

TECHNOLOGICAL PROGRESS AND URBAN SPATIAL RESTRUCTURING IN GUANGDONG PROVINCE

YUHAO CHENG¹, KANGPEI ZHONG^{1,2} AND ZHENG NAN^{3,4,*}

¹School of Business

Guangzhou College of Technology and Business

No. 28, Nanhuan Road, Shiling, Huadu District, Guangzhou 510850, P. R. China
{ chengyuhao; zhongkangpei }@gzgs.edu.cn

²Faculty of Creative Tourism and Intelligent Technologies

Macao University of Tourism

Colina de Mong-Há, Macau 999078, P. R. China
b242356@utm.edu.mo

³Faculty of Global Studies

Musashino University

3-3-3 Ariake, Koto-ku, Tokyo 135-8181, Japan

⁴Social Science Research Institute

International Christian University

3-10-2 Osawa, Mitaka, Tokyo 181-8585, Japan

*Corresponding author: p002765a@icu.ac.jp

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ABSTRACT. *Rapid urbanization in China has led to extensive urban sprawl, while technological progress is reshaping regional development patterns. This study investigates how technological advancement influences urban land expansion using panel data from 21 prefecture-level cities in Guangdong Province (2015-2025). Employing a Spatial Durbin Model (SDM) with time-fixed effects, we find that (i) technological progress significantly curbs local urban expansion – a one-unit increase in the technological change index reduces the built-up area growth rate by approximately 32 percentage points; (ii) there exists a positive spatial spillover effect – technological improvement in one city accelerates expansion in neighboring cities, with a spillover coefficient of 1.64; (iii) industrial structure plays a moderating role: a larger tertiary sector strengthens the local restraining effect, while a larger secondary sector in adjacent areas amplifies the spillover effect. These findings provide empirical support for policies that promote technology-driven intensive land use and coordinated regional development.*

Keywords: Technological progress, Urban expansion, Spatial spillover, Industrial structure, Guangdong Province

1. Introduction. Guangdong Province stands as a microcosm of China's uneven development, exhibiting a typical "core-periphery" spatial structure [1]. While Shenzhen and Guangzhou rank among the world's most innovative cities, cities in northern Guangdong such as Heyuan and Yunfu remain trapped in traditional industrial structures, with urbanization rates 20 percentage points below the provincial average [2]. This stark internal heterogeneity creates a unique natural experiment for studying how technological progress reshapes urban spatial patterns. Over the past decade, the rapid diffusion of digital technologies has not only transformed production processes but also fundamentally altered

the geography of economic activity [3,4]. In core cities, technological innovation has enabled vertical intensification of land use, slowing outward expansion [5]. In peripheral cities, however, technological spillovers from the core have triggered industrial transfers, driving unprecedented urban growth [6]. This dual dynamic – “core compression and peripheral expansion” – poses both challenges and opportunities for Guangdong’s pursuit of high-quality urbanization.

The traditional model of urban expansion, which relies heavily on extensive factor inputs, has led to a series of problems in China, including disorderly urban sprawl, low efficiency in land use, and ecological degradation [7]. As China enters the digital economy era, technological progress has emerged as a key force reshaping urban development [8]. On the one hand, advances in artificial intelligence, big data, and smart city management have greatly improved the efficiency of urban land use, allowing cities to generate more economic output in less physical space [9]. Moreover, improvements in transportation and communication technologies have reduced the cost of intercity interactions, facilitating the transfer of industries from core to peripheral cities and driving urban expansion in these regions [10-12].

Existing literature on the driving forces of urban spatial expansion has accumulated extensive results, but most studies focus on traditional factors such as population agglomeration, economic growth, and local government land finance [13-15]. While recent studies have begun to examine the impact of technology on expansion [5,16], they suffer from two key limitations. First, research remains heavily skewed toward core hubs like the Yangtze River Delta [16], overlooking the internal dynamics of technological diffusion between core and peripheral cities within a single province. Second, existing empirical evidence often relies on datasets that precede the full-scale integration of the digital economy (post-2015), thereby failing to account for the specific spatial restructuring effects triggered by big data and digital services.

This study addresses these gaps by examining 21 prefecture-level cities in Guangdong Province from 2015 to 2025. We make three main contributions to the literature. First, we provide the first comprehensive analysis of technological progress and urban expansion at the provincial level in Guangdong, revealing the spatial dynamics between the PRD core and non-PRD peripheries. Second, we focus specifically on the digital economy era, documenting how digital technologies reshape urban spatial patterns through new mechanisms. Third, we identify the linear moderating effects of industrial structure, showing that tertiary industry development strengthens local land use intensification while secondary industry development enhances cross-regional spillover effects.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops research hypotheses. Section 3 describes the data and methodology. Section 4 presents the empirical results and discussion. Section 5 concludes with policy implications.

2. Literature Review and Research Hypotheses.

2.1. Digital technological progress and land use intensity. The relationship between technological progress and urban expansion has been a subject of long-standing debate in urban economics. Early monocentric city models suggested that advances in transportation and communication technologies reduce time-space friction costs, leading to urban sprawl [17-19]. However, recent studies have shown that in the digital economy era, technological progress increasingly exerts an inhibitory effect on urban expansion through three distinct mechanisms [20,21].

First, the factor substitution effect: Digital technologies enable enterprises to replace land-intensive production processes with knowledge-intensive ones. According to the law

of diminishing marginal returns, as the technological level improves, the marginal productivity of capital and labor per unit land area increases significantly [22,23]. Consequently, enterprises and residents are incentivized to increase technological investment as a substitute for increasingly expensive land factors, facilitating vertical intensification – often described as “seeking space upward” [24].

Second, the industrial structure optimization effect: Technological progress facilitates a transition from land-intensive traditional manufacturing toward high-value, low-land-dependent digital services [25,26]. This transition decouples urban economic growth from the horizontal extension of physical territory. Empirical studies observe an inverse relationship between industrial upgrading and land demand elasticity; specifically, a 10-percentage-point rise in the tertiary industry’s share corresponds to a 0.11-0.14 reduction in industrial land supply elasticity [27,28]. Furthermore, recent analysis suggests that a similar increase in the digital services sector leads to a 0.15 decline in this elasticity, reinforcing the role of the digital economy in curbing spatial expansion [15].

Third, the smart governance effect: The integration of big data, remote-sensing technology, and smart-city management platforms empowers local governments to scientifically delineate urban growth boundaries and optimize land-use allocation [9,29]. By leveraging real-time monitoring and predictive analytics, authorities can mitigate irrational spatial sprawl and prioritize the secondary development of existing ‘stock land’ rather than relying on ‘incremental land’ expansion.

Based on the integrated logic of factor substitution, industrial upgrading, and enhanced governance, we propose the following hypothesis:

H1: Technological progress exerts a significant inhibitory effect on the expansion of the local urban spatial scale.

2.2. Spatial spillover effect. According to New Economic Geography, urban centers do not operate in isolation but function as interconnected nodes within a regional system [30]. Technological progress inherently possesses spatial spillover attributes, as tacit knowledge and specialized information transcend administrative boundaries through personnel mobility and R&D collaborations [31]. Within a provincial urban system, these spillovers from core innovation hubs can significantly reshape the development trajectories of peripheral cities.

Technological progress in core cities escalates local land rents and environmental compliance thresholds, creating a ‘push effect’ that compels land-intensive industries to relocate to peripheral regions [32,33]. As peripheral cities absorb these industrial transfers, the requisite construction of specialized industrial parks, expanded logistical networks, and residential infrastructure catalyzes significant urban spatial expansion. This process is highly visible in Guangdong Province, where the PRD core has undergone a strategic decoupling from low-end manufacturing, transferring these sectors to eastern, western, and northern Guangdong since 2015.

Consequently, we propose H2: Technological progress exerts a significant positive spatial spillover effect on the spatial expansion of neighboring cities.

2.3. Industrial structure as a moderator. The effect of technological progress on urban spatial expansion is not uniform across cities but is moderated by local industrial structure. Different industries have different land requirements and spatial agglomeration preferences, leading to heterogeneous responses to technological progress.

In terms of local spatial expansion, the scale of the tertiary industry is a key condition determining whether technological progress can improve space use efficiency. The scale of the tertiary industry functions as a critical moderating condition. Because digital services are characterized by high knowledge intensity and low land dependence, a robust

tertiary sector allows a city to better absorb technological dividends into agglomeration economies [35,36]. In such environments, technological progress incentivizes the concentration of high-end services within urban cores, utilizing three-dimensional and vertical spatial patterns to accommodate economic growth [37]. Conversely, in cities where the tertiary industry is underdeveloped, technological progress may lack the structural ‘receptors’ needed to drive intensification, potentially resulting in continued outward expansion.

In terms of cross-regional spatial spillovers, the scale of the secondary industry serves as a crucial infrastructural carrier. When core cities export land-intensive manufacturing, peripheral cities with a robust secondary sector offer superior industrial supporting facilities and established supply chains, creating powerful Marshallian externalities that attract relocating firms [38,39]. The absorption of these enterprises necessitates large-scale land expropriation and the expansion of industrial park boundaries, thereby accelerating spatial expansion.

Consequently, we propose H3a: A larger tertiary industry strengthens the inhibitory effect of technological progress on local urban expansion, H3b: A larger secondary industry in neighboring cities amplifies the positive spillover effect of technological progress on urban expansion.

3. Data and Methodology.

3.1. Data sources. This study uses balanced panel data from 21 prefecture-level cities in Guangdong Province covering the period 2015 to 2025. This timeframe is particularly significant as it encompasses the rapid development of China’s digital economy, including the widespread adoption of mobile Internet, cloud computing, and artificial intelligence. The primary data sources include various issues of the Guangdong Statistical Yearbook, China Urban Statistical Yearbook, and municipal government work reports. Missing data are supplemented using provincial and municipal statistical bulletins and official public sources.

To ensure comparability across years, all monetary indicators (e.g., gross regional product, and government expenditure) have been adjusted to constant 2020 prices using the GDP deflator. We exclude any observations with abnormal fluctuations that cannot be explained by economic factors, resulting in a final sample of 231 city-year observations.

3.2. Variable definitions.

Dependent Variable. This study employs the urban built-up area growth rate ($Area_{it}$) as the dependent variable [40]. The built-up area includes developed land, transportation infrastructure, and public service facilities. The growth rate of the built-up area captures the physical spatial expansion of urban construction zones and serves as a direct measure of urban spatial development.

Independent Variable. The Malmquist Productivity Index is calculated using Data Envelopment Analysis (DEA) [41]. The index is further decomposed into efficiency change, scale change, and technological change based on the established decomposition approach [42,43]. In this study, technological change (TC_{it}) is used as the core explanatory variable, as it captures pure technological progress rather than improvements in efficiency or scale. Following previous methodological frameworks [44], the number of employees at year-end and total fixed asset investment are used as input variables, while output per capita serves as the output variable for the calculation of urban productivity efficiency.

Control Variables. Drawing on empirical literature regarding the drivers of urban expansion [14,45], the following control variables are included:

POP_{it} : Permanent population at year-end (10,000 people), which reflects the demand for urban space from population growth

GOV_{it} : General public budget expenditure as a share of GDP (%), which captures the degree of government intervention in urban development

$ROAD_{it}$: Urban road network density (km/km²), which measures the level of transportation infrastructure

FDI_{it} : Foreign direct investment as a share of GDP (%), which reflects the degree of openness to the global economy

3.3. Model specification. Given the likely spatial dependence of urban expansion and technological progress, we employ a Spatial Durbin Model (SDM) for regression analysis. The SDM is the most appropriate model for this study as it accounts for both the spatial dependence of the dependent variable and the spatial spillover effects of the independent variables. The baseline model is specified as follows:

$$Area_{it} = \alpha + \beta \cdot TC_{it} + \delta \sum_{j=1}^N \omega_{ij} \cdot TC_{jt} + \gamma X_{it} + f_t + \varepsilon_{it} \quad (1)$$

where, $Area_{it}$ = the urban built-up area growth rate in city i at time t ; TC_{it} = technological change; ω_{ij} = the spatial weight between cities i and j ; X_{it} = a vector of control variables; f_t = year fixed effect; ε_{it} = the error term; α = constant term; β = direct effect coefficient of technological progress; δ = spatial spillover effect coefficient of technological progress; γ = coefficient vector of control variables; $N = 21$ cities.

3.4. Spatial weight matrix. Standard spatial econometric theory guides the construction of appropriate weight matrices that capture intercity interactions [46,47]. Unlike previous studies that use economic-geographic weight matrices for PRD analysis, we construct a binary contiguity weight matrix where $\omega_{ij} = 1$ if cities i and j share a common border, and $\omega_{ij} = 0$ otherwise. This choice is motivated by three factors: (i) Guangdong's diverse geography (mountains, rivers, coastlines) creates natural boundaries that shape intercity interactions; (ii) Administrative and infrastructure linkages are strongest between contiguous cities; (iii) The binary contiguity matrix avoids the endogeneity issues associated with economic-based weights, which are themselves influenced by urban expansion and technological progress.

To investigate the moderating effects of industrial structure, we extend the baseline SDM by including interaction terms between technological progress and the output share of the secondary and tertiary industries:

$$Area_{it} = \alpha_0 + \beta_1 \cdot TC_{it} + \beta_2 \cdot (TC_{it} \cdot Ind_{it}) + \delta_1 \sum_{j=1}^N \omega_{ij} \cdot TC_{jt} + \delta_2 \sum_{j=1}^N \omega_{ij} \cdot (TC_{it} \cdot Ind_{jt}) + \gamma X_{it} + f_t + \varepsilon_{it} \quad (2)$$

where Ind_{it} represents the output share of the secondary or tertiary industry in city i at time t .

4. Empirical Results and Analysis.

4.1. Descriptive statistics. Table 1 presents descriptive statistics for the full sample. The average annual growth rate of built-up areas in Guangdong Province is 3.24%, with a standard deviation of 12.55%, indicating substantial variation across cities. Notably, cities in the PRD have an average growth rate of 2.1%, while non-PRD cities grow at 4.8%, confirming the faster expansion in peripheral regions. The Technological Change (TC) index has a mean value of 0.96, ranging from 0.33 to 1.87, with PRD cities averaging 1.23

TABLE 1. Descriptive statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Area	%	3.24	12.55	−2.24	24.3
TC	—	0.96	0.51	0.33	1.87
POP	10,000 people	605.05	418.22	238.31	1954.41
GOV	%	16.80	13.60	7.40	33.30
ROAD	km/km ²	6.91	7.71	0.60	15.43
FDI	%	0.69	0.89	0.06	1.96

and non-PRD cities averaging 0.78, reflecting the significant technological gap between core and periphery.

4.2. Spatial autocorrelation analysis. Before conducting spatial econometric regression, we test for spatial autocorrelation in technological progress using Moran’s I statistic. The results in Table 2 show that Moran’s I for TC is significantly negative in all years from 2021 to 2025, indicating a “spatial repulsion” effect in technological progress across Guangdong. This means that technologically advanced cities tend to be surrounded by less advanced cities, and vice versa. This pattern is particularly pronounced at the provincial level, where the PRD forms a high-technology cluster surrounded by lower-technology regions in eastern, western, and northern Guangdong.

TABLE 2. Moran’s I for Technological Change (TC)

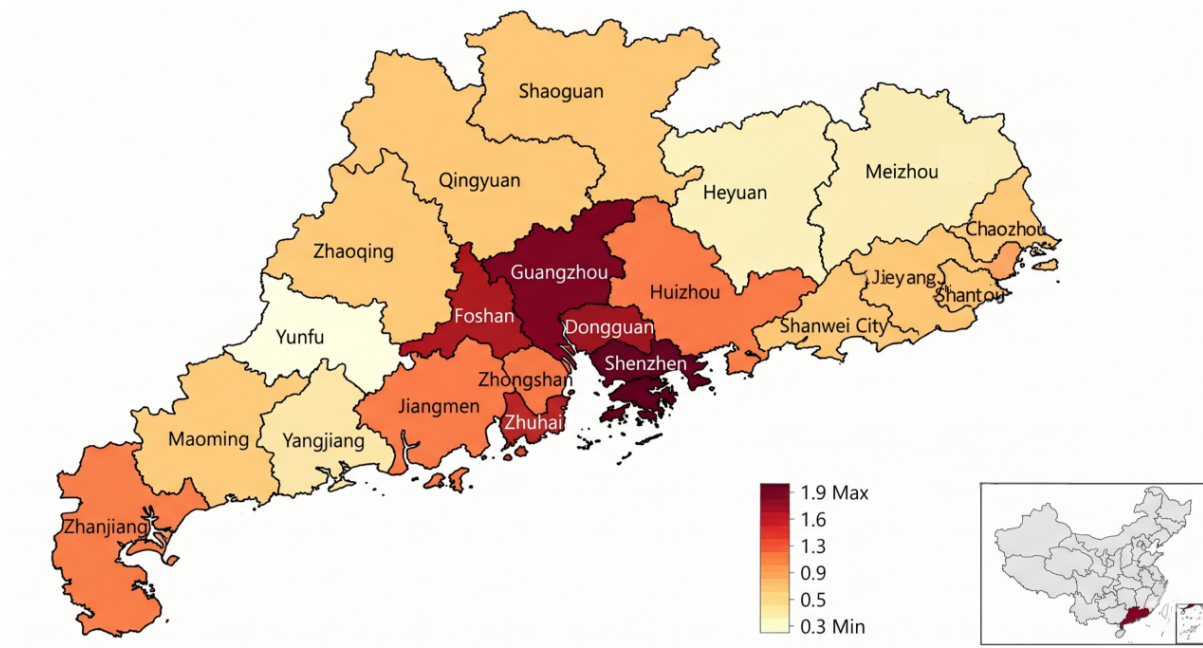
Year	Moran’s I
2021	−0.16
2022	−0.44**
2023	−0.22
2024	−0.65***
2025	−0.29

Note: ** and *** significant at 5% and 1%, respectively.

This spatial repulsion pattern is clearly illustrated in Figure 1, which presents the geographical distribution of technological change indices across 21 prefecture-level cities in Guangdong Province in 2025. These indices are calculated directly from our DEA-Malmquist analysis using the official data sources described in Section 3.1, with values ranging from 0.33 to 1.87 as reported in the aggregate descriptive statistics (Table 1).

The figure reveals a distinct core-periphery gradient: the Pearl River Delta core cities exhibit the highest levels of technological progress (dark red shades), forming a contiguous high-technology cluster in the central-southern part of the province. In contrast, peripheral cities in northern, eastern, and western Guangdong have significantly lower technological progress indices (light yellow to orange shades). This clear geographical clustering of high-technology cities surrounded by lower-technology neighbors partially explains the statistically significant negative Moran’s I statistic.

4.3. Spatial econometric model selection. To determine the appropriate spatial econometric model, we conduct a series of diagnostic tests. The results in Table 3 show that the LM-Error test is significant at the 5% level, while the LM-Lag test is not significant, indicating the presence of spatial error autocorrelation. The LR tests reject the null hypotheses that the SDM degenerates into either the Spatial Lag Model (SLM) or the Spatial Error Model (SEM) at the 1% level, confirming the suitability of the SDM.



Note: The color gradient ranges from 0.3 (minimum, light yellow) to 1.9 (maximum, dark red). The inset map shows the location of Guangdong Province in China.

FIGURE 1. (color online) Spatial distribution of technological progress indices in Guangdong Province, 2025

TABLE 3. Spatial econometric test results

Test	Statistic
LM-Lag	1.24
LM-Error	2.72**
Effect test (both vs. id)	25.35***
Effect test (both vs. time)	12.17
Hausman	12.15*
Wald	10.16**
LR (SDM-SLM)	26.88***
LR (SDM-SEM)	28.75***

Note: *, **, and *** significant at 10%, 5%, and 1%, respectively.

The Hausman test supports a fixed-effects specification, and the joint significance test indicates that time fixed effects should be included.

4.4. Baseline regression results. Table 4 reports the estimation results from the time-fixed effects SDM. Column (1) presents the results with only the core explanatory variable, while columns (2) to (5) gradually add control variables. The results consistently show that technological progress has a significant negative direct effect on urban expansion, with the coefficient stabilizing at approximately -32.2 in the full model (column (5)). This means that a one-unit increase in the technological change index reduces the built-up area growth rate by about 32.2 percentage points, providing strong support for Hypothesis H1. This finding confirms that digital-era technological progress has fundamentally decoupled economic growth from extensive land use in technologically advanced regions [16,48].

In contrast, the spatial spillover coefficient of technological progress ($\omega \cdot TC$) is significantly positive, with a value of 1.64 in the full model. This indicates that technological

TABLE 4. Baseline regression results

Variable	(1)	(2)	(3)	(4)	(5)
TC	−52.48*** (−3.67)	−48.47*** (−3.42)	−42.37*** (−3.17)	−32.49** (−2.43)	−32.20** (−2.42)
$\omega \cdot$ TC	2.43*** (2.99)	2.18*** (2.45)	1.88** (2.25)	1.64*** (2.13)	1.64*** (2.11)
POP		0.06** (1.99)	0.05** (1.97)	0.04* (1.92)	0.04* (1.92)
GOV			2.17*** (4.46)	1.46** (2.08)	1.35** (2.01)
ROAD				4.69*** (5.68)	4.25*** (5.15)
FDI					0.05 (1.45)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Adj. R ²	0.07	0.08	0.11	0.12	0.12

Note: *, **, and *** significant at 10%, 5%, and 1%, respectively. T-statistics are in parentheses.

improvement in one city accelerates urban expansion in neighboring cities, confirming Hypothesis H2. This positive spillover effect is primarily driven by industrial transfer from core to peripheral cities [33,49]. The magnitude of the spillover effect suggests that a one-unit increase in the average technological progress of neighboring cities leads to a 1.64 percentage points increase in the local built-up area growth rate.

Among the control variables, population size, government intervention, and transportation infrastructure all have significant positive effects on urban expansion, which is consistent with theoretical expectations. FDI has a positive but insignificant effect, possibly due to the heterogeneous impact of foreign investment on different types of cities.

4.5. Robustness tests. To verify the reliability of the baseline results, we conduct two robustness tests. First, we replace the binary contiguity weight matrix with an inverse distance weight matrix, where the weight between two cities is the reciprocal of their geographical distance. Second, we replace the transportation infrastructure variable with the logarithm of total urban road length. The results in Table 5 show that the core explanatory variables maintain their expected signs and statistical significance, confirming the robustness of our findings.

4.6. Moderating effect analysis. Table 6 presents the results of the moderating effect analysis. Column (1) shows the results with the interaction term between technological progress and secondary industry output share, while column (2) shows the results with the interaction term between technological progress and tertiary industry output share.

The results in column (1) indicate that the interaction term between technological progress and secondary industry share has a significant positive spatial spillover effect ($\omega \times$ Interaction coefficient = 0.02, $p < 0.1$). This means that for every one-percentage-point increase in the secondary industry share of neighboring cities, the positive spillover effect of technological progress on local urban expansion increases by 0.02 percentage points. This provides strong support for Hypothesis H3b. This finding highlights the critical role of manufacturing bases in absorbing industrial transfers from core cities [39].

In column (2), the interaction term between technological progress and tertiary industry share has a significant negative direct effect (Interaction coefficient = -0.02 , $p < 0.05$). This indicates that for every one-percentage-point increase in the local tertiary

TABLE 5. Robustness test results

Variable	(1) Inverse distance weight	(2) Alternative road measure
TC	-52.57** (-2.17)	-1.45*** (-4.58)
$\omega \cdot TC$	1.57* (1.86)	2.27*** (3.32)
POP	0.04* (1.88)	0.86** (2.07)
GOV	1.52** (2.11)	0.34** (2.43)
FDI	0.01 (1.25)	0.01 (1.13)
Year fixed effect	Yes	Yes
Adj. R ²	0.13	0.16

Note: *, **, and *** significant at 10%, 5%, and 1%, respectively. T-statistics are in parentheses.

TABLE 6. Moderating effect regression results

Variable	(1) Tech $\times$ Secondary industry	(2) Tech $\times$ Tertiary industry
TC	-56.14** (-2.07)	39.26*** (-2.65)
Interaction	0.08 (1.31)	-0.02** (2.12)
$\omega \cdot TC$	0.96* (1.90)	0.53 (1.19)
$\omega \cdot Interaction$	0.02* (1.91)	0.00 (1.52)
Controls	Yes	Yes
Year fixed effect	Yes	Yes
Adj. R ²	0.16	0.18

Note: *, **, and *** significant at 10%, 5%, and 1%, respectively. T-statistics are in parentheses.

industry share, the inhibitory effect of technological progress on local urban expansion strengthens by 0.02 percentage points. This confirms Hypothesis H3a. This result is consistent with previous studies showing that service-oriented economies are more conducive to intensive land use [35].

4.7. Discussion. Our findings reveal a clear “core compression-peripheral expansion” pattern of urban spatial restructuring in Guangdong Province driven by technological progress. This pattern has also been observed in other major Chinese urban agglomerations [1] and reflects the functional division of labor within the provincial urban system, where core cities specialize in knowledge-intensive and digital service industries, while peripheral cities undertake manufacturing industries transferred from the core.

The significant inhibitory effect of technological progress on local urban expansion confirms that digital technologies have fundamentally changed the relationship between economic growth and land use. In core cities such as Shenzhen and Guangzhou, technological progress has enabled the development of high-rise office buildings, smart industrial parks, and digital service clusters that generate enormous economic value in limited physical space [2,9]. This has allowed these cities to maintain rapid economic growth without

extensive outward expansion, marking a transition from the traditional extensive development model to an intensive development model.

The positive spatial spillover effect of technological progress indicates that the benefits of technological innovation are not confined to core cities but also extend to peripheral regions through industrial transfer [33,49]. This process has driven rapid urban expansion in peripheral cities such as Qingyuan, Shaoguan, and Heyuan, which have become important manufacturing bases for Guangdong Province. However, this expansion also poses challenges, including potential environmental degradation and inefficient land use if not properly managed [7].

The linear moderating effects of industrial structure provide important insights into the mechanisms underlying these spatial dynamics. The stronger inhibitory effect in cities with larger tertiary industries confirms that service-oriented economies are more conducive to intensive land use. Meanwhile, the stronger spillover effect in regions with larger secondary industries highlights the critical role of manufacturing bases in absorbing industrial transfers from core cities. This suggests that industrial structure is a key determinant of how technological progress shapes urban spatial patterns.

Compared with previous studies that focus on the PRD urban agglomeration [1,16], our full-province analysis reveals a more complete picture of how technological progress reshapes urban spatial patterns. We show that the spatial dynamics extend beyond the PRD to include the entire province, with technological spillovers driving urban expansion in non-PRD regions. This finding highlights the importance of provincial-level coordination in promoting balanced urban development [15].

5. Conclusions and Policy Implications.

5.1. Conclusions. Using panel data from 21 prefecture-level cities in Guangdong Province (2015-2025) and a time-fixed effects Spatial Durbin Model, this study addresses gaps in existing Pearl-River-Delta-only and pre-digital era research by revealing a unified “core compression-peripheral expansion” spatial restructuring pattern driven by technological progress. Our key findings are as follows.

First, technological progress significantly inhibits local urban sprawl. It has decoupled economic growth from extensive land use in advanced regions, allowing cities to achieve sustained development through vertical intensification rather than outward expansion.

Second, technological progress generates positive spatial spillovers. Technological advancement in core cities accelerates urban expansion in neighboring areas, as core regions retain knowledge-intensive industries while transferring land-intensive manufacturing to peripheries. This cross-regional dynamic explains the divergent growth trajectories between the Pearl River Delta and non-PRD regions.

Third, the industrial structure presents a linear moderating pattern. A larger local tertiary sector strengthens the inhibitory effect of technological progress on local expansion, while a larger secondary sector in neighboring cities amplifies the spillover effect. No statistically significant threshold effect was identified in this analysis.

5.2. Policy implications. The findings of this study have important policy implications for promoting high-quality urbanization and coordinated regional development in Guangdong Province and other similar regions.

Implement differentiated urban development strategies. Core PRD cities should abandon expansion-driven growth and focus on intensive land use and high-value, low-land-dependent industries. Peripheral cities should selectively undertake industrial transfers matching their local capacity and avoid blind, disorderly land development.

Strengthen provincial-level cross-regional coordination. Establish unified technological collaboration and industrial layout mechanisms to guide orderly industrial transfer, prevent vicious competition between cities, and promote a rational division of labor within the province.

Leverage digital technologies for smart urban governance. Use big data, remote sensing, and artificial intelligence to improve urban planning accuracy, monitor urban expansion in real time, and optimize land use allocation.

5.3. Limitations and future research. This study has some limitations that should be acknowledged. First, our analysis is limited to Guangdong Province, and the findings may not be generalizable to other regions with different economic and geographical characteristics. Future research could expand the sample to include other provinces in China to test the generalizability of our results. Second, we use the built-up area growth rate as the only measure of urban expansion. Future research could use more comprehensive measures of urban expansion, such as population density and land use structure, to provide a more complete picture. Third, we do not explore the heterogeneous effects of different types of technological progress on urban expansion. Future research could distinguish between digital technologies and traditional industrial technologies to examine their different impacts.

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Author Biography



Yuhao Cheng received his Master's degree in Economics from Yokohama National University, Japan, in 2019, and obtained his Ph.D. in Economics from the same university in 2022. He previously served as a Project Mentor for the World Bank at Yokohama National University. In the same year, he became a Lecturer at the Guangzhou College of Technology and Business, China, where he also holds the position of Program Director for the Cross-border E-commerce major. His primary research interests include applied econometrics, game theory, and industrial organization economics.



Kangpei Zhong received his Master of Engineering degree from South China University of Technology, China, in 2017. He worked for several years in banking and has extensive professional experience in the financial sector. In 2022, he became a Lecturer at Guangzhou College of Technology and Business, China, and he is currently pursuing his Doctor of Business Administration at the Faculty of Creative Tourism and Intelligent Technologies, Macau University of Tourism, Macau SAR, China. His main research interests are e-commerce, digital transformation and digital marketing. He is a Certified Economist.



Zheng Nan received his M.A. in Public Economics from International Christian University (ICU), Japan, in 2019, and his Ph.D. from ICU in 2021. He is currently an Adjunct Lecturer in the Department of Global Business, Faculty of Global Studies, at Musashino University, Japan, and a Research Fellow at ICU. His research interests include cryptocurrency markets and market microstructure, financial networks, machine learning applications in finance, nonlinear time series analysis, and econophysics. His research focuses particularly on systemic risk and innovation in digital finance.