Digital Infrastructure Development and Regional Market Segmentation: New Evidence from the "Broadband China" Policy

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Abstract

Regional market segmentation (SEG) has hindered China's high-quality economic development, while digital infrastructure construction (DIC) can accelerate intraregional factor mobility, which is crucial to breaking down SEG. Using panel data from 110 prefecture-level cities in the Yangtze River Economic Belt of China from 2011 to 2021, this study analyzes the impact of DIC on regional SEG, employing a time-varying difference-in-differences model, and treating the "Broadband China" pilot policy as a quasi-natural experiment. The results reveal that DIC significantly mitigates regional SEG, and this conclusion remains valid following a series of model validity and robustness tests. The mechanism analysis confirms that DIC reduces regional SEG by enhancing urban market potential and fostering technological innovation. Heterogeneity analysis shows that the mitigating effects of DIC on regional SEG are particularly pronounced in cities characterized by high information search costs, a low digital divide, low market concentration, and particularly among small and mid- to lower-tier cities. The results provide crucial insights concerning the positive impact of DIC, which is essential for accelerating China's transition to a new development pattern that emphasizes a strong domestic market and for strategically implementing differentiated policies.

Keywords: *digital infrastructure construction; regional market segmentation; Broadband China; time-varying in-Difference-in-Difference-in-Difference*

JEL Classification*: R12, O16, C23*

Article history: Received: November 2024; Accepted: March 2025; Published: March 2025

1 INTRODUCTION

Accelerating domestic general circulation and realizing high-quality economic development are important strategies for China's economic development at present and in the near future; however, the phenomenon of market segmentation (SEG) is more prominent in China due to differing regional endowments and policy orientations. This is largely detrimental to the formation of economies of scale and the operation of a national market competition mechanism, reducing the efficiency of resource allocation in the national market (Yu er al., 2022), and seriously hampers the process of high-quality economic development. Moreover, under the dual pressure of the "GDP championship" and "tax competition", the SEG phenomenon caused by local government officials interfering in the market and restricting resource factor flow via administrative control remains prevalent (Peng et al., 2022). The reason for this is that administrative control of the flow of resources across regions is an advantageous strategy for local governments in the short-term competitive game of promoting growth and promotion. Therefore, alleviating or eliminating the problem of SEG is a significant practical problem that China must solve to advance high-quality economic development.

The SEG phenomenon in China has been a popular research topic; however, the related literature has predominantly focused on measurement, evaluation, and causes and effects (Kheir & Portnov, 2023). For example, the primary methods of measuring regional SEG have included

https://doi.org/10.7441/joc.2025.01.07

the production method (Young, 2000), trade method (Poncet, 2003), price index method (Parsley & Wei, 2001a), relative price method (Fu & Zhu, 2024), and other forms. Using such measures, most studies have determined that although segmentation is evident in China's regional markets, the degree of segmentation exhibits a decreasing trend (Ma et al., 2021). Moreover, most scholars have agreed that SEG causes difficulties integrating domestic markets and widens the income gap between urban and rural areas and regions, which has seriously affected regional economies' high-quality development (Beladi et al., 2019; Yang et al., 2018).

To alleviate this impact, it is important to first identify the causes of SEG in China. Specifically, the causes have been categorized as institutional and natural segmentation. From the perspective of institutional segmentation, vertical governmental institutional arrangements that are implemented according to differing criteria such as industry, enterprise size, ownership, region, and other factors have caused policy inequalities between market participants, resulting in market segmentation (Zhao & Zhou, 2017). Furthermore, local governments' formulation and implementation of "race to the bottom" policies that maximize local interests according to administrative boundaries and restrictions on the movement of factors and commodities can also lead to "block" fragmentation of regional markets (Wu et al., 2020). Regarding naturalistic segmentation, factors such as transportation costs, information friction, and language differences can foment SEG (Zhang et al., 2024; Krugman, 1993; Allen, 2014). Some scholars have also examined SEG in terms of technological factors, arguing that underdeveloped infrastructure can increase trade costs and hinder regional participation in market integration (Donaldson, 2015). Although a large number of studies have analyzed the reasons for the formation of SEG, limited research has examined the path of SEG. For example, Hu et al. (2025) found that the government can effectively alleviate SEG by playing the role of the Economic Coordination Committee. Qi and Hao (2022) argued that accelerating privatization can break down SEG. However, these initiatives are institutional approaches, and the implementation process has high requirements for China's laws, regulations, and economic formations and challenges such as high resistance to reform and arduous demands, and it is often difficult to meet policies' expectations. Therefore, exploring new paths to break SEG has become a popular topic of widespread concern in the academic community and an important practical problem that needs to be solved urgently (Li et at., 2025; Wu, et al., 2023).

The contemporary digital economy is reshaping the pattern of world economic development as a new driving force for economic development of all countries (Ma et al., 2022). As the foundational architecture and technological underpinning of the digital economy, DIC has prompted developed nations in Europe and America to race in formulating strategic blueprints, implementing extraordinary incentive policies, and even establishing technological alliances through coalition-building tactics (Liu et al., 2024; Hossain et al., 2024). For instance, the United States has formulated multiple national-level digital economy development strategies, such as the "National Cyber Strategy," "5G FAST Plan" and the "National AI Research and Development Strategic Plan," aimed at enhancing DIC, strengthening cybersecurity, and advancing technological innovation and application in the digital domain (Wang et al., 2024). Similarly, the European Union has been implementing the "Digital Single Market Strategy" and "European Digital Strategy," aiming to dismantle digital barriers among member states and facilitate cross-border trade. As the second largest digital economy in the world, China had a digital economy of $7.8 trillion in 2023, providing new opportunities to stimulate consumption, drive investment, and advance high-quality development (Wang et al., 2022; Aparisi-Torrijo et al., 2024). With the in-depth integration and development of the digital economy across all fields of the economy and society, digital infrastructure construction (DIC) provides new channels for breaking regional restrictions and promoting the flow of production factors by leveraging the advantages of accelerated information dissemination, information use, and spanning geographic time and space (Hong et al., 2023). Furthermore, by virtue of its network externalities, DIC can promote network information aggregation through replication, sharing, and cooperation and significantly reduce the transaction costs of resource factors and economic activities' dependence on time and space, blurring market boundaries and promoting regional market integration (Sheng et al., 2024a). It has also been argued that DIC can improve distribution efficiency and optimize the business environment, which subsequently promotes market integration. However, some scholars have held the opposite view, arguing that rapid internet development leads to increased regional competition, which triggers monopoly segmentation and has negative spillover effects (Xie et al., 2018).

Previous research has provided a solid foundation for the research in this study; however, some shortcomings remain. First, existing literature on SEG measurement has predominantly used provincial-level data, which have a small sample size and cannot effectively reflect the internal differences of provinces with large geographical areas and considerable differences in economic development. Second, previous studies have not yet developed a unified perspective concerning the impact of DIC on SEG, and insufficient attention has been paid to the mechanism of action and heterogeneity. Accordingly, this study takes the Yangtze River Economic Belt (YREB) as an example, using the "Broadband China" pilot policy as a quasi-natural experiment, and constructs a time-varying difference-in-differences (DID) model to investigate the effects and mechanisms of DIC on SEG. We choose the YREB as the object of study because it straddles eastern, central, and western China, is the mainstay of China's high-quality economic development, has a high degree of regional market activity, and is highly representative of the potential for DIC.

The marginal contributions of this study compared with existing studies are in three main areas. First, focusing on the YREB, we measure SEG at the municipal level, reflecting the degree of SEG in greater detail. Second, the study innovatively explores the mechanism of DIC on SEG from two paths of market potential and technological innovation, providing a novel perspective for clarifying the mechanism of DIC affecting SEG. Third, we extend the analysis of differences in the effects of DIC on the impact of SEG due to factors such as information search costs and market concentration, providing a new perspective from which local governments can tailor policies to local conditions.

The remainder of this paper is structured as follows. Section 2 presents the theoretical hypotheses. Section 3 details our methodology and data specification. Section 4 outlines the result and related discussion. Section 5 conducts mechanism testing and heterogeneity analysis. Section 6 provides the conclusion and policy implications of this study.

2 THEORETICAL HYPOTHESES

Digital infrastructure is significantly networked, informatized, and digitized and can affect SEG in many ways. First, DIC accelerates the aggregation and cross-regional dissemination of market information, weakens the restraining effect of factors such as administrative boundaries on factor flow, and diminishes the degree of SEG between supply and demand due to geographic distance (Liang et al., 2024). For example, regional producers and consumers can conduct market activities remotely through 5G networks, satellite internet, artificial intelligence, and other communication network–type digital infrastructure. DIC can also break down regional trade barriers, enhance regional connectivity, advance the accurate and efficient matching of supply and demand across regions, and increase the frequency of interaction between regional markets (Meng & Xu, 2025). Second, DIC can improve information transparency and reduce information search costs. For example, DIC for information services (represented by big data centers, cloud computing, and "Internet of Things" platforms) have smoothed the information communication channels between the two sides of the market transactions, which reduces the differences in the arbitrageable prices of commodities between regions and alleviates the problem of two-tier commodity pricing, which promotes the establishment of a unified national market. Finally, DIC can reduce information asymmetry between the subjects of economic activity and increase production factor allocation efficiency in the market (Galperin & Fernanda, 2017). Specifically, consumers rely on digital infrastructure to access information about products that are farther away, and can choose to buy products from outside the country. In addition, providers can collect consumers' online information data using big data and other data analytics to accurately formulate and implement differentiated marketing strategies based on consumers' heterogeneous preferences to gain access to new markets (Lu et al., 2023; Uddin, 2024). In summary, we propose research Hypothesis 1.

H1: Digital infrastructure construction can alleviate regional market segmentation.

The long-tail theory suggests that low storage or distribution costs and individualized, fragmented, and small-volume demand distributed in the tails of different segments of a market are superimposed to form a market of enormous size (Hinz et al., 2011). However, distance and space constraints, physical stores' service scope, the display space for commodities always being limited, and merchants' tendency not to display commodities with smaller market demand on shelves can result in difficulties with meeting the needs of the long-tail market. DIC makes it possible to precisely locate and match all kinds of information and resource elements—online and offline and between virtual and physical space—promoting the flow of numerous elements in the market within a shorter period of time. This not only enhances the efficiency of market resource allocation, but also enables consumers to more readily access relevant information about potential trading partners. By empowering consumers to select goods or services from a broader geographical scope, it stimulates diversified and refined demand patterns. For producers, leveraging digital infrastructure enables them to expand the sales reach of their products while also intensifying competition across different regions, thereby driving improvements in economic efficiency. Meanwhile, in-depth data mining and analysis facilitate efficient resource matching among firms, thereby lowering the costs incurred in identifying trading partners and finalizing agreements. As evidenced, DIC objectively fosters a dynamic market environment conducive to dismantling trade barriers, effectively expanding market potential and injecting new momentum into accelerating the establishment of a nationally unified market (Xia et al., 2023). Moreover, expanded market potential can connect and integrate discrete and fragmented territorial and regional markets, which can optimize the urban scale system, urban–rural relations, and enterprise scale structure across urban agglomerations. This can weaken the effect of barriers caused by policies promoting local protection and designated trading in each region, integrating segmented local markets into a unified market (Qiu et al., 2021). In addition, greater market potential incurs higher costs for local government protection, reducing the likelihood that SEG will prevail. In summary, we propose Hypothesis 2.

H2: Digital infrastructure construction can alleviate regional market segmentation by unlocking urban markets' potential.

Technologically underdeveloped regions will protect key local industries by dividing regional markets and limiting the outflow of key internal resource factors to establish positioning in cross-regional cooperation negotiations. DIC can bridge the technological gap between regions by enhancing cities' technological innovation, disrupting local protectionist practices and institutional constraints, strengthening inter-regional cooperation, and fostering integrated development. First, DIC can reduce information acquisition and transaction costs in the process of technological innovation (Abeliansky & Hilbert, 2017; Tang et al., 2021; Liu et al., 2023; Chen et al., 2024), and its open-sharing characteristics makes the asset application of research and development (R&D) activities and related costs decrease simultaneously, making it easy for innovation subjects to obtain the required data elements. Second, DIC accelerates knowledge and technology spillover and strengthens cooperative links between different innovation subjects (Wang & Wang, 2024). This promotes cross-regional knowledge and information sharing and increases the channels through which innovation subjects receive diversified information, providing expedient and accurate market information from networked enterprises, capturing changes in the market demand for innovative products, and ultimately improving technological innovation. Finally, DIC changes the production and service paradigm from a unitary model in which the producer provides a product to the consumer to one in which the two interact in both directions, which is evidenced by the digital environment in which the producer provides the product and the consumer provides feedback. This paradigm shift allows producers to fully understand the real demand for various products, stimulating firms' R&D needs and technological innovation practices (Chen et al., 2025). Technological innovation can promote the free flow of commodities and factors by improving the circulation of logistics and information flow, easing the degree of SEG. When a low-level region is flooded with high-quality products and services, it will also compel the region's technological innovation capacity, narrowing inter-regional market differences and alleviating the SEG phenomenon caused by the protection of local key industries. In summary, we propose research Hypothesis 3.

H3：Digital infrastructure construction can mitigate regional market segmentation through technological innovation.

3 METHODOLOGY AND DATA SPECIFICATION

3.1 METHODOLOGY

We take the "Broadband China" pilot policy as a quasi-natural experiment, using a time-varying DID model to evaluate the effects of DIC on SEG, the model is established as follows:

$$y_{it}=\alpha_0+\alpha_1 did_{it}+\alpha_2 X_{it}+v_i+u_t+\varepsilon_{it} \tag{1}$$

where y_{it} is the explanatory variable indicating the degree of SEG of city i in year t, and did_{it} is the independent variable indicating the policy implementation status of city i in year t, which takes a value of 1 if city i was selected as a "Broadband China" pilot city, and 0 otherwise. α_1 measures the net effect of the "Broadband China" policy on SEG. X_{it} denotes the control variables, α_2 is the coefficient to be estimated for the control variables, α_0 is the constant term, v_i is city fixed effect, u_t indicates time fixed effect, and ε_{it} is the error term.

We also construct a mediating effect model to examine the mechanism of DIC affecting SEG. The study references Jiang (2022), and the model is established as follows:

$$Regulation_{it}=\lambda_0+\lambda_1 D_{it}+\lambda_2 X_{it}+v_i+u_t+\varepsilon_{it} \tag{2}$$

where $Regulation_{it}$ denotes the mediating variables of market potential and technological innovation, and the remaining variables are defined as in the baseline regression.

3.2 DATA SPECIFICATION

3.2.1 DATA SOURCES

This study uses panel data from 110 prefecture-level cities in the YREB from 2011 to 2021 as the sample for examination. In measuring SEG, we use the consumer price index for eight categories of goods, which include food, tobacco and alcohol; clothing; health care; household goods and services; other goods and services; transportation and communications; education, culture, and entertainment; and housing. The data are obtained from the China Statistical Yearbook, the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, the China Statistical Yearbook on Science and Technology, the National Economic and Social Development Statistical Bulletin of prefecture-level cities in the YREB, the official websites of national and local statistical bureaus, the National Research Network database, and the EPS data platform for the corresponding years. We determined a small portion of missing data using the interpolation method.

3.2.2 CORE VARIABLES

Dependent variable: SEG index. We quantify the degree of SEG using the SEG index, which is a measure of the extent to which factor mobility is impeded between regions. Due to the advantages of easy access to price data and high sensitivity to changes in market supply and demand, this study uses the correlation price method to measure SEG by analyzing the relative price information of the eight commodities named above between regions.

As the raw data are chained indices of consumer prices, we use the following formula to measure relative prices (Gui et al., 2006):

$$\Delta Q_{ijt}^{k}=ln\left(p_{it}^{k}/p_{jt}^{k}\right)-ln\left(p_{it}^{k}/p_{jt-1}^{k}\right)=ln\left(p_{it}^{k}/p_{it-1}^{k}\right)-ln\left(p_{jt}^{k}/p_{jt-1}^{k}\right) \tag{3}$$

To avoid influencing the relative price variance ($var\Delta Q_{ijt}^{k}$) due to the different orders of placement in two regions, we take absolute values for relative prices as follows:

$$|\Delta Q_{ijt}^{k}|==\left|ln\left(p_{it}^{k}/p_{it-1}^{k}\right)-ln\left(p_{jt}^{k}/p_{jt-1}^{k}\right)\right| \tag{4}$$

We use ARCGIS 10.0 software to construct an adjacency matrix reflecting the bordering cities of each city and the relative price data of the eight types of commodities for 518 pairs of bordering cities in 11 years. To measure the degree of SEG more accurately, it is essential to consider the fact that commodity price changes are not only affected by differences in inter-regional market environments, but may also be affected by nonadditive effects due to the heterogeneity of the commodities themselves. In view of this, this study references the demean method proposed by Parsley and Wei (2001b) for the treatment. The method assumes that the variation in commodity prices consists of price changes caused by the characteristics of the commodity itself (a^k) and random changes related to the regional market environment (ε_{ijk}^{k}), i.e., $\left|\Delta Q_{ijk}^{k}\right|=a^k+\varepsilon_{ijk}^{k}$. To eliminate the effect of the commodities' own characteristics, we calculate the mean $\left|\Delta \overline{Q}_{ijt}^{k}\right|$ of the relative prices between 518 pairs of cities for a given year and commodity. The relative price change for each city (q_{ijt}^{k}) is then expressed as the difference between ε_{ijt}^{k} and $\overline{\varepsilon}_{ijt}^{k}$ as follows:

$$q_{ijt}^{k}=\varepsilon_{ijt}^{k}-\overline{\varepsilon}_{ijt}^{k}=\left|\Delta Q_{ijt}^{k}\right|-\left|\Delta \overline{Q}_{ijt}^{k}\right|=(a^k-\overline{a}^k)+(\varepsilon_{ijt}^{k}-\overline{\varepsilon}_{ijt}^{k}) \tag{5}$$

We then calculate the variance $var(q_{ijt})$ of the relative price fluctuations (q^k_{ijt}) of the eight categories of commodities between each region, which are combined accordingly to obtain the SEG index of 110 cities in the YREB as follows:

$$var(q_{nt})=\frac{\sum_{i\neq j} var(q_{nt})}{N} \tag{6}$$

where n is the region and N is the number of bordering cities in the region. Through the measurement, this study obtained 1,210 observations for assessing the degree of SEG. According to the relevant algorithm and its economic implications, a smaller SEG index indicates a closer connection between regions.

Independent variable: We use the "Broadband China" pilot policy as a proxy for DIC. According to the policy's strategy implementation plan issued by government of the People's Republic of China in 2013, the Ministry of Industry and Information Technology of the People's Republic of China and National Development and Reform Commission approved pilot cities in three batches in 2014, 2015, and 2016, with a total of 117 selected pilot cities across the country. Figure 1 shows the urban distribution and pilot time of the "Broadband China" pilot policy in the YREB region. The study area includes the 110 cities in the YREB, including pilot cities. If city i is included in the "Broadband China" pilot in year t, it takes the value of 1, otherwise it takes the value of 0.

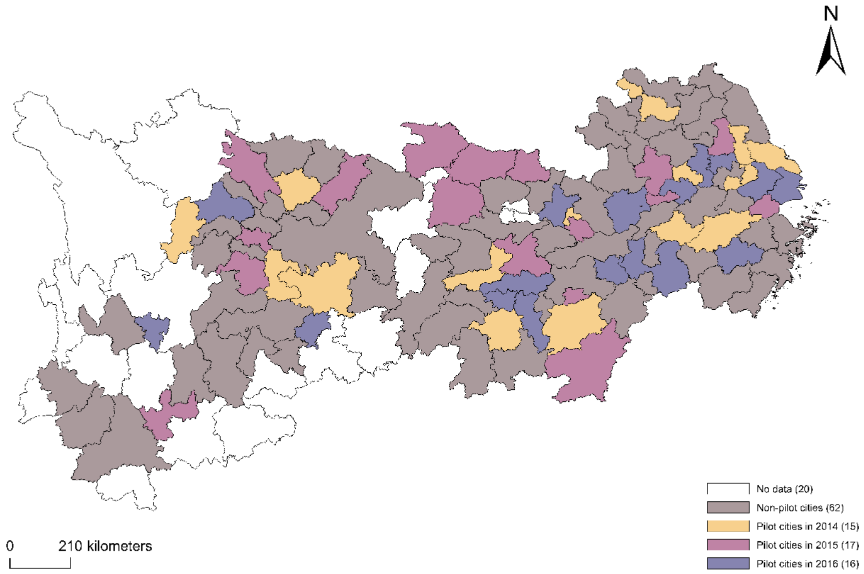

Figure 1 Year and number of cities in the YREB where the"Broadband China" policy was piloted

Note: This map is produced based on the standard map with review number GS (2023) 2767 downloaded from the Standard Map Service website of the State Administration of Surveying, Mapping, and Geographic Information, with no modifications to the base map.

Mechanism variables: Market potential and technological innovation

According to the previous explanation, market potential indicates the potential development effect that economic development in other regions may have on a region. This study adopts Harris's (1954) measure, with 2011 as the base period, and uses deflated 2011–2022 city GDP data to measure the market potential, which is calculated as follows:

$$MP_{it}=\frac{\sum_{i\neq j} GDP_{jt}}{d_{ij}} \tag{7}$$

where MP_{it} represents the market potential index of region i in year t, GDP_{it} is the total GDP of region j in year t, and d_{ij} is the geographic distance between regions i and j. This method describes the market potential of region i as the weighted sum of the GDP of other regions, where the weight is the inverse of the distance, which means that the influence of “iceberg transportation cost” cause the spillover effect of the economic development of other cities on this city to become smaller as the distance increases.

Considering that a city’s investment in science and technology R&D has an impact on the quality of economic development in current and later periods, referencing the existing literature (Zhao & He, 2024), we adopt the ratio of the city’s science and technology expenditure to the local government’s general expenditure to measure technological innovation to examine the relationship between DIC and the city’s technological innovation.

3.2.3 CONTROL VARIABLES

Considering that cities’ characteristic factors may have an impact on SEG, this study controls for the following variables.

Government intervention (*Gov*). The degree of government intervention reflects the local government’s ability to protect the market and is one of the main motives establishing SEG, which we measure by the ratio of local general public budget expenditure to regional GDP (Song et al., 2024).

Human capital (*Hig*). Human capital accelerates the concentration of labor in high-tech industries, which affects regional product supply and market share. This is measured by the ratio of the number of students enrolled in general undergraduate schools to the total population at the end of the year (Liang et al., 2024).

Financial development (*Fdl*). We take the ratio of year-end deposit and loan balances of financial institutions to regional GDP as the measure (Ren et al., 2018).

Infrastructure (*Fund*). This study takes the ratio of fixed asset investment to gross regional product to measure (Yin et al., 2018).

Population density (*Pop*). We take the ratio of regional resident population to urban area to express (Xu et al., 2021).

Degree of openness to the outside world (*Trade*). Given that SEG is mainly about limiting the impact of the inflow of foreign goods on local industries, this study adopts the ratio of total exports and imports to regional GDP as the measure (Li & Wang, 2022).

The specific variable settings and descriptive statistics are presented in Tables 1 and 2.

Tab.1-Variable types, name, symbol, and descriptions

Variable types	Variable names	Variable symbols	Variable descriptions
Dependent Variable	Market segmentation index	Seg	Measured under the relevant price method
Independent Variable	Network infrastructure	Did	Use the “Broadband China” policy (dummy variable) as the core explanatory variable
Mediator Variable	Market potential	Mp	Using 2011 as the base period and using deflated city GDP data for 2011-2021
	Level of urban science and technology investment	Lsti	Science and technology expenditures/general government expenditures (%)
Control Variable	Government intervention	Gov	General public budget expenditure/GDP (%)
	Level of human capital	Hig	Number of students enrolled in general undergraduate programs/Total population at the end of the year (%)
	Level of financial development	Fdl	Balance of deposits and loans of financial institutions at the end of the year/gross regional product（%）
	Level of infrastructure	Fund	Fixed Asset Investment/Gross Regional Product (%)
	Population density	Pop	Regional resident population/urban area (Persons per square kilometer)
	Degree of openness to the outside world	Trade	Total exports and imports/gross regional product (%)

Source: own research

Tab.2-Descriptive statistics of variables

Variable	Observations	Mean	SD	Min	Median	Max
Seg	1210	2.036	2.146	0.235	1.389	16.289
Did	1210	0.279	0.448	0.000	0.000	1.000
Mp	1210	716.817	324.886	143.859	658.571	2001.761
Lsti	1210	0.022	0.019	0.001	0.017	0.163
Gov	1210	0.198	0.083	0.088	0.182	0.489
Hig	1210	0.019	0.024	0.001	0.011	0.121
Fund	1210	0.866	0.297	0.236	0.851	2.058
Fdl	1210	2.428	0.938	1.096	2.223	5.915
Pop	1210	5.999	0.625	4.035	6.040	6.994
Trade	1210	0.160	0.219	0.001	0.083	1.168

Source: own research

4 RESULTS AND DISCUSSION

4.1 BASELINE REGRESSION RESULT

To examine the impact of DIC on SEG, this study conducts a regression of equation (1), and the results are shown in Table 3. Columns (1) and (2) present regression results without and with control variables, respectively. The results show that the regression coefficients of DID are significantly negative, regardless of the inclusion of control variables and the fact that the size of the coefficients is not significantly different, which demonstrates that DIC significantly mitigates the degree of SEG in treated cities. DIC is widely used in international trade activities, which strengthens trade cooperation between countries as a new engine for global economic integration and economic growth (Zhou et al., 2022; Liu & Nath, 2013; Lv et al., 2021; Guo et al., 2022). This study further narrows the scope of the research object by demonstrating that DIC can significantly mitigate SEG as well, providing new empirical evidence on the role of DIC.

Tab.3-The regression results of SEG on DIC

Variable	Model(1)	Model(2)
Did	-0.605** (0.243)	-0.547** (0.243)
Gov		-4.576 (3.412)
Hig		-27.643** (11.930)
Fund		0.639 (0.492)
Fdl		-0.298 (0.436)
Pop		2.753 (2.633)
Trade		0.530 (1.540)
Constant	2.205*** (0.068)	-12.807 (15.779)
Time effect	YES	YES
Urban effect	YES	YES
Observations	1210	1210
Adj-R^2	0.301	0.313

Source: own research，robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1，clustering robust standard errors in parentheses. All subsequent tables are the same.

4.2 VALIDATION OF ECOSYSTEM MODELS TEST

4.2.1 PARALLEL TREND TEST

An important assumption of the time-varying DID model for assessing policy effectiveness is that treatment and control groups satisfy the parallel trend assumption. That is, prior to “Broadband China” pilot implementation, the SEG of the treatment and control groups should have a consistent trend. As a result, we reference Li et al. (2016) and use the event study method to conduct a parallel trend test with the following model:

$$y_{it}=\alpha_0+\sum_{m=-4}^{7}\theta_m D_{i,t+m}+\lambda_1 X_{it}+v_i+u_t+\varepsilon_{it} \quad (8)$$

where y_{it} is the SEG index of city i in year t, and $D_{i,t+m}$ is a series of dummy variables that take the value of 1 if city i implemented the "Broadband China" pilot in year $t+m$, and 0 otherwise. m represents the number of periods before and after the implementation of the pilot program, and some cities in the YREB zone implemented the pilot program from 2014 to 2016; therefore, m can take all integers between [−4,7]. θ_m denotes the difference in the SEG index between pilot and nonpilot cities in year m, λ_1 denotes the control variables, X_{it} is the set of control variables, α_0 is the constant term, v_i is individual fixed effect, u_t is time fixed effect, and ε_{it} is the random error term. The results of the parallel trend test are presented in Figure 2.

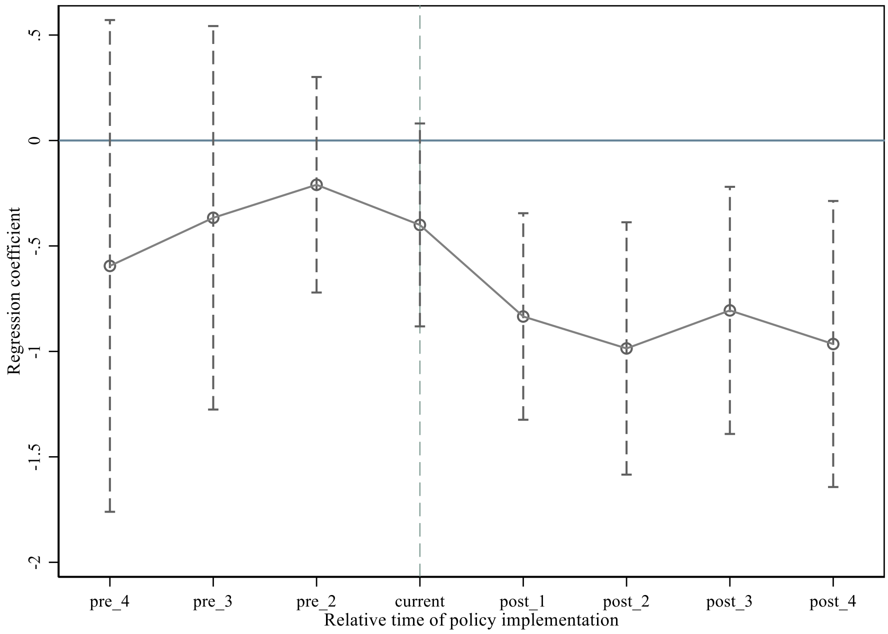

Fig.2-Parallel trend test chart

As illustrated in Figure 2, the estimated coefficients do not significantly differ from 0 prior to "Broadband China" pilot policy implementation, indicating no significant difference between the pilot cities and non-pilot cities, which satisfies the parallel trend assumption.

4.2.2 TIME PLACEBO TEST

To confirm that the difference in SEG between pilot and non-pilot cities is not caused by time variation, we construct a false policy pilot time by advancing the policy pilot by two and three years and pushing it back by two and three years, respectively, and rerun equation (1), and the results are presented in Table 4. The results reveal that the estimates of the policy advancing by two and three years fail the significance test, indicating no systematic differences in time trends between treatment and control group cities. In contrast, the coefficient estimates of two and three years following policy implementation passed the significance test at 5% and 10% levels, respectively, indicating that DIC is influential and the policy effect is sustainable.

Tab4- Time placebo test

Variables	Policy advanced by 2 years	Policy advanced by 3 years	Policy deferred for 2 years	Policy deferred for 3 years
Did	-0.102	0.071	-0.502**	-0.372*
	(0.350)	(0.514)	(0.209)	(0.220)
Constant	-12.923	-13.229	-13.280	-13.390
	(16.444)	(16.426)	(15.584)	(15.816)
Controls	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES
Observations	1210	1210	1210	1210
Adj-R^2	0.309	0.309	0.312	0.310

4.2.3 URBAN PLACEBO TEST

To confirm that the baseline regression results are not affected by omitted variables or unobservable city characteristics, this study references Hao et al. (2022), conducting a placebo test by randomly assigning treatment group cities. We randomly select 48 sample cities as false pilot cities, and the remaining cities are treated as non-pilot cities, and rerun equation (1). On this basis, we repeat the process 500 times, obtaining 500 regression coefficients and corresponding p-values, presenting the specific distribution in Figure 3. The results demonstrate that most of the spurious regression coefficients focus around 0 and follow normal distribution, excluding the possibility that the benchmark regression estimates are disturbed by unobservable factors.

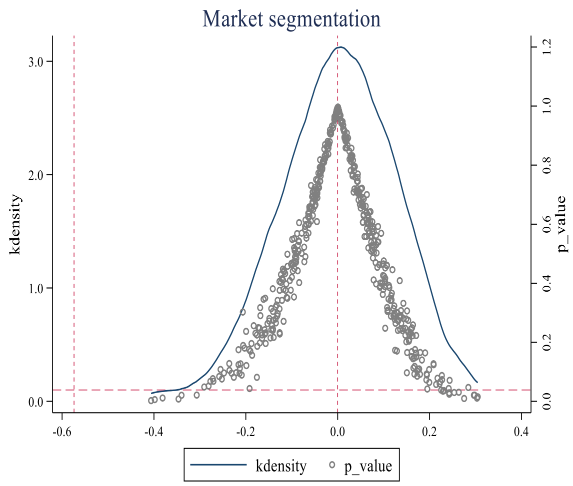

Fig.3- Urban placebo test

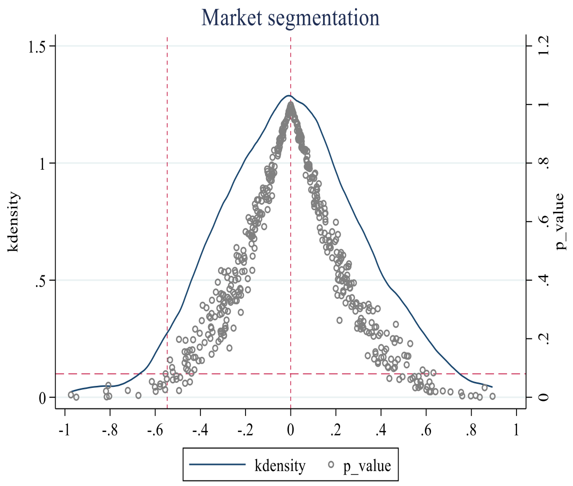

Fig.4- Mixed placebo test

4.2.4 MIXED PLACEBO TEST

Due to differences in the timing of policy shocks in the pilot cities, it is essential to randomize the pseudo treatment group dummy variable ($Group^{random}$) and the pseudo policy shock dummy variable ($Post^{random}$). To ensure that the pseudo policy variables do not have impacts, this study constructs a pseudo "Broadband China" pilot policy and applies 500 random shocks on the 110 sample cities, and 48 cities are randomly selected as the experimental group, and the policy time is randomly set to obtain 500 groups of dummy variables Did^{random} (i.e., $Group^{random} \times Post^{random}$), and the kernel density and p-value distributions of 500 β^{random} are presented in Figure 4. Density and its p-value distribution are also presented in Figure 4. The results show that β^{random} produced during the randomized treatment is predominantly concentrated around 0 and the p-values are mostly higher than 0.1, while the estimated coefficient for the actual policy is -0.547, which significantly differs from the results of the placebo test, confirming the robustness of our benchmark results.

4.2.5 GOODMAN-BACON DECOMPOSITION

In the two-way fixed effects (TWFE) model, the heterogeneity of treatment effects across groups and treatment times can lead to a bad control group and negative weighting problems, and the regression results can be seriously biased when the proportion of negatively weighted samples is large. We reference the decomposition method of Goodman-Bacon (2021), and categorize the sample into three groups, introducing "have not yet received the treatment," "received the treatment earlier," and "never received the treatment" as control groups. The results are shown in Table 5, revealing the estimate of "earlier" treatment group as a control group is −0.014, with a weight of 7.00%. Since the proportion of inappropriate treatment effect is small, and its estimation value is relatively small, it does not cause much interference to the regression results, indicating that the research conclusion remains robust.

Tab.5-Goodman-Bacon decomposition table

Groups	*Estimates*	*Weight*
"Not yet processed" is the control group	-0.018	0.036
"Earlier treatment" is the control group	-0.014	0.070
"Never processed" for control group	-0.641	0.894

4.3 ROBUSTNESS TESTS

4.3.1 STEADY DID

In time-varying DID, the heterogeneity of treatment effects can bias TWFE estimates, biased treatment effects of different batches of pilot policies, and the impacts on cities may change dynamically over time; therefore, this study employs the heterogeneous robustness estimator. First, we calculate group–period average treatment effects referencing the estimators proposed by De and d'Haultfoeuille (2024) and Gardner (2022). This approach reduces estimation bias by excluding the earlier treatment group as a control group, excluding the interference of potentially bad control groups in the results. Second, referencing Borusyak et al. (2024), we employ interpolated estimators to estimate the counterfactual results for each treatment group using samples that had not yet received treatment and those that had never received the treatment, calculating the difference between the true and counterfactual results. Finally, using the stacked regression estimator proposed by Cengiz et al. (2019), we constructed the dataset and matched untreated and not-yet-treated observations for the treatment group to rerun the regression by adding group–city and group–time fixed effects. Comparing the corresponding results with the double fixed effects, the results are shown in the figure 5. The above estimation method is broadly consistent with the previous TWFE results in terms of trend, confirming that the estimation results are robust.

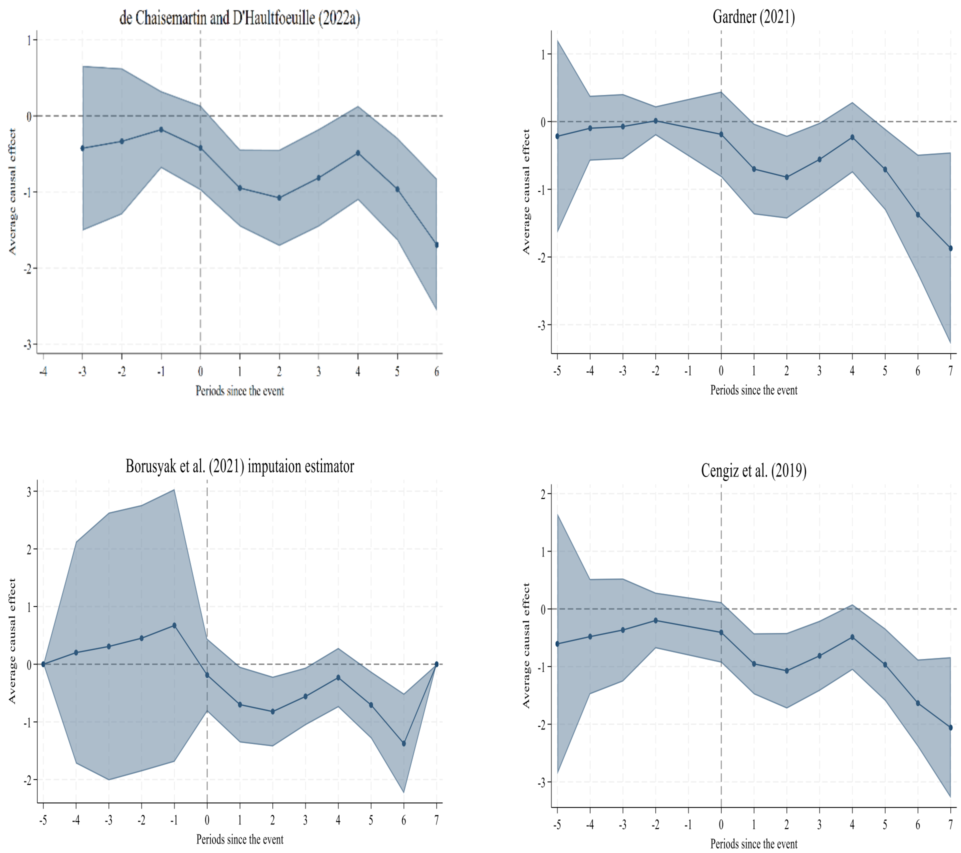

Fig.5-Robust-DID

4.3.2 INCLUDING A BASELINE VARIABLE TO MITIGATE SELECTION

If the list of "Broadband China" city pilots is related to factors such as cities' economic development, historical mission, and geographic location, then differences in these factors may have different impacts on SEG over time, resulting in estimation bias. To avoid the effect of non-randomization of the "Broadband China" pilot policy choice, we introduce the interaction term between the city-level benchmark factor and the time trend in equation (1) in the following equation:

$$segmentation_{it}=\alpha_3+\beta_3+\theta_3 X_{it}+\lambda Z_c \times trend_t+\varphi_i+\mu_t+\gamma_{it} \tag{9}$$

where Z represents the variables associated with cities' baseline factors, including dummy variables for whether a city is a capital city or a central city and a geographic variable of the city's degree of surface relief. *Trend* represents the time trend term.

The results are presented in Table 6. The results indicate that the mitigating effect of the "Broadband China" pilot policy on SEG remains significant at the 5% level, regardless of whether city-by-city or all city benchmark factors are included in the interaction term with the time trend, indicating that pilot cities were randomly selected. The "Broadband China" pilot cities in the YREB are located in different geographic locations, which themselves have differentiated economic development and demonstrates the randomness of pilot cities' selection.

Tab.6- Robust test

Variables	Model (3)	Model (4)	Model (5)	Model (6)
Did	-0.556**	-0.570**	-0.603**	-0.590**
	(0.232)	(0.234)	(0.248)	(0.231)
Constant	-15.214	-19.667	66.563	72.037
	(24.111)	(30.998)	(64.870)	(74.934)
Capitalcity*Year	YES	NO	NO	YES
Centercity*Year	NO	YES	NO	YES
Rdls*Year	NO	NO	YES	YES
Controls	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES
Observations	1210	1210	1210	1210
Adj-R^2	0.313	0.333	0.316	0.316

4.3.3 PROPENSITY SCORE MATCHING-DID METHOD

Since the “Broadband China” pilot policy is a quasi-natural experiment, this introduces a potential problem of selective bias in observational research data. Therefore, this study further conducts a robustness test based on a multi-temporal propensity score matching (PSM)-DID model. As PSM is applicable to cross-sectional data and DID is applicable to panel data, existing literature has introduced two research approaches: constructing cross-sectional PSM and period-by-period matching. We sequentially employ panel data transformation and period-by-period methods for matching. The results are shown in Table 7. The results after correcting for sample selection remain significantly negative, and are consistent with the benchmark regression results. This analytical method effectively excludes the interference of individual differences on the regression results and further validates the mitigating effect of DIC on SEG.

Tab.7- Robust test

Variables	Section PSM	Period by period
Did	-0.6929***	-0.6516**
	(-2.7567)	(-2.5510)
Constant	-10.543	0.202
	（16.585）	（12.362）
Controls	YES	YES
Time effect	YES	YES
Urban effect	YES	YES
Observations	1607	961
Adj-R^2	0.0010	0.024

4.3.4 ADDRESSING POTENTIAL ENDOGENEITY

To address potential endogeneity concerns, we re-estimate equation (1), lagging all control variables by one period, and the results are shown in Model (7) of Table 8. The results reveal that the sign and significance of the DID coefficients remain consistent with those of the baseline regression, but the degree of control becomes slightly weaker due to the control variables lagging one period, resulting in a slight increase in the estimated coefficients, once again validating the robustness of the study’s benchmark findings. To further ensure the reliability of the baseline regression, this paper refers to the method of Huang et al. (2019) and uses the historical data of post offices in 1984 for each city as an instrumental variable for DIC. The selected instrumental variable (IV) is cross-sectional in nature and thus cannot be directly applied to panel data econometric analysis. To address this limitation, we draw upon the methodological innovation of Nunn and Qian (2014) by introducing a time-varying interaction term to construct a panel-adapted IV framework. Construct interaction terms between the previous year's national internet user population and the number of post offices in each city in 1984, and use them as instrumental variables for DIC. The results of the instrumental variable regression are presented in Table 8. Model (9) shows the second-stage regression results. The coefficient of Did_IV is significantly negative at the 5% level, indicating that DIC continues to alleviate regional SEG after accounting for potential endogeneity issues. Additionally, for the null hypothesis of "underidentification of the instrumental variables," the Cragg-Donald Wald F statistic is 25.651, which exceeds the Stock-Yogo critical value at the 10% significance level, indicating no weak instrument issue in the model. The LM statistic rejects the null hypothesis at the 1% significance level, confirming that the instrumental variables are identifiable.

Tab.8- Robust test

Variables	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
Did	-0.593*** (0.182)		-0.537** (0.249)	-0.551** (0.241)	-0.550** (0.238)	-0.537** (0.244)
Did_IV		-6.5648** (2.9322)				
Constant	-0.593*** (0.182)	-13.6296 (16.8357)	-12.887 (15.764)	-13.793 (15.439)	-12.950 (15.711)	-14.338 (15.228)
Controls	NO	YES	YES	YES	YES	YES
L. Controls	YES	NO	NO	NO	NO	NO
NEDC	NO	NO	-0.092 (0.354)	NO	NO	-0.147 (0.856)
SCP	NO	NO	NO	0.652* (0.381)	NO	0.675* (0.390)
NBDCPZ	NO	NO	NO	NO	-0.058 (0.864)	-0.171 (0.363)
Time effect	YES	YES	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES	YES	YES
Observations	1100	1210	1210	1210	1210	1210
Adj-R^2	0.345		0.313	0.316	0.313	0.316

4.3.5 EXCLUDING INTERFERENCE OF OTHER POLICIES

The National E-commerce Demonstration City, Smart City Pilot, and National Big Data Comprehensive Pilot Zone Pilot policies are closely related to the "Broadband China" pilot. To rule out the interference of these policies on SEG, we introduce dummy variables for the implementation years of each of these three policies into the baseline regression model, and present the results in the last four columns of Table 8. The results reveal that the estimated DID coefficients are significantly negative for all three policies, whether they are added sequentially or combined, indicating that other policies implemented during the sample observation period have limited interference with the benchmark regression, which remain robust, validating research Hypothesis 1.

5 MECHANISM TESTING AND HETEROGENEITY ANALYSIS

5.1 MECHANISM TESTING

5.1.1 MARKET POTENTIAL

The theoretical mechanisms in the previous section argue that DIC can alleviate SEG by increasing cities' market potential; therefore, we examine the mechanism of action from an empirical perspective, presenting the regression results in Table 9. As shown in column (2), the estimated DID coefficients are all significantly positive, indicating that the "Broadband China" pilot policy improved the market potential of cities in the treatment group and verifying that improved market potential is a significant channel through which DIC alleviates the SEG of the regional market, which validates Hypothesis 2. Increased DIC not only expands market demand and market potential, but also facilitates cross-regional and cross-industry transactions of factor resources and promotes economic activities on a wider scale. This suggests that when cities are hit by external shocks, expanded market potential can diminish the negative impact on urban productivity, contributing to stable economic development and increasing cities' resilience to shocks.

Tab.9- Mechanism analysis

Variables	Market potential	Technological innovation
Did	0.113**	0.002*
	(0.053)	(0.001)
Constant	-0.105	-0.018
	(1.728)	(0.031)
Controls	YES	YES
Time effect	YES	YES
Urban effect	YES	YES
Observations	1210	1210
Adj-R^2	0.971	0.825

5.1.2 SCIENTIFIC AND TECHNOLOGICAL LEVEL

As shown in column (3) of Table 9, the estimated DID coefficients are all significantly positive, which indicates that the "Broadband China" pilot policy improves technological innovation in treatment cities and verifies that improved technological innovation is a significant channel through which SEG is mitigated through DIC.Hypothesis 3 is thus verified. This result suggests that cities' improved DIC reduces firms' transaction costs and enhances enterprises' ability to actively absorb new technologies, enabling cities to adjust and adapt quickly in response to external shocks and move toward a new, more competitive growth path, establishing a sustained impetus for high-quality economic development, similar to the findings of Tian and Lu (2023). However, in contrast to Zhang's (2022) findings that the digital economy confers characteristics such as non-rivalry of information products, zeroing of the marginal cost of information, the absence of online digital markets, and the emergence of big data as a key input. The author argued that this results in strategic practices from digital economy industrial organizations such as self-preferential treatment, refusal to engage in transactions, predatory mergers and acquisitions, and differential pricing, which makes regional external technological monopoly more pronounced. This perspective emphasizes the impact of the endogenous characteristics of the digital economy on industrial organizations' and competitive practices, which may overlook the macro-regulatory role of the government and the advantages of cooperation between market players.

5.2 HETEROGENEITY ANALYSES

5.2.1 INFORMATION SEARCH COSTS

Differences in information search costs may affect the degree of SEG. In this study, referencing previous research (Zhu & Grigoriadis, 2022), we select the dialect differentiation index of each region to indirectly reflect the cost of information search, dividing the sample accordingly to conduct a group regression to analyze the heterogeneous impact of DIC on SEG under different information search costs. If the dialect differentiation index of the region is higher than the median of the sample, it is defined as a region with high information search costs, otherwise it is defined as a region with low information search costs (Shamdasani, 2021), and the results of the regression are shown in Table 10. The results show that DIC in regions with high dialect indexes significantly mitigates SEG. A possible explanation is that the demand side in regions with higher information search costs is more likely to retrieve information on the reputation of the counterparty through information service functions such as trading digital platforms, avoiding transactions with counterparties of poor product quality, and thus reducing the degree of information asymmetry between counterparties in regional trade.

Tab.10- Heterogeneity analysis

Variables	High information search costs	Low information search costs	High digital divide	Low digital divide	High market concentration	Low market concentration
Did	-1.129*** (0.347)	-0.044 (0.336)	-0.584** (0.256)	-1.257*** (0.322)	-0.355 (0.641)	-0.629** (0.282)
Constant	-8.217 (22.659)	-0.044 (0.336)	-13.015 (17.435)	-99.036 (74.785)	-34.509** (14.834)	2.909 (16.454)
Controls	YES	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES	YES
Urban effect	YES	YES	YES	YES	YES	YES
Observations	649	561	1063	132	231	979
R-squared	0.359	0.296	0.321	0.759	0.382	0.328

5.2.2 DIGITAL DIVIDE

The existence of a “digital divide,” whereby differences in access to and use of technology and information between regions may lead to unequal market access. Internet penetration intuitively reflects the equalization of digital opportunities, with higher internet penetration meaning that more people have access to the conveniences and opportunities brought about by DIC, while lower internet penetration suggests that some regions may be lagging behind in terms of access to information, economic opportunities and so on. In this paper, we refer to the existing research (Zhao et al., 2020), and select the number of internet households per 100 people in each city at the beginning of the observation period (2011) to reflect the digital divide between regions, and those higher than the median are defined as high “digital divide,” and vice versa as low “digital divide.” Accordingly, group regression was conducted, and the results are shown in Table 10. The results suggest that DIC has a better effect on mitigating market segmentation in areas where the initial “digital divide” is low. A possible explanation is that when the "digital divide" is significant, market entities in regions with underdeveloped digital infrastructure and those with weaker capabilities in accessing, evaluating, and utilizing information struggle to benefit from market dividends. These entities face competitive disadvantages and significant market access inequalities, which to some extent offsets the positive effect of DIC in mitigating SEG.

5.2.3 MARKET CONCENTRATION

Market concentration refers to the number and share of major suppliers or exchanges in a market, and when a small number of firms control the majority of the market, they can restrict competition through price controls, market access restrictions, and other means, resulting in a monopolistic or oligopolistic market structure. For this reason, this paper matches the top 100 commodity exchanges in China in 2011, as counted in the China Commodity Exchange Market Statistics Yearbook 2012, with the sample cities. In this paper, the market concentration is assigned as follows: if there is a trading market in the list in the sample city, it is positioned as an area with higher market concentration and the variable is assigned a value of 1; otherwise, it is defined as an area with lower market concentration and the variable is assigned a value of 0. The results are shown in Table 10, revealing that the mitigating effect of DIC on SEG is concentrated in the subsample with low market concentration. A possible explanation is that increased market concentration offsets the mitigating effect of DIC on SEG.

5.2.4 CITY SCALE

A city's size may affect the formulation and implementation of government policies, resulting in different impacts of DIC on SEG. Therefore, referencing the circular of the state council on the adjustment of the standard for the division of city scale, we divide cities into small, medium-sized, large, very large and mega cities, using cities' permanent population as the statistical caliber. Due to the small sample size of very large and mega cities in the sample, they are combined with large cities, dividing the sample into small, medium, and large cities for group regression. The results are shown in Table 11, revealing that DIC significantly mitigates SEG in small cities, which is likely because the larger the city is, the richer the resources it already possesses, and the stronger the existing agglomeration effect within the city, which can offset the mitigating effect of DIC on SEG. In contrast, smaller cities have relatively large development space. They are more responsive to the market and have greater potential to benefit from digital transformation and smart upgrading.

Tab.11- Heterogeneity analysis

Variables	Small city	Medium-sized city	Large city
Did	-0.943* (0.485)	-0.330 (0.358)	-0.312 (0.505)
Constant	-32.817 (34.490)	12.273 (22.465)	-28.682 (18.403)
Controls	YES	YES	YES
Time effect	YES	YES	YES
Urban effect	YES	YES	YES
Observations	429	418	363
Adj-R^2	0.323	0.393	0.311

5.2.5 CITY LOCATION

The YREB spans China's three major eastern, central, and western regions, with obvious differences in resource endowments and industrial structure, which makes the impact of DIC on SEG likely to be regionally heterogeneous. For this reason, based on the principle of China's geographic division, we classify cities in the provinces of Shanghai, Jiangsu, Zhejiang, and Anhui as upstream cities; cities in the provinces of Jiangxi, Hubei, and Hunan as midstream cities; and cities in the provinces of Chongqing, Sichuan, Guizhou, and Yunnan as downstream cities, to investigate heterogeneity in the effect of DIC on SEG among different regions. The results are shown in Table 12, revealing that the mitigating effect of DIC on SEG is primarily concentrated in midstream and downstream cities. Consistent with previous research findings (Mao et al., 2024), we conclude that the mitigating effect of DIC on SEG is primarily concentrated in midstream and downstream cities. A possible explanation is that upstream cities have relatively higher marketization and integration levels, while SEG is more severe in midstream and downstream cities with relatively less developed economies (Jones & Tonetti, 2020). In addition, the digital infrastructure in midstream and downstream cities is weak, and the user penetration rate is low. In these cities, the network and scale effects of DIC are more prominent, and the marginal utility of digital resource utilization is higher. This enables midstream and downstream cities to make better use of the input resources for DIC, thus playing a more powerful role in promoting the formation of a unified national market.

Tab.12- Heterogeneity analysis

Variables	Upstream city	Midstream city	Downstream city
Did	0.046	-1.044**	-1.191*
	(0.249)	(0.392)	(0.616)
Constant	11.046	18.663	-59.147***
	(8.695)	(21.180)	(12.676)
Controls	YES	YES	YES
Time effect	YES	YES	YES
Urban effect	YES	YES	YES
Observations	451	396	363
Adj-R^2	0.199	0.382	0.393

5.3 DISCUSSION

This study makes three contributions to the existing literature. First, we present a novel investigation of the impact of DIC on SEG. Previous literature has focused on the impact of the internet on international trade. For example, Freund and Weinhold (2002) examined U.S. exports and imports of 14 services to 31 countries between 1995 and 1999, determining that internet development in these countries positively affected bilateral trade with the United States. Subsequently, the authors further extended their analysis to examine merchandise trade, with the same findings (Freund & Weinhold, 2004). In addition, Tang et al. (2025) argued that internet expansion has made a significant contribution to bilateral trade. In contrast to previous research, this study finds that DIC, which is generally a socially prioritized capital investment, can also alleviate SEG within a country.

Second, Fu and Zhu (2024) analyzed special commodity markets such as agricultural markets, finding that DIC exacerbates SEG. The reason for this may be that agricultural products have certain special characteristics, and small farmers, who are the main suppliers in China's agricultural products market, may find it difficult to process and use market information effectively due to low digital literacy. For other commodity markets, DIC eases SEG, which may be explained by supplying agents in such markets being more responsive and taking appropriate measures in response to market changes, which diminishes the formation of SEG.

Third, the results of our mechanism tests indicate that DIC mitigates the degree of SEG by increasing treated cities' market potential and technological innovation, which mitigates SEG. Previous studies have demonstrated that DIC has a significant positive effect on enterprises' independent innovation and cross-regional collaborative innovation (Mao et al., 2024). However, the mechanism of action primarily contributes to advancing the formation of a unified national market by improving distribution efficiency, deepening the division of labor, reducing transaction costs, and reinforcing the effect of urban networks (Sheng et al., 2024b). The findings of this study provide new evidence regarding the impact of DIC on SEG.

6. CONCLUSIONS AND POLICY IMPLICATIONS

6.1 CONCLUSIONS

Based on a dataset covering 110 prefecture-level cities in China's YREB from 2011 to 2021, this study analyzes the impact of DIC on SEG and cities' heterogeneous characteristics using the time-varying DID model as a quasi-natural experiment referencing the "Broadband China" pilot policy, with the following main conclusions. First, DIC significantly mitigated SEG over the sample period. This finding remains robust after model validity tests such as a parallel trend test, a placebo test, Goodman-Bacon decomposition and robustness tests such as robust DID, including of benchmark variables, PSM-DID, endogeneity treatment, and excluding the interference of related policies. Second, the effect of DIC on SEG is heterogeneous in terms of information search costs, digital divide, market concentration, city size, and geographic location. Specifically, mitigating effect of DIC on SEG is more pronounced for cities with high information search costs, a low digital divide, low market concentration, low population size, and in the middle and lower reaches of the YREB. Third, in terms of the mechanisms of action, DIC mainly alleviates SEG by increasing market potential and technological innovation.

6.2 POLICY IMPLICATIONS

Based on these findings, this paper draws the following policy implications. First, focusing on key areas of big data and the Internet of things, and in response to society's realistic demand for digitally skilled personnel, government leaders must actively foster digital talent in higher education institutions and enhance collaborative cultivation among colleges and universities, research institutes, and enterprises. Focusing on core areas such as mobile communications, cloud computing, and other crucial infrastructure has increased efforts in technological research, innovated new approaches to technological R&D, and steadily expanded the supply of digital products, allowing more market players to enjoy the dividends of DIC. Second, to foster a national unified data factor market, China should draw on the experience of developed countries led by the United States in establishing various large-scale and specialized data factor markets—such as the BDEX Data Exchange, Mashape Data Exchange Platform, and Gepredix Industrial Data Exchange Platform—by clarifying data ownership rights and accelerating the development of large-scale data factor markets. In terms of development approaches, it is essential to not only innovate data-sharing models by establishing a national unified distributed data factor sharing network but also formulate and refine data market transaction rules along with corresponding dispute resolution mechanisms, while further accelerating infrastructure development for the data factor market.

Policymakers must fully stimulate regional market potential and enhance regional technological innovation capacity. First, it is essential to deepen market-oriented system reform, fully leverage the decisive influence of the market on resource allocation efficiency, regulate the local economic order, and achieve rational production factor and resource allocation within the region. At the same time, market-oriented system reform could promote regional cooperation, weaken local protectionism, strengthen intercity economic ties, and enhance market potential. Second, digital network infrastructure construction is crucial for promoting the combination of internet development and technological innovation that relies on new capabilities such as big data analytics to attract more innovative talent and fundamental resources. Such efforts will advance the accumulation and agglomeration of human resources and establish a more supportive digital infrastructure environment for technological innovation.

Government leaders must promote DIC in accordance with local conditions, considering local economic development differences. Cities that are relatively underdeveloped and have a wide digital divide should focus on improving DIC coverage, the accessibility of physical digital channels, and the affordability of digital infrastructure to increase residents' access to information and knowledge. Preferential finance and industry taxation policies should be actively introduced in regions with low market concentration to encourage network service providers and related enterprises to invest in DIC and effectively leverage the positive effects of DIC in mitigating SEG. Regions with low information search costs, high market concentration, and more developed economies should leverage existing economic foundations and resource concentration advantages, focus on building and upgrading digital information platforms, improve urban development by upgrading urban intelligence, and further advance the in-depth integration of DIC and urban development.

Notably, this study also has certain limitations and shortcomings. First, due to data availability, the heterogeneity analysis does not regress the degree of SEG across industries, which would help to further clarify the formation mechanism of SEG and provide more specific policy recommendations. Second, the mechanism research in this study is primarily a macro level examination of market potential and urban technological innovation. Future research can examine DIC from the micro level to examine how regional SEG can be alleviated by shortening the information distance between markets in different regions and reducing the information asymmetry concerning product prices in different regions. Such analyses will deepen the theoretical and mechanistic explanations of the relationship between DIC and SEG.

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