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Original Paper

The Impact of Data Agglomeration on Export Structure Upgrading in Cities: A Factor Mobility Perspective

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Abstract

The digital economy and export upgrading are important topics of common concern for policymakers and academics during the period of high-quality economic development. From the perspective of factor mobility, this paper constructs the two-way fixed effect, mediation effect, and spatial Durbin models to analyze the impacts of data agglomeration on urban export structure upgrading. Using panel data of 280 cities at the prefecture level and above in China from 2005 to 2018, the empirical analysis reveals a positive impact of data agglomeration on urban export structure upgrading, with capital transfer and technology diffusion further reinforcing this impact. Additionally, data agglomeration promotes urban export structure upgrading by optimizing innovation resource allocation and exhibits a spatial spillover effect on urban export structure upgrading. Finally, the facilitating effect on urban export structure upgrading is heterogeneous. Consequently, it is imperative to expedite the construction of new digital infrastructure, foster the integration and symbiotic evolution of data and traditional production factors, and implement distinct innovation development pathways based on regional comparative advantages.

Keywords

Data agglomeration, Urban export structure upgrading, Factor mobility, Mediation effect model, Spatial Durbin model

1. Introduction

Since the reform and opening-up began, China has created a "miracle of economic growth" and "miracle of foreign trade", gradually becoming the world's largest exporter. In the early stage of reform, China heavily relied on processing trade exports due to the limited availability of advanced materials and technology. To promote this type of trade, the government issued a range of preferential policies aimed at stimulating import processing and processing trade, which attracted invested enterprises, so that processing trade now accounts for half of China's foreign trade (Cai & Han, 2022). However, the feature of "both heads outside" in processing trade has inherent limitations. On the one hand, it renders this trade vulnerable to fluctuations in the international market. On the other hand, the low productivity of the export sector and extensive growth mode prevent Chinese enterprises from climbing up the global value chain. As the cost advantage of production factors gradually diminishes and the uncertainty in the international market intensifies, the traditional factor-driven trade growth mode becomes unsustainable (Sun et al., 2022). Therefore, it is imperative to chart a foreign trade development path that strikes a balance between export scale and structure. Cities, serving as the primary entities for foreign trade activities, bear the significant responsibility of elevating export products to more advanced levels. The structure of urban exports is an important indicator of regional trade quality, and its upgrading is crucial for optimizing the country's overall foreign trade. Thus, the effective promotion of urban Export Structure Upgrading (ESU) has evolved into a pressing practical challenge requiring immediate attention.

Currently, the whole world is characterized by the advent of the digital economy era, wherein data assume a fundamental and strategic role in socioeconomic development, emerging as the primary driving force for economic progress (Xu et al., 2023). Notably, within China, local governments have demonstrated a steadfast commitment to augmenting their digital economy initiatives, with a dedicated focus on nurturing the data factors market and expediting the process of data factors valorization. According to the China Digital Economy White Paper (2023) released by the ICT, the scale of China's digital economy surged to 50.2 trillion yuan in 2022, accounting for 41.5% of the country's GDP. The rapid development of China's digital economy injects new vitality into the high-quality development of the economy and necessitates fresh requirements for the generation and application of high-quality data.

Regarding the impact of data, some of the literature notes that data can penetrate the various links of the industrial supply chain to popularize digital technology. This culminates in efficient enhancements through the reorganization and upgrading of various factors, resulting in a multiplier effect on total factor productivity (Wen et al., 2022; Wang, 2023), thus further promoting the transformation of traditional industries and fostering the interconnectivity of socioeconomic activities (Guan et al., 2022; Pang et al., 2023). Simultaneously, data can optimize the allocation of existing production resources, thereby engendering a paradigm shift in production methodologies and economic structures. Furthermore, data themselves serve as an abundant and invaluable production resource, alleviating the shortage of traditional production factors (Miao, 2021). The widespread utilization of data not only reduces production costs but also enables industries to cultivate fresh comparative advantages, thus driving the upgrading of industrial structure and continuously self-reinforcing along with the expansion of the scale of production and trade (Yang et al., 2021; Zhang & Jiang, 2021). It is widely acknowledged that the accumulation of data factors can promote enterprise production and socioeconomic development.

Concerning the impact of data on ESU, some of the literature argues that the digital economy and digital technology can not only promote the expansion of export volume but also boost the optimization of the export structure (Bojnec & Fertoő. 2009; Zhao et al., 2022; Chiappini & Gaglio, 2023). First, in terms of trade costs, communication technology, the internet, and other information infrastructure can reduce information asymmetry in international trade and decrease transportation and coordination expenses in the export process, thus promoting the growth of export trade (Niru, 2014; Lin, 2015). Second, concerning trade structure, the digital economy facilitates the transformation of urban ESU by augmenting human capital and fostering technological innovation (Zhang & Duan, 2023; Qian & She, 2023). It has also been argued in the literature that the impact of data on ESU is characterized by spatial heterogeneity (Ma et al., 2022; Zhou et al., 2022), and the positive spillover effect of the digital economy on export trade has become a new driver of the high-quality development of export trade in the new era (Yu et al., 2021). Hence, delving into the exploration of how Data Agglomeration (DA) influences ESU is a worthwhile endeavor.

In the process of digital economy development, the mobility of production factors, including labor, capital, technology, and knowledge, has significantly accelerated across society. Notably, data, as a new factor that can facilitate the free mobility of factors through the production network, capital network, and business information network, provides a unique opportunity for ESU. However, most of the existing studies fail to consider the impact of DA on ESU from the perspective of factor mobility. Consequently, this research explores the relationship between DA and ESU through the lens of factor mobility. We attempt to determine whether DA promotes ESU by harnessing panel data from 280 cities in China from 2005 to 2018 and exploring the effect of DA using various econometric models. Compared to the existing literature, the marginal innovations and contributions are mainly in the following aspects: First, based on the factor mobility perspective, this paper unveils the mechanisms of how DA affects ESU, considering different production factor mobilities. Second, in order to explore the mechanism of "data agglomeration→innovation resources optimization allocation→export structure upgrading", this paper uses the mediating model to explore the intrinsic mechanisms of DA promoting ESU caused by the innovative talents agglomeration, innovation fund investment, and the digital technology. Third, this paper applies the spatial spillover test by the spatial Durbin model to evaluate how DA affects ESU in neighboring cities. Last, considering the individual characteristics of different cities, this paper analyzes the heterogeneity of DA effects on ESU based on geographic location, resource intensity, and human capital. This study aims to provide insights for future policy formulation related to the development of China's digital economy and foreign trade.

2. Theoretical Analysis and Hypotheses

The urban ESU is influenced by production factors cost and total factor productivity (Yu, 2015). Historical evidence from successive technological revolutions demonstrates that new factors typically exhibit characteristics such as low costs, widespread accessibility, and increased mobility, which contribute to the reconfiguration of the social-economic organization mode and the transformation of the techno-economic paradigm (Perez, 2010). In the era of the digital economy, data emerges as a novel production factor, possessing three distinct techno-economic characteristics: low-cost replication, noncompetitiveness, and nonexclusivity. These features address the scarcity and irreplaceability of traditional production factors and break the spatial and geographic constraints of traditional factor agglomeration. In addition, data can also facilitate the development of export trade by promoting the free mobility of factors and improving the production process. On the one hand, data exhibit a substitution effect on traditional production factors. In emerging industries such as artificial intelligence, new energy, and new materials, the extensive application of automation and intelligent technology has led to the replacement of a significant amount of simple and procedural labor, prompting the labor factor to shift to consumer service industries with greater demand for labor, which enhances the efficiency of factor supply and demand matching in production and circulation. According to the theory of new economic geography, the free mobility of production factors across regions inevitably leads to agglomeration effects, resulting in economies of scale (Li & Peng, 2020). Under the effect of economies of scale, the production cost of enterprises is greatly reduced, and productivity is improved, thereby further driving the urban ESU.

On the other hand, with its high mobility and permeability, data are integrated with traditional production factors to form new productive forces. This integration prompts the digital transformation of traditional factors and realizes the digitization of the forms of factor existence, production, configuration, and application. The integration of data with labor to form digital labor can optimize the employment structure and reduce labor costs, thus enhancing labor productivity. Similarly, the integration of data with capital empowers the process of corporate financial innovation and investment decision-making and enables corporations to identify operational risks and optimize capital investment flows to maximize resource efficiency. Moreover, integrating data with technology can lead to product performance breakthroughs and business process innovations. The integration of the above factors promotes the agglomeration of high-value-added and high-tech industries, which helps cities form a comparative advantage in the production and export of high-complexity products and thus promotes the optimization of the export structure (Liu & Xie, 2018). We therefore propose the following hypothesis:

Hypothesis 1: DA promotes ESU, and the mobility of production factors like labor, capital, and technology further promotes ESU.

Innovation resources contain a variety of variables, such as human capital, capital, technology, and data, providing an objective representation of the market's multiple resources. The agglomeration of innovation resources serves as a crucial impetus for enhancing both production and economic efficiency, facilitating the transformation of industrial structure and promoting economic development (Fan et al., 2023). Although the data is not directly involved in the production of materials and products, the agglomeration and sharing of data can shorten the production and circulation processes of innovative production factors such as capital and talent, promote optimal resource allocation, and enhance the efficiency of matching innovative production factors (Peng & Tao, 2022).

First, DA can give rise to new industries, new business forms, and new modes of operation, creating more nonprocedural intellectual positions. This in turn increases the demand for highly skilled labor and optimizes the structure of human capital (Wu et al., 2023). In addition, digital technology has significantly reduced the costs of information transmission and sharing, expanding the channels for individuals to leverage their knowledge, skills, and experience. This contributes to raising the skill level of the labor force and promoting the endogenous accumulation of specialized human capital. Second, DA drives the agglomeration effect of innovation capital. This effect ensures a stable supply of capital for urban innovation activities and provides financial support for investment activities. Consequently, corporations are prompted to enhance their resilience against risks, accelerate industrial transformation, and facilitate ESU (Feng, 2023). Moreover, the network effect of digital technologies, such as big data, cloud computing, and artificial intelligence, fosters the sharing of innovation resources and overcomes the spatial and temporal limitations in resource allocation, thus promoting breakthroughs in core technology and open innovation within corporations. The application of digital technologies also facilitates technology spillover effects, leading to the output of innovation results, thereby driving technology-intensive industries, including new materials, information communication, and high-end equipment, which expands the market scope of export products and increases the uniqueness of export products. Finally, the application of data is conducive to information sharing between upstream and downstream enterprises in the industrial chain, the real-time transmission of information on the latest needs of end customers, and the enhanced efficiency of innovation resource allocation. At the same time, data application shortens the length of the enterprise supply chain, improves efficiency, and provides a new impetus and resources for innovation activities (Bhargava et al., 2013). The application of data thus promotes the allocation of innovation resources among industries, boosts industrial structure change and industrial digitalization development, and ultimately promotes ESU. Accordingly, we propose the following hypothesis:

Hypothesis 2: DA can promote ESU by optimizing innovation resource allocation.

With its low cost and easy replicability, data can be efficiently transmitted and replicated among different data carriers and platforms, which continuously weakens and blurs the boundaries of economic activities among various sectors. In addition, data can shorten spatial and temporal distance through efficient information transmission and enhance the closeness and depth of interregional economic activities (Zhang et al., 2022). The wide application of the data effectively improves the operational efficiency of the digitalized industrial sector while providing high-quality and convenient network technology and services (Choi et al., 2022). Simultaneously, the convergence of high-tech talent, high-tech enterprises, and R&D institutions enhances interregional economic and technological exchanges, further generating spatial spillover effects in neighboring regions (He & Jian, 2022; Lai et al., 2023). Consequently, products are propelled to climb up to the stage of intermediate products with higher technological content and added value. The enhancement of DA, while promoting ESU, strengthens the correlation with the exports of neighboring cities and then generates spillover effects on the ESU of neighboring cities. We therefore advance the following hypothesis:

Hypothesis 3: DA has spatial spillover effects on ESU in neighboring cities.

3. Empirical Research Design

3.1 Model Construction

To study the impact of DA on the ESU, we establish the following regression model:

$$ESU_{it} = \alpha_0 + \alpha_1 DA_{it} + \beta Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

among them, ESU represents the dependent variable, DA represents the independent variable. Z represents a set of control variables, μ_i and δ_t denote individual fixed effects and time fixed effects, respectively, and ε_{it} represents the stochastic perturbation term. In eq. (1), α_1 denotes the effect of the level of data agglomeration on the upgrading of the city's export structure when all other conditions are constant.

In addition, to explore the role played by factor mobility in the impact of DA on ESU, we introduce the interaction term between the level of DA and the mobility of production factors (labor migration, capital transfer, and technological diffusion) based on eq. (1) and construct the following equation:

$$ESU_{it} = \alpha_0 + \alpha_1 DA_{it} + \alpha_2 FM_{it} + \alpha_3 FM_{it} * DA_{it} + \beta Z_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

FM_{it} is represented by labor migration (LM_{it}) capital transfer (CT_{it}) and technology diffusion (TD_{it}) Coefficient α_3 indicates whether DA has an impact on ESU by affecting factor mobility. If $\alpha_3 > 0$, DA promotes ESU by enhancing the free mobility of factors.

3.2 Variable Measurement and Description

3.2.1 Dependent Variable

Because export technology complexity can objectively reflect the involvement of trade entities in the global value chain's division of labor during the process of international integration (Mao, 2019), this paper employs export technology complexity as a measure of ESU. Its specific measurement draws on the research of Hausmann (2003), which involves calculating a weighted average of technical indicators characterizing all exporting countries, with the weight assigned based on the ratio of a product's share of a country's total exports to the share the total exports of that product from all exporting countries. The complexity of exports at the product level in a given year ($Prody_h$) is quantified as follows:

$$Prody_h = \sum_{q=1}^{n} \frac{\frac{X_{q,h}}{X_q}}{\sum_{q=1}^{n} \frac{X_{q,h}}{X_q}} Y_q \tag{3}$$

In eq. (3), the subscripts q and h denote the exporting country and product, respectively, Xq_h

denotes the export amount of product h from country q, X_q presents the total export amount of product h from country q, and Y_q represents the per capita GNP of country q. Meanwhile, following the measurement method of Zhou et al. (2019), we aggregate data initially obtained at the product level at the city level, accounting for the product export amounts as weights. In eq. (4), Xf_h and X_f denote export value of product h of city f and the total export value of city f, respectively:

$$Es_f = \sum_{h=1}^{n} \frac{X_{f,h}}{X_f} prody_h \tag{4}$$

3.2.2 Key Independent Variable

The data is embodied in digitized information and knowledge, so the construction of regional digital infrastructure and the effectiveness of digital applications are important embodiments of DA. We drew on the research method of Yang and Gong (2022) and employed the following four-dimensional indicators to reflect the level of DA: digitalization infrastructure, digitalization equipment, digitalization application, and digitalization effectiveness. Correspondingly, we defined a series of subsidiary metrics, which include the ratio of information industry employees to the total urban employment, the mobile phone penetration rate, the mobile internet penetration rate, and the proportion of telecommunication business revenue to GDP. We adopted the entropy value method to objectively assign weights to the above secondary indicators and measure the level of DA.

3.2.3 Factor Mobility Variables

(1) Labor migration (LM_{it}). We refer to Zhang (2013) to measure urban labor migration by the difference between the total population change and the natural change in the urban population for each city:

$$LM_{it} = \frac{Totalp_{i,t} - Totalp_{i,t-1}}{Total_{i,t-1}} - e_{it} \tag{5}$$

where $Totalp_{i,t}$ and $Totalp_{i,t-1}$ represent the total urban population of city i in the t and $t-1$ periods, respectively. We choose the year-end resident population of the city to represent the total urban population; e_{it} represents the natural population growth rate of the city. A larger LM_{it} represents a higher level of cross-regional labor mobility.

(2) Capital transfer (CT_{it}). Regarding the measurement of the scale of capital flows, this paper draws on Li and Lu (2007) and uses the change in the national share of total social fixed investment in each city in that year as a measure of capital flows. The formula is as follows:

$$CT_{i,t} = \frac{I_{i,t}}{\sum_{i=1}^{280} I_{i,t}} - \frac{I_{i,t-1}}{\sum_{i=1}^{280} I_{i,t-1}} \tag{6}$$

where $I_{i,t}$ and $I_{i,t-1}$ represent the total social fixed capital investment of city i in the t and $t-1$ periods, respectively. A larger CT_{it} represents a higher level of capital flows across regions.

(3) Technology diffusion (TD_{it}). The technology diffusion examined in this paper is the interregional technology flow, and to a certain extent, the cross-regional flow of technology can be regarded as a kind of technological progress. Keller (2000) believed that the research and development of new patents depend on the existing patent base, which indirectly reflects the process of technology diffusion. Therefore, we adopted the growth rate of the number of patents granted in cities to indicate technology diffusion.

3.2.4 Control Variables

We consider the following control variables: (1) economic development ($\ln PGDP_{it}$) which is expressed using the natural logarithm of the city's per capita GDP; (2) industrial structure ($INDUS_{it}$) measured by the ratio of the city's secondary industry to GDP; (3) education (EDU_{it}) measured by the ratio of education professionals to total urban employment; (4) openness ($OPEN_{it}$) measured by the ratio of the city's total import and export trade to the city's GDP; and (5) marketization (MAR_{it}) expressed using a marketization index.

3.3 Data Sources

We use panel data from 280 prefecture-level cities and above in China from 2005 to 2018. Except for the measured data of ESU from the Foreign Trade Database and the city innovation index from the Industrial Development Research Center of Fudan University, all other data comes from the Statistical Yearbook of Chinese Cities, Statistical Yearbook of Prefectural Cities and Above, and the National Bureau of Statistics.

4. Empirical Analysis

4.1 Baseline Results

The impact of DA on ESU is estimated by the two-way fixed effect model based on eq. (1). Table 1 presents the results of baseline regression. In column 1, we control only for time and area fixed effects, and the results show that DA has a regression coefficient on ESU of 2.034, and it passes the significance test at the 1% level, demonstrating that DA has a significant positive impact on ESU. Columns 2 to 6 provide the regression results after gradually introducing control variables. When all control variables are included, the coefficient of DA on ESU is 1.222, which still exhibits a statistically significant positive influence. Notably, this change is smaller compared to the results in column 1, showing that DA can effectively promote ESU. One possible reason for this is that DA can reduce the input and transaction costs and improve the value conversion rate of the original factors in the enterprise operation system. At the same time, DA enables enterprises to realize product upgrading through technological innovation, thus contributing to the optimization of ESU.

For the control variables, it is clear that the coefficient of $\ln PGDP$ is significantly positive at the 1% level, which demonstrates that economic development is a key factor in ESU and that economic growth can be promoted through the implementation of a series of stabilizing measures to enhance ESU. In addition, the coefficient of $INDUS$ is significantly negative, which reveals that industrial structure measured by the proportion of secondary industry inhibits ESU to a certain extent. The coefficient of *EDU* is significantly positive, indicating that the increase in education level ensures that more highly qualified and skilled personnel are engaged in production and management work, thus fostering ESU. Moreover, the positive and significant coefficient of *OPEN* reflects that the higher the degree of openness is, the higher the level of ESU is. Furthermore, the coefficient of *MAR* is positive but nonsignificant. This can be explained by the fact that there are still issues like unbalanced development and imperfect price and competition mechanisms within the process of marketization, so marketization does not have a significant impact on urban ESU.

Table 1. Benchmark Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ESU	ESU	ESU	ESU	ESU	ESU
DA	2.034***	1.772***	1.304***	1.294***	1.222***	1.222***
	(5.82)	(5.20)	(4.03)	(3.97)	(3.70)	(3.68)
lnPGDP		0.164***	0.004**	0.004***	0.006**	0.066***
		(3.63)	(2.16)	(3.15)	(2.23)	(3.32)
INDUS			-0.017***	-0.017***	-0.016***	-0.016***
			(-9.94)	(-9.79)	(-9.67)	(-9.65)
EDU				0.002	0.002	0.254**
				(0.79)	(0.78)	(2.24)
OPEN					0.104*	0.178**
					(1.78)	(2.30)
MAR						0.050
						(0.05)
Constant	0.466***	2.027***	1.227***	1.203***	1.194***	1.194***
	(19.25)	(4.75)	(5.06)	(5.06)	(5.03)	(5.03)
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No. of obs	3,920	3,920	3,920	3,920	3,920	3,920
R-squared	0.943	0.945	0.952	0.952	0.952	0.952

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

To accurately assess the interaction among DA, production factor mobility, and ESU, this paper introduces labor migration, capital transfer, and technology diffusion variables. Table 2 shows the results of the regression based on eq. (2). First, in column 1, the coefficient of DA is positive and significant at the 1% level. However, the interaction term between DA and labor migration is found to be nonsignificant, suggesting that DA fails to contribute to ESU by promoting labor migration. The reason for this is that the siphoning effect and substitution effect brought by DA have a mutual game and offset the effect of labor migration. On the one hand, the greater level of DA in developed regions has spurred the emergence of new high-tech industries, leading to shifts in the industrial structure and adjustments in the demand for jobs, thereby attracting labor inflow and promoting labor migration. On the other hand, the automation of certain manual tasks through artificial intelligence and big data has resulted in structural unemployment, thus dampening the levels of labor migration. Additionally, in column 2, it is obvious that the coefficient of the interaction term between DA and capital transfer is significantly positive, demonstrating that capital transfer strengthens the impact of DA in promoting ESU. Moreover, based on column 3, it can be found that the coefficient of the interaction term of DA and technology diffusion is significantly positive, suggesting that the deep integration of data and technology factors brought by the digital economy introduces fresh impetus to engage in ESU. The above discussion substantiates the validity of hypothesis 1.

Table 2. Results of the Mechanism

Variables	(1)	(2)	(3)
	ESU	ESU	ESU
DA	1.233***	0.350	0.631**
	(3.73)	(0.87)	(2.26)
LM	0.000		
	(0.32)		
DA*LM	0.001		
	(-0.12)		
CT		-0.305***	
		(-3.72)	
DA*CT		1.177**	
		(2.17)	
TD			0.000***
			(4.21)
DA*TD			0.574**
			(2.05)
Constant	1.188***	1.089***	1.119***
	(4.96)	(4.58)	(4.84)
City FE	YES	YES	YES
Year FE	YES	YES	YES
Controls	YES	YES	YES

No. of obs	3,920	3,920	3,920
R-squared	0.952	0.954	0.955

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

4.2 Robustness Test

In order to further assess the reliability of the regression results, we carry out a robustness test involving alterations to key variables. First, the ratio of the city's general trade exports to the total exports of general trade and processing trade is used to remeasure ESU. Column 1 in Table 3 shows that the impact of DA on ESU remains significantly positive at the 5% level. This consistency with the previous benchmark regression results reinforces the robustness of our research conclusions. Second, the level of DA is remeasured using principal component analysis to address potential measurement errors. Column 2 reports the results of DA measured by this method, which show that the impact of DA in promoting ESU is still significant, thus fully demonstrating that the core conclusions are not affected by the potential observation bias of variables and confirming the robustness of our benchmark regression. Last, considering the special political and economic status of provincial capital cities and municipalities directly under the central government, we conduct a separate regression analysis that excludes these cities. The results in column 3 reveal that the regression coefficient of DA remains positive and significant at the 5% level, so the robustness of the empirical conclusions of this paper is verified.

Table 3. Results of the Robustness Test

Variables	(1)	(2)	(3)
	ESU	ESU	ESU
DA	0.309**	0.050***	0.362**
	(2.38)	(2.87)	(2.05)
Controls	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
No.of obs	3920	3920	3500
R-squared	0.963	0.953	0.956

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

5. Further Analysis

5.1 Mediation Effect Test

It is known from the previous analyses that DA significantly contributes to ESU. However, how DA affects ESU needs to be further explored. Therefore, we construct a mediation effect model to reveal the mechanism of action, and the specific model is as follows:

$$ESU_{it} = \alpha_0 + \alpha_1 DA_{it} + \rho Z_{it} + \mu_{1i} + \delta_{1t} + \varepsilon_{1it} \tag{7}$$

$$INNO_{it} = \delta_0 + \theta_1 DA_{it} + \eta Z_{it} + \mu_{2i} + \delta_{2t} + \varepsilon_{2it} \tag{8}$$

$$ESU_{it} = \zeta_0 + \zeta_1 DA_{it} + \xi INNO_{it} + \pi Z_{it} + \mu_{3i} + \delta_{3t} + \varepsilon_{3it} \tag{9}$$

In the above models, $INNO$ denotes the efficiency of innovation resource allocation, i.e., the mediating variable. The data utilized for this variable is the city innovation index measured by the Industrial Development Research Center of Fudan University (2017). The results of the mechanism analysis are presented in Table 4. In columns 1 and 2, it is apparent that optimizing the allocation of innovation resources is an effective mediating variable for DA in promoting ESU. This is manifested in the following ways. First, in column 1, the coefficient of the key independent variable (DA) in optimizing the allocation efficiency of innovation resources ($INNO$) is significantly positive, indicating that DA boosts the optimal allocation of urban innovation resources. In addition, the coefficient of the allocation efficiency of innovation resources in column 2 is also significantly positive. This demonstrates that the improvement of the allocation of innovation resources enables better integration with the data factors invested in the hi-tech sector, ultimately resulting in the production and export of higher-quality products. Additionally, the effect of DA on ESU in column 2 is still significantly positive, and the coefficient of 0.791 is smaller than the regression coefficient of 1.222 from the baseline column 2 in Table 1. This demonstrates that after variables of innovative resource allocation are accounted for, the driving effect of DA on ESU is slightly diminished. All of the above results collectively indicate that DA promotes ESU through the important intermediary mechanism of optimizing the allocation of innovation resources, thus substantiating hypothesis 2 established above.

Table 4. Results for Mediation Effect

Variables	(1)	(2)
	ESU	ESU
DA	0.449***	0.791***
	(0.002)	(0.284)
INNO		0.001***
		(0.000)
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES
No.of obs	3,920	3,920
R-squared	0.968	0.955

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

5.2 Spatial Spillover Test

The impact of DA on ESU may have spillover effects in addition to local effects. Therefore, the spatial econometric model is employed in this paper to test the spatial spillover effect of the impact of DA on ESU. Before testing whether there is a spatial effect, we conduct a spatial correlation test on ESU and DA. The spatial correlation is calculated using $Moran's\,I$ under a spatial-weights matrix based on geographic adjacency, and the results are reported in Table 5. The positive and significant $Moran's\,I$ at the 5% level refutes the H_0 (the data are randomly distributed), indicating that there is a positive spatial autocorrelation. To put it another way, there is a certain degree of spatial agglomeration between DA and ESU in space.

Table 5. Moran's I of ESU and DA (2005-2018)

Year	ESU			DA		
	Moran's I	Z	P value	Moran's I	Z	P value
2005	0.2862***	7.1914	0.000	0.1722***	4.9418	0.000
2006	0.2633***	6.6319	0.000	0.4298***	12.0180	0.000
2007	0.2485***	6.2642	0.000	0.4763***	12.8954	0.000
2008	0.2416***	6.0919	0.000	0.4098***	10.8943	0.000
2009	0.2417***	6.0901	0.000	0.3731***	9.8380	0.000
2010	0.2480***	6.2423	0.000	0.3982***	10.4610	0.000
2011	0.2526***	6.3500	0.000	0.4265***	11.2238	0.000
2012	0.2263***	5.6975	0.000	0.4496***	11.7933	0.000
2013	0.1946***	4.9104	0.000	0.4390***	11.4575	0.000
2014	0.1568***	3.9748	0.000	0.4476***	11.7037	0.000
2015	0.1738***	4.4047	0.000	0.4139***	10.8974	0.000
2016	0.1713***	4.3301	0.000	0.4018***	10.3473	0.000
2017	0.1601***	4.0564	0.000	0.3234***	8.1681	0.000
2018	0.1322***	3.3652	0.000	0.2738***	6.9250	0.000

The spatial Durbin model can analyze the spatial effects of the dependent variables based on the independent variables, address the problem of redundant or omitted variables, and reduce the parameter estimation bias of the independent variables and other errors. Therefore, we adopt the spatial panel Durbin model (SPDM) for this study. Table 6 reports four spatial weight matrices ($W1$ is the spatial adjacency matrix, $W2$ is the spatial geographic distance matrix, $W3$ is the spatial economic distance weight, and $W4$ is the economic-geographical nested matrix) of the SPDM estimation results, which shows that the spatial correlation coefficients of ESU are positive and significant under above spatial weight matrices. The effects of the DA on ESU are significantly positive at the 1% level, demonstrating that DA among cities has common regional externalities, which can effectively promote the dissemination, sharing, and allocation of information and technology. It is conducive to urban ESU and thus brings about a positive spatial spillover effect. Furthermore, the coefficients of the spatial lag term of ESU are significantly positive under all four weight matrices, indicating that the spatial effect of foreign trade upgrading exists objectively and that the improvement of neighboring ESU will drive local ESU. Moreover, the estimated parameters of the direct and indirect effects of DA on urban ESU are both significantly positive. This indicates that DA not only promotes local ESU but also promotes ESU in neighboring cities. In other words, there is a substantial spatial spillover effect of DA on the ESU of neighboring cities, thereby verifying Hypothesis 3.

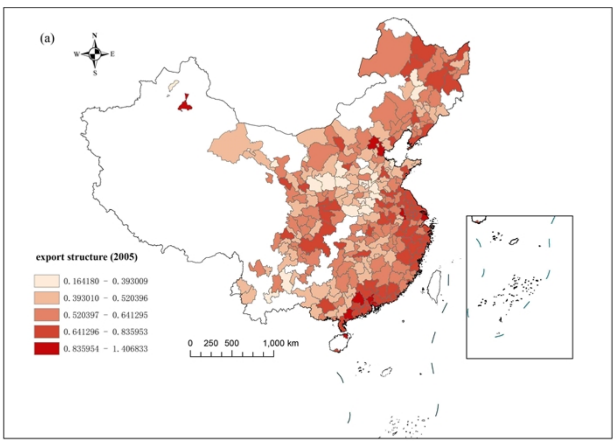
Table 6. Results of the SPDM

Variables	(1)	(2)	(3)	(4)
	W1	W2	W3	W4
DA	1.245***	1.262***	1.266***	1.251***
	(0.335)	(0.347)	(0.323)	(0.328)
W*DA	0.927*	3.102**	0.284**	0.423***
	(0.554)	(0.245)	(0.676)	(0.728)
rho	0.265**	0.765***	0.0420*	0.0546**
	(0.118)	(0.0524)	(0.0543)	(0.0557)
Controls	YES	YES	YES	YES
Direct effect	1.228***	1.243***	1.280***	1.261***
	(0.349)	(0.354)	(0.332)	(0.338)
Indirect effect	0.704**	0.949***	0.310***	0.349**
	(0.357)	(0.464)	(0.385)	(0.309)
Total effect	1.932***	2.192*	1.590***	1.610**
	(0.489)	(0.464)	(0.392)	(0.603)
No.of obs	3920	3920	3920	3920
R-squared	0.243	0.030	0.235	0.235

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3 Heterogeneous Effects Test

The analysis mentioned above shows that DA significantly contributes to ESU; nevertheless, this analysis based on the overall sample will overlook differences among cities. Cities in China may differ in terms of their economic scale, policy implementation, and openness, which may lead to heterogeneity in the effect of DA on ESU in different cities. Figure 1 clarifies the differences in the level of ESU among Chinese cities, where (a) and (b) show the level of ESU among Chinese cities in 2005 and 2018, respectively. In 2005, China's most economically developed coastal areas exhibited higher levels of ESU, and the Yangtze River Delta region and some provincial capitals displayed more optimized ESU than other inland cities. In 2018, the overarching trend persisted, with coastal cities maintaining more advanced ESU than inland cities. Nevertheless, the ESU of some inland cities, such as Zhengzhou, displayed a gradual improvement as a result of the geographic diffusion of economic and trade activities from coastal cities to inland cities, as well as the transfer of industries. Therefore, we divide the sample cities into coastal and border cities and inland cities based on geographic location. Meanwhile, we also consider the diversity in resource endowment and other individual characteristics across cities and their varying roles in the urban export upgrading impact of DA by grouping the sample according to resource endowment situation and the level of human capital. In general, resource-intensive cities may rely heavily on the extraction and processing of natural resources such as minerals, agriculture, and forests, which is not conducive to enhancing the technological content of export products and ESU. Therefore, the sample is dichotomously divided into resource-intensive and non-resource-intensive cities according to the National Sustainable Development Plan for Resource-based Cities issued by the State Council of China in 2013. In addition, we categorize the level of human capital into high and low human capital regions according to its level compared to the nationwide average, where the human capital indicator is measured by the share of education expenditure within total fiscal expenditure.



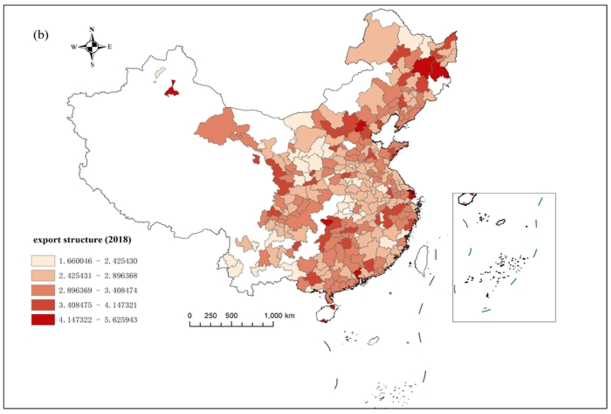


Figure 1a & 1b. ESU in Chinese Cities in 2005 (left) and 2018 (right)

Table 7 presents the heterogeneous effect of DA in distinct regions. First, based on columns 1 and 2, there is an obvious difference in the impact of DA on coastal and border cities and inland cities. The possible reasons for this fact are that: relative to the level of DA in coastal and border cities, inland cities originally exhibited a lower level of digitization, and the development of industrial digitization and digitized industries had not yet formed a scale. Consequently, this regional difference in the degree of DA widened the difference in the effect of ESU. Second, the coefficients of DA are significantly positive in both columns 3 and 4, indicating that DA realizes export upgrading in two types of cities. Contrary to expectation, the effect of non-resource-intensive cities is more obvious than that of resource-intensive cities. This situation stems from the fact that resource-intensive cities predominantly rely on primary resource processing, resulting in limited product diversity and low value-added products. Over time, this scenario has led to the risk of a "resource trap", which hampers the development of technology-intensive products and the enhancement of ESU. Therefore, the effect of DA on the ESU in resource-intensive cities is relatively less significant. Finally, the coefficients of DA on ESU in columns 5 and 6 are significantly positive, indicating that DA can achieve ESU in two types of cities. Admittedly, the positive contribution of DA in the high human capital group is higher than that in the low human capital group, which illustrates that the promotion effect of DA on ESU in the low human capital group is weaker. This can be explained by the fact that human capital as a carrier of technology can directly facilitate technological advancement and realize the evolution of technology levels from low to high, thus driving the upgrading of product structures and the growth of emerging industries. In addition, the collaborative interaction between human capital and the data factors engenders a synergistic effect, thereby empowering the improvement of production efficiency and technological innovation. Finally, we used Fisher's permutation for all subsample regression results to test for differences in coefficients between groups for grouped regressions, and the p-values were all less than 0.1, clearly rejecting the original hypothesis and indicating that the coefficients of the grouped regressions were significantly different between the two groups.

Table 7. Results of City Heterogeneity

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Landlocked Cities	Coastal or border cities	Non-resource intensive	Resource intensive	Low human capital	High human capital
DA	0.777**	1.258***	1.336***	0.666*	0.866**	1.665***
	(1.98)	(2.86)	(3.96)	(1.76)	(2.06)	(3.37)
Controls	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No.of obs	2,954	966	2,408	1,512	1,988	1,512
R-squared	0.957	0.945	0.959	0.949	0.942	0.949
Diff p-value	0.020		0.090		0.000	

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1; Diff p-value is the p-value to test whether the regression coefficients of DA in the regression results of the two sample groups are significantly different from each other.

6. Conclusions and Policy Implications

6.1 Conclusions

Against the background of the gradual weakening of traditional factor cost advantages and the incomplete formation of new competitive advantages, ESU has become an urgent need in the transformation and upgrading of China's foreign trade. Undoubtedly, ESU cannot be separated from the effective support of the digital economy and data factors, and the exploration of how data factors influence ESU has become a hot topic of significant interest in both political and academic circles. In this paper, we explain the impact of DA on ESU and its functioning mechanism at the theoretical level. Subsequently, we propose corresponding research hypotheses and then empirically verify them by adopting diverse econometric methods. Several conclusions emerge from the analysis. Above all, the increase in the level of DA significantly promotes ESU, with this impact being influenced by the mobility of production factors, particularly through the reinforcing mechanisms of capital transfer and technology diffusion. In addition, we discover that DA can promote ESU by optimizing the allocation of innovation resources. Furthermore, we find that DA has a spatial spillover effect on ESU. It not only enhances the ESU of the host city but also has a positive impact on the ESU of neighboring cities, fostering the overall coordinated development of the region. Ultimately, there is heterogeneity in the promotion effect of DA on ESU, which is more prominent in coastal and border cities, non-resource-intensive cities, and cities with high human capital.

6.2. Policy Implications

Chinese policymakers are considering ways to elevate the level of DA and promote ESU, so this study presents the following policy suggestions.

Firstly, from a national perspective, it is imperative to engage in comprehensive planning to expedite the aggregation of data factors and enhance overall digital competitiveness. On the one hand, we should accelerate the development of advanced digital infrastructure and establish forward-thinking digital platforms. This will provide fertile ground for the digital transformation of export enterprises. Meanwhile, the government should implement appropriate policies that are preferential toward export enterprises to alleviate the cost pressures they face during the data factors input phase. On the other hand, it is crucial to implement tailored measures according to the geographical location, resource endowment, and the level of economic and technological development of different cities. Secondly, it is essential to promote the integration of data and traditional production factors into production and stimulate the synergistic evolution of factors to jointly drive ESU. On the one hand, corporations should increase their utilization of data in production, thereby amplifying the productive capacity of traditional factors and optimizing the factors' configuration to enhance production efficiency. On the other hand, export enterprises should actively employ new, high-end production factors such as data, recognize the value-added effect of data factors on traditional production factors, and increase their understanding of the laws of evolution of production factors and technological innovation. Thirdly, each city should continuously optimize the allocation of innovation resources to enhance urban innovation capacity. It is critical to systematically eliminate regional institutional barriers and promote the free mobility of innovation resources among different innovation entities.

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