The Impact of “Smart City” Pilot Construction on China’s Export Product Quality

Abstract: Based on the quasi-natural experiment of “Smart City” pilot construction, this paper employs a difference-in-differences (DID) model to empirically analyze the impact of smart city policies on the quality of China’s export products. The findings reveal that smart city construction significantly enhances export product quality through mechanisms such as promoting technological innovation, improving informatization, and optimizing resource allocation. Furthermore, the heterogeneity analysis indicates that the policy effect of smart city construction is more pronounced in economically developed areas and cities with a higher degree of openness.

Keywords: Smart City, Export Product Quality, Difference-in-Differences, Technological Innovation

Introduction

The construction of smart cities has become a crucial topic in global urban governance and development. With the continuous advancement of Information and Communication Technology (ICT), the concept of smart cities has been adopted by an increasing number of countries and cities. This adoption aims to enhance urban resource management capabilities, optimize living environments, and promote comprehensive economic and social development (Liu Zhongnan, 2024).

The concept of a smart city was first introduced by IBM in 2008, emphasizing the improvement of urban operations through data analysis and information sharing (Xie Shenxiang, Gao Xinrui, 2023). Since then, scholars have extensively discussed the definitions and implications of smart cities. Some studies argue that smart cities rely on emerging technologies such as big data, artificial intelligence, and the Internet of Things to achieve efficient resource allocation and sustainable development (Zhang Minghui, 2023). Against this backdrop, data and technology have become indispensable elements in smart city construction, supporting the intelligent transformation of various sectors (Chen Baoqi et al., 2024).

Regarding the significance of smart city policies, research generally agrees that these policies can significantly improve urban management efficiency and the quality of life for residents (Zou Zhi, 2024). Moreover, smart city construction has facilitated the integration of the digital economy with the real economy, promoted the structural upgrading of the service industry, and improved the business environment of cities (Kong Jianzhong, 2024; Yu Yang et al., 2022). Urban innovation and information infrastructure play a critical mediating role in this process, further enhancing the effectiveness of these policies (Chen Baoqi et al., 2024).

In recent years, studies on the impact of smart city construction on export product quality have gradually increased. Some scholars believe that by applying intelligent technologies such as industrial robots and automated production lines, firms can improve production efficiency and product quality, thereby gaining a competitive edge in international markets (Zhou Jing et al., 2024). Additionally, human capital is considered a crucial mediating factor that can further enhance product quality through skill improvements in a smart city environment (Yang Lianna et al., 2024). Moreover, the optimization of supply chain technologies has been shown to indirectly influence export product quality by improving the quality of intermediate goods and reducing costs (Ma Yeqing et al., 2024).

Despite the extensive research on various impacts of smart city construction, some research gaps remain. For instance, the specific mechanisms through which smart city initiatives influence the export quality of small and medium-sized enterprises (SMEs) are underexplored. Additionally, the relationship between smart city construction and green, sustainable development requires further investigation. Future research could adopt interdisciplinary approaches, combining perspectives from environmental science and economics to examine the long-term impacts of smart city construction on export product quality.

II. Research Design

(i)Econometric Model Construction

To verify the relationship between smart city construction and the quality of China's export products, this study constructs a difference-in-differences (DID) model based on the preceding theoretical analysis. The regression model is formulated as follows:

$$Quality_{ict} = \alpha_0 + \theta Smart_i \times Post_{ct} + \alpha_1 X_{ict} + \gamma E_{ct} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In this model, $Quality_{ict}$ represents the quality of export products, where subscripts i, c , and t denote the sample firms, sample cities, and the time of policy implementation, respectively. X_{ict} and E_{ct} are control variables that vary with time and individual characteristics, and α_1 and γ are the coefficients for these control variables. *X* represents a set of firm-level variables influencing export activities, while *E* includes regional-level controls. μ_i and λ_t represent individual and time fixed effects, respectively. Since the model incorporates both individual and time fixed effects, dummy variables for the treatment group and policy period are unnecessary. ε_{it} denotes the error term.

(ii)Variable Selection

1.Dependent Variable: Export Product Quality (quality). This paper calculates export product quality using the method proposed by Khandelwal et al. (2013), based on demand inference. The key assumption is that product price, after controlling for other factors, significantly influences the quantity sold. Therefore, under constant conditions, products with higher market shares are considered of higher quality. The calculation process for firm *i* exporting product *k* to country m in year *t* is as follows:

$$q_{imkt} = p_{imkt}^{-\sigma} \gamma_{imkt}^{\sigma-1} \frac{E_{mt}}{P_{mt}} \quad (2)$$

Where *p*, *q*, *s*, γ, *E*, and *P* represent the price of the export product, the quantity exported, the elasticity of substitution, product quality, the level of consumer spending, and the price index, respectively. Taking natural logarithms on both sides of Equation (2) and reorganizing provides the econometric regression equation:

$$\ln q_{imkt} = X_{mt} - \sigma \ln p_{imkt} + \varepsilon_{imkt} \quad (3)$$

Where $X_{mt} = \ln E_{mt} - \ln P_{mt}$ is a "time-export country" dummy variable that changes over time and export destination, encapsulating random disturbances that include product quality information. The average export price of a product to other countries (excluding country *m*) serves as an instrumental variable for the price of exports to country *m*. After accounting for price and product type factors, the regression on Equation (3) results in a quantified expression for product quality:

$$quality_{imt} = \ln \hat{\gamma}_{imt} = \frac{\hat{\varepsilon}_{imt}}{\sigma - 1} = \frac{\ln q_{imt} - \ln \hat{q}_{imt}}{\sigma - 1} \quad (4)$$

Following the approaches of Shi Bingzhan (2014), Manova and Yu (2017), and Wei Hao and Zhang Yupeng (2020), this paper normalizes the measured export product quality to serve as a comparable indicator across different product types, standardizing Equation (3):

$$r\_quality_{imkt} = \frac{quality_{imt} - \min quality_{imt}}{\max quality_{imt} - \min quality_{imt}} \quad (5)$$

Where $\max quality_{imt}$ and $\min quality_{imt}$ represent the maximum and minimum values of export product quality calculated at the firm level for all export destinations under the same HS8 code in a given year. The standardized quality values, ranging from 0 to 1, eliminate scale effects, enabling aggregation and comparison at various dimensional levels of the same HS code.

Finally, the paper calculates a weighted average of the export product quality indicators at the firm level based on export amounts, yielding an overall export product quality ($Quality\_Firm$) for:

$$RQuality\_Firm_{it} = Mean_{\Omega}\left[\frac{Value_{imkt}}{\sum_{\Omega} Value_{imkt}} \times R\_Quality_{imkt}\right] \quad (6)$$

In Equation (6), $\frac{Value_{imkt}}{\sum_{\Omega} Value_{imkt}}$ represents the weight, $R\_Quality_{imkt}$ denotes the standardized quality of product k exported by firm i to country m in year t, $Quality\_Firm_{it}$ representing the overall quality of products exported by firm i to all countries (regions) in year t. The variable $Value_{imkt}$ denotes the set of firm-year samples. The variable Value refers to the export amount of product k by firm i to country m in year t. Using the steps outlined, the paper ultimately determines the quality of products exported by firm i in year t.

After obtaining product-level export quality, we aggregate it at the city level using Equation (1), weighted by the export value of the goods as a proportion of the total export value of the city:

$$Exquality_{ct} = \sum \left(\frac{Value_{ctij}}{\sum Value_{ct}}\right) * R\_quality_{tij} \quad (7)$$

Where $Value_{ctij}$ is the export value of product i from city c to country j in year t, $\sum Value_{ct}$ is the total export value of all goods from city c in year t, and $R\_Quality_{tij}$ is the product-level export quality previously measured. $Exquality_{ct}$ is the calculated export quality level of city c in year t.

2. Independent Variable: The core independent variable in this study is the dummy variable for the establishment of smart city policies (did). This research focuses on the pilot cities designated in 2012, 2013, and 2014, defining these three batches of pilot cities as the experimental group and the non-pilot cities as the control group. The variable did is used as the independent variable, which is constructed as the interaction term of the policy pilot time variable (time) and the policy implementation variable (treat). During the policy implementation period from 2012 to 2014, the time variable is set to 1, while for the non-implementation periods from 2010 to 2011 and 2015 to 2021, it is set to 0. The treat variable is considered a fictional variable for the policy trial area; it takes a value of 1 if the city is within the three batches of pilot cities and 0 otherwise.

3. Control Variables: To minimize research bias caused by omitted variables, the following control variables are selected:Economic Development Level (eco): Represented by the per capita GDP of the region.Financial Development Level (fin): Measured as the ratio of the total balance of deposits and loans of financial institutions in the region to the Gross Regional Product (GRP).Foreign Direct Investment Level (fdi): Represented by the logarithm of the actual use of foreign capital in the city during the year, serving as a proxy variable.Degree of Openness (open): Measured by the ratio of the total value of imports and exports to the regional GDP.Urbanization Level (urban): Calculated as the ratio of the urban population to the total population, representing the level of urbanization.Industrial Structure (ia): Measured by the proportion of employees in the tertiary industry to the total population, reflecting the city’s industrial structure.Education Level (edu): Represented by the number of higher education students per 100,000 people in the region.Infrastructure Construction (infra): Measured by the per capita urban road area of the city.

(iii) Data Sources Explanation

The data used in this study primarily comes from the “China City Statistical Yearbook,” “China Customs Import and Export Database,” and the China Research Data Service Platform. Since calculating the quality of city export products requires HS6 code product information from micro-enterprise exports in the China Customs Import and Export Database, there is significant missing data for years after 2016, and the available export product information for earlier years is also relatively incomplete (Yang Hangying, Qiang Yongchang, 2024). Therefore, this study adopts the methods of Chen Shiyi and Chen Dengke (2018) and Chao Xiaojing et al. (2020). Specifically, the quality of export products in each city for years post-2016 is estimated by multiplying the proportion of the added value of the tertiary industry to GDP by the provincial-level export product quality.

The data used in this research spans the period from 2010 to 2021. Cities that underwent administrative boundary adjustments at the prefecture level during this period were excluded, while those with sub-prefecture level boundary changes were retained. Cities with severe data deficiencies were also removed. Ultimately, the study constructs a balanced panel data set of 220 cities at or above the prefecture level from 2010 to 2021, including 92 smart cities and 128 non-smart cities. Smart cities are treated as the experimental group, while non-smart cities serve as the control group for analysis.

III. Analysis of empirical results

(i) Baseline regression analysis

Table 1 Analysis of baseline regression results

	(1)	(2)
	quality	quality
did	0.036***	0.009***
	(7.041)	(2.842)
eco		-0.012**
		(-2.180)
fin		-0.004**
		(-2.068)
fdi		0.455***
		(5.562)
open		-0.008
		(-0.816)
urban		-0.018
		(-0.978)
ia		0.670***
		(30.424)
edu		0.478***
		(4.106)
infra		-0.000
		(-0.536)
market		-0.000
		(-0.100)
_cons	0.258***	0.121*
	(95.399)	(1.912)
Year FE	Yes	Yes
City FE	Yes	Yes
N	3267	3267
R^2	0.015	0.926

Note: ***, *** and ** denote significance at the 1%, 5% and 10% significance levels, respectively, with standard deviations in parentheses.

In model (1), the core independent variable did has a significant positive impact on export product quality, with a coefficient of 0.036, passing the 1% significance level test. This indicates that the implementation of the smart city pilot policy can significantly enhance the quality of China's export products. In model (2), after controlling for more explanatory variables, the coefficient of did decreases to 0.009 but remains significant, demonstrating that the impact of the smart city pilot policy on improving the quality of export products remains robust.

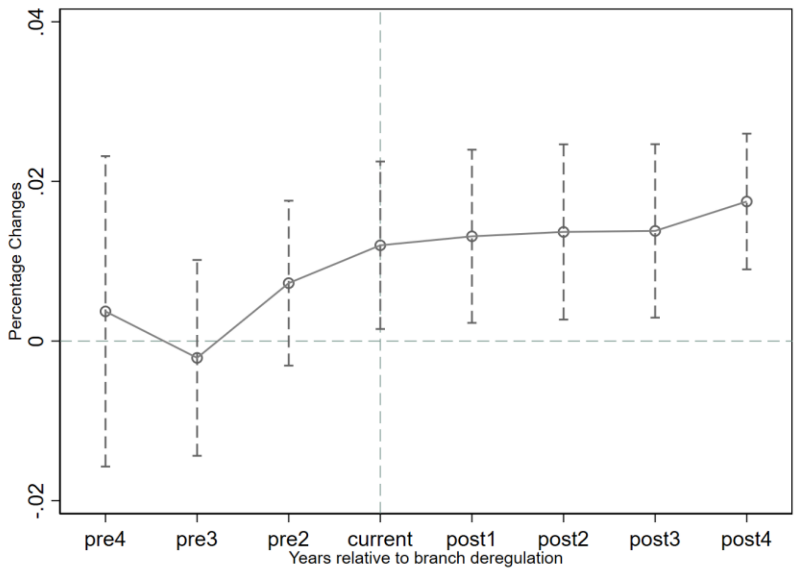
Additionally, in model (2), the economic development level (eco) and financial development level (fin) have a negative effect on product quality, with coefficients of -0.012 and -0.004, respectively, both significant at the 5% level. This suggests that economic and financial development may pose certain challenges to export product quality. In contrast, industrial structure (ia) and education level (edu) both have a significant positive impact on product quality, with coefficients of 0.670 and 0.478, respectively, and both passing the 1% significance level test. This highlights that technological advancement and human capital accumulation play a crucial role in enhancing the quality of China's export products.

However, the coefficients for openness level (open), urbanization level (urban), infrastructure level (infra), and market environment (market) are not significant, indicating that these factors do not have a notable impact on the quality of China's export products. Regarding the R^2 value, the goodness of fit of model (2) has significantly improved, reaching 0.926, suggesting that the model explains most of the variation in the dependent variable, making the results relatively robust.

(ii) Effective estimation tests

1 Parallel trend test

Figure 1 Parallel trend test results

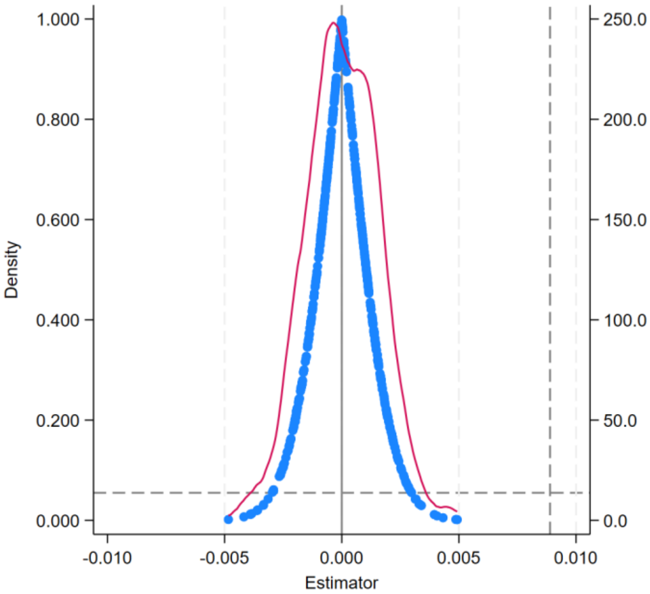


The results of the parallel trend test are shown in Table 1. As indicated in Table 1, prior to policy implementation, the intervals corresponding to the policy shock times pre4, pre3, and pre2 all contain zero. This suggests that there is no significant difference in the export product quality (Quality) data between the experimental group and the control group cities, thus passing the parallel trend test. Furthermore, after policy implementation, corresponding to the policy shock times post1 to post4 in the figure, the test coefficients show an upward trend. Starting from the first year after the policy shock, the intervals mostly do not cross zero, indicating that the difference between the experimental and control groups began to widen from 2012 onwards. Although there was a brief narrowing of the difference one to two years after policy implementation, the overall trend shows that the gap between the experimental and control groups continues to widen. This generally aligns with the basic assumption of parallel trends: before the policy, the experimental and control groups had similar trends, while after the policy, a significant difference emerged.

In summary, this study successfully satisfies the parallel difference-in-differences assumption, thereby enhancing the reliability of the research findings and the accuracy of causal inference. Therefore, the experimental data in this section meet the parallel trend hypothesis, confirming the validity of the method and the robustness of the experimental results.

2 Placebo test

Figure 2 Placebo test results



Potential omitted variables may impact the baseline regression results. To minimize experimental error, this study adopts a placebo test, following the approach used by Li Qingyuan et al. (2021), by replacing the experimental group cities. The data used in this study are sourced from 220 prefecture-level cities in China, 92 of which are pilot cities. In the placebo test, 92 cities are randomly selected from the 220 to serve as a fictitious experimental group, while the remaining cities form a fictitious control group. This random selection process is repeated 500 times to complete the placebo test, with the distribution of estimated coefficients and t-values presented in Figure 2.

Figure 2 shows the distribution of coefficient estimates from the 500 experiments, which roughly follows a normal distribution, with most regression coefficients centered around zero. The dashed line, representing the actual estimated value of the core independent variable did, appears at the high tail of the distribution. This indicates that the likelihood of observing the actual effect of the smart city pilot policy by random chance is relatively low, suggesting that the policy's positive impact on export product quality is not significantly affected by omitted variables.

Hence, when the policy timing or sample composition changes, the corresponding fictitious policy effects are not significant and differ considerably from the actual effects, further validating the robustness of the experimental results.

(iii) Robustness test analysis

Table 2 Robustness test results

	PSM-DID (1)	PSM-DID (2)	GMM (1)	GMM (2)	IV (1)	IV (2)
	quality	quality	quality	quality	did	
iv					0.042***	
					(3.820)	
L.quality			0.432***	0.592***		
			(25.869)	(24.945)		
did	0.037***	0.010***	0.010***	0.009***		0.248***
	(6.962)	(3.192)	(3.859)	(3.296)		(3.613)
eco		-0.011*	-0.003	-0.008**	0.150***	-0.043***
		(-1.863)	(-0.960)	(-2.481)	(6.217)	(-3.547)
fin		-0.003	0.001	-0.002*	0.027**	-0.005
		(-1.497)	(0.852)	(-1.706)	(2.488)	(-1.202)
fdi		0.466***	-0.005	-0.005	0.764	0.287**
		(5.510)	(-0.105)	(-0.105)	(1.519)	(2.259)
open		-0.003	-0.009**	-0.003	-0.122***	0.029**
		(-0.290)	(-2.139)	(-0.677)	(-3.563)	(2.179)
urban		-0.027	-0.003	0.000	-0.020	0.026
		(-1.436)	(-0.334)	(0.018)	(-0.223)	(1.118)
ia		0.665***	0.406***	0.330***	-0.215*	0.751***
		(29.205)	(24.366)	(17.880)	(-1.714)	(20.549)
edu		0.465***	0.082*	0.084*	-0.227	0.011
		(3.873)	(1.957)	(1.894)	(-0.514)	(0.096)
infra		-0.000	-0.000	-0.000	0.001***	-0.000***
		(-0.654)	(-1.136)	(-0.486)	(3.157)	(-3.212)
market		-0.000	-0.003***	-0.002***	0.019**	-0.008***
		(-0.275)	(-4.825)	(-2.782)	(2.172)	(-3.054)
_cons	0.258***	0.109*	0.071**	0.044	-1.563***	0.539***
	(89.002)	(1.662)	(2.362)	(1.409)	(-6.840)	(4.493)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	No	No
R^2	0.016	0.932			0.136	0.327
N	2937	2928	2981	2705	3267	3267
AR(1)				17.970***		
AR(2)				-0.340		

To verify the robustness of the impact of the “Smart City” pilot policy on the quality of China’s export products, this study employs three different methods: Propensity Score Matching Difference-in-Differences (PSM-DID), Generalized Method of Moments (GMM), and Instrumental Variable (IV) approach. This multi-angle analysis aims to further enhance the reliability and explanatory power of the research findings.

1. Propensity Score Matching Difference-in-Differences (PSM-DID)

To mitigate the impact of sample selection bias on the research results, this study first applies the PSM-DID method. The regression results are shown in columns (1) and (2) of Table 2. By using propensity score matching, the policy implementation group and the non-implementation group are matched based on their characteristics before the policy was introduced, ensuring the comparability of the two sample groups. The Difference-in-Differences method is then used to estimate the causal effect. The regression results indicate that the Smart City pilot policy continues to have a significantly positive impact on export product quality in the matched sample, demonstrating the robustness of the positive effect of the Smart City policy.

2. Generalized Method of Moments (GMM)

Given the potential dynamic inertia in export product quality, this study further employs the GMM method for robustness testing. As shown in columns (3) and (4) of Table 2, GMM is suitable for dynamic panel data models that include lagged dependent variables, helping to control for the lag effect of the dependent variable and addressing potential endogeneity issues. The results reveal that the lagged dependent variable, L.quality , is significant, confirming the dynamic nature of export product quality. Additionally, the Smart City pilot policy remains significantly positive in the GMM model, indicating a positive impact on export product quality. Moreover, the AR(1) and AR(2) test results suggest no second-order serial correlation, consistent with the assumptions of the GMM model.

3. Instrumental Variable Method (IV)

To further address potential endogeneity issues, this study introduces the Instrumental Variable approach. As shown in columns (5) and (6) of Table 2, the selection of instrumental variables is based on the principle that they must be highly correlated with the “Smart City” pilot policy but uncorrelated with the error term. The study uses terrain ruggedness as an instrumental variable (Xie Shenxiang, Gao Xinrui, 2023). Terrain ruggedness is highly related to the cost of urban infrastructure construction and the selection of Smart City policies but does not directly affect export product quality, thus meeting the exogeneity requirement of the instrumental variable. The IV model estimation results indicate that the instrumental variable is effective, and the coefficient of the did variable remains significantly positive after controlling for endogeneity, achieving a 1% significance level. This further confirms the causal effect of the Smart City policy on export product quality and strengthens the robustness of the research conclusions.

These three robustness testing methods validate the reliability and causal interpretability of the research findings from different perspectives. PSM-DID reduces sample selection bias, GMM controls for dynamic inertia and endogeneity, and the IV approach addresses endogeneity issues. All methods indicate that the “Smart City” pilot policy significantly enhances the quality of China’s export products, supporting the robustness and credibility of the research conclusions.

(iv) Heterogeneity analysis

Table 3 Results of heterogeneity analysis

	(1) High level of economic development	(2) Low level of economic development	(3) High level of external development	(4) Low level of external development
	quality	quality	quality	quality
did	0.012**	0.005	0.013***	0.006
	(2.385)	(1.086)	(2.850)	(1.389)
Control variable	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	1633	1634	1624	1616
R^2	0.951	0.910	0.938	0.929

To further explore the differential impact of smart city policies on export product quality, this study conducts heterogeneity tests based on economic development levels and degrees of openness. The analysis results are shown in Table 3.

1. Heterogeneity Test Based on Economic Development Level

the sample is divided into high and low economic development level groups, and regression analysis is conducted to evaluate the policy effects. The results indicate that in cities with high economic development levels, the coefficient of the policy variable did is significantly positive at the 1% significance level, suggesting that smart city policies significantly enhance export product quality in these areas. However, in cities with lower economic development levels, the did coefficient is not significant, indicating that the policy effect is not evident in less developed regions. This phenomenon may be attributed to the fact that cities with higher economic development levels have better infrastructure and conditions for technological innovation, allowing them to leverage the benefits of smart city construction more effectively. In contrast, cities with lower economic development levels face challenges such as inadequate infrastructure and limited technological resources, which hinder the ability of smart city initiatives to improve export product quality (Model 2). In some cases, these cities may even experience resource constraints that further weaken the policy's impact.

2. Heterogeneity Test Based on Degree of Openness

The impact of smart city construction on export product quality also varies significantly across cities with different degrees of openness. The empirical results presented in Table 3 show that in cities with a high degree of openness, smart city construction significantly enhances export product quality (Model 3). This effect may be due to these cities' greater access to advanced international technologies, management practices, and market resources, facilitating the continuous improvement of export product quality. Conversely, in cities with a lower degree of openness, smart city construction does not significantly improve export product quality (Model 4), possibly due to limited access to international market resources and fewer channels for technology transfer. In some instances, these cities may even experience adverse effects due to intensified competition.

In summary, smart city policies have a significant positive impact in cities with high economic development levels and greater openness, whereas the effects are limited in regions with fewer resources and less external market exposure. This indicates that there are notable regional differences in the effectiveness of smart city policies in promoting export product quality. Future policy formulation should consider the economic and openness characteristics of different cities to achieve more targeted and effective interventions, maximizing the overall benefits.

IV. Conclusion and Implications

This study empirically examines the impact of smart city policies on the quality of China's export products and analyzes this impact from the perspectives of economic development level and degree of openness. The results show that smart city construction significantly enhances the quality of China's export products, and this effect is more pronounced in economically developed and highly open cities.

Smart city policies have played a positive role in improving the quality of China's export products, especially by optimizing digital infrastructure and enhancing urban management efficiency, thereby driving overall product quality improvement. The analysis also reveals that regional differences in economic development level and degree of openness significantly influence the effectiveness of these policies. Cities with higher economic development and greater openness can more effectively leverage the resource and technological advantages brought by smart city initiatives, leading to the continuous optimization of export product quality.

1. Strengthen Smart City Construction: The government should further expand the coverage of smart city policies, particularly in regions with relatively underdeveloped infrastructure and technological conditions. Increased investment and optimized policy support are needed to achieve more balanced regional development. Additionally, integrating

smart city construction with industrial upgrading should be promoted, making full use of emerging technologies and intelligent methods to enhance urban competitiveness comprehensively.

2. Optimize Regional Development Strategies: Given the variation in policy effects across cities with different levels of economic development and openness, the government should implement regionally coordinated development strategies. In less economically developed and less open cities, investment in infrastructure should be increased, particularly in transportation, logistics, and digitalization, to establish the foundational conditions necessary for improving export product quality.

3. Enhance International Cooperation and Resource Allocation: The government should deepen the strategy of opening up to the outside world, strengthen cooperation with countries along the Belt and Road Initiative and international markets, and optimize resource allocation to promote trade facilitation. This would help cities and enterprises gain more opportunities in the global market and further improve product quality. Additionally, learning from international best practices could enhance the application of smart city policies in boosting export product quality.

In conclusion, the “Smart City” pilot initiatives have a significant positive impact on the quality of China’s export products, although the policy effects vary with regional economic and openness levels. Future policy-making should account for these differences to achieve more targeted and effective interventions, providing robust support for the continuous improvement of China’s export product quality.

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