program's intended orientation (Ministry of Commerce of the People's Republic of China, 2018).

Furthermore, to alleviate concerns that pilot eligibility may also be associated with resource advantages, we include a rich set of firm-level controls—explicitly including financial resource proxies (e.g., Cash Flow)—and absorb time-invariant heterogeneity via firm fixed effects μ_i and common macro shocks via year fixed effects δ_t (Gormley & Matsa, 2014). Standard errors are clustered at the firm level to account for within-firm serial correlation (Bertrand et al., 2004).

4. Empirical analysis

4.1. Descriptive statistics

Table 2 reports the descriptive statistics. The dependent variable, $\ln\left(Export\right)$, exhibits substantial variation, indicating significant heterogeneity in export performance across firms. Crucially, the treatment variable DID has a mean of 0.011. While pilot firms comprise only 1.1% of the sample, the extensive pool of non-pilot firms serves as a rich "donor pool." This structure enables us to construct highly comparable counterfactuals via Propensity Score Matching (PSM), thereby mitigating potential selection bias. Furthermore, control variables such as $Size$ and $CashFlow$ display sufficient variation. Substantive Innovation also shows significant dispersion, supporting our subsequent examination of impact channels.

Table 2. Descriptive statistics of the main variables

Variable	N	Mean	SD	Min	Median	Max
ln(Export)	28121	19.075	2.336	0	19.291	24.575
Resilience	14,008	4.352	8.681	–0.839	0.721	32.558

End of Table 2

Variable	N	Mean	SD	Min	Median	Max
Intensity	10,448	0.238	0.228	0.000	0.163	0.931
DID	28126	0.011	0.105	0.000	0.000	1.000
SI	28,107	1.337	1.368	0.000	1.099	5.485
EU	18,920	0.109	0.017	0.075	0.105	0.198
IU	18,920	1.275	1.071	0.144	0.974	6.317
Size	28126	22.139	1.272	19.313	21.928	26.452
ROA	28126	0.037	0.067	–0.578	0.039	0.220
Lev	28126	0.406	0.200	0.028	0.398	0.934
FirmAge	28126	2.899	0.353	1.099	2.944	3.689
Top1	28126	0.334	0.144	0.076	0.314	0.758
SOE	27482	0.285	0.452	0.000	0.000	1.000
CashFlow	28124	0.049	0.067	–0.226	0.047	0.282
TobinQ	27790	1.992	1.214	0.795	1.612	17.676

4.2. Baseline regression results

Table 3 presents the baseline results estimated using a stepwise regression strategy. The results indicate that the coefficient of the core explanatory variable, DID, remains consistently positive and significant at the 1% or 5% level, regardless of the inclusion of control variables. Moreover, the magnitude of the coefficient is stable, fluctuating within a narrow range between 0.41 and 0.45. In Column (4), which incorporates the full set of control variables and two-way fixed effects, the estimated coefficient is 0.425. This suggests that even after rigorously controlling for potential omitted variable bias, supply chain digitalization exerts a significant promoting effect on firms' export performance, thereby supporting Hypothesis H1.

It is worth noting that, since log-linear OLS models tend to assign higher weight to observations with smaller baselines, this estimate might partially capture the "inflated" volatility associated with micro-enterprises during their initial transformation phase, potentially leading to an upward bias. Consequently, the coefficient of 0.425 should be interpreted with caution as an "upper bound" of the policy effect. To mitigate such scale-related noise and obtain a more precise estimate of the net effect, we employ non-parametric methods, such as Poisson Pseudo Maximum Likelihood and Double Machine Learning, in subsequent analyses. Additionally, the explanatory power of the model improves steadily with the inclusion of control variables, and the signs of the coefficients for all covariates are consistent with theoretical expectations.

Table 3. Baseline regression results

Variable	(1)	(2)	(3)	(4)
	ln(Export)	ln(Export)	ln(Export)	ln(Export)
DID	0.452***	0.409**	0.411**	0.425**
	(2.642)	(2.435)	(2.420)	(2.524)
Size		0.912***	0.882***	0.887***
		(22.296)	(20.806)	(21.228)

End of Table 3

Variable	(1)	(2)	(3)	(4)
	ln(Export)	ln(Export)	ln(Export)	ln(Export)
FirmAge		0.678***	0.625***	0.644***
		(3.295)	(3.069)	(3.144)
SOE		0.042	0.040	0.036
		(0.421)	(0.402)	(0.362)
Lev			0.404***	0.379***
			(2.738)	(2.592)
ROA			0.725***	0.722***
			(3.804)	(3.815)
CashFlow			0.991***	0.997***
			(6.505)	(6.468)
Top1				0.146
				(0.539)
TobinQ				–0.005
				(–0.477)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	27,766	27,180	27,178	26,851
Adj.R2	0.823	0.849	0.850	0.851

Notes: t-statistics in parentheses. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Parallel trends test

The validity of the Difference-in-Differences model strictly hinges on the Parallel Trends Assumption. To verify whether the treatment and control groups shared comparable evolutionary paths prior to the policy intervention, and to further investigate the intertemporal dynamic characteristics of the policy effect, we employ established event study frameworks and construct the following model:

$$\ln\left(Export_{i,t}\right) = \alpha + \sum_{k=-5,k\neq-1}^{4} \beta_k \times D_{i,t}^{k} + \gamma X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}. \quad (3)$$

Figure 1 plots the temporal distribution of the estimated coefficients β_k along with their 95% confidence intervals. The empirical results provide robust support for the parallel trends assumption and delineate a dynamic evolution process of the digital dividend, characterized by a transition from "weak to strong": First, the pre-treatment trends satisfy statistical parallelism. Prior to the implementation of supply chain digitalization ($k < 0$), the estimated coefficients fluctuate marginally around zero, and their 95% confidence intervals all contain the null value. This indicates that within the observation window preceding the policy shock, there were no systematic differences in export performance between the treatment and control groups. This finding rules out potential selection bias arising from pre-existing trends, establishing a solid foundation for the causal identification of the baseline regression results.

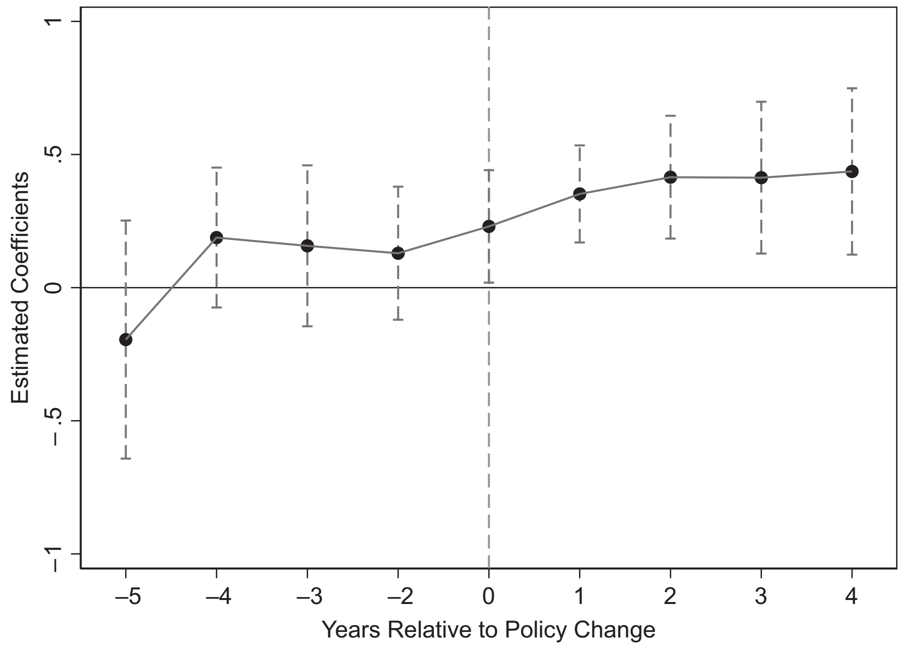


Figure 1. Parallel trends test

Second, the policy effect initially emerges in the implementation year and subsequently exhibits a trend of continuous enhancement. From the perspective of the dynamic trajectory, in the year of policy implementation, i.e., 2018 ($k = 0$), the estimated coefficient begins to deviate from the zero interval and displays weak statistical significance. Although supply chain digitalization began to play a role in optimizing resource allocation during its introductory year, its export-promoting effect had not yet been fully unleashed in the initial stage, manifesting a transitional characteristic of being "effective but limited in intensity." However, over time ($k \geq 1$), the statistical significance of the estimated coefficients increases rapidly, and their magnitudes show a steady upward trend. As firms cross the initial technological adaptation threshold, the deep integration of digital infrastructure with supply chain processes generates sustained efficiency dividends, thereby underpinning the long-term growth of export performance.

4.4. Multidimensional robustness checks

To verify the reliability of the baseline regression results, we conduct a series of robustness checks across three dimensions: estimation methods, sample sensitivity, and variable measurement. The results are reported in Table 4.

Given that the log-linear OLS model may yield biased estimates due to the neglect of zero trade flows and heteroscedasticity, we re-estimate the model using the raw values of exports via Poisson Pseudo Maximum Likelihood (PPML) (Column 1) (Weidner & Zylkin, 2021). The results show that the coefficient of the core explanatory variable is 0.222, significant at the 1% level. This discrepancy suggests that the baseline OLS estimate indeed captured some volatility amplified by the logarithmic transformation, whereas the PPML results filter out this noise, providing a more conservative lower bound for the policy effect. Even based on this conservative estimate, the promoting effect of supply chain digitalization on export performance remains robust.

Secondly, logarithmic models tend to magnify minor increments of micro-enterprises into substantial volatility (i.e., the "low base effect"). To eliminate such inflated growth noise and isolate external shocks, we exclude the bottom 5% of the sample (Column 2) and introduce a pandemic intensity control, measured by the logarithm of the number of infections in the firm's province (Column 3) (Bae et al., 2021; He et al., 2022). Furthermore, Column (4) controls for "Industry × Year" fixed effects to absorb macroscopic cyclical shocks. The results show that the DID coefficient remains stable within the range of 0.375 to 0.398, with no change in significance levels. This indicates that the core conclusion possesses high sample robustness and is not driven by outliers or specific external environmental factors.

Thirdly, to further investigate the comprehensive impact of supply chain digitalization on the "quality" and "structure" of export performance, we introduce Export Resilience and Export Intensity as alternative dependent variables in Columns (5) and (6), respectively. The regression results show a significantly positive coefficient for export resilience, indicating that digitalization not only brings about an expansion in export scale but also significantly fortifies firms' risk-buffering capabilities against external shocks. The coefficient for export intensity is significant at the 1% level. This implies that supply chain digitalization triggers a structural leap in the firm's market orientation, substantively increasing its dependency on and penetration into international markets.

Table 4. Multidimensional robustness checks

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	PPML	Excl. Low Export	Control Covid	Ind x Year FE	Resilience	Intensity
DID	0.222***	0.375***	0.398**	0.383**	3.103***	0.059***
	(2.890)	(2.772)	(2.305)	(2.195)	(2.572)	(3.013)
Pandemic			0.034*			
			(1.872)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	NO	Yes	Yes
Ind x Year	NO	NO	NO	YES	NO	NO
Observations	26,851	24,127	23,605	26,707	13742	9979
Adj.R^2		0.871	0.848	0.860	0.734	0.399

Notes: t-statistics in parentheses. 'Controls' include firm-level characteristics (Size, Age, SOE, etc.). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Robustness check: PSM-DID

Table 5 and Figure 2 present the covariate balance diagnostics. The results indicate that PSM effectively eliminates the significant pre-existing differences between the treatment and control groups. Specifically, the standardized bias for all covariates drops drastically to single digits, and all post-match t-tests yield p-values exceeding 0.10. This alignment confirms that the matching procedure successfully constructs a statistically comparable control group, thereby satisfying the balancing assumption.

Table 5. Balance statistics

Variable	Sample	Treated	Control	% Bias	t-stat	p-value
Size	Unmatched	24.024	22.09	147.9	40.37	0
	Matched	24.024	23.983	3.1	0.53	0.595
FirmAge	Unmatched	2.975	2.895	22.3	5.8	0
	Matched	2.975	2.977	–0.6	–0.11	0.914
SOE	Unmatched	0.648	0.276	80.2	21.36	0
	Matched	0.648	0.671	–5.1	–0.91	0.361
Lev	Unmatched	0.561	0.403	86.2	20.47	0
	Matched	0.561	0.567	–3.2	–0.62	0.535
ROA	Unmatched	0.045	0.038	13	2.98	0.003
	Matched	0.045	0.045	0.6	0.14	0.889
CashFlow	Unmatched	0.058	0.049	13.6	3.65	0
	Matched	0.058	0.058	0.4	0.07	0.948
Top1	Unmatched	0.349	0.338	7.7	2	0.045
	Matched	0.349	0.347	1.6	0.28	0.782
TobinQ	Unmatched	1.571	2	–37.1	–9.15	0
	Matched	1.571	1.561	0.8	0.17	0.861

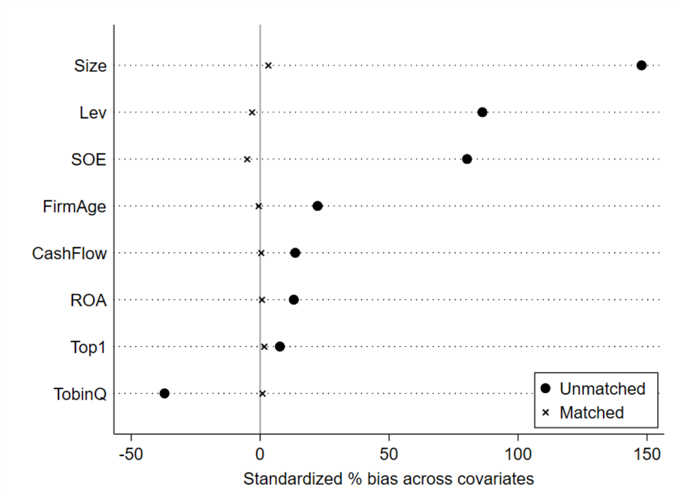


Figure 2. Covariate balance check

Although the baseline regression controls for multi-dimensional fixed effects, the firm's decision to undergo supply chain digitalization may still be endogenous to its internal resource endowments, leading to potential self-selection bias. To overcome the limitations inherent in any single counterfactual framework, we employ three distinct matching and weighting techniques: period-by-period Propensity Score Matching (PSM), Inverse Probability

Weighting (IPW), and Entropy Balancing (EB). Each method offers a unique trade-off: While period-by-period PSM strictly controls for temporal mismatch, it may suffer from sample attrition; IPW mitigates this information loss by weighting the full sample, thereby preserving generalizability (Busso et al., 2014); whereas Entropy Balancing further circumvents reliance on specific propensity score specifications, achieving the strictest covariate balance by forcing alignment on higher-order moments (Athey & Imbens, 2022; Hainmueller, 2012). Table 6 reports the estimates from these approaches. The empirical results reveal that, despite substantial variations in sample size across methods, the estimated coefficients of DID exhibit remarkable stability. They consistently fall within the narrow range of [0.334, 0.389] and remain statistically significant at the 5% level or better. We thus infer that the baseline findings are not driven by sample selection bias or specific model specifications, corroborating a robust causal effect of supply chain digitalization on promoting firm export performance.

Table 6. PSM-DID

Variable	(1)	(2)	(3)
	Year-by-Year PSM	IPW-DID	Entropy Balancing
DID	0.389**	0.326**	0.334**
	(2.058)	(2.084)	(2.143)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	942	26,851	26,851
Adj.R^2	0.871	0.861	0.867

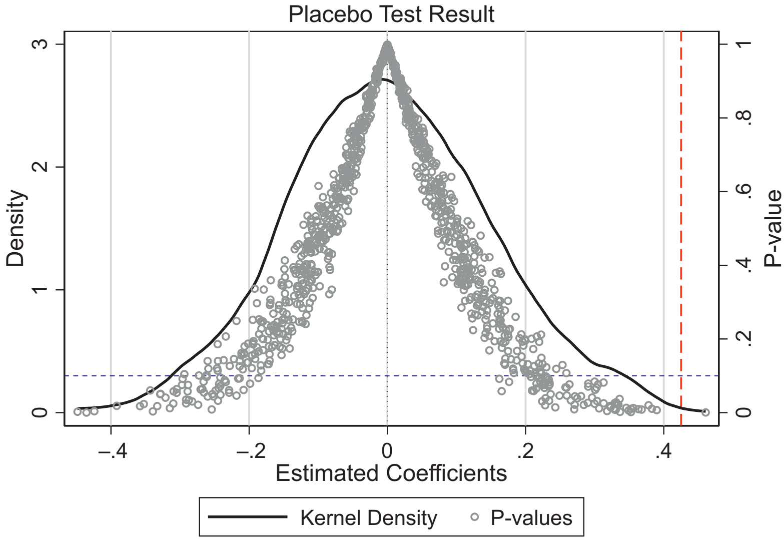
Notes: *t* statistics in parentheses. Column (1) uses year-by-year 1:1 nearest neighbor matching. Column (2) uses Inverse Probability Weighting (IPW). Column (3) uses Entropy Balancing. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6. Placebo test

To further rule out the interference of unobservable omitted variables, we conduct a placebo test by randomly assigning pseudo-treatment status and policy timing to firms. This counterfactual simulation is repeated 1,000 times to generate an empirical distribution of placebo DID estimators (Cai et al., 2016; Chetty et al., 2009). Figure 3 visualizes the results. The kernel density curve of the falsified coefficients exhibits a standard normal distribution centered around zero, with the majority of associated p-values exceeding the 0.1 significance level. Strikingly, our true benchmark coefficient of 0.425 (red dashed line) is located in the extreme right tail, standing as a distinct statistical outlier. This evidence implies that the probability of our findings being driven by random factors or unobserved confounders is negligible, thereby confirming the robustness of the causal inference.

4.7. Spillover effects

To address potential violations of the Stable Unit Treatment Value Assumption (SUTVA) caused by the "strong permeability" of digital technology, we adopt the "leave-one-out" approach to construct geographic and industrial spillover indices ($Spill\_Geo$ and $Spill\_Ind$) (Leary & Roberts, 2014; Miguel & Kremer, 2004). Table 7 reports the results. First, we find significant positive externalities. As shown in Columns (1) and (3), the agglomeration of pilot firms within



Note: The vertical dashed line represents the true benchmark coefficient .425.

Figure 3. Placebo test

the same city or industry significantly drives the export growth of non-pilot firms, with coefficients of 0.040 and 0.043, respectively. This confirms the existence of regional and industrial positive spillover effects. Crucially, however, the direct effect remains dominant. When controlling for these spillovers in the full sample (Columns 2 and 4), the coefficients of the core explanatory variable DID (0.431 and 0.409) remain robustly significant and are an order of magnitude larger than the spillover effects. This evidence suggests that while companies can benefit from the "free-riding" of technology diffusion, the direct efficiency gains from a firm's own digital transformation are the primary driver of export performance.

Table 7. Geographic and industry spillover effects

Variable	(1)	(2)	(3)	(4)
	Geo: Control Only	Geo: Full Sample	Ind: Control Only	Ind: Full Sample
DID		0.431^{**}		0.409^{**}
		(2.564)		(2.452)
Spill_Geo	0.040^{**}	0.042^{**}		
	(2.218)	(2.334)		
Spill_Ind			0.043^{***}	0.045^{***}
			(2.682)	(2.881)
Controls	Yes	Yes	Yes	Yes
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	26,172	26,851	26,172	26,851
Adj.R^2	0.847	0.851	0.847	0.851

Notes: *t* statistics in parentheses. Columns (1) and (3) restrict the sample to control firms. Columns (2) and (4) use the full sample. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.8. Double machine learning for causal inference

To mitigate potential biases arising from functional form misspecification in traditional linear models, we employ the Double Machine Learning (DML) framework combined with the Random Forest algorithm (Breiman, 2001; Chernozhukov et al., 2018). The estimation results are reported in Table 8. Column (2) presents the estimates based on the Partial Linear Model (PLM), yielding a coefficient for the core explanatory variable of 0.397, which is significant at the 1% level. Column (3) reports the results from the Interactive Model, which allows for treatment effect heterogeneity. The estimated Average Treatment Effect on the Treated (ATET) is 0.345, also statistically significant at the 1% level.

The coefficients across both specifications are comparable in magnitude and consistently positive. Furthermore, the distribution derived from 10-fold cross-validation resampling demonstrates high estimation stability. These findings suggest that the promoting effect of digital transformation on export performance remains robust even after rigorously controlling for high-dimensional covariates and their non-linear interactions.

Table 8. Double machine learning

Variable	(1) OLS	(2) DML-PLM	(3) DML-ATET
DID	0.425**	0.397***	0.345***
	(2.524)	(3.537)	(3.064)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	27145	27145	27145

Notes: *t* statistics in parentheses. DML uses Random Forest (10 reps). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Further analysis

5.1. Mediation effect of substantive innovation

Table 9 investigates the mediating role of substantive innovation. Controlling for SI in the baseline model (Column 3) partially absorbs the direct policy effect, reducing the coefficient from 0.425 to 0.406, which signals a classic partial mediation mechanism. To rigorously validate this, a Bootstrap procedure with 500 replications is employed, yielding an estimated indirect effect of 0.019. Crucially, the 95% confidence interval of [0.004, 0.048] strictly excludes zero, thereby confirming the statistical establishment of this mediation channel. Quantitatively, this substantive innovation pathway accounts for approximately 4.47% (0.019/0.425) of the total export-promoting effect. While this proportion may appear numerically modest at first glance, it is both theoretically expected and economically profound. The total export dividend of supply chain digitalization is heavily driven by immediate operational efficiencies—such as reduced matching frictions, lowered transaction costs, and optimized logistics—which naturally dominate the short-term variance. However, the portion mediated by substantive innovation represents a fundamental outward shift of the firm's technological frontier, a process that inherently requires a longer gestation period. Unlike routine efficiency gains that are subject to diminishing marginal returns, this structural upgrade equips firms with the dynamic capabilities required to secure a sustainable competitive edge in global markets. Therefore, rather than being a mere spurious statistical artifact, substantive innovation serves as a vital structural pathway that strategically complements direct operational improvements.

Table 9. Mediation analysis: the role of substantive innovation

Variable	(1)	(2)	(3)
	Total Effect	Mechanism(SI)	Direct Effect
DID	0.425**	0.424**	0.406**
	(2.524)	(2.363)	(2.431)
SI			0.045***
			(3.331)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	26818	26822	26818
Adj.R^2	0.851	0.653	0.851
Indirect Effect			0.019
95% CI			[0.004, 0.048]

Notes: t statistics in parentheses. Bootstrap results (500 reps) are reported at the bottom of Column (3). * p < 0.1, ** p < 0.05, *** p < 0.01.

5.2. Moderation effect test: industry vs. firm-level uncertainty

Table 10 presents the moderation results, distinguishing between systemic industry-level shocks (EU) and idiosyncratic firm-level fluctuations (IU).Column (1) shows that industry-level uncertainty significantly strengthens the policy effect: the coefficient of $DID \times EU$ is positive (0.172) and significant at the 5% level. This indicates that digitalization delivers greater export benefits in volatile industry environments. Systemic turbulence creates information scarcity and coordination challenges that digital tools are uniquely positioned to address. By embedding data analytics, platform integration, and algorithm-driven logistics, firms can transform external volatility into agility. Consequently, digitalization functions as an adaptive strategic buffer against industry-wide shocks rather than a mere routine efficiency enhancer.

Conversely, the results in Column (2) reveal a contrasting pattern. The coefficient of $DID \times IU$ is negative (–0.408) and statistically insignificant, indicating that firm-specific volatility does not systematically moderate the digitalization–export link. Unlike systemic shocks that compel collective adaptation, idiosyncratic instability—such as erratic sales, governance inefficiencies, or strategic inconsistency—generates internal noise. Digital technologies cannot compensate for managerial distraction or fragmented resource allocation. Thus, while systemic uncertainty amplifies the strategic value of digitalization, idiosyncratic uncertainty merely blurs the operational signal without yielding additional returns.

Together, these findings establish a critical boundary condition: digitalization yields substantial strategic dividends under systemic turbulence, where external shocks make agility indispensable, but its efficacy is severely constrained by firm-level noise and strategic misalignment. For policymakers, this suggests that digital transformation initiatives are most impactful when targeting industries exposed to external volatility, rather than firms merely struggling with internal instability.

Table 10. DID with triple interactions: industry vs firm-level uncertainty

Variable	(1)	(2)
	ln(Export)	ln(Export)
DID	0.342**	0.374**
	(2.099)	(1.970)
DID × EU	0.172**	
	(2.047)	
DID × IU		–0.408
		(–1.598)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	18188	17916
Adj.R^2	0.835	0.854

Notes: *t* statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

5.3. Heterogeneity analysis

Table 11 explores the heterogeneous impacts of supply chain digitalization on export performance across three critical dimensions: firm size, industry sector, and pre-existing digital maturity.

Table 11. Heterogeneity of policy effects

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Small	Large	Non-Manu	Manu	Low-Dig	High-Dig
DID	–0.175	0.437**	0.498**	0.408*	0.373	0.442**
	(–0.401)	(2.344)	(2.036)	(1.893)	(1.470)	(2.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13273	13578	4672	22139	13438	13413
Adj.R^2	0.796	0.812	0.861	0.861	0.823	0.874

Notes: *t* statistics in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Columns (1) and (2) partition the sample into small and large firms. The export-promoting effect is exclusively concentrated in large enterprises, while remaining negative and insignificant for small firms. This divergence highlights a binding resource threshold. Large firms, benefiting from economies of scale, can readily absorb the substantial fixed costs of digital integration, whereas small firms struggle to translate these tools into immediate export advantages due to capital and talent constraints.

Columns (3) and (4) reveal a nuanced divergence between non-manufacturing and manufacturing sectors. While positive in both, the effect is more pronounced and robust in the non-manufacturing sector. For trade and service-oriented firms, digitalization rapidly eliminates information asymmetry and cross-border matching frictions, yielding immediate returns.

In contrast, the effect for manufacturing firms is only marginally significant. Upgrading manufacturing supply chains requires the deep integration of cyber-physical systems. Such "hard" transformations entail longer cycles and heavier asset investments, causing export dividends to materialize more gradually.

Turning to firms' digital maturity, we first construct a firm-level digitalization index by parsing the Management Discussion and Analysis sections of annual reports. Using Python-based NLP tools, we aggregate the frequencies of digitalization-related keywords and partition the sample at the median into "Low-Dig" and "High-Dig" cohorts (Loughran & McDonald, 2011; Wu et al., 2021). Columns (5) and (6) reveal a clear asymmetry: highly digitalized firms capture significantly larger gains, while their less digitalized counterparts see muted or insignificant improvements. Digital tools here act as a strategic amplifier: they magnify the absorptive capacity of firms, enabling them to effectively translate policy signals into innovation, coordination, and export performance. For firms lagging in digital adoption, however, the absence of adequate infrastructure and complementary assets means that the policy support dissipates before materializing into export advantages.

6. Conclusions and policy implications

This paper exploits China's 2018 Supply Chain Innovation and Application Pilot Program as a quasi-natural experiment to evaluate the causal impact of policy-driven supply chain digitalization on firms' export performance. The empirical evidence demonstrates a substantial export-promoting effect. While we observe positive spatial and industrial spillovers, the direct policy benefits remain overwhelmingly dominant. Mechanism tests highlight the pivotal role of substantive innovation as a key transmission channel, equipping firms with core technological breakthroughs beyond mere operational efficiencies. Furthermore, moderation analysis uncovers a distinct asymmetry in risk mitigation: a digitalized supply chain acts as an adaptive strategic buffer against systemic, industry-level uncertainty, yet it fails to effectively mitigate idiosyncratic, firm-specific volatility. Crucially, heterogeneity tests underscore a binding resource constraint in the distribution of these policy dividends: the export-enhancing effects are highly asymmetric, accruing predominantly to large enterprises, non-manufacturing sectors, and firms with high pre-existing digital maturity. Together, these findings lend robust support to a broader theoretical framework of "policy-driven adaptation, innovation conversion, and environmental response," reaffirming that supply chain digitalization functions as a contingent dynamic capability rather than a universally accessible technological fix.

Despite these robust findings, the study has limitations. By focusing exclusively on listed firms, it may overstate the digital readiness of the broader economy, particularly SMEs. In addition, the relatively short policy window restricts the ability to capture long-term structural transformations. Future work should draw on non-listed firms, cross-sector evidence, and cross-country comparisons to deepen our understanding of how supply chain digitalization reshapes global trade dynamics over time.

For policymakers, our results offer three critical insights. First, to prevent the exacerbation of the "digital divide," policies targeting supply chain digitalization must be tiered and inclusive, lowering entry barriers and providing targeted support for SMEs, while leveraging leading large firms as demonstrators. Second, robust data governance and interoperability standards are essential to unlock deep digital supply chain synergies across sectors. Finally, in an era characterized by rising global volatility, policy designs should move beyond one-off hardware interventions toward fostering firms' dynamic capabilities—enabling them not only to adopt digital supply chain tools but to systematically transform them into resilience, adaptability, and long-term competitiveness.

By reframing supply chain digitalization as a dynamic capability rather than a mere technological upgrade, this study underscores its critical role not only in enhancing firm-level exports but also in redefining the structural resilience of economies in an increasingly turbulent global order.

Author contributions

JS conceptualized the core research framework and supervised the entire study. LH took charge of the methodological design, performed the empirical analysis, and drafted the original manuscript. BS and YT contributed to data curation and the literature review. YJ finalized the manuscript's formatting and proofreading. All authors critically reviewed and approved the final version for submission.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ai, M., Yu, Y., & Bu, Y. (2025). The impact of digital transformation of resource-based enterprises on green innovation: Mechanism analysis based on TOE framework. *Innovation and Green Development*, *4*(4), Article 100262. https://doi.org/10.1016/j.igd.2025.100262

Angrist, J. D., & Pischke, J.-S. (2008). *Mostly harmless econometrics*: *An empiricist's companion*. Princeton University Press. https://doi.org/10.2307/j.ctvcm4j72

Appio, F. P., Frattini, F., Petruzzelli, A. M., & Neirotti, P. (2021). Digital transformation and innovation management: A synthesis of existing research and an agenda for the future. *Journal of Product Innovation Management*, *38*(1), 4–20. https://doi.org/10.1111/jpim.12562

Athey, S., & Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, *226*(1), 62–79. https://doi.org/10.1016/j.jeconom.2020.10.012

Bae, K.-H., El Ghoul, S., Gong, Z., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. *Journal of Corporate Finance*, *67*, Article 101876. https://doi.org/10.1016/j.jcorpfin.2020.101876

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275. https://doi.org/10.1162/003355304772839588

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–176. https://doi.org/10.1257/jep.28.2.153

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Brynjolfsson, E., Hui, X., & Liu, M. (2019). Does machine translation affect international trade? Evidence from a large digital platform. *Management Science*, *65*(12), 5449–5460. https://doi.org/10.1287/mnsc.2019.3388

Busso, M., DiNardo, J., & McCrary, J. (2014). New evidence on the finite sample properties of propensity score reweighting and matching estimators. *The Review of Economics and Statistics*, *96*(5), 885–897. https://doi.org/10.1162/REST_a_00431

Cai, X., Lu, Y., Wu, M., & Yu, L. (2016). Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. *Journal of Development Economics*, *123*, 73–85. https://doi.org/10.1016/j.jdeveco.2016.08.003

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, *21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

Chetty, R., Looney, A., & Kroft, K. (2009). Salience and taxation: Theory and evidence. *American Economic Review*, *99*(4), 1145–1177. https://doi.org/10.1257/aer.99.4.1145

Daniel, J., Maroun, E. A., Garza-Reyes, J. A., El Jaouhari, A., & Samadhiya, A. (2026). From information asymmetry to transparency: Blockchain-enabled digital transformation in manufacturing supply chains. *Supply Chain Management*: *An International Journal*, *31*(2), 275–296. https://doi.org/10.1108/SCM-09-2025-0903

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The role of government effectiveness. *International Journal of Production Economics*, *258*, Article 108790. https://doi.org/10.1016/j.ijpe.2023.108790

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, *59*(1), 110–128. https://doi.org/10.1080/00207543.2019.1582820

Durman, S., Iyiola, K., Alzubi, A. B., & Aljuhmani, H. Y. (2025). Dynamic capabilities in action: Digital capability, business model innovation and absorptive capacity. *Management Decision*. https://doi.org/10.1108/MD-04-2025-0951

Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research*, *112*, 119–127. https://doi.org/10.1016/j.jbusres.2020.03.004

General Office of the State Council of the People's Republic of China. (2017). *Guiding opinions on actively promoting supply chain innovation and application*. https://www.gov.cn/gongbao/content/2017/content_5234516.htm (in Chinese).

Gereffi, G. (2020). What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. *Journal of International Business Policy*, *3*(3), 287–301. https://doi.org/10.1057/s42214-020-00062-w

Ghosh, D., & Olsen, L. (2009). Environmental uncertainty and managers' use of discretionary accruals. *Accounting*, *Organizations and Society*, *34*(2), 188–205. https://doi.org/10.1016/j.aos.2008.07.001

Gormley, T. A., & Matsa, D. A. (2014). Common errors: How to (and not to) control for unobserved heterogeneity. *The Review of Financial Studies*, *27*(2), 617–661.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, *162*, Article 120392. https://doi.org/10.1016/j.techfore.2020.120392

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, *20*(1), 25–46. https://doi.org/10.1093/pan/mpr025

He, J., Ma, X., & Wei, Q. (2022). Firm-level short selling and the local COVID-19 pandemic: Evidence from China. *Economic Modelling*, *113*, Article 105896. https://doi.org/10.1016/j.econmod.2022.105896

Irvine, P. J., & Pontiff, J. (2009). Idiosyncratic return volatility, cash flows, and product market competition. *The Review of Financial Studies*, *22*(3), 1149–1177. https://doi.org/10.1093/rfs/hhn039

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning* & *Control*, *32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Jiang, G., Lee, C. M. C., & Yue, H. (2010). Tunneling through intercorporate loans: The China experience. *Journal of Financial Economics*, *98*(1), 1–20. https://doi.org/10.1016/j.jfineco.2010.05.002

Jiang, L., & Bai, Y. (2022). Strategic or substantive innovation? The impact of institutional investors' site visits on green innovation evidence from China. *Technology in Society*, *68*, Article 101904. https://doi.org/10.1016/j.techsoc.2022.101904

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations* & *Production Management*, *37*(1), 10–36. https://doi.org/10.1108/IJOPM-02-2015-0078

Kano, L., Tsang, E. W. K., & Yeung, H. W.-c. (2020). Global value chains: A review of the multi-disciplinary literature. *Journal of International Business Studies*, *51*(4), 577–622. https://doi.org/10.1057/s41267-020-00304-2

Kong, D., Xu, M., & Kong, G. (2017). Inside pay gap and firm innovation. *Economic Research Journal*, *52*(10), 144–157 (in Chinese).

Leary, M. T., & Roberts, M. R. (2014). Do peer firms affect corporate financial policy? *The Journal of Finance*, *69*(1), 139–178. https://doi.org/10.1111/jofi.12094

Li, K.-S., & Xiong, Y.-Q. (2022). Host country's environmental uncertainty, technological capability, and foreign market entry mode: Evidence from high-end equipment manufacturing MNEs in emerging markets. *International Business Review*, *31*(1), Article 101900. https://doi.org/10.1016/j.ibusrev.2021.101900

Li, Y., Dai, J., & Cui, L. (2020). The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics*, *229*, Article 107777. https://doi.org/10.1016/j.ijpe.2020.107777

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Luo, S., Xiong, Z., & Liu, J. (2024). How does supply chain digitization affect green innovation? Evidence from a quasi-natural experiment in China. *Energy Economics*, *136*, Article 107745. https://doi.org/10.1016/j.eneco.2024.107745

Luo, Y. (2021). New OLI advantages in digital globalization. *International Business Review*, *30*(2), Article 101797. https://doi.org/10.1016/j.ibusrev.2021.101797

Ma, H., Zou, J., & Zou, H. (2024). The longer, the farther? The internationalization of Chinese firms. *Chinese Management Studies*, *18*(5), 1514–1536. https://doi.org/10.1108/CMS-12-2022-0445

Ma, J., Li, Q., Zhao, Q., Liou, J., & Li, C. (2024). From bytes to green: The impact of supply chain digitization on corporate green innovation. *Energy Economics*, *139*, Article 107942. https://doi.org/10.1016/j.eneco.2024.107942

Miguel, E., & Kremer, M. (2004). Worms: Identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, *72*(1), 159–217. https://doi.org/10.1111/j.1468-0262.2004.00481.x

Ministry of Commerce of the People's Republic of China. (2018). *Notice on announcing the list of national pilot cities and pilot enterprises for supply chain innovation and application*. https://ltfzs.mofcom.gov.cn/gylcxyyy/zcfb/art/2018/art_ddec3ef620174303b97962fdaeec1c42.html (in Chinese).

Mithas, S., Tafti, A., & Mitchell, W. (2013). How a firm's competitive environment and digital strategic posture influence digital business strategy. *MIS Quarterly*, *37*(2), 511–536. https://doi.org/10.25300/MISQ/2013/37.2.09

Mohsin, A. K. M., Rashed, M., Gerschberger, M., Plasch, M., Ahmed, S. F., Dritan, O., & Islam, M. F. (2025). Smart supply chains: How do resilience and dynamic capabilities drive corporate performance? *The International Journal of Logistics Management*, *36*(7), 330–363. https://doi.org/10.1108/IJLM-12-2024-0783

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), Article 103773. https://doi.org/10.1016/j.respol.2019.03.018

Peng, H., Zhang, Z., & Tao, Z. (2026). The impact of supply chain innovation on corporate sustainable development: Evidence from the supply chain innovation and application pilot policy. *Sustainability*, *18*(3), Article 1358. https://doi.org/10.3390/su18031358

Peng, Y., & Tao, C. (2022). Can digital transformation promote enterprise performance?—From the perspective of public policy and innovation. *Journal of Innovation & Knowledge*, *7*(3), Article 100198. https://doi.org/10.1016/j.jik.2022.100198

Pfeffer, J., & Salancik, G. R. (1978). *The external control of organizations*: *A resource dependence perspective*. Harper & Row.

Shen, H., Yu, P., & Wu, L. (2012). State ownership, environmental uncertainty and investment efficiency. *Economic Research Journal*, *47*(7), 113–126 (in Chinese).

Siems, E., Seuring, S., & Schilling, L. (2023). Stakeholder roles in sustainable supply chain management: A literature review. *Journal of Business Economics*, *93*(4), 747–775. https://doi.org/10.1007/s11573-022-01117-5

Sodhi, M. S., & Tang, C. S. (2021). Supply chain management for extreme conditions: Research opportunities. *Journal of Supply Chain Management*, *57*(1), 7–16. https://doi.org/10.1111/jscm.12255

Spieske, A., & Birkel, H. (2021). Improving supply chain resilience through industry 4.0: A systematic literature review under the impressions of the COVID-19 pandemic. *Computers & Industrial Engineering*, *158*, Article 107452. https://doi.org/10.1016/j.cie.2021.107452

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405–2415. https://doi.org/10.1109/TII.2018.2873186

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Tian, Y., & Cui, L. (2025). Supply chain resilience and digital transformation: Perspectives from a supply chain network. *Humanities and Social Sciences Communications*, *12*(1), Article 1738. https://doi.org/10.1057/s41599-025-06011-3

Usai, A., Fiano, F., Petruzzelli, A. M., Paoloni, P., Briamonte, M. F., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*, 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Veit, D. J., & Thatcher, J. B. (2023). Digitalization as a problem or solution? Charting the path for research on sustainable information systems. *Journal of Business Economics*, *93*(6), 1231–1253. https://doi.org/10.1007/s11573-023-01143-x

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Wang, S., Chen, F., & Yang, X. (2024). Environmental, social and governance performance: Can and how it improve internationalization of Chinese A-share listed enterprises. *Heliyon*, *10*(13), Article e33492. https://doi.org/10.1016/j.heliyon.2024.e33492

Wang, Y., Wang, T., & Wang, Q. (2024). The impact of digital transformation on enterprise performance: An empirical analysis based on China's manufacturing export enterprises. *PLoS ONE*, *19*(3), Article e0299723. https://doi.org/10.1371/journal.pone.0299723

Weidner, M., & Zylkin, T. (2021). Bias and consistency in three-way gravity models. *Journal of International Economics*, *132*, Article 103513. https://doi.org/10.1016/j.jinteco.2021.103513

Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity. *Management World*, *37*(7), 130–144 (in Chinese).

Yang, J., Li, H., Zhang, L., & Xu, G. (2025). Digital transformation's impact on substantive innovation: A life-cycle perspective. *Internet Research*. https://doi.org/10.1108/INTR-08-2024-1204

Zhan, H., Shen, H., & Guo, H. (2025). Research on the impact of ESG scores on corporate substantive and strategic green innovation. *Innovation and Green Development*, *4*(1), Article 100201. https://doi.org/10.1016/j.igd.2024.100194

Zheng, H., Han, J., & Yang, K. (2023). Trade facilitation and firm export resilience: Empirical evidence from the Authorized Economic Operator system. *Collected Essays on Finance and Economics*, (7), 30–39 (in Chinese).

Zouari, D., Ruel, S., & Viale, L. (2021). Does digitalising the supply chain contribute to its resilience? *International Journal of Physical Distribution & Logistics Management*, *51*(2), 149–180. https://doi.org/10.1108/IJPDLM-01-2020-0038