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Flexible Spatial Multilevel Modelling of Neighbourhood Satisfaction in Beijing

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Flexible Spatial Multilevel Modelling of Neighbourhood Satisfaction in Beijing

Abstract:

This paper develops an innovative and flexible Bayesian spatial multilevel model to examine the socio-spatial variations in perceived neighbourhood satisfaction, using a large-scale household satisfaction survey in Beijing. In particular, we investigate the impact of a variety of housing tenure types on neighbourhood satisfaction, while controlling for household and individual socio-demographic attributes and geographical contextual effects. The proposed methodology offers a flexible framework for modelling spatially clustered survey data widely used in social science research by explicitly accounting for spatial dependence and heterogeneity effects. The results show that neighbourhood satisfaction is influenced by individual, locational and contextual factors. Homeowners, except those of resettlement housing, tend to be more satisfied with their neighbourhood environment than renters. Moreover, the impacts of housing tenure types on satisfaction vary significantly in different neighbourhood contexts and spatial locations.

Key Words: spatial statistics, multilevel modelling, neighbourhood satisfaction, housing tenure, Beijing

Chinese cities have experienced enormous housing and neighbourhood changes as the country transits from a centrally-planned economy to a market one. Before 1978, the majority of urban residents rented housing from their work units. The subsequent housing reforms resulted in various housing tenure types and significant socio-economic stratification. A large number of studies have examined the consequences of the housing reforms, such as improved housing conditions and rising inequalities (Wang and Murie 2000; Huang and Jiang 2009; Logan et al. 2010). Relatively few studies focus on residents' perceptions of residential environments as a result of significant housing and neighbourhood changes. Nonetheless, it is important to research neighbourhood satisfaction as it reflects neighbourhood quality, and has significant impacts on overall life satisfaction (e.g. Ibem and Aduwo 2013).

This paper aims to fill the gap by examining the spatial patterns and determinants of neighbourhood satisfaction, especially, the impacts of housing tenure types. This is important because China's housing reforms result in a variety of housing tenure types that differ in neighbourhood environments, especially in terms of services and facilities, access to transportation nodes, and geographic location relative to the city centre. The study will enhance our understanding of how the housing reforms are experienced by individuals through their subjective evaluation of residential environment. It is also conducive to policies aimed at delivering better residential environments.

We develop an innovative and flexible spatial multilevel modelling approach to examine the determinants of neighbourhood satisfaction while controlling for potential group dependence, spatial correlation and heterogeneity effects. Our data come from a large-scale household satisfaction survey in Beijing. Similar to other surveys with clusters presented by spatial units, our data are both hierarchical and spatial in nature

(Dong et al. 2016). Hierarchically, respondents nest into districts, potentially leading to within-district dependencies. That is, neighbourhood satisfaction levels of individuals in the same district tend to be more similar than those from different districts. This is often termed group dependence effect and modelled using the multilevel approach (e.g. Raudenbush and Bryk 2002; Goldstein 2003). Spatially, the higher-level geographical units (e.g. districts) might not be independent and thus their effects upon individuals could be spatially correlated in a way that respondents in closer districts tend to report similar levels of neighbourhood satisfaction (Haining 2003). Moreover, relationships between certain variables might vary across geographical contexts because of either generic contextual differences or unmodelled geographical unobservables. By using a rigorous spatial multilevel modelling approach which accounts for both within-district dependence and between-district spatial correlation and heterogeneity, we provide robust evidence that neighbourhood satisfaction is influenced by individual, locational and contextual factors. Meanwhile, neighbourhood satisfaction exhibits significant spatial clustering patterns, and heterogeneous associations between housing tenure types and neighbourhood satisfaction are found in urban Beijing.

In the following sections we first review previous studies on neighbourhood satisfaction and then locate our study into the Chinese context by outlining the housing reforms and different housing tenure types. This is followed by the introduction of the spatial multilevel method and the Beijing survey. We then discuss the empirical findings about spatial patterns and determinants of neighbourhood satisfaction, with conclusions at the end.

Previous studies on neighbourhood satisfaction

Neighbourhood satisfaction measures individual perception of the quality of neighbourhood environments in meeting expectations and aspirations (Salleh 2008; Feijten and Van Ham 2009). People tend to construct 'an ideal standard' of residential environment based on their needs, experience and aspirations, then make comparisons between their actual and ideal ones. They have high levels of satisfaction when the actual environment is consistent with or better than the ideal one. On the contrary, they might feel dissatisfied. Neighbourhood environment is a multi-faceted concept, including both location characteristics and social environments (Swaroop and Krysan 2011). Connerly and Marans (1988) support four dimensions of neighbourhood environment: physical setting; access to activity nodes; services and facilities; and socio-cultural setting. Parkers et al. (2002) incorporate crime, safety, pollution and noise when examining the reasons why individuals were dissatisfied with their neighbourhood in the UK.

Previous studies have shown that a wide range of factors at individual and neighbourhood levels influence neighbourhood satisfaction (e.g. Basolo and Strong 2002; Grief 2015). Individual factors include age, gender, marital status, education, family composition and household income, as they influence an individual's needs and expectations of the neighbourhood environment. Neighbourhood factors include the physical environment, such as distances to the nearest river, park, recreation centre and transportation nodes, and the socioeconomic context. Empirical studies have shown that older people with high-level education and income are more likely to feel satisfied with their neighbourhoods (Lu 1999).

Housing tenure represents an area of particular interest, as various housing policies worldwide promote homeownership (Saunders 1990). Yet its impact on neighbourhood satisfaction is inconclusive. Some studies demonstrate that homeowners are more satisfied with their neighbourhood than renters, as homeownership is related to security, social status and involvement in a neighbourhood (e.g. Elsinga and Hoekstra 2005; Swaroop and Krysan 2011). However, Parkers et al. (2002) reveals that homeowners had low neighbourhood satisfaction in areas where the share of homeownership is low, indicating the important role of neighbourhood contexts in shaping the relationship between housing tenure and neighbourhood satisfaction. Greif (2015) also refutes the universal positive impact of homeownership on neighbourhood satisfaction. Drawing on data from the Los Angeles Family and Neighbourhood Survey, he finds that homeowners are more satisfied with neighbourhood than renters only in advantaged communities.

Housing and neighbourhood changes in China

Over the past three decades, China's housing system has experienced significant changes, especially in tenure types, as a result of pro-market housing reforms that promote homeownership (Liu et al. 2013). Housing was regarded as a form of social welfare in urban areas under state socialism (1949-1978). The majority of urban residents lived in houses allocated by work units. After 1978, housing privatisation was gradually conducted across the country where existing work-unit housing was sold to occupants at heavily discounted prices. The real estate market has been developed rapidly, especially since 1998 when welfare distribution of housing was finally abolished by the State. Compared with work-unit housing, commercial properties tend to have higher building standards and better facilities/amenities in their neighbourhoods, including landscaped gardens, a variety of shops and restaurants (Wu 2005).

In contrast, the subsidised housing sector targeting low and moderate-income households lags behind (see Huang (2012) for a review). The Economic and Comfortable Housing (*jingji shiyong fang* 经济适用房, hereafter ECH), as the main type of affordable housing in China, was advocated after 1998 to promote homeownership by setting house prices around 40% lower than the market level and capping developer profit margin at 3% (Liu and Wong 2015). ECH owners get partial property rights as they can only sell their units after five years' residence. However, both governments and real estate developers are reluctant to construct ECH due to low profitability and the great drain on public finance (Zou 2014). Some ECH neighbourhoods are located in suburban areas where amenities and quality services (e.g. schools and hospitals) are lacking.

In the meantime, urban neighbourhoods have witnessed enormous changes through massive urban renewal projects. Many inner-city neighbourhoods of pre-1949 origin and work-unit compounds have been demolished and replaced by glossy offices, retail complexes and luxurious apartments. In the inner city of Beijing, 280,000 homes were reportedly demolished in the 1990s, and 605,000 more were torn down in the 2000s (Liu and Wong 2015). Numerous residents consequently lost their original homes. Those unable to afford commercial properties *in situ*, being laid-off or with low-income, had to move to resettlement housing, most of which was at the city fringe with poor amenities. Although studies revealed that some residents were satisfied with their resettlement due to improved housing conditions (Li and Song 2009), social conflicts were widely reported as a result of forced demolition, low compensation, prolonged waiting periods for resettlement and lack of amenities in resettlement neighbourhoods (Fang 2006).

The housing reforms result in a variety of housing tenure types, including privatised work-unit housing, commercial properties, subsidised housing ECH, and resettlement housing. They are located in neighbourhoods with different facilities, services and geographic location relative to the city centre, which are likely to influence residents' neighbourhood satisfaction. Existing literature on China has primarily focused on housing inequalities and social stratification as a result of the housing reforms. Very few studies examine the spatial patterns and determinants of residents' own evaluation of neighbourhood environment. This study will fill the gap by examining the role of a variety of housing tenure types on neighbourhood satisfaction in urban Beijing through a rigorous spatial multilevel model introduced below.

Methods

This study develops a Bayesian spatial multilevel model to investigate the determinants of neighbourhood satisfaction. To start, a Bayesian non-spatial multilevel model (MLM) can be expressed as (Gelman et al. 2004),

$$satisfaction_{jk} = a + H'_{jk}\boldsymbol{\beta} + S'_{jk}\boldsymbol{\gamma} + L'_{jk}\boldsymbol{\delta} + N'_{k}\boldsymbol{\varphi} + u_k + \varepsilon_{j,k} \quad (1)$$

$$u_k \sim N(0, \sigma^2);\ \varepsilon_{j,k} \sim N(0, \sigma_e^2);$$

$$\{a, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\} \sim N(0, b);$$

$$\sigma^2 \sim \text{inverse gamma}(e, f); \sigma_e^2 \sim \text{inverse gamma}(e_0, f_0).$$

In the equation, *j* and *k* are individual and area indicators (districts in this study). Neighbourhood satisfaction ($satisfaction_{jk}$) is related to a series of individual and district-level variables. *H* represents a set of housing tenure types. *S* contains demographic and socio-economic variables at the individual level, such as age, gender, education, family structure, residential length and income. *L* refers to variables of proximity to the nearest park, subway station and recreational facility. N represents district-level covariates. Vectors of $\{a, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\}$ are fixed regression coefficients that we seek to estimate. Relatively diffuse priors are specified for fixed regression coefficients, for instance, a normal distribution with mean zero and a large variance (b = 100).

The unobserved district-level contextual effects upon satisfaction disparity are captured through the vector $\boldsymbol{u}$, which follow an independent normal distribution, $N(0, \boldsymbol{I}\sigma^2)$. Modelling the district-level unobservables in the MLM allows considerations of heterogeneity between districts as to how perceived neighbourhood satisfaction varies across space. Moreover, possible correlations of residents' satisfaction levels in the same district are also captured, for example the covariance of outcomes of residents i and j in district k, $\text{cov}(satisfaction_{ik}, satisfaction_{jk}) = \text{cov}(u_k + \varepsilon_{i,k}, u_k + \varepsilon_{j,k}) = \sigma^2$. The vector $\boldsymbol{\varepsilon}$ represents the individual-level residuals assumed to follow an independent normal distribution, $N(0, \sigma_e^2)$. Inverse Gamma distributions are specified for the two variance parameters σ_e^2 and σ^2 with shape and scale parameters (e_0, f_0) and (e, f) (Gelman et al. 2004).

Notwithstanding these benefits with the MLM, there are two undesirable features with Equation (1) when modelling neighbourhood satisfaction using geographically clustered survey data. First, the independence assumption on the district-level random effect $\boldsymbol{u}$ is likely to be violated due to possible spatial dependence effects; i.e., aggregated neighbourhood satisfaction tends to be spatially correlated at the district level. This is because residents tend to express similar satisfaction level towards certain amenities and services of close spatial proximity. The standard non-spatial MLM has been found to produce biased estimates of random effects and inefficient fixed effect estimation (Congdon 2014; Dong and Harris 2015; Dong et al. 2016). To capture the potential spatial dependence effects[1], a specific type of conditional autoregressive (CAR) prior (LCAR), developed by Leroux et al. (1999), is specified for $\boldsymbol{u}$:

$$u_k|\boldsymbol{u_{-k}}, W, \lambda, \tau^2 \sim N(\frac{\lambda \sum_{k \sim l} u_l}{1-\lambda+\lambda w_{k+}}, \frac{1}{\tau^2(1-\lambda+\lambda w_{k+})}), \quad (2)$$

$$\boldsymbol{u} \sim MVN(\boldsymbol{0}, \Omega_{\text{LCAR}}); \Omega_{\text{LCAR}} = \tau^2(L_W - W);\ L_W = \text{ diag}\,(1-\lambda+\lambda w_{k+});$$

$$\tau^2 \sim \text{gamma}(e', f');\ \text{logit}(\lambda) \sim \text{logitbeta}(2{,}2).$$

Where w_{k+} is the number of neighbours that district k has and $\boldsymbol{u_{-k}} = (u_1, \ldots, u_{k-1}, u_{k+1}, \ldots, u_K)$ are random effects excluding district k. The spatial weights matrix is presented by W, the elements of which are defined on the basis of geographical contiguity: $w_{kl} = 1$, if the k-th and the l-th districts share boundaries (denoted by $k \sim l$) and 0 otherwise. In the LCAR model, the conditional expectation of u_k, $E(u_k|\boldsymbol{u_{-k}})$, is the weighted average of the random effects of its neighbours. The parameter λ is a spatial correlation parameter, measuring the strength of spatial dependence, while τ^2 is a precision parameter, which is the inverse of a variance parameter (e.g. σ^2). The whole set of full conditionals of all K random effects gives rise to a unique Gaussian Markov Random Field (GMRF), $\boldsymbol{u} \sim MVN(\boldsymbol{0}, \Omega_{\text{LCAR}})$, with the precision matrix Ω_{LCAR} defined in the equation (Congdon 2014). A Gamma distribution is specified for τ^2 with the shape and scale parameters being e' and f', while a logitbeta(2,2) prior for λ on the logistic scale is specified (Rue et al. 2014).

The second undesirable feature in Equation (1) concerns the assumed homogeneous effects of housing tenure types on neighbourhood satisfaction across districts. Geographical contexts might serve as a compound yet unobservable factor, rendering associations of housing tenure types to neighbourhood satisfaction varying

[1] We acknowledge that there are other approaches to modelling spatial dependence, such as spatial econometrics, geostatistics and other types of CAR models (e.g. Anselin 1988; Haining 2003; Banerjee et al. 2004). We use a LCAR model because it has been shown to be more reliable than other CAR models (Lee 2011).

across districts. Considering spatial heterogeneity, the regression slopes of housing tenure variables are further allowed to vary across districts:

$$satisfaction_{jk} = a + H'_{jk}\boldsymbol{\beta}_k + S'_{jk}\boldsymbol{\gamma} + L'_{jk}\boldsymbol{\delta} + N'_k\boldsymbol{\varphi} + u_k + \varepsilon_{j,k} \tag{3}$$

$$\boldsymbol{\beta}_{k,p} = \boldsymbol{\beta}_p + \boldsymbol{\theta}_{k,p}, p=1, 2, \ldots, P;$$

$$\boldsymbol{u} \sim MVN(\mathbf{0}, \Omega_{\mathrm{LCAR}}); \boldsymbol{\theta}_{k,p} \sim N(0, 1/\tau_p^2);\ \varepsilon_{j,k} \sim N(0, \sigma_e^2);$$

$$\{a, \boldsymbol{\beta}_p, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\} \sim N(0, b);\ \tau_p^2 \sim \mathrm{gamma}(e'', f'');\ \mathrm{logit}(\lambda) \sim \mathrm{logitbeta}(2,2)$$

For a specific housing tenure variable (e.g., owner of commodity housing), its effect is divided into two parts: a fixed part $\boldsymbol{\beta}_p$ and a random part $\boldsymbol{\theta}_{k,p}$ that varies across districts. Equation (3) provides a flexible spatial multilevel modelling approach. First, potential spatial dependence of the random effect $\boldsymbol{\theta}_p$ can be incorporated in the same way how spatial dependence of the random effect $\boldsymbol{u}$ is captured. Second, the cross-level interactions can be included in the model to examine the role of district-level variables to explain the heterogeneous effect of housing tenure types on neighbourhood satisfaction. Therefore, a spatial multilevel approach allows simultaneously accounting for the within-district dependence (often termed group dependence in the MLM literature), and the between-district spatial dependence and heterogeneity effects.

The model is implemented by using the R-INLA package, which implements approximate Bayesian inference using an efficient Integrated Nested Laplace Approximation (INLA) approach in R (Rue et al. 2009; Rue et al. 2014). As abovementioned, normal priors with mean zero and variance 100 are used for fixed regression coefficients and intercept terms. Following Ugarte et al. (2014), a minimally informative prior (the default prior in R-INLA) is assigned to [$1/\sigma_e^2$, τ^2, τ_p^2], for instance, $\log(\tau^2) \sim$ logGamma(1, 5e-05). The hyper-prior distribution for the spatial correlation parameter λ is informative as our initial analysis suggested a medium level of spatial dependence at the district level (see the following section). As the choices of hyper-prior distribution might influence the posterior inferences of model parameters in complex spatial models (Ugarte et al. 2014), a sensitivity analysis is conducted to assess the impact of different hyper-prior choices on model parameter estimation.

Data and Variables

Our data come from a large-scale residential satisfaction survey conducted in Beijing in 2005, with detailed information on perceived neighbourhood environment. This is the first and most comprehensive individual-level satisfaction survey conducted in Beijing that collects residents' socio-demographics and their evaluation of living environment. The purpose was to evaluate Beijing's general livability, including the convenience of the public transport system, human and physical environment, and health and safety conditions. The target population were residents living in urban Beijing, including 134 districts or *Jiedao* in total, for at least six months. The survey adopted a stratified random sampling strategy, with the sample size in each district about 0.1% of its total population. Altogether 11,000 questionnaires were issued by post, and 7,647 were returned, of which 6,544 were valid. The survey has been reported to be representative of the overall characteristics of Beijing's population, when compared with the census data (Zhang et al. 2006). To ensure the reliability of multilevel modelling approaches, we drop districts with less than five observations. Those with key variable values missing are further dropped, leading to the final sample size of 6467 distributed in 130 districts.

Dependent variable

We derive residents' overall neighbourhood satisfaction from specific survey questions on satisfaction with six dimensions of neighbourhood environment, i.e., physical location, living amenities, safety, socio-cultural setting, access to transport and pollution. For each dimension, respondents were asked to rate their satisfaction levels from one (very dissatisfied) to five (very satisfied). Moreover, there is a question asking respondents to rate the importance of each dimension.[2] The weights were used to calculate an overall neighbourhood satisfaction score for each respondent, accounting for individual heterogeneity in rating the six dimensions of neighbourhood environment. The overall satisfaction scores approximate to a continuous normal distribution with a mean of 3.144 (standard deviation 0.562), and thus are modelled as a continuous variable in this study.[3]

Figure 1 shows the average satisfaction scores for each district in urban Beijing, with the breaking points the lower quartile, median and upper quartile of satisfaction scores. It seems that people living in the inner city were more satisfied with their neighbourhood than those in the suburbs. This might be explained by convenient transportation links and various amenities in the inner city. Figure 1 also shows a clustering spatial pattern. We then use the Moran's I statistic based on the spatial weights matrix specified in Equation (3) to test the statistical significance of spatial dependence. The resultant Moran coefficient is 0.196, with p-value less than 0.01. This provides an initial justification for incorporating the spatial dependence effect into the standard MLM when modelling neighbourhood satisfaction.

[Figure 1 about here]

[2] The order of the relative importance of neighbourhood environment domains for each respondent is presented from one (least important) to six (most important). The weights assigned to each category are 5% (least important), 10%, 14%, 19%, 24% and 28% (most important) respectively, following Zhang et al. (2006). We also tried other weighting schemes but the modelling results remain similar.

[3] For analysing satisfaction levels of each individual dimension of neighbourhood environment, it is arguable that an ordinal response model should be employed. However, as discussed above the study is interested in the socio-spatial variations of overall neighbourhood satisfaction, which approximate well to a normal distribution. The development of a Bayesian spatial multilevel ordinal response model is, however, on our research agenda for appropriately analysing individual domain of neighbourhood satisfaction.

Individual and neighbourhood level predictors

The survey provides detailed information on respondents' demographic and socio-economic characteristics, such as age, gender, monthly income, education and family structure. Housing tenure is a set of six dichotomous variables: owners of commodity housing, work-unit housing, ECH and resettlement housing, renters of work-unit housing, and renters of private housing. Length of residence[4], monthly household income and education are included in the analysis, as they are shown to be important predictors of neighbourhood satisfaction (Greif 2015). Last, a set of locational variables is included in the model to measure local urban amenities, including distances to public transit, green space and recreational facilities.

Four district-level (*Jiedao*) variables from the 2000 Fifth Census are derived to investigate observable contextual effects on neighbourhood satisfaction. They are population density, the proportion of houses built before 1949, the number of crimes per 1,000 people and the median educational level. These district variables are included in the model because first, they help explain the sources of neighbourhood satisfaction at the district level, and second, the cross-level interactions between individual and district variables help us understand how the impact of housing tenure types on neighbourhood satisfaction varies with local contexts.

Table 1 presents a cross-tabulation of housing tenure types and key variables used in the study. It shows that owners of commodity housing, work-unit housing and ECH are more satisfied with neighbourhood than renters, with commodity property owners at peak satisfaction levels. However, owners of resettlement housing have the

[4] Residence length is based on two survey questions. The first is a binary question asking whether the respondent had lived in the current residence for more than ten years. If the answer is "no", the respondent was further asked when he/she moved into the current residence. Therefore, residence length in our study is a right-censored variable. We extract two variables to capture the effect of residence length. The first is *Residence length* (< 10), which is a right-censored variable with a value of ten indicating residence length above 10 years. The second is a dummy variable, *Residence length* (> 10), in which one indicates residence length above ten years.

lowest levels of satisfaction. The result from an ANOVA test suggests a significant difference in neighbourhood satisfaction between different tenure types. In terms of income, 41.73% of the private renters had monthly income below 3,000 yuan, while 51.18% of the owners of commodity properties earned over 5,000 yuan. This is not surprising as commodity houses are more expensive than other types. Private renters were predominantly young, with 62.47% below 30 years old. The corresponding percentage for work-unit housing owners was only 37.24%. As work-units stopped allocating housing after 1998, many young people did not have opportunities to purchase such housing. For private renters, more than a third were single and about half lived with their children. Over 60% of the respondents in other tenure types stayed with their children. Regarding education, 75.21% of the commodity property owners and 70.14% of the ECH owners went to college or university, while only half of resettlement housing owners did. As some ECH in Beijing was reserved for public sector workers and university lecturers, ECH residents have a relatively higher educational level than those in resettlement housing. A higher percentage of homeowners than renters lived in the residence for over ten years. For example, a third of commodity housing owners stayed in their homes for more than ten years, while the percentages for renters of private and work-unit housing were only 10.73% and 8.06%, respectively.

[Table 1 about here]

Model estimation and results

A single-level linear regression model, MLM and spatial MLM were estimated with the individual and district- level covariates and cross-level interaction variables. Only statistically significant cross-level interaction terms between housing tenure type variables and district-level variables, experimented by using the simple linear regression model, are incorporated in the final model specification. The association between one tenure variable *Owners of work-unit housing* and perceived neighbourhood satisfaction was found varying across districts.

We adopt two commonly used indices in Bayesian inference to measure model fit: deviance information criterion (DIC, Spiegelhalter et al. 2002) and marginal log-likelihood. Smaller DIC and larger log-likelihood indicate a better model fit. Table 2 provides the results of model comparison. Unsurprisingly, the simple linear model provides the poorest model fit in terms of both DIC and log-likelihood, as neither the spatial dependence effect nor the heterogeneity effect is modelled. There is substantial decrease of DIC, indicating significant improvement in model fit gained moving from the simple linear regression model to the MLM. This demonstrates the importance of modelling district-level unobservables in neighbourhood satisfaction inequality. Moreover, by capturing spatial dependence in the district-level unobservables and the heterogeneity in the association between housing tenure types and neighbourhood satisfaction, the proposed spatial MLM significantly outperforms the MLM as indicated by the substantial decrease in DIC and increase in log-likelihood.

[Table 2 about here]

Table 3 presents the estimation results from the final spatial MLM. A moderate spatial dependence effect is found in the random intercept, with λ equal to 0.605 and a 95% credible interval of [0.227, 0.882]. Following Blangiardo et al. (2013), the posterior marginal variance of the random intercept, estimated as the empirical variance of the median of the random intercepts, is about 0.015. In total, the district-level variances (intercepts and slopes) account for about 9.3% of the total variance in neighbourhood satisfaction, conditioning on the fixed effect. Figure 2 maps the estimated median random intercepts of each district, with breaking points the lower, median and upper quartiles of the variable. It shows the variation of neighbourhood satisfaction in each district conditioning on fixed covariate effects.

[Table 3 about here]

[Figure 2 about here]

Table 3 shows statistically significant associations between housing tenure types and neighbourhood satisfaction, after controlling for individual, locational and contextual variables. Owners of commodity housing, ECH and work-unit housing are more likely to feel satisfied with their neighbourhood than private renters, everything else being equal. This is in agreement with previous studies showing homeowners tend to feel more satisfied with their neighbourhood than renters (Lu 1999). Homeownership is closely related to security, freedom and independence. Compared with renters, homeowners might invest more time participating in local activities, interacting with neighbours and developing social networks, which might enhance their neighbourhood satisfaction. The results also show that commodity housing ownership has the highest impact on neighbourhood satisfaction, followed by that of ECH and work-unit housing. This can be explained by the fact that commercial properties have better facilities and amenities in their neighbourhoods than other housing types. Compared with private renters, renters of work-unit housing appear to have significantly higher levels of satisfaction. A possible explanation is that work-unit housing provides more stable accommodation at a lower cost.

On the other hand, the satisfaction level for owners of resettlement housing is not differentiating from that of private renters, challenging the universal positive impact of homeownership on neighbourhood satisfaction in the Chinese context. This result might reflect the huge variation in the quality of resettlement housing and the complexity of the resettlement process. Many local residents were likely forced to move to poor-quality resettlement housing in the urban fringe, far away from their familiar neighbourhoods and social ties, and thus they might report a low level of neighbourhood satisfaction. An interesting finding is that the effect of resettlement housing on satisfaction is significantly influenced by district characteristics – the proportion of houses built before 1949. More specifically, the neighbourhood satisfaction level of residents in resettlement housing increases with the proportion of old buildings in the district. Districts with a large proportion of houses built before 1949 are mainly inner-city districts where most urban regeneration occurred. This suggests that people who lost their original houses during urban regeneration were more willing to live in areas close to their original places rather than on city fringes. A similar significant interaction effect can be found between *Owners of work-unit housing* and *Buildings1949*, i.e., owners of work-unit housing were more likely to report satisfaction with neighbourhood comprising a larger proportion of old buildings. These findings demonstrate the important role of local contexts in influencing the relationship between housing tenure types and neighbourhood satisfaction.

The effects of most socio-economic and locational variables are in line with previous studies. Table 3 shows a significantly positive effect of income on neighbourhood satisfaction, which supports previous findings that people with higher income tend to be more satisfied with their neighbourhood (Lu 1999; Ballas and Tranmer 2012). Distinctions exist between different age cohorts, as middle-aged people

(30-59) tend to report lower levels of neighbourhood satisfaction than people in other age groups. Females in our study are less likely to express satisfaction than males. We also found a threshold effect in the association between residential length and neighbourhood satisfaction. People living in their residence for over ten years tend to be more satisfied than those with a residence of less than ten years. However, when the residence length is below ten years, it is no longer significant. With respect to locational variables, proximity to parks or green spaces is significantly positively associated with neighbourhood satisfaction.

Robust checks

We further conduct a sensitivity analysis to check whether our model parameter estimates are robust to the choices of hyperprior parameters. Regarding the hyperpriors for the spatial correlation parameter (λ), we also use a non-informative prior logitbeta (1,1), which approximates a [0,1] uniform distribution. Another two hyperpriors include logitbeta (4,2) that favours a value of λ close to 0.67 and logitbeta (0.5,0.5) that prefers extremely large or small values of λ. For the two district-level variance parameters, other hyperpriors including logGamma (1,0.1), logGamma (1,0.01), and logGamma (1,0.001) are used to test the sensitivity of the variance estimates. Table 4 presents the sensitivity of the effects of housing tenure types on neighbourhood satisfaction by using different hyperpriors. The results show that these coefficient estimates are stable, as differences only exist in the fourth decimal under different hyperpriors. It confirms that our model results in Table 3 are robust.

[Table 4 about here]

Conclusion

Drawing on a large-scale satisfaction survey in Beijing, we develop an innovative spatial multilevel modelling approach to examine the spatial patterns and determinants of neighbourhood satisfaction, especially the impacts of housing tenure types and geographical contexts. The study improves our understanding of neighbourhood satisfaction in China in several ways. First, considering housing tenure types as a series of variables rather than a dichotomous one (owner or renter), we find great heterogeneity in the effects of tenure types on neighbourhood satisfaction. For instance, owners of commodity properties, work-unit housing and ECH are more satisfied with their neighbourhoods than private renters, while owners of resettlement housing have similar satisfaction levels to private renters. Renting work-unit housing significantly correlates with higher neighbourhood satisfaction than private renting. Our results challenge the universal positive impact of homeownership on neighbourhood satisfaction, and demonstrate the importance of differentiating housing tenure types when analysing their impacts on neighbourhood satisfaction in transitional China.

Second, the impacts of housing tenure types on neighbourhood satisfaction vary significantly across local geographical contexts. When interacting the variables of owners of resettlement housing and the proportion of houses built before 1949, we find that residents in resettlement housing tend to be more satisfied with neighbourhoods in districts with larger proportions of old buildings. Districts comprising many old buildings are primarily located in the inner city where many urban renewal projects took place. This suggests an important source of neighbourhood dissatisfaction for resettled residents is relocation to urban fringes far away from their original places. These findings demonstrate spatial heterogeneity between tenure types and neighbourhood satisfaction and the importance of a careful consideration of geographical contexts in the analysis. This further justifies the spatial multilevel modelling approach we developed to investigate neighbourhood satisfaction by accounting for both the spatial dependence and heterogeneity effects.

Neighbourhood satisfaction is further influenced by individual and locational variables. Males with higher incomes and residence lengths over ten years tend to be more satisfied with their neighbourhoods. Age makes a difference and middle-aged people are less likely to express neighbourhood satisfaction. Proximity to a park is positively associated with neighbourhood satisfaction.

The study has limitations. First, given the cross-sectional nature of our data, we are unable to shed light on the causal claims of the relationship between housing tenure types and neighbourhood satisfaction. Panel data are needed to control for unobserved personal characteristics. Second, our survey does not record information on housing satisfaction. Therefore, we are unable to disentangle the relationship between housing and neighbourhood satisfaction. Despite these caveats, the study adds to knowledge by rigorously examining the spatial patterns and determinants of neighbourhood satisfaction using an innovative spatial multilevel model.

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Literature Cited

Anselin, L. 1988. *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic.

Ballas, D., and M. Tranmer. 2012. "Happy People or Happy Place? A Multilevel Modelling Approach to the Analysis of Happiness and Well-being." *International Regional Science Review* 35(1): 70-102.

Banerjee, S., B. P. Carlin and A. E. Gelfand. 2004. *Hierarchical Modelling and Analysis for Spatial Data*. Chapman & Hall/CRC, Boca Raton, FL.

Basolo, V., and D. Strong. 2002. "Understanding the Neighborhood: from Residents' Perceptions and Needs to Action." *Housing Policy Debate* 13(1): 83-105.

Blangiardo, M., M. Cameletti., G. Baio., and H. Rue. 2013. "Spatial and Spatio-temporal Models with R-INLA." *Spatial and Spatio-temporal Epidemiology* 7: 39-55.

Congdon, P. 2014. *Applied Bayesian Modelling*. Chapman & Hall/CRC, Boca Raton.

Connerly, C., and R. Marans. 1988. "Neighborhood Quality: A Description and Dnalysis of Indicators." In: Huttman E and van Vliet W (eds) Handbook of housing and the built environment in the United States. New York: Greenwood, pp.37-61.

Dong, G. P., and R. Harris. 2015. "Spatial Autoregressive Models for Geographically Hierarchical Data Structures." *Geographical Analysis* 47: 173-191.

Dong, G. P., J. Ma., R. Harris., and G. Pryce. 2016. "Spatial Random Slope Multilevel Modeling using Multivariate Conditional Autoregressive Models: a Case Study of Subjective Travel Satisfaction in Beijing." *Annals of the American Association of Geographers* 106(1): 19-35.

Elsinga, M., and J. Hoekstra. 2005. "Homeownership and Housing Satisfaction." *Journal of Housing and the Built Environment* 20(4): 401-424.

Fang, Y. 2006. "Residential Satisfaction, Moving Intention and Moving Behaviours: a Study of Redeveloped Neighbourhoods in Inner-city Beijing." *Housing Studies* 21(5):671-694.

Feijten, P., and M. Van. Ham. M. 2009. "Neighbourhood Change… Reasons to Leave?" *Urban Studies* 46(10): 2103–2122.

Galster, G. 1987. "Identifying the Correlates of Residential Satisfaction: An Empirical Critique." *Environment and Behaviour* 19: 539–568.

Gelman, A., B. P. Carlin., H. S. Stern., and D. B. Rubin. 2004. *Bayesian Data Analysis*. Chapman & Hall/CRC.

Goldstein, H. 2003. *Multilevel Statistical Methods* (third edition). London, Arnold.

Greif, M. 2015. "The Intersection of Homeownership, Race and Neighbourhood Context: Implications for Neighbourhood Satisfaction." *Urban Studies* 52(1): 50-70.

Haining, R. 2003. *Spatial data analysis: Theory and practice*. Cambridge, UK: Cambridge University Press.

Huang, Y. 2004. "The Road to Homeownership: a Longitudinal Analysis of Tenure Transition in Urban China (1949–94)." *International Journal of Urban and Regional Research* 28(4): 774–95.

Huang, Y. 2012. "Low-income Housing in Chinese Cities: Policies and Practices." *China Quarterly* 212: 941-964.

Huang, Y., and W. Clark. 2002. "Housing Tenure Choice in Transitional Urban China: a Multilevel Analysis." *Urban Studies* 39(1): 7-32.

Huang, Y., and L. Jiang. 2009. "Housing Inequality in Transitional Beijing." *International Journal of Urban and Regional Research* 33(4): 936-956.

Ibem, E., and E. Aduwo. 2013. "Assessment of Residential Satisfaction in Public Housing in Ogun State, Nigeria." *Habitat International* 40: 163-175.

Kasarda, J., and M. Janowitz. 1974. "Community Attachment in Mass Society." *American Sociological Review* 39: 328-39.

Lee, D. 2011. "A Comparison of Conditional Autoregressive Models Used in Bayesian Disease Mapping." *Spatial and Spatio-temporal Epidemiology* 2: 79-89.

Leroux, B., X. Lei., and N. Breslow. 1999. "Estimation of Disease Rates in Small Areas: a New Mixed Model for Spatial Dependence." In: Halloran M and Berry D. (Eds), Statistical models in epidemiology, the environment and clinical trials. Springer-Verlag, New York, pp. 135-178.

Li, S., and Y. Song. 2009. “Redevelopment, Displacement, Housing Conditions, and Residential Satisfaction: A Study of Shanghai.” *Environment and Planning A* 41:1090-1108.

Liu, R., and T. Wong. 2015. “The Allocation and Misallocation of Economic Housing in Beijing: Target Groups Versus Market Forces.” *Habitat International* 49: 303-315.

Liu, Z., Y. Wang., and R. Tao. 2013. “Social Capital and Migrant Housing Experiences in Urban China: A Structural Equation Model Analysis.” *Housing Studies* 28(8): 1155-1174.

Logan, J., Y. Fang., and Z. Zhang. 2010. “The Winners in China’s Urban Housing Reform.” *Housing Studies* 25(1):101-117.

Lu, M. 1999. “Determinants of Residential Satisfaction: Ordered Logit vs. Regression Models.” *Growth and Change* 30: 264-287.

Parkes, A., A. Kearns., and R. Atkinson. 2002. “What Makes People Dissatisfied with Their Neighbourhoods.” *Urban Studies*, 39(13): 2413-2438.

Raudenbush, S. W., and A. S. Bryk. 2002. *Hierarchical Linear Models Applications and Data Analysis Methods*. Sage, New York.

Rue, H., S. Martino., and N. Chopin. 2009. “Approximate Bayesian Inference for Latent Gaussian Models by Using Integrated Nested Laplace Approximations.” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 71: 319-392

Rue, H., S. Martino., F. Lindgren., D. Simpson., A. Riebler., and E. T. Krainski. 2014. “INLA: Functions Which Allow to Perform a Full Bayesian Analysis of Structured Additive Models Using Integrated Nested Laplace Approximations.” URL: http: //www.r-inla.org/.

Salleh, A. 2008. “Neighbourhood Factors in Private Low-cost Housing in Malaysia.” *Habitat International* 32(4): 485-494.

Saunders, P. 1990. *A Nation of Home Owners*. London: Unwin Hyman.

Spiegelhalter, D., N. Best., B. P. Carlin., and A. Van. Linde. 2002. “Bayesian Measures of Model Complexity and Fit (with discussion).” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64: 583-639.

Swaroop, S., and M. Krysan. 2011. “The Determinants of Neighborhood Satisfaction: Racial Proxy Revisited.” *Demography* 48:1203-1229.

Ugarte, M. D., A. Adin., T. Goicoa., and A. F. Militino. 2014. “On Fitting Spatio-temporal Disease Mapping Models using Approximate Bayesian Inference.” *Statistical Methods in Medical Research* 23: 507-530.

Wang, Y., and A. Murie. 2000. "Social and Spatial Implications of Housing Reform in China." *International Journal of Urban and Regional Research* 24(2): 397-417.

Zhang, W., W. Yin., and J. Zhang. 2006. *A study of liveable cities in Beijing, China*. Beijing, China: Beijing Social Sciences Academic Press.

Zou, Y. 2014. "Contradictions in China's Affordable Housing Policy: Goals vs. Structure." *Habitat International* 41(1): 8-16.

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Tables

Table 1. Summary of socio-economic and demographic variables by homeownership types

	Renters of		Homeowners of			
	Private housing	Work-unit housing	Commodity housing	Work-unit housing	ECH	Resettlement housing
Neighbourhood satisfaction	3.04	3.10	3.24	3.15	3.18	3.01
Monthly income (%)						
< 3,000 (yuan)	41.73	32.43	16.18	25.15	20.21	32.62
3,000-4,999	35.88	39.89	32.64	42.66	39.38	39.29
5,000-9,999	16.54	22.71	35.28	25.94	32.56	23.10
> 10,000	5.85	4.97	15.90	6.25	7.85	5.00
Age (%)						
< 30	62.47	40.79	44.72	37.24	45.30	37.38
30-39	19.72	21.02	28.54	22.00	26.90	24.29
40-49	12.34	23.16	20.42	26.26	21.88	24.52
50-59	4.33	13.67	4.86	11.63	5.28	10.48
60+	1.15	1.36	1.46	2.87	0.64	3.33
Education (%)						
Compulsory	10.56	10.40	2.85	7.13	5.28	13.57
Secondary	26.59	33.45	21.94	27.10	24.58	34.52
Tertiary	62.85	56.16	75.21	65.77	70.14	51.90
Female (%)	10.88	15.21	20.28	34.91	12.05	6.67
Single (%)	37.02	15.82	16.53	16.67	21.62	10.95
Two-person family (%)	17.68	15.82	19.17	13.15	18.15	15.00
Family with children (%)	45.29	68.36	64.31	70.17	60.23	74.05
Residence length (> 10) (%)	10.73	8.06	33.39	24.18	15.94	10.73
Residence length (< 10) (years)	2.93	5.07	3.56	5.02	3.71	4.06
Log of distance to the nearest subway station	7.22	6.94	7.30	6.98	6.96	7.21
Log of distance to the nearest park	7.73	7.30	7.86	7.59	7.80	7.80
Log of distance to the nearest recreational facility	6.67	6.39	6.82	6.51	6.82	6.68
Population density (1,000 persons/km^2)	29.15	30.74	25.67	31.62	26.94	28.77
Buildings1949 (%)	0.03	0.06	0.03	0.04	0.05	0.05
Crime rate	3.43	3.24	2.84	3.09	2.91	2.59
Low education (%)	15.43	9.35	23.53	30.38	12.92	8.39
N	786	885	1440	2159	777	420

Table 2. Model comparison results

	DIC	P_D	Log-likelihood
Single-level linear regression model	10504.78	31.01	-5453.11
MLM (Equation (1))	10188.00	115.41	-5341.28
Spatial MLM (Equation (3))	10141.74	152.76	-5328.19

Note. “MLM” represents a random intercept multilevel model and “Spatial MLM” a spatial multilevel model with random intercepts specified using a LCAR prior, and the random slope of *Owners of work-unit housing* specified using an independent normal prior. There was not statistically significant spatial dependence found in the random slopes of *Owners of work-unit housing* (Moran’s I of equals 0.02 with p-value > 0.1)).

Table 3. Estimation results from the spatial multilevel model

	Posterior median	2.5%	97.5%
Intercept	3.604*	3.215	3.993
Renting work-unit housing	0.056*	0.003	0.109
Owners of ECH	0.133*	0.077	0.189
Owners of commodity housing	0.140*	0.091	0.189
Owners of work-unit housing	0.074*	0.019	0.128
Owners of resettlement housing	-0.072	-0.149	0.004
Residence length (< 10 years)	0.006	-0.004	0.016
Non-movers (> 10 years)	0.083*	0.032	0.134
Female	-0.037*	-0.064	-0.011
Age_30-39	-0.040*	-0.075	-0.005
Age_40-49	-0.109*	-0.148	-0.071
Age_50-59	-0.181*	-0.234	-0.128
Age_above 60	-0.075	-0.175	0.024
Monthly income_below 3,000	-0.066*	-0.100	-0.031
Monthly income_5,000-9,999	0.086*	0.053	0.119
Monthly income_above 10,000	0.173*	0.122	0.224
Two-person family	-0.011	-0.058	0.035
Family with children	-0.034	-0.073	0.005
Secondary education	0.004	-0.052	0.061
Tertiary education	0.042	-0.014	0.097
Log of distance to the nearest subway station	-0.021	-0.047	0.005
Log of distance to the nearest park	-0.051*	-0.083	-0.019
Log of distance to the nearest recreational facility	-0.002	-0.026	0.021
Population density	0.000	-0.039	0.040
Buildings1949	-0.010	-0.128	0.106
Crime rate	-0.015	-0.062	0.033
Low education	-0.035	-0.126	0.056
Buildings1949 × Owners of resettlement housing	0.224*	0.076	0.372
Low education × Owners of resettlement housing	0.205*	0.066	0.343
Buildings1949 × Owners of work-unit housing	0.127*	0.021	0.236
Individual-level variance			
σ_e^2	0.274	0.265	0.284
District-level variance			
Variance (Intercept)	0.053	0.031	0.096
Variance (Owners of work-unit housing)	0.013	0.006	0.026
λ	0.605	0.227	0.882

Note. "*" indicates the significance level of 0.05. Omitted dummy variables are: renting private housing; male; age below 30; monthly income between 3,000 and 4,999; single household; nine-year compulsory education. The variable *Residence length (< 10 years)* represents an interaction term—*Residence length* (< 10)×(1 - *Residence length* (> 10)).

Table 4. A sensitivity analysis of key model parameter estimation using different hyperpriors

	Priors	Mean/ Std.dev	Renting work-unit housing	ECH	Owners of commodity housing	Owners of work-unit housing	Owners of resettlement housing
λ	logitbeata	0.646	0.056	0.133	0.140	0.074	-0.072
	(1,1)	0.195	0.027	0.029	0.025	0.028	0.039
	logitbeata	0.591	0.056	0.133	0.140	0.074	-0.072
	(2,2)*	0.176	0.027	0.029	0.025	0.028	0.039
	logitbeata	0.691	0.056	0.133	0.140	0.074	-0.072
	(4,2)	0.160	0.027	0.028	0.025	0.028	0.039
	logitbeata	0.691	0.056	0.133	0.140	0.074	-0.072
	(0.5,0.5)	0.206	0.027	0.029	0.025	0.028	0.039
District-level variance (Intercept)	Loggamma	0.066	0.056	0.133	0.140	0.074	-0.072
	(1,0.1)	0.016	0.027	0.029	0.025	0.028	0.039
	Loggamma	0.056	0.056	0.133	0.140	0.074	-0.072
	(1,0.01)	0.016	0.027	0.029	0.025	0.028	0.039
	Loggamma	0.057	0.056	0.133	0.140	0.074	-0.072
	(1,0.001)	0.016	0.027	0.029	0.025	0.028	0.039
	Loggamma	0.056	0.056	0.133	0.140	0.074	-0.072
	(1,5e-5)*	0.016	0.027	0.028	0.025	0.028	0.039
District-level variance (Owners of work-unit housing)	Loggamma	0.023	0.056	0.132	0.139	0.072	-0.073
	(1,0.1)	0.006	0.027	0.029	0.025	0.030	0.039
	Loggamma	0.016	0.056	0.133	0.140	0.073	-0.072
	(1,0.01)	0.005	0.027	0.028	0.025	0.028	0.039
	Loggamma	0.014	0.056	0.133	0.140	0.074	-0.072
	(1,0.001)	0.005	0.027	0.028	0.025	0.028	0.039
	Loggamma	0.014	0.056	0.133	0.140	0.074	-0.072
	(1,5e-5)*	0.005	0.027	0.029	0.025	0.028	0.039

Note. Hyperpriors used in the study of neighbourhood satisfaction in Beijing are marked with an asterisk (*). Fixed regression coefficient estimation for homeownership types are nearly identical with differences observed only in the fourth decimal. Other fixed regression coefficient estimates has a similar pattern.

Figures

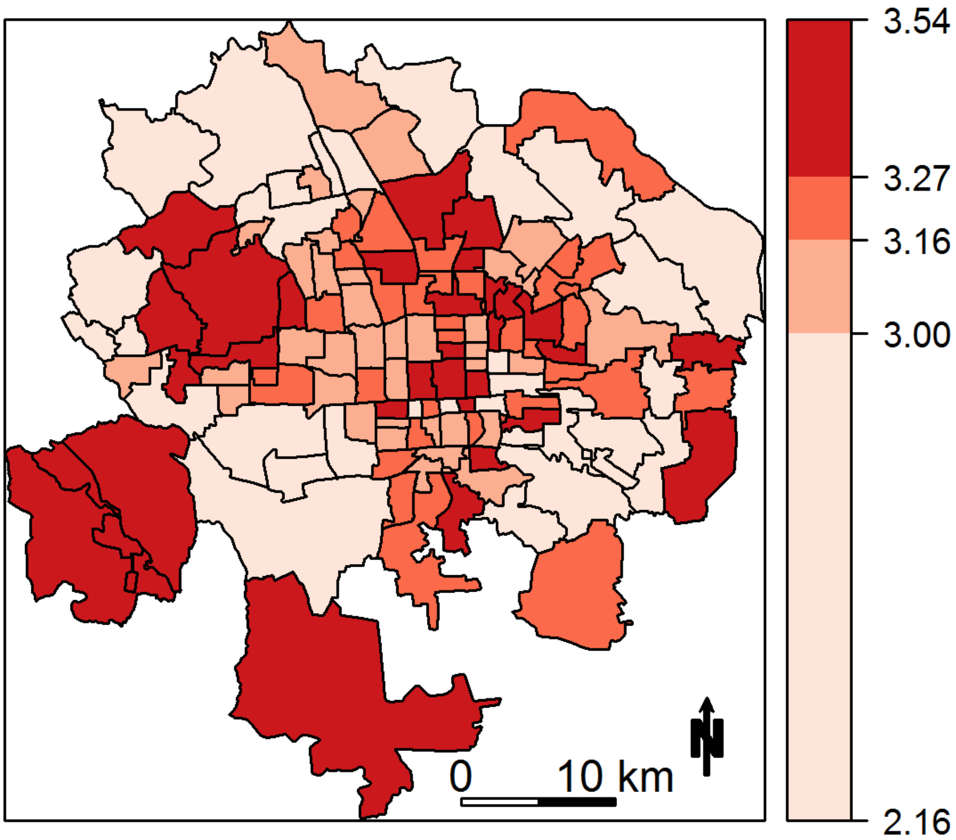

Figure 1. Map displays the spatial pattern of neighbourhood satisfaction (on a five-point scale) in urban Beijing

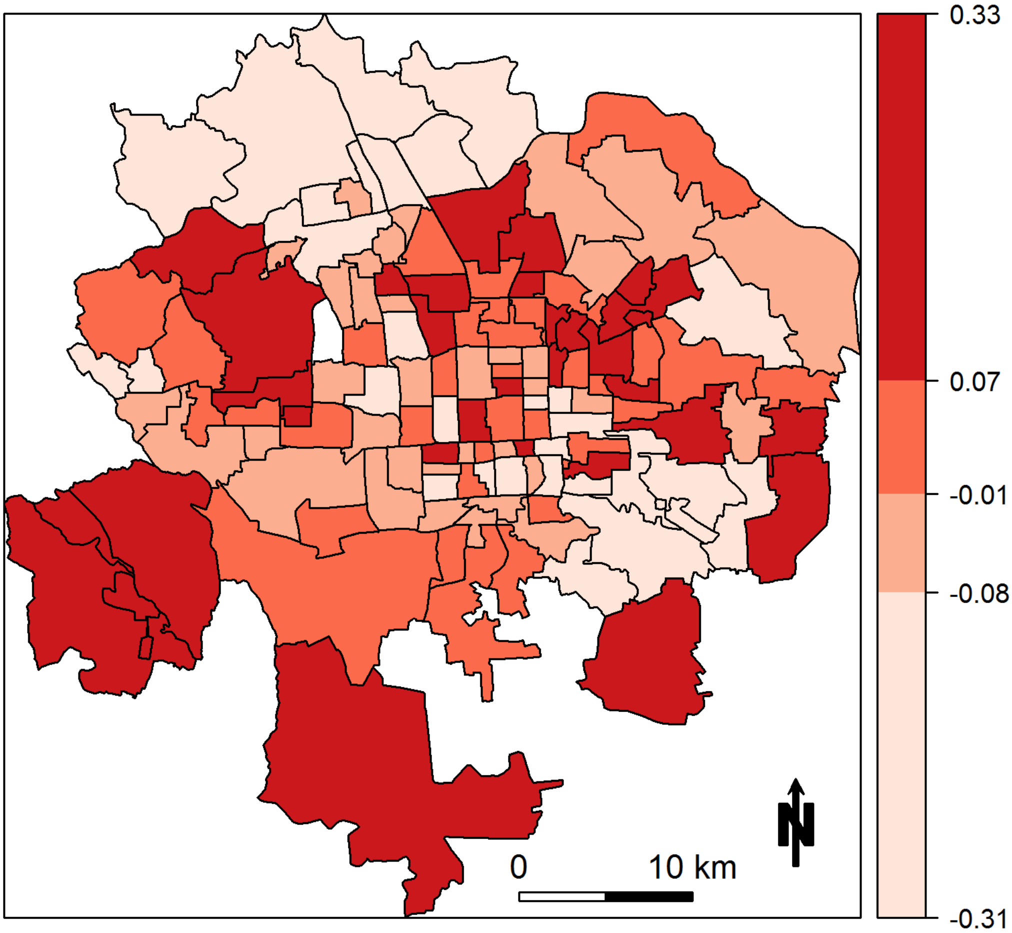

Figure 2. Map displays the spatial pattern of the district-level random effects in urban Beijing