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Residential Environment and Subjective Well-being in Beijing: A Fine-grained Spatial Scale Analysis using a Bivariate Response Binomial Multilevel Model

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Abstract

Existing literature has examined the determinants of subjective well-being (SWB) in China from the social, economic and psychological perspectives. Very few studies explore the impacts of residential environment on SWB. Drawing on a large scale questionnaire survey in Beijing, this paper investigates the role of residential environment by decomposing the variations of SWB at fine-grained spatial scales, i.e. district and neighbourhood levels. A bivariate response binomial multilevel model is employed to assess the relative importance of geographical contexts and individual characteristics, in particular, the household registration (hukou) status, in influencing SWB. The results show significant heterogeneities in SWB among districts and neighbourhoods. Neighbourhood types are significantly correlated with SWB, with residents in commercial housing neighbourhoods reporting higher levels of SWB than those in work-unit and affordable housing neighbourhoods. However, the impacts of neighbourhood types are not uniformly experienced by people with different hukou status. Migrants tend to express lower levels of SWB than local residents. Such disparities are more pronounced in urban villages compared with other neighbourhoods.

Keywords: subjective well-being; residential environment; neighbourhood types; hukou status; multilevel model

1. Introduction

Over the last three decades China has experienced dramatic economic growth and massive urban transformation. In particular, the housing reforms since 1980 have resulted in distinct residential environment, both physical and social, in different neighbourhood types, in terms of location, access to services and facilities, and residents' socio-economic composition. Such environment is likely to influence residents' subjective wellbeing (SWB hereafter) because it affects the amenities, opportunity structure and the degree of livability of the locality (Veenhoven, 1995; Schneider, 2016). SWB refers to an individual's cognitive (e.g. life satisfaction) and affective (e.g. happiness) evaluations of his or her own life (Dolan et al., 2008). It differs from the traditional focus of wellbeing which is in health sciences such as illness and impairments (Diener et al., 2012). SWB is regarded as a comprehensive and direct indicator of human welfare. A large number of studies have examined its influencing factors in China from the economic, social and psychological perspectives (Appleton and Song, 2008; Bian et al., 2015). Yet, relatively few studies have explored the impacts of residential environment, with exceptions of limited empirical evidence on residential satisfaction variations across different social groups (e.g. Li and Wu, 2013). Even fewer studies examine the role of neighbourhood and the interaction between individual characteristics and residential environment.

Our goal in this paper is to fill in the above gap by examining the relationship between residential environment and SWB in transitional China with enormous housing reforms and neighbourhood changes. Drawing on data from a large-scale questionnaire survey in Beijing, we examine the impacts on SWB of demographic, socio-economic factors, neighbourhood type and other contextual variables measured at fine-grained spatial scales, i.e.

districts and neighbourhoods. In particular, we address the following research questions: to what extent residents' SWB is influenced by geographical contexts and individual characteristics; how it varies spatially among districts and neighbourhoods; how such spatial variations contribute to explaining the variance in SWB; and finally, how the contextual variables at district and neighbourhood levels interact with individual attributes in shaping SWB.

We aim to add to literature in three aspects. First, previous studies have primarily focused on the impacts of individual factors on SWB in China, such as education and income. We acknowledge that institutional factors, in particular, housing policies and the household registration (hukou) system, are crucial in influencing residential environment and SWB. Housing reforms result in diverse neighbourhood types, including those dominated by commercial properties, work-unit and affordable housing. Disparities in land use and house price generate inequalities among different neighbourhood types in terms of residential environment, including physical location, facilities and residents' demographic/economic composition. This is likely to influence residents' life satisfaction and happiness (Morrison, 2007). The hukou system is another important institution influencing SWB in that it defines a person's access to housing, employment, benefits and services (Huang, 2004). Migrants, defined as people who moved to a new place and whose hukou status remains at their place of origin (Chan, 2009), are excluded from entitlement to local social benefits, such as subsidised housing and minimum living allowance. Such discrimination results in inequalities between migrants and local residents in terms of housing outcomes, resources and opportunities. We will explore the variations of SWB among different neighbourhood types and between individuals with different hukou status under these institutional settings.

A second contribution is that we employ multilevel models to examine the impacts of residential environment on SWB, together with the interaction effects between individual attributes and neighbourhood and district characteristics. Multilevel modelling techniques enable us to disentangle the individual and contextual effects on SWB and to investigate the heterogeneous effects of neighbourhood types and hukou status across local contexts. This results in more accurate estimates and a better understanding of the impacts of residential environment at different scales on SWB. Lastly, previous studies compare SWB between regions or nations by using data at city or national levels (Aslam and Corrado, 2011; Deeming and Hayes, 2012). Very few studies focus on variations of SWB at neighbourhood level. By using a unique dataset in Beijing's neighbourhoods, we are able to differentiate the impacts of residential environment at a more detailed spatial scale than previous studies.

The rest of the paper is structured as follows. We start with a review of previous studies on SWB, and then discuss the spatial scales in Chinese cities and the hukou institution. Based on previous studies and the Chinese context, we set out our hypotheses. This is followed by the discussions of data, methodology and empirical findings. Finally, we conclude the paper with a summary of main findings.

2. Previous studies on SWB

Research on SWB dates back to mid-20th century when psychologists explored the relationship between mental health and happiness. Since then a wide range of studies have explored SWB from different disciplinary perspectives, including economics (e.g. Easterlin, 2001), sociology (e.g. Diener et al., 2012) and geography (Ballas and Tranmer, 2011). They focus on individuals' subjective assessment of life, including positive emotions such as happiness and an evaluative judgement of life satisfaction. Happiness is 'based on positive and negative emotions at a moment in time (for example, joy and anxiety), while 'life satisfaction' is based on a more reflective assessment of how well life is going (for example, fulfilment of goals)' (Burchardt, 2013, p.3). There are critiques about these indicators, for example, happiness is regarded as being 'too narrow' and subject to temporal changes; life satisfaction is influenced by individuals' previous experience and adaption to constraints (Diener et al., 2012). Despite these critiques, these two terms are widely used to measure SWB.

Demographic characteristics, economic resources, employment status, health and social networks are important factors influencing SWB (e.g.Veenhoven, 2015). Previous studies find a U-shaped relationship between age and SWB, with mid-aged people less likely to be happier because of family duties and career burdens (Dolan et al., 2008).Easterlin (2001) reported that higher income leads to higher levels of SWB, as wealthy people can afford resources conducive to improving happiness. However, many studies show that increasing income in industrialised countries does not result in noticeable increase in average SWB (Dolan et al., 2008). This is called 'the Easterlin paradox', which suggests the importance of non-economic factors influencing SWB, especially when certain essential material needs are met. It also implies that the impact of income on SWB may be larger in poorer countries than in developed ones. A recent study by Deeming and Hayes (2012) find that access to the welfare system in modern societies contributes to SWB.

Researchers in health geography have emphasised the importance of space in shaping health and SWB (Kearns and Moon, 2002, Veenhoven 2015). They have shown the significant influences of social determinants and neighbourhood effects on wellbeing (e.g. Wilkinson and Pickett, 2009; Marmot, 2008). For example, Marmot (2008) argues that inequalities in health are driven not only by the unequal distribution of wealth, but by the inequitable access to economic, social and environmental resources. Places matter because they are socially structured and represent differential amenities and opportunity structures, including access to physical resources, such as parks, transport nodes, clean air and water, as well as social services and support (Kearns and Moon, 2002). The livability hypothesis, developed by Veenhoven (1995), echoes this and indicates that SWB is driven by physical living conditions within specific social and institutional settings. If individual needs are consistent with the settings, the degree of livability and SWB are higher. Empirical studies have explored the relationship between residential environment and SWB. For example, Cunado and Gracia (2013) reported that air pollution decreases residents' happiness or life satisfaction, as air pollution reduces the quality of life and the level of livability. Other location-specific factors, such as urban density and natural views, are also found to influence SWB (Morrison, 2007).

Studies on SWB in China have focused on social and economic determinants, such as income, age, health and social support. For example, Appleton and Song (2008) examines life satisfaction of urban residents using the 2002 urban household survey, and finds that low inflation enhances life satisfaction. Bian et al. (2015) examines happiness using data from a survey in western China, and concludes that people are happier when connected to wider social networks. Smyth et al. (2008) analyse the relationship between air pollution and happiness in urban China, and concludes that a reduction of air pollution contributes to residents' happiness. Some studies focus on hukou status, and reported that the average happiness score of rural migrant households in cities was lower than that of households in the countryside (Knight and Gunatilaka, 2010). The authors explain the result as discrimination against migrants in cities as well as migrants' increased aspiration after migration.

Previous studies primarily draw on survey data and employ a single level regression model to examine the influence of individual factors on SWB in China. Relatively less is known about the impact of the place, i.e. residential environment in this paper. Moreover, a single level model is problematic in analysing clustered survey data, because it ignores the fact that the distribution of socioeconomic variables and SWB at different spatial levels may be subject to the influence of grouping (Ballas and Tranmer, 2011). Multilevel modelling enables us to decompose the variations in SWB to different spatial scales, and is regarded as an effective empirical means of 'capturing place' (Kearns and Moon, 2002, p.611). Before we discuss our research design, we shall outline the spatial hierarchy and institutional factors in the Chinese context.

3. Spatial Hierarchy and the Hukou System in China

There are four spatial hierarchies in a Chinese city: city (Shi), mega-district (Shixiaqu), district (Jiedao) and neighbourhood (Juzhu xiaoqu). We aim to explore SWB heterogeneity at the finest two spatial scales in Beijing.

3.1 District and Neighbourhood

District Heterogeneity

District is the fundamental census administration unit in Chinese cities. The average population of a district in Beijing was about 86,000 with a standard deviation of about 48,000 (Beijing Municipal Bureau of Statistics, 2012). There is great heterogeneity in terms of land use patterns, public facilities and residents' social-demographic composition among districts (Zheng and Kahn 2008). Two reasons exist. First, the municipal government sets up differential development plans for districts. For instance, districts surrounding the Forbidden City focus on heritage preservation, while those near the Olympic Park are positioned as a window of showcasing modernity and development. Under such guidance, districts exhibit different development patterns, leading to differential residential environment. Second, since the land reforms in the 1980s, land use rights have been transacted on the market. This led to differential land use mix and physical environment at different locations (Zheng and Kahn, 2008). Such geographical heterogeneity has been found to be an important factor in explaining the variations in residential satisfaction (e.g. Dang et al., 2014). It is likely to influence residents' SWB. Therefore, our first hypothesis is as follows.

Hypothesis 1: individuals' SWB vary significantly between districts after accounting for variations of individual characteristics (i.e. the compositional effect).

Neighbourhood Heterogeneity

A neighbourhood is composed of residential buildings with similar designs, recreational facilities and open space. Its area is usually less than one square kilometre in Beijing, and the population ranges from a thousand to several thousands. Four neighbourhood types are identified according to the dominant housing tenure and land supply: those dominated by work-unit housing, affordable housing, commercial properties, and urban villages (e.g. Huang, 2004; Wu, 2005; Wu et al., 2013). When a neighbourhood was initially constructed, most of the properties had the same tenure. There are changes over time; e.g. flats in an affordable-housing neighbourhood can be transacted as commercial properties after residents hold them for five years. However, neighbourhoods have dominant housing types which define residential environment in terms of location, living environment, infrastructure, and residents' socio-economic attributes.

Work-unit housing was the major housing type before 1980 when the public sector dominated the urban economy and work units were responsible for constructing, allocating and maintaining housing as a benefit for their employees. It was allowed to be sold to existing tenants at a heavily subsidised price during the housing reformsAs a result, residents living in a work-unit neighbourhood may share some attributes in common because of current/previous affiliation to work units, although turnover in these neighbourhoods has increased dramatically in recent years. Affordable housing, another type of subsidised housing emerging in the 1990s, includes economical and comfortable housing (ECH), low-rent housing and public rental housing. It is low-cost housing sold or rent to median- and low-income households who are unable to afford commercial properties via the market.

Municipal governments tend to build affordable housing in remote areas without good access to employment opportunities and public services such as schools and hospitals, because of low land prices. This leads to unfavourable living environment in these neighbourhoods. Commercial properties result from the development of a housing market. Their price is determined by the market and purchasers have full property rights. These properties tend to have higher building standards than work-unit and affordable housing. They also include a variety of facilities such as landscaped gardens, shops, restaurants as well as apartment cleaning service (Wu, 2005). Lastly, urban villages are former rural settlements which were engulfed into a city by its expansion. Local villagers extended their housing and rent rooms to supplement income. Urban villages become popular residential areas for migrants because of its convenient location and cheap housing. However, they are characterised by over-crowding, ambiguous property rights as a result of illegal building extension, lax development control, informal and insufficient service provision (Zheng et al., 2009; Li and Wu, 2013).

The above four types of neighbourhoods have specific boundaries designated by urban planners, with differential social and physical environment. We assume that heterogeneity among different neighbourhood types might influence residents' SWB.

Hypothesis 2: individuals' SWB varies significantly between neighbourhoods. In addition, variation in SWB at the neighbourhood scale is expected to be larger than that at the district scale, because neighbourhoods represent the immediate living environment.

3.2 The Household Registration System

At individual level, the most important institutional factor affecting SWB is the hukou system. The system, implemented in 1958, is a social control measure that divides Chinese citizens into rural and urban hukou categories in different localities. Different hukou holders are entitled to different social benefits and services that are geographically confined (Chan, 2009).

In this spatial disequilibrium, urban residents have access to better public services than rural residents, and residents in larger cities have access to even better services than those in smaller cities (Ding, 2003). Such inequalities existed before the economic reforms, supported by policies restraining individuals' self-initiated migration, especially from rural to urban areas (Chan, 2009). With the gradual relaxation of migration control after 1978, millions of people have ignored the hukou system and moved to cities to seek better life. However, it is extremely difficult for them to register their hukou at destination. Without local hukou status, they are not entitled to local benefits and services, resulting in inequalities between local residents and migrants (Chan, 2009). For example, access to urban housing is tied to hukou status; people without local urban hukou status are prevented from accessing subsidised housing. Migrants are also denied unemployment insurance and minimum living allowance. They even find it difficult to send their children to local authority schools in some cities (Li, 2012). Such inequalities between migrants and local residents are likely to reduce migrants' SWB.

Hypothesis 3: individuals' SWB is significantly influenced by hukou status, with migrants reporting lower levels of SWB than local residents.

4. Research Design

4.1 Data

Our data come from a large-scale questionnaire survey conducted by the Chinese Academy of Sciences in Beijing in 2013. It covered all districts in urbanised areas, using the PPP sampling method (probability proportionate to the population). In each district, residents who had lived there for more than six months were randomly selected to participate in the survey (Zhang et al., 2015). The questionnaire records information on respondents' demographic and socio-economic characteristics including age, gender, education, income, jobs, place of residence, housing tenure and household registration. We used the provided residence addresses to obtain the information on neighbourhood type by checking the largest Chinese web search engine Baidu.[1] Among the 5000 questionnaires initially distributed, 2606 (52%) recorded detailed residence addresses which were successfully matched to 354 neighbourhoods located in 97 districts in urban Beijing. Figure 1 displays the spatial distribution of these neighbourhoods.

[Figure 1 about here]

Following previous studies we use two indicators to measure SWB, life satisfaction and happiness. They are based on two survey questions, "All things considered, how satisfied are you with your life as a whole? And how happy are you with your life as a whole?" The responses are recorded on a 5-point Likert scale with "1 = very unsatisfied/unhappy"; "2 = unsatisfied/unhappy"; "3 = fair"; "4 = satisfied/happy"; and "5 = very satisfied/happy". The majority of the respondents (about 67.3%) are satisfied (or very satisfied) with life, and 28.6% report fair satisfaction. Less than 5% are (very) unsatisfied. A similar pattern is observed for happiness where 58.5% of the respondents are (very) happy while 4.9% are (very) unhappy. To empirically examine potential sources of life satisfaction and happiness, we recoded the two indicators into binary variables: 1 for very satisfied and satisfied (or very happy and happy), and 0 for others.

Table 1 provides a list of dependent and explanatory variables used in our study. Following previous SWB literature (Dolan et al., 2008), individual's demographic and socio-economic characteristics, such as age, gender, income, educational achievement, marital status, employment and self-rated health conditions are included in our model. Hukou status is included to test Hypothesis 3. At the neighbourhood level, four neighbourhood type binary

[1] Baidu is the largest Chinese web search engine, which provides accurate and reliable geolocation and search services.

variables are used to test the impacts upon SWB of living in different neighbourhoods characterised by distinct housing types and residential environment. Variables at the district level were extracted from the 2010 population census, including the proportion of migrants, proportion of affordable housing stock, mean educational attainment and proportion of housing stock built before 1949. These variables are expected to capture the social and demographic variations among districts.

4.2 A bivariate response binomial multilevel model

Our data have a three-level structure; individuals nest hierarchically into neighbourhoods that further nest into districts. Consequently, multilevel models are employed to control for the dependence effects at both the neighbourhood and district scales. Multilevel models allow for a reliable decomposition of variations in SWB at different levels and robust estimation of between-neighbourhood and between–district heterogeneity effects, while controlling for individual characteristics (Ballas and Tranmer, 2011). As SWB are measured by two different but related indicators, life satisfaction and happiness, they are modelled jointly in a bivariate response binomial multilevel model. Such a joint model produces more reliable estimates than two separate models because it takes into account the dependence between the two indicators (Baldwin et al., 2014). Multivariate responses can be conveniently incorporated into a multilevel model by creating an extra artificial level (i.e. individual-response pairs) that defines a multivariate structure (Rasbash et al., 2012; Browne et al., 2012). Each SWB indicator is estimated by a probit model, in which the correlation between the two response variables is accommodated by using a bivariate normal distribution. The bivariate response probit multilevel model is specified as follows (Rasbash et al., 2012),

$$Resp_{1,jkl} \sim Binomial\ (1, \pi_{1,jkl}) \tag{1}$$

$$Resp_{2,jkl} \sim Binomial\ (1, \pi_{2,jkl}) \tag{2}$$

$$cov\begin{bmatrix}Resp_{1,jkl}|\pi_{1,jkl}\\Resp_{2,jkl}|\pi_{2,jkl}\end{bmatrix}=\begin{bmatrix}g(\pi_{1,jkl}) & \\ \rho_{12}\left[g(\pi_{1,jkl})*g(\pi_{2,jkl})\right]^{0.5} & g(\pi_{2,jkl})\end{bmatrix} \quad (3)$$

$$probit(\pi_{1,jkl})=a_{1,0}+\sum_{i=1}^{I}\beta_{1,i}x_{ijkl}+\sum_{m=1}^{M}\gamma_{1,m}z_{mkl}+\sum_{n=1}^{N}\delta_{1,n}w_{nl}+f_{1,l}+v_{1,kl} \quad (4)$$

$$probit(\pi_{2,jkl})=a_{2,0}+\sum_{i=1}^{I}\beta_{2,i}x_{ijkl}+\sum_{m=1}^{M}\gamma_{2,m}z_{mkl}+\sum_{n=1}^{N}\delta_{2,n}w_{nl}+f_{2,l}+v_{2,kl} \quad (5)$$

$$\begin{bmatrix}v_{1,kl}\\v_{2,kl}\end{bmatrix}\sim N(0,\Omega_v)\ ;\ \Omega_v=\begin{bmatrix}\sigma_{v_1}^2 & \\ \sigma_{v_1v_2} & \sigma_{v_2}^2\end{bmatrix} \quad (6)$$

$$\begin{bmatrix}f_{1,l}\\f_{2,l}\end{bmatrix}\sim N(0,\Omega_f)\ ;\ \Omega_f=\begin{bmatrix}\sigma_{f_1}^2 & \\ \sigma_{f_1f_2} & \sigma_{f_2}^2\end{bmatrix}. \quad (7)$$

In the equations, *j*, *k* and *l* are individual, neighbourhood and district indicators, respectively. Life satisfaction and happiness are presented by $Resp_{1,jkl}$ and $Resp_{2,jkl}$, each of which follows a binomial distribution with probability parameters $\pi_{1,jkl}$ and $\pi_{2,jkl}$. Equation (3) gives the covariance matrix between life satisfaction and happiness at the individual level where $g(\pi_{.,jkl}) = \pi_{.,jkl} \times (1 - \pi_{.,jkl})$ are two variance parameters and the parameter ρ_{12} measures the correlation between the two SWB indicators. Equations (4) and (5) use the probit link function of probabilities of life satisfaction and happiness (the inverse of the cumulative density function of a standard normal distribution) to a range of individual-level predictors (x_{ijkl}), neighbourhood type variables (z_{mkl}) and district-level variables (w_{nl}), as well as the unobservable neighbourhood effect ($v_{.,kl}$) and district effect ($f_{.,l}$). The covariance matrix of unobservable neighbourhood effects upon individuals' life satisfaction and happiness is presented in Equation (6) and the district-level covariance matrix in Equation (7). Parameters $\sigma_{v_1}^2$ and $\sigma_{v_2}^2$ measure variations among neighbourhoods within districts of life satisfaction and happiness on the probit scale and $\sigma_{v_1v_2}$ measures the covariance of the two SWB indicators among neighbourhoods within districts. Finally, $\sigma_{f_1}^2$ and $\sigma_{f_2}^2$ measure the between-district variations of life satisfaction and happiness and $\sigma_{f_1f_2}$ the covariation of the two. At the individual level, the variances of residuals from the life satisfaction and happiness equations are set to one under the probit link function.

We use the variance partition coefficient (VPC, Jones et al., 2015) to apportion the total variances of the SWB indicators to different scales: districts and neighbourhoods, conditioning on fixed covariate effects. Using a latent variable approach (Goldstein et al., 2002), the proportions of variances of life satisfaction and happiness among districts are given by,

$$\sigma_{f1}^2/(\sigma_{f1}^2 + \sigma_{v1}^2 + 1) \text{ and } \sigma_{f2}^2/(\sigma_{f2}^2 + \sigma_{v2}^2 + 1), \tag{8}$$

which also assess the correlations of outcomes within the same district but different neighbourhoods.

The proportions of variances among neighbourhoods within districts are given by,

$$(\sigma_{v1}^2)/(\sigma_{f1}^2 + \sigma_{v1}^2 + 1) \text{ and } (\sigma_{v2}^2)/(\sigma_{f2}^2 + \sigma_{v2}^2 + 1), \tag{9}$$

which measures SWB variations due to neighbourhood differences net of district differences. The intra-neighbourhood correlations, which assess the correlations of outcomes within the same neighbourhood and district, are measured by $(\sigma_{f1}^2 + \sigma_{v1}^2)/(\sigma_{f1}^2 + \sigma_{v1}^2 + 1)$ and $(\sigma_{f2}^2 + \sigma_{v2}^2)/(\sigma_{f2}^2 + \sigma_{v2}^2 + 1)$. The correlations between the two SWB indicators are quantified as $\sigma_{f_1 f_2}/\sigma_{f_1}\sigma_{f_2}$ at the district level, $\sigma_{v_1 v_2}/\sigma_{v_1}\sigma_{v_2}$ at the neighbourhood scale within districts and ρ_{12} at the individual level within neighbourhoods.

The model is fitted using Markov chain Monte Carlo (MCMC) methods, implemented in MLwiN (Rasbash et al., 2012). Diffuse prior distributions are specified for all model parameters. The statistical inferences on model parameters are based on one MCMC chain, which consists of 200,000 iterations with a burn-in of the first 100,000 iterations that allows the MCMC chain to converge, identified by using conventional diagnostic tools (Browne et al., 2012). We further retain every tenth sample to reduce autocorrelation in the MCMC chain.

5. Results and discussions

We first present summaries on the distribution of SWB across different types of neighbourhoods in Beijing. Then we estimate an "intercept-only" model without covariates. We calculate VPCs to show the relative importance of neighbourhoods and districts as sources of variations in SWB, and quantify the correlations between life satisfaction and happiness at different levels. After that, we estimate models with individual characteristics, neighbourhood- and district-level covariates. Finally, we add cross-level interaction terms to test potential interaction between individual attributes and neighbourhood characteristics.

5.1 SWB in different types of neighbourhood

Variations in SWB across different types of neighbourhoods were observed. Commercial housing neighbourhoods and urban villages have larger proportions of residents who are satisfied or happy with their lives than affordable and work-unit housing neighbourhoods (Figure 2). A larger variability of the probability of life satisfaction and happiness is observed in urban villages than other neighbourhood types, according to the 95% confidence intervals associated with the probability estimates. We further compare the SWB proportions between local residents and migrants, and find discrepancies in SWB between the two groups except for those in work-unit housing neighbourhoods. The greatest contrast is found between local residents and migrants in urban villages, with local residents having the highest probabilities of life satisfaction and happiness while migrants experiencing the lowest probabilities amongst the four neighbourhood types. The non-overlapping 95% confidence intervals of SWB between local residents and migrants might demonstrate the potentially important impact of hukou status upon SWB (Figure 2).

[Figure 2 about here]

5.2 The intercept-only model

Table 2 displays the results of the intercept-only model. For life satisfaction, the between-districts and the between-neighbourhoods within-districts variances are 0.051 and 0.196, respectively. The VPC at the district and neighbourhood levels are, therefore, 0.041 and 0.157, i.e., 4.1% of the total variance in life satisfaction is attributable to district differences while 15.7% is due to within-district neighbourhood differences. For happiness, about 6% and 14% of the total variance are accounted for by differences between districts and neighbourhoods, respectively. For both indicators, neighbourhoods play a larger role in explaining variations than do districts.[2] The result demonstrates the need to examine the SWB variations at fine-grained spatial scales such as neighbourhoods. As to the correlations between the SWB indicators, we find life satisfaction and happiness are closely correlated at all three levels—individuals, neighbourhoods and districts, with correlation coefficients being 0.739, 0.842 and 0.765, respectively. This justifies the appropriateness of a joint model of the two indicators.

5.3 The model with fixed effect covariates

Individual characteristics, neighbourhood types and district-level variables are added in the model to explain the variations in SWB. The results are presented in Table 3. Variances among districts and among neighbourhoods within districts have slightly decreased to 0.027 and 0.132 for life satisfaction. Yet, the spatial heterogeneity of life satisfaction especially at

[2] It is acknowledged that the scale and boundary defined for the higher level units matter, as variations tend to increase with spatial granularity. Also, the arbitrariness of geographical boundaries of units, in the sense that the true living contexts of individuals are unobservable, might cast uncertainties to the decomposition of total variations in SWB to different scales.

the neighbourhood scale is still fairly substantial after adjusting for a range of fixed covariate effects. The variances of happiness at the district- and neighbourhood-level remain stable. The results therefore support our Hypotheses 1 and 2 that both neighbourhood and district variables contribute to explain the variations in SWB and that there is greater heterogeneity between neighbourhoods than districts in the socio-spatial distribution of SWB.

Table 3 shows significant impacts of neighbourhood types on individuals' SWB. For life satisfaction, residents in work-unit and affordable housing neighbourhoods tend to report lower levels of life satisfaction compared with those in commercial housing neighbourhoods, everything else equal. This might be explained by better living environment in commercial housing neighbourhoods. It is surprising to find that living in urban villages is associated with a higher level of life satisfaction than living in commercial housing neighbourhoods. However, such a difference is not homogeneous between migrants and local residents, as we shall discuss later. In terms of happiness, living in affordable housing neighbourhoods is significantly associated with lower levels of happiness than living in commercial housing neighbourhoods. This may be related with the remote location of affordable housing neighbourhoods with insufficient access to employment opportunities, public facilities and amenities. Meanwhile, the levels of happiness are not distinguishable between living in urban villages and neighbourhoods of commercial and work-unit housing. At the district level, the proportion of people with academic degrees (bachelor or above) is found to be significantly and positively associated with life satisfaction, ceteris paribus. Districts with a higher proportion of affordable housing stock are related to a lower level of happiness. The district-level proportions of migrants and building stocks before 1949 are not significantly associated with SWB.

With respect to the individual-level variables, migrants tend to report significantly lower levels of life satisfaction and happiness than local residents, holding everything else constant. The finding supports our Hypothesis 3. In terms of other individual characteristics, most of the findings are in agreement with previous studies (e.g. Dolan et al., 2008). Age has a non-linear association with life satisfaction and happiness; younger and older people tend to report higher levels of SWB than middle-aged adults, ceteris paribus. Household income is significantly and positively related to life satisfaction and happiness. Whilst married people tend to have higher levels of life satisfaction, the impact of marriage on happiness is not statistically significant. Distinctness in life satisfaction is also found between people with different educational achievement—people with tertiary education are associated with higher levels of life satisfaction compared with those without university/college experience. However, educational achievement is not statistically significantly associated with happiness. Self-rated health status is found to be significantly associated with life satisfaction and happiness, consistent with previous studies. Renters are less satisfied and happier than home owners, confirming the positive role of homeownership on SWB.

5.4 The model with cross-level interactions

The results of the models with cross-level interaction terms are reported in Table 4.[3] Most regression coefficients of the individual-variables have similar signs to the previous ones. We focus on the interaction effects of neighbourhood types and Hukou status.

Table 4 shows that migrants still tend to express lower levels of life satisfaction and happiness than local residents, after adding the interaction terms. There are, however, heterogeneities in SWB for migrants living in different neighbourhood types. Compared with migrants living in commercial housing neighbourhoods, those living in work-unit housing neighbourhoods tend to report higher levels of life satisfaction, whereas those living in urban

[3] We were aware of the possible multicollinearity issue in the model with a series of cross-level interaction terms. As it was unable to calculate the variance inflation factor (VIF) for each variable in a bivariate probit multilevel model, the correlation coefficients between the independent variables were calculated. All of them were under 0.5, implying that multicollinearity is less of an issue.

villages report statistically significantly lower levels of life satisfaction, ceteris paribus. Part of the reasons might be the poor living conditions and insufficient provision of facilities and services in urban villages compared with commercial and work-unit housing neighbourhoods (Zheng et al., 2009). In terms of happiness, it appears that living in different types of neighbourhood does not make a difference for migrants, suggesting that migrants tend to report lower levels of happiness uniformly across neighbourhoods than local residents. Overall, the results support our hypothesis that individuals' SWB is significantly influenced by hukou status.

At the neighbourhood level, living in affordable and work-unit housing neighbourhoods is consistently associated with lower life satisfaction than living in commercial housing neighbourhoods. For local residents, living in urban villages is related to a significantly higher level of life satisfaction and happiness compared with living in commercial housing neighbourhoods. Many urban villagers built high-density apartments on their housing site after their farmland was appropriated by the city government during urban expansion, and make a living by renting rooms to migrants (Zheng et al., 2009). For them, poor living conditions and informal service provision might be well compensated by considerable rental income. This might lead to a high level of life satisfaction.

5.5 Discussions

Our results show significant variations in SWB for residents living in different types of neighbourhood. The residential environment in these neighbourhoods influences individuals' access to amenities, facilities and services. This is consistent with previous studies on health geography highlighting the important role of space in shaping individuals' subjective wellbeing (e.g. Kearns and Moon, 2002). Moreover, such space is socially structured, as different types of neighbourhoods are consequences of the housing reforms; various housing polices and the development of the housing market result in differential residential environment. The urban government benefits financially by selling the use rights of land to developers to construct commercial properties. Indeed, some local governments rely on land finance to boost their fiscal revenue, in order to deliver services and infrastructure projects, especially after the 1994 tax reforms which result in a mismatch between fiscal revenue and expenditure (Cao et al., 2008). Therefore, local governments have incentives to sell the use rights of land in good location to developers for profit (Dang, 2014). Compared with other housing types, commercial properties have the highest building standards, and access to landscaped gardens, transportation nodes, and public services including schools and hospitals. It is therefore not surprising to find that residents in commercial property neighbourhoods are more likely to express higher levels of life satisfaction and happiness. In contrast, affordable housing is subsidised by local governments to help improve housing conditions for low- or median- income urban residents, as a response to the call from the central government for better housing provision. Local governments are reluctant to allocate land for affordable housing due to low profitability and the great drain on public finance. Because of political accountability measure that holds local officials accountable for not fulfilling top-down political mandates (GOOSC, 2011), many local government officials focus on the required amount of affordable housing supply but tend to ignore other aspects such as the quality of housing, location, and accessibility. Many affordable housing neighbourhoods are situated in peri-urban areas with poor access to amenities and facilities. Unequal access to resources is likely to lead to disparities in SWB for residents in different neighbourhoods.

Affordable housing also accommodates some urban residents whose houses were demolished during urban renewal projects and who were unable to purchase commercial properties in their original locality due to financial constraints. It is possible that relocated residents in affordable housing neighbourhoods may express lower levels of life satisfaction and happiness, because of their previous experience of resettlement rather than the quality of residential environment. Previous studies on the impacts of relocation as a result of urban regeneration on SWB are mixed. Some studies find that residents are satisfaction with resettlement because their housing conditions improved after relocation (Li, 2012). However, others reported negative impacts of relocation on life satisfaction, as some residents were displaced and their social networks were damaged (Fang, 2006). However, the nature of our cross-sectional data does not allow us to explore the dynamic process of displacement and its consequences on SWB. Another limitation of using cross-sectional data is that we are unable to control for unobserved characteristics which might influence people's selection into different neighbourhoods and their SWB. For example, all else being equal, cheerful people may perform better in the labour market and are capable of purchasing commercial properties. They also tend to express happiness and life satisfaction. Longitudinal data would be useful in investigating the impacts of self-selection and unobserved characteristics on SWB.

Our results also demonstrate that migrants express lower levels of SWB than local residents, especially for those living in urban villages. The finding corresponds with Knight and Gunatilaka (2010) which reported migrants' low happiness score. It is also consistent with previous studies on migration which reveal disadvantaged positions of migrants in Chinese cities as a result of the hukou institution (Chan, 2008; Li 2012). For example, migrants suffer from formal and informal obstacles to securing well-paid urban jobs, and are concentrated in low-skilled jobs including those 3D ones (Dirty, Demeaning and Dangerous) (Li, 2003; Chan & Buckingham, 2008). Their occupational attainment cannot be entirely explained by productivity-related characteristics, suggesting the existence of labour market discrimination against them (Chen, 2011). Moreover, migrants have limited access to social benefits without local hukou status, as we discussed in Section 3. The majority of migrants rent housing from the private market. Many live in over-crowded houses in urban villages with inadequate facilities (Li 2012). Although both local residents and migrants live in urban villages and share similar neighbourhood environment, living conditions for local residents are much better, in terms of housing size and facilities. Local residents have their own kitchen and toilet which are lacking for many migrants. Without farmland, many villagers make a living by renting extra rooms and benefit enormously from the rapid increase of house prices and rents in recent years, which in turn is a disadvantage to migrants. Local residents also benefit from assets collectively owned by the village. In contrast, migrants face fewer housing choices, and are confronted with institutional barriers to accessing local services such as schooling for their children. All these factors may explain the pronounced disparities of SWB between local residents and migrants in urban villages.

6. Conclusion

Drawing on data from a large-scale questionnaire survey in Beijing, this paper adds to literature by examining the relationship between SWB and residential environment measured at district and neighbourhood levels, the finest spatial scale in a Chinese city. A bivariate response binomial multilevel modelling approach is employed to decompose the variation of SWB at the district, neighbourhood and individual levels, allowing for the assessments of the relative importance of geographical contexts on SWB, together with the interaction effects between individual attributes and geographical contexts.

The results show significant heterogeneities in SWB among districts and neighbourhoods in Beijing, with larger variations observed at neighbourhood level than those among districts. This demonstrates the important impacts of the immediate residential environment, i.e. neighbourhood, on residents' SWB. In addition, neighbourhood types are found significantly related to SWB. Residents in commercial housing neighbourhoods tend to report higher SWB than those living in affordable and work-unit housing neighbourhoods. However, the neighbourhood type effects are not uniformly applied to local residents and migrants. Migrants generally have lower levels of life satisfaction and happiness compared with local residents, as a result of the hukou institution which excludes migrants from assessing subsidised housing and local social benefits.

The rapid urbanisation, experienced in China in the past three decades, will continue. Predictably more and more rural migrants will move to cities and become urban citizens. Policy initiatives are needed to reduce or remove differential treatments between migrants and local residents. The central government announced a new round of hukou reforms in 2014 to abolish the rural and urban hukou status and replace it with a resident card system. The implementation and consequences of the new reforms, especially in terms of extending benefits and services to migrants, are yet to be examined. As urban villages will continue to accommodate a large number of migrants, it is important that urban planners and local governments take measures to enhance the quality of rental housing there, besides allowing migrants to apply for public rental housing on an equal footing with local residents.

This study is based on a cross-sectional questionnaire survey in Beijing only. Besides the limitation mentioned in the Discussion section, it can be improved in the following aspects. First, we use neighbourhood types to proxy residential environment, without access to data on building styles, facilities and services. Future work may explore further the role of residential environment by using more indicators of access to facilities and amenities. Second, self-rated health is included as a determinant of SWB in this study and many other studies (Dolan et al., 2008). However, there might be a two-way relationship between health and SWB, as SWB might influence subjective perception of health. The correlation between health and SWB might therefore be over-estimated. Future study should examine the interaction mechanism between health and SWB. Third, the impacts of social networks and relative income are found to be important factors influencing SWB in recent studies (Schneider, 2016). We are unable to examine these effects in the paper due to data unavailability. Despite these limitations, the study represents an important attempt in advancing our understanding of residential environment and SWB in a large Chinese city using rigorous multilevel models at fine-grained spatial scales.

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Tables

Table 1. Summary of key variables used in the study

Variables	Description	Proportions (%)/ means
Outcome variables		
Life Satisfaction	Very satisfied or satisfied	67.3%
Happiness	Very happy or happy	58.5%
Independent variables		
Individual level		
Non-Beijing hukou	People without Beijing hukou or migrants	29.8%
Gender	Female as base category	48.6%
Age	<20	2.5%
	20-29	37.1%
	30-39	28.5%
	40-49	17.2%
	50-59	10.8%
	>60	3.9%
Marital status	Married	65.0%
Monthly Income (Chinese yuan)	< 3,000	5.3%
	3,000-4,999	19.0%
	5,000-9,999	36.2%
	10,000-15,000	22.6%
	15,001-20,000	9.2%
	20,001-30,000	4.7%
	30,000+	3.0%
Education	Junior high schooling	10.7%
	Senior high schooling	28.0%
	College degree and above (base)	61.3%
Employment	Unemployed	2.5%
Self-rated health	Self-rated health scores	3.5
Renter	House renters	29.7%
Neighbourhood level		
Commercial housing	Neighbourhood dominated by commercial housing (base)	44.4%
Affordable housing	Neighbourhood dominated by affordable housing	25.4%
Work-unit housing	Neighbourhood dominated by work-unit housing	25.4%
Urban villages	Urban villages	4.8%
District level		
Migrant percentages	Percentage of migrants in each district	37.2
Degree percentages	Percentage of population with bachelor degrees and above	26.2
Affordable housing percentages	Percentage of households living in	7.3

	affordable housing	
Old building stock	Percentage of housing stock built before 1949	12.5

Note. Age and income are included in models as continuous variables. Age categories are recoded from 1 to 6 corresponding to the increase of age bands. Income categories are converted to a continuous variable using the midpoints of each income band. It is further transformed to a log scale in models. The variable, self-rated health, is on a five-point Likert scale ranging from one being very unhealthy to five being very healthy.

Table 2. Variance decomposition results from the intercept-only model.

	Life satisfaction Variance	Happiness Variance	Covariances
	Median/ 95% credible intervals	Median/ 95% credible intervals	
District level	0.051 [0.017-0.108]	0.074 [0.024-0.143]	0.047 [0.010-0.099]
Neighbourhood level	0.196 [0.113-0.297]	0.175 [0.097-0.271]	0.156 [0.087-0.235]
Individual level	1	1	0.739

Table 3. Model estimation results with independent variables at the individual, neighbourhood and district levels.

Variables	Life Satisfaction			Happiness		
	Median	2.5%	97.5%	Median	2.50%	97.50%
Intercept	0.094	-0.166	0.356	-0.192	-0.447	0.087
Individual level fixed effect estimates						
Age	-0.102*	-0.196	-0.004	-0.055	-0.134	0.029
Age Squared	0.064*	0.022	0.106	0.08*	0.04	0.122
Male	0.027	-0.083	0.135	-0.036	-0.141	0.066
Married	0.302*	0.137	0.466	0.085	-0.072	0.235
Income	0.088*	0.026	0.154	0.09*	0.025	0.161
Non-Beijing Hukou	-0.223*	-0.373	-0.072	-0.145*	-0.292	-0.003
Education (Reference: College degree and above)						
Junior high school and below	-0.257*	-0.46	-0.045	-0.051	-0.238	0.158
Senior high school	-0.133	-0.272	0.005	-0.052	-0.184	0.081
Unemployed	0.037	-0.325	0.395	-0.099	-0.451	0.262
Self-rated health	1.085*	0.969	1.208	0.902	0.765	1.024
Renter	-0.287*	-0.44	-0.142	-0.204*	-0.355	-0.057
Neighbourhood level fixed effect estimates						
Neighbourhood type (Reference: Commercial housing)						
Work-unit housing	-0.265*	-0.449	-0.064	-0.124	-0.314	0.079
Affordable housing	-0.242*	-0.406	-0.062	-0.28*	-0.434	-0.105
Urban villages	0.258	-0.119	0.641	0.206	-0.179	0.607
District level fixed effect estimates						
Migrant percentages	-0.107	-0.72	0.539	0.003	-0.687	0.684
Degree percentages	1.181*	0.452	1.952	0.533	-0.301	1.497
Affordable housing percentages	-0.47	-1.32	0.311	-0.979*	-1.867	-0.051
Old building stock	0.215	-0.382	0.786	-0.037	-0.695	0.626
Random effect estimates						
σ_f^2	0.027	0.007	0.063	0.08	0.03	0.157
$\sigma_{f_1 f_2}^2$	0.038	0.009	0.082			
σ_v^2	0.132	0.066	0.226	0.133	0.056	0.239
$\sigma_{v_1 v_2}^2$	0.104	0.04	0.181			
ρ_{12}	0.681	0.632	0.73			

Note: the symbol * represents statistical significance at the 95% credible interval.

Table 4. Estimation results of the model with cross-level interactions.

Variables	Life Satisfaction			Happiness		
	Median	2.5%	97.5%	Median	2.5%	97.5%
Intercept	0.109	-0.14	0.429	-0.131	-0.417	0.138
Individual level fixed effect estimates						
Age	-0.095*	-0.202	-0.014	-0.061	-0.161	0.021
Age Squared	0.067*	0.028	0.109	0.086*	0.047	0.128
Male	0.02	-0.091	0.133	-0.053	-0.164	0.059
Married	0.287*	0.129	0.461	0.07	-0.077	0.237
Income	0.094*	0.013	0.175	0.081*	0.005	0.158
Non-Beijing Hukou	-0.251*	-0.462	-0.045	-0.17*	-0.353	-0.006
Education (Reference: College degree and above)						
Junior high school and below	-0.25*	-0.436	-0.06	-0.031	-0.238	0.174
Senior high school	-0.13	-0.267	0.012	-0.043	-0.171	0.09
Unemployed	0.041	-0.318	0.39	-0.114	-0.464	0.223
Self-rated health	1.087*	0.959	1.215	0.902*	0.769	1.043
Renter	-0.304*	-0.444	-0.166	-0.225*	-0.371	-0.088
Neighbourhood level fixed effect estimates						
Neighbourhood type (Reference: Commercial housing)						
Work-unit housing	-0.374*	-0.591	-0.167	-0.154	-0.372	0.056
Affordable housing	-0.267*	-0.484	-0.067	-0.377*	-0.578	-0.167
Urban villages	0.679*	0.113	1.287	0.876*	0.253	1.528
District level fixed effect estimates						
Migrant percentages	-0.419	-1.204	0.329	-0.119	-1.031	0.688
Degree percentages	1.056*	0.316	1.776	0.368	-0.518	1.221
Affordable housing percentages	-0.583	-1.462	0.289	-1.122*	-2.083	-0.128
Old building stock	0.097	-0.565	0.739	-0.166	-0.876	0.565
Cross-level interactions						
Non-Beijing hukou × Work-unit housing	0.316*	0.03	0.617	-0.025	-0.317	0.279
Non-Beijing hukou × Affordable housing	0.018	-0.222	0.283	0.203	-0.051	0.443
Non-Beijing hukou × Urban villages	-0.638*	-1.237	-0.046	-0.347	-0.915	0.210
Random effect estimates						
σ_f^2	0.029	0.008	0.064	0.077	0.031	0.151
$\sigma_{f_1 f_2}^2$	0.041	0.013	0.084			
σ_v^2	0.122	0.06	0.212	0.135	0.075	0.215
$\sigma_{v_1 v_2}^2$	0.099	0.045	0.166			
ρ_{12}	0.682	0.63	0.732			

Note: the symbol * represents statistical significance at the 95% credible interval.

Figures

Figure 1. The study area and locations of sampled neighbourhoods.

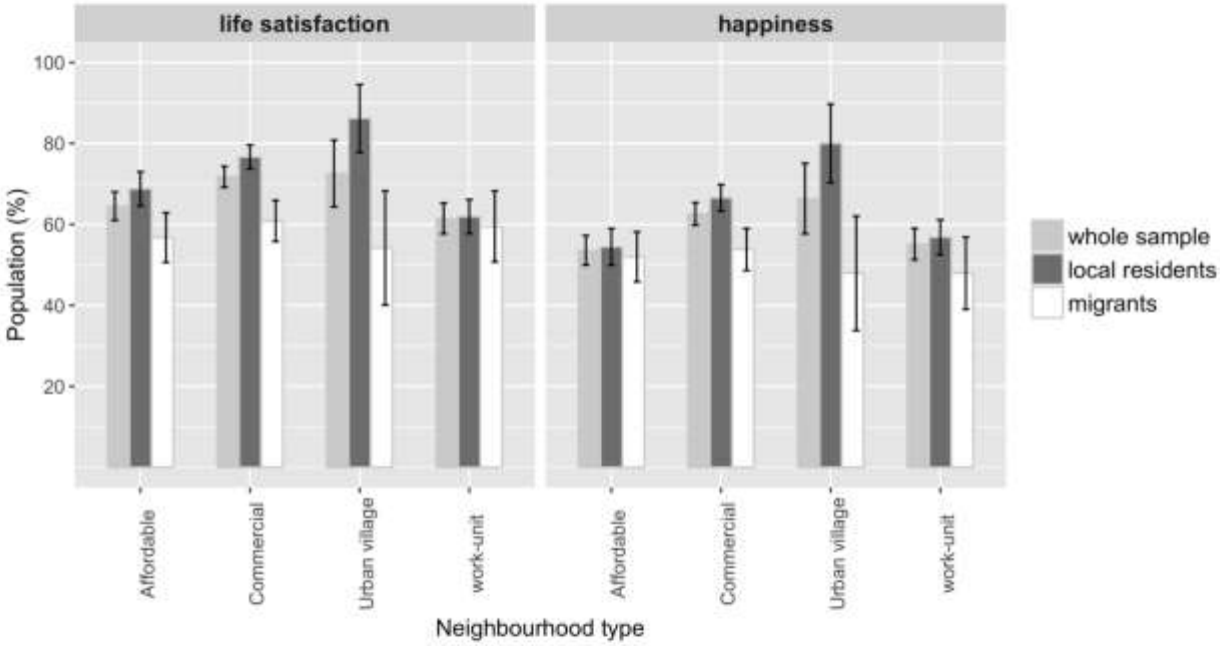

Figure 2. Population (%) in life satisfaction and happiness between different neighbourhood types and individual's hukou status. The error bars present the 95% confidence intervals of the population estimates.