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О. Экономическое развитие, инновации, технологические изменения и рост
O. Economic Development, Innovation, Technological Change, and Growth

ПРОСТРАНСТВЕННО-ВРЕМЕННОЙ АНАЛИЗ ВЗАИМОСВЯЗИ МЕЖПРОВИНЦИАЛЬНОЙ МИГРАЦИИ И ЭКОНОМИЧЕСКОГО РАЗВИТИЯ КИТАЯ: ДАННЫЕ БИВАРИАЦИОННОГО АВТОКОРРЕЛЯЦИОННОГО ИССЛЕДОВАНИЯ (2000–2024)

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Аннотация. Хотя межрегиональная миграция является ключевым фактором развития региональных экономик Китая, существующие исследования часто пренебрегают ее динамической пространственной зависимостью. В данном исследовании количественно оценивается пространственно-временная взаимозависимость между межрегиональной миграцией и экономическим развитием в 31 провинции Китая в 2000–2024 гг. Посредством использования двумерного пространственного авторегрессионного анализа (глобальный индекс Морана и локальный индекс пространственной автокорреляции LISA) данных провинциального уровня Национального бюро статистики Китая характеризуется влияние миграции на модели роста валового регионального продукта. Результаты анализа позволяют выявить три этапа эволюции региональной агломерации: 1) начальная стадия крайней концентрации экономической активности и миграционных потоков в восточных прибрежных регионах (2000–2009); 2) фаза их частичной перебалансировки в сторону западных провинций (2010–2019); 3) завершающий этап политически обусловленного многополюсного перераспределения (2020–2024). Также обнаруживаются различные пространственные режимы, характеризующиеся отрицательной автокорреляцией в период децентрализации (2005–2014) и появлением кластеров в новых агломерационных узлах (2015–2019).

Ключевые слова: миграция населения; экономическое развитие; пространственный анализ; региональная агломерация; индекс Морана; LISA; Китай.

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SPATIAL-TEMPORAL ANALYSIS OF THE RELATIONSHIP BETWEEN INTERPROVINCIAL MIGRATION AND ECONOMIC DEVELOPMENT IN CHINA: DATA FROM A BIVARIATIVE AUTOCORRELATION STUDY (2000–2024)

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Abstract. Although interregional migration is a key factor in the development of China's regional economies, existing studies often neglect its dynamic spatial dependence. This study quantitatively assesses the spatiotemporal relationship between interregional migration and economic development in 31 provinces of China from 2000 to 2024. By using bivariate spatial autoregressive analysis (global Moran's I and local spatial autocorrelation index (LISA)) on provincial-level data from the National Bureau of Statistics of China, the impact of migration on GRP growth patterns is characterised. The results of the analysis allow us to identify three stages of regional agglomeration evolution: 1) the initial stage of extreme concentration of economic activity and migration flows in the eastern coastal regions (2000–2009); 2) the phase of their partial rebalancing towards the western provinces (2010–2019); 3) the final stage of policy-induced multipolar redistribution (2020–2024). Different spatial regimes are also found, characterised by negative autocorrelation during the period of decentralisation (2005–2014) and the emergence of clusters in new agglomeration hubs (2015–2019).

Keywords: population migration; economic development; spatial analysis; regional agglomeration; Moran's I; LISA; China.

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Introduction

China's transformation into a «migratory nation» (with 376 mln migrants, according to the 2020 census[1]) fundamentally reshapes regional economies. Yet, the spatially heterogeneous feedback between migration and GRP growth remains inadequately quantified, particularly under evolving policy regimes. While E. S. Lee's push-pull model [1] and P. Krugman's core-periphery theory [2] frame migration drivers, prior studies neglect dynamic spatial interdependencies in rigorous econometric analysis. K. W. Chan [3] and C. C. Fan [4] document migration trends but lack granular analysis of provincial clustering patterns (e. g., high-high (HH) and low-low (LL) traps). L. Anselin's spatial association framework [5] remains underutilised in this context.

The purpose of this work is to investigate the causal reciprocity between net migration and GRP growth across 31 provinces in China (2000–2024). To achieve this goal, we will map migration's spatial evolution using net inflow data; quantify migration – GRP interdependence via bivariate Moran's I and LISA clustering.

Theoretical framework of linking migration, economic geography, and spatial interdependence

Population migration patterns in post-reform China are fundamentally shaped by the push-pull dynamics formalised by E. S. Lee (1966) [1], where interregional disparities create distinct origin «push» factors (e. g., limited rural livelihoods, underdeveloped infrastructure) and destination «pull» forces (urban job opportunities, higher wages). Eastern coastal regions emerged as dominant migration magnets through comparative advantages in globalised manufacturing [3], while central and western provinces experienced accelerated labour outflows due to agricultural marginalisation and industrial stagnation [4]. This selective migration intensified regional inequalities, as human capital depletion in sending regions (particularly Northeast China's rust belt) reduced productivity growth potential, establishing a self-reinforcing cycle of divergence [6].

The resultant economic geography aligns with P. Krugman's core-periphery model (1991) [2], where decreasing transport costs and scale economies trigger circular causation: initial coastal industrialisation attracted migrant labour pools, which further boosted agglomeration economies in manufacturing clusters. This explains

[1]Press conference on the main data results of the seventh national population census and answers to reporters' questions // National Bureau of Statistics of China : website. URL: https://www.stats.gov.cn/xxgk/jd/sjjd2020/202105/t20210511_1817280.html (date of access: 07.10.2025) (in Chin.).

the emergence of Yangtze River delta as «core» regions with cumulative GDP growth exceeding interior «peripheries» by 4.2 % annually (2000–2020). However, recent dispersion trends, including rising return migration to central provinces since 2015, reflect modified core – periphery dynamics where policy interventions (e. g., strategy «Rise of Central China») create secondary growth poles through infrastructure investment and industrial relocation.

Critically, these processes exhibit inherent spatial dependence, as migration decisions and economic outcomes in one province influence neighbouring regions through: labour market spillovers (proximity to high-wage zones alters local opportunity costs) [7]; and policy emulation where regional development strategies diffuse geographically. L. Anselin's (1995) spatial econometrics framework formalises these interdependencies, necessitating methods like local indicators of spatial association (LISA) clustering to detect [5] HH traps (high in-migration, or high growth, e. g. urban agglomeration of Yangtze River Delta and Pearl River Delta); LL traps (depopulation, or low growth, e. g. Northeast provinces); spatial outliers (e. g., resource-rich but isolated western regions as low-high (LH) zone before 2015) [8].

This tripartite theoretical integration explains why migration-economic correlations manifest as statistically significant spatial regimes (as identified in this work 2005–2019 LISA results), while non-significance in transitional periods (2000–2004; 2020–2024) reflects institutional shocks (World Trade Organization accession, pandemic disruptions) temporarily overriding structural forces. Furthermore, the concept of market potential from new economic geography [2; 7] helps explain the synergistic effects within major urban agglomerations. Regions like the Yangtze River delta or the Chengdu-Chongqing Economic Circle not only possess inherent advantages but also create self-reinforcing cycles by offering vast integrated markets, which attract both labour and capital, further amplifying their economic potential and spatial clustering effects.

Methodological note on spatial weights and model selection

For this study, a first-order queen contiguity weight matrix was primarily employed, defining neighbours as provinces sharing a common border or vertex. This choice is grounded in the assumption that migration and economic spillovers are most immediate between adjacent territories [5; 9]. While alternative matrices (e. g., based on economic distance or inverse squared geographical distance) were tested in preliminary analyses, the queen contiguity matrix provided the most consistent and interpretable results for identifying broad regional clusters, which is the primary aim of this exploratory spatial data analysis. We acknowledge that a more complex model, such as the spatial Durbin model (SDM), could better distinguish direct effects from spatial spillovers and control for variables like foreign direct investment or infrastructure. However, the core objective of this paper is to establish and visualise the fundamental spatial interdependence between migration and GRP growth using bivariate Moran's I, which provides an intuitive foundation for future SDM-based causal inference. The decision to forego control variables at this stage was to maintain clarity in isolating the primary bivariate relationship.

Spatial evolution patterns of population migration in China

Regional dynamics and provincial heterogeneity (2000–2024). The provincial net inflow data reveal distinct regional divergence and temporal shifts in migration patterns. Eastern provinces dominated migration attraction initially, with Guangdong, Zhejiang, and Shanghai collectively absorbing 40–60 % of national inflows during 2000–2014 (peaking at 10.1 mln persons in Guangdong, 2010–2014). However, after 2015, eastern dominance waned: Guangdong's inflow plummeted from 10.1 mln persons (2010–2014) to 395.0 thds persons (2020–2024), while Shanghai and Beijing turned negative (–170 thds persons and –164 thds persons in 2015–2019). Conversely, central and western regions transitioned from net outflows to selective inflows. Anhui shifted from –3.36 mln persons (2010–2014) to +539 thds persons (2020–2024), and Sichuan reversed from –6.19 mln persons (2000–2004) to +1.1 mln persons (2020–2024). The northeast experienced severe depletion, with Heilongjiang's outflow intensifying from –2.42 mln persons (2010–2014) to –1.4 mln persons (2020–2024). This divergence underscores three distinct phases (fig. 1):

1) eastern hyper-concentration (2000–2009). Massive inflows (> 2 mln persons) into coastal provinces, notably Guangdong, Shanghai, Beijing, Zhejiang, Jiangsu, and Tianjin;

2) rebalancing with western Gains (2010–2019). Emergence of net inflows in western provinces including Xinjiang, Chongqing, Shaanxi, Ningxia, Tibet, and Guizhou;

3) multi-polar redistribution (2020–2024). Policy-driven reversals in central provinces (e. g., Shanxi, Hubei, Hunan) amid eastern saturation. This phase was significantly influenced by the short-term impacts of China's dynamic zero-COVID policy, which imposed strict mobility restrictions, disrupting traditional migration patterns and temporarily decoupling the migration – GRP relationship.

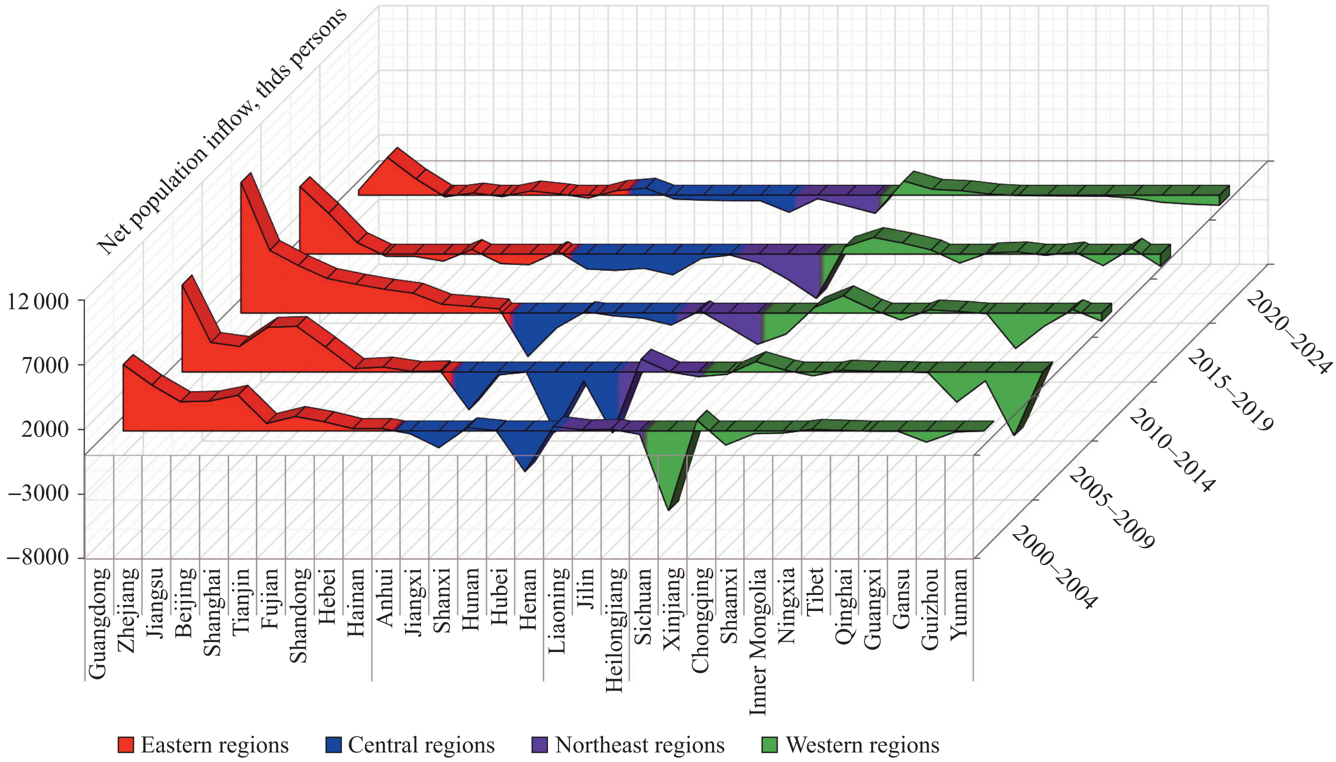

Fig. 1. Net population inflow by province 2000–2024 (calculated and presented in graphical form based on data from National Bureau of Statistics of China (NBS))

The 21st century marks China's transition from a low-mobility «rural society» to a «migratory nation». According to the seventh national census data[2], there were 376 mln migrants in 2020, among them, the inter-provincial migrant population is 125 mln. This migration phenomenon is characterised by three evolutionary dimensions:

1) scale evolution. Migration surged until 2010 (with an annual growth rate of 8.5 % between 2005 and 2010), then slowed (2.17 % from 2010 to 2015) and declined (−0.83 % from 2015 to 2019). This trend reflects urban saturation and rising living costs in eastern hubs, alongside industrial relocation to central and western provinces (e. g., base of company *Foxconn* in Zhengzhou).

2) directional pluralisation. While coastal clusters (the Yangtze River delta, the Pearl River delta, and the Beijing-Tianjin Region) absorbed over 60 % of inflows before 2010, post-2010 witnessed inland urbanisation (The Sichuan-Chongqing Region saw a net inflow surge to 1.45 mln between 2020 and 2024, driven by policies «Western Development»); interior hubs (central provinces (e. g., Hubei, Hunan) reduced population losses through initiatives «Rise of Central China»); return migration (Anhui shifted from a net outflow (−3.36 mln between 2010 and 2014) to an inflow (+0.54 mln between 2020 and 2024) as manufacturing relocated (fig. 1)).

3) structural transformation. Migration has diversified beyond rural-urban flows (city-to-city mobility rose to 37.9 % of total flows, linked to high-skilled labour chasing jobs in tech and finance); demographic upgrading (college-educated migrants increased from 3.2 % (2000) to 13.3 % (2020), notably in Zhejiang and Guangdong); household migration (family relocations (involving ≥ 3 members) exceeded 53.5 %, raising demands for the integration of urban welfare systems. This structural upgrading towards more skilled and stable migration flows likely contributes to higher productivity and economic growth in destination regions [7], a dimension that merits further quantitative analysis.

The author believes that spatial clustering and «Hu Huanyong line» resilience. Migration networks reinforced the «Hu Huanyong line» (southeast – 93.8 % population; northwest – 6.2 %[3]). Coastal clusters exhibited intensified agglomeration (e. g., Yangtze River delta urban agglomeration), while western nodes (Chengdu, Xi'an) emerged as secondary poles. Despite inland gains, the southeast's share of inflows remained > 75 % (2020), confirming the line's stability as an economic-geographic anchor [10; 11].

[2]Main data of the seventh national population census // National Bureau of Statistics of China : website. URL: https://www.stats.gov.cn/english/PressRelease/202105/t20210510_1817185.html (date of access: 15.07.2025).

[3]Heihe – Tengchong line [Electronic resource] // Wikipedia. URL: https://ru.wikipedia.org/wiki/Линия_Хэйхэ_—_Тэнчун (date of access: 12.10.2025) (in Russ.).

Interactive effects between population migration and regional economic development

The first law of geography proposed by the renowned Swiss-born American geographer W. R. Tobler states: «Everything is related to everything else, but near things are more related than distant things» [11, p. 236]. Applying this principle to regional economic issues highlights those economic activities within regions, cities, and other socioeconomic systems are fundamentally interconnected, not spatially isolated. Moreover, these spatial connections diminish as the distance between regions and cities increases.

In studies examining spatial autocorrelation, common statistical indicators include Moran's I, Geary's C, and the Getis – Ord Gi statistic. This paper specifically investigates the impact of interregional population migration on regional economic development in China since the 21st century, focusing on the interactive effects between these phenomena. To analyse this interaction spatially, we utilise the net population inflow rate (x) for regions and its GRP growth rate (y) as our key variables. Consequently, the bivariate global Moran's I and bivariate local Moran's I (LISA) statistics are selected as the primary analytical tools to reveal the spatial interdependencies between population migration patterns and regional economic growth. We can draw from the classic work on bivariate spatial autocorrelation by L. Anselin and S. I. Lee et al. The global bivariate spatial autocorrelation formula is as follows:

$$\text{Moran's I}_{x,\,y} = \frac{n\sum_i \sum_j \omega_{ij}\left(x_i - \bar{x}\right)\left(y_j - \bar{y}\right)}{S_0\sqrt{\sum_i \left(x_i - \bar{x}\right)^2}\sqrt{\sum_i \left(y_i - \bar{y}\right)^2}}, \qquad (1)$$

where x_i – net population inflow rate of region i; y_i – GRP growth rate of region i; x_j – net population inflow rate of region j; y_j – GRP growth rate of region j; $\bar{x}$, $\bar{y}$ – mean (average) values of x and y respectively; n – number of regions (n = 31 in this work); ω_{ij} – spatial weight between region i and j; S_0 – aggregate of all the spatial weights, $S_0 = \sum_i \sum_j \omega_{ij}$ [9, 13–15].

The geographic data for this research come from the National Geographic Information Center's website[4]; the economic data are obtained from the NBS[5]. It is important to note that the NBS provides two distinct calculation methods for the net population inflow indicator.

1. Net inflow is calculated as the difference between the permanent resident population and the registered (hukou) population. The permanent resident population includes individuals who continuously reside in a specific area for over six months (regardless of local registration status, encompassing both locals and migrants). The registered population includes citizens with official household registration in that specific locality according to their resident identity card[6].

2. Net inflow is equal to the difference between permanent resident population and the natural population growth. While natural population growth is defined as births minus deaths.

However, the registered population data used in method 1 relies primarily on the decennial national census. This makes method 1 unsuitable for generating continuously accessible data for the period 2000–2024. In contrast, all the component indicators required for method 2 (permanent resident population, births, deaths) are readily available annually on the NBS official website. Therefore, the author has chosen to utilise the calculation method 2 for this study.

After completing all preparatory work, calculations using formula (1) were performed via the software *GeoDa*, and the results of the bivariate global Moran's I are presented in table. Generally, the global Moran's I ranges from –1 to 1. Statistical significance is determined when the z-score or p-value meets the criteria[7] ($p < 0.05$ or $|z| > 1.96$).

1. $I > E(I)$. Positive spatial association between the province's (region's) variable x (net population inflow rate) and the variable y (GRP growth rate) in its neighbouring provinces (regions). This suggests spatial synergy or clustering of similar values.

2. $I < E(I)$. Negative spatial association between the province's (region's) variable x and variable y in its neighbouring provinces (regions). This suggests spatial mismatch or dissimilarity.

3. $I = E(I)$. This suggests spatial randomness. There is no discernible spatial pattern in the relationship between the local value of x and the neighbouring values of y.

[4]National catalogue service for geographic information // National Catalogue Service For Geographic Information : website. URL: https://www.webmap.cn/commres.do?method=dataDownload (date of access: 18.07.2025) (in Chin.).

[5]National accounts_Gross Regional Product // National Bureau of Statistics of China : website. URL: https://data.stats.gov.cn/english/easyquery.htm?cn=E0103 (date of access: 15.07.2025).

[6]Major figures on 2020 population census of China // Ibid. URL: https://www.stats.gov.cn/sj/pcsj/rkpc/d7c/202303/P020230301403217959330.pdf (date of access: 15.07.2025) (in Chin.).

[7]How spatial autocorrelation (Global Moran's I) works [Electronic resource] // Esri. URL: https://desktop.arcgis.com/zh-cn/arcmap/10.3/tools/spatial-statistics-toolbox/h-how-spatial-autocorrelation-moran-s-i-spatial-st.htm (date of access: 15.07.2025) (in Chin.).

Table reveals significant spatial dynamics in the relationship between provincial net migration and GRP growth across China from 2000 to 2024. The Moran's I values fluctuate markedly between periods, with three statistically significant outcomes (2005–2009, 2010–2014, and 2015–2019) and two non-significant results (2000–2004 and 2020–2024).

The strong negative autocorrelation ($I = -0.253$, $p = 0.010$) in 2005–2009 suggests economic decentralisation, possibly linked to China's policy «Go West» that incentivised investment in inland provinces, dispersing growth away from coastal hubs. Conversely, the highly positive autocorrelation ($I = 0.420$, $p = 0.001$) during 2015–2019 indicates intensified clustering of growth and migration in developed regions, aligning with initiatives like the Pearl River delta urban agglomeration that amplified regional polarisation. The shift to non-significance in 2020–2024 ($I = -0.013$, $p = 0.488$) likely reflects pandemic disruptions. COVID-19 restrictions impeded labour mobility, weakening migration – GRP linkages, while stimulus policies temporarily boosted lagging regions.

Results of the bivariate global Moran's I values for 2000–2024

Variables	Period				
	2000–2004	2005–2009	2010–2014	2015–2019	2020–2024
Observations	31	31	31	31	31
$E(I)$	−0.033	−0.033	−0.033	−0.033	−0.033
Mean	−0.012	0.010	0.003	−0.021	−0.013
SD	0.096	0.095	0.096	0.099	0.093
z-Score	1.337	–2.759	–1.832	4.461	0.003
Moran's I	0.116	−0.253	−0.173	0.420	−0.013
p-Value	0.095	0.010**	0.031*	0.001***	0.488

N o t e s: 1. Symbols ***, **, * denote significance at the 1, 5, and 10 % levels, respectively. 2. In cases period 2010–2014 where $p < 0.05$ but $|z| < 1.96$, software *GeoDa*'s *z*-score is empirically derived (based on permutation standard deviation), not theoretical. 3. Observations do not include Hong Kong, Macau, and Taiwan.

To comprehensively identify which provinces (regions) exhibit significant spatial dependence between net population inflow and economic development, the bivariate local Moran's I should be applied. Its calculation formula is as follows:

$$\text{Moran's } \mathrm{I}_{i(x,\, y)} = \frac{x_i - \bar{x}}{S^2} \sum\nolimits_j \omega_{ij} \left(y_j - \bar{y} \right),$$

where $S^2 = \frac{1}{n-1} \sqrt{\sum\nolimits_i \left(x_i - \bar{x} \right)^2} \sqrt{\sum\nolimits_i \left(y_i - \bar{y} \right)^2}$; the notations for the remaining mathematical symbols are the same as in formula (1) [9; 13–15].

Based on the aforementioned research findings, we selected data from three periods (2005–2009, 2010–2014, and 2015–2019). Using software *GeoDa*, we then repeated the calculation of the local Moran's I to analyse the relationship between provincial net population inflow rates and GRP growth rates. Furthermore, to provide a clearer interpretation of the results, the authors utilised software *QGIS* to generate significance maps and cluster maps for China's provinces based on this bivariate indicator (fig. 2).

While cluster maps typically categorise spatial patterns into four distinct types.

1. HH cluster. The region exhibits a high *x*-value (net population inflow rate), and its neighbouring regions also show high *y*-values (GRP growth rate), indicating a synergistic cluster of high population attraction and strong economic growth.

2. LL cluster. The region has a low *x*-value, and its neighbouring regions also display low *y*-values, indicating a cluster of low population attraction and sluggish economic growth.

3. LH cluster. The region shows a low *x*-value, but its neighbouring regions have high *y*-values, indicating a potential outflow area where population is drawn towards neighbouring economically vibrant regions.

4. High-low (HL) cluster. The region presents a high *x*-value, but its neighbouring regions show low *y*-values, which would indicate an anomaly where population inflow occurs despite relatively poor economic conditions in the surrounding areas. Notably, this HL cluster pattern was not observed in this study.

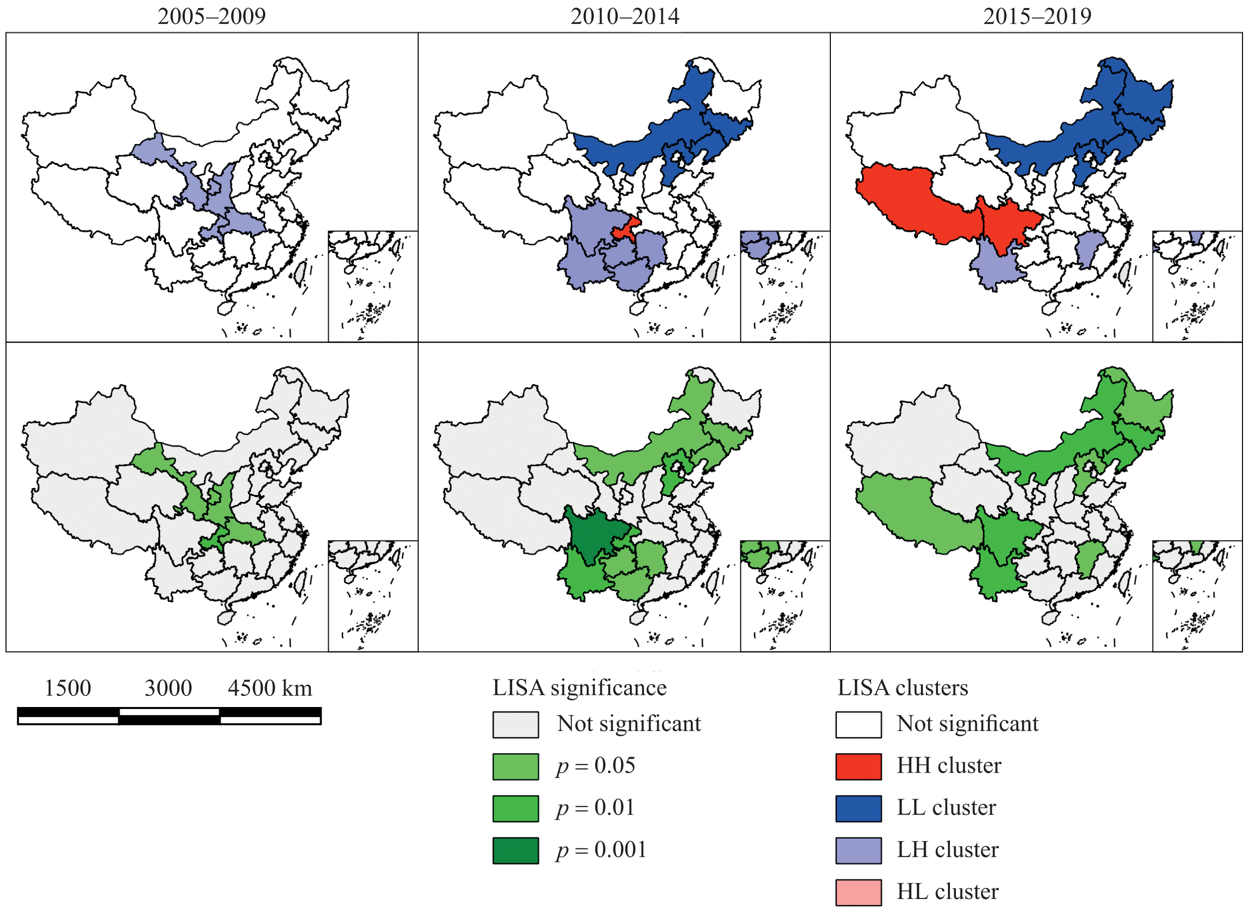

Fig. 2. Bivariate LISA cluster map and significance map of net population inflow rate and GRP growth rate (calculated and presented in graphical form using formula (2))

Based on the bivariate LISA cluster analysis presented in fig. 2, three key spatial regimes emerge across 2005–2019. During 2005–2009, significant LH clusters dominated (e. g., Hubei, Shaanxi, Chongqing, Gansu), indicating provinces with net population outflows surrounded by high-growth neighbours, reflecting labour suction toward coastal hubs under classic core-periphery dynamics. By 2010–2014, this pattern fragmented: western provinces like Sichuan and Yunnan persisted as LH zones, while inland hubs like Chongqing transitioned to HH status ($LISA\_I = 0.626$, $p = 0.004$), signaling synergistic migration-driven growth. The 2015–2019 phase reveals intensified polarisation: northeast provinces (Heilongjiang, Jilin, Liaoning) solidified as LL traps (Heilongjiang: $LISA\_I = 4.299$, $p = 0.012$), whereas interior nodes like Sichuan (HH status, $p = 0.010$) and Tibet (HH status, $p = 0.024$) emerged as secondary growth poles. Crucially, traditional magnets (Guangdong, Zhejiang, Shanghai) showed no significant clustering despite high migration volumes, suggesting saturation effects diluted their spatial synergy.

The author believes that, these shifts underscore two divergent forces. First, policy recalibration (e. g., policy «Rise of Central China») enabled migration-led convergence in select interior provinces, breaking path dependency. Second, structural constraints deepened territorial traps in the Rust Belt, where outflows amplified economic decline. The absence of HL clusters confirms migration remains economically selective, inflows rarely target low-growth peripheries. This bifurcation highlights the limitations of agglomeration-centric policies; regions without preexisting advantages (e. g., human capital, infrastructure) failed to convert return migration into sustainable growth, perpetuating spatial inequality despite dispersion trends.

Conclusions

This study demonstrates that interregional migration in 21^{st} century China has dynamically reshaped economic geography through spatially heterogeneous feedback loops. Theoretically, migration patterns evolved from Lee's push-pull mechanics toward Krugman-esque core-periphery dynamics, later disrupted by policy-induced secondary agglomerations. Empirically, three phases emerged: hyper-concentration in eastern hubs (2000–2009), partial rebalancing toward western regions (2010–2019), and multi-polar redistribution (2020–2024).

Spatial econometrics revealed non-linear migration – GRP interdependencies: significant negative autocorrelation (2005–2009) signaled decentralisation during «Go West» industrialisation, while strong positive clustering (2015–2019) marked reinvigorated agglomeration in advanced regions.

Crucially, local analysis (LISA) identified divergent provincial trajectories, HH clusters in Sichuan and Tibet versus entrenched LL traps in the northeast, underscoring that migration alone cannot resolve regional disparities without complementary investments in human capital and institutional quality. The pandemic-induced non-significance (2020–2024) further exposes the fragility of migration-dependent growth models. These findings necessitate spatially differentiated policies: fostering synergies in emerging hubs while addressing cumulative disadvantages in lagging regions through targeted innovation ecosystems and welfare integration. These findings necessitate spatially differentiated policies. For emerging HH clusters (e. g., Sichuan, Tibet), policy should focus on strengthening industrial chain collaboration and improving agglomeration efficiency to prevent congestion costs. This aligns with national strategies like the New Urbanization Plan (2021–2035), emphasising the development of county-level urbanisation as secondary nodes. For entrenched LL traps (e. g., Northeast China), policies must address cumulative disadvantages through targeted investments in human capital, innovation ecosystems, and welfare integration to break the cycle of out-migration and economic decline. The discussion on the political economy of space by Chinese scholars highlights that regional coordination requires not just market forces but also strategic central government intervention to manage these spatial inequalities effectively.

This study has several limitations. First, the data for 2020–2024 were anomalous due to the COVID-19 pandemic and related containment policies, which may obscure longer-term trends. Second, the methodological approach, while robust for identifying spatial associations, does not fully address endogeneity issues. For instance, the possibility of reverse causality, where economic growth itself attracts migration, requires further investigation using models capable of stronger causal inference. Third, the provincial-level analysis may mask heterogeneity within provinces, and the conclusions might not be directly applicable to small and medium-sized cities. Future research should incorporate more granular data, control variables, and spatial econometric models like the SDM to better isolate causal mechanisms and spillover effects.

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