Received: 5 March 2022 | Accepted: 27 January 2023

DOI: 10.1002/psp.2649

RESEARCH ARTICLE

WILEY

Detecting spatial heterogeneity in the determinants of intercity migration in China

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Abstract

Spatial variations exist in migration patterns and the processes causing the observed patterns. Yet, far less attention has been given to the latter. Even if a few studies have engaged in spatial heterogeneity in the process of migration, the scale multiplicity is not emphasised. This research aims to address these gaps with evidence from Chinese cities. To facilitate international comparisons, we use data on intercity migration over a 5-year interval instead of the floating population. Following an elaboration of highly imbalanced migration patterns at the city scale, we detect spatial heterogeneity in the processes underlying these patterns based on 17 potential determinants in four domains (namely labour market conditions, site-specific amenities, agglomerative effects, and institutional dividends) by multiscale geographically weighted regression. The results indicate that cities' attractiveness to migrants depends on a broad spectrum of factors whose influences are location-dependent and exhibit specific patterns, including east–west, south–north, and southwest–northeast gradient patterns, as well as discrete clustered and concentric patterns. The diagnostic analysis has confirmed that the provenance of spatial-varying effects is irrelevant to the nonlinearity. These effects are also scale-sensitive, showing that the influencing scales of the labour market status and agglomeration factors tend to be larger (i.e., their effects are spatially stationary) than those relevant to amenities and policies, which vary considerably (i.e., the impacts of some factors change significantly over space). These findings regarding spatial heterogeneity deepen our understanding of migration in China and highlight the fact that there is no 'one size fits all' approach for government policies designed to attract migrants.

KEYWORDS

China, intercity migration, migration pattern, multiscale geographically weighted regression, scale multiplicity, spatial heterogeneity

1 | INTRODUCTION

Geographical patterns of migration and the mechanisms underlying them are critical research topics in population geography (Yu et al., 2020). One prominent feature of migration is spatial variation. It is not only migration patterns that vary spatially. The processes, that is, the mechanisms underlying observed migration distributions (Fotheringham & Sachdeva, 2022a), can also vary over space, meaning that the factors that attract migrants vary according to location. These spatial variations are called 'spatial heterogeneity' or 'nonstationarity' (Fotheringham et al., 2002). It is caused by the goal-oriented nature of migratory behaviour, that is, the fact that people migrate from one place to another to achieve certain goals and are therefore influenced differently by the same factors (Rijnks et al., 2018). From a geographical perspective, a lack of spatial uniformity is the result of large-scale regional effects or administrative subdivisions that delineate the reach of some processes (Páez & Scott, 2004). Such nuances make it a challenge to disentangle the effects of various factors on migration decision-making.

Various models have been proposed to investigate the determinants of migration flows. Of these, the gravity-type spatial interaction model has been applied most extensively (Wang et al., 2022). Other models have also been developed based on different conceptualisations of migration decision-making processes, such as random utility models (Rowe et al., 2022). These approaches have been successful in revealing the mechanisms driving migration behaviours. However, they fall short in their lack of capability to incorporate the geographical context, as their underlying assumption is that the effects of the determinants of migration do not change across space.

Scale is a crucial concept when examining population migration from a spatial perspective. Observed migration patterns are sensitive to the scale of the spatial units used for analysis (e.g., province, city and county). The concept also refers to the spatial scale over which the conditional process connecting a change in x to a change in y is relatively stable (Fotheringham & Sachdeva, 2022a). This is unobservable directly and must be inferred. Different processes involve varying spatial scales, that is, some are constant over space while others vary spatially (Fotheringham et al., 2017). A small number of studies have focused on spatial heterogeneity in migration processes (Rijnks et al., 2018; Royuela et al., 2010; Szymanowski & Latocha, 2021; Wang et al., 2019); however, those analyses neglected the possibility of scale multiplicity across factors.

This study uses China as a case study for the detection of spatial heterogeneity in the process of intercity migration. China is an ideal case study for this phenomenon because of its rapid urbanisation and the geographical diversity of its cities. We build on the literature in three ways. First, we contend that a 'one-size-fits-all' mentality is not the best way to understand the determinants of migration patterns. Global statistics based on the conventional gravity-type model cannot adequately represent relationships that are spatially nonstationary, and in fact, doing this may even be misleading at local levels. Our findings, for example, suggest that air quality has different effects on cities' attractiveness to migrants in different parts of China. We also use the diagnostic analysis suggested by Sachdeva et al. (2021) to avoid the possibility of model misspecification and confirm that the location-dependent parameter estimates are due to spatial heterogeneity rather than nonlinearity. Demonstrating the spatial nonstationarity that underpins attractiveness to migrants helps to provide a scientific basis for region-specific policymaking. A place-based approach to regional development policy, and in particular population changes, may be the most suitable moving forward (Rijnks et al., 2018).

Second, we consider scale multiplicity to avoid the local effects of spatial processes being exaggerated. The multiscale geographically weighted regression (MGWR) can simultaneously capture spatial heterogeneity and homogeneity. Our results indicate that destination attributes relating to amenities and policies tend to exert influences at different spatial scales while the effects of economic factors are relatively spatial-stationary. This means that ignoring spatial heterogeneity, and in particular scale multiplicity, may cause severe estimation bias, given the rising importance of amenities in migration decisions.

Finally, this study extends existing work on Chinese migration by adopting a finer spatial scale. Migrants are a major force in China's economic growth (Wu et al., 2019), with the intercity migrant population accounting for 9.01% of China's workforce in 2015. Because of China's declining natural population growth, Chinese cities must 'fight' for a continuous population influx to maintain their success (Wang et al., 2022). Previous investigations of Chinese migration have largely focused on the provincial scale (Mu et al., 2021). Examining migration at the city scale allows for a more comprehensive understanding of China's migratory patterns and the mechanisms underlying them, yielding more nuanced implications for policymaking. We also facilitate international comparisons by defining intercity migrants based on a widely used measure in migration research worldwide: migration over a 5-year interval, rather than the floating population based on *hukou* status that has been applied in previous studies (Su et al., 2018; Wu et al., 2019). This makes our findings regarding spatial heterogeneity in migration more comparable to those of other countries.

Against the above background, we focus on two lines of enquiry: (i) the spatial patterns of intercity migration in China and (ii) the spatial-varying processes that produce these patterns and the scale of the effect of each determinant in a specific domain via MWGR. We begin with a review of the relevant literature (Section 2), followed by a description of the research methodology (Section 3). In Section 4, we describe our discoveries regarding spatial patterns of intercity migration in China, while Section 5 covers the model comparison and diagnostic analysis. Section 6 presents our results showing spatial heterogeneity in the migration processes. Section 7 outlines our conclusions.

2 | LITERATURE REVIEW

2.1 | Determinants of migration

The study of migration processes has a long history, with several different streams of research aiming to elucidate the origins and extent of population migration and the mechanisms underlying it (Wang et al., 2019). The neoclassical model, which is typically regarded as a disequilibrium perspective, views migration as a response to regional differentials in job opportunities (Rodríguez-Pose & Ketterer, 2012; Scott, 2010). In this view, migrants tend to move from low-wage areas with labour surpluses towards high-wage areas with labour shortages (Whisler et al., 2008). In contrast, the equilibrium model suggests that migration is driven by more than just economic opportunities. Location-specific amenities can compensate for less desirable economic factors, and people are willing to relocate to places with low salaries but abundant amenities (Nelson & Ehrenfeucht, 2020). This line of research dates back to the late 1970s, when the term 'amenities' initially referred to the climate. Graves's (1979) study unveiled the role of temperature and humidity in US migration patterns. For the purposes of public policy, the concept of amenities has since been expanded to include recreational facilities, quality of social life (e.g., tolerance and openness), and social networks (Scott, 2010; Whisler et al., 2008).

However, there has been vigorous debate about the relative importance of economy-related versus amenity-related factors in migration choices (Buch et al., 2014; Nelson & Ehrenfeucht, 2020). The inconsistency in results is believed to be caused by differences in the intrinsic features of countries (Lee & Kim, 2019). For example, Ferguson et al. (2007) suggested that amenity-driven migration was less common in Canada than in the United States. Similarly, amenities have been shown to be mostly of secondary concern, after career prospects, for skilled Chinese interprovincial migrants (Y. Liu & Shen, 2014). People's priorities in this 'either-or' choice are also heterogenous across life-course stages and educational levels (Niedomysl, 2008). For example, some researchers have argued that people who are about to retire respond more to amenities than their younger counterparts (Ferguson et al., 2007; Scott, 2010). Buch et al. (2017) argued that for skilled migrants, cultural amenities such as tolerance and openness are a priority.

2.2 | Research on migration in China

China has seen unprecedented large-scale rural-to-urban and interregional migration since the late 1970s, attracting heightened interest in its spatial patterns and their underlying determinants (Shen, 2012). In interpretations rooted in the neoclassical approach, Chinese internal migration has typically been deemed the result of an imbalance in regional development between the coast and inland, as well as between urban and rural areas (Y. Liu & Shen, 2014). Amenities such as climate (Y. Liu & Shen, 2017) and welfare resources (Xia & Lu, 2015) have been regarded as secondary. However, with China's economy maturing and standards of living improving, amenities have become increasingly important in migration decisions.

Furthermore, migration in China—or, more broadly, in socialist transitional economies—must be seen as the combined outcome of market forces and government arrangements, a characteristic that sets them apart from Western developed countries (Y. Liu et al., 2014). The administrative hierarchies of regions strongly influence migration patterns in China. Chinese cities are categorised into one of several administrative hierarchies, each of which has different decision-making powers (Chan & Zhao, 2002). A positive relationship has been found between a city's level in the administrative hierarchy and its attractiveness to migrants (T. Liu et al., 2015). The policies of central and local governments also affect mobility. The *hukou* system, for example, has been a major obstacle to the free movement of labour across space (Y. Liu & Shen, 2014). The *hukou* reform in the 1980s had a one-off but fundamental effect on early migration waves (Shen, 2013). Since then, the central government has gradually relaxed *hukou* restriction and local governments have been granted more discretion over migration policies. However, it remains difficult, if not impossible, for migrants to transfer their *hukous* to first-tier cities (Wu et al., 2019). Despite this barrier, even cities with strict migration controls saw an increase in migrants between 2011 and 2016 (Wu et al., 2019). Other government interventions include policies related to socio-economic development. Gu (2021) found that national and provincial development zones influenced individual migration decisions. Government-led policies do not always work as expected, however. According to Wu et al. (2019), state intervention did not always help cities located in the National Priority Zone to attract migrant populations.

Previous investigations of Chinese migration have primarily focused on large geographical areas such as provinces, losing sight of variations among cities within the same province (Mu et al., 2021). A growing body of literature, however, has shifted attention to migration between cities (Mu et al., 2021; Wang et al., 2019; Wu et al., 2019). 'Zooming in' from the provincial to the city scale allows not only a further disaggregation of migratory patterns but also more nuanced insights into the determinants of migration choices. Previous research has found that the provincial boundary in China is analogous to the 'border effect' noted in international migration studies, with migrants moving within the same province differing significantly from those moving interprovincially (Su et al., 2018).

One common feature of these studies is that they identify migrants as people whose cities of residence differ from their cities of *hukou* registration (i.e., the floating population). This definition is instructive in many aspects, but it has some drawbacks compared with other widely used measures such as migration over a 5-year period. Counting migrants using the former excludes *hukou* migration (migrants who acquire local *hukou* after migration) and return migration (migrants who move back to the place where they are *hukou*-registered). Thanks to the relaxation of the *hukou* restriction and the rapid socioeconomic progress in inland China, there has been a significant increase in both of these groups. This measure also reflects the cumulative results of millions of migrants over several decades (Mu et al., 2021), and is therefore too blunt to capture changes over the short term. More crucially, the measure is unique to China, making it difficult to generalise the findings. In this study, we use migration over a 5-year interval to identify intercity migrants, as these figures are more comparable to those of other countries.

2.3 | Spatial heterogeneity and migration

Most analyses of the determinants of migration do not take into account the geographical context, although many include a description of migration patterns. Gravity-type spatial interaction models have been developed to forecast mobility flows between places, and they incorporate various conceptualisations of the decision-making processes (e.g., random utility models; Rowe et al., 2022). These models implicitly assume spatial-stationary associations between migration and potential factors. However, this hypothesis is problematic when analysing spatially heterogenous processes (Fotheringham & Sachdeva, 2022a). Location-dependent relationships may exist in different parts of study areas, especially in a country as geographically diverse as China. Spatial heterogeneity has perhaps the most detrimental influence on modelling results, as there are often issues with spatial data that can lead to errors and inefficient parameter estimation (Páez & Scott, 2004).

Two considerations support our claim that spatial heterogeneity is present in migration. In a broad sense, the social processes that involve individual beliefs, preferences, and behaviours are presumably location-dependent (Fotheringham & Sachdeva, 2022a). Migration can be viewed as a goal-oriented behaviour in which people choose their migratory destinations based on certain motives, resulting in a sorting mechanism (Rijnks et al., 2018). Some regions might appeal more to people who are migrating for employment, while others might be more attractive to those migrating for other purposes. From a geographical perspective, such a lack of spatial uniformity may result from large-scale regional effects or administrative subdivisions that limit the reach of some processes (Páez & Scott, 2004).

Various techniques have been developed to address this issue. These techniques are generally grouped according to two broad approaches (Fotheringham & Sachdeva, 2022b; Sachdeva et al., 2022). The first of these approaches involves models that require local regions of analysis within the study area to be defined a priori, for example, multilevel models and spatial regime models. Similarly, some migration researchers have divided the analysed regions into multiple subareas and applied conventional global regression within each of them. For instance, Wu et al. (2019) observed that the volume of migration in eastern China was proportional to employment and wage, whilst these relationships were muted or negative in other areas. Similar regional variations have also been seen in other nations such as Italy (Etzo, 2011; Marinelli, 2011) and Russia (Sardadvar & Vakulenko, 2016). However, this approach isolates each subarea, and it is also difficult to justify the choice of spatial units. The second approach involves techniques that estimate process heterogeneity directly from the data without creating prespecified groups. A typical example in this category is the geographically weighted regression (GWR)-type model (Fotheringham et al., 2002). These models have been applied in a small number of studies to explore spatially nonstationary associations between migration and pertinent factors in Spain (Royuela et al., 2010), the Netherlands (Rijnks et al., 2018), Poland (Szymanowski & Latocha, 2021), and China (Wang et al., 2019).

Although the processes affecting migration patterns are clearly spatially heterogeneous, the extent to which their effects vary is unknown: this is referred to as the 'scale' and can be measured by the bandwidth in GWR-type models (Fotheringham & Sachdeva, 2022b). Given that migration outcomes are treated as a complex interplay of socioeconomic conditions, the underlying factors in various domains may differ in their scales of effect. Simply put, the effects of some factors are constant over space, while others vary. In one study regarding migrants' perceived acceptance, Gu et al. (2022) found that the influencing scales of individual characteristics (e.g., age) are smaller than those of external incentive variables (e.g., GDP). However, very few, if any, studies on migration patterns have considered scale multiplicity. Previous studies, such as that of Wang et al. (2019), have detected the spatial-varying processes of migration using GWR or mixed GWR, under the assumption that each response-to-predictor relationship operates at the same or a dichotomous spatial scale(s). This tends to exaggerate the local effects of processes (Sachdeva et al., 2022). In contrast, the extended version of GWR, MGWR, allows the effects of determinants to vary at different scales (Fotheringham et al., 2017).

Can we, however, be certain that variations in parameter estimates can be attributed to spatial heterogeneity? According to Sachdeva et al. (2021), a nonlinear conditional relationship between x and y, with the assumption that x exhibits a particular geographical pattern, offers an alternative explanation for observed variations. The resulting local parameters in a model such as GWR or MGWR would also demonstrate a distinctive spatial pattern if, for instance, there is a U-shaped relationship between x and y and the distribution of x is such that it decreases from south to north. Some studies have revealed nonlinear conditional relationships between migration and specific determinants, such as the inverted U-shaped influence of housing prices on the destination choices of Chinese migrants (Zhang et al., 2017). As a consequence, we cannot be sure of the provenance of spatial-varying parameters without a diagnostic check for nonlinearity. This study conducts a diagnosis of this phenomenon, which has been understudied in local modelling analysis, including in the analysis of migration.

3 | RESEARCH METHODOLOGY

3.1 | Selection of dependent and independent variables

The migration data used in this research is drawn from the 1% National Population Sampling Survey of 2015. A 'migrant' is defined here as a person whose city of residence on the enumeration date (1 November 2015) differs from their city of residence 5 years before. To focus on labour migration, we restrict our sample to those aged 18–60. Our study's dependent variable is the attractiveness of cities to migrants, which is reflected by the (in-)migration intensity (*InMigR*). We select the independent variables based on theory and the literature, and they include measures of labour market conditions, site-specific amenities, agglomeration and institutional dividends (Table 1). These covariates are described below, along with the justification for their use in our work.

Both economic and noneconomic determinants contribute to utility differentials, causing potential migrants to move from one place to another (Rodríguez-Pose & Ketterer, 2012). Economic

TABLE 1 Description of variables.

Categories	Abbreviation	Definition	Expected sign
Dependent variable	*InMigR*	The ratio of migrants to city's population aged 18–60 (%)[a]	
Independent variables			
Labour market conditions	*Unempl*	Unemployment rate in 2010 (%)[b]	–
	Wage	Average wage in 2010 (yuan, in logarithm)[b]	+
	EmpGrowth	Average growth rate of employees between 2011 and 2015 (%)[b]	+
Site-specific amenities	*SdElev*	Standard deviation of elevation (in logarithm)[f]	–
	Comfort	Natural comfort index[e]	–
	Housing	Housing price in 2010 (yuan, in logarithm)[c]	–
	EmpCul	The share of employees in culture, sports and entertainment industries in total employees in 2010 (%)[b]	+
	Culture	Dialect diversity index[h]	–
	Med	The number of doctors per 10,000 people in 2010[b]	+
	Edu	The teacher–student ratio in primary schools in 2010 (student =1)[b]	+
	Trans	The number of buses per 10,000 people in 2010[b]	+
	Air	Average $PM_{2.5}$ concentration between 2010 and 2015[d]	–
Agglomeration	*HHI*	Herfindahl–Hirschman Index in 2010[b]	±
	Pop	Hierarchies from 1 to 6 based on the size of urban population in 2015 by Natural Break Classification[a]	±
Institutional dividends	*Admin*	A dummy variable, =1 if it is a municipality, provincial capital or city with separate state planning; otherwise, =0	+
	UAs	A dummy variable, =1 if it is a membership of UA; otherwise, =0[i]	+
	Zone	The number of national and provincial development zones in 2010[g]	+

Note: The Natural Comfort Index (NCI) is calculated by the following formula: $NCI = |(T - 0.55(1 - RH)(T - 58)) - 65|$, where T represents the temperature (°F), RH represents the relative humidity (%). The smaller the NCI is, the more pleasant natural living conditions would be. The temperature and relative humidity are average values from 2000 to 2015.

$HHI = \sum_{i=1}^{n} \left(\frac{x_i}{x}\right)^2$, where x_i/x denotes the proportion of employees in the ith industry to the total employees. The smaller HHI is, the more diverse the industrial structure would be.

[a]1% national population sampling survey in 2015.

[b]China city statistical yearbook.

[c]China statistical yearbook for regional economy.

[d]Atmospheric Composition Analysis Group at Washington University in St. Louis (https://sites.wustl.edu/acag/datasets/surface-pm2-5/).

[e]Daily meteorological data set of basic meteorological elements of China National Surface Weather Station.

[f]Calculated based on ASTER Global Digital Elevation Model V003.

[g]Catalogue of China Development Zone Audit Announcement 2018.

[h]Obtained from Xu et al. (2015).

[i]There is no unanimous definition on the member cities of each UA. We mainly adopt Fang's (2015) research to identify UA members.

determinants include labour market conditions such as unemployment rate (*Unempl*), average wage (*Wage*) and employment growth rate (*EmpGrowth*) (Buch et al., 2017; Ferguson et al., 2007; Lee & Kim, 2019). Site-specific amenities (noneconomic determinants) are becoming increasingly vital in shaping migration choices in China (Wu et al., 2019). These include a variety of aspects related to the natural environment and quality of life (Rodríguez-Pose & Ketterer, 2012). In this study, the former is represented by the standard deviation of elevation (*SdElev*) and the Natural Comfort Index (*Comfort*). It is assumed that people prefer moderate climatic conditions and flat terrain. A variety of factors are included to gauge the quality of life. For example, our study takes the destination city's housing price (*Housing*) into consideration, which brings the parameter estimates of (nominal) *Wage* closer to the influence of real wage (Xia & Lu, 2015). Public services are also partially capitalised into housing prices, thus lessening the odds of omitted-variable bias (Xia & Lu, 2015). Informed by Buch et al. (2017) and Zheng (2016), we use the percentage of employees in the culture, sports and entertainment industries (*EmpCul*) to represent the quantity of recreational facilities, expecting that migrants would be attracted to cities with abundant cultural amenities. Dialect diversity (*Culture*) is chosen to approximate intrinsic cultural barriers, and this is predicted to impede migration inflow due to the importance of culture in developing social networks (Ma & Zhao, 2018). Other variables of interest are the public services provided by host cities, including the number of doctors per 10,000 people (*Med*), the teacher–student ratio in primary schools (*Edu*), and the number of buses per 10,000 people (*Trans*), which capture the status of healthcare, education and transportation, respectively. Also included is the $PM_{2.5}$ concentration (*Air*) to represent air quality.

Agglomeration is known to be an important reflection of job availability and urban amenities (Buch et al., 2017; Ferguson et al., 2007; Miguélez & Moreno, 2014). We include two variables—the Herfindahl–Hirschman Index (*HHI*) and population-based hierarchies (*Pop*)—to examine the attraction of cities in relation to industrial and population agglomeration. The results are anticipated to shed light on the ongoing debate in China regarding population control in first-tier cities. Clear a priori expected relationships are difficult to infer from the literature.

Our analysis also incorporates the role of institutional dividends in predicting the attractiveness of cities to migrants. The first, and arguably most significant, variable considered is the level of cities in the administrative hierarchy (*Admin*), which differentiate high-level cities (municipalities directly under the central government, sub-provincial cities, and provincial capitals) from low-level cities (ordinary prefecture cities). A dummy variable (*UAs*) is also established to indicate whether a city is a member of an urban agglomeration (UA) in light of the growing significance of UAs in promoting new-type urbanisation in China (Fang, 2015). Cities that are members of these agglomerations benefit from policy support from different levels of government for purposes such as regional integration. Finally, we include the number of national and provincial development zones (*Zone*). Development zones encourage capital, enterprises and labourers to congregate in specific areas through favourable policies (Gu, 2021).

Variance inflation factors (VIFs) are calculated to test for multicollinearity among the variables. All of the VIF values are lower than 3.5, indicating no strong collinearity. Another issue often encountered in spatial analysis involving migration data is the risk of endogeneity issues. Migration is influenced by regional economic conditions, but it also reshapes the structural characteristics of regions (Rodríguez-Pose & Ketterer, 2012). It is considered impossible for potential migrants to respond instantly to changes in regional differentials. This means that the dependent and independent variables should be introduced with different time structures (Rodríguez-Pose & Ketterer, 2012), with the dependent variable lagging behind independent variables by 5 years in this research.

In this study, the geographical units are 336 cities at prefecture level or above and autonomous areas. These constitute the basic units involved in the decision-making of migrants and the policy-making of local governments (Lao & Gu, 2020). This is also the smallest spatial scale at which many of the socioeconomic indicators of interest are available in China. Hong Kong, Macao and Taiwan are excluded. Due to the large number of missing entries in the data from autonomous areas, a subset of 285 cities out of 336 units is chosen as samples for regression analysis.

3.2 | MGWR

MGWR allows parameter estimates to vary at different spatial scales and is applied to uncover spatial heterogeneity in the relationships between migration intensities and their determinants (Fotheringham et al., 2017). MGWR adopts the function expressed below:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i, \tag{1}$$

where y_i represents the in-migration intensity of city i located at (u_i, v_i), x_{ij} represents the jth predictor variable of city i, $\beta_0(u_i, v_i)$ is the intercept, and ε_i is the random error term. $\beta_j(u_i, v_i)$ denotes the jth variable's spatial-varying parameter estimates. *bwj* denotes its optimal bandwidth, giving information on the variation of the conditioned process linking a change in x to a change in y. The larger this bandwidth is, the more stable the influence of this variable across space. A global model is an extreme case of a local model with extremely large bandwidths. To achieve optimal bandwidth selection, the dependent and independent variables are standardised before calibration.

The MGWR is calibrated using a back-fitting algorithm initialised using GWR parameter estimates. Based on these initial values, the calibration procedure operates iteratively. For every iteration, location-specific coefficients can be calculated by the following equation:

$$\widehat{\beta_{bwj}(u_i, v_i)} = [X_j^T W_{bwj}(u_i, v_i) X_j]^{-1} X_j^T W_{bwj}(u_i, v_i) y, \tag{2}$$

where $\widehat{\beta_{bwj}}(u_i, v_i)$ is the vector of local estimates, X_j is the matrix of predictor variables, y is the dependent variable as mentioned above and $W_{bwj}(u_i, v_i)$ is the spatial weighting matrix which allows neighbours closer to the location (u_i, v_i) to have stronger impacts on local parameter estimations. There is a kernel function and a bandwidth designed to control data borrowing (i.e., spatial scale). In this study, the adaptive bi-square kernel function is selected. The bi-square kernel estimates local parameters based on the nearest neighbours, regardless of the influence of the remaining observations. The adaptive kernel is designed to handle the issue of irregularly shaped study areas.

The above iteration terminates when the difference between parameter estimates from successive iterations converges to a predefined threshold (e.g., 10^{-5}). The MGWR is implemented using the MGWR2.2 software package (https://sgsup.asu.edu/sparc/multiscale-gwr). Note MGWR can also be conducted by Python (Oshan et al., 2019).

4 | SPATIAL CHARACTERISTICS OF INTERCITY MIGRATION INTENSITY IN CHINA

The spatial characteristics of migration intensity at the city scale between 2010 and 2015 are shown in Figure 1. Several prominent features are summarised in this section.

Based on the average in-migration intensities across four geographic regions (the east, northeast, centre and west), eastern China is the most alluring destination (10.15%), followed by the west (5.89%), centre (4.68%) and northeast (3.00%). Regional disparities in terms of migration distribution within and between provinces are also analysed using the Theil index. These results show that variations between cities within the same province accounted for more than 70% of the overall disparity, while the variations between provinces are less salient.

China's administrative orientation means that policy support and resource allocation among cities is largely influenced by their position

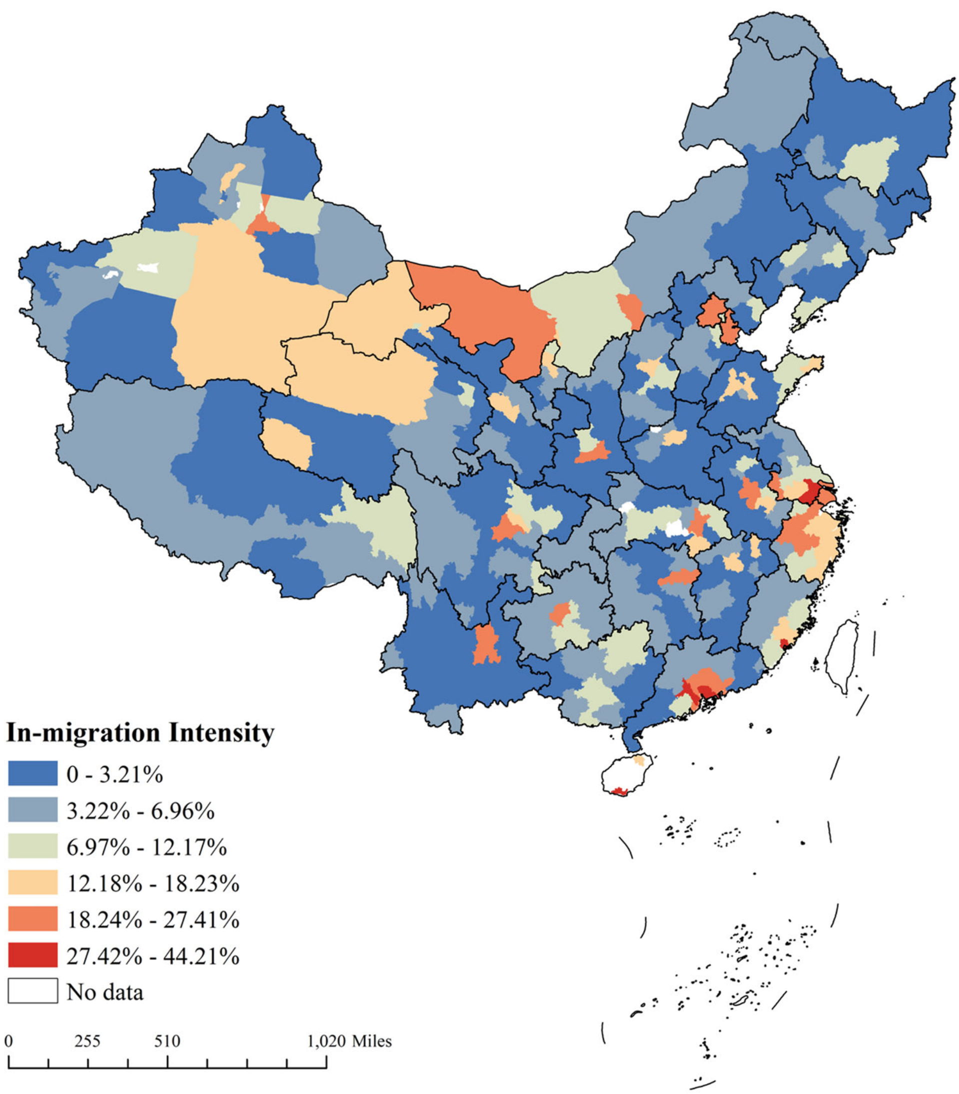

FIGURE 1 The spatial distribution of intercity migration intensity in China, 2010–2015.

in the administrative hierarchy (Chan & Zhao, 2002). Cities that are high in the administrative hierarchy are found to have an edge in 'fighting' for labour: the average rate of in-migration to those cities during the period under investigation is 17.34%. In comparison, only 5.08% of the working-age population of ordinary prefecture-level cities is from elsewhere.

Another feature regarding the distribution of labour migrants is that most of them gravitate toward urban agglomerations. The Yangtze River Delta and Pearl River Delta UAs serve as the two largest receivers of migration in 2010–2015, attracting 17.74% and 17.60% of labour flows nationwide, respectively. These member cities collectively account for only 28.61% of Chinese territory but have 68.89% of the total population aged between 18 and 60 and 86.92% of intercity migrants.

Cities with larger populations show larger agglomerations of migrants. We find that cities' migration rates have a significant correlation with their urban population size ($r = 0.519$), suggesting a trend for Chinese megacities, most of which have imposed stringent population controls, to be perceived as more attractive destinations than their small and medium-sized counterparts. Rapid urbanisation processes commonly lead to the concentration of populations in megacities (Zou & Teng, 2021), a phenomenon that has previously occurred in most developed countries.

5 | MODEL COMPARISON AND DIAGNOSTIC ANALYSIS

We construct three regression models, including ordinary least square (OLS), GWR, and MGWR, and compare them to find the one with the best fit. As shown in Table 2, MGWR outperforms OLS and GWR by allowing spatial-varying estimates and multiple bandwidths: the AICc and R-square of MGWR are 423.827 and 0.859, compared with equivalent values of 542.153 and 0.660 for OLS and 490.643 and 0.805 for GWR, respectively. The RSS produces a similar outcome. It is further determined that GWR-type models eliminate the significant spatial dependency in the OLS model's residuals that can lead to endogeneity problems.

In some scenarios, however, observed spatially varying parameter estimates can result from the misspecification of nonlinearity as spatial heterogeneity (Fotheringham & Sachdeva, 2022b). A diagnostic analysis is necessary to determine whether there has been an inappropriate application of functional form. This can be realised via a screening procedure in which the local estimates are plotted against their respective covariates (Sachdeva et al., 2021). If there is a clear structure to this plot, the spatial-varying estimates are due to the nonlinear relationship. Conversely, the absence of a discernible structure indicates that the processes being modelled are spatially heterogeneous. Following this diagnostic procedure, no structural relationship is evident between the selected variables and their corresponding estimates; the largest r^2 value is 0.07 (*Comfort*), confirming that the local variations in parameter estimates result from intrinsically heterogeneous relationships across space.

TABLE 2 The model fit metrics for OLS, GWR and MGWR.

Model Index	OLS	GWR	MGWR
Goodness of fit (R^2)	0.660	0.805	0.859
Corrected Akaike information criterion (AICc)	542.153	490.643	423.827
Residual sum of squares (RSS)	96.883	55.485	40.18
Moran's *I* of residuals	0.128*,**,***	−0.018	−0.042

Abbreviations: GWR, geographically weighted regression; MGWR, multiscale geographically weighted regression; OLS, ordinary least square.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6 | DETECTING SPATIAL HETEROGENEITY IN MIGRATION PROCESSES: THE DETERMINANTS OF INTERCITY MIGRATION WITH SPATIALLY VARYING EFFECTS

6.1 | Overview of MGWR results

The summary statistics for the parameter estimates from the MGWR calibration are shown in Table 3. The following analysis is based on the mean value of each variable's location-specific estimates. As expected, the results for the variables associated with labour market conditions (*Unempl*, *Wage* and *EmpGrowth*) are significant, signifying that a thick labour market (i.e., low unemployment rates, high wages, and increasing labour demand) attracts migrants.

The natural amenity represented by *Comfort* is another prominent element. After the other variables are controlled, cities with pleasant temperatures and humidity appeal more to migrants. When examining modern amenities, we find that the coefficient of *Housing* is positive, meaning that migrants do not avoid cities with higher housing prices. The model also confirms that good transport infrastructure (*Trans*) is important in attracting migrants, as is good air quality (*Air*). Other destination amenities, including *EmpCul*, *Med*, *Edu* and *Culture*, fail to pass the 10%-level significance test in any city. One potential explanation for this is that individuals' desire for cultural amenities may be skill- or age-biased (Brown & Scott, 2012; Buch et al., 2017; Marinelli, 2011), and thus have minimal effects at the population level. Further, in China, public services are tied with the *hukou* system. Non-*hukou* migrants do not have the same access to welfare resources as the locals in host cities (Zou & Teng, 2021).

Both measurements of agglomerative effects (*HHI* and *Pop*) are shown to attract intercity migrants, suggesting that a higher degree of industrial specialisation and population concentration is beneficial to labour inflow. These results are consistent with those of Wang et al. (2022) and Xia and Lu (2015). This is most likely because economies of scale and lower production costs are often related to larger population size and higher industrial agglomeration.

Institutional dividends also influence a city's attractiveness to labour migrants. In line with theoretical expectations, cities that are

TABLE 3 Summary statistics of parameter estimates from MGWR.

Variables	Min	Mean	Max	SD	The number of cities passing the 10%-level significance test
Unempl	−0.069	−0.036	−0.001	0.017	45
Wage	−0.004	0.041	0.152	0.036	35
EmpGrowth	−0.048	0.128	0.345	0.126	121
SdElev	0.003	0.013	0.048	0.007	0
Comfort	−0.138	−0.122	−0.089	0.009	285
Housing	−0.174	0.260	0.617	0.174	143
EmpCul	0.041	0.045	0.063	0.004	2[a]
Culture	−0.008	−0.007	−0.000	0.001	0
Med	0.015	0.031	0.049	0.007	0
Edu	0.014	0.019	0.028	0.002	0
Trans	0.088	0.108	0.115	0.005	285
Air	−0.460	−0.046	0.241	0.135	94
HHI	−0.043	0.203	0.366	0.115	230
Pop	0.043	0.091	0.110	0.013	165
Admin	−0.090	0.342	0.739	0.211	228
UAs	0.014	0.044	0.059	0.014	74
Zone	−0.302	−0.038	0.161	0.133	132
Intercept	−0.062	−0.021	0.039	0.021	0

[a]Only two of the 285 sample cities (i.e., Urumchi and Karamay in Xinjiang province) have a *p* value of *EmpCul* less than 0.1 (0.094 and 0.089, respectively). As a result, we do not believe the proportion of employees in cultural industries is as significant as other factors in predicting Chinese migration distribution.

high in the administrative hierarchy (*Admin*) and are members of UAs (*UAs*) tend to have high migration intensities, ceteris paribus. Notably, the average coefficient of *Admin* is the largest. Oddly, however, cities with more development zones (*Zone*) generally receive fewer migrants. It seems, therefore, that these initiatives may not function as expected to agglomerate flows of capital, labour and technology.

In addition to mean values, MGWR also provides spatial-varying parameter estimates for variables. For clarity, here we only present the local estimates of selected variables that pass the 10%-level significance test in some or all cities (Figure 2). The legends of these plots show negative estimates in blue, positive estimates in red and nonsignificant estimates in grey.

The optimal variable-specific bandwidths (the primary merit of MGWR compared with other techniques) are provided in Figure 3, along with 95% confidence intervals to indicate bandwidth selection uncertainty. These have been loosely categorised into three groups: global scale (larger than two-thirds of the sample cities, i.e., 190), local scale (fewer than one-third of sample cities, i.e., 95) and regional scale (95–190 cities). The parameter estimates associated with *Unempl*, *Wage*, *Comfort*, *Trans*, *HHI*, *Pop* and *UAs* are global, with large optimal bandwidths close to the size of the entire study area. The influences of *EmpGrowth* and *Zone* vary regionally, with respective bandwidths of 185 and 112. The bandwidths for *Housing*, *Air* and *Admin* exhibit spatial nonstationarity at a local scale, suggesting that their effects on cities' migration intensities change dramatically over short distances.

6.2 | Spatially heterogeneous processes in migration patterns

As already noted, the processes underlying migration are unknown and must be inferred from observed migration patterns. Here, we present a framework that facilitates the understanding of spatially heterogeneous processes of intercity migration in China (Figure 4). Clearly, the processes of spatial heterogeneity demonstrate some degrees of spatial dependency: cities with (non)significant associations are geographically clustered. Overall, the spatial features of these associations can be summarised as east–west, south–north and southwest–northeast gradient patterns, as well as discrete clustered and concentric patterns.

Traditional neoclassical theories view economic returns as the basic magnet for potential migrants, which frames differences in job availability and wages as the driving forces behind migration (Rodríguez-Pose & Ketterer, 2012; Wu et al., 2019). However, we find that the influences of *Unempl* and *Wage* are only significant in a small number of cities. The former demonstrates an east–west decreasing pattern. Lower unemployment rates significantly boost the inflow of labour migrants in the southeast of China (i.e., Shanghai, Jiangsu, Zhejiang and Fujian), where lots of jobs are available due to intensive foreign-invested and labour-intensive manufacturing. The effects of higher wages (*Wage*) show a discrete clustered distribution, only functioning in southwest and northwest cities to recruit labourers. This is probably because most of these cities are located in underdeveloped areas in China, leading to a prominent marginal effect of wages on cities' attractiveness. These results also imply that income differentials perhaps are not as vital as theories suggest (Biagi et al., 2011; Sardadvar & Vakulenko, 2016). The employment growth rate (*EmpGrowth*) has a substantial effect in practically all of the southern cities, showing a gradient decline from south to north.

In terms of site-specific amenities, *Comfort* significantly affects the migration intensities of all cities and there is a clear spatial pattern of decrease from east to west. Climatic conditions are particularly important in the northeast of China due to its extremely cold winter. The number of buses per 10,000 people (*Trans*) exerts a spatially decreasing pull effect in all Chinese cities from south to north. This may be because most Chinese rural migrants opt to live in peripheral areas to minimise their living expenses, and as a result, they are likely to value public transportation for commuting (Liao & Wang, 2019). The remaining two modern amenities present a more complicated pattern of influences. For example, there is a positive relationship between the attractiveness of cities located in coastal provinces and

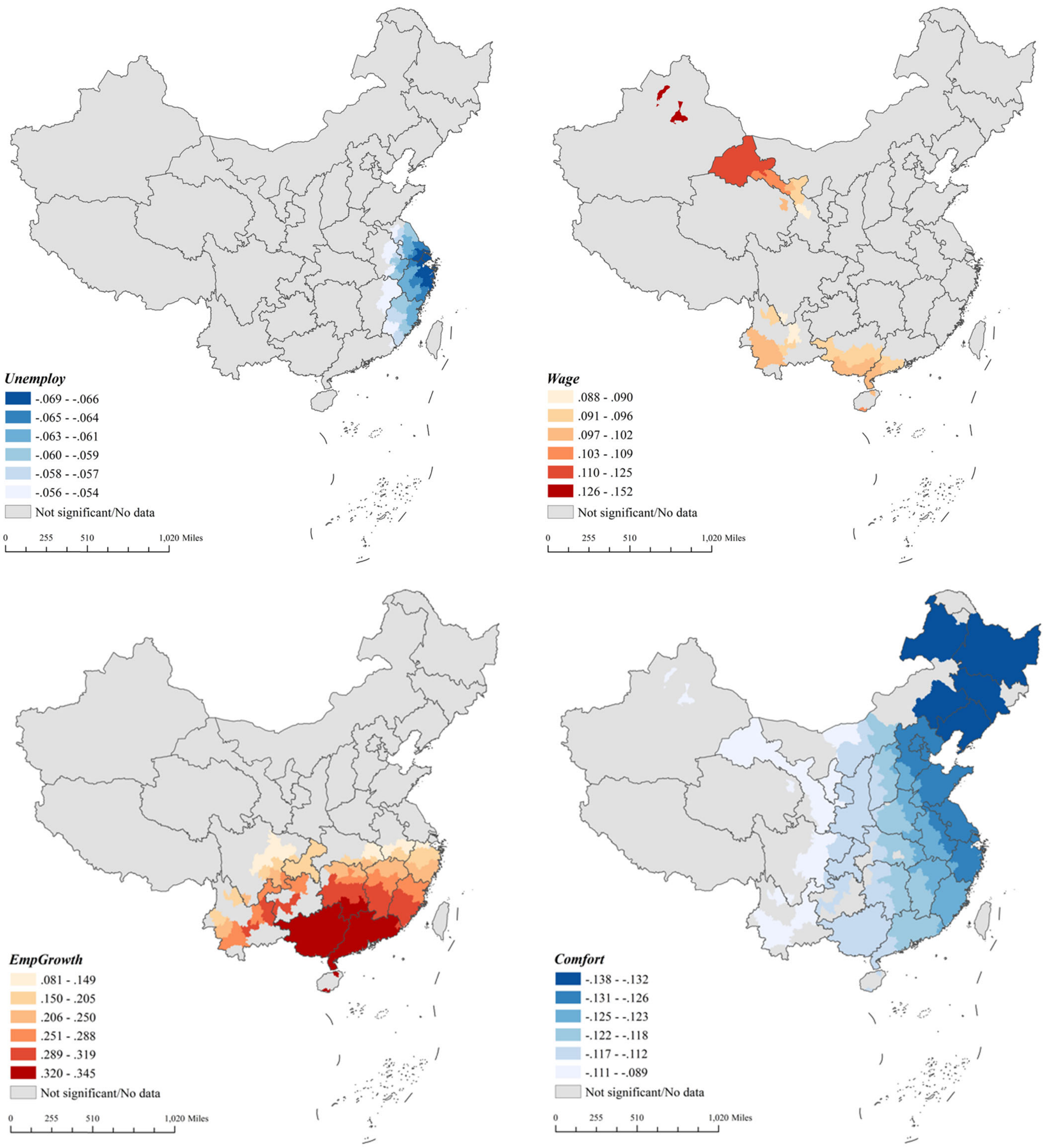

FIGURE 2 Spatially varying parameter estimates of variables that pass the 10%-level significance test.

their housing prices (*Housing*). This may be because housing prices are partly a reflection of certain unobservable public services whose pull force on migrants outweighs the costly consumption associated with high property prices (Xia & Lu, 2015). Housing prices also have substantial effects in some cities in Sichuan, Shaanxi and Gansu, which are geographically distant from eastern China. Higher property values make these cities relatively alluring to people from nearby regions. Similarly, the association between migration and air quality (*Air*) is also characterised by complex clustered patterns. Good air quality is an asset allowing Guangdong, Guangxi and Hainan to compete for migrants. The same relationship is also found in northern China, where air quality is the poorest nationwide (Zhou & Cheng, 2021). Improvements in air quality in this region have a significant marginal impact on the

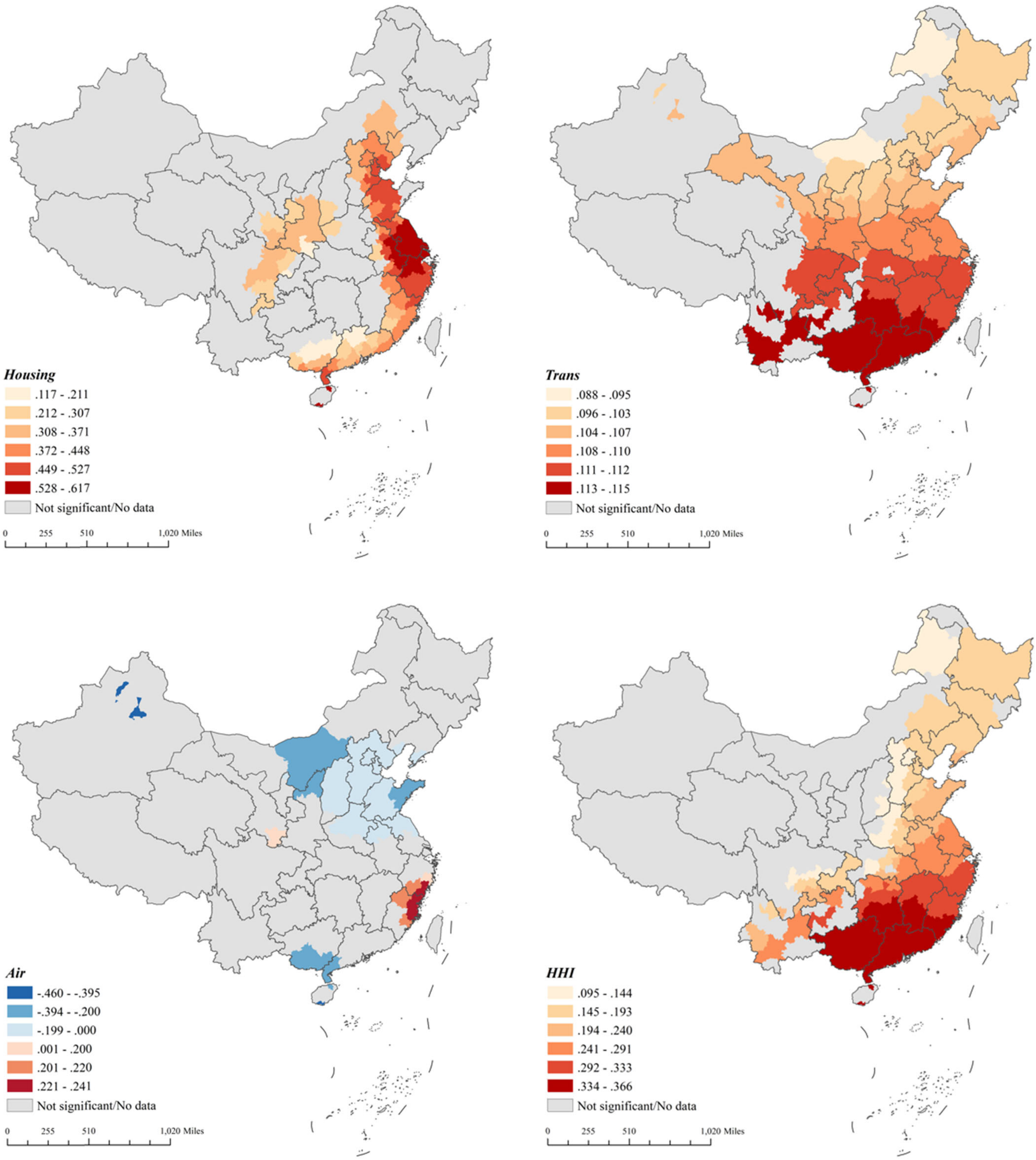

FIGURE 2 Continued

allure of cities in this area, given its close relationship with physical health. However, an inverse correlation is found in part of Zhejiang and Fujian. This may be because their intensive manufacturing industries, most of which fall at the lower end of industrial value chains, provide numerous job openings while also harming the local environment (Zhou & Cheng, 2021).

There is an overall south–north declining trend in the coefficients of *HHI* and *Pop*. This increased emphasis on agglomerative effects may occur because risk-averse migrants tend to move to cities equipped with more job options and a higher probability of boosting their productivity and income (Betz et al., 2016; Rodríguez-Pose & Ketterer, 2012; Zheng, 2016). Both industrial specialisation and

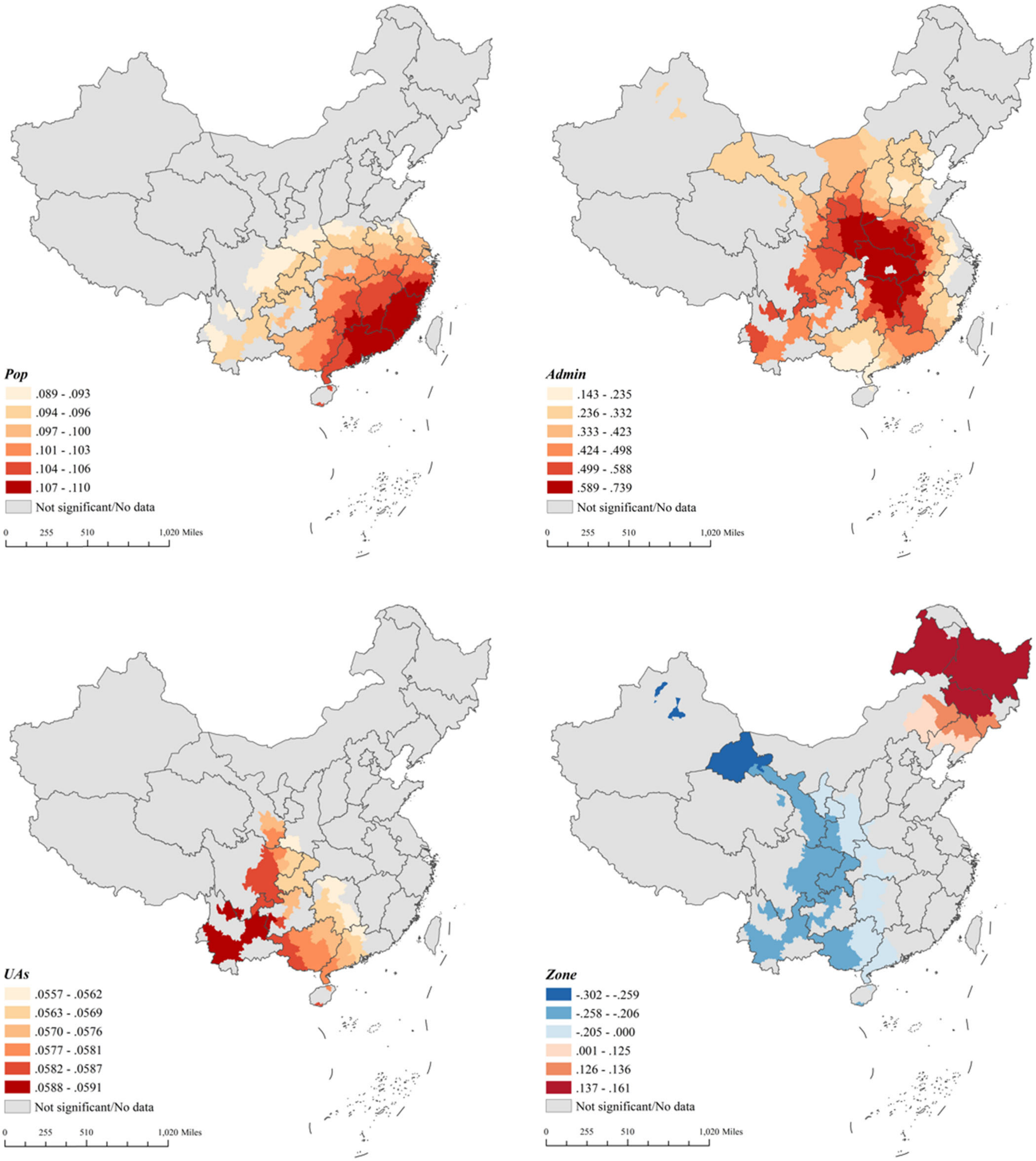

FIGURE 2 Continued

population concentration have a more substantial influence on place attractiveness to migrants in South China than elsewhere, a pattern that in turn leads to the further reinforcement of existing migration patterns.

Position in the administrative hierarchy (*Admin*) is a significant factor in intercity migration, and its effect has a concentric structure that decreases from the centre to surroundings. Even though *Admin* has long been acknowledged as significant in migration, we find that this is not the case for every city, particularly those in the east and northeast. Interestingly, only southwestern cities benefit from being members of UAs, with this effect showing a southwestern–northeastern declining trend.

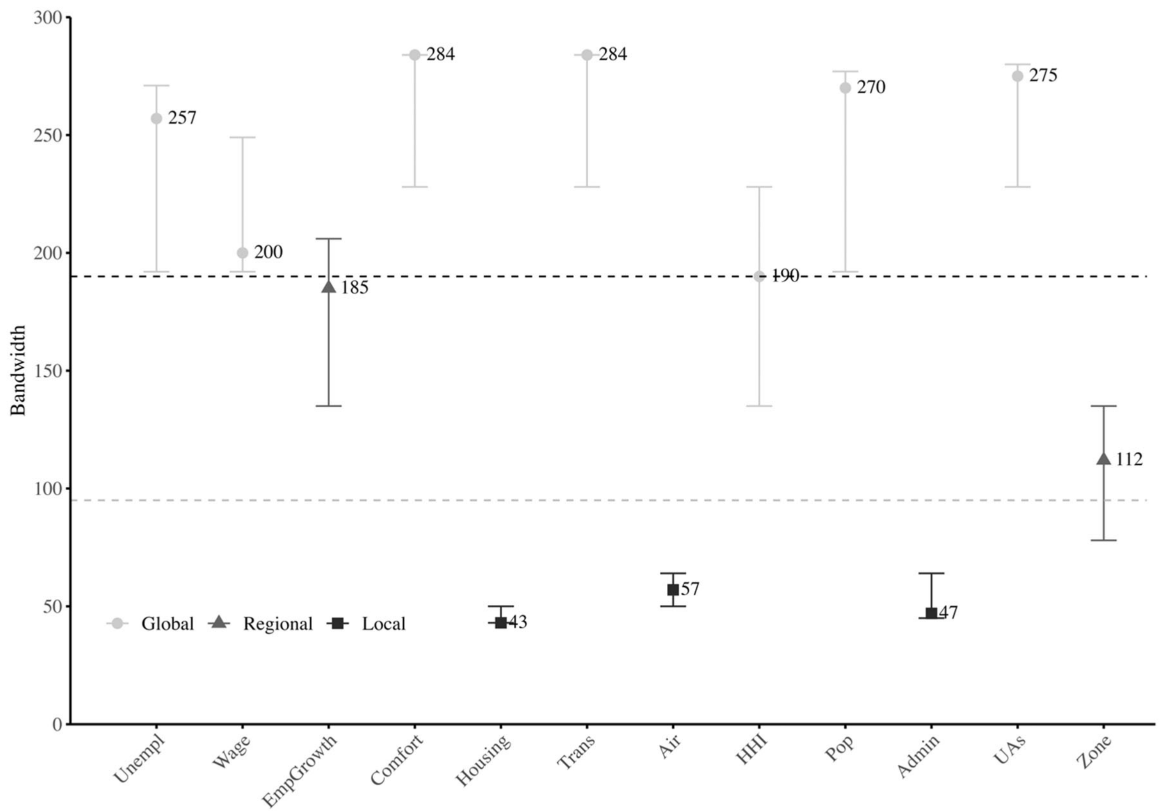

FIGURE 3 Optimal bandwidths of variables and respective 95%-level confidence intervals.

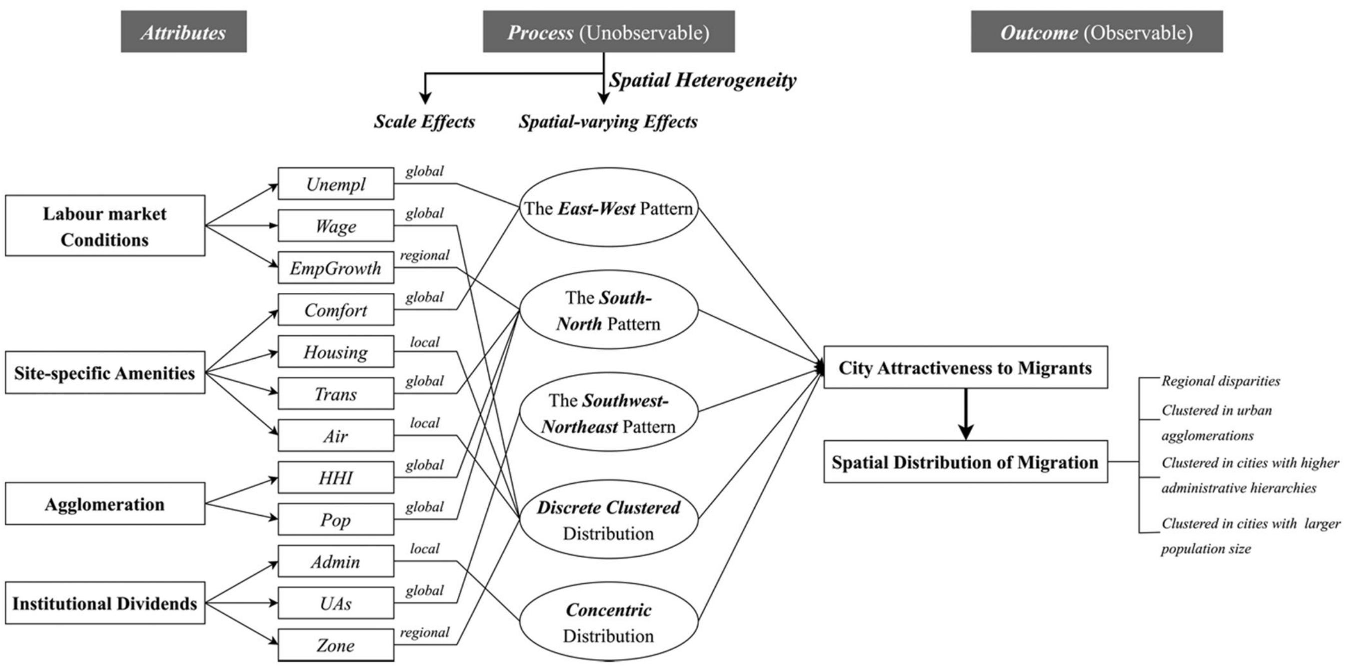

FIGURE 4 Spatially heterogeneous processes in migration.

This may be because the results are susceptible to a definition of UA members that is still ambiguous in China. The central and local governments determine the members of UAs, guided mainly by the idea of spatial proximity. The estimated location-specific influences of the number of national and provincial development zones (*Zone*), positive in the northeast but negative in the west, do not entirely align with expectations either. Due to the solid industrial base and high levels of urbanisation, northeastern cities are more likely to benefit from the establishment of development zones. Given the recent economic downturn and cultural embeddedness, these initiatives might eventually accelerate intercity mobility within this region as people move in search of better employment.

As shown in Figures 3 and 4, the above response-to-predictor relationships are scale-sensitive. Variables associated with local economies, such as *Unempl*, *Wage*, *EmpGrowth*, *HHI* and *Pop*, generally operate at larger scales. The other factors, those relevant to amenities and institutional dividends, operate at varying spatial scales ranging from local to global. Employment appears to remain the main driver of migration in China. However, people with different sociodemographic features prioritise amenities differently when making migration decisions. Amenity-type variables such as *Air* therefore show greater spatial variability than the relatively homogenous economic demands. Our results also show that economic factors exert a stronger influence in southern Chinese cities than their northern counterparts, probably owing to the developed market economy and business environment. The above-mentioned variations support our argument that a 'best-on-average' process may be unrepresentative of, or may even hide, intriguing and important local differences.

7 | CONCLUDING REMARKS

Using intercity migration data in China, we investigate spatial heterogeneity in the processes that produce observed migration patterns. One important contribution of our study to the migration literature is the identification of the spatial-varying effects of various factors and the unique spatial scales—local, regional or global—on which these factors affect migration. We begin the empirical analysis by outlining the geographies of migration and showing that intercity migration patterns are marked by striking spatial imbalances. More labour migrants are attracted by cities in eastern China, cities at higher levels in the administrative hierarchy, cities located in urban agglomerations and cities with larger populations.

We then select potential determinants from different domains, including labour market conditions, site-specific amenities, agglomeration and institutional dividends, and use MGWR to investigate the underlying heterogeneous processes that shape these migration patterns. First, we show that MGWR outperforms the traditional global and basic GWR models in model fit and in capturing unobserved heterogeneity. We also confirm that the source of spatial-varying estimates is spatial heterogeneity rather than nonlinearity. The econometric results suggest that these processes not only vary over space but also exhibit specific patterns, including east–west (*Unempl*, *Comfort*), south–north (*EmpGrowth*, *Trans*, *HHI*, *Pop*), southwest–northeast (*UAs*), discrete clustered (*Wage*, *Housing*, *Air*, *Zone*) and concentric (*Admin*) patterns.

We also pay considerable attention to scale multiplicity, which sets our study apart from previous work. We find that spatial heterogeneity and homogeneity co-exist in migration processes. Economic factors tend to exert relatively stationary influences on the attractiveness of cities to migrants, while the effects of variables relevant to amenities and policies vary on a range of spatial scales. Given the growing significance of the latter two types of factors in migration decisions, ignoring spatial heterogeneity and scale multiplicity may undermine modelling accuracy and hide important local differences.

In sum, the marked difference between the spatial relationships we observed indicates that there is no 'one size fits all' approach to improving place attractiveness to migrants in China. For instance, economic incentives may not work as expected in northern cities to compete for labour compared with southern cities for whatever reason. Similarly, government-led policies, such as the establishment of development zones, do not function identically in every city. It should therefore be kept in mind that policymaking must adapt to local circumstances.

We re-ran the econometric model with the floating population in place of our 5-year migration measure. The results indicate that spatial heterogeneity in the processes of migration is independent of the time window we studied (2010–2015), and this is also evident in accumulated migratory patterns. Under this definition, some economy-related factors operate at a relatively smaller scale (i.e., *Wage*), mainly because a large proportion of migrants have stayed at their destinations for years and are therefore likely to have different needs than more recent migrants. This result highlights the importance of maintaining a consistent definition of 'migration' in migration studies. Our conclusions, which are based on migration over a 5-year interval, may be more comparable to those from other countries than the findings of previous China-based research.

There are several limitations to this study, each opening avenues for further investigation. First, we only investigate spatial heterogeneity in the associations between migration and destination-specific attributes. A further probe using origin-specific data could be beneficial in integrating spatial heterogeneity into the classic *Push–Pull* theory. Due to data availability, we do not focus on temporal changes in heterogeneous relationships. By considering temporal changes, we could examine whether the aforementioned differences in the bandwidths of economic and non-economic factors are robust. It would also be worthwhile to examine the most recent Chinese intercity migration patterns when the relevant datasets become available (e.g., the Seventh Population Census in 2020).

ACKNOWLEDGEMENTS

This work has received support from CUHK Vice-Chancellor's PhD Scholarship and CUHK Research Committee Research Fellowship Scheme.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article: Li, S., Gu, H., & Shen, J. (2023). Detecting spatial heterogeneity in the determinants of intercity migration in China. *Population, Space and Place*, 29, e2649. https://doi.org/10.1002/psp.2649