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The Impact of Digitization on Urban Social–Ecological Resilience: Evidence from Big Data Policy Pilots in China

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Abstract: Digitization plays a vital role in fostering economic and social development. This study empirically investigates the impact of digitization on urban industrial structures, technological innovation, public service levels, and social–ecological resilience. Various approaches, including the two-tier stochastic, spatial econometric, and panel threshold models, have been employed to analyze panel data from 287 cities from 2008 to 2023. These data are examined through a quasi-natural experiment analyzing the evolution of urban social–ecological resilience following China's promotion of the national comprehensive pilot zone for big data. The findings are as follows. (1) The positive effects of digitization on urban social and ecological resilience substantially outweigh the negative effects, with an overall increasing trend in the positive net effect, albeit with significant regional differences. (2) Digitalization exhibits a significant spatial spillover effect, enhancing local social–ecological resilience while inhibiting improvements in neighboring cities. (3) Technological innovation and public service levels positively affect social–ecological resilience, whereas industrial structure upgrading has a negative indirect effect. Both industrial structure upgrading and public service levels demonstrate nonlinear effects under the threshold constraints of the intermediary mechanism. (4) In terms of policy mechanisms, regional differences in the urban industrial structure, innovation capacity, and public service levels must be considered. This approach is essential for promoting the organic integration of digitization across regions, mitigating the polarization effect, and enhancing the diffusion effect.

Keywords: digitization; social–ecological resilience; comprehensive pilot zone; spillover effects; nonlinear effect

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1. Introduction

As China experiences a gradual shift toward high-quality development, expanding digital infrastructure, establishing diverse digital service platforms, and applying digital technologies across various sectors have created new opportunities to enhance urban social and ecological resilience. Nonetheless, the structural differences across cities and the unequal effects of digital empowerment continue to pose significant issues. In this context, it is crucial to reveal the value of digitization and foster harmonized regional development, while strengthening high-level digital support to fully empower economic and social development. In 2024, China introduced guiding opinions on promoting the digital transformation of cities in the entire region, setting the goal that several livable, resilient, and smart cities with unique characteristics will be formed by 2027. As a crucial approach

to fostering regional digital transformation, it is essential to examine how digitization can enhance the resilience of urban social and ecological systems.

Socio-ecological system (SES) resilience is designed to provide frameworks for enhancing human–environment interactions and offering ways to mitigate risks associated with natural and unpredictable event-induced hazards through various adaptation and mitigation strategies. From an SES perspective, urban social–ecological resilience is shaped by intricate and dynamic interactions among interdependent subsystems, including economic, social, ecological, regulatory, and physical environments. Urban socio-ecological resilience denotes the capacity of cities to mitigate effectively and efficiently, cope with, respond to, recover from, and adapt to shocks or stressors, such as climate change and policy reform.

The link between digitization and its impact on economic growth, social distribution, and urban social–ecological resilience is rarely discussed. Digitization can enhance industrial chain resilience and stimulate economic growth by optimizing resource allocation and facilitating the transmission of market information. It may destabilize employment and contribute to structural imbalances in the social distribution [1]. In the labor market, Zemtsov suggested [2] that digitization can create barriers to employment opportunities and labor market matching, leading to employment exclusion in certain sectors and long-term employment reductions, thereby elevating future urban social risks. In terms of the social income distribution, Aly [3] and Tao [4] indicated that while digitization can boost digital trade and the economy, it also tends to intensify income disparities between regions, lessening the ability of social systems to withstand external shocks.

Since 2016, China's digital transformation has been reasonably enhanced. The 20th National Congress of the Communist Party of China (CPC) emphasized the importance of accelerating the construction of a digital China and promoting the deep integration of the digital economy with the real economy. In 2021, the *Outline of the Fourteenth Five-Year Plan for National Economic and Social Development and the Visionary Objectives for 2035* proposed leveraging digital transformation to initiative changes in production modes, lifestyles, and governance. By 2024, with the release of China's *Guidelines on Promoting City-wide Digital Transformation*, the restraints on further progressing digitization and promoting synergistic economic and social development were alleviated. Consequently, whether digitization can stimulate urban development, establish policy dividends and contribute to harmonized economic and social development has garnered attention.

Previous studies have addressed the impact of digitization on sustainable urban development, focusing on its effects on total factor productivity and macroeconomic performance through optimized resource allocation [5] and its role in enhancing urban governance capabilities [6,7]. However, digitization may also constrain traditional economic sectors [8] and complicate regional development coordination [9,10]. Previously, studies have explored the effects of digitization on social and ecological dimensions, including urban social services [11], environmental protection [12,13], and inclusive development [14]. Nonetheless, these studies were largely micro-level and fragmented, leaving open the question of whether digitization can promote synergistic development in the production, living, and ecological domains, thereby enhancing urban social–ecological resilience.

It can be seen that most studies have explored the economic and social effects of different types of digitization at the regional and industrial levels, providing sufficient references for subsequent research. However, it is easy to ignore the spatial correlation factors, and most studies mainly focused on the influence relationship between digitization and other factors. Moreover, the regional scale of previous studies was relatively large, and the effect of digitization in specific regions or at smaller regional scale needs further investigation. As a result, this study will research the relationship between digitization

and urban socio-ecological resilience by mainly focusing on the spatial spillover effects of digitization on social–ecological resilience across different regions.

Against this background, this study addresses the following key questions. Does digitization enhance urban social–ecological resilience? Is there heterogeneity in its effects and do spatial spillovers occur? What are the mechanisms through which digitization impacts urban socio-ecological resilience? The marginal contributions of this study are twofold. (1) By employing the quasi-natural experiment of the national big data comprehensive pilot reform, this study extends the research scope from economic resilience to the broader concept of social–ecological resilience, offering new insights into the evaluation of urban digital transformation. (2) It examines the impact of digitization on urban social–ecological resilience at the regional and macroeconomic levels, providing empirical evidence for big data pilot reforms and resilient urban growth, while also offering theoretical support for advancing urban digital transformation.

2. Literature Review and Hypothesis Development

Considering the deficient competition, increasing returns to scale, and restricted factor mobility, digitization has a dual influence on urban social–ecological resilience [15]. Firstly, digitization within urban environments facilitates the clustering of data-driven industries, enterprises, and skilled professionals, integrating them through digitization and intelligent systems, and establishing collaborative ecosystems that benefit from increasing economies of scale [15]. By fostering digitization and technological innovation, some regions have successfully promoted industrial clustering, created employment opportunities, and stimulated the economy. Furthermore, digitization enables the distribution of infrastructure and information platforms across neighboring regions, removing barriers to the flow of data and production factors through the exchange and sharing of talent and resources [16]. This promotes the dissemination and diffusion of technological innovations, reshapes urban production and service models, and generates a radiating effect that enhances inter-regional development.

Secondly, the over-concentration of digitization may create a digital divide, resulting in an unequal distribution of resources, talent, and investments among regions. This imbalance restricts sustainable opportunity creation in some areas. Additionally, digitization may exaggerate labor substitution through technology, leading to biases in the factor allocation and intensifying discrepancies in the labor market [17]. This could reduce employment opportunities in traditional industries [18] and disturb urban social security systems, inclusive growth and social–ecological inequalities across cities [19]. Effective urban governance can mitigate these challenges by optimizing data resource allocation, improving labor market matching, identifying social risks, enhancing industrial structures, and increasing social well-being, facilitating a dynamic equilibrium between emerging and traditional industries.

Digitization also alleviates the limitations of geographical distances among cities, allowing economic activities, social divisions of labor, and public services to surpass regional boundaries. This enhances the linkages across regions, enabling more accurate assessments of the market demand, supply resource, and economic opportunities. As a result, the efficiency of resource allocation, public health and environmental quality, sustainable economic growth and social inclusiveness are promoted [20,21]. Given the spatial characteristics of digitization, including the centripetal force and centrifugal force [22], the impact of digitization on urban social–ecological resilience is likely to manifest spatial spillover effects, influenced by the geospatial distribution of data elements over time [23]. Additionally, geographic proximity and dynamic competition can amplify these spatial spillover effects. Based on this research background, the following hypotheses are proposed:

Hypothesis 1. *Digitization impacts urban social–ecological resilience.*

Hypothesis 2. *Digitization generates spatial spillover effects on urban social–ecological resilience.*

Digitization also transforms the geographic constraints on urban public services and enhances the efficiency of public service delivery. Since 2016, China has steady advanced the policy of establishing comprehensive pilot zones for national big data, promoting the deep integration of digitization across various sectors of the economy and society. This initiative has reasonably boosted the implementation of the *run at most once* reform [24], focusing on high-frequency governmental public services and leveraging big data to modernize service delivery through integrated networks and service platforms. The reform has established a comprehensive and efficient governmental operations system, a high-quality and accessible universal service system, and an intelligent and coordinated governance system [25]. With the ongoing construction of China's big data comprehensive pilot zones, digitization strengthens connectivity among the government, enterprises, and society, facilitating factor circulation, driving capital and talent clustering, and creating a new economic geospatial structure [26].

Integrating digitization with traditional urban industries introduces new production factors and transforms productivity, production relations, and organizational models, contributing to industrial upgrading [27,28]. Through digitization, traditional industries can leverage digital technologies to enable timely feedback and information responses, reducing information asymmetry, transaction costs, and resource mismatches. This ultimately enhances industrial production efficiency and innovation capacity [29]. In the context of industrial upgrading, digitization can boost urban industries' innovation capabilities, producing high-quality new products, stimulating new consumer demand, creating new consumption hotspots, increasing the total social demand, and promoting economic growth. Economic growth, in turn, indirectly raises residents' income levels through social redistribution, promoting community well-being and enhancing urban social–ecological resilience [30].

Moreover, digitization improves the productivity of urban economic systems and drives the synergistic development of production, living, and ecological spaces by advancing social and ecological systems [31]. It is important to note that the digitization index of the eastern region surpasses that of the central and western regions in China, demonstrating significant regional disparities in the extrinsic conditions and potential factors affecting the impact of digitization on urban social–ecological resilience. Abid's study [32] reveals that the influence of digitization on technological innovation, resource allocation efficiency, and economic development is complex and evolves progressively over time. In the initial stages of digitization, its driving effects may not be immediately significant due to its nascent state. This limitation may hinder its effectiveness and constrain the mediating role of technological innovation and public services in enhancing urban social–ecological resilience [33]. Based on this background, we formulated the following hypotheses:

Hypothesis 3. *Digitization influences urban social–ecological resilience through upgrading industrial structures, driving technological innovation, and enhancing public service.*

Hypothesis 4. *Digitization exerts a nonlinear effect on urban social–ecological resilience, constrained by the threshold of mediating variables.*

3. Research Area, Methods, and Data

3.1. Research Area

This study covers various regions, including Guizhou and Chongqing in Western China, Henan in Central China, Inner Mongolia, Beijing, Tianjin, Hebei, and Shenyang in Northern China, and Shanghai, Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Huizhou, Zhuhai, Jiangmen, and Zhaoqing in Southeastern China. It covers a total area of 1,864,000 square kilometers, ranging from Guizhou, an economically underdeveloped province in the west, to the financial center of Shanghai, an economically developed center of finance in the east, and the innovation center of Shenzhen and other cities.

To facilitate data collection, calculation and comparative analysis in each administrative region, this study takes the 287 prefecture-level cities in these regions as the research unit and sets the pilot cities carrying out the construction of the national comprehensive pilot zone for big data as the treatment group and the other non-pilot cities as the control group. The geographic locations of the pilot cities are shown in Figure 1.

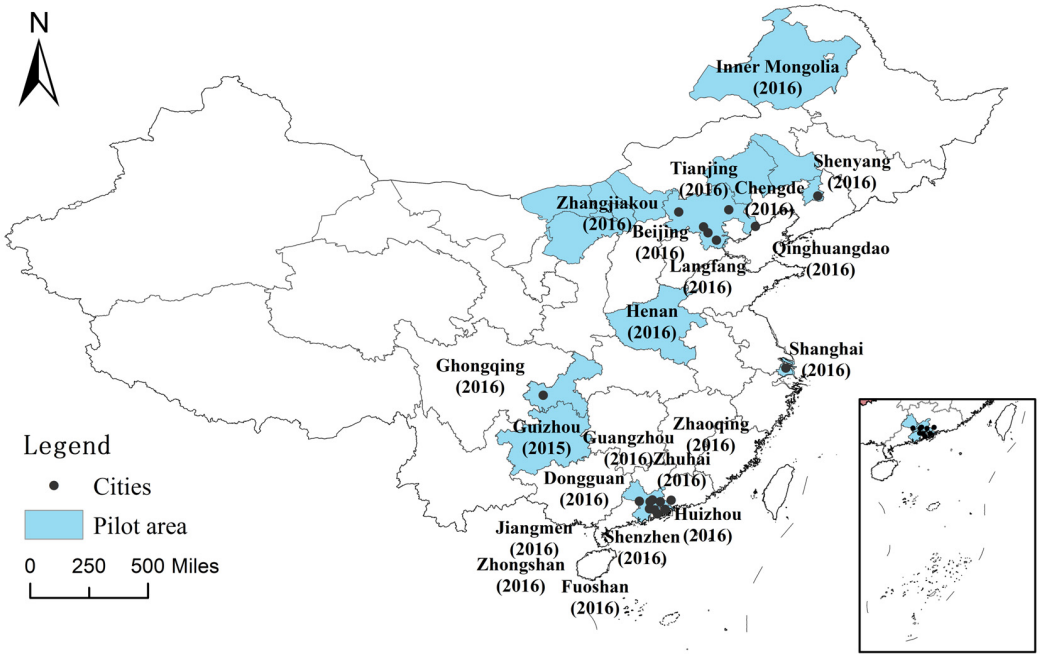


Figure 1. Distribution of the national big data comprehensive pilot cities in China.

3.2. Research Design

3.2.1. Benchmark Regression

The baseline regression model was employed to test the impact of digitization on the social–ecological resilience of various cities, considering the data's completeness and availability. Its mathematical representation is as follows:

$$\ln \mathrm{Rse}_{it} = \alpha_0 + \alpha_1 \ln \mathrm{DIG}_{it} + \alpha_2 \mathrm{DIG}_{it}^2 + \alpha_3 \ln \mathrm{X}_{it} + \mu_t + \nu_i + \varepsilon_{it} \quad (1)$$

$\ln \mathrm{Rse}_{it}$ is the level of urban social–ecological resilience, $\ln \mathrm{DIG}_{it}$ is the level of digitization, X_{it} is the control variable, μ_t is the time-fixed effect, ν_i is the individual-fixed effects, and ε_{it} is the error term. We added the factor's quadratic term to test the potential for a nonlinear relationship between digitization and urban social–ecological resilience (DIG_{it}^2).

3.2.2. Two-Tier Stochastic Frontier Modeling

According to the existing literature, digitization may positively and negatively affect social and ecological resilience. This study constructs a two-tier stochastic frontier model to

investigate the bilateral impact of big data policy pilots on urban social–ecological resilience. The model allows for the assessment of the combined effects of the bilateral impact of digitization on the social and ecological system development of different regions under the same framework, as well as quantifying the dualistic impact of digitization on urban socio-ecological resilience.

To effectively identify the positive and negative effects of digitization on urban social–ecological resilience, and its net effect, we reference the methods of Kumbhakar and Parameter [34], Lei et al. [35], and others. We assume that a social–ecological resilience boundary exists in each city that is determined by the economic and social characteristics of the current period. The typical bilateral stochastic frontier model is constructed as follows:

$$\mathrm{Rse_{it}} = \mu(\mathrm{x_{it}}) + \mathrm{w_{it}} - \mathrm{u_{it}} + \mathrm{v_{it}} = \mu(\mathrm{x_{it}}) + \xi_{\mathrm{it}} \tag{2}$$

where $\mu(\mathrm{x_{it}})$ represents the frontier level of social–ecological resilience, $\mathrm{x_{it}}$ is the characteristic variables of the sample cities, ξ_{it} is the residuals, $\mathrm{w_{it}}$ represents the positive effect of digitization, $\mathrm{w_{it}} \geq 0$, $\mathrm{u_{it}}$ indicates the negative effect of digitization, and $\mathrm{u_{it}} \geq 0$, $\mathrm{v_{it}}$ is a random perturbation term reflecting an unobservable effect. When $\mathrm{w_{it}}$ and are both 0, the model degenerates into a typical ordinary least squares (OLS) model.

Considering that OLS models may produce biased estimates due to $\xi_{\mathrm{it}} \neq 0$, it is more appropriate to use maximum likelihood estimation (MLE). Therefore, this study assumes that $\mathrm{v_{it}}$ obeys a normal distribution when $\mathrm{w_{it}}$ and $\mathrm{u_{it}}$ obey an exponential distribution, where they are independent of each other and independent of $\mathrm{x_{it}}$, i.e., $\mathrm{v_{it}} \sim \mathrm{i.i.d.N}(0, \sigma_{\mathrm{v}}^2)$, $\mathrm{w_{it}} \sim \mathrm{i.i.d.EXP}(\sigma_{\mathrm{w}}, \sigma_{\mathrm{w}}^2)$, and $\mathrm{u_{it}} \sim \mathrm{i.i.d.EXP}(\sigma_{\mathrm{u}}, \sigma_{\mathrm{u}}^2)$. σ_{w}^2 and σ_{u}^2 denote the variance under the condition that the sprawl effect and the agglomeration effect obey an exponential distribution, respectively, σ_{v}^2 denotes the variance under the condition that the random perturbation term obeys a normal distribution, and $\mathrm{w_{it}}$, $\mathrm{u_{it}}$, and $\mathrm{v_{it}}$ are independent. All are independent of the urban characteristic variable $\mathrm{x_{it}}$. Based on the above assumptions, maximum likelihood estimation (MLE) is used to estimate the values of the parameters. Knowing that the composite disturbance term $(\mathrm{w_{it}} - \mathrm{u_{it}} + \mathrm{v_{it}})$ is ξ_{it}, the probability density function is computed as follows:

$$\begin{aligned} f(\xi_{it}) &= \frac{\exp(a_{it})}{\sigma_u + \sigma_w}\Phi(c_{it}) + \frac{\exp(b_{it})}{\sigma_u + \sigma_w}\int_{-h_{it}}^{+\infty}\varphi(z)dz \\ &= \frac{\exp(a_{it})}{\sigma_u + \sigma_w}\Phi(c_{it}) + \frac{\exp(b_{it})}{\sigma_u + \sigma_w}\Phi(h_{it}) \end{aligned} \tag{3}$$

Among them, $\varphi(\bullet)$ and $\Phi(\bullet)$ are the probability density function and cumulative distribution function of the standard normal distribution, respectively, i.e., $\mathrm{a_{it}} = \sigma_{\mathrm{v}}^2/(2\sigma_{\mathrm{u}}^2) + \xi_{\mathrm{it}}/\sigma_u$, $\mathrm{b_{it}} = \sigma_{\mathrm{v}}^2/(2\sigma_{\mathrm{w}}^2) - \xi_{\mathrm{it}}/\sigma_{\mathrm{w}}$; additionally $\mathrm{h_{it}} = \xi_{\mathrm{it}}/\sigma_{\mathrm{v}} - \sigma_{\mathrm{v}}/\sigma_{\mathrm{w}}$, and $\mathrm{c_{it}} = -\xi_{\mathrm{it}}/\sigma_{\mathrm{v}} - \sigma_{\mathrm{v}}/\sigma_{\mathrm{u}}$.

For a sample containing n observations, the log-likelihood function is estimated as follows:

$$\ln \mathrm{L}(\mathrm{X};\theta) = -\mathrm{n}\ln(\sigma_{\mathrm{u}} + \sigma_{\mathrm{w}}) + \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln[\exp(\mathrm{a_{it}})\Phi(\mathrm{c_{it}}) + \exp(\mathrm{b_{it}})\Phi(\mathrm{h_{it}})] \tag{4}$$

where $\theta = (\beta, \sigma_{\mathrm{w}}, \sigma_{\mathrm{u}}, \alpha_{\mathrm{w}})^{\mathrm{T}}$, according to the log-likelihood function obtained from the parameter of the maximum likelihood estimates. Regarding the conditional density function of $\mathrm{w_{it}}$ and $\mathrm{u_{it}}$, the estimation of the conditional expectation to ascertain the sprawl impact

and agglomeration effect, which causes the city's actual social–ecological resilience level to deviate from the 'resilience boundary' degree, is expressed as follows:

$$E(1-e^{-w_{it}}/\xi_{it}) = 1 - \frac{\lambda}{1+\lambda}\frac{[\Phi(c_{it}) + \exp(b_{it}-a_{it})\exp(\sigma_v^2/2 - \sigma_v h_{it})\Phi(h_{it}-\sigma_v)]}{\exp(b_{it}-a_{it})[\Phi(h_{it}) + \exp(a_{it}-b_{it})\Phi(c_{it})]} \quad (5)$$

$$E(1-e^{-u_{it}}/\xi_{it}) = 1 - \frac{\lambda}{1+\lambda}\frac{[\Phi(h_{it}) + \exp(a_{it}-b_{it})\exp(\sigma_v^2/2 - \sigma_v c_{it})\Phi(c_{it}-\sigma_v)]}{\Phi(h_{it}) + \exp(a_{it}-b_{it})\Phi(c_{it})} \quad (6)$$

where $\lambda = 1/\sigma_u + a/\sigma_w$. Equation (5) denotes the intensity of the sprawl effect, Equation (6) denotes the intensity of the agglomeration effect, and the net effect on urban social–ecological resilience resulting from digitization is denoted as follows:

$$NE = E(1-e^{-w_{it}}/\xi_{it}) - E(1-e^{-u_{it}}/\xi_{it}) = E(e^{-u_{it}} - e^{-w_{it}}/\xi_{it}) \quad (7)$$

3.2.3. Spatial Effect Model

To consider the policy reform effects of the construction of the national comprehensive big data pilot zone carried out in China in 2016, we divided the sample cities into the treatment and control groups, added the time variable to generate the dummy variable (DID), and constructed the spatial difference-in-differences model (spatial-DID). The model is constructed as follows:

$$\begin{aligned} \ln Rse_{it} &= \alpha_0 + \lambda_1\textstyle\sum_{j=1}^{n} W_{ij}\ln Rse_{it} + \alpha_1 DID_{it} + \alpha_2 \ln DIG_{it} + \alpha_3 \ln X_{it} \\ &+\lambda_2\textstyle\sum_{j=1}^{n} W_{ij}DID_{it} + \lambda 3\sum_{j=1}^{n}\ln DID_{it} + \lambda_4\sum_{j=1}^{n} W_{ij}\ln X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (8)$$

$$\varepsilon_{it} = \rho\textstyle\sum_{j=1}^{n} W_{ij}\varepsilon_{it} + \varphi_{it};\ \varphi_{it}N(0,\sigma^2 I_n) \quad (9)$$

where I_n is the unit rectangle of $n \times 1$; ρ is the spatial autoregressive coefficient; λ is the spatial spillover coefficient; and DID_{it} is a dummy variable reflecting the policy reforms, which consists of the interaction term of the grouped dummy variable and the time dummy variable, and if a city implements the policy of the national comprehensive pilot zone for big data in a certain year, the city takes $X = 1$; otherwise, $X = 0$. X_{it} denotes the characteristic variable of the sample city, and μ_i and γ_t denote the individual fixed effect and annual fixed effects. If $\lambda_1 = \lambda_2 = \lambda_3 = 0$, then Model (8) is SEM. If $\rho = \lambda_2 = \lambda_3 = 0$, then Model (8) is SLM. If $\rho = 0$, then Model (8) is SDM. The definitions of the other variables are the same as above.

3.2.4. Mediating Effect Model

This study constructs the following recursive mode l to explore the mediating effect of industrial structure optimization, technological innovation, and public services on urban social–ecological resilience. The specific model is constructed as follows:

$$\ln Rse_{it} = \alpha_0 + \beta_0 \ln DIG_{it} + \beta_1 \ln X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (10)$$

$$\ln M_{it} = \alpha + \eta_0 \ln DIG_{it} + \theta_1 \ln X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (11)$$

$$\ln Rse_{it} = \alpha + \delta_0 \ln DIG_{it} + \varphi_1 \ln M_{it} + \delta_1 \ln X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (12)$$

In Equations (11) and (12), M_{it} is the mediating variable, and the other variables have the same meaning as in Equation (1). The regression coefficients η_0; φ_1 are significantly positive, which proves that the mediating variable has a significant mediating effect on the enhancement of urban social–ecological resilience.

3.2.5. Panel Threshold Effect Model

Affected by the threshold of the mediating variables, the relationship between digitization and urban social–ecological resilience may be nonlinear. Therefore, this study constructs the following panel regression model with threshold variables:

$$\begin{aligned} \ln \mathrm{Rse}_{it} = {} & \alpha_0 + \beta_0 \ln \mathrm{M}_{it} \times \mathrm{I}(\ln \mathrm{M}_{it} \le \lambda_{n-1}) + \beta_{n-1} \ln \mathrm{M}_{it} \times \mathrm{I}(\lambda_{n-1} < \ln \mathrm{M}_{it} \le \lambda_n) \\ & + \beta_n \ln \mathrm{M}_{it} \times \mathrm{I}(\ln \mathrm{M}_{it} \ge \lambda_n) + \sum \beta_m \ln \mathrm{X}_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (13)$$

where $\mathrm{I}(\bullet)$ denotes the indicator function of 0 or 1; λ_{n-1}, λ_n denotes the threshold; M_{it} denotes the mediating variable; and the meanings of the other variables are shown in Model (12).

3.3. Variable Selection and Measurement

3.3.1. Explained Variable

Urban social–ecological resilience (Rse), which is a reflection of the ability of cities to continue to maintain normal and stable operations in the face of a series of external disturbances or shocks, involves a large amount of information and complex relationships among economic, and social and ecological systems [36,37]. An urban social–ecological system is a composite system composed of these three subsystems, and its level of resilience, like that of other systems, is largely related to the interactions [38]. There are a wide range of interactions between digitization and socio-economic and ecological development [20,27]. Regarding the metrics of the urban social–ecological resilience indicators, the widely adopted methods mainly include the utility index method [39], the coupling coordination degree model [40], the entropy value method [41], and the TOPSIS method [42]. The coupling coordination degree model reflects the changes in the level of coordination between system variables by evaluating the dynamic development of each system in different periods, while it cannot effectively describe the changes in different systems. The entropy value method determines the weight of each indicator by calculating the entropy value of each indicator, which requires less data. However, the integrated evaluation method can effectively measure the portrayal of the urban sustainable development capability by multiple indicators and characteristics, which provides an effective way to measure the improvement in urban social and ecological resilience [43].

Based on statistics published by the Chinese government, the existing literature, and the characteristics of the pilot region, this study designs an indicator system containing 12 indicators, which are presented in Table 1.

The entropy method determines the variation in each indicator to avoid the influence of subjective weighting on the urban social–ecological resilience evaluation. To visually determine each city's resilience, the TOPSIS (short for Technique for Order Preference by Similarity to an Ideal Solution) ranks the objects according to the distance between the detection and evaluation objects and the optimal and worst solutions.

Given the distinct economic structures across China's eastern, central, and western regions, this study utilizes the proportion of added value from the tertiary sector relative to the total industrial added value as a proxy for industrial structure upgrading trends. Recognizing the significance of investment in science and technology research and development (R&D), as well as the information technology sector for urban innovation, two specific indicators are selected: the ratio of employees in the information technology industry to the total urban labor force and the ratio of science and technology expenditure to the overall budget expenditure. These indicators capture the level of local government investment in innovation and technology. Additionally, to measure social development, this study incorporates several indicators, including the GDP per capita, social security

expenditure per capita, registered unemployment rate, and disposable income per urban resident. These metrics provide a comprehensive assessment of the societal affluence and reflect various dimensions of the population's quality of life, serving as direct indicators of social system development.

Table 1. Comprehensive evaluation index system for urban social–ecological resilience and the digitization level.

Dimension	Secondary Indicator	Tertiary Indicator	Criterion Attribute	Literature Support
Urban social–ecological resilience	Economic development and quality	GDP per capita	+	[44]
		Advanced industrial structure index	+	[21]
		Financial self-sufficiency rate	+	[45]
		External trade dependence	−	[46]
	Social well-being and improvement	Per capita disposable income of urban residents	+	[47]
		Urban registered unemployment rate	−	[48]
		Urban social security expenditure	+	[49]
		Hospital beds per 10,000 population	+	[46]
	Ecological adaptation and adjustment	Greening coverage	+	[43]
		Energy consumption per unit of GDP	−	[50]
		Industrial sulfur dioxide emissions per capita	−	[51]
		Solid waste emissions per capita	−	[52]
Level of digitization	Basic conditions	Big data infrastructure investment	+	[26,53]
		Number of employees in the information technology industry	+	[15,45]
	Digital application	Digital public services	+	[54]
		Digital finance and Internet development	+	[55,56]
	Driving force for innovation	Investment in science and technology research and development	+	[57,58]
		Information technology industry inputs	+	[27,59]

The intensification of digitization, increased urban data infrastructure development, and increased electricity consumption have exerted additional pressure on the ecological environment. To assess urban greening and beautification, this study employs two indicators: the green coverage rate of built-up areas and green area per capita. Additionally, metrics including the electricity consumption, sulfur dioxide (SO_2) emissions, carbon dioxide (CO_2) emissions, and industrial solid waste emissions are employed to assess the environmental impact of industrial pollutants, significantly contributing to the decline of ecosystem resilience.

Using Stata 18 software, this study calculates the social–ecological resilience levels of 287 Chinese cities from 2008 to 2023. To visualize the spatial and temporal distribution characteristics of the social–ecological resilience levels more clearly, ArcGIS 12.0 software is employed. The natural breaks classification method is used to map the calculated resilience values to their corresponding status positions. Figure 2 illustrates the cities' social–ecological resilience levels in both 2013 and 2023. Over time, most cities' social–ecological resilience levels exhibit an upward trend. Spatially, the distribution of urban social–ecological resilience has gradually expanded toward the central and eastern parts of the country, with the eastern, southcentral, and other regions displaying a pronounced high–high agglomeration effect.

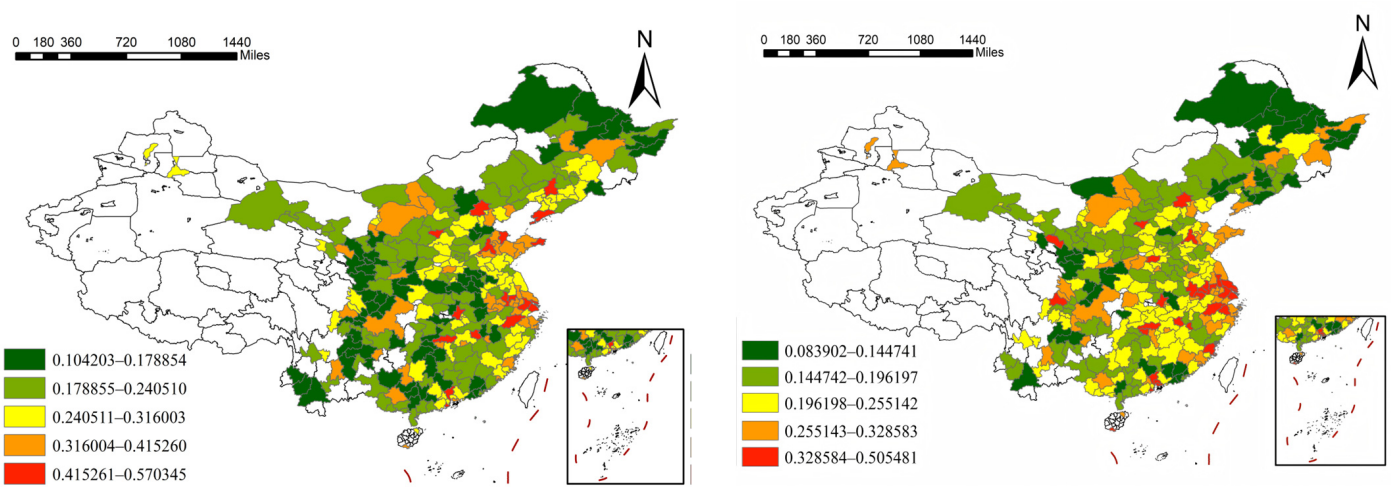


Figure 2. Spatial pattern of China's urban social–ecological resilience in 2013 and 2023.

3.3.2. Independent Variable: DIG

Although there is still a lack of uniform standards in the methodology for assessing the level of digitization, we borrowed the framework of Dou and Gao [60], focusing on three aspects: the basic conditions of the data industry, the digital application scenarios, and the dynamics of digital innovation, We chose six sub-indicators to construct an evaluation index system (see Table 1 for details), and we adopted the entropy-weight-based TOPSIS method to measure the digitization (DIG) development level.

The common indicators for measuring agglomeration include the Hoover index, E-G index, Gini coefficient, and location entropy [61]. Since location entropy can reflect the spatial distribution characteristics of data elements more realistically, this study also adopts location entropy to measure the spatial difference in digitization, which is calculated by the following formula:

$$\mathrm{DIG_entropy}_{ij} = \left(\frac{e_{ij}}{\sum_i e_{ij}} \right) / \left(\frac{\sum_j e_{ij}}{\sum_i \sum_j e_{ij}} \right) \quad (14)$$

where e_{ij} represents the proportion of employment in the city's data elements service industry to the total employment in the region, and the denominator represents the proportion of employment in the country's data elements service industry to the total employment in the country. A higher value of location entropy indicates that a region has a higher degree of agglomeration and a higher level of specialization in the data elements service industry.

Figure 3 shows the spatial pattern of the digitization levels in Chinese cities. Figure 3 shows urban digitization and a clear distribution pattern in time and space. There is a clear increase in the time trend. In terms of the spatial distribution pattern, digitization has shifted from a relatively decentralized agglomeration to a high type of agglomeration, with particularly prominent spatial characteristics in the Yangtze River Delta, the Pearl River Delta, the Beijing–Tianjin–Hebei region, and the Sichuan–Chongqing region.

3.3.3. Intermediate Variables

Based on the previous literature, this study chooses industrial structure upgrading (IS), technological innovation (TT), and public service level (SS) as mediating mechanism variables.

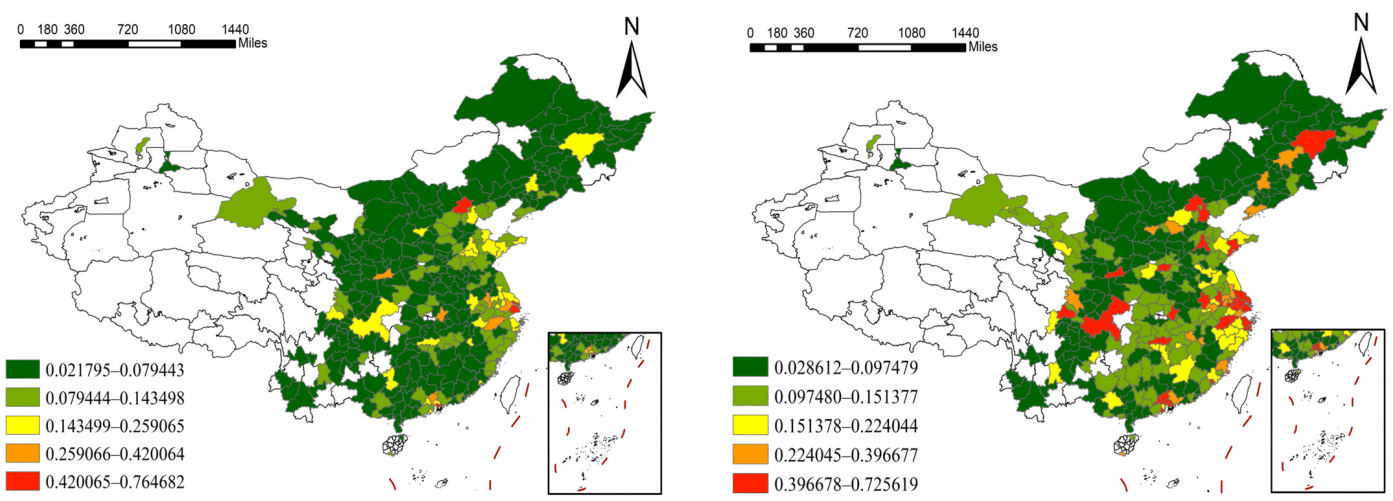


Figure 3. Spatial pattern of China's urban digitization level in 2013 and 2023.

Industrial structure upgrading (IS): Drawing on Du et al. [62] and Ren et al. [63], industrial structure optimization is represented by constructing an industrial structure upgrading index. The formula for measuring the index is as follows:

$$IS = \sum_{i=1}^{3} I_i \times i = I_1 + I_2 \times 2 + I_3 \times 3 \quad (15)$$

where I_i denotes the industry-to-GDP ratio for industry i.

Technological innovation (TT): Based on Wang et al. [29], this study uses the ratio of science and technology R&D investment to fiscal expenditure to measure the technological innovation capacity of cities.

Level of public services (SS): Referring to Yu and Li's study [64] of China's social security system, this study uses the per capita social insurance and social welfare expenditures to measure the level of public services in each city.

3.3.4. Control Variables

Considering the numerous factors affecting urban social–ecological resilience, control variables such as the investment in innovation, fiscal decentralization, level of urbanization, average employee wage, unemployment rate and population density are introduced to reduce the research errors.

Innovation investment (Invest): The R&D intensity reflects a city's R&D level more than its size suitability [53]. In this study, the ratio of the city's scientific and technological R&D investment (R&D) to the sum of the value added by the secondary and tertiary industries is used to measure the level of innovation investment.

Degree of fiscal decentralization (Fiscal): The degree of fiscal decentralization reflects the financial autonomy of local governments. It can reflect the ability of local governments to intervene in digital transformation [65]. This study selects the local public budget expenditure ratio to GDP to measure the fiscal decentralization index.

Urbanization level (Urban). As China's urbanization process accelerates, the degree of integration of urban industries and population also increases, affecting urban social–ecological resilience and sustainable development [22]. In this study, the ratio of the number of urban residents to the total resident population is chosen to measure the level of urbanization.

Average employee wage (Wage): Residents' income can affect consumption, which in turn affects the social well-being of residents in urban communities [56]. In this study, the

average annual wage of employees is logarithmically processed to obtain a proxy variable for residents' income, which is used to measure the average wage level of employees.

Unemployment rate (Unemp): The unemployment rate is the key to observing economic and social development and predicting urban industrial restructuring and transformation [66]. In this study, the logarithm of the urban unemployed population is chosen to measure the level of unemployment.

Population density (Pop): The population density is a key variable affecting the urban form and function and is crucial for urban planning and socio-economic development [67]. In this study, the ratio of the city's resident population to the national area of the administrative region is used to measure the population density.

3.4. Data Sources

This study is based on China's city panel data from 2008 to 2023, covering 287 cities in China's Beijing–Tianjin–Hebei, Yangtze River Delta, Pearl River Delta, Chengdu–Chongqing Economic Circle, and Yangtze River Basin and Yellow River Basin regions. The main data come from the China Statistical Yearbook, China Financial Yearbook, China Industrial Statistical Yearbook, and China Urban Statistical Yearbook. Some indicators are converted from relevant calculation formulae and initial data, and some missing data are filled in by interpolation. Considering the possibility of nonlinear relationships between data, we adopt a neural-network-based interpolation method to ensure the reliability of the interpolated data. To prevent data outliers, all the indicators are indented by 1%. For the descriptive statistics of major variables, please refer to Table 2.

Table 2. Descriptive statistics of the variables.

Variables	Symbol	Unit	Obs	Mean	SD	Min	Max
Urban social ecological resilience	Rse	-	4305	0.225	0.0840	0.0960	0.485
Digitization level	DIG	-	4305	0.112	0.104	0.0240	0.613
Fiscal decentralization	ln Fis	ln%	4305	−1.726	0.427	−2.585	−0.558
Industrial structure upgrading	ln IS	ln%	4305	0.771	0.0960	0.486	0.954
Technological innovation	ln TT	ln%	4305	−4.332	1.328	−7.918	−1.497
Social security level	ln SS	ln%	4305	5.424	0.975	3.198	7.370
Average wage level	lnWage	CNY	4305	14.38	0.948	12.52	16.54
Urban unemployment rate	lnunemp	%	4305	3.064	0.731	1.610	2.460
Population density	ln Pop	-	4305	−13.31	1.033	−15.83	−10.72
Per capita GDP	Gdpper	CNY	4305	53,594	31,665	11,222	146,266
Urbanization level	urbanrate	%	4305	56.29	14.63	28.70	89.16

4. Results and Discussion

4.1. Results of Benchmark Regression

4.1.1. Analysis of the Independent Variable

Table 3 shows the results of the benchmark regression. To compare the estimation results of the FF model, this study reports the results of both the random effects model and the ordinary least squares model. The results in Table 3 shows that the impact of ln DIG on ln Rse is consistently positive and statistically significant at the 1% significance level (showcased using the RE, OLS and FE models), irrespective of the inclusion of control variables. According to the results of the FE model, an increase in the composite index ln DIG by 1% corresponds to a 0.1014% improvement in ln Rse, signifying that DIG positively contributes to the enhancement of Rse, which verifies Hypothesis 1 proposed above.

Table 3. Estimation results of the benchmark regression model and two-tier stochastic frontier model.

Variables	(1) lnRse (OLS)	(2) lnRse (RE)	(3) lnRse (FE)	(4) lnRse (MLE)
ln DIG	0.1746 ***	0.1294 ***	0.1014 ***	0.062 ***
	(19.1125)	(7.3250)	(9.3819)	(0.016)
DIG^2	−0.0962	−0.3683 ***	−0.3079 ***	−0.284
	(−1.3047)	(−3.7708)	(−5.9357)	(0.212)
DIG_entropy	−0.0788 ***	−0.0237 ***	−0.0192 ***	−0.007
	(−18.1427)	(−5.1859)	(−6.2809)	(0.005)
ln IS	0.8920 ***	0.2532 *	0.1709 ***	0.039
	(23.7069)	(1.8392)	(2.6817)	(0.157)
ln TT	0.0091	−0.0915 ***	−0.0930 ***	−0.133 ***
	(1.2953)	(−9.6507)	(−18.0761)	(0.016)
ln SS	0.1102 ***	0.0612 ***	0.0623 ***	0.043 ***
	(28.7892)	(12.9571)	(19.7054)	(0.009)
ln Invest	0.0386 ***	0.1306 ***	0.1291 ***	0.167 ***
	(4.9799)	(13.0540)	(23.4685)	(0.018)
ln Fis		−0.2797 ***	−0.2842 ***	−0.167 ***
		(−15.9022)	(−26.5951)	(0.023)
ln Urban		−0.1054 **	0.0231	0.186 ***
		(−2.3767)	(0.9924)	(0.053)
ln Wage		0.0858 ***	0.0888 ***	0.067 ***
		(7.9880)	(11.1931)	(0.022)
ln unemp		−0.2296 ***	−0.2259 ***	−0.231 ***
		(−13.7790)	(−23.5054)	(0.022)
ln Pop		−0.0728 ***	−0.4024 ***	−0.541 ***
		(−5.8594)	(−18.2744)	(0.049)
Constant	−2.1101 ***	−3.6194 ***	−8.5413 ***	−10.400 ***
	(−40.8582)	(−11.3053)	(−21.1582)	(0.938)
Individual effect	NO	NO	YES	YES
Time effect	NO	YES	YES	YES
Log likelihood				1315.0482
Wald (chi2)				13,582.62
Observations	4305	4305	4305	4305
R-squared	0.661	0.7382	0.957	0.746

Note: T-statistics in parentheses in (1), (3); z-statistics in parentheses in (2); standard errors in parentheses in (4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Notably, the results in Table 3 indicate that the influence of DIG^2 on Rse is negative and statistically significant at the 1% level (showcased using the FE, and RE models). This observation suggests an inverted U-shaped nonlinear relationship between digitization and urban social–ecological resilience. Furthermore, the locational entropy DIG_entropy also significantly impacts DIG_entropy according to the results of the OLS, RE, and FE models, implying that digitization exerts a regional competitive effect on urban social–ecological resilience.

4.1.2. Measurement of Effects of Digitization on Urban Social–Ecological Resilience

Model 4 (MLE) in Tables 3 and 4 further decomposes the positive, negative, and net effects of digitization on urban social–ecological resilience. In terms of the impact coefficients, the decomposition coefficient pertaining to the positive influence stands at 0.1136, indicating that for every one-unit increase in digitization, the promotion effect on urban social–ecological resilience is 0.1136 units. The inhibition effect is 0.0376 units, and the decomposition coefficient of the net effect is 0.0761. Considering the proportion of these two effects, they account for 43.47% of the total variance in digitization. Among them, the positive effect accounts for 90.15% and the negative effect accounts for 9.85%, indicating the preponderant positive influence of digitization over its negative counterpart.

Table 4. Measurement and variance decomposition of the impact effects of the two-tier stochastic frontier model.

	Definition	Variables	Coefficient
ln DIG	Random error	σ_v	0.1365
	Positive effect	σ_w	0.1136
Variance decomposition	Negative effect	σ_u	0.0376
	Net effect	$\sigma_w - \sigma_u$	0.0761
	The total variance of the random error term	$\sigma_v^2 + \sigma_w^2 + \sigma_u^2$	0.0330
	The proportion of the two in the total variable	$(\sigma_w^2 + \sigma_u^2)/(\sigma_v^2 + \sigma_w^2 + \sigma_u^2)$	0.4347
	The proportion of positive effect	$\sigma_w^2/(\sigma_w^2 + \sigma_u^2)$	0.9015
	The proportion of negative effect	$\sigma_u^2/(\sigma_w^2 + \sigma_u^2)$	0.0985

Table 5 measures the dual effects of digitization leading to the deviation of urban social–ecological resilience from the frontier growth level. The mean results indicate that the positive effect caused urban social–ecological resilience growth to surpass the frontier level by 11.4%, with the negative effect falling below the frontier level by 3.8%. Combining these two effects ultimately leads to urban social–ecological resilience growth surpassing the frontier level by 7.6%. Columns 4–6 display the distribution characteristics of the three effects measured by quartiles. The results from the Q1 to Q3 quartiles exhibit an overall upward trend. Specifically, the net effect in the Q1 quartile is 10.1%, and the net effects in the Q2 and Q3 quartiles are 5.3% and 2.5%, respectively, indicating that under the influence of digitization, the urban social–ecological resilience growth levels of 25% of cities increased by 10.1%. In comparison, 75% of cities have only increased by 2.5%.

Table 5. Estimates of the degree of deviation of the impact effects.

Variables	Mean	Std. Dev	Q1	Q2	Q3
Positive effect	0.114	0.079	0.066	0.089	0.133
Negative effect	0.038	0.009	0.031	0.035	0.041
Net effect	0.076	0.085	0.101	0.053	0.025

Figures 4–6 show the frequency distribution characteristics of digitization's positive, negative, and net effects. Both types of effects exhibit right-skewed tails, with the negative effect beginning to diminish around 0.07, whereas the positive effect diminishes around 0.4, indicating a long-tail characteristic of the positive effect of digitization. Figure 6 illustrates that the distribution of the net effect is around zero, indicating that digitization in certain cities does not necessarily contribute to urban social–ecological resilience growth, but rather has a negative effect, where the positive effect dominates.

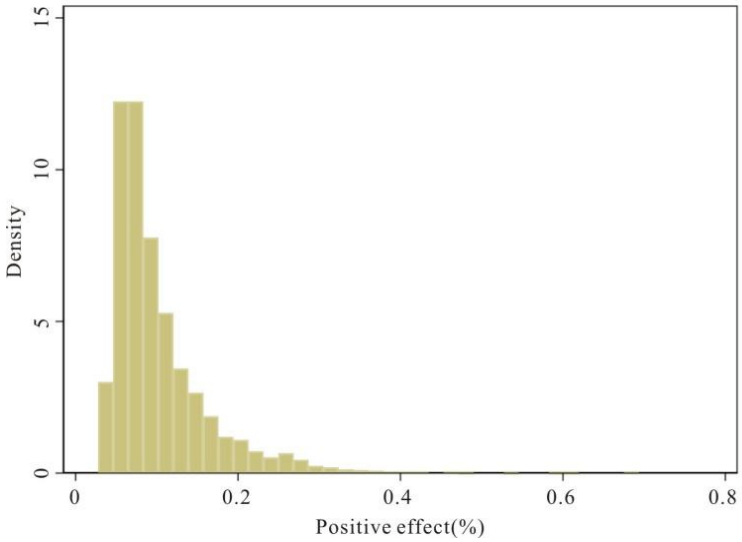


Figure 4. Frequency distribution of the positive effect.

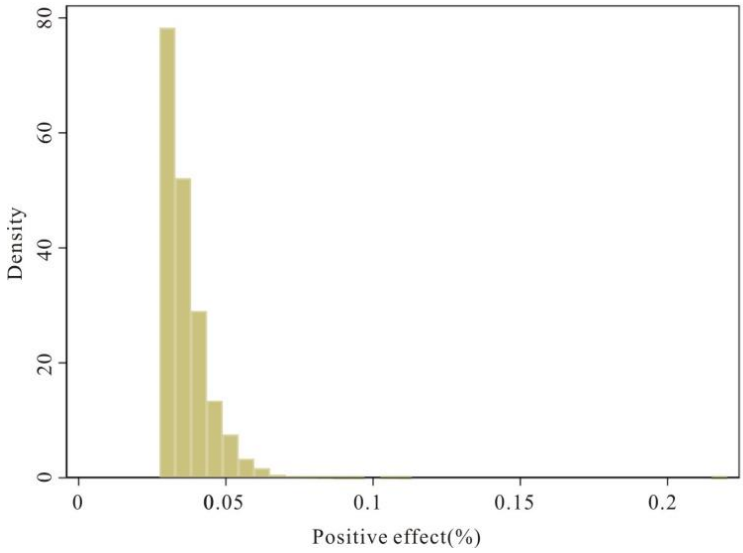


Figure 5. Frequency distribution of the negative effect.

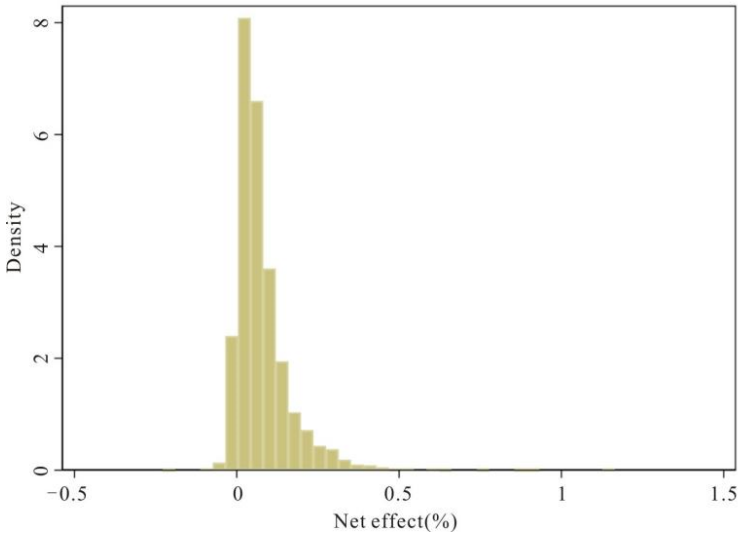


Figure 6. Frequency distribution of the net effect.

4.1.3. Robustness Test

To support the reliability of the findings, the following robustness tests were conducted. (1) Replacement of the independent variables. The digitization is recalculated and replaced by the city's digital financial index, and then a regression test is conducted. The results are consistent with those of previous studies, indicating the robustness of the results (more results are available in Appendix A Table A1). (2) Change the sample size. Taking the construction of the national big data comprehensive pilot area in 2016 as the boundary, the sample data are split into two sample sets, 2008–2016 and 2016–2023, and the outliers are eliminated before the regression analysis. The regression results show that the core explanatory variable DIG remains significant at 1%. (3) Endogeneity issues. We address the potential endogeneity problem by constructing a dynamic panel model with a generalized method of moments estimation. The dynamic panel estimation model is as follows:

$$\ln \mathrm{Rse}_{it} = \delta_0 + \delta_1 \ln \mathrm{DIG}_{it} + \delta_2 \ln \mathrm{Rse}_{i,t-1} + \delta_m X_{it} + \mu_t + \nu_i + \varepsilon_{it} \quad (16)$$

where $\ln \mathrm{Rse}_{i,t-1}$ denotes one period of lag in the social–ecological resilience level, and the other variables' meanings are consistent with Equation (12). The regression analysis shows that the AR (1) statistic and Hansen's test exceed 0.1, indicating the validity of the model estimation results, and the effect of digitization on urban social–ecological resilience is still significant, with the regression coefficient being greater than zero. Therefore, it can be deduced that the results of this study are robust.

4.1.4. Heterogeneity Test

Due to the differences in the resource endowment and economic development conditions across regions, the impact of data element agglomeration on urban socio-ecological resilience may exhibit regional heterogeneity. According to Zhang and Liu's categorization [52] of China's administrative regions, China is divided into four distinct regions: eastern, central, western, and northern. Subsequently, a regression analysis of the heterogeneity was conducted for these four regions, which is available in Table 6. The results show that digitization positively impacts all four regions at the 1% significance level, but the coefficients are higher in the western and northern regions than in the eastern and central regions. However, DIG^2 has an insignificant effect in the central region. It exhibits a negative effect at the 1%, 1% and 10% significance levels in the eastern, western, and northern regions, respectively, and DIG_entropy has a negative effect at the 1% significance level in only the western and northern regions. This indicates a significant inverted U-shaped nonlinear relationship between data element agglomeration and urban socio-ecological resilience in the east, west and north, and that data element agglomeration in the west and north regions exhibits a regional competitive effect on urban socio-ecological resilience.

4.2. Regress Results of a Spatial Econometric Model

4.2.1. Spatial Correlation Test and Model Selection

This study used Moran's index to test the spatial correlation between the major changes. According to Table 7, digitization and urban social–ecological resilience are significantly and positively correlated from 2009 to 2023. Therefore, it was appropriate to use a spatial econometric model to examine the spatial effect of digitization on social–ecological resilience.

Table 6. Regional heterogeneity test results.

	(1) East	(2) Central	(3) West	(4) North
ln DIG	0.0634 *** (5.2653)	0.0295 ** (2.1971)	0.1700 *** (6.9863)	0.0984 *** (5.3654)
DIG^2	−0.2642 *** (−5.0772)	−0.0573 (−0.6284)	−0.3244 *** (−3.1973)	−0.1961 * (−1.6664)
DIG_entropy	−0.0058 (−1.3604)	−0.0034 (−0.5345)	−0.0337 *** (−5.6630)	−0.0311 *** (−2.9833)
Constant	−7.0854 *** (−17.7600)	−9.1256 *** (−9.3893)	−8.5640 *** (−9.6265)	−8.5542 *** (−10.7506)
R-squared	0.9766	0.9612	0.9298	0.9727
F	112.4348 ***	93.7877 ***	76.1550 ***	140.1006 ***
Observations	1058	795	1511	941

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

Table 7. Moran's index of ln Rse and ln DIG.

Year	lnRse			lnDIG		
	Moran's I	Z-Statistic	*p*-Value	Moran's I	Z-Statistic	*p*-Value
2009	0.4791	6.9558	0.0000	0.2180	6.1560	0.0000
2010	0.4528	6.5774	0.0000	0.2292	6.5167	0.0000
2011	0.4546	6.6050	0.0000	0.2880	8.0220	0.0000
2012	0.4365	6.3431	0.0000	0.3444	9.3810	0.0000
2013	0.4380	6.3666	0.0000	0.3609	9.8692	0.0000
2014	0.4188	6.0938	0.0000	0.3721	10.1166	0.0000
2015	0.4584	6.6642	0.0000	0.4543	12.1074	0.0000
2016	0.4313	6.2712	0.0000	0.4471	11.8432	0.0000
2017	0.4494	6.5310	0.0000	0.4415	11.6654	0.0000
2018	0.4588	6.6681	0.0000	0.4328	11.4171	0.0000
2019	0.4149	6.0351	0.0000	0.3913	10.3226	0.0000
2020	0.4762	6.9176	0.0000	0.3717	9.7837	0.0000
2021	0.4431	6.4404	0.0000	0.4247	11.1416	0.0000
2022	0.4884	7.0938	0.0000	0.4299	11.2451	0.0000
2023	0.4536	6.5919	0.0000	0.4324	11.3231	0.0000

First, we performed the Lagrange multiplier (LM) test on the model. The results from both the spatial error maximum likelihood (LM-error) and spatial lag maximum likelihood (LM-lag) tests were significant, and the *p*-value of the robustness LM test result was 0.0000 (Table 8). This indicates that the SLM and SEM pass the test, and the spatial effects model should be chosen. Next, Wald and likelihood ratio (LR) tests were conducted. The significant test results indicate that the SDM must be considered SLM or SEM. Thirdly, we conducted the Hausman test. The results of the Hausman test are significant, rejecting the original hypothesis that random effects are preferred over fixed effects, suggesting that fixed effects are the most appropriate when selecting the SDM. Finally, the joint significance LR test was conducted. The results indicate that two-way fixed effects are optimal. Based on the above test results, this study selects the SDM with two-way fixed effects for empirical testing and analysis.

Table 8. Test results of the model selection.

Test	Statistic	*p*-Value
LM-lag	16.260 ***	0.0000
LM-error	129.156 ***	0.0000
Robust LM-lag	28.461 ***	0.0000
Robust LM-error	141.357 ***	0.0000
Wald-SEM	4792.21 ***	0.0000
Wald-SAR	3211.30 ***	0.0000
LR-lag	924.06 ***	0.0000
LR-error	218.05 ***	0.0000
Hausman	76.88 ***	0.0000
LR test for spatial fixed effects	5056.83 ***	0.0000
LR test for time fixed effects	3237.21 ***	0.0000

*** $p < 0.01$.

4.2.2. Regression Results of SDM

To ensure the reliability of the results, Table 9 also provides results for the SEM and SLM with two-way fixed effects. In Table 9, the SEM, SDM, and SLM coefficients are significantly positive. The SDM results show that the coefficient of the dummy difference variable sdid is 0.0540, Wsdid is −0.1499, ln DIG is 0.1485, and W ln DIG is −0.1080. All of them are significant at the 1% level, which suggests that the policy reforms of the national comprehensive pilot zone for big data have a significant impact on urban social–ecological resilience's ln Rse-promoting effect. However, the policy competition of the comprehensive big data pilot reform in neighboring regions has a spatial inhibitory effect on the region's enhanced social–ecological resilience. This finding verifies Hypothesis 2 proposed above.

Table 9. Results of the spatial econometric model.

Variable	SDM	SLM	SEM
sdid	0.0540 *** (5.5491)	−0.0111 (−1.3794)	0.0258 *** (2.7110)
ln DIG	0.1485 *** (18.1553)	0.1093 *** (17.5518)	0.1388 *** (18.1238)
DIG^2	−0.4778 *** (−7.4276)	−0.6206 *** (−9.7051)	−0.5397 *** (−8.3266)
DIG_entropy	−0.0353 *** (−12.1293)	−0.0258 *** (−9.0423)	−0.0315 *** (−11.1703)
ln IS	−0.0669 ** (−2.0586)	−0.1629 *** (−5.3869)	−0.0984 *** (−3.0338)
ln TT	0.0039 (1.5825)	0.0063 *** (2.6581)	0.0105 *** (4.3376)
ln SS	0.0689 *** (23.2475)	0.0576 *** (23.3302)	0.0710 *** (24.2841)
Wsdid	−0.1499 *** (−9.6317)		
W ln DIG	−0.1080 *** (−9.6834)		
$WDIG^2$	0.1491 (1.3875)		

Table 9. *Cont.*

Variable	SDM	SLM	SEM
WDIG_entropy	0.0105 ** (1.9931)		
W ln IS	0.0805 (1.5385)		
W ln TT	−0.0281 *** (−7.4843)		
W ln SS	−0.0345 *** (−8.4502)		
Spatial rho	0.5903 *** (45.1564)	0.4557 *** (35.9621)	0.6536 *** (54.7605)
R-squared	0.378	0.488	0.560

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

4.2.3. Spatial Spillover Effect Test

The results from Table 10 show that the direct coefficient ln DIG is 0.1446 and the indirect coefficient is −0.0483. This indicates that ln DIG makes a positive contribution to the ln Rse of the region; however, the development of ln DIG in neighboring regions is detrimental to the ln Rse of the region. The main reason may be that the ln DIG development of neighboring regions will cause various production factors to transfer to the neighboring regions, thus changing the allocation of factors and ultimately hindering the ln Rse enhancement. In addition, the direct coefficient of DIG_entropy is −0.0369 and the indirect coefficient is −0.0219, and both have a significance level of 1%. This also indicates that regional competition in terms of DIG has a significant inhibitory effect on the Rse of the region. This finding also verifies Hypothesis 2.

Table 10. Results of the spatial spillover effect.

Variable	sdid	lnDIG	DIG^2	DIG_entropy	lnIS	lnTT	lnSS
Direct	0.0349 *** (−3.6849)	0.1446 *** (−18.6818)	−0.4913 *** (−7.7422)	−0.0369 *** (−12.3230)	−0.0596 * (−1.8620)	−0.0002 (−0.0774)	0.0697 *** (−21.715)
Indirect	−0.2608 *** (−9.3099)	−0.0483 ** (−2.4528)	−0.2757 (−1.2443)	−0.0219 ** (−1.9958)	0.0935 −0.8859	−0.0566 *** (−7.2784)	0.0112 (−1.5365)
Total	−0.2259 *** (−8.0052)	0.0963 *** −4.5717	−0.7670 *** (−3.1422)	−0.0588 *** (−4.7634)	0.0339 −0.2919	−0.0568 *** (−6.2744)	0.0809 *** (−10.349)

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

4.3. Mechanism Test

4.3.1. Mediating Effect Test

The results from Table 11 and Models (1), (2), and (3) reveal the positive effects of the three mediating variables, ln IS, ln TT, and ln SS with ln DIG, all at the 1% significance level, and Model (4) reflects the effect of ln DIG and ln IS, ln TT, and ln SS together on ln Rse. From the results of Model (4), the coefficient between ln IS and ln Rse is −0.07 at the 5% significance level, indicating that there is a negative impact relationship between industrial structure upgrading and urban social–ecological resilience, which may be related to the negative impact of industrial structure upgrading on the labor market, leading to income differentiation.ln TT, ln SS and ln Rse show a significant positive impact relationship, indicating a synergistic effect between the level of technological innovation and public service and the ln Rse value. This finding verifies Hypothesis 3.

Table 11. Test results of the mechanisms.

	(1)	(2)	(3)	(4)
	lnIS	**lnTT**	**lnSS**	**lnRse**
ln DIG	0.013 ***	1.082 ***	0.706 ***	0.150 ***
	(0.004)	(0.048)	(0.041)	(0.008)
DIG^2	−0.094 ***	0.668 *	−0.099	−0.516 ***
	(0.030)	(0.401)	(0.337)	(0.065)
DIG_entropy	−0.001	−0.211 ***	−0.172 ***	−0.036 ***
	(0.001)	(0.018)	(0.015)	(0.003)
ln IS		−0.265	0.039	−0.070 **
		(0.203)	(0.170)	(0.033)
ln TT	−0.002		−0.065 ***	0.006 **
	(0.001)		(0.013)	(0.002)
ln SS	0.001	−0.094 ***		0.070 ***
	(0.001)	(0.018)		(0.003)
W ln DIG	0.050 ***	−1.254 ***	−0.750 ***	−0.113 ***
	(0.005)	(0.066)	(0.057)	(0.011)
$WDIG^2$	−0.175 ***	2.378 ***	1.924 ***	0.075
	(0.050)	(0.663)	(0.557)	(0.108)
WDIG_entropy	−0.003	0.268 ***	0.049 *	0.014 ***
	(0.002)	(0.032)	(0.027)	(0.005)
W ln IS		−1.141 ***	0.170	−0.023
		(0.317)	(0.267)	(0.052)
W ln TT	−0.005 ***		0.120 ***	−0.030 ***
	(0.002)		(0.019)	(0.004)
W ln SS	−0.001	0.126 ***		−0.036 ***
	(0.002)	(0.025)		(0.004)
Spatial rho	0.442 ***	0.345 ***	0.601 ***	0.579 ***
	(0.017)	(0.017)	(0.013)	(0.013)
sigma2_e	0.002 ***	0.374 ***	0.264 ***	0.010 ***
	(0.000)	(0.008)	(0.006)	(0.000)
C.V.	YES	YES	YES	YES
u	YES	YES	YES	YES
v	YES	YES	YES	YES
N	4305	4305	4305	4305

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Panel Threshold Effect Test

This study uses the threshold model to further verify the nonlinear relationship under the threshold constraints of the mediating variables. The threshold test and estimation results are given in Table 12, in which both industrial structure upgrading and the public service level pass the significance test of the single-threshold effect with a 5% significance level. However, the single-threshold effect of technological innovation is not significant. This shows that upgrading industrial structures and public service levels has threshold effects and nonlinear relationships regarding the impact of ln DIG on ln Rse. This finding verifies Hypothesis 4.

Table 12. Threshold effect test and threshold value estimation results.

Variable	Number	Value	Confidence Interval	F-Value	*p*-Value	10%	5%	1%
ln IS	Single	0.6778	[0.6728,0.6792]	62.54 **	0.0400	51.1605	61.0073	70.3194
ln TT	None	−4.7589	[−4.817, −4.7523]	23.77	0.5300	40.3970	47.6600	60.5126
ln SS	Single	5.5305	[5.5115, 5.5387]	103.27 **	0.0100	71.0246	76.7956	86.6803

Standard errors in parentheses; ** $p < 0.05$.

The results of Model (1) in Table 13 show that when the level of industrial structure upgrading ln IS is below the threshold value of 0.6778, the impact of ln DIG on ln Rse is 0.13105, but after exceeding the threshold value of 0.6778, the impact of ln DIG on ln Rse decreases to 0.10802. Model (3) shows that when the level of public service ln SS is below the threshold value of 5.5305, the impact of ln DIG on ln Rse is 0.10238 at the 1% significance level. As the public service level increases, the effect of ln DIG on ln Rse rises to 0.13277 at the same 1% significance level when ln SS exceeds the threshold value of 5.5305. This indicates that the level of public services significantly facilitates and enhances urban social–ecological resilience. This finding further verifies Hypothesis 4.

Table 13. The results of the threshold effect analysis.

Variables	Threshold	lnRse (1)	lnRse (2)	lnRse (3)
ln DIG	(ln IS $\leq$ 0.6778)	0.13105 ***		
	(ln IS > 0.6778)	0.10802 ***		
	(ln TT $\leq$ −4.7558)		0.11509 ***	
	(ln TT > −4.7558)		0.12909 ***	
	(ln SS $\leq$ 5.5305)			0.10238 ***
	(ln SS > 5.5305)			0.13277 ***
Control variables		Yes	Yes	Yes
Constant		−1.4043 ***		−1.6803 ***
Observations		4305		4305

Standard errors in parentheses; *** $p < 0.01$.

5. Conclusions and Implications

5.1. Main Findings

This study yields several critical findings. Regarding the core explanatory variables, implementing of the national comprehensive big data pilot zone policy significantly promoted the concentration of data elements within the cities, thereby enhancing urban social–ecological resilience. However, the regional competition induced by this agglomeration exert a negative spillover effect on neighboring cities, impeding their social and ecological resilience. This finding substantiates the dual impact of the national comprehensive big data pilot zone policy on regional sustainable development, emphasizing its beneficial and adverse effects.

In relation to the control variables, this study finds that urban social–ecological resilience has benefited from the policy reforms associated with the national big data comprehensive pilot zone. Nevertheless, the competitive dynamics associated with industrial structure upgrading and digitization also exert inhibitory effects on social–ecological resilience. Competition from the comprehensive big data pilot policies, digitization, technological innovation, and the public service levels in neighboring cities all demonstrate significant negative impacts on the resilience of urban social–ecological systems. Moreover, the re-

gion's technological innovation has yet to reach a level of maturity sufficient to produce substantial positive effects on local social–ecological resilience.

From a mechanistic perspective, digitization enhances urban social–ecological resilience through several pathways. First, data-driven industrial structure upgrading and socially inclusive development contribute positively to resilience. Data have traversed the stages of development, processing, circulation, and application, seamlessly integrating into social production and human existence. The low pollution and high output qualities have facilitated the effective upgrading and optimization of the regional industrial structure, thereby mitigating the negative impact of social production on the social ecosystem. Second, establishing comprehensive big data pilot zones facilitates the concentration of urban data elements, which fosters technological innovation. Policy experiments represent a trial-and-error approach to policy implementation, characterized by distinct Chinese attributes. Local governments with pilot area quotas are more motivated to emphasize their data advantages, promote the expansion of digital technology application scenarios, and thus stimulate technical innovation inside the pilot area. Furthermore, the clustering of data elements facilitates the exchange and sharing of information across various sectors and fields, thereby enabling local governments to effectively enhance decision-making accuracy, optimize resource allocation efficiency and bolster social and ecological resilience across regions. However, the empirical results (Table 10) indicate that both the direct and indirect effects of location entropy concerning digital talent agglomeration on the spatial spillover effect of urban social–ecological resilience are negative. This suggests that competition for digital factor agglomeration among Chinese cities surpasses cooperation, hindering the coordinated transformation of traditional industries into digitalization across cities. Consequently, policies should promote spatial equilibrium in the distribution of digital resources across regions, thereby facilitating China's envisioned transformation of regional digital governance.

5.2. Policy Recommendations

Given the positive influence of the national comprehensive big data pilot zone policy on urban social and ecological resilience, as well as its spatial effects, the government should assume a macro-guiding and policy-coordinating role, delineate key areas for cities to advance the construction of comprehensive big data pilot zones, rationally guide the equitable distribution of public resources, leverage big data platforms to advance industrial structure upgrades and technological innovation, improve the accessibility of public services, and mitigate the negative spillover effects of industrial spaces in neighboring cities, thereby fostering regional development.

Considering the influence of the control variables on urban social and ecological resilience, the government should intensify policy support for digital-driven scientific and technological innovation. Additionally, industrial development strategies should align with each city's geographic location, industrial structure, talent concentration, and stage of digitization. Policymakers should capitalize on the comparative advantages of different cities to promote the integrated development of industrial digitization and digital industrialization, attract big data investment, and cluster information technology talent. This will facilitate big data integration across the primary, secondary, and tertiary industries and lead to coordinated regional and industrial development.

Considering the mediating variables' role and threshold effect on the impact of digitization on urban social–ecological resilience, several measures are necessary. First, promote the upgrading of regional industrial structures, dismantle digital silos, and guide the coordinated development of industrial digitization and digital industrialization. Second, regulate the potential negative impacts of digitization on the industrial concentration,

employment, and income distribution, while encouraging its innovative application in inclusive urban development. Third, guiding the balanced aggregation of big data enterprises and resources across cities, and promoting the sharing of digital and service resources among governments, enterprises, cities, and communities will contribute to sustainable development. In addition, the empirical results (Table 6) indicate that the concentration of digital elements in western and northern Chinese cities significantly hinders urban social and ecological resilience. Consequently, the government ought to prioritize enhancing digital infrastructure investment and cultivating digital expertise in the western and northern areas. Digital governance capacities should be enhanced to facilitate the digital transformation and modernization of conventional sectors in these regions while advancing urban social and ecological resilience. Furthermore, the eastern and central regions must persist in enhancing the technological advancement of application scenarios, including digital manufacturing, the digital economy, and digital services, to generate a ripple effect on the western and northern regions, thereby facilitating the digital transformation and enhancement of cities throughout China.

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Appendix A

Table A1. Estimation results of the robustness check.

Variables	(1) lnRse (OLS)	(2) lnRse (RE)	(3) lnRse (FE)	(4) lnRse (MLE)
ln DIG	0.0657 *** (10.8260)	0.1372 *** (6.1126)	0.1203 *** (7.7684)	0.0364 *** (0.0113)
DIG^2	−0.1455 *** (−27.3463)	−0.0000 (−1.1688)	−0.0000 *** (−3.1854)	−0.0000 *** (0.0000)
*DIG*_entropy	0.8538 *** (22.0898)	−0.0744 *** (−5.2916)	−0.0539 *** (−5.7467)	−0.0587 *** (0.0061)
ln IS	0.0122 * (1.7658)	0.2312 (1.6439)	0.1463 ** (2.2998)	0.6932 *** (0.0419)
ln TT	0.1224 *** (33.2915)	−0.0841 *** (−8.8911)	−0.0877 *** (−17.1900)	−0.0637 *** (0.0064)
ln SS	0.0615 *** (8.0582)	0.0672 *** (13.5809)	0.0672 *** (20.1742)	0.0945 *** (0.0032)

Table A1. *Cont.*

Variables	(1) lnRse (OLS)	(2) lnRse (RE)	(3) lnRse (FE)	(4) lnRse (MLE)
ln Invest	0.0657 *** (10.8260)	0.1364 *** (13.0145)	0.1341 *** (23.3731)	0.1210 *** (0.0068)
ln Fis		−0.2401 *** (−11.6142)	−0.2553 *** (−20.7285)	−0.2421 *** (0.0093)
ln Urban		−0.1471 *** (−3.0480)	−0.0185 (−0.7550)	0.1146 *** (0.0164)
ln Wage		0.0806 *** (7.4068)	0.0809 *** (9.9616)	0.0555 *** (0.0045)
ln Unemp		−0.2275 *** (−13.8810)	−0.2235 *** (−23.5517)	−0.1801 *** (0.0122)
ln Pop		−0.0615 *** (−4.6918)	−0.3868 *** (−17.4901)	−0.0252 *** (0.0039)
Constant	−2.6831 *** (−64.3521)	−3.9891 *** (−12.5066)	−8.7448 *** (−22.2406)	−4.2819 *** (0.1209)
Individual effect	NO	NO	YES	YES
Time effect	NO	YES	YES	YES
Log Likelihood				1275.3657
Wald (chi2)				12,460.78
Observations	4305	4305	4305	4305
R-squared	0.666	0.7081	0.956	0.746

Note: The standard error is shown in parentheses. Statistical significance is denoted by asterisks: *, **, and *** correspond to sig-nificance levels of 10%, 5%, and 1%, respectively.

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