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# Inequality in Beijing: A Spatial Multilevel Analysis of Perceived Environmental Hazard and Self-Rated Health

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Environmental pollution is a major problem in China, subjecting people to significant health risk. Surprisingly little is known, though, about how these risks are distributed spatially or socially. Drawing on a large-scale survey conducted in Beijing in 2013, we examine how environmental hazards and health, as perceived by residents, are distributed at a fine (subdistrict) scale in urban Beijing and investigate the association between hazards, health, and geographical context. A Bayesian spatial multilevel logistic model is developed to account for spatial dependence in unobserved contextual influences (neighborhood effects) on health. The results reveal robust associations between exposure to environmental hazards and health. A unit decrease on a five-point Likert scale in exposure is associated with increases of 15.2 percent (air pollution), 17.5 percent (noise), and 9.3 percent (landfills) in the odds of reporting good health, with marginal groups including migrant workers reporting greater exposure. Health inequality is also evident and is associated with age, income, educational attainment, and housing characteristics. Geographical context (neighborhood features like local amenities) also plays a role in shaping the social distribution of health inequality. The results are discussed in the context of developing environmental justice policy within a Chinese social market system that experiences tension between its egalitarian roots and its pragmatic approach to tackling grand public policy challenges. *Key Words:* *environmental hazard, environmental justice, geographical context, self-rated health, spatial multilevel modeling.*

环境污染是中国的一项重大问题，让人们暴露在显著的健康威胁之中。但令人讶异的是，这些风险在空间或社会上如何分佈却鲜为人知。我们运用 2013 年在北京进行的大规模调查，检视北京城市中住民所认知的环境灾害和健康在细微尺度（小区）的分布，并探讨灾害、健康与地理脉络之间的关联性。本文建立一个贝叶斯空间多层次罗吉特模型，以阐明对健康而言未受注意的脉络影响（邻里效应）的空间依赖。研究结果揭露了暴露于环境灾害和健康之间的强健关联性。李克特五点尺度量表中，暴露程度下降一点，与增加百分之十五点二（空气污染）、百分之十七点五（噪音），以及百分之九点三（垃圾掩埋）回报健康良好的机率有关，而包含移民工的边缘团体则回报较高的暴露程度。健康不平等同样是显著的，并与年龄、所得、受教育程度，以及住宅特徵有关。地理脉络（诸如地方环境的邻里特徵）同时在形塑健康不平等的社会分布中具有影响。研究的结果，在中国的社会市场系统内建立环境正义政策的脉络中进行讨论，而该系统经了解决宏观公共政策挑战的平等主义根源和务实取向之间的紧张关系。 *关键词：* *环境灾害，环境正义，地理脉络，自我评量的健康，空间多层次模式化。*

La contaminación ambiental es un problema importante en China, que somete la salud de la gente a riesgos significativos. Sin embargo, sorprende lo poco que se sabe acerca de cómo se distribuyen estos riesgos espacial o socialmente. Con base en un estudio a gran escala llevado a cabo en Beijing en 2013, examinamos el modo como las amenazas ambientales y la salud, según las perciben los residentes, se distribuyen a fina escala (subdistrito) en la Beijing urbana, e investigamos la asociación entre amenazas, salud y contexto geográfico. Se desarrolló un modelo bayesiano logístico espacial de nivel múltiple para tomar en cuenta la dependencia espacial en influencias contextuales no observadas (efectos de vecindario) sobre la salud. Los resultados revelan asociaciones robustas entre la exposición a los riesgos ambientales y la salud. Una unidad de disminución en exposición en la escala de cinco puntos de Likert está asociada con incrementos del 15.2 por ciento (contaminación aérea), 17.5 por ciento (ruido) y 9.3 por ciento (vertederos) con la probabilidad de informar buena salud, frente al reporte de exposición más grande de grupos marginados, incluso trabajadores migratorios. La desigualdad en salud también es evidente y se la asocia con edad, ingreso, logros educativos y características de

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la vivienda. El contexto geográfico (rasgos del vecindario, por ejemplo, comodidades locativas) también juega un papel en configurar la distribución social de la desigualdad en salud. Los resultados se discuten en el contexto del desarrollo de una política de justicia ambiental en un sistema de mercadeo social chino sometido a tensión entre sus raíces igualitarias y su aproximación pragmática para abordar los retos de la política pública a lo grande. *Palabras clave: amenazas ambientales, justicia ambiental, contexto geográfico, salud autoevaluada, modelado espacial a nivel múltiple.*

China's rapid industrialization and urbanization have given rise to a wide range of environmental hazards, including ambient air pollution, water pollution, and hazardous industrial waste. These environmental risks lead to an estimated 2.4 million premature deaths in China each year (World Health Organization [WHO] 2009). Lim et al. (2012) provided a comprehensive health risk assessment for sixty-seven risk factors in twenty-one world regions for 1990 and 2010 that provides a context for this environmental disease burden. Their results show that the contribution of risk factors to global disease burden have shifted substantially during this period, from risks for communicable diseases in children to those for noncommunicable diseases in adults. Their analysis also reveals that in 2010 ambient particulate pollution ranks as the ninth greatest risk to health globally but ranks fourth in East Asia (after high blood pressure, tobacco smoking, and a diet low in fruits). Air quality in many Chinese cities is among the worst in the world, and by 2010 China had 40 percent of all premature deaths due to poor air quality (Lim et al. 2012).

High disease burden due to ambient particulate matter in the United States (Pope, Ezzati, and Dockery 2009; Pope et al. 2011) has recently led to a tightening of their ambient annual average particulate standard for PM<sub>2.5</sub> from 15  $\mu\text{g}/\text{m}^3$  to 12  $\mu\text{g}/\text{m}^3$ , a revision supported by an economic analysis that revealed economic gains (health and welfare benefits, less implementation costs) of up to \$9 billion annually (U.S. Environmental Protection Agency 2013). This is still above the WHO recommended annual limit value for PM<sub>2.5</sub> of 10  $\mu\text{g}/\text{m}^3$ . In contrast, the equivalent standard in China is 35  $\mu\text{g}/\text{m}^3$  (Ministry of Environmental Protection [MEP] 2012), and although some improvement has occurred in recent years following introduction of pollution control measures, this standard is routinely breached, often by a very large margin (Zhao, Zhang, and Fan 2014), and air quality remains a major public health concern in both Beijing and China more generally. Although poor air quality is arguably the most pressing environmental health issue in China, industrialization and urbanization have brought a range of other environmental hazards that also pose serious risks to public health, including industrial waste, chemical

toxins, and water pollution (J. Zhang et al. 2010; Gong et al. 2012).

Globally, studies of the social distribution of environmental quality have been conducted at both national and urban scales, although the latter dominate due to data limitations at the national scale. Collectively, such studies provide much evidence to show that marginal social groups (poor, ethnic, children) bear unequal burdens with respect to environmental "bads," including waste and industrial emissions and outdoor air pollution (e.g., G. Mitchell and Dorling 2003; Lucas et al. 2004; Brulle and Pellow 2006; Namdeo and Stringer 2008; Pearce and Kingham 2008). Attempts are also being made to extend these analyses over time to gain insight into the evolution of such environmental inequalities. G. Mitchell, Norman, and Mullin (2015) reviewed this longitudinal environmental justice literature before presenting their own empirical analysis of air quality change in Britain between 2001 and 2011, which showed that improvement is greatest in affluent areas and that deprived areas bear a disproportionate and rising share of declining air quality, a pattern that they concluded would contribute to increasing inequality in respiratory health. The contribution that environmental inequalities make to health inequalities has received relatively little attention in general (Pearce et al. 2010) and is an area that has largely been neglected in developing countries. This includes China, where there is little understanding of environmental hazard and health inequality, especially at the intracity scale.

Holdaway (2010) provided an overview of the major environment-related health risks China faces and concluded that "a careful examination of the linkages between environmental problems, poverty and ill-health is needed [and that], in short, we need to know much more about the geography and demography of environmental health risks in China, and which population groups are particularly vulnerable" (21). The deleterious health effect of exposure to environmental hazards in the Chinese context has been the subject of recent research, via national and city-region analyses using individual data drawn from small national samples (e.g., Z. Feng et al. 2012; Chen, Chen, and Landry 2013) or multicity time series observations (e.g., Zhou et al. 2015). Significant adverse effects of ambient air

pollution (PM<sub>2.5</sub>, PM<sub>10</sub>, and SO<sub>2</sub>), toxic industrial waste, and water pollution on physical health (e.g., respiratory and cardiovascular diseases), mortality, and morbidity were identified (e.g., Lu et al. 2015; Zhou et al. 2015). Some studies have also examined the social distribution of environmental hazards and found that the adverse impacts of environmental pollution are unevenly distributed across socioeconomic and demographic strata, with greater risk and harm borne by vulnerable or deprived groups, particularly older people and migrants (Chen, Chen, and Landry 2013; Zhao, Zhang, and Fan 2014). This is consistent with environmental justice studies of developed countries (Gee and Payne-Sturges 2004; Walker 2009; Pearce et al. 2010; Chakraborty, Maantay, and Brender 2011).

The reliance on sample data in Chinese environmental inequality studies and lack of any spatially resolved analysis of environmental hazards and health inequalities is mainly attributed to data constraints. In China, data on environmental pollution and health outcomes are collected by different agencies for different purposes and are not usually publicly accessible or shared across platforms (Holdaway 2010). Environmental pollution statistics (e.g., air quality, industrial waste, water pollution) are reported in aggregate at the city scale and so cannot be used to identify disproportionate exposure to environmental hazards at the intraurban level (Chen, Chen, and Landry 2013). Furthermore, China has no national health survey for all populations, and data on disease and injury reported by hospitals are similarly only published at the city scale. Thus, in the absence of close government support, it is impossible to access small-area data on environmental hazards and health for China, which constrains more meaningful assessment of the role of environmental hazards in health and health inequality (Holdaway 2010) and prevents robust environment-health deprivation analysis for individual city regions.

A further analytical consideration relates to the measurement of environmental hazards in China. G. Mitchell and Walker (2007) noted that in environmental equity analyses a spectrum of hazard measurement exists, with proximity to hazard being the simplest and cheapest form of analysis (and hence most widely used), followed by an increase in sophistication and accuracy (and expense) with pollution hazard measured in terms of emission, concentration, exposure, dose, and finally health response. Payne-Sturges and Gee (2006) and Peek et al. (2009) classified environmental hazard as objective or subjective, with *objective* referring to “the potential for or occurrence of exposure to an environmental contaminant or hazard condition” (Payne-Sturges and Gee 2006, 158) and

*subjective* referring to personal perception of exposure to environmental hazard (Peek et al. 2009; Chen, Chen, and Landry 2013). Residential proximity to environmental hazards is the most widely used surrogate of pollutant dose or health outcome and is widely used in environmental health research (Chakraborty, Maantay, and Brender 2011), but in China, even this rather crude analysis is data constrained, because access to geolocated data on urban environmental hazards, such as toxic landfills or traffic pollution, is unavailable. Without these data, objective proximity analyses and more advanced pollutant concentration analyses that consider complex urban meteorological conditions (Richardson, Shortt, and Mitchell 2010) are not possible. On the other hand, subjective measures of environmental hazard have an advantage in that they can additionally capture chronic stress associated with exposure to a hazard, which has been considered as important as (or even more important than) objective measures in predicting health outcomes (Peek et al. 2009; Corsi et al. 2012; Chen, Chen, and Landry 2013). Such psychological effects are also regarded as important in health promotion (A. Lee and Maheswaran 2010). Given the lack of reliable objective small-area data on environmental hazards in China, we draw on subjective measures of exposure to environmental hazard (Chen, Chen, and Landry 2013) to provide insight into the association among environmental hazards, demography, and health in urban Beijing.

Our view is that China presents a particularly interesting and important case for analysis of the social distribution of environmental quality. This is interesting from an environmental justice perspective, because China is a country pursuing a social market economy (with the fastest growing consumer economy in the world and a rising middle class) yet politically advocates egalitarian principles that imply all environmental inequality is unjust. Exploration of associations between environment, health, and demography in this context is thus likely to be both fascinating and informative in terms of developing Chinese environmental, public health, and wider social policy. China also clearly faces major environmental pollution problems, with serious public health implications. Understanding the social distribution of environmental hazards is thus important in informing our understanding of the drivers of disease burden and health inequalities in China and thus helping to develop environmental and public health policy better targeted at the appropriate hazards, people, and places.

Analyzing the geographical context at a finer spatial scale than previously possible also permits a better

understanding of how various geographical attributes influence environmental–health inequalities. Methodologically, accounting for spatial effects is important because this improves model estimation efficiency when a spatial pattern exists in the distribution of health outcomes and the covariates under examination (Arcaya et al. 2012; D. Lee and Mitchell 2013; Pierewan and Tampubolon 2014; Dong et al. 2016). Although this contextual effect (also known as the neighborhood effect) on health has been examined in the social epidemiology literature using multilevel models (e.g., Duncan, Jones, and Moon 1998; Subramanian, Jones, and Duncan 2003; Merlo et al. 2006), it has rarely been considered when investigating the impacts of environmental hazards on health inequalities.

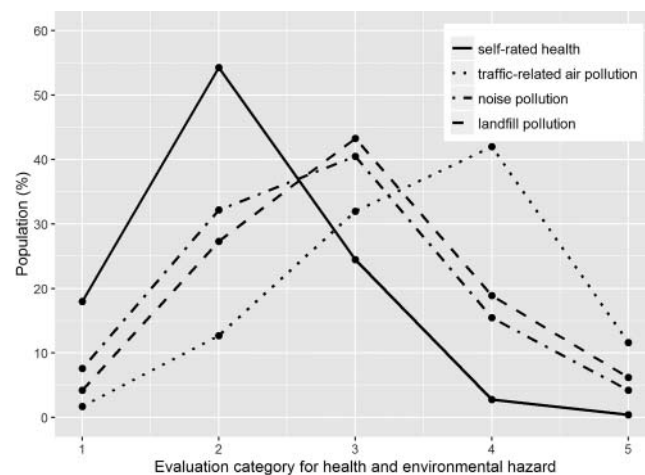
Our study addresses this gap by providing an intracity study to first examine how environmental hazards and health are distributed at a fine (subdistrict) spatial scale in a Chinese megacity, drawing on a large-scale survey conducted in Beijing in 2013. Next we investigate association of environmental hazards as perceived by residents, with their self-rated health and geographical context. A Bayesian spatial multilevel logistic model has been developed to analyze the correlated geographical contextual effect on health inequality by incorporating a spatial conditional autoregressive (CAR; Besag, York, and Mollie 1991) process in a standard multilevel logistic model. We examine the subjective measure of perceived exposure to three main urban environmental hazards—traffic-related air pollution, noise, and toxic landfills. We investigate the associations of perceived environmental hazards and self-rated health while controlling for a wide range of socioeconomic and demographic characteristics that could potentially confound the environment–health relationship. Next we present the data sources and variables and then detail how a Bayesian spatial multilevel logistic model is developed to analyze the spatially dependent contextual (neighborhood) effect on health inequality. Results of this analysis are presented and discussed with respect to the evidence for environmental and health inequality in Beijing, the importance of environmental hazard and geographical context in explaining health inequality, and the broader issues of inequality and environmental justice in China.

## Data and Variables

Our analysis draws on a large-scale residential satisfaction and health survey conducted during the summer of 2013 in Beijing. The aim of the survey was to assess

residents' health status and satisfaction with their surrounding environment. Only residents living in their current residences for at least 6 months were included in the survey. A spatial stratified random sampling strategy was adopted, with about 0.1 percent of the population in each of Beijing's six urban districts sampled. In total, 7,000 questionnaires were issued and about 6,000 were returned (self-completion by post), of which 5,733 were valid. The samples are representative of Beijing's urban population at the time of the 2010 population census data. Further details of the survey, including sample profiles, are provided in W. Zhang et al. (2015). Based on the detailed locational information of each respondent's residence, a two-level membership structure was formed, first assigning individuals to subdistricts (*Jiedao*)<sup>1</sup> and then using the subdistricts boundary data to determine connectivity to all other subdistricts (using a spatial weights matrix). Subdistricts were subsequently referred to as districts for simplicity.

Self-rated health is the outcome variable measured by asking this question: In general, how would you evaluate your overall health status? The responses were quantified on a 5-point Likert scale ranging from 1 (*very good*) to 5 (*very bad*). Figure 1 shows the proportion of respondents in each category. The majority (>50 percent) of residents rate their overall health status as good, with 18 percent and 24 percent of residents reporting their health status as very good or fair, respectively. Less than 4 percent of residents assess their health status as bad or very bad. Mean self-rated health was 2.13 ( $SD = 0.74$ ). To have comparability with prior health research in the Chinese context and facilitate model implementation (Z. Feng et al. 2012),



**Figure 1.** Population (%) in self-rated health (1 = *very good*, 5 = *very poor*) and perceived exposure to environmental hazard (1 = *very low*, 5 = *very high*) categories.

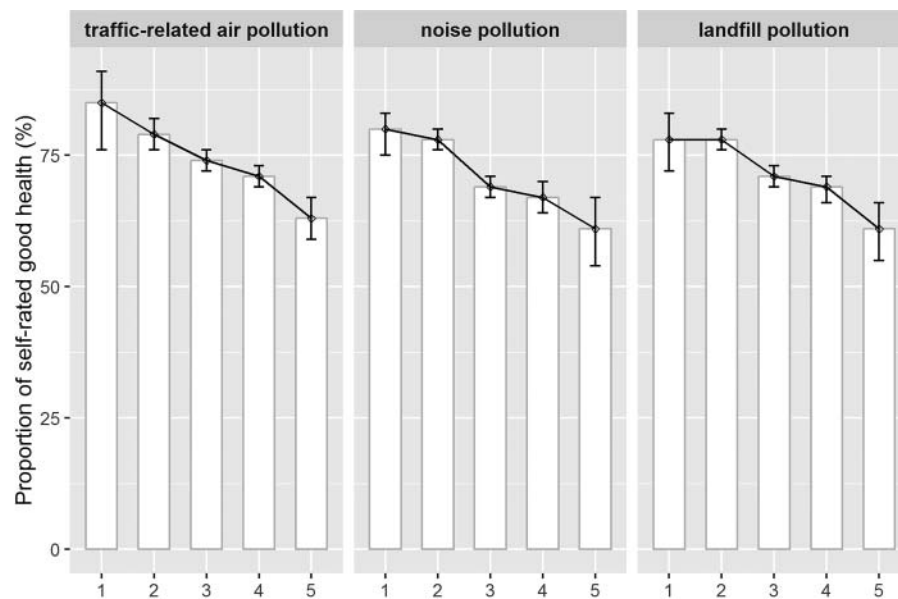
the outcome of self-rated health was further recoded into a binary variable: 1 for good and very good and 0 for fair, bad, and very bad.

Perceived environmental hazards considered in this research focus on three dimensions: exposure to traffic-related air pollution, noise, and landfills (e.g., municipal waste, industrial waste, and construction waste), objective statistics on which are usually not available at a fine spatial scale in China. Therefore, exposure to various types of pollution was assessed by the following questions: How would you evaluate the exposure to (traffic-related air pollution, noise, landfills) in your neighborhood? with answers given on a 5-point Likert scale ranging from 1 (*very low*) to 5 (*very high*). The proportion of each category in these environmental exposures perceived by residents is also provided in Figure 1. There is an obvious variation between the percentages of each category for the three measures, with mean scores of perceived exposure to traffic-related air pollution, noise, and landfills of 3.49, 2.76, and 2.96, respectively. The proportion of residents reporting good or very good health status at different levels of exposure to environmental hazards is illustrated in Figure 2, with a 95 percent confidence interval calculated based on standard logistic models. Overall, the probability of reporting good health status experiences a steady decrease with increasing exposure to environmental hazard as perceived by residents.

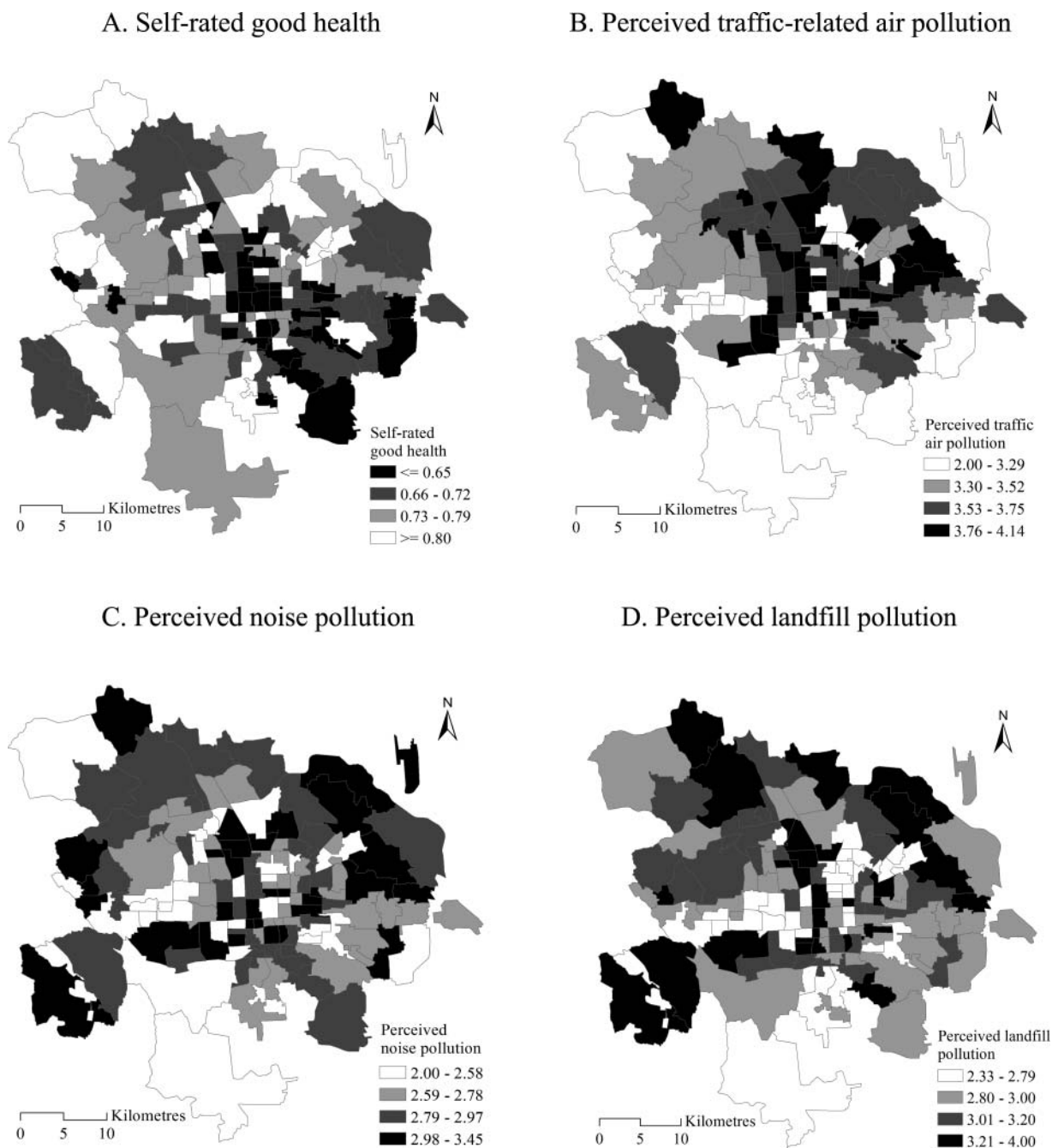
Next, we illustrate the spatial distribution of self-rated health and perceived environmental hazards at the district level in urban Beijing (Figure 3). The

nonuniform patterns of health outcome and exposure to various environmental hazards are evident. For instance, Figure 3A depicts the proportion of self-rated health status being good or very good in each district in urban Beijing and suggests clustering of districts with a lower proportion of good health in the inner city and areas to its southeast. The Moran's  $I$  (spatial autocorrelation) statistic of the proportion of good health is about 0.096 ( $p$  value  $< 0.05$ ), suggesting spatial dependence among districts, which should therefore be considered when modeling inequality of health outcome. A further assessment of unexplained variations in health outcomes at the district level (residuals) after adjusting for the covariate effects is discussed later.

Other covariates in our health analysis are broadly divided into three categories. The first includes a range of household and individual sociodemographic characteristics, including age, gender, monthly income, education, marital status, residence status (migrants vs. local residents), employment, and family structure (the presence of children). Housing attributes of tenure, area (floor space), and type (*Danwei*, commodity, affordable, and self-built) are also included in the model (Table 1), because these variables are commonly believed to be associated with health inequality. Additionally, a set of locational variables, measured at the individual level, is incorporated in the model, including proximity (geographical distance from residence) to the city center, the nearest green park, and hospital. The proximity measures were transformed to a logarithmic scale to reduce the potential



**Figure 2.** Population (%) reporting good or very good health by environmental hazard (1 = *very low*, 5 = *very high*) category with 95 percent confidence intervals.



**Figure 3.** Spatial distribution of self-rated good health and perceived environmental hazard indexes at subdistrict level in urban Beijing.

for heteroscedasticity. Finally, a district-level variable—the population density of each district, derived from the sixth population census in Beijing in 2010 and used as a proxy of measurement of multiple dimensions of urban form—was also included in the model. A comprehensive consideration of these covariates in the model helps to better understand the associations between variables, particularly individual-level environmental pollution exposure perceived by residents and their self-rated health.

### Developing a Bayesian Spatial Multilevel Logistic Model

We assume that associations between perceived environmental hazard and self-rated health might be mediated by district-level random effects and that these effects are not independent but exhibit spatial dependency. Therefore, we developed a Bayesian spatial multilevel logistic model, incorporating a spatial CAR (Besag, York, and Mollie 1991) process, to analyze the spatially

**Table 1.** Key sociodemographic attributes in the residential satisfaction and health survey

Variable names	Description	Proportion (%)
Age	<20	2.6
	20–29	40.3
	30–39	29.6
	40–49	16.0
	50–59	8.5
	60+	3.0
Monthly income (RMB)	<3,000	8.2
	3,000–4,999	20.5
	5,000–9,999	34.3
	10,000–15,000	20.8
	15,000+	16.2
Gender	Male as base category	50.6
Marital status	Married	60.6
Residence status	Migrants	35.6
Housing tenure	Owners	50.8
Housing type	Commodity housing	45.1
	Affordable housing	22.9
	<i>Daiwei</i> housing	11.9
	Self-built housing	19.9
Housing area (square meters)	80+	44.4
	40–80	33.0
	<40	22.6
Child presence	Household with child under 6	13.6
Employment	Employed	84.7
Education	Primary	10.2
	Secondary	26.6
	Tertiary	63.2

Note: RMB = renminbi, official Chinese currency.

dependent contextual (neighborhood) effect on health inequality to provide a more robust insight into the association between hazard, health, and place variables.

Self-rated health is modeled as a binomial distribution with a logit link function. To start with, a general Bayesian multilevel logistic model is expressed as (Congdon 2014)

$$Y_{j,k} \sim \text{Binomial}(1, p_{jk}); \quad (1)$$

for  $j = 1, \dots, J; k = 1, \dots, K$ ,

$$\ln(p_{jk}/1 - p_{jk}) = \eta_{jk} = a + P'_{jk}\boldsymbol{\beta} + L'_{jk}\boldsymbol{\gamma} + S'_{jk}\boldsymbol{\delta} + D'_k\boldsymbol{\varphi} + u_k,$$

$$u_k \sim N(0, \sigma^2),$$

$$\{a, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\} \sim N(0, b); \sigma^2 \sim \text{inverse gamma}(e, f),$$

where  $j$  and  $k$  are individual and district indicators, respectively. The log odds are related to a linear

predictor ( $\eta_{jk}$ ), which depends on a set of additive covariate effects.  $P$  represents perceived environmental hazards (traffic-related air pollution, noise, and landfills),  $L$  refers to locational variables (proximity to the city center, the nearest green park, and hospital), and  $S$  includes socioeconomic and demographic characteristics (age, income, gender, education, marital and employment status, presence of children, and housing attributes of tenure, area, and type).  $D$  represents the urban form indicator (population density) at the district level. Vectors of  $\{a, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\}$  are fixed regression coefficients that we seek to estimate, which quantify the impacts of corresponding covariates on self-rated health on the logistic scale. Relatively diffuse priors are usually specified for fixed regression coefficients; for instance, a normal distribution with mean zero and a very large variance (e.g.,  $b = 100$ ).

The unobserved effect from district  $k$  (contextual effects) on individuals' health is indicated by  $u_k$ , which follows a normal distribution with mean zero and variance  $\sigma^2$ . Following the Bayesian hierarchical modeling convention (Gelman et al. 2004), an inverse gamma distribution is specified for  $\sigma^2$  with a shape parameter  $e$  and a scale parameter  $f$ .

The district effects ( $\mathbf{u}$ ) in a standard multilevel logistic model (Equation 1) are restrictively assumed to be independent of each other. That is, district effects  $u_m$  and  $u_n$  are not correlated even when districts  $m$  and  $n$  are geographically adjacent, which is clearly not the case as shown in Figure 3. To capture the potential dependence among district effects, a specific CAR model developed by Leroux, Lei, and Breslow (1999), denoted as LCAR, is specified for  $\mathbf{u}$ , given by

$$u_k | \mathbf{u}_{-k}, W, \lambda, \tau^2 \sim N\left(\frac{\lambda \sum_{k \sim l} u_l}{1 - \lambda + \lambda w_{k+}}, \frac{1}{\tau^2(1 - \lambda + \lambda w_{k+})}\right), \quad (2)$$

$$\tau^2 \sim \text{gamma}(e', f'); \text{logit}(\lambda) \sim N(0, 100).$$

In Equation 2  $w_{k+}$  is the number of neighbors of district  $k$ , and  $\mathbf{u}_{-k} = (u_1, \dots, u_{k-1}, u_{k+1}, \dots, u_j)$  indicates random effects other than district  $k$ . The overall neighborhood structure (or 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. The scalar  $\tau^2$  is the precision parameter, which is the inverse of the variance parameter (i.e.,  $1/\sigma^2$ ). A gamma



distribution is specified for  $\tau^2$  with the shape and scale hyperparameters being  $e'$  and  $f'$ . Finally, the parameter  $\lambda$  is a spatial correlation parameter measuring the strength of spatial dependence (Congdon 2014). A diffuse normal prior for  $\lambda$  on the logistic scale was specified in line with the default choice when implementing the model by using a fast and accurate integrated nested Laplace approximation (INLA) approach via the R-INLA package (Rue, Martino, and Chopin 2009; Rue et al. 2014). Under LCAR specification of spatial dependence effects, the conditional expectation of  $u_k$ ,  $E(u_k | \mathbf{u}_{-k})$ , is the weighted average of the random effects of its neighbors. The whole set of full conditionals for all  $K$  random effects give rise to a unique Gaussian Markov random field,  $\mathbf{u} \sim \text{MVN}(\mathbf{0}, \mathbf{\Omega}_{\text{LCAR}})$  with the  $K$  by  $K$  precision matrix  $\mathbf{\Omega}_{\text{LCAR}}$  being (MacNab 2011; Congdon 2014)

$$\mathbf{\Omega}_{\text{LCAR}} = \tau^2 (L_W - W); \quad L_W = \text{diag}(1 - \lambda + \lambda w_{k+}), \quad (3)$$

where  $\text{diag}(\cdot)$  is a diagonal matrix with entries equal to numbers in the bracket. When  $\lambda$  is equal to zero, LCAR reduces to an independent normal prior as in Equation 1 while turning to an intrinsic CAR when  $\lambda$  is equal to one (Besag, York, and Mollie 1991). Therefore, our preferred statistical model for examining the disparity of self-reported health is given by

$$\begin{aligned} \ln(p_{jk}/1 - p_{jk}) \\ = \eta_{jk} &= a + P'_{jk}\boldsymbol{\beta} + L'_{jk}\boldsymbol{\gamma} + S'_{jk}\boldsymbol{\delta} + D'_k\boldsymbol{\varphi} + u_k \quad (4) \\ \mathbf{u} &\sim \text{MVN}(\mathbf{0}, \mathbf{\Omega}_{\text{LCAR}}(\lambda, \tau^2)), \\ \{a, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\varphi}\} &\sim N(0, b); \\ \tau^2 &\sim \text{gamma}(e', f'); \quad \text{logit}(\lambda) \sim N(0, 100). \end{aligned}$$

We term the method a spatial LCAR multilevel logistic model. It is useful to note that when there is no spatial correlation among district-level random effects ( $\lambda = 0$ ), Equation 4 reduces to a standard multilevel logistic model.

Two aspects with the spatial LCAR multilevel logistic model are worth mentioning. First of all, other types of CAR priors such as an intrinsic CAR, proper CAR, and convolution CAR (or the BYM model; Besag, York, and Mollie 1991) can also be used to capture the spatial correlation effect among districts (for a thorough technical review, see Banerjee, Carlin, and Gelfand [2004] and Congdon [2014]). LCAR prior, however, has been shown to outperform other CAR priors when

modeling spatial dependence (D. Lee 2011; MacNab 2011; Dong et al. 2016). Second, it is also possible to model random effects  $\mathbf{u}$  either using a simultaneous autoregressive (SAR) approach in line with the spatial econometrics literature (Dong and Harris 2015) or using a geostatistical approach by approximating districts with their centroids (Chaix et al. 2005). Incorporating SAR or geostatistical models into a standard multilevel modeling framework, however, requires a large amount of programming and involves extensive computational burdens, which would inhibit wide applications of the methods. By contrast, with the advent of the INLA Bayesian inference approach implemented in the open-source R-INLA package (Rue et al. 2014), different CAR priors could be flexibly incorporated into standard multilevel models, tailored to specific research questions and data.

The methodologies just presented were implemented using the R-INLA package (<http://www.r-inla.org/>), which is an interface of the C package INLA with R (Rue, Martino, and Chapin 2009; Rue et al. 2014). We estimated three models with increasing complexity: a standard logistic model, a multilevel logistic model (Equation 1), and a spatial LCAR multilevel logistic model (Equation 4). Normal priors with mean zero and variance 100 were used for fixed regression coefficients and intercept terms in all three models. Following Ugarte et al. (2014), for the spatial LCAR multilevel logistic model, a minimally informative prior was assigned to  $\tau^2$ ,  $\log(\tau^2) \sim \text{logGamma}(1, 5e-05)$ . The same prior was given to  $(1/\sigma^2)$  in the multilevel logistic model. The hyper-prior distribution for the spatial correlation parameter  $\lambda$  is  $\text{logit}(\lambda) \sim N(0, 100)$ . Because the choices of hyper-prior distribution can influence the posterior inferences of model parameters especially in complex spatial models (Ugarte et al. 2014), a sensitivity analysis was conducted using different hyper-priors for  $\log(\tau^2)$  including  $\text{logGamma}(1, 0.01)$ ,  $\text{logGamma}(1, 0.001)$ , and  $\text{logGamma}(0.01, 0.01)$  and for  $\text{logit}(\lambda)$  including  $N(0, 10)$  and  $N(0, 200)$ . In most cases the results were not sensitive to choices of hyperpriors, because only slight differences were observed for the estimates of the spatial precision and correlation parameters and the estimation of regression coefficients remains very stable.

With respect to comparison of the three models, we adopt two commonly used indexes in Bayesian inference: the deviance information criterion (DIC; Spiegelhalter et al. 2002) and the Bayes factor (BF) calculated using marginal likelihoods of two competing models (Kass and Raftery 1995). The DIC is

calculated as the sum of the posterior mean of the deviance (twice the negative log-likelihood of a model) and the number of effective model parameters ( $P_D$ ). A smaller value of DIC provides a better model fit. As a rule of thumb, if two competing models differ in DIC by more than 10, the one with smaller DIC is regarded as a better model (Spiegelhalter et al. 2002). Because the model estimation output from R-INLA includes the log-likelihood for the model fitted, BFs can be readily calculated to compare competing model specifications.

Model comparison results for the three models are presented in Table 2. We find a substantial decrease in DIC values (from 5,689 to 5,637) for the multilevel logistic model compared to the single-level logistic model, underlining the importance of unobserved district effects in explaining the disparity in self-rated health in Beijing. In addition, the incorporation of spatial correlation in district random effects in the spatial LCAR multilevel logistic model further reduces DIC values by more than 10, compared to the multilevel logistic model. The significant increase in model fit demonstrates the benefit and necessity of considering district random effects as spatially dependent rather than independent. Furthermore, the Moran's  $I$  statistic of the district-level residuals from the multilevel logistic model is about 0.156 with a  $p$  value less than 0.01, demonstrating the unmodeled spatial correlations in self-rated health. Using the BF statistics, we draw the same conclusion, because the data strongly favor the spatial LCAR multilevel logistic model against its counterpart nonspatial, multilevel logistic model by a factor of about 300. Furthermore, the spatial correlation parameter  $\lambda$  is about 0.903 with a 95 percent credible interval of [0.523, 0.953], indicating

that correlations among district-level random effects are fairly large. Therefore, we rely on the estimation results from the spatial LCAR multilevel model in the following sections.

## Results

### Self-Rated Health and Sociodemographic Characteristics

The estimates from the spatial LCAR multilevel logistic model demonstrate that some of the sociodemographic variables are significantly correlated with self-rated health in urban Beijing (Table 3). The strongest effect on health is found for people with the highest income level (odds ratio = 2.005 with a 95 percent credible interval of [1.475, 2.724]), followed by people with monthly income between 10,000 RMB and 15,000 RMB (odds ratio = 1.536 with a 95 percent credible interval of [1.158, 2.034]; see Figure 4). This suggests a threshold effect of income on subjective health evaluation—only people with high levels of income tend to be positively associated with good health, whereas people with medium-level income are not significantly distinguishable from low-income residents. This supports findings from previous studies that demonstrate a significant impact of household income on self-rated health, although the correlation is likely to be nonlinear (e.g., Subramanian and Kawachi 2004; Z. Feng et al. 2012). Distinctness in odds of self-rated good health is also found between different age cohorts: Older people tend to be significantly associated with lower odds of self-rated good health, whereas young people (twenty years old and younger) are more likely to report good health (Table 3 and Figure 4).

The odds of reporting good health for people with tertiary education is increased by 29.4 percent compared to people with low-level education attainment, whereas gender, marital status, and employment are not significantly associated with self-rated health, *ceteris paribus*. The *hukou* household registration system (which identifies a person as a resident of an area and is linked to welfare benefits and controls on mobility) does not seem to make a significant difference to health outcome, because migrants (those without a Beijing *hukou*) were not significantly correlated with lower odds of good health than local residents. There might be a self-selection effect, because there is great probability that migrants aiming for better job opportunities and payment were more likely to report good health status (Chen et al. 2014). Causal inference of migration effects on self-rated health is

**Table 2.** Model fit comparisons

	DIC	$P_D$	Log-likelihood	BF
Logistic model	5,689.34	29.86	-2,990.95	545,795
Multilevel logistic model	5,637.84	79.64	-2,983.45	301
Spatial LCAR multilevel logistic model	5,627.13	71.23	-2,977.74	

Note: DIC = deviance information criterion;  $P_D$  = number of effective model parameters; log-likelihood = marginal log-likelihood from each model; BF = Bayes factor with the preferred model being the spatial LCAR multilevel logistic model; LCAR = a conditional autoregressive model developed by Leroux, Lei, and Breslow (1999). For example, the BF of spatial LCAR multilevel logistic model against multilevel logistic model is calculated as  $\exp((-2,977.74) - (-2,983.45))$ , which equals about 301.

**Table 3.** Estimation results from the spatial LCAR multi-level logistic model

	Posterior median odds ratios	2.5%	97.5%
Age			
20–29	0.358*	0.192	0.617
30–39	0.244*	0.129	0.430
40–49	0.235*	0.122	0.420
50–59	0.186*	0.096	0.336
60+	0.096*	0.047	0.187
Female	0.962	0.843	1.097
Marital status	1.142	0.94	1.389
Education			
Secondary	1.05	0.832	1.322
Tertiary	1.294*	1.019	1.638
Employment	1.018	0.827	1.25
Income (RMB)			
3,000–4,999	1.091	0.84	1.413
5,000–9,999	1.187	0.92	1.528
10,000–15,000	1.536*	1.158	2.034
15,000+	2.005*	1.475	2.724
Residence status	0.972	0.82	1.15
Child presence	1.023	0.833	1.261
Housing tenure	1.066	0.892	1.273
Housing area (m <sup>2</sup> )			
40–80	0.886	0.754	1.041
<40	0.972	0.802	1.18
Housing type			
Daiwei housing	0.954	0.749	1.218
Commodity housing	1.279*	1.06	1.542
Affordable housing	1.01	0.828	1.231
Log of distance to the nearest hospital	1.12*	1.019	1.23
Log of distance to the nearest green park	0.949	0.837	1.074
Log of distance to the city center	1.31*	1.104	1.556
Log of population density	0.96	0.855	1.076
Perceived traffic air pollution	0.848*	0.781	0.921
Perceived noise pollution	0.826*	0.762	0.894
Perceived landfill pollution	0.906*	0.835	0.984
$\lambda$	0.903*	0.523	0.953
$\sigma^2$	0.287	0.134	0.567

Note: RMB = renminbi, official Chinese currency; LCAR = a conditional autoregressive model developed by Leroux, Lei, and Breslow (1999).

\*Statistically significant at the 95% percent credible level.

beyond the purpose of this study and is not examined here.

Regarding the housing attributes and using self-built housing as the base category, we find that people living in commodity housing (houses purchased or rented at market rates) are significantly associated with a greater chance of reporting good health than their counterparts,

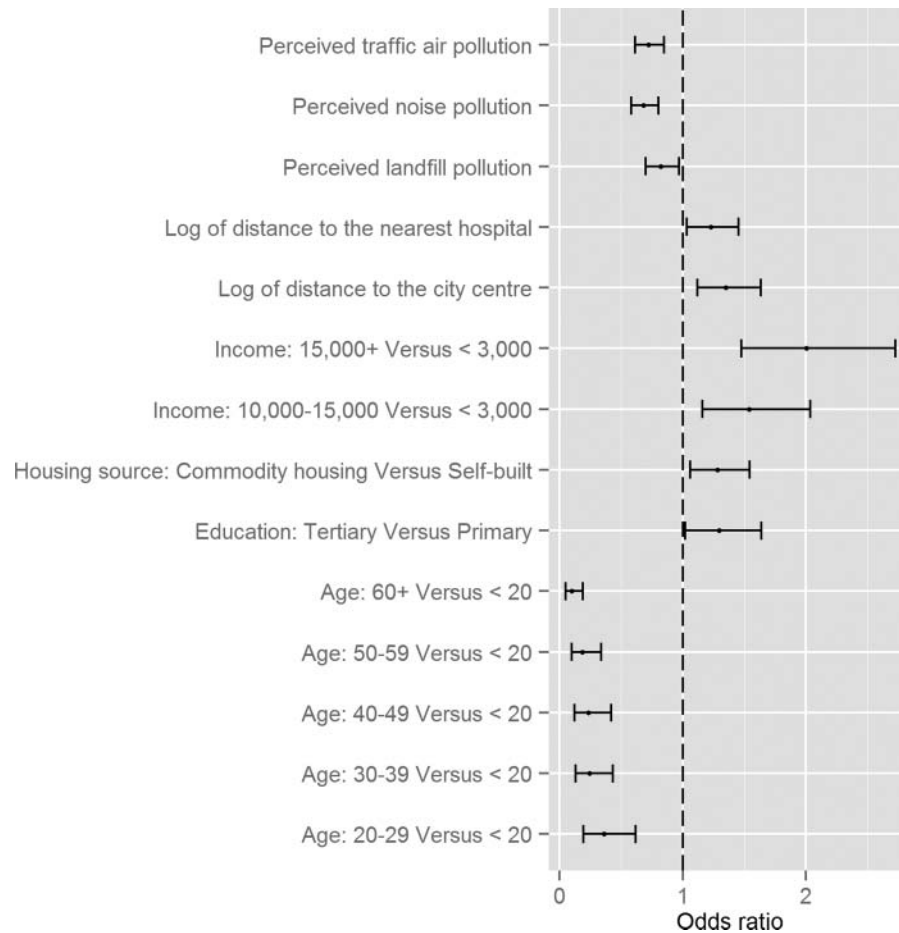
all else being equal. In contrast, people living in affordable housing (houses sold at marginally above cost to low- or middle-income families) or *Danwei* housing (houses allocated from their work units) are not significantly different, statistically, in terms of odds of good health, from those living in self-built houses. Housing tenure, area (floor space), and presence of children in the household are not correlated with self-rated health status.

### Self-Rated Health and Locational Factors

With respect to locational variables, people residing in neighborhoods close to the city center and to hospitals have statistically significantly higher odds of reporting good health. With respect to city center proximity, we speculate that its significance is a function of the location of industrial activity. In China's transitional economy, the spatial distribution of industries in Beijing has been subjected to the dual forces of the government and the market—the former includes government's industrial decentralization policies such as retiring the secondary industries and advancing the tertiary industries (J. Feng and Zhou 2005) and a highly restrictive land use zoning system in the inner city, whereas the latter is mainly in relation to the urban land market, transport costs, and economic agglomeration effects. The effect on the city's industrial structure is seen in the relocation of manufacturing industries away from the city center to be replaced by cleaner tertiary industries. Residents of suburban areas might thus be more exposed to hazardous activities (manufacturing, toxic landfills, etc.) that residents perceive as harmful to health. Close proximity to hospitals might indicate good access to hospital treatment in case of illness, which in turn could enhance the probability of self-rated good health.

### Self-Rated Health and Perceived Environmental Hazards

All three of the perceived environmental hazards are found to be significantly associated with subjective health evaluation (Table 3), with those who perceived lower exposure to traffic-related air pollution, noise, and landfills more likely to report good health status. A unit decrease on a 5-point Likert scale in exposure is associated with increases of 15.2 percent (air pollution), 17.4 percent (noise), and 9.4 percent (landfills) in the odds of reporting good health, all else being equal. To assess the robustness of identified individual-level negative



**Figure 4.** The impacts of significant covariates on self-rated health based on the results in Table 3 (a value  $> 1$  indicates positive effect and a value  $< 1$  indicates negative effect).

associations between perceived environmental hazards and self-rated health, we further included in the model (Table 3) two district-level variables. The first is the district-level measurement of environmental hazards, derived from individuals' perceived environmental hazards using an econometrics approach (Raudenbush and Sampson 1999; Mohnen et al. 2011). The econometrics-based measurement of environmental hazards provides a proxy of the objective contextual (districts) information on environmental hazards in a more reliable way than a simple averaging of individual subjective responses to districts (Mohnen et al. 2011).<sup>2</sup> The second variable added to the model is the proportion of the elderly population (sixty-five and older) in each district calculated from the sixth population census in Beijing in 2010, aiming to capture the potential association between population demographics and self-rated health at the district level.

A spatial LCAR multilevel logistic model is implemented and the results are provided in Table 4. Results

show that perceived environmental hazards are still significantly correlated with self-rated health. The estimated odds ratios of the three perceived environmental hazards remain quite close to the estimates reported in Table 3. The econometrics-based measurement of the district-level environmental hazards is not significantly associated with self-rated health at the district level, nor do we find a statistically significant association between the proportion of the elderly and self-rated health at the district scale. It is worth noting that estimates of other fixed covariate effects in terms of both magnitude and statistical inferences are very similar with that reported in Table 3. To conclude, individuals' perceptions of environmental hazards are significantly and robustly associated with their self-assessments of personal health. This is also consistent with a growing body of literature that draws a complementary conclusion that exposure to urban greenspaces raises well-being and in doing so can reduce health inequalities between rich and poor (Gilbert 2016).

**Table 4.** Estimation results from the spatial LCAR multi-level logistic model with perceived environmental hazards as binary variables

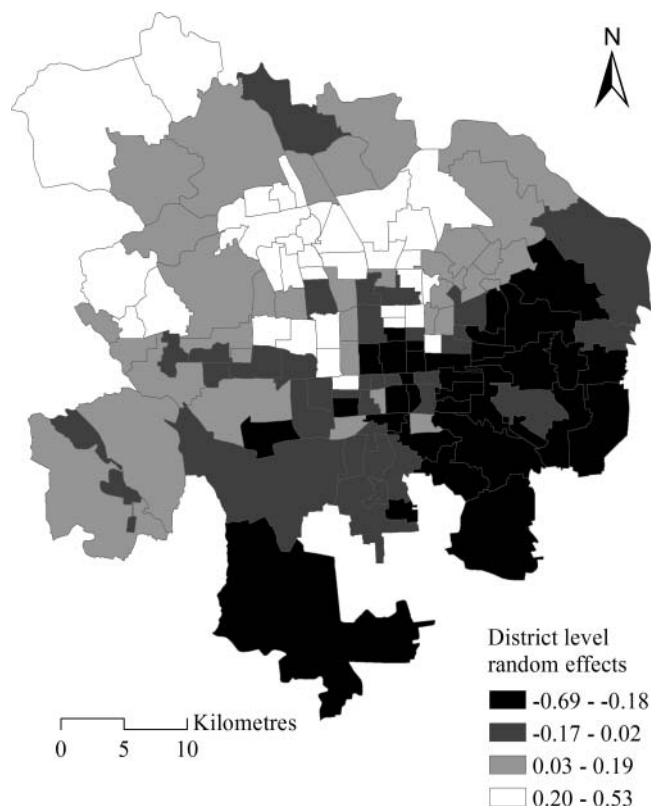
	Posterior median odds ratios	2.5%	97.5%
Age			
20–29	0.36*	0.193	0.62
30–39	0.245*	0.129	0.432
40–49	0.235*	0.122	0.421
50–59	0.186*	0.096	0.336
60+	0.096*	0.047	0.186
Female	0.962	0.843	1.097
Marital status	1.144	0.941	1.391
Education			
Secondary	1.049	0.831	1.322
Tertiary	1.291*	1.017	1.635
Employment	1.015	0.824	1.246
Income (RMB)			
3,000–4,999	1.091	0.840	1.413
5,000–9,999	1.189	0.921	1.53
10,000–15,000	1.54*	1.161	2.04
15,000+	2.011*	1.480	2.733
Residence status	0.973	0.822	1.152
Child presence	1.027	0.836	1.267
Housing tenure	1.067	0.892	1.274
House area (m <sup>2</sup> )			
40–80	0.885	0.754	1.04
<40	0.972	0.801	1.179
Housing type			
Daiwei housing	0.952	0.746	1.215
Commodity housing	1.277*	1.058	1.54
Affordable housing	1.009	0.828	1.231
Log of distance to the nearest hospital	1.117*	1.016	1.228
Log of distance to the nearest green park	0.948	0.834	1.076
Log of distance to the city center	1.317*	1.107	1.567
Log of population density	0.973	0.860	1.101
District-average of environment hazard	1.259	0.662	2.382
Proportion of the elderly (65+)	0.994	0.967	1.022
Perceived traffic air pollution	0.846*	0.778	0.918
Perceived noise pollution	0.823*	0.759	0.892
Perceived landfill pollution	0.905*	0.833	0.983
$\lambda$	0.895*	0.496	0.995
$\sigma^2$	0.297	0.139	0.584

Note: RMB = renminbi, official Chinese currency; LCAR = a conditional autoregressive model developed by Leroux, Lei, and Breslow (1999).

\*Statistically significant at the 95% percent credible level.

### Geographical Contextual Effect

After Campos-Matos, Subramanian, and Kawachi (2016), the impact of geographical context on self-rated



**Figure 5.** District-level random effects on self-rated health. The breaking points correspond to the lower, median, and upper quartiles of the district effects.

health was quantified by the median odds ratio (MOR), which transforms the between-area variance (in our case, the district-level variance) on the logit scale to a more interpretable odds ratio scale, thus making it comparable to the odds ratio of terms in the fixed part of the model. Essentially, MOR approximates (in the median) the elevated risk that would occur when moving individuals from a low-risk to high-risk area (Merlo et al. 2006). In our study, MOR measures the enhanced chance of self-rated good health if relocating an individual from districts with small residuals (i.e., small district effects and so low proportions of self-rated good health) to districts with large residuals. In a standard multilevel logistic model, the MOR is approximately computed as  $\exp[0.95 \times \sqrt{\sigma^2}]$  (Merlo et al. 2006). In the spatial LCAR multilevel logistic model, however, the calculation of MOR is complicated. The quantity  $\sigma^2$  in the spatial LCAR multilevel logistic model is the conditional variance of each district effect ( $u_k$ ), whereas the input parameter in the MOR formulation requires a marginal variance. In line with Blangiardo et al. (2013), an estimate of the posterior marginal variance for the spatially structured district-level random effect can be computed empirically as the variance of the

posterior median (or mean) of district-level random effects.

From the estimation result of the spatial LCAR multilevel logistic model (Table 3), the conditional variance  $\sigma^2$  is about 0.287 and the posterior marginal variance of the district-level random effect is about 0.073, suggesting the heterogeneity effect across districts. The MOR of the model is about 1.292, indicating that, in median, there is a 29.2 percent increase in the odds of reporting good health for an individual when moving toward districts with high-level random effects (districts that enhance self-rated health).

Figure 5 illustrates the estimated posterior median of district-level random effects on the logit scale. The breaking points correspond to the lower, median, and upper quartiles of the district effects, with darker colors indicating stronger negative effects—decreasing the odds of reporting good health. Two important patterns are observable. First, there is a distinct spatial pattern: High and low values of district-level random effects each form clusters due to the fairly large spatial correlation parameter  $\lambda$  identified (Table 3). Second, there appears to be a northwest–southeast divide in the district-level random effects—individuals living in the southeast area of urban Beijing tend to have a lower probability of reporting good health, *ceteris paribus*.

## Discussion

### Geographical and Social Distributions of Health and Environmental Hazards

According to recent analyses of air quality (PM<sub>2.5</sub>) data released by the Chinese Ministry of Environmental Protection, air quality in Chinese cities improved by, on average, 16 percent (15.2 percent in Beijing) in the first half of 2015 (China Dialogue 2015). China increasingly recognizes the importance of environmental protection, with its strongest environmental targets and measures to date in its thirteenth five-year national development plan and from January 2015 a strengthened environmental protection law (including a system of accumulating fines for continued violation, performance assessment of public officials that considers environmental issues and not just economic growth, and scope for nongovernmental organizations to take legal action against polluters on behalf of the public; MEP 2014).

Despite encouraging improvements in air quality, it is too early to judge how effective these initiatives will

be, given that they also come at a time of economic slowdown and reduction in industrial activity. It is clear, however, that a major challenge remains, as indicated by analysis of fine particulate (PM<sub>2.5</sub>) concentrations for 2014 and 2015 (Greenpeace East Asia 2016). These data show that the annual average PM<sub>2.5</sub> value in 366 Chinese cities was 50.2  $\mu\text{g}/\text{m}^3$  (with 80 percent of cities in breach of the standard) and in Beijing, 80.4  $\mu\text{g}/\text{m}^3$ . This analysis is based on hourly air quality data collected by the cities and made available via the China National Environmental Monitoring Center but is limited to one or a few monitoring stations in each city and so cannot be used to infer spatial patterns in air quality; in practice each city value will mask much greater geographical variability.

The limited spatial nature of such environmental data is problematic, because as the twelfth five-year Environment and Health Plan (MEP 2011) noted, a

lack of baseline data became a bottleneck in addressing environment and health problems. Since the 1990s, no nationwide or regional large scale environment and health investigation has been carried out. Basic and continuous investigations and monitoring have not been included in the routine work. Lack of basic investigation and survey data lead to unclear baseline information on *geographic distribution of the health impacts caused by environmental pollution*, the degree of health damage, and the development trend. (3, italics added)

Our study provides an insight into the spatial distribution of environmental hazards and their association with self-rated health, through the first spatially resolved (subdistrict) environmental health risk analysis for urban Beijing. Our analysis is based on individual-level data, something that Collins et al. (2015) argued for to clarify mechanisms underlying environmental inequalities, although our approach was motivated by necessity, due to the lack of required data for more aggregate units. Our study also develops a Bayesian spatial multilevel logistic model to analyze the dependent geographical context (neighborhood) effect on health inequality when exploring these associations. Results show that this method outperforms a standard multilevel model and that a significant geographical context effect on health inequality exists. This underlines the importance of geography in understanding health inequalities and the need to model spatial effects in environmental health research.

A clear finding is that self-rated health and perceived environmental hazards are both unevenly distributed at the district scale in urban Beijing

(Figure 3). By and large, people resident in districts of the inner city and areas to its southeast have a lower proportion of health rated as good or very good. With respect to environmental hazards, those districts with higher exposure to traffic-related air pollution are found in the inner city and northern areas of urban Beijing where the car ownership rate is higher than in other areas, whereas districts with more noise pollution and landfills are mostly distributed in suburban areas, probably because this is where most manufacturing industry is located.

Our analysis also demonstrates a clear association between perceived environmental hazard and self-rated health—rates of good health fall as perception of environmental hazard rises, for all three hazards studied, consistent with research elsewhere (e.g., Peek et al. 2009; Chen, Chen, and Landry 2013). This association might be the product of objective processes, whereby a poor-quality environment induces poor health through physical pathways (e.g., inhalation of fine particles causes respiratory illness), or it might be a subjective process, in that self-rated health is mediated by perceived environmental risk. Due to the lack of spatially resolved and objectively measured environmental hazard and health data, it is not yet possible to determine the relative importance of these health determinants. It is reasonable to assume, however, that the objective health determinants are very important, given, for example, that  $PM_{2.5}$  concentrations in Beijing are above  $80 \mu g/m^3$  as an annual average, eight times the WHO annual guide value, and that concentrations will likely vary a great deal spatially. The likely high importance of environmental determinants of health in China's cities indicates a clear need

for a more systematic and comprehensive program to collect objective, spatially resolved data on environment and health to support evidence-led environmental health risk management, and health promotion.

Nevertheless, the subjective perception of health determinants should not be overlooked in health promotion or environmental risk management and regulation (Elliott et al. 1999; Lora-Wainwright 2015). Environmental risk management in China is predominantly a top-down objective process that does not consider public perceptions of environmental hazards or attitudes to risk and risk acceptance (L. Zhang et al. 2013). This is in contrast to environmental risk management elsewhere (e.g., Bickerstaff and Walker 2001; DEFRA 2011), where public participation in environmental risk assessment and management, particularly those risks to human health, is now seen by both state and public as a means to raise welfare in a cost-efficient manner. A key factor here is that understanding subjective perceptions of risk and having a dialogue between public and state are important elements in identifying and understanding risks and prioritizing mitigation options. This is an important point in the context of China's revised Environmental Protection Law, which now enables the public to bring prosecutions against polluters who fail to comply with environmental legislation.

Our study also reveals health and environment inequalities across demographic and socioeconomic strata in Beijing. First, differences in health status are found with age: Older people have significantly lower odds of reporting good health (Figure 6); this is as might be expected, although we note that with a subjective self-rated health metric, perceptions of good

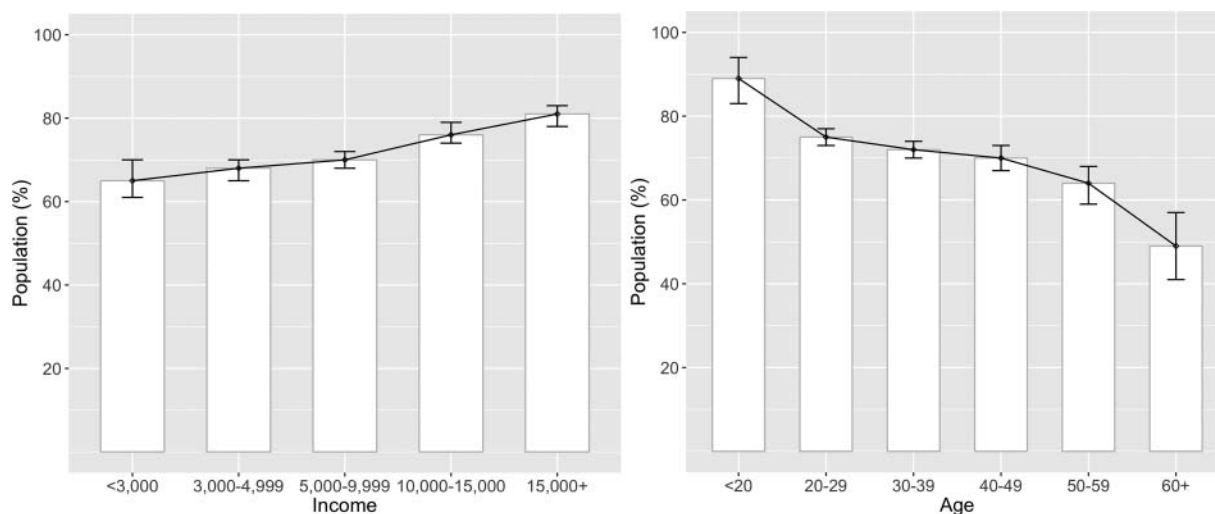


Figure 6. Population (%) in self-rated good health across income categories and age cohorts.

health are likely to display some age dependency. China has an aging population, and effective policies on health care, insurance, and welfare are needed to improve health in the elderly. Second, an obvious

variation also exists by educational attainment—people with tertiary education have 29.4 percent higher odds of reporting good health compared to those with low-level attainment. Third, people living in the

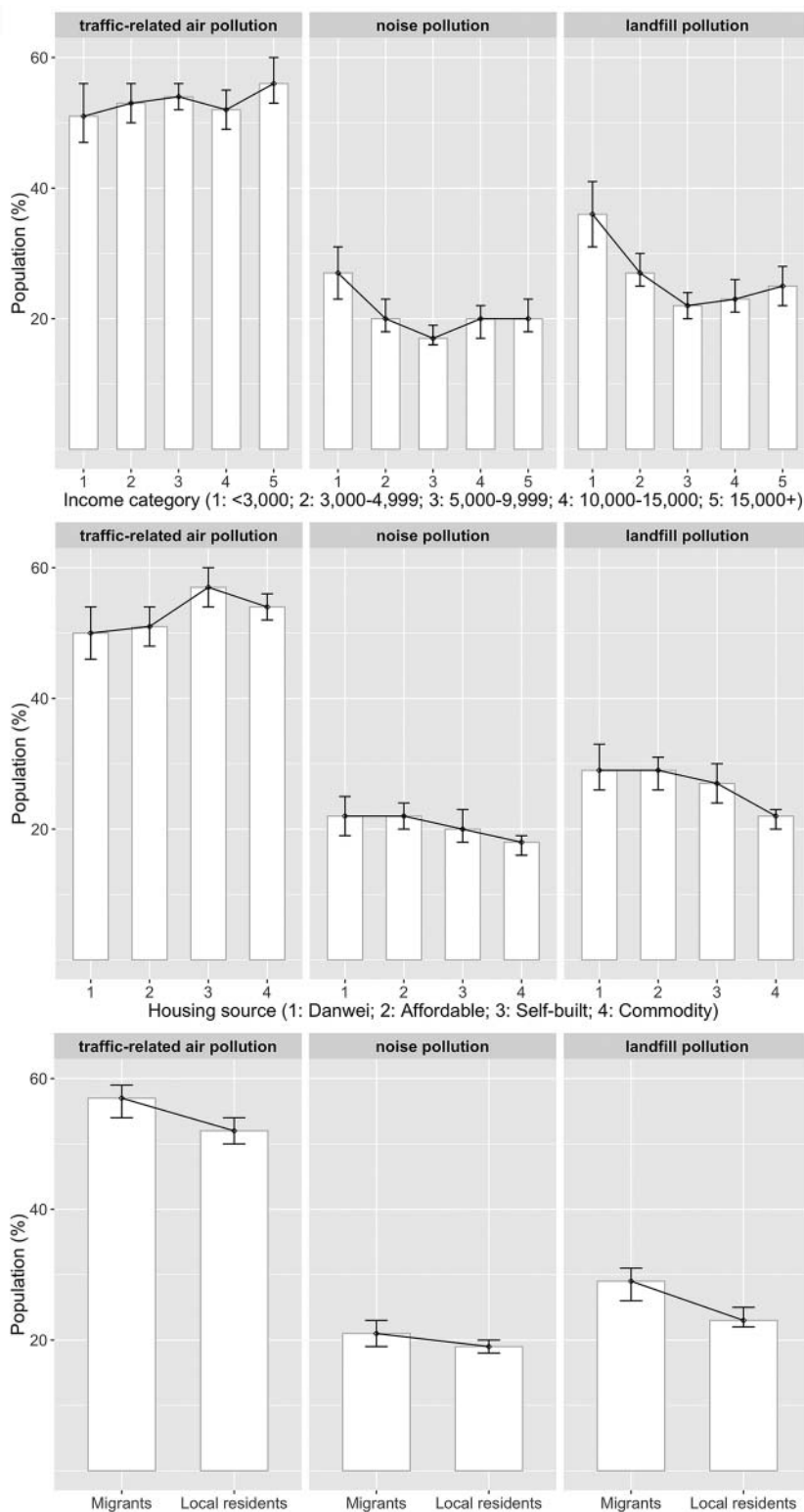


Figure 7. Population (%) in perceived high (and very high) exposure to environmental hazards across different sociodemographic strata.



higher quality commodity housing, who have enhanced economic power and also a greater ability to avoid high exposure to environmental pollution (Figure 7), are significantly associated with a greater chance of reporting good health. People with lower income also self-report poorer health (Figure 6), consistent with an extensive literature in which poor health is mediated by income-related diet, lifestyle, social networks, access to health services, and environmental factors, including living and working conditions (Dahlgren and Whitehead 1991).

With respect to environmental hazards, which have potential adverse effects on health, we observe that socially disadvantaged groups generally report greater exposure (Figure 7). Perceived environmental hazards are biased toward migrants, those without a Beijing *hukou*, which supports previous findings that the adverse health effects of environmental hazards are more detrimental for rural-to-urban migrants than for urbanites (Chen, Chen, and Landry 2013). Those residents in lower quality and less expensive *Danwei* and affordable housing also report higher exposure to noise pollution and toxic landfills than those in the more comfortable commodity housing. An income effect is also evident, with those with lower incomes more likely to perceive high or very high exposure to environmental hazards (noise, toxic landfills), which is consistent with the social distribution of pollution observed in developed countries (Pearce et al. 2010; Mitchell, Norman, and Mullin 2015). The exception here relates to air quality, where those with higher incomes and commodity housing more frequently perceive air quality to be poor. The reasons for this are uncertain—it could be because air quality in the more affluent northern suburbs is objectively worse (due to higher levels of car ownership and commuting) or because higher income confers a greater demand for good air quality, which is not met because of the generally very high level of air pollution across the city.

Our study has sought to gain an insight into the geographical distribution of self-rated health and perceived environmental hazard in Beijing and to explore their association with social characteristics. Given the static nature of our data, we are unable to shed light on the hypothesis that income inequality itself is a social determinant of health in Beijing, with people experiencing “status anxiety” from being in a competitive hierarchy that causes stress and subsequently ill health (e.g., Wagstaff and Doorslaer 2000; Wilkinson and Pickett 2006). Recent research in China on the role of this effect is equivocal (Baeten, Van Ourti, and Van Doorslaer 2013;

Bakkeli 2016) and further work is needed. In our analysis, both the environmental hazards and health are subjectively evaluated by residents; hence, their association might be overestimated due to individual attributes (e.g., personality traits) unobserved in this research. Without spatially resolved and objectively measured data on environmental hazards and health, however, we are unable to determine the causal effects of these health determinants. Nevertheless, we have established that perceived environmental hazard is linked to self-rated health, with exposure to poor air quality, noise, and landfill sites all resulting in lower levels of self-rated health, and that environmental inequality exists in Beijing (and by extension we assume, other Chinese cities)—socially deprived groups, the poor, and migrants who have unequal access to housing, public services, and welfare experience a disproportionately high exposure to environmental pollution and any associated disease burden.

### Environmental Justice in Beijing

It is rarely simple to judge whether such inequality is also unjust, but this interpretation is more complex in China than for most countries, given the very radical shifts in income equality and living standards experienced in its recent history. Following the social revolution of 1949, equality increased in China’s urban economy as firms became state owned or controlled, with people assigned to jobs by a bureaucracy rather than selection through competition. The market reforms after 1978 (e.g., decollectivization, fewer restrictions on migration, an opening up to foreign investment and competition), although by no means an abandonment of the egalitarian doctrine, were widely seen as pragmatic means of delivering necessary economic growth. Rapid growth ensued, with the effect that 680 million people were lifted out of poverty from 1981 to 2010, and the extreme poverty rate fell from 84 percent in 1980 to 10 percent in 2013 (Economist 2013).

Whyte (2012) noted that before the market reforms, the equality achieved was produced by a process of leveling down as opposed to affirmative action to help the disadvantaged, whereas after 1978, the “tide of economic development lifted all Chinese boats, but at unequal speeds” (229). In the 1990s the freedom to join or start a business, coupled with mass privatization of housing, led to extraordinary growth in wealth for some, such that income inequality has risen from a Gini coefficient of 0.30 in 1980 to 0.55 in 2012 (compared to the U.S. value of 0.45; Xie and Zhou 2014). The rich in China have gotten richer,

but the poor have not gotten poorer, and economic development has dramatically raised living standards. This economic development has been achieved at great cost to the supporting environment, however.

In interpreting environmental inequality, the Chinese case is evidently complicated by the interplay of extreme changes in income inequality, environmental quality, and poverty. In Western market economies, procedural justice is often seen to take priority over distributive justice in such interpretations. That is, as long as processes (e.g., market dynamics, residential sorting, planning) that produce environmental inequalities are seen as fair, those environmental inequalities tend not to be seen as unjust. Exceptions occur when environmental hazards are seen to be inherently unacceptable; for example, when environmental quality standards are breached. Such standards reflect the social contract between citizen and state and are designed to protect health irrespective of status; hence, when minority groups bear the burden of such breaches, claims of environmental injustice can be supported (Mitchell, Norman, and Mullin 2015).

In interpreting environmental inequality in Beijing, it is appropriate to ask whether these inequalities are a product of just processes, to which the answer is likely no. Whyte (2012) described how in the urban economy of the 1960s, school leavers were assigned jobs by a bureaucracy, rather than through merit and competition, with wages, housing, and benefits then dependent on the assigned job and work unit. Inequalities within a production team were small but much larger between production units and across the urban–rural divide. Opportunities to gain wealth under the later market reforms were also bureaucratically determined, particularly in the case of workers then able to migrate to the city but who then experienced discrimination in terms of wages, benefits, housing, and, for their children, access to education.

For Beijing we lack objective data on the social distribution of environmental hazards, but poor environmental quality is clearly widespread and severe. Although wealthier residents might have greater economic power to locate away from the most environmentally hazardous locations, in practice they have a rather limited choice of low-hazard locations to which to relocate. Average fine particulate concentrations for Beijing are about an order of magnitude above the WHO guideline value, which suggests a saturation effect with respect to compliance to air quality standards. That is, unjust distributions are arguably not found in Beijing with respect to compliance with air quality standards, because these standards are very probably breached for everyone.

Environmental inequalities highlight a tension in Chinese governance, in that they reflect unequal processes that are contrary to its egalitarian principles, yet the accompanying development has been key to poverty reduction. As environmental quality improves, we anticipate a substantial increase in environmental inequality, as a “good” environment emerges and is preferentially captured by the affluent. This will include environmental metrics intended to protect everyone regardless of status (e.g., health-based environmental quality standards), so environmental injustice is also likely to increase in urban China. The extent to which such inequality is acceptable in Chinese policy circles will again depend on the balance struck between egalitarian ideology and pragmatism—this time, pragmatism directed not at poverty reduction but at environmental improvements that protect human health. Given current social inequality in China, it is unrealistic to expect environmental measures to deliver equal protection for all.

To maximize public welfare, tackling China’s acute environmental problems might well take precedence over equity issues. From a justice perspective, though, it is important to consider environment and health inequalities so that environmental management measures offer adequate protection to the most vulnerable groups. Environmental protection, public health, and social justice issues are increasingly integrated in Western countries’ policymaking, but in China they remain rather isolated, and environmental policy is focused on environmental protection and resource preservation (Holdaway 2010), without integration into wider health and social policy. We recommend that policy makers develop (1) greater recognition that environmental and health inequalities exist at various social and spatial scales; (2) capacity to determine what causes these inequalities; (3) procedures to quantify the costs and benefits of policies, plans, and projects that affect the environment and health and determine the social distribution of those impacts (such procedures are now advocated in Western economies; see, e.g., the UNECE Aarhus Protocol, U.S. Environmental Justice Executive Order, UK treasury “Green Book” guidance); and (4) decision-making frameworks to determine where the balance between efficiency (welfare gains) and equity (welfare distribution) should lie, which might usefully be supported by providing opportunity for citizen involvement in environmental decision making. A larger evidence base is also needed to support the Chinese government in developing more effective and just environmental and public health policies.

## Conclusion

Our study uses 2013 social survey data to develop the first small-area analysis of environmental hazards and human health for a Chinese megacity and in doing so addresses the call for examination of the role of geography and demography in the relationships between environmental hazards and health in China (Holdaway 2010). Our results reveal that environmental hazards and health, as perceived by Beijing residents, are unevenly distributed across the city and that these distributions display strong social gradients. Health inequalities exist with respect to income, educational attainment, and housing characteristics, and clear environmental inequalities exist, associated with income, housing type, and, in particular, resident status, with poorer migrant workers without a Beijing *hukou* (household registration) experiencing a disproportionately high exposure to environmental hazard and associated disease burden. As suggested by Kwan (2012a, 2012b), contextual (neighborhood) factors help explain these inequalities, as evidenced through the development of a Bayesian spatial multilevel logistic model, which underlines the importance of geography in explaining health inequality (Chakraborty 2009).

Given the serious environmental pollution in China's cities, a more systematic and comprehensive program is needed to collect objective, spatially resolved data on environment and health to support evidence-led environmental health risk management, and health promotion. Further research is needed to improve understanding of the social and spatial distribution of environmental quality, the role of environmental hazards in Chinese health, and the relationships among environment, health, place, and demography.

Our observations on inequalities in environmental hazard and health are discussed within a wider environmental justice context. In Western economies, raising environmental quality has the effect of improving health and reducing health inequalities (R. Mitchell and Popham 2008), but in China improving urban environmental quality is likely to first exaggerate environment and health inequalities, given the extremely high levels of pollution, and very significant social inequality. Improving environmental quality must be a public policy goal, however, and should lead to reduced health impacts overall. Chinese policy makers are therefore likely to experience tension between adherence to egalitarian principles and pragmatic actions needed to raise public welfare. China has faced such tension before, when market-oriented policies were introduced to tackle extreme poverty. Policy

makers do need to proactively address environment and health inequalities, however, to mitigate the more extreme injustices that might be ahead. This requires a clear strategy to integrate environment, health, and justice concerns within effective public policy decision-making frameworks.

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## Notes

1. Beijing has sixteen districts, six of which are usually referred to as urban areas of Beijing, whereas the other ten districts are more rural areas. Each of these districts includes dozens of subdistricts or *Jiedao(s)*, the basic administrative unit in China and the finest spatial unit at which limited census variables and geographical boundary data are available. As both administrative and census unit, the *Jiedao* subdistricts are important in terms of a variety of public facility provision, including health care and education. The average population of subdistricts in the six urban districts was about 86,000 (standard deviation of about 48,000) in 2010. Nonetheless, we do acknowledge that there are heterogeneities in sociodemographics within subdistricts due to the large population.
2. We apply econometrics to calculate a proxy of objective environmental hazards at the district level. At its heart, the econometrics approach employs multilevel models to estimate area-level measurement from corresponding individual responses while controlling for possible individual heterogeneity and dependencies both within individuals and areas (Raudenbush and Sampson 1999; Mohnen et al. 2011). A three-level random intercept model was specified to derive our district-level measures of environmental hazards, drawing on Mohnen et al. (2011, 664):

$$p_{ijk} = \gamma_{000} + D'_{ijk}\mathbf{a} + X'_{ijk}\mathbf{\beta} + v_{00k} + u_{0jk} + e_{ijk},$$

where  $p_{ijk}$  is the response to item  $i$  of individual  $j$  living in district  $k$ ;  $\gamma_{000}$  is the grand mean of district-level

environmental hazard;  $D$  is an  $N$  by  $(m - 1)$  item indicator matrix where  $N$  is the sample size and  $m$  is the number of items (three in this study);  $\chi$  includes individual-level variables, adjusting observable individual heterogeneity in item responses;  $\alpha$  and  $\beta$  are regression coefficients to estimate. Terms  $v_{ook}$ ,  $u_{ojk}$ , and  $e_{ijk}$  are residuals at the district, individual, and item levels, respectively, of which  $v_{ook}$  serves as a proxy of district-level environmental hazard. The average estimated reliability of the district-level environmental hazard is about 0.723, a value that can be considered to be adequate by a conventional criterion (Mohnen et al. 2011, 664).

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