Empowering Industrial Chain Resilience through Artificial Intelligence: Evidence from Chinese Provincial Panel Data

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Abstract: Amidst profound global changes exposing industrial chains to unprecedented disruption risks, this study investigates whether and how Artificial Intelligence (AI), a strategic General Purpose Technology (GPT), enhances Industrial Chain Resilience (ICR). Grounded in a framework integrating theories of technological paradigms and endogenous growth, we analyze balanced panel data from 30 Chinese provinces from 2013 to 2023. We employ a Two-Way Fixed Effects model and address endogeneity using a robust instrumental variable approach based on historical telecommunication data and a Bartik shift-share instrument. The findings reveal that AI exerts a significant, positive, and linear effect on ICR, suggesting current applications are in a phase of increasing returns. We further show that this empowerment operates through two core pathways: stimulating technological innovation and promoting industrial structure upgrading. Notably, AI's impact is context-dependent; while stronger in manufacturing-heavy and marketized regions, it demonstrates a higher marginal contribution in digitally lagging areas, revealing a significant "technological catch-up effect." These findings collectively establish AI as a critical endogenous driver for building a secure and resilient national industrial system.

Keywords: Artificial Intelligence; Industrial Chain Resilience; Technological Innovation; Industrial Structure Upgrading; Instrumental Variable; Digital Divide; Leapfrogging

1. Introduction

The global economy is undergoing a paradigm shift. The long-standing logic of "efficiency-first" that has governed global industrial and supply chains is being fundamentally challenged by intensifying geopolitical risks and recurring systemic shocks. This has catalyzed a pivot towards a new strategic focus on security, robustness, and controllability, with nations increasingly prioritizing the resilience of their industrial ecosystems [1]. For major manufacturing hubs deeply integrated into the global economy, enhancing Industrial Chain Resilience (ICR)—the capacity of an industrial system to resist shocks, recover rapidly, and evolve through proactive restructuring—has become a critical policy imperative.

Concurrently, a new technological revolution centered on Artificial Intelligence (AI) is unfolding at an unprecedented pace. AI has rapidly evolved into a strategic General Purpose Technology (GPT), acting as an endogenous variable that alters production functions and reshapes the economic landscape. A burgeoning body of literature has documented AI's profound, "efficiency-enhancing" impact on firm-level productivity, particularly with the advent of generative AI [2]. However, a significant gap remains in our understanding. While the field has begun to explore how digital technologies like AI can be leveraged for operational resilience through tools like digital twins [3], AI's specific role in fortifying macroeconomic "security"—namely ICR at a systemic level—remains a theoretical and empirical "black box."

Specifically, three critical questions remain unanswered: First, does AI genuinely empower Industrial Chain Resilience from a macro-provincial perspective, or does it merely introduce new digital vulnerabilities? Second, if the empowerment effect exists, through what transmission mechanisms does micro-level algorithmic adoption aggregate into macro-level industrial robustness? Third, given the vast disparities in resource endowments and infrastructure across different regions—a well-documented feature of the digital economy [4]—does the empowerment effect of AI exhibit spatial heterogeneity or boundary conditions?

To systematically answer these questions, this study integrates Complex Adaptive Systems (CAS) theory and Endogenous Growth Theory to empirically test the relationship between AI and ICR. Utilizing a comprehensive provincial panel dataset from China covering the period 2013-2023, we construct a multidimensional evaluation system for ICR. We employ a rigorous econometric framework, including Two-Way Fixed Effects (TWFE) models, mediation analysis, and an Instrumental Variable (IV) strategy combining historical telecommunication data with Bartik shift-share instruments.

The marginal contributions of this paper are threefold. First, it pivots the theoretical narrative of AI from a purely "efficiency-driven" perspective to a "security and resilience" framework, operationalizing a dynamic evaluation index for ICR that captures infrastructure, resistance, recovery, and sustainable evolution. Second, it unpacks the causal black box by empirically validating a dual-mechanism model consisting of "technological innovation" and "industrial structure upgrading." Third, through nuanced heterogeneity analysis, we uncover a counter-intuitive "technological catch-up effect." We provide robust empirical evidence that AI yields disproportionately higher marginal returns in infrastructure-lagging regions, thereby offering fresh theoretical insights into how advanced digital technologies can help bridge, rather than exacerbate, the regional digital divide.

2. Literature Review and Theoretical Hypotheses

2.1 The Direct Effect of AI on ICR

From the perspective of Complex Adaptive Systems (CAS) theory, an industrial chain is an open, dynamic network composed of interacting agents such as suppliers, manufacturers, and distributors [5]. The resilience of this complex system depends heavily on the sensitivity, learning capacity, and adaptability of its micro-agents to environmental perturbations. AI, characterized by advanced predictive algorithms, machine learning, and big data processing capabilities, significantly reduces information asymmetry and transaction frictions across the supply chain [6].

By implementing predictive maintenance, demand forecasting, and digital-twin simulations, AI shifts supply chain risk management from "reactive recovery" to "proactive defense"[7]. During external shocks—such as sudden labor shortages or logistics interruptions—AI-driven automation (e.g., intelligent robotics) and smart resource allocation provide crucial buffering capacities, ensuring production continuity and agile supply-demand rebalancing[8]. Therefore, we posit that AI acts as a systemic stabilizer.

Hypothesis 1 (H1): AI exerts a significant and positive direct effect on enhancing Industrial Chain Resilience.

2.2 The Mediating Role of Technological Innovation

Endogenous Growth Theory posits that knowledge accumulation and continuous technological breakthroughs are the ultimate drivers of systemic robustness and long-term economic growth [9]. AI is widely recognized by economists as an "invention of a method of invention"[10]. It profoundly reshapes the traditional R&D paradigm through approaches like AI for Science, drastically reducing trial-and-error costs, accelerating high-throughput screening, and facilitating knowledge spillover across upstream and downstream sectors [11].

This technology-driven innovation effect allows industrial chains to break through "chokehold" technologies and reduce dependency on high-risk external nodes. By accumulating profound technological redundancy and intellectual property, the industrial chain gains the "anti-fragile" capability to evolve and adapt when faced with targeted technological blockades or geopolitical sanctions.

Hypothesis 2 (H2): Technological innovation mediates the positive relationship between AI and Industrial Chain Resilience.

2.3 The Mediating Role of Industrial Structure Upgrading

Based on macroeconomic structural change theories and the Schumpeterian concept of "creative destruction," severe technological shocks induce the reallocation of production factors. AI accelerates the flow of capital, labor, and data from low-efficiency traditional sectors towards high-value-added, technology-intensive sectors.

Furthermore, AI blurs the rigid boundary between manufacturing and services, fostering the deep integration of the digital and real economies (e.g., service-oriented manufacturing). This structural upgrading enhances the "flexibility" and "complexity" of the industrial chain. A highly advanced and flexible industrial structure provides greater financial slack (profit margins) and risk-diversification capabilities, allowing the regional economic system to absorb sector-specific shocks without collapsing.

Hypothesis 3 (H3): Industrial structure upgrading mediates the positive relationship between AI and Industrial Chain Resilience. Methodology and Data.

3. Methodology and Data

3.1 Model Specification

To test the baseline hypothesis (H1) regarding the direct impact of AI on ICR, we construct a Two-Way Fixed Effects (TWFE) panel data model. The mathematical specification is as follows:

$$Res_{it}=\alpha_0+\alpha_1 AI_{it}+\alpha_z Z_{it}+\delta_{it}+\varepsilon_{it} \quad (1)$$

Where:

Res_{it} denotes the Industrial Chain Resilience of province i in year t.

AI_{it} represents the Artificial Intelligence development level.

Z_{it} is a vector of control variables.

α_1 is the core coefficient of interest, expected to be significantly positive.

A_z captures the province unobservable individual fixed effects.

δ_{it} captures the year fixed effects to control for macroeconomic shocks.

ε_{it} is the idiosyncratic error term.

To test the mediating mechanisms (H2 and H3), we adopt the two-step mediation approach recommended in recent econometric literature to mitigate endogeneity bias inherent in traditional three-step methods. The mechanism models are formulated as:

$$MEDit=\beta 0+\beta 1\ AIit+\beta z\ Zit+\varepsilon it \quad (2)$$

Where MEDit represents the mediating variables: Technological Innovation ($Tech_{it}$) and Industrial Structure Upgrading ($Struc_{it}$). If β1 is significantly positive, combined with the theoretical logic, the mediating pathway is established.

3.2 Variables Measurement

(1) Dependent variable: Industrial Chain Resilience (Res)

ICR is a complex, dynamic concept. Based on the evolutionary resilience framework, we construct a multidimensional evaluation system comprising four primary dimensions:

Infrastructure (e.g., highway density, internet broadband access);

Resistance Capability (e.g., labor productivity, R&D input);

Recovery Capability (e.g., industrial profit margins, government expenditure);

Sustainable Development (e.g., energy consumption per unit of GDP, industrial waste utilization).

We utilize the entropy weight method (EWM) to objectively assign weights to 10 secondary indicators and calculate the comprehensive ICR index for each province.

(2) Independent variable: Artificial Intelligence (AI)

Given the lack of direct macro-level AI investment data, we measure regional AI development using the natural logarithm of the number of registered AI-related enterprises. Using a text-mining approach on the Tianyancha corporate database, enterprises whose business scope includes keywords like "machine learning," "computer vision," "natural language processing," and "intelligent sensors" are aggregated at the provincial level.

(3) Mediating variables

Technological Innovation (Tech): Measured by the number of patent applications accepted in the province, which directly reflects the active innovation output driven by technology.

Industrial Structure Upgrading (Struc): Measured by the Theil index, which captures the rationalization and advancement of the industrial structure. A value closer to 0 indicates a more optimized structure.

(4) Control variables (Z)

To isolate the net effect of AI, we control for: Economic development (lngdp, log of real GDP); Population density (lnpop); City size (Size, urbanization rate); Informatization level (Infor, ratio of telecommunication business volume to GDP); and Green development level (Green, urban green space area).

3.3 Data Sources

The dataset comprises a balanced panel of 30 Chinese provinces covering the period 2013-2023. Data are primarily sourced from the China Statistical Yearbook, China Industry

Statistical Yearbook, and the National Bureau of Statistics. Missing values were addressed using linear interpolation.

4. Empirical Results

4.1 Baseline Regression Results

The baseline regression using the TWFE model. A Hausman test (χ^2=23.09, p<0.001) strongly rejected the random-effects model. That includes all control variables. The coefficient of AI is 0.013 and statistically significant at the 1% level, indicating that a 1-unit increase in AI adoption increases ICR by 0.013 units. This confirms H1. Furthermore, introducing a quadratic term (AI^2) yielded an insignificant result (p=0.279), rejecting the inverted-U hypothesis and suggesting that China's AI application is currently in a linear ascent phase of dividend release.

4.2 Mechanism Analysis

Following Equation (2), we tested the mediating channels.

Technological Innovation: AI significantly and positively impacts regional patent applications (β=1.944, p<0.01). AI drastically reduces R&D friction, building the technological autonomy required for resilience. H2 is supported.

Industrial Structure Upgrading: AI significantly promotes industrial upgrading (β=0.0018, p<0.05). By facilitating factor reallocation from low- to high-efficiency sectors, AI enhances systemic flexibility and financial buffering. H3 is supported.

4.3 Endogeneity and Robustness Checks

To address reverse causality and omitted variable bias, we implemented an Instrumental Variable (IV) strategy using 2SLS. We constructed two IVs:

Historical IV: The interaction term between the number of landline telephones per 10,000 people in 1984 and a time trend. (Relevance: Path dependence of tech infrastructure; Exogeneity: 1984 data cannot be influenced by current ICR shocks).

Bartik Shift-Share IV: The interaction between a province's initial AI share in 2013 and the national AI growth rate (excluding the focal province).

As shown in Table 1, the Kleibergen-Paap Wald F-statistic (32.07) exceeds the Stock-Yogo critical values, ruling out weak IVs. The Hansen J-test (p=0.749) confirms IV exogeneity. In the second stage, the coefficient of AI remains significantly positive (0.0147, p<0.05).

Further robustness checks—including System GMM for dynamic panel bias, lagging the AI variable by one period, replacing AI with industrial robot density, and excluding major municipalities—all yielded consistent results.

Table 1. IV-2SLS Estimation Results

Variables	IV: 1984 Telecom	IV: Bartik Share	IV: Combined
AI	0.0148 *(-2.33)	0.0244 (-0.74)	0.0147* (-2.35)
Controls	Yes	Yes	Yes
Province/Year FE	Yes	Yes	Yes
KP Wald F-stat	36.52	2.15	32.07
Hansen J P-value	-	-	0.749

As shown in Table 1, the Kleibergen-Paap Wald F-statistic in the combined model is 32.07, ruling out weak instruments. The Hansen J-test (p=0.749) confirms IV exogeneity. The second-stage coefficient remains significantly positive (0.0147), confirming the net causal effect. Robustness checks—including System-GMM for dynamic panel bias and replacing the AI proxy with industrial robot density—all yielded consistent conclusions.

4.4 Heterogeneity Analysis

To understand the boundary conditions, we split the sample based on regional characteristics:

Industrial Structure: The positive effect of AI is highly significant in regions with a high proportion of manufacturing (β=0.0077, p<0.01), but insignificant in low-manufacturing regions. This proves that the real economy (manufacturing) is the indispensable physical carrier for AI to generate resilience.

Institutional Environment: In regions with higher marketization, AI's marginal contribution is 34% higher than in lagging regions. Efficient markets reduce institutional transaction costs, amplifying AI's allocative efficiency.

Digital Infrastructure (The Catch-up Effect): Counter-intuitively, the marginal effect of AI is stronger in regions with lagging digital infrastructure (β=0.0137, p<0.01) compared to advanced regions (β=0.0102, p<0.05). This indicates a "technological catch-up effect"—in regions where traditional infrastructure is poor, AI acts as a vital substitute to bridge coordination gaps, yielding higher marginal returns and helping to close the regional digital divide.

5. Heterogeneity Analysis and Discussion

The national average effect masks crucial spatial disparities. We split the sample based on structural and institutional dimensions.

(1) Industrial structure: The positive effect of AI is highly significant in regions with a high proportion of manufacturing ($\beta=0.0077$, $p<0.01$) but insignificant in low-manufacturing regions. This highlights "contextual dependence." AI requires a robust real economy as a physical carrier; without industrial use-cases, AI algorithms face a "hollowing out" dilemma.

(2) Institutional environment: In regions with higher marketization, AI's marginal contribution ($\beta=0.0087$) is substantially higher than in less marketized regions ($\beta=0.0065$). Efficient markets and low transaction costs act as an "amplifier," facilitating the free flow of data and capital required for AI deployment.

(3) Digital infrastructure (The "catch-up" paradox):

Intuitively, AI should perform better in areas with superior networks. However, our results show that the marginal empowerment effect of AI is paradoxically stronger in regions with lagging digital infrastructure ($\beta=0.0137$, $p<0.01$) compared to advanced regions ($\beta=0.0102$, $p<0.05$).

We interpret this as a profound "Technological Catch-up Effect". In advanced coastal regions, supply chains are already highly optimized, leading to diminishing marginal returns. Conversely, in lagging inland regions characterized by severe information asymmetry, AI acts as a powerful substitute for traditional infrastructure. It provides a "leapfrog" capability, allowing these regions to overcome historical deficits at a lower marginal cost, thereby bridging the regional digital divide.

6. Conclusion and Policy Implications

6.1 Conclusion

This study provides robust empirical evidence that AI is a critical endogenous driver of Industrial Chain Resilience. Our findings reveal that: (1) AI exerts a robust, linear positive impact on ICR. (2) This empowerment is driven by a dual-mechanism of technological innovation and industrial structure upgrading. (3) The effect exhibits significant contextual dependence: it requires a solid manufacturing base and marketized institutions to thrive. Importantly, AI demonstrates a profound "technological catch-up effect," offering disproportionately higher marginal resilience gains to regions with lagging traditional digital infrastructure.

6.2 Policy Implications

Based on these findings, we propose the following policy recommendations to leverage AI for national supply chain security:

Optimize Computing Layout to Bridge the Digital Divide: Policymakers should capitalize on AI's catch-up effect by promoting cross-regional computing power allocation (e.g., China's "East-to-West Computing Resource Transfer" project). Subsidizing cloud-based AI access for central and western regions will enable them to leapfrog traditional infrastructure constraints.

Deepen Digital-Real Economy Integration: Given that AI requires a manufacturing carrier, policies should avoid the "hollowing out" of industries. Governments should incentivize "Chain-Master" enterprises to develop vertical industry Large Language Models (LLMs) and share modular AI solutions with downstream SMEs, fostering a symbiotic, resilient ecosystem.

Foster "AI for Science" to Break Technology Chokeholds: To strengthen the innovation mediator, national R&D funds should prioritize AI-driven scientific discovery paradigms in critical sectors (e.g., advanced materials, semiconductors) to build technological redundancy and autonomy.

Dismantle Institutional Barriers: Enhance marketization by establishing unified data property rights and trading mechanisms. A flexible, agile regulatory environment will minimize the institutional transaction costs of AI adoption, fully unleashing its multiplier effect on supply chain resilience.

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