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Original Research

Population Flow, Urban Innovation and Carbon Emissions from Urban Agglomerations: A Spatial Econometric Analysis Based on Major Urban Agglomerations in China

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Abstract

Exploring the impact of population flow on carbon emissions in urban agglomerations against the background of urban innovation is of great significance for promoting regional low-carbon coordinated development and responding to climate change. Taking China's three major urban agglomerations as the research object, this study introduces spatial factors to analyze the impact and mechanisms of heterogeneous population mobility on carbon emissions in the context of innovation. The findings reveal the following: (1) Carbon emissions in China's three major urban agglomerations exhibit spatial correlation, and the spatial effects of different types of labor mobility on carbon emissions are complex. High-skilled labor flow helps reduce carbon emissions and mitigates the adverse impact of urban innovation on carbon emissions; low-skilled labor flow increases carbon emissions but is difficult to integrate with urban innovation, and the impact of urban innovation on carbon emissions does not change with the influence of low-skilled labor mobility. (2) There are significant differences in the spatial spillover effects of heterogeneous population flows on carbon emissions among China's three major urban agglomerations. Due to the stronger administrative characteristics of the Beijing-Tianjin-Hebei urban agglomeration compared to other urban agglomerations, the spatial spillover effects of carbon emissions from heterogeneous population flows are not significant. In contrast, the Yangtze River Delta and Pearl River Delta urban agglomerations have relatively higher levels of integration, resulting in significant spatial spillover effects of carbon emissions from heterogeneous population flows. The article concludes by suggesting that institutional barriers hindering population mobility should be continuously removed, the positive interaction among cities should be activated, and the low-carbon development of urban agglomerations should be promoted.

Keywords: population flow, urban innovation, carbon emissions, urban agglomerations

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Introduction

China is actively fulfilling its carbon emission reduction commitments, striving to achieve carbon peaking by 2030 and carbon neutrality by 2060. As the mainstay of China's new urbanization, urban agglomerations bear the heavy responsibility of achieving carbon peaking first. They are the focus and key to achieving carbon peaking at the regional level, as well as a powerful engine for implementing the innovation-driven development strategy. Currently, except for a few megacities, China's cities are gradually relaxing their household registration restrictions. Over the next few decades, China will continue to face large-scale population mobility, and urban agglomerations are the target locations for population mobility [1]. How population mobility affects the realization of the "dual carbon" goals in urban agglomerations and how to coordinate with innovation to achieve China's green and low-carbon development are all issues that urgently need to be addressed. Therefore, taking urban agglomerations as the research object, exploring the correlation mechanism and spatio-temporal evolution trend among population flow, urban innovation, and carbon emissions is of great significance for promoting regional low-carbon coordinated development and facilitating the realization of China's modernization goals.

Current research mainly focuses on three areas: population flow and innovation, innovation and carbon emissions, and population flow and carbon emissions. Firstly, the connection between innovation and carbon emissions remains ambiguous. Most studies indicate that innovation enhances carbon emission efficiency and facilitates emission reduction [2, 3]. However, if a large amount of capital investment is needed to support innovation, technological progress will neither promote an increase in production efficiency nor reduce carbon emissions [4, 5]. Wang et al. (2019) [6] highlighted that, when accounting for the deviations in technological progress, advancements within the industrial sector do not necessarily lead to a reduction in carbon emissions. Rather, the expansion of production capacity results in a rebound effect on carbon emissions. Secondly, there is also no unanimous agreement regarding the influence of population flow on regional innovation. Some scholars believe that population mobility, especially the flow of high-quality talents, has led to knowledge spillover, promoting technological innovation in the inflow areas. Moreover, population mobility is conducive to alleviating the mismatch between regional resource supply and demand and promoting regional innovation [7-10]. However, some other scholars believe that due to the unbalanced regional development in China, population mobility has exacerbated the misallocation of resources, which is not conducive to regional innovation [11]. Moreover, restrictions inherent in China's current household registration system can lead to mismatches in labor supply for some industries, potentially hindering regional innovation [12, 13]. The labor force's migration, as a production factor, influences resource reallocation within regions and significantly impacts regional innovation. Thirdly, the correlation between population movement and carbon emissions has garnered increasing attention in recent years, with a focus on the impact of population flow on carbon emissions using the STIRPAT model in numerous studies. Pan et al. (2021) [14] examined the influence of shifts in China's population composition on carbon emissions between 1995 and 2018 by constructing a multiple regression model. The research highlighted that population size is the primary factor influencing carbon emissions in China. Bu et al. (2022) [15], drawing on panel data from provincial-level regions in China spanning from 2000 to 2019 and employing the spatial Durbin model in their research, demonstrated that population migration has a considerable detrimental impact on provinces experiencing net outward migration. Wu et al. (2021) [16] utilized panel regression and fixed-effects modeling to observe that the alleviation of regional population aging and the improvement of knowledge structures resulting from population mobility contribute to the decrease in carbon emissions. He et al. (2022) [17] constructed a theoretical model of carbon emissions for two regions and three industries under the general equilibrium analysis framework and found that the mobility of skilled labor can effectively reduce carbon emissions. Gao et al. (2021) [18] started from a spatial perspective and inferred that China's large-scale population mobility is related to greater trade carbon emissions by constructing a carbon transfer network.

There are several issues worth further exploration in the research on the relationship between population flow, urban innovation, and carbon emissions. Firstly, most existing literature overlooks the typical fact of heterogeneity among migrant populations. China has now entered a new phase of high-quality economic development, and the impact of heterogeneous population mobility on urban innovation varies. High-skilled and low-skilled labor should also have different effects on promoting urban innovation and carbon emissions [19]. Considering labor heterogeneity helps to comprehensively and objectively clarify the impact of population flow on carbon emissions. Secondly, existing research lacks exploration of the relationship between population flow, urban innovation, and carbon emissions, and the role of urban innovation in population mobility and carbon emissions is often overlooked. Most existing studies have demonstrated the pairwise relationships among the three variables, but the impact of population mobility on carbon emissions, while influencing urban innovation, has not been fully elucidated. By placing heterogeneous population mobility, urban innovation, and carbon emissions within the same research framework and revealing the role of urban innovation between population mobility and carbon emissions, it is possible to grasp the correlation among these three variables. Thirdly, due to the limitation of heterogeneous mobile population data, current empirical studies are confined to provincial or specific cities, overlooking investigations into urban agglomerations. However, urban agglomerations, as the main bodies for mitigating climate change and achieving the goals of carbon peaking and carbon neutrality, are not only important units for energy conservation and emission reduction, but also the main carriers of urban innovation. Focusing research efforts on urban agglomerations allows for an exploration of the intricate relationship among heterogeneous population flow, urban innovation, and carbon emissions, facilitating a deeper understanding of the spatial impact of carbon emissions in urban agglomerations, promoting harmonized regional eco-friendly progress, and meeting national carbon emission reduction objectives.

Based on this, this paper will explore the underlying mechanisms linking heterogeneous population flow, urban innovation, and carbon emissions in urban agglomerations from both theoretical and empirical perspectives. The possible marginal contributions are outlined below: Firstly, population flow, urban innovation, and carbon emissions are integrated into a unified analytical framework to elucidate the impact of heterogeneous population flow and urban innovation on carbon emissions. Secondly, employing spatial econometric analysis models to match micro data with macro data, this study quantitatively analyzes the impact of heterogeneous population mobility on carbon emissions within China's three major urban agglomerations – the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions – and the spatial effects associated with such impacts. Finally, it is important to highlight that the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta urban agglomerations were selected as the research subjects because they are China's most promising urban agglomerations and have all been elevated to national strategic status. Building these three urban agglomerations into world-class urban agglomerations is a key driver for China's future low-carbon development and holds significant implications for the development of other urban agglomerations.

Materials and Methods

Mechanism Analysis and Research Hypothesis

Impact of Heterogeneous Population Flow on Carbon Emissions

Population flow reshapes the age and skill composition of the workforce across regions, serving as a vital driver of social and economic advancement and influencing regional carbon emissions. The essence of population mobility is the flow of human capital. Compared with production resources such as physical capital, human capital is regarded as the most sustainable production resource for promoting social and economic development. Human capital often flows from regions with low production efficiency to those with high production efficiency, thereby maximizing utility. Therefore, population mobility facilitates efficient human capital allocation, enhances resource utilization efficacy, boosts production efficiency, and diminishes carbon emissions [16, 17]. Population flow enhances energy and production efficiency, which can lead to a reduction in carbon emissions. Nevertheless, improvements in energy use efficiency and production efficiency will lower product costs, expand consumption demand, and inevitably increase carbon emissions. The resource allocation effect of population flow varies based on skill diversity, consequently affecting carbon emissions differently. Specifically, highly skilled populations migrate to areas with high demand for skilled labor under the guidance of labor market signals, thereby improving regional energy efficiency and productivity, which helps reduce carbon emissions. Conversely, the low-skilled population only has ordinary knowledge and skills, and the flow scale is usually large, resulting in a scale effect of carbon emissions greater than the energy-boosting effect, leading to an increase rather than a decrease in carbon emissions. Based on this, hypothesis 1 is proposed.

Hypothesis 1: Population flow alters resource allocation, and this effect varies by skill level, leading to differential impacts on carbon emissions.

Hypothesis 1.1: High-skilled population flow is conducive to reducing carbon emissions.

Hypothesis 1.2: Low-skilled population flow will lead to an increase in carbon emissions.

Impact of Urban Innovation on Carbon Emissions

The core driver of rapid economic development in a country or region is innovation, which determines the level of productivity in that country or region [20, 21]. Innovation typically encompasses the creation of new technologies as well as the enhancement and refinement of existing ones. The neoclassical school of thought, represented by Solow, incorporates innovation into economic growth models, viewing innovation as an endogenous variable of economic growth and technological innovation as a decisive economic growth factor or influencing factor [22, 23]. Studies utilizing the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) have shown that innovation plays a positive role in reducing carbon emissions [5, 6]. It is undeniable that technological innovation has changed the original optimal allocation state of labor, capital, and land, improved energy utilization efficiency and production efficiency, and is conducive to reducing carbon emissions. However, while technological innovation enhances efficiency, it also reduces costs and expands energy consumption demand, resulting in an increase in carbon emissions instead of a decrease [24]. Based on this, hypothesis 2 is proposed.

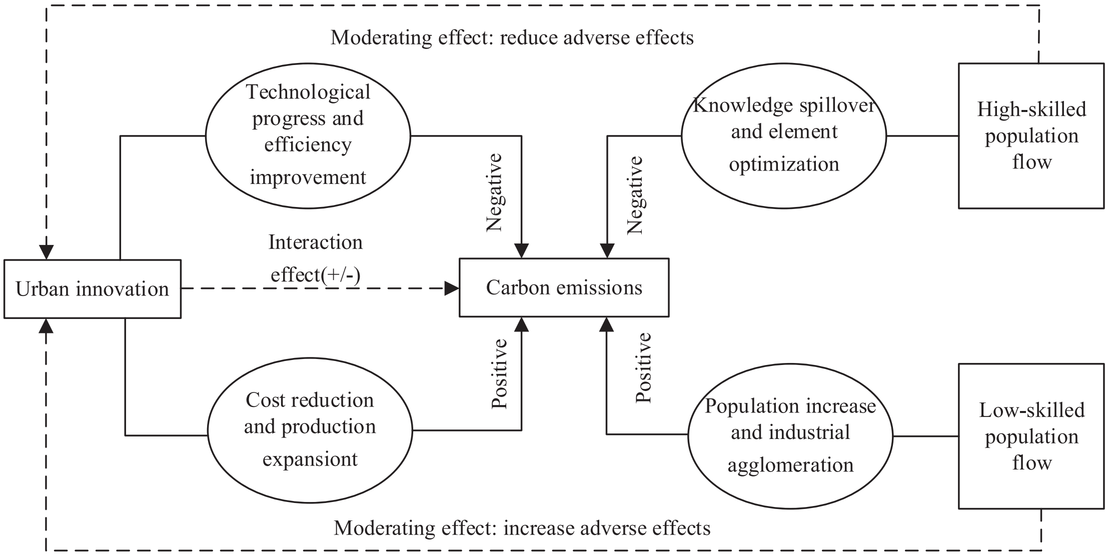

Fig. 1. Mechanism path diagram.

Hypothesis 2: Urban innovation changes the state of allocation of labor, capital, and land and is one of the most important factors affecting regional carbon emissions, but the impact varies across regions.

The Moderating Effect of Heterogeneous Population Flow between Urban Innovation and Carbon Emissions

Population mobility is the result of the automatic adjustment of the allocation of urban production factors, exerting a significant influence on regional innovation [9, 10], moderating the impact of regional innovation on carbon emissions. Specifically, the influence of urban innovation on carbon emissions fluctuates based on the mobility of individuals with diverse skill sets: the high-skilled floating population typically boasts advanced knowledge and skills, strong learning and knowledge absorption capabilities, making them adept at mastering cutting-edge technologies that are market leaders and not easily replicable, thus enabling seamless integration with urban innovations. Conversely, the low-skilled floating population, comprising the majority of mobile individuals, often relies on interactions with peers and high-skilled workers to enhance knowledge and job skills, exhibiting lower levels of integration into urban innovation compared to their high-skilled counterparts. As previously stated, since the migration of highly skilled workers helps reduce carbon emissions, while the migration of low-skilled workers increases carbon emissions, heterogeneous population migration plays a certain moderating role in the impact of urban innovation on carbon emissions. Based on this, hypothesis 3 is proposed.

Hypothesis 3: The impact of urban innovation on carbon emissions will vary with heterogeneous population flow.

The mechanism path diagram of this article is shown in Fig. 1.

Research Methodology

Research Model Design

Drawing on the analytical framework of the Environmental Kuznets Curve(EKC) and the Stochastic IPAT equation, heterogeneous population flow and urban innovation factors are added to the analysis model. Considering the interaction between heterogeneous population flow and urban innovation, the interaction term between the two is introduced into the model. The following basic econometric model is constructed:

$$y_i=\alpha_i+\beta_1 pgdp_i+\beta_2 pgdp_i^2+\beta_3 flow_i \\ +\beta_4 inno_i+\beta_5 flow_i\times inno_i+\beta_6 z_i+\varepsilon_i \tag{1}$$

Among them, y_i represents carbon emissions; $pgdp_i$ represents per capita GDP; $pgdp_i^2$ represents the square of per capita GDP; $flow_i$ represents the scale of heterogeneous population flow. Based on the heterogeneity of labor skill level, population mobility is divided into high-skilled population flow (*flow-h*) and low-skilled population mobility (*flow-l*); $inno_i$ represents urban innovation; α_i represents the constant term; z_i represents the control variable; and ε_i represents the random error term.

Spatial Correlation Test

Previous studies have pointed out that carbon emissions have spatial correlation [17]. If spatial factors are ignored, biased estimates are likely to occur. Therefore, the Global Moran's Index is used to test the spatial correlation. The calculation formula is as follows:

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{2}$$

$$S^2=\sum_{i=1}^{n}(x_i-\bar{x})^2/n \tag{3}$$

Among them, the S^2 in formula (2) is represented by formula (3); x_i represents the per capita carbon emissions of city i; n represents the number of samples; and w_{ij} is the spatial weight matrix. Research generally uses geographic distance weighting matrices and adjacency weighting matrices, while this study uses geographic distance weighting matrices. The global Moran index typically ranges from (-1) to (1). A higher index indicates stronger positive spatial correlation in carbon emissions among cities, suggesting a high degree of similarity in carbon emissions between cities; a lower index indicates stronger negative spatial correlation in carbon emissions among regions, suggesting significant differences in carbon emissions between regions; an index of 0 indicates no correlation in carbon emissions between regions, with no discernible patterns in their variation.

Spatial Econometric Model Setting

Since carbon emissions exhibit obvious spatial correlation characteristics, the basic econometric model (1) is spatially expanded to construct the following spatial econometric model:

$$\begin{aligned} y_i=&\alpha_i+\rho Wy_i+\beta_1 pgdp_i+\beta_2 pgdp_i^2\\ &+\beta_3 flow_i+\beta_4 inno_i+\beta_5 flow_i\times inno_i+\beta_6 z_i+\varepsilon_i \end{aligned} \tag{4}$$

$$\begin{aligned} y_i=&\alpha_i+\beta_1 pgdp_i+\beta_2 pgdp_i^2+\beta_3 flow_i\\ &+\beta_4 inno_i+\beta_5 flow_i\times inno_i+\beta_6 z_i+\varepsilon_i \end{aligned} \tag{5}$$

$$\varepsilon_i=\varphi W_{\varepsilon_i}+\mu_i \tag{6}$$

Among them, formula (4) is the Spatial Lag Model (SLM), which introduces the spatial variable of carbon emission based on formula (1) and is represented by W_{yi}, where W is the spatial weight matrix, and ρ is the spatial autoregressive coefficient. If $\rho > 0$ and passes the significance test, it indicates that carbon emissions have positive spatial spillover effects; if $\rho < 0$ and passes the significance test, it indicates that carbon emissions have negative spatial spillover effects. Formula (5) is the Spatial Error Model (SEM), which introduces a spatial variable of error based on formula (1), represented by $W_{\varepsilon i}$.

Effect Decomposition

Since spatial econometric models differ from traditional econometric models, their model fitting results not only include the effects of heterogeneous population mobility and urban innovation on local carbon emissions, but also the spillover effects of heterogeneous population mobility and urban innovation. Therefore, in the analysis process, heterogeneous population mobility, urban innovation, and the interaction terms between the two are decomposed into direct effects and indirect effects. For convenience of representation, formula (4) is generalized to formula (7):

$$Y=C_n+\lambda WY+\beta X+\alpha WX+\varepsilon \tag{7}$$

According to formula (7), it can be obtained:

$$(I_n-\lambda W)Y=C_n+\beta X+\alpha WX+\epsilon \tag{8}$$

$$Y=\sum_{r=1}^{k} S_r(W)X_r+C_nV(W)+V(W)\epsilon \tag{9}$$

$$V(W)=(I_n-\lambda W)^{-1} \tag{10}$$

$$S_r(W)=V(W)\left(I_n\beta_r\right)+W\alpha_r \tag{11}$$

Formula (11) can be expanded as:

$$\begin{bmatrix} Y_1\\ Y_2\\ \cdots\\ Y_n \end{bmatrix}=\begin{bmatrix} S_r(w)_{11} & S_r(w)_{12} & \cdots & S_r(w)_{1n}\\ S_r(w)_{21} & S_r(w)_{12} & \cdots & S_r(w)_{2n}\\ \cdots & \cdots & \cdots & \cdots\\ S_r(w)_{n1} & S_r(w)_{n2} & \cdots & S_r(w)_{nn} \end{bmatrix}\begin{bmatrix} X_{1k}\\ X_{2k}\\ \cdots\\ X_{nk} \end{bmatrix}+C_nV(W)+V(W)_\varepsilon \tag{12}$$

In formula (12), the main diagonal element of the coefficient matrix of X_{nk} is the influence of the explanatory variable X on the carbon emissions of city i, representing the direct effect; the non-principal diagonal element of the coefficient matrix of X_{nk} is the explanatory variable X of other cities on the impact of urban j carbon emissions, representing the indirect effect; the sum of all elements of the coefficient matrix of X_{nk}, representing the total effect.

Variable Settings

The explained variable is carbon emissions (CO_2). Referring to the studies of Xu (2022) [25] and Wang (2024) [26], urban carbon emissions are categorized into three ranges of carbon emissions. They are respectively: (1) all direct carbon emissions within the urban jurisdiction (mainly including carbon emissions generated from transportation and construction, industrial production processes, agriculture, forestry and land use changes, as well as waste treatment activities); (2) indirect carbon emissions related to energy that occur outside the urban area (mainly including carbon emissions generated from purchased electricity, heating, and cooling to meet urban consumption needs); (3) carbon emissions caused by urban activities but generated outside the urban area (mainly including carbon emissions generated in the production,

Table 1. Descriptive statistics of the main variables.

Beijing-Tianjin-Hebei				
Variable	Mean	Std	Min	Max
CO_2	10002.65	15865.30	2533.00	68026.80
flow-h	15.56	55.33	-45.91	305.80
flow-l	51.90	165.51	-226.16	636.66
inno	1940.91	6830.80	4.00	46847.00
market	0.43	0.11	0.11	0.68
density	544.30	226.60	91.36	876.90
pgdp	41535.80	29772.20	9947.00	176659.00
stru	0.47	0.09	0.19	0.60
N	182			
Yangtze River Delta				
Variable	Mean	Std	Min	Max
CO_2	6032.00	15039.00	1516.00	96882.50
flow-h	9.99	37.47	-29.60	323.31
flow-l	61.80	147.60	-142.30	805.59
inno	1585.70	3031.70	1.00	21233.00
market	0.53	0.13	0.05	0.86
density	683.45	377.00	188.95	2305.80
pgdp	64508.00	36437.00	7500.00	174628.00
stru	0.51	0.08	0.30	0.75
N	364			
Pearl River Delta				
Variable	Mean	Std	Min	Max
CO_2	3752.90	727.73	2604.50	5793.50
flow-h	30.13	44.86	-21.71	214.40
flow-l	234.58	231.75	-412.40	679.70
inno	2234.60	4110.30	6.00	21248.00
market	0.54	0.13	0.27	0.82
density	761.88	409.80	266.70	2278.40
pgdp	78309.00	42653.00	12315.00	189568.00
stru	0.50	0.09	0.25	0.66
N	126			

transportation, use and waste disposal processes when purchasing goods outside the urban jurisdiction).

The key explanatory variable is the heterogeneous population flow. Based on China's unique household registration policy, to avoid including temporary residents, the mobile population is defined as those who do not reside in their household registration location, have resided in another location for one month or longer, and are of working age, over 15 years old. Since the existing statistical data in China cannot obtain the annual population mobility data, based on the definition of population mobility, the availability of data and the needs of research, drawing on the research of Ye et al. (2018) [27], the difference between the permanent resident population and the registered population is used to measure the scale of population mobility, with a larger value indicating a larger scale of population mobility. Considering the heterogeneous characteristics of population mobility, population mobility is divided into high-skilled and low-skilled population mobility. Using the educational attainment classification from the China Migrants Dynamic Survey (CMDS) as a reference standard, population mobility among those with junior college, bachelor's, and graduate degrees is defined as high-skilled population mobility, while mobility among those with other educational attainments is defined as low-skilled population mobility. Then, based on the proportion of different educational qualifications and the scale of population mobility, the scales of high-skilled and low-skilled population mobility are calculated.

The mechanism variable is urban innovation (*inno*). Urban innovation refers to the use of innovative elements such as technology, knowledge, human resources, and culture to drive urban development. The number of patents granted per 10,000 people in a city is used to measure urban innovation.

The control variables contain industrial structure, marketization level, population density, and economic growth. Among them, industrial structure (*stru*) is measured using the share of industrial value added in GDP; drawing on the studies of Luo et al. (2019) [28] and Xu et al. (2019) [29], marketization level (*market*) is expressed as the proportion of urban private and self-employed workers to overall urban employment; population density (*density*) is obtained by dividing the number of permanent residents in the region by the local administrative area; economic growth (*pgdp*) is measured using GDP per capita.

Data Sources

The relevant data are mainly derived from the China Urban Statistical Yearbook. Data on the flows of high-skilled and low-skilled people were calculated based on data from the China Migrants Dynamic Survey (CMDS) and relevant data from the Urban Statistical Yearbook. It should be noted in particular that the data from the CMDS are only published until 2018, so this paper defines the study period as 2005-2018. Descriptive statistics of the main variables are shown in Table 1.

Results and Discussion

Dynamic Evolution of Heterogeneous Population Flow, Urban Innovation, and Carbon Emissions in Three Major Urban Agglomerations

Dynamic Evolution of Heterogeneous Population Flow

Fig. 2 illustrates the kernel density distribution of heterogeneous population flow scale in the three major urban agglomerations, showcasing the dynamic evolution of this population movement. Regarding the curve's distribution position, the low-skilled population mobility curve in the Beijing-Tianjin-Hebei urban agglomeration has shifted significantly to the right, indicating that the scale of low-skilled population mobility in the Beijing-Tianjin-Hebei urban agglomeration generally showed an upward trend during the period from 2005 to 2018. The curves representing the low-skilled population flow in the Yangtze River Delta and Pearl River Delta urban agglomerations notably shifted to the right between 2005 and 2012. However, the rightward shift of the low-skilled population flow curve in the Yangtze River Delta urban agglomeration was less pronounced from 2012 to 2018, suggesting a lack of significant growth in the low-skilled population flow scale during this period. Conversely, the curve depicting the low-skilled population flow in the Pearl River Delta urban agglomeration shifted to the left from 2012 to 2018, indicating a decreasing trend in the scale of low-skilled population flow. From 2005 to 2018, the curves representing the high-skilled population flow in the three major urban agglomerations consistently shifted to the right, suggesting an overall increasing trend in the scale of high-skilled population flow within these regions. Regarding the curve's shifted position, the upward trend of the low-skill population flow curve in the Yangtze River Delta Urban Agglomeration suggests an increase in the concentration of the low-skill population flow scale. Conversely, the curves representing low-skill population flow in the Beijing-Tianjin-Hebei and Pearl River Delta urban agglomerations decreased, indicating a reduction in the concentration of the low-skill population flow scale distribution. The movement of the high-skilled population mobility curves in the Beijing-Tianjin-Hebei region and the Pearl River Delta urban agglomeration is exactly opposite, indicating that the distribution concentration of the high-skilled population mobility scale in the Beijing-Tianjin-Hebei region and the Pearl River Delta urban agglomeration has increased. Regarding the curve's shape, the curves in both the Beijing-Tianjin-Hebei and Pearl River Delta urban agglomerations have transitioned from single peaks to multiple peaks, indicating a growing polarization in the scale of low-skilled and high-skilled population flow between cities in these areas. Regarding the curve's width, the curves for the three major urban agglomerations narrow, suggesting a reduction in the gap between the scales of high-skilled and low-skilled population flow among cities, demonstrating dynamic convergence characteristics.

Dynamic Evolution of Urban Innovation

Fig. 3 displays the kernel density distribution of urban innovations in the three major urban agglomerations, illustrating the dynamic evolution of urban innovation. Regarding the curve's distribution position, the urban innovation curves have all shifted to the right, indicating that the scale of urban innovation in the three major urban agglomerations is generally on the rise. Regarding the curve's shifted position, the upward shift of urban innovation curves in the Yangtze River Delta and Pearl River Delta urban agglomerations indicates an increased concentration of urban innovation

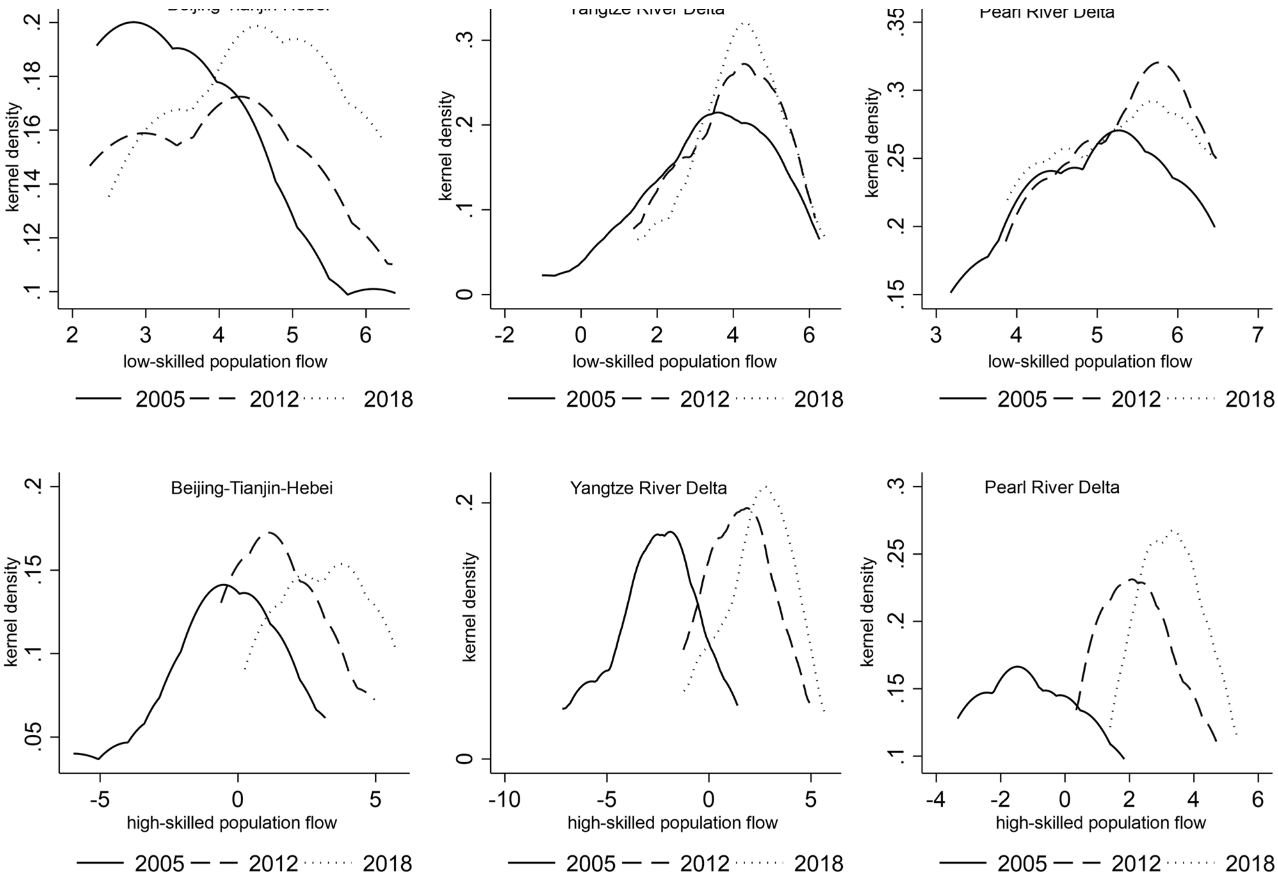

Fig. 2. Kernel density distribution of the scale of heterogeneous population flow in the three major urban agglomerations, 2005-2018.

scale among cities. Conversely, the downward shift of the urban innovation curve in the Beijing-Tianjin-Hebei urban agglomeration signifies a reduced concentration of urban innovation scale distribution among cities. Regarding the curve's width, the widening of urban innovation curves in the Beijing-Tianjin-Hebei and Pearl River Delta urban agglomerations suggests an increase in the gap between cities regarding the scale of urban innovation, demonstrating dynamic discrete characteristics. Conversely, the narrowing of the urban innovation curve in the Yangtze River Delta urban agglomeration signifies a reduction in the gap between cities in terms of urban innovation scale, displaying dynamic convergence characteristics.

Dynamic Evolution of Carbon Emissions

Fig. 4 displays the kernel density distribution of carbon emissions in the three major urban agglomerations, illustrating the dynamic evolution of carbon emissions. Regarding the curve's distribution position, the carbon emission curves of the three major urban agglomerations have all shifted to the right, indicating a general upward trend in carbon emissions. Regarding the curve's shifted position, the upward shift of the carbon emission curve in the Beijing-Tianjin-Hebei urban agglomeration indicates an increased concentration in the distribution of carbon emissions. Conversely, the downward shift of the carbon emission curves in the Yangtze River Delta and Pearl River Delta urban agglomerations suggests a reduction in the concentration of carbon emissions distribution. Regarding the curve's width, the carbon emission curves of the three major urban agglomerations are all widening, suggesting an increasing gap in carbon emissions between cities and demonstrating dynamic discrete features.

The Impact of Heterogeneous Population Flow and Urban Innovation on Carbon Emissions

Spatial Correlation Test

According to formula (2), the spatial correlation of carbon emissions was tested, and the results are shown in Table 2. The global Moran index of carbon emissions from the three major urban agglomerations has passed the significance test, indicating that carbon emissions in the three major urban agglomerations are not randomly distributed in space, but rather exhibit a significant spatial correlation. Therefore, traditional OLS models cannot be used for regression analysis, and spatial econometric models must be used for further research.

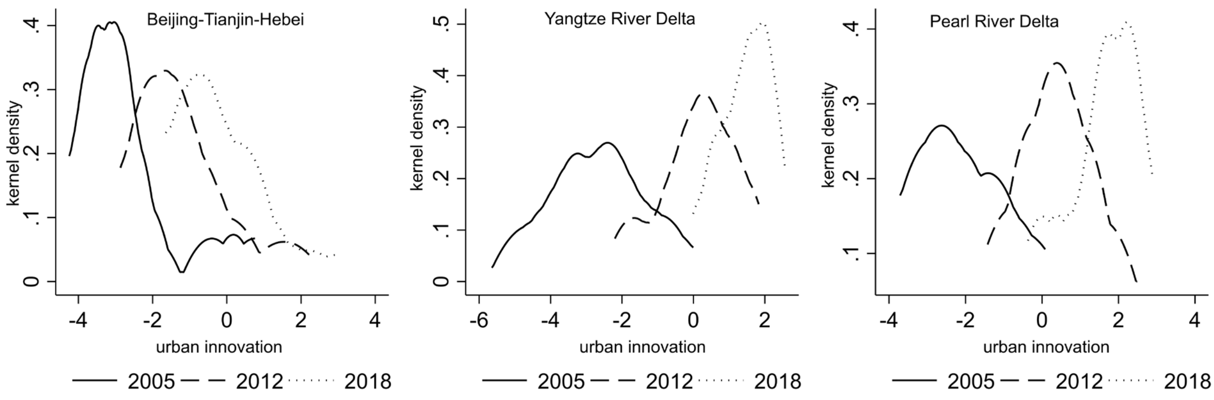

Fig. 3. Distribution of kernel densities of urban innovation in the three major urban agglomerations, 2005-2018.

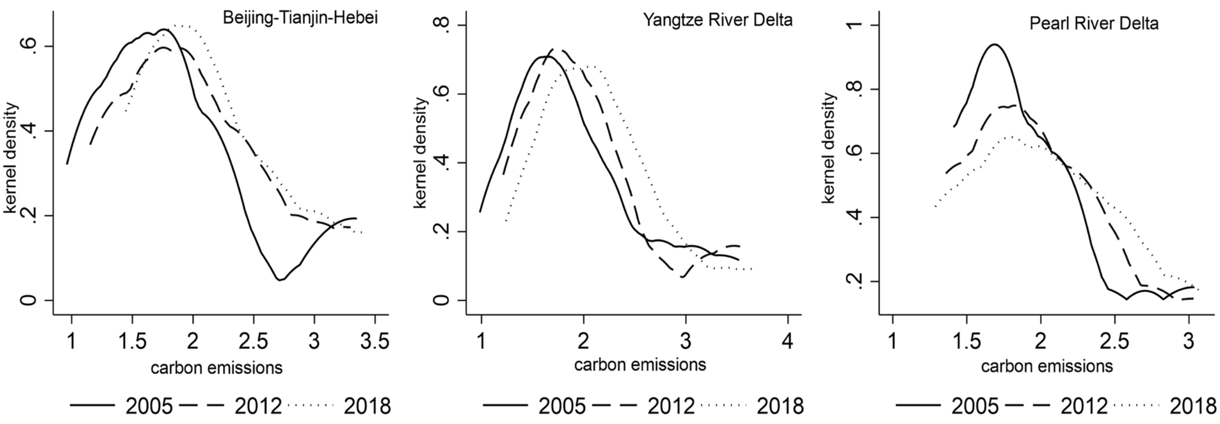

Fig. 4. Kernel density distribution of carbon emissions in the three major urban agglomerations, 2005-2018.

Model Applicability Test

A model applicability test was conducted to select the correct spatial regression model, and the results are shown in Table 3. As shown in Table 3, both the LM-ERR and LM-LAG tests are significant at the 1% level, and the Spatial Error Model and the Spatial Lag Model are significant at the 1% level, indicating that the Spatial Error Model is superior to the Spatial Lag Model. Based on the above, the model further passed the Wald test and LR test, and combined with the results of the Hausman test, the Spatial Durbin Fixed Effects Model was finally selected as the analytical model.

Analysis of Spatial Regression Results

The results of the regression analysis in Table 4 present the exploration of the moderating influence of diverse population flows on the relationship between urban innovation and carbon emissions. The results indicate that both high-skilled and low-skilled population mobility significantly impact carbon emissions in the three major urban agglomerations. Specifically, the regression coefficient for high-skilled population flow is significantly negative, suggesting that high-skilled population mobility contributes to reducing carbon emissions. Conversely, the regression coefficient for low-skilled population flow is significantly positive, indicating that low-skilled population mobility increases carbon emissions. The regression results of the three major urban agglomerations are relatively consistent, indicating that the analysis results have a certain degree of robustness. Hypotheses 1, 1.1, and 1.2 have been verified. The spatial regression coefficients are significantly negative, which contrasts with the sign of the global Moran Index. This is primarily due to the inclusion of additional explanatory variables in the spatial regression analysis. The findings also indicate that as China places greater emphasis on energy conservation and emission reduction, cities have implemented policies to lower carbon emissions. However, due to the absence of overarching design and effective planning, these measures often fail to achieve synergistic effects, resulting in a spatial negative correlation.

Decomposition of Effect

The estimated coefficients of the Spatial Durbin Model may exhibit bias and inadequately capture the influence of independent variables on dependent variables. Therefore, this study employs partial

Table 2. Trends in the global Moran Index of carbon emissions in the three major urban agglomerations.

	Beijing-Tianjin-Hebei		Yangtze River Delta		Pearl River Delta	
Year	Moran'I	P-value	Moran'I	P-value	Moran'I	P-value
2005	0.221*	0.078	0.024***	0.001	0.084***	0.004
2010	0.227*	0.074	0.015***	0.002	0.098***	0.002
2015	0.253*	0.054	0.027***	0.000	0.016***	0.005
2018	0.240*	0.057	0.015***	0.002	0.070***	0.006

Note: *, **, and *** respectively indicate significance at the 10%, 5%, and 1% levels.

differentiation to dissect the impact of relevant independent variables on carbon emissions into direct and indirect effects. The direct effect signifies the influence of heterogeneous population flow, urban innovation, and their integration on local carbon emissions. Meanwhile, the indirect effect indicates the impact on carbon emissions in surrounding cities. The total effect is the combination of the direct and indirect effects. This framework assesses the breakdown of the impact of heterogeneous population flow on carbon emissions within the three major urban agglomerations and the role of urban innovation.

The effect decomposition results are presented in Table 5. Firstly, the direct and indirect effects of high-skilled population flow on carbon emissions in the Yangtze River Delta and Pearl River Delta urban agglomerations are both significantly negative, while the interaction term between highly skilled population mobility and urban innovation is significantly positive. This indicates that an increase in the scale of highly skilled population mobility helps reduce carbon emissions in local and surrounding cities, while mitigating the adverse effects of urban innovation on carbon emissions. However, the interaction between these factors masks the impact of urban innovation on carbon emissions. Secondly, both the direct and indirect impacts of low-skilled population flow on carbon emissions in the Pearl River Delta urban agglomeration are significantly positive, indicating that an increase in the scale of low-skilled labor mobility leads to higher carbon emissions in both local and surrounding cities. Thirdly, the direct and indirect effects of the interaction term between the high-skilled population flow and urban innovation are in the Yangtze River Delta and Pearl River Delta urban agglomerations are both significantly positive, but the indirect effect of this interaction in the Beijing-Tianjin-Hebei urban agglomeration is not significant. This suggests that the integration of high-skilled population mobility and urban innovation in the Yangtze River Delta and Pearl River Delta urban agglomerations masks the independent effect of urban innovation on carbon emissions. Lastly, the indirect effects of high-skilled population mobility on carbon emissions vary significantly across the three urban agglomerations, indicating differing spatial spillover effects. Specifically, the spatial spillover effect of increased high-skilled population mobility on carbon emissions is not significant in the Beijing-Tianjin-Hebei urban agglomeration. In contrast, increased high-skilled population mobility in the Yangtze River Delta and Pearl River Delta urban agglomerations mitigates the adverse impact of urban innovation on carbon emissions in surrounding cities, with a clear spatial spillover effect. Hypotheses 2 and 3 were verified.

Table 3. Model applicability test.

Urban Agglomerations	Beijing-Tianjin-Hebei	Yangtze River Delta	Pearl River Delta
LM-Lag	235.870(0.000)	20.851(0.000)	9.154(0.002)
RLM-Lag	109.848(0.000)	108.343(0.000)	1.753(0.085)
LM-Error	153.159(0.000)	263.784(0.000)	11.907(0.001)
RLM-Error	27.180(0.000)	176.292(0.000)	3.239(0.072)
Wald-Lag	27.840(0.000)	48.880(0.000)	75.980(0.000)
LR-Lag	24.300(0.000)	49.900(0.000)	61.900(0.000)
Wald-Error	20.190(0.005)	56.760(0.000)	56.760(0.000)
LR-Error	35.700(0.000)	57.600(0.000)	63.560(0.000)
Hausman test	150.790(0.000)	414.760(0.0000)	509.660(0.000)

Note: The numbers in parentheses represent p-values.

Table 4. Results of Spatial Measurement of Three Major Urban Agglomerations.

Variable	Beijing-Tianjin-Hebei	Yangtze River Delta	Pearl River Delta
flow-h	-0.001^{***} (-5.540)	-0.010^{***} (-3.130)	-0.005^{***} (-3.580)
flow-l	0.004^{***} (8.770)	0.004^{***} (14.810)	0.001^{***} (4.220)
inno	0.325^{***} (7.820)	-0.017 (-0.760)	0.010 (0.520)
flow-h*inno	0.004^{***} (4.640)	0.006^{***} (4.670)	0.001^{***} (3.590)
flow-l*inno	0.001 (0.410)	-0.001^{***} (-4.690)	0.001^{**} (2.440)
W-flow-h	-0.012 (-0.090)	-0.044 (-1.360)	0.001 (0.240)
W-flow-l	-0.003 (-0.660)	-0.003 (-1.200)	0.004^{***} (3.220)
W-inno	0.273 (1.450)	-0.064 (-0.350)	0.019 (0.440)
W-flow-h*inno	-0.001 (-0.040)	0.033^{***} (2.680)	-0.001 (0.390)
W-flow-l*inno	0.004^{**} (2.230)	-0.006^{***} (-3.750)	-0.001^{*} (-1.880)
Rho	-0.450^{**} (-2.020)	-0.413^{*} (-1.660)	-0.352^{**} (-2.280)
Control Variable	YES	YES	YES
Time Effect	YES	YES	YES
R^2	0.948	0.747	0.747
Obs	182	364	126

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; t-statistics are in parentheses. This convention applies to subsequent tables unless otherwise noted.

Overall, heterogeneous population mobility and urban innovation within the Beijing-Tianjin-Hebei urban agglomeration, as well as the integration of these two factors, have a significant impact on local carbon emissions, but do not affect carbon emissions in surrounding cities. In contrast, the spatial effects of heterogeneous population mobility and urban innovation on carbon emissions in the Yangtze River Delta and Pearl River Delta urban agglomerations are significantly higher than those in the Beijing-Tianjin-Hebei urban agglomeration. The differences in the impact of heterogeneous population mobility and urban innovation on carbon emissions across the three urban agglomerations primarily stem from their distinct regional locations and developmental characteristics. Specifically, the Beijing-Tianjin-Hebei urban agglomeration is a capital-centric urban agglomeration with a stronger administrative character than other urban agglomerations, resulting in less pronounced spatial spillover effects. The Yangtze River Delta urban agglomeration, although spanning multiple provinces, has a higher degree of integration. The Pearl River Delta urban agglomeration is confined within Guangdong Province, making coordination easier. Therefore, the spatial spillover effects of the Yangtze River Delta and Pearl River Delta urban agglomerations are more pronounced.

Robustness Analysis

In order to further verify the reliability of the analysis results, referring to most of the existing studies, two methods of replacing the estimated model with lagged key explanatory variables are used to further conduct robustness analyses, and the test results are shown in Table 6. Firstly, ordinary least squares (OLS) regression is used, and columns (1), (3), and (5) in the table show the re-estimation results using the OLS model. The results show that the sign and significance of the coefficients of the main explanatory variables remain largely consistent with the results of the previous analyses, indicating that the model setting did not affect the reliability of the core findings. Second, potential robustness issues are mitigated by introducing lagged one-period values of the core explanatory variables. Considering the possible lagged effects of population

Table 5. Decomposition of Spatial Effects of Carbon Emissions.

	Beijing-Tianjin-Hebei			Yangtze River Delta			Pearl River Delta		
Variables	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
flow-h	-0.010*** (-5.560)	-0.004 (-0.450)	-0.017* (-1.660)	-0.013*** (-2.940)	-0.028 (-1.190)	-0.038 (-1.500)	-0.005*** (-3.470)	-0.010** (-2.470)	-0.015*** (-2.980)
flow-l	0.004*** (9.670)	-0.003 (-1.380)	0.001 (0.300)	0.005*** (15.330)	-0.004* (-1.900)	0.001 (0.060)	0.001*** (5.580)	0.001*** (2.790)	0.002*** (3.480)
inno	0.325*** (8.760)	0.116 (0.770)	0.441*** (2.610)	-0.013 (-0.650)	-0.028 (-0.190)	-0.043 (-0.280)	0.019 (0.860)	0.112 (1.080)	0.132 (1.120)
flow-h*inno	0.004*** (4.800)	-0.002 (-0.470)	0.002 (0.550)	0.006*** (4.030)	0.022** (2.300)	0.003*** (2.730)	0.002*** (3.280)	0.004** (2.450)	0.006*** (2.810)
flow-l*inno	-0.001 (-0.013)	0.003** (2.090)	0.003* (1.920)	-0.001*** (-4.140)	-0.004*** (-2.870)	-0.005*** (-3.190)	0.006 (1.440)	0.001 (0.460)	0.001 (0.700)

mobility and urban innovation on carbon emissions, the lagged one-period values of the core explanatory variables (L-flow-h, L-flow-l, L-inno, and lagged interaction terms) are introduced for the regression, and the results are shown in columns (2), (4), and (6) of the table. The results of the lagged variable regressions are almost identical to the previous regression findings, further validating the robustness of the core findings.

Endogeneity Analysis

When examining the relationship between heterogeneous population flow and carbon emissions, endogeneity issues such as bidirectional causality and estimation bias may arise. To address this concern, this study employs the instrumental variable approach, specifically the two-stage least squares (2SLS) method, to mitigate endogeneity. Drawing on Tian et al.'s (2025) study [30], this paper selects the "urban unemployment insurance coverage rate" as an instrumental variable for the mobility of the highly skilled population. From the perspective of relevance, high-skilled individuals tend to prioritize long-term benefits such as employment stability and risk protection when selecting a destination. A well-developed unemployment insurance system can therefore enhance a city's appeal to high-skilled migrants. In terms of exogeneity, the unemployment insurance system is not directly influenced by urban carbon emission levels, nor is it directly linked to the mechanisms driving carbon emissions. It is important to note that the chosen instrumental variable is more suitable for high-skilled population flow than for low-skilled flow. This is because high-skilled individuals typically face higher job transition costs, while low-skilled migrants exhibit greater employment mobility, are less sensitive to unemployment insurance, and base their mobility decisions more on immediate job availability. Furthermore, high-skilled migrants are more likely to consider public services and social security offered by the city, whereas low-skilled migrants focus more on short-term income and employment opportunities. Therefore, this study focuses on high-skilled population flow as the endogenous variable.

Table 7 presents the results of the 2SLS estimation. The results of the first stage regression show that the coefficient of the instrumental variable on the mobility of the highly skilled population is significantly positive, verifying the correlation between the instrumental variable and the endogenous variable. The F-value of the first stage is greater than the critical value of 10, indicating no weak instrument variable problem, and the Kleibergen-Paap LM test results are significant, rejecting the original hypothesis of "instrumental variables are not identifiable". The results of the second stage regression show that after controlling for endogeneity, the coefficient of the effect of the mobility of highly skilled people on carbon emissions is significantly negative. This indicates that after eliminating the interference of two-way causality and omitted variables, the mobility of high-skilled people still significantly suppresses carbon emissions, which is consistent with the conclusion of the baseline regression. Meanwhile, the Durbin-Wu-Hausman test results are significant, rejecting the original hypothesis of "no endogeneity", indicating the necessity of the application of the instrumental variables method and the reliability of the processed results.

Conclusions

This paper takes China's three major urban agglomerations as its research object, matching China Migrants Dynamic Survey (CMDS) data with macro urban data, fully considering the heterogeneity of population skills and spatial factors, to explore the impact of changes in the scale of population mobility on carbon emissions in the context of urban innovation. Based on the research results, we propose recommendations from the perspectives of talent optimization, urban innovation, and regional coordinated development to provide a reference for promoting low-carbon development in different urban agglomerations:

Table 6. Robustness test results.

	Beijing-Tianjin-Hebei		Yangtze River Delta		Pearl River Delta	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
flow-h	-0.003* (-3.980)		-0.013*** (-2.630)		-0.007*** (-2.970)	
flow-l	0.011* (7.510)		0.009*** (12.880)		0.003*** (3.320)	
inno	0.401*** (7.230)		-0.025 (-1.040)		0.009* (1.23)	
flow-h*inno	0.009*** (5.100)		0.011*** (5.670)		0.005*** (3.990)	
flow-l*inno	-0.003 (-0.770)		-0.003*** (-5.090)		0.004*** (3.060)	
L-flow-h		-0.001*** (-3.120)		-0.009*** (-2.990)		-0.004*** (-2.32)
L-flow-l		0.003*** (6.990)		0.002*** (10.320)		0.001* (2.980)
L-inno		0.339*** (7.090)		0.011 (-0.780)		0.007 (0.450)
L-(flow-h*inno)		0.002*** (3.880)		0.005*** (3.980)		0.001* (3.020)
L-(flow-l*inno)		0.005 (0.930)		-0.002*** (-3.210)		0.001* (2.120)
Control Variable	YES	YES	YES	YES	YES	YES
Time Effect	YES	YES	YES	YES	YES	YES
R^2	0.894	0.769	0.715	0.698	0.715	0.696
Obs	182	156	364	312	126	108

(1) Optimize Policies for Heterogeneous Population Mobility to Align with Low-Carbon Goals

Given the significant differences in the impact of high-skilled and low-skilled labor mobility on carbon emissions, targeted policies should be developed to guide the rational flow of labor and enhance its synergy with low-carbon development. First, attract and retain high-skilled talent. High-skilled labor mobility can significantly reduce carbon emissions and mitigate the adverse effects of urban innovation on carbon emissions. Policies should focus on removing institutional barriers that hinder high-skilled labor mobility, such as cumbersome household registration restrictions and unequal access to public services (e.g., education,

Table 7. IV-2SLS regression results.

Variables	flow-h	CO_2
	First-stage regression	Second-stage regression
flow-h		-0.022** (0.013)
IV	0.015*** (0.008)	
First-stage F-statistic	19.550(p=0.000)	
Cragg-Donald Wald F test	63.838(>10% critical value)	
Kleibergen-Paap LM test	65.841(p=0.000)	
Durbin-Wu-Hausman test	8.808(p=0.003)	
Obs	672	

Note: Standard errors are in parentheses.

healthcare, social security). Urban agglomeration governments can establish incentive mechanisms, including tax breaks for high-skilled talent, funding for innovative research projects, and housing subsidies, to attract and retain talent. Additionally, creating international talent hubs and fostering cross-city collaboration platforms (such as joint research institutes and innovation zones) can promote the aggregation of high-skilled labor, thereby amplifying its emissions reduction effects. Second, improve the human capital of low-skilled migrant workers. The migration of low-skilled workers increases carbon emissions and has a low degree of integration with urban innovation. In response, policies should prioritize improving the skills of low-skilled migrant workers through vocational training programs and lifelong learning plans. These programs can be tailored to the needs of low-carbon industries (such as renewable energy and energy-efficient manufacturing) to enhance their adaptability to green production. Additionally, promoting inclusive education and skill certification systems can help low-skilled migrant workers better absorb the technological spillovers generated by urban innovation, thereby reducing the carbon intensity of their economic activities.

(2) Guide Urban Innovation toward a Low-Carbon Trajectory

While urban innovation may exacerbate carbon emissions, it can be used to reduce emissions when combined with the mobility of highly skilled populations. Policies should guide urban innovation toward low-carbon development and strengthen the synergistic effects of innovation and heterogeneous labor. First, prioritize support for low-carbon technology research and development. Governments should increase funding for low-carbon technology research and development (such as renewable energy and energy-efficient infrastructure) and establish innovation incentive mechanisms (such as patent protection and subsidies) to encourage enterprises and research institutions to focus on emission reduction technologies. This will help mitigate the potential increase in carbon emissions driven by capital-intensive or energy-consuming sectors. Second, promote the integration of highly skilled labor with innovation entities. To fully leverage the regulatory role of highly skilled migrant populations in offsetting the carbon emissions associated with innovation, collaborative platforms should be established between highly skilled talent, businesses, and academic institutions. For example, inter-city talent exchange programs within urban clusters can enhance knowledge spillovers, ensuring that highly skilled labor effectively participates in and shapes the low-carbon innovation process.

(3) Strengthen Regional Coordination to Amplify the Spatial Spillover Effects of Talent and Innovation

The three major urban agglomerations in China exhibit significant differences in terms of spatial spillover effects, necessitating the formulation of targeted regional coordination strategies. First, administrative barriers within the Beijing-Tianjin-Hebei urban agglomeration should be reduced. The Beijing-Tianjin-Hebei urban agglomeration exhibits relatively weak spatial spillover effects, partly due to strong administrative intervention. Therefore, efforts should be made to break down administrative barriers between regions. A unified coordination mechanism could be established to harmonize emissions reduction policies, standardize emissions monitoring systems, and promote resource sharing (e.g., energy, transportation). This would foster more integrated labor and innovation factor markets, enabling the spillover effects of skilled labor mobility and low-carbon innovation to permeate across cities. Second, deepen the integration of the Yangtze River Delta and Pearl River Delta urban agglomerations. Given the strong spatial spillover effects of the Yangtze River Delta and Pearl River Delta urban agglomerations, regional integration should be further deepened to amplify low-carbon synergies. This includes coordinating carbon pricing mechanisms, establishing cross-city carbon trading markets, and coordinating industrial relocation. For example, joint investment in cross-city green infrastructure construction can promote the flow of highly skilled labor and low-carbon technologies, enhancing the positive spillover effects of talent inflow and innovation on emissions reduction.

Nevertheless, there are still some deficiencies in the text, and it is expected that they can be further improved in future research. On the one hand, the measurement of heterogeneous population mobility indicators needs to be further precise. The measurement of the scale of population mobility at the urban level in China lacks annual statistical data. The indirect measurement method adopted in this paper is bound to have certain errors. Future research is expected to build relevant empirical models based on more accurate annual statistical data and calculation methods, accurately analyze the impact of heterogeneous population mobility on carbon emissions in urban agglomerations against the background of urban innovation, and put forward more targeted suggestions for giving full play to the mutual spatial role among urban agglomerations to promote low-carbon development. On the other hand, this paper only explores the relationship between population mobility, urban innovation, and carbon emissions. However, there are still other mechanisms and factors that play important roles in this process beyond urban innovation. Future research needs to incorporate more factors for analysis and capture multi-dimensional paths to reduce carbon emissions in urban agglomerations while improving the existing theoretical framework.

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Conflict of Interest

The authors declare no conflict of interest.

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