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A spatial analysis of air pollution and environmental inequality in Beijing, 2000-2010

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Abstract

Whilst air pollution is a major problem in China, little is known about how it is distributed socially and how such distributions are changing over time. We use population census and air quality data for 2000 and 2010 to explore socio-spatial and temporal inequalities in air pollution for Beijing. We find that clear environmental inequalities exist with respect to measures of social disadvantage, such as hukou migrant status, very young children (aged 0-4 years), and the elderly (aged ≥ 65 years). Our temporal analysis reveals that environmental inequality increases for migrants and the elderly, who bear a disproportionate and rising share of declining air quality from 2000 to 2010. Regression results emphasise the spatial and temporal variations in environmental inequality, as the associations between air pollution and social demographics differ between different urban zones of Beijing and their geographic patterns change significantly over time.

Keywords

Air pollution; environmental justice; spatial regression model; China

Introduction

Reducing health inequalities is a major international development goal that has long received public policy support. Much evidence exists to show that marginal social groups (poor, ethnic, children) bear unequal environmental burdens and hence experience above average environmental health risks (e.g. Pastor et al. 2005; Brulle and Pellow 2006; Walker 2009), although the contribution these environmental inequalities make to health inequalities has received relatively little attention (Pearce et al. 2010). Analyses of environmental inequality at fine-grained spatial scales with a temporal dimension are rare, with few developed for China, despite it having 40% of the world's premature deaths due to poor air quality (Lim et al. 2012). Little is known about how this health burden is distributed spatially and socially, or how these distributions are changing over time. As a result, there is very limited understanding of environmental inequalities in China, significantly inhibiting the development of health sensitive environmental policy.

Environmental justice (EJ) is a key concept at the intersection of environmental sustainability and social justice discourses that seeks to ensure that all people enjoy equal access to a clean environment and equal protection from environmental hazards irrespective of ethnic and socio-economic status (Cutter 1995). This popular definition address the two most common conceptions of EJ, distributive justice and procedural justice. Distributive justice is concerned with the fair distribution of environmental impacts and access to environmental goods and services, whilst procedural justice is concerned with ensuring fairness in decision making that affects the environment, and equal access to judicial redress in environmental matters. In terms of distributions, justice theories are used to articulate and differentiate between unequal and unfair. An unequal distribution (e.g. of environmental quality) may be viewed as unfair/unjust (or not) depending upon the position subscribed to, whether that be utilitarianism, libertarianism, or a Rawlsian egalitarianism conception based on need, desert, or entitlement. The scope of EJ continues to evolve beyond these core interests, with growing attention to issues of recognition (as participative justice relies upon recognition and respect for all those involved), as well as interest from post-structural geographers including the use of performative practices to study and understand EJ (Jamal and Hales, 2016). Walker (2009) and Schlosberg (2013) review and discuss recent developments of environment justice theory.

Globally, the EJ literature is large and remains dominated by distributional studies, with earliest analyses from the USA, showing that noxious industrial facilities and waste treatment and disposal plants were predominantly located in communities of colour (e.g. UCCCRJ 1987; Bowen 2002). This evidence led to an Executive Order, requiring the promotion of environmentally just development, and the establishment of The Office of Environmental Justice in the US EPA to coordinate federal efforts to integrate environmental justice into all policies, programs, and activities. EJ policy subsequently spread internationally, with for example, the ratification of the UN ECE Arhus convention on the environment (UNECE 1999).

As indicated above, socially unequal environmental burdens are not necessarily unjust and many argue that in addition to how a 'fair' distribution is conceived, consideration must also be given to how unequal distributions develop. Insight into processes producing environmental inequalities has been sought through EJ studies that add a time dimension, and which are thus better able to test theories about how unequal distributions arise (see Mitchell et al., 2015 for a review). Theories include: overt and historic discriminatory siting of environmental hazards, post-siting population dynamics (e.g. movement of minorities to an environmental hazard for area benefits such as work or better housing; movement away from a hazard by those that can afford to, leaving a concentration of minorities who cannot), capacity for collective action to resist environmental hazardous, and cultural risk theory, with households trading off environmental risk for other benefits the area offers or simply ignoring the risk.

Understanding how unequal distributions arise is then important in judging whether inequality is also unfair. However, where environmental impacts are likely to be injurious to health, and particularly where legal environmental standards are breached, claims of environmental injustice are better supported. Mitchell and Dorling (2003) showed that in the UK in 2001, about 2.5 million people lived in areas where air quality did not comply with national (EC) standards; of these people, over half were amongst the poorest in the country. Because air quality standards, intended to protect public health, are agreed as part of the social contract between the state and its citizens, it can be concluded that this is an environmental injustice which policy makers and planners need to address.

Although EJ research has broadened its scope to address a wider range of hazards, this interest in air pollution remains high, given the clear health links and prevalence of poor air quality. Evidence for the health impact of poor air quality is strong, and the Global Burden of Disease project ranked outdoor air quality (fine particulates) as the ninth greatest threat to human health globally (fourth in East Asia) with 3.2 million premature deaths and 76 million years of healthy life lost each year (Lim et al. 2012). The European Environment Agency estimated that 18–21% of Europe's population experience particulate concentrations exceeding the EC standards, with an estimated average loss of healthy life of 8 months per person (EEA 2012). EJ studies imply that the poor and other marginal groups will bear a disproportionate share of these health burdens. For example, the latest estimate of UK national disease burden attributed to outdoor air quality is 40,000 (± 25%) premature deaths each year (RCP 2016), with distributional analysis revealing that of those people resident in areas that failed annual average fine particulate standards in 2011, 85% were in the poorest 20% of the population (Mitchell et al. 2015).

Where data permits, EJ analysis can be extended over time to gain insight into the evolution of environmental inequalities. Mitchell et al (2015) present a dynamic analysis of air pollution change in Britain between 2001 and 2011, with results showing that air quality improvement is greatest in more affluent areas with deprived areas bearing a disproportionate and rising share of declines in air quality, a pattern that they concluded would exacerbate respiratory health inequalities (although a reduced disease burden overall was expected). However, such dynamic EJ studies are rare, hampered by a lack of coherent longitudinal data, and have to date been limited to developed countries, predominantly North America, Europe and Japan (see review in Mitchell et al. 2015). Many of the most pressing public health related environmental inequalities are emerging in developing countries, including China, yet these countries are almost absent from the EJ literature.

Serious air pollution is probably the most pressing environmental issue in China, and a major public health concern. Air quality in Chinese cities is among the worst in the world, with 1.2 million premature deaths due to poor air quality in 2010 (Lim et al. 2012). Understanding how this environmental burden is socially distributed, who is most impacted, and how these distributions have evolved over time is key in determining how to better protect the health of the most vulnerable social groups in China. China also presents a particularly interesting case in the EJ field, as it is a country pursuing a social market economy (and is the fastest growing consumer economy in the world, with a rising middle class) yet holds to an egalitarian political doctrine which implies that all environmental inequality is unjust. Exploration of public health and EJ issues in this context is likely to be both fascinating, and supportive of environmental and public health policy (Ma et al. 2017).

However, the development of economic, environmental and sustainability policy in China gives little attention to social equity concerns and their links with public health, and the evidence base is poorly developed. Prior studies have focused on environmental inequalities at a coarse spatial scale (cities, districts) and conclusions cannot be applied to the finer scales important to understanding public health impacts and inequalities without invoking the modifiable areal unit problem (Kwan 2012). Others studies focus on correlation between perceived environmental hazard and health outcome (Chen 2013), but employ a static analysis that constrains our understanding of the evolution of environmental inequality over time, and hence its implications for health inequalities.

As the nation's capital and one of China's largest metropolitan areas, Beijing has undergone rapid urbanisation since the 1980s, and its urban population ratio has risen from 77.5% in 2000 to 85.9% in 2010 (Beijing Statistical Bureau 2010). However, China's megacities are less dense than other international megacities, and Beijing's urban sprawl has been accompanied by large increases in car use, creating serious problems of traffic congestion, energy consumption and air pollution (Ma et al. 2014). Air quality in Beijing is amongst the worst in the world, with the annual average $PM_{2.5}$ concentration reaching 80.4 $\mu g/m^3$ for 2015 (Greenpeace East Asia 2016). For comparison equivalent annual average $PM_{2.5}$ standards are 35 $\mu g/m^3$ in China (a 15 $\mu g/m^3$ standard exists for areas requiring special protection, such as resorts), 25 $\mu g/m^3$ in the EU, 12 $\mu g/m^3$ in the USA, whilst the WHO guideline value is 10 $\mu g/m^3$. Clearly

Beijing's severe air pollution has potentially highly significant environmental, social and health impacts, but these remain largely unquantified.

Therefore, in this research focused on Beijing, China, we characterise the spatial and social distributions of air quality (fine particulate $PM_{2.5}$ concentrations) at fine geographical level and explore the nature and evolution of environmental inequalities. This is achieved through combining recently released high-resolution (1 x 1 km grid) air-quality data from the Atmospheric Composition Analysis Group (van Donkelaar et al. 2016) and the population censuses of Beijing at the sub-district level for 2000 and 2010. Spatial econometric models are also employed to investigate the relationships between air pollution and socio-economic disadvantage over the decade. We present an urban environmental inequality study based on observed (rather than perceived) environmental data in China with a fine-grained spatio-temporal analysis, and thus add a new dimension to the environmental justice literature worldwide. More importantly, this research improves the understanding of environmental inequality needed to inform the Chinese governments' environmental and public health policy.

Data and methods

Air quality data

China records air quality data via the official real-time air pollution monitoring station network, where hourly ground concentration data for several air pollutants are recorded by the Ministry of Environmental Protection of China. However, these data are only available from 2013 and for Beijing are limited to just a few monitoring stations, masking geographical variability (Ma et al. 2017), and making the data unsuited for our purpose. Therefore, here we use model-based annual concentrations at ground-level for 2000 and 2010 from the Atmospheric Composition Analysis Group (van Donkelaar et al. 2016). We focus on the finest particulate matter fraction ($PM_{2.5}$), thought to make the greatest contribution to the global disease burden attributed to poor air quality, some 3 million premature deaths in 2013 (Forouzanfar et al. 2015). This fraction is also strongly associated with combustion sources including vehicle traffic, which emits primary particulates plus other gases (e.g. NO_X, SO_2) that react to produce secondary pollutants including nitrate and sulphate particulates. van Donkelaar et al (2016) estimated global surface level $PM_{2.5}$ concentrations by combining satellite based observations (Aerosol Optical Depth) with a chemical transport model, with results calibrated to ground-based observations of $PM_{2.5}$ using Geographically Weighted Regression. The $PM_{2.5}$ concentrations are available for 1998 to 2015 (at http://fizz.phys.dal.ca/~atmos/martin/?page_id=140) at a spatial scale of about 1 x 1 km, much finer than previously available for China. We acknowledge that there are limitations when applying this global-scale pollution data in a specific city due to different meteorological conditions. We have conducted a validation check using the $PM_{2.5}$ concentrations derived from real-time air quality monitoring stations in 2013 (when such data firstly become available) with a block-Kriging approach (Bivand et al. 2013). This shows that the calculated $PM_{2.5}$ concentrations from block-Kriging are in line with the global surface level $PM_{2.5}$ concentrations, as indicated by a Pearson correlation coefficient of 0.83. Therefore, we argue that the use of this model-based pollution measure is not expected to cause serious issues to our results.

On the basis of these data, we then calculate annual average $PM_{2.5}$ concentrations at the sub-district (or Jiedao) scale in Beijing for 2000 and 2010 separately. The sub-district is the basic administrative unit in China. Sub-districts contain neighbourhoods, and in Beijing the 318 sub-districts had a population of about 86,000 each (standard deviation 45,000) in 2010, against a city wide population of 19.6 million. Thus sub-districts are geographically still quite large, but are the finest spatial unit at which the population census and geographical boundary data are available. We overlay the Beijing sub-district polygon data with the 1×1 km $PM_{2.5}$ concentration grids, and then calculate the weighted annual averages of $PM_{2.5}$ concentrations for each sub-district as:

$$C_k = \sum_{i=1}^{m} \frac{S_{ik}}{S_k} C_i \qquad (1)$$

where C_k represents the calculated annual $PM_{2.5}$ concentration for sub-district k, m refers to the number of grids falling within (or intersecting with) sub-district k. S_{ik} is the area of grid i falling in sub-district k, S_k refers to the total area of sub-district k, and C_i refers to the $PM_{2.5}$ concentration level of grid i.

Demographic data

The demographic data is from the fifth and sixth population census of Beijing for 2000 and 2010 at the sub-district geography. All residents are required to answer a short census form containing basic information on the household and individual socio-demographics (e.g. gender, age, education), while a sample of 10% of the total population in each sub-district are randomly selected to complete a long census form, which elicits additional information on attributes such as housing area, employment and occupation. In particular, residential status, or hukou, is a legal record for regulation and administration of residents in mainland China, which registers basic socio-demographic information, original and current residential location, and the rural or urban residence status. In many cases, the hukou system is regarded as an entrenchment of rights for local or urban residents only. Migrants and rural residents are thus restricted in their access to particular goods and services that are key to social welfare. These include admission to certain schools and hospital services, and the right to purchase a private house or a car. The hukou system is widely criticised as a tool that blocks social mobility and exacerbates rural-urban inequalities across China (Wu and Treiman, 2004). Accordingly, we derive the social metrics of residential status (or hukou), very young children and the elderly who are particularly vulnerable to air pollution, as well as employment status (unemployment rate) from the 2000 and 2010 population census data, to determine the social distribution of air pollution. In line with Ma's (2010) equity analysis of industrial facilities in Henan province of China, we do not address ethnicity in our analysis, as many western EJ studies do, as about 96% of the population of Beijing are Han people.

Analytical methods

This research involves both descriptive analysis and multivariate regression analysis. First and foremost, we use a GIS to map the spatial distributions of air pollution and proportions of the disadvantaged social groups of migrants, very young children (aged 0-4 years), the elderly (aged 65 years and above), and the rate of unemployment for each sub-district in Beijing, and then relate the air pollution data and social demographic data at the sub-district geography for both 2000 and 2010. The $PM_{2.5}$ concentrations by sub-districts in 2000 and 2010 have been assigned to the corresponding demographic census populations at the sub-district level to represent their exposures to air pollution for 2000 and 2010, respectively (Buzzelli and Jerrett 2003; Milman 2006). We then conduct a preliminary investigation of environmental inequality by plotting air quality against relevant social metrics in deciles of equal population. Specifically, data are analysed by ranking all sub-districts by residential (migrant) status, very young children, the elderly and employment status for 2000 and 2010. The sub-districts are then divided into equal population deciles and sorted into ascending order for each demographic attribute, so that the upper deciles are characterised by the greatest proportion of people of the specified attribute. Average $PM_{2.5}$ concentrations for each decile are then calculated from the sub-district $PM_{2.5}$ values for 2000 and 2010, respectively. This is a widely used type of distributional analysis in the EJ literature and although statistically simple, is a powerful analysis as it deals with the entire population rather than relying on comparison of a population sample to national averages.

Next, we employ a set of regression models to isolate associations between key socio-economic variables and air pollution, while controlling for locational and industrial structure attributes of each sub-district. To deal with the spatial pattern of air pollution, two analysis strategies are implemented. First, the second-order polynomials of the coordinates (Easting and Northing) of sub-districts are included in our model to capture the global spatial smoothness trend of air pollution. Second, a popular spatial econometric model, the spatial error model (SEM) is specified for the air pollution model to tackle the remaining spatial correlation (or auto-correlation). The importance of spatial econometric models in environmental equity research is highlighted by Laurian (2008). Following Anselin (1988), the SEM is specified as,

$$Pollution = \alpha_0 + X'\boldsymbol{\gamma} + L'\boldsymbol{\beta} + f(Easting, Northing) + \boldsymbol{\omega};$$
$$\boldsymbol{\omega} = \rho W\boldsymbol{\omega} + \boldsymbol{\varepsilon} \qquad (2)$$

where X refers to the socio-economic variables of interest and L represents some control variables including spatial location (e.g. distance to city centre and city zonal variables), population density, and industrial structure; f (Easting, Northing) is the spatial smoothness terms applied to the coordinates of each analysis unit, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are two regression coefficient vectors to estimate, $\boldsymbol{\varepsilon}$ is a vector of independent random residuals each following a Normal distribution, N(0, σ^2); $\boldsymbol{\omega}$ is the model error vector, specified as a simultaneous auto-regressive spatial process with a multivariate Normal distribution, MVN($\mathbf{0}$, $[(I-\rho W)'(I-\rho W)]^{-1}$). W is a row-normalised spatial weights matrix specifying the connection structure of analysis units, and ρ the estimated spatial auto-regressive parameter. We extract W based on geographical contiguity of sub-districts: w_{kj} = 1 if sub-districts k and j share a border, and 0 otherwise.

The causal associations between spatial distributions of social and economic disadvantage and air pollution, evidencing environmental inequality, are complex, arguably more so than previously recognised. Bailey at al 2018 show that, driven by a mix of socio-economic processes including path dependency, market sorting and heterogeneous residential locational preferences, the association between aggregated patterns of air pollution and deprivation (or poverty) in Scotland varies both spatially and temporally. To address such potential spatial heterogeneity effects, our study area is delineated into four city developmental zones (Table 1) according to the Beijing Statistical Bureau (2010), allowing spatial variability in environmental inequality to be analysed. We implement SEM by using an open source software package spdep (Bivand et al. 2013) in R. To reduce the potential heteroscedasticity and multi-collinearity issues, all variables except for zonal dummy variables are transformed to a standard Normal distribution in our modelling analysis. Definitions and summary statistics of key variables are presented in Table 1.

[Table 1 about here]

Results

Spatial Distribution of Air pollution and Socio-economic Disadvantage in Beijing

Figure 1 maps annual average $PM_{2.5}$ concentrations at the sub-district geography for Beijing in 2000 and 2010. The area wide annual mean value of $PM_{2.5}$ concentration is

64.1 μg/m^3 in 2010, compared to 53.6 μg/m^3 in 2000, a significant increase (about 20%) reflecting urban growth, industrialisation and motorisation over the decade. The number of sub-districts where $PM_{2.5}$ concentrations below China's limit value of 35 μg/m^3 for fine particulate matter (MEP 2012) has decreased significantly, from 16.3% in 2000 to 8.5% in 2010. In contrast, there are 37.6% of sub-districts with annual mean $PM_{2.5}$ concentrations above 65 μg/m^3 (no sub-districts above 80 μg/m^3) in 2000, rising to 57.1% of sub-districts above 65μg/m^3 and in particular 13.5% above 80 μg/m^3 by 2010 in the Beijing metropolis. However, possibly due to the meteorological factors (e.g. temperature and wind speed) and domestic coal consumption, there is a significant seasonal variation of $PM_{2.5}$ concentrations in Beijing, which were much higher in winter than in summer as reported by Sun et al (2004). The high $PM_{2.5}$ concentrations in Beijing is partly due to meteorology that creates the red alert smog episodes (especially in winter) which push up the annual average.

[Figure 1 about here]

The average $PM_{2.5}$ concentration by sub-district also varies significantly, with a clear division of $PM_{2.5}$ concentrations from the northeast to southwest across the metropolis. Annual average $PM_{2.5}$ concentrations in most sub-districts of north and southwest Beijing are relatively low, ranging from 20.6 μg/m^3 to 46.2 μg/m^3 over 2000-2010. In contrast, average $PM_{2.5}$ concentrations are much higher in southern Beijing, with most sub-districts exceeding 69.0 μg/m^3 in 2000 and 79.0 μg/m^3 in 2010. This division is possibly due to higher vegetation and mountain coverage in north and west Beijing, a prevailing northwest wind (especially in smoggy winters) and more pollution sources (e.g. heavy industries) in south Beijing. Average $PM_{2.5}$ concentrations in the central urban and inner-suburban zones of Beijing are notably much higher than in the outer-suburban and city fringe zones for 2000 and 2010, probably due to high population density and growing car use in these urban areas (Ma et al. 2014).

Figure 2 illustrates the spatial distribution of socio-economic disadvantage for the sub-district geography in Beijing in 2010. It shows that geographic variation of the proportions of migrants, very young children (0-4 years), the elderly (≥ 65 years) and the rate of unemployment is evident across Beijing. For instance, clustering of sub-districts with a high proportion of migrants and very young children are mainly located in the inner-suburban zone, where work opportunities exist and housing is more affordable than the central urban zone. In contrast, the rate of unemployment is higher in the outer-suburban and city fringe zones, particularly in western Beijing.

[Figure 2 about here]

Social Distribution of Air Pollution for 2000 and 2010

On the basis of air pollution and population census data, we first investigate the social distribution of $PM_{2.5}$ concentration by hukou status in Beijing for 2000 and 2010. We define migrants as residents who departed from their original registered residence more than six months ago, and who now live in a different area away from their original registered residence, without local hukou. Figure 3 illustrates the distribution of $PM_{2.5}$ concentration for migrants in 2000 and 2010. All deciles by hukou experience breaches of China's limit value for $PM_{2.5}$ concentration of 35 μg/m^3, although those with a high proportion of migrants experience more extreme exceedances. The 2000 pattern shows a steady increase in $PM_{2.5}$ concentration as the percentage of migrants increases. The sub-districts where most migrants are resident have an annual average $PM_{2.5}$ concentration of 68.4 μg/m^3 in 2000 (D10), compared to 41.6 μg/m^3 for the sub-districts where the majority are local residents (D1). Thus areas with a high proportion of migrants tend to experience a high level of air pollution, a finding consistent with prior studies that show the disadvantaged migrant group perceive higher levels of environmental hazard than local residents for Beijing (Chen et al. 2013; Ma et al. 2017).

[Figure 3 about here]

By 2010, many groups experience a significant increase in $PM_{2.5}$ concentration. The sub-districts where the majority are local residents (D1) experience the least serious air pollution, with an annual average $PM_{2.5}$ concentration of 48.5 $\mu g/m^3$ in 2010, and a marginal decline in air quality from 2000. In contrast, most of the other sub-districts experience a significant decline in air quality, including those with the higher percentage of migrants where $PM_{2.5}$ concentrations are at least double the annual limit value of 35 $\mu g/m^3$ (more than 75 $\mu g/m^3$ for D6-D10). These data display a clear social gradient in air pollution in the Beijing metropolis, with migrants tending to be resident in the most polluted areas.

Figure 4 shows that there are significant variations in $PM_{2.5}$ concentrations for very young children (aged 0-4 years) in 2000 and 2010. For deciles with a high proportion of very young children the mean $PM_{2.5}$ concentration is 66.8 $\mu g/m^3$ in 2000, well above that of the 'few very young children' sub-districts (D1 has the fewest children aged 0-4, and a mean annual $PM_{2.5}$ concentration of 42.7 $\mu g/m^3$ in 2000), indicating that very young children are likely to reside in highly polluted sub-districts. This general pattern is repeated for 2010, with a notable increase in $PM_{2.5}$ concentration (e.g. D9 increases by 24%, from 61.5 to 76.3 $\mu g/m^3$, 2000-2010), and a rising prevalence of very young children is associated with higher $PM_{2.5}$ concentrations. This might suggest that, with the relaxation of hukou system in Beijing by 2010, very young children are more likely to live with their adult parents in the more polluted urban areas (Figure 2) where work opportunities exist and housing is more affordable. A consequence of this demographic process is that very young children, who are particularly vulnerable to air pollution, will experience declining air quality and rising health impacts. It might then be anticipated that currently proposed relaxations of the hukou system might exacerbate this problem.

[Figure 4 about here]

Figure 5 shows the $PM_{2.5}$ distribution of the elderly (aged 65 years and above) for 2000 and 2010. The general pattern of the elderly is similar to that of very young children (aged 0-4 years), that is, areas with a high proportion of the elderly also have a much higher mean annual $PM_{2.5}$ concentration compared with the 'few elders' sub-districts. However, in 2010, the social gradient becomes much steeper, where the higher deciles experience increasingly large rises in $PM_{2.5}$ (e.g. D8 rises by 18%, from 66.9 to 78.7 $\mu g/m^3$, 2000-2010), with one decile (D1) experiencing a marginal increase, from 47.6 $\mu g/m^3$ to 49.3 $\mu g/m^3$. Furthermore, in 2000 annual average concentrations in the sub-districts with the highest proportion of the elderly (D10) is 43% above that of those districts with few elders (D1), rising to 59% in 2010. This reveals growing environmental inequality in Beijing over the decade.

[Figure 5 about here]

Similar age based inequality in air quality (NO_2) was first described by Mitchell and Dorling (2003) for the UK, with the age-gradients being interpreted in the context of established patterns of rural-urban migration. As people in the UK age they tend to be first exposed to relatively high air pollution levels, as birth rates in urban areas tend to be above that of the population as a whole. Very young children in the UK experience above average exposure, as couples tend to have children in the more polluted urban areas for work opportunities. The children-exposure patterns for Beijing are remarkably similar. However, a key difference exists for the elderly between the Mitchell and Dorling age analysis of the UK, and our observations for Beijing. From the midlife (>45 years) onwards exposure levels fall in the UK, reaching their lowest levels amongst the elderly who are most likely to live furthest away from the centres of pollution. In contrast, the elderly (≥65 years) in Beijing tend to be resident in the more polluted urban areas (Figure 2), similar to the exposure pattern for very young children (aged 0-4 years). This may be due to a combination of China's one-child policy (1979-2016) that affects household structure, and very high housing prices in Beijing that affect household location. Many of the elderly live with the extended family, providing child care for their grandchildren and receiving support from their children (Cong and Silverstein 2012) with the family resident in the (more polluted) urban areas for access to work by the adult children.

Moreover, we use unemployment (distinct from economically inactive) as an indicator of lack of economic power, and hence disadvantage. Figure 6 shows that in 2000 air pollution falls as the rate of unemployment rises. This is likely because sub-districts with a high rate of unemployment in 2000 are located mainly in the urban fringe zone of Beijing, such as Miyun and Huairou to the north and Mentougou to the west, where industry was less prevalent and air quality comparatively good (Figure 1)

(D1 unemployment rate is 6%, D10 is 18%). However, by 2010, the pattern changes significantly, with the worst air quality now coincident with areas of highest unemployment (D1 unemployment rate is 2%, D10 is 10%). D10, with the highest unemployment rate has a mean annual $PM_{2.5}$ concentration of 42.0 μg/m^3 in 2000, rising by 48% to 62.3 μg/m^3 in 2010. In contrast, D1, with the lowest unemployment rate experienced a 10% reduction from 59.4 μg/m^3 to 53.3 μg/m^3.

[Figure 6 about here]

This changing pattern is rooted in the economic restructuring and industry decentralisation that has been a common feature of Chinese cities since the 1980's, including Beijing. Historically, the urban centre has been dominated by industrial and administrative functions, with workers housed close to work in Danwei compounds. The rise of the tertiary sector, with many services jobs in the centre (commercial, office, retail) displaced the traditional industrial base, which suburbanised to capitalise on the land value of their central location, and which were encouraged to relocate by the city government due to the pollution created. As the traditional work unit began to dissolve, and workers were no longer tied to their Danwei housing, the process of suburbanisation was further fuelled, with the old run-down Danwei housing increasingly swept away to be replaced by tertiary economic activities and expensive luxury housing (Wang and Chai 2009). Thus employment opportunities have been good in the central urban districts where tertiary growth has been strong, and low unemployment rates are associated with improved air quality following industry suburbanisation (evident in D1 of Figure 6). The suburban districts have experienced a reduction in unemployment following industrial suburbanisation, but also a substantial increase in $PM_{2.5}$ concentration. These data illustrate the trade-off between economic development and environmental pollution in China, as well as the more complex nonlinear relationship between economy (as unemployment) and air quality at the sub-district scale in Beijing (Bailey et al. 2018).

Table 2 presents the changes in annual $PM_{2.5}$ concentration by socio-economic disadvantage over 2000-2010. While almost all groups (except D1 for unemployment rate) experience an absolute decline in air quality by 2010, the relative changes vary across different socio-economic groups. For instance, deciles with a lower proportion of migrants and very young children (e.g. D2) experience a greater share of declines in air quality over the decade, while the decile with the highest rate of unemployment (D10) experiences a significant increase (more than 48%) in $PM_{2.5}$ concentration by 2010. These data suggest that the relationships between the disadvantaged socio-economic groups and air pollution ($PM_{2.5}$) are not simple linear relationships.

[Table 2 about here]

Statistical Modelling Analysis

Estimation results from OLS and SEM in 2000 and 2010 are reported in Table 3. Despite global spatial smoothness in air pollution being captured by polynomial terms of coordinates of sub-district centroids and the distance to city centre variable, spatial auto-correlation in the residuals of the OLS model is found to be statistically significant, as evidenced by a Moran's I statistic of 0.344 with a p-value < 0.001 in 2000. A likelihood-ratio test also supports that the SEM significantly outperforms OLS models in 2010 (Table 3). Moreover, statistical inferences between OLS and SEM differ substantially for a few variables due to the relatively large spatial auto-correlation effects indicated by large magnitudes of ρ in both census years. We therefore discuss environmental inequality and its temporal dynamics based on estimates from SEM over 2000-2010.

[Table 3 about here]

In 2000, it shows that the proportion of migrants is positively associated with air pollution (with a significance level of 5%), indicating sub-districts with higher proportions of migrants tend to experience, ceteris paribus, higher air pollution in the outer-suburban zone (Zone 3, the base category). However, the interaction terms between zonal dummy variables and migrant variable show that the migrant-pollution association in the inner-suburban zone (Zone 2) differs significantly from that in the outer-suburban zone, while the central urban zone (Zone 1) and city fringe zone (Zone 4) do not. This suggests that environmental inequality for migrants exists in Beijing in 2000. For 2010, the estimates on migrant and its interaction terms with zonal variables remain consistent with that in 2000, with a key difference being an increase in the magnitude of the pollution-migrant association in the city fringe zone.

The proportion of very young children is positively and statistically significantly associated with air pollution in the outer-suburban zone in 2000. The magnitude of the association witnesses a substantial decrease in the central urban zone, reaching about -0.11, which is not statistically significantly differentiated from zero (χ^2 equal to 0.098 with a p-value of 0.755). A statistically significant negative association between the distributions of pollution and the elderly is found in the outer-suburban zone in 2000, suggesting that sub-districts with higher proportions of the elderly are associated with lower air pollution. However, temporal changes in environmental inequality of air pollution are evident over 2000-2010. For instance, the coefficient of proportion of the elderly becomes positive in 2010 from negative in 2000 (both statistically significant), suggesting the elderly experience a disproportionate share of air pollution in the outer-suburban zone by 2010. By and large, these results show spatio-temporal variations in environmental inequality for the disadvantaged social groups across Beijing.

As shown in Table 3, there are clear global spatial patterns in the distribution of air pollution in Beijing as indicated by the statistically significant polynomial terms of geo-coordinates of sub-districts in both years. These terms also partially control for the global smoothness of model-based derivations of air pollution data. Also, there is a significant negative pollution gradient when moving away from the city centre of Beijing. Economic structure (manufacturing employment proportions) becomes significantly negatively associated with air pollution in 2010, which is likely due to Beijing's industrial policies initiated from the late 1990s, forcing most manufacturing factories to move out of the central urban zone and upgrade their production technology, to welcome the 2008 Beijing Olympic Games (Schoolman and Ma 2012).

Discussion and Conclusions

The study presents a Chinese urban environmental inequality analysis based on observed environmental quality, and includes a temporal dimension. Our modelling results reveal that clear environmental inequalities exist with respect to hukou migrant status, and age, whilst inequalities are not statistically significant for the unemployed. Results also emphasise the spatial and temporal variations in environmental inequality. Spatially, environmental inequality for the disadvantaged social groups, including migrants, children and the elderly, differ between different city zones of Beijing, calling for a local perspective of environmental inequality research. This corroborates the study by Bailey et al (2018), who argue that variant patterns of environmental inequality in different areas are likely to be driven by different social and economic processes. Temporally, the associations between air pollution and social demographics and their geographic patterns could change significantly over time, as reported in prior studies (Buzzelli et al. 2003; Laurian and Funderburg 2014).

In 2000, migrants without a Beijing hukou and the elderly experience $PM_{2.5}$ concentrations that are higher than in areas with the fewest hukou migrants and elders. In air quality exposure terms, the unemployed tend to experience better air quality in 2000, due to their more frequent suburban location. Beijing experiences major economic and demographic changes from 2000-2010, a period where its air quality declines substantially (c. 20% average increase in annual average $PM_{2.5}$ concentration). Environmental inequality increases for hukou status and the elderly (areas of high migrant and elder prevalence have particulate concentration of about 60% higher than low prevalence areas), whilst the gradient for unemployment reverses, with areas of highest unemployment now experiencing $PM_{2.5}$ levels about 17% above those of low unemployment areas.

These results are interpreted in the context of reforms that have taken place as China moves from a centrally planned, to a market economy. Economic development, transportation and housing construction are intertwined with each other in a region (Kruize et al. 2007). The capitalisation of land value in central urban areas has resulted in shift of the more polluting industries out of the centre to the suburbs (Zhao et al. 2014). At the same time, housing reform, including the relaxation of the Danwei system has seen a dissolving of the tight spatial bonds of home and work, creating a residential property market, a population that commutes further and increasingly by car, and residential sorting of households by economic power. Land market dynamics can induce greater environmental pollution and disproportionate environmental impacts, as market mechanisms tend to locate pollution sources in poor neighbourhoods and concentrate the disadvantaged social groups in more polluted areas (Buzzelli et al. 2003; Laurian 2008; Slater and Pedersen 2009).

These processes are consistent with the observations of environmental inequality by age. These are remarkably similar to children-air quality observations for the UK, with a process of urban-rural transition evident. That is, a process of demographic churn in which young adults move to the more polluted urban locations for work and education opportunities, and later start a family. The notable difference is with respect to the elderly, who in Beijing experience the greatest levels of exposure, in contrast to the UK where the elderly tend to reside in cleaner rural and suburban locations. This difference may be due to China's one-child population policy and very high housing price in Beijing, that causes more of the elderly to live with their working age children in urban locations, to care for grandchildren and receive care.

Our temporal analysis develops the understanding of the relationship of environmental inequality to environmental quality. In a comparable UK air quality analysis, Mitchell et al (2015) found that air quality improvement tended to occur where more affluent groups lived, whilst the more deprived groups tended to experience most of any air quality deterioration. In Beijing, environmental inequality increases for the disadvantaged social groups, such as migrants and the elderly over 2000-2010. With air pollution policy interventions such as more stringent vehicle and industrial emission regulations, as well as relocation of power stations in Beijing, the environmental quality will improve and the environmental inequality might increase, as a "good" environment is mostly captured by the affluent (Ma et al. 2017). We begin to see the possible emergence of a common pattern linking environmental inequality and changing environmental quality. There is of course a judgement that must be made as to where the problem lies, and what is more important – equity or environmental quality? A very clean environment implies little problem on either count, whilst a grossly polluted one such as we see in Beijing means environmental clean-up may justifiably be prioritised over equity concerns so as to lower disease burden. The greatest inequalities are likely to occur at the transition between 'good and bad' environmental quality, and it is here that policy makers must decide whether to focus on environment and health, or environment and health 'for all'. However, to date, no such discourse is evident in China's environmental policy discussion, where the topic of environmental inequality has just started to emerge.

While this research provides a distributional spatio-temporal analysis of environmental inequality in Beijing, it does not reveal the mechanisms that lead to higher pollution in some particular areas and establish causal processes of environmental inequality (Hockman and Morris 1998; Deacon and Baxter 2013). Under the ecological analysis framework and without individual mobility information, it is not possible to disentangle potential causal competing mechanisms of most interest, particularly discriminatory siting of undesirable polluters versus market sorting mechanisms that see disadvantaged groups disproportionately exposed following their movement into polluted areas for cheaper housing and work opportunities, and/or the movement away of the more affluent (Pastor et al. 2001; Richardson et al. 2010; Depro et al. 2015). Due to data limitations, we use sub-district level $PM_{2.5}$ concentration to approximate air pollution exposure of populations, and the health impacts of such environmental risks has not been investigated, a common challenge in prior environmental inequality studies (Lakes et al. 2014; Laurian 2008).

Understanding how such questions are addressed in China presents an interesting avenue for further research. Other research questions associated with our analysis include: extending the analysis to other Chinese cities to test whether the patterns observed in Beijing over space and time can be generalised; confirming the role of the demographic, economic, housing and transport policies and trends on the observed environmental inequalities; linking environmental inequalities to health outcome data to better understand what drives health inequalities in Beijing; and developing the understanding of those other factors related to age and disadvantage that contribute further to health inequality. Finally, we note that in much environmental inequalities research, the most exposed yet least able to avoid pollution (children, the poor) contribute least to that pollution (e.g. Mitchell and Dorling 2003). We suspect this holds true for Beijing, but such a state of affairs, often used to support claims of environmental injustice, remains to be tested.

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Table 1. Descriptions of variables used in the study.

Variable names	Definition
Distance to city centre	Distances of each sub-district (centroid) to city centre (km)
Population density	Population density of each sub-district (1000 persons / km^2)
Percent migrants	Proportion of the total number of migrants in a sub-district
Percent children	Proportion of the total number of children (0-4 years) in a sub-district
Percent the elderly	Proportion of the total number of the elderly (≥ 65) in a sub-district
Percent manufacturing employment	Proportion of the total number of people employed in manufacturing (e.g. steel, textile, chemistry) industries in a sub-district
Unemployment rate	Proportion of the unemployed in a sub-district
Percent crowd housing	Proportion of people with a small house (housing area per capita ≤ 12 m^2) in a sub-district
Zone 1	Central urban zone, including Dongcheng and Xicheng districts
Zone 2	Inner-suburban zone, including Haidian, Chaoyang, Fengtai and Shijingshan districts
Zone 3	Outer-suburban zone, including Fangshan, Daxing, Tongzhou, Shunyi and Changping districts
Zone 4	City fringe zone, including Mentougou, Yanqing, Huairou, Miyun and Pinggu districts
Easting	X-coordinate of the centroid of a sub-district
Northing	Y-coordinate of the centroid of a sub-district

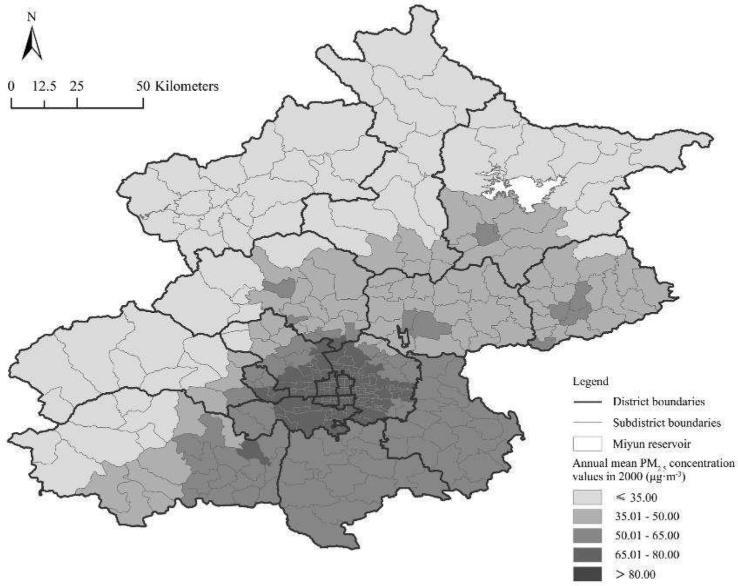
Table 2. Change in annual $PM_{2.5}$ concentration by social-economic groups, 2000-2010.

	Migrant		Children		The elderly		Unemployment rate	
Equal population decile	Absolute change (μg/m^3)	Relative change (%)	Absolute change (μg/m^3)	Relative change (%)	Absolute change (μg/m^3)	Relative change (%)	Absolute change (μg/m^3)	Relative change (%)
1	6.9	16.6	7.4	17.3	1.7	3.6	-6.1	-10.2
2	19.7	42.2	17.2	34.3	16.8	36.9	8.8	15.8
3	18.3	33.8	11.8	20.3	15.3	29.8	9.6	16.1
4	9.1	14.4	14.2	24.9	22.0	42.4	12.2	21.8
5	7.9	12.7	10.7	16.9	16.6	27.9	9.9	18.0
6	13.5	20.9	11.5	18.4	8.7	13.3	12.9	23.2
7	11.0	16.3	12.4	19.2	11.7	18.1	17.2	32.9
8	11.3	17.0	13.9	22.2	11.8	17.6	13.8	26.5
9	8.9	13.3	14.9	24.2	9.4	13.5	13.4	25.8
10	6.7	9.7	8.4	12.5	9.8	14.3	20.3	48.4

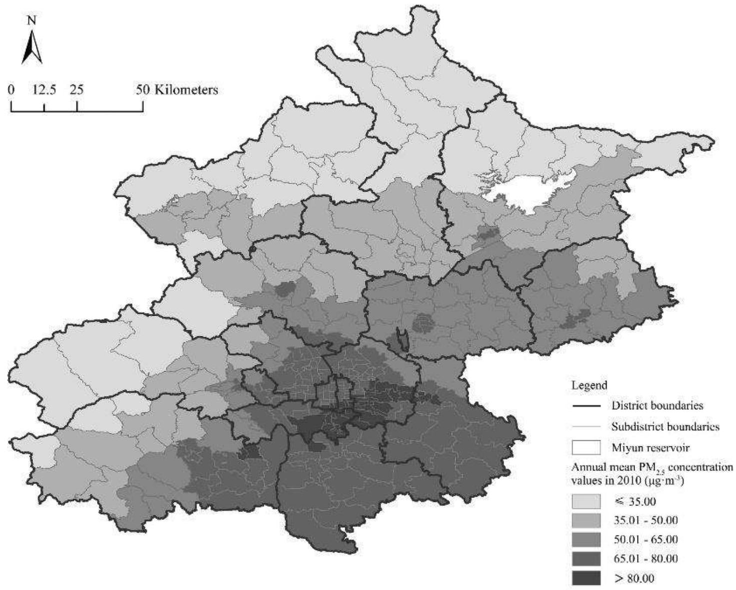
Table 3. Model estimation results for 2000 and 2010.

	Year 2000		*Year 2010*	
	OLS	SEM	OLS	SEM
Intercept	-0.262**	-0.448**	-0.129*	-0.224*
Distance to city centre	-0.42**	-0.845**	-0.561**	-0.855**
Population density	0.122**	0.017	0.147**	0.039*
Percent migrants	0.218**	0.116**	0.062	0.122**
Percent children	0.076	0.860**	0.063	-0.127**
Percent the elderly	-0.263**	-0.183**	0.065	0.219**
Percent manufacturing employment	0.083*	0.023	-0.108**	-0.111**
Percent unemployed	-0.045	-0.013	-0.021	-0.01
Percent crowd housing	0.07**	0.017	0.008	0.038
Zone 1 × Percent migrants	-0.204	-0.106	-0.052	-0.097
Zone 2 × Percent migrants	-0.094	-0.162**	-0.077	-0.141
Zone 4 × Percent migrants	-0.298	-0.073	1.021*	1.17**
Zone 1 × Percent children	-0.104	-0.871**	-0.106	0.121
Zone 2 × Percent children	-1.377	-0.445	0.146	0.247**
Zone 4 × Percent children	-0.026	0.713	-0.248	-0.405
Zone 1 × Percent the elderly	0.22	0.163*	-0.016	-0.191*
Zone 2 × Percent the elderly	0.269**	0.169**	-0.168	-0.26**
Zone 4 × Percent the elderly	0.472	-0.040	0.092	-0.046
Zone 1 × Percent unemployed	-0.026	-0.009	0.018	-0.009
Zone 2 × Percent unemployed	-0.050	-0.018	-0.008	-0.003
Zone 4 × Percent unemployed	0.041	0.000	-0.006	0.011
Zone 1	0.561**	0.044	-0.135	0.035
Zone 2	0.179	0.131	0.204*	0.179
Zone 4	0.158	0.128	0.447**	0.55**
Easting squared	0.342**	0.282**	0.423**	0.403**
Easting	-0.074	0.105	0.031	0.088
Northing squared	-0.506**	-0.585**	-0.477**	-0.44**
Northing	0.066*	0.189**	0.126**	0.19**
Easting × Northing	0.083**	-0.114*	-0.062**	-0.063
λ		0.943**		0.861**
σ^2	0.088	0.034	0.1	0.04
AIC	197.5	8.345	200.5	11.89

Note: the symbols "*" and "**" represent significance levels of 10% and 5%, respectively.

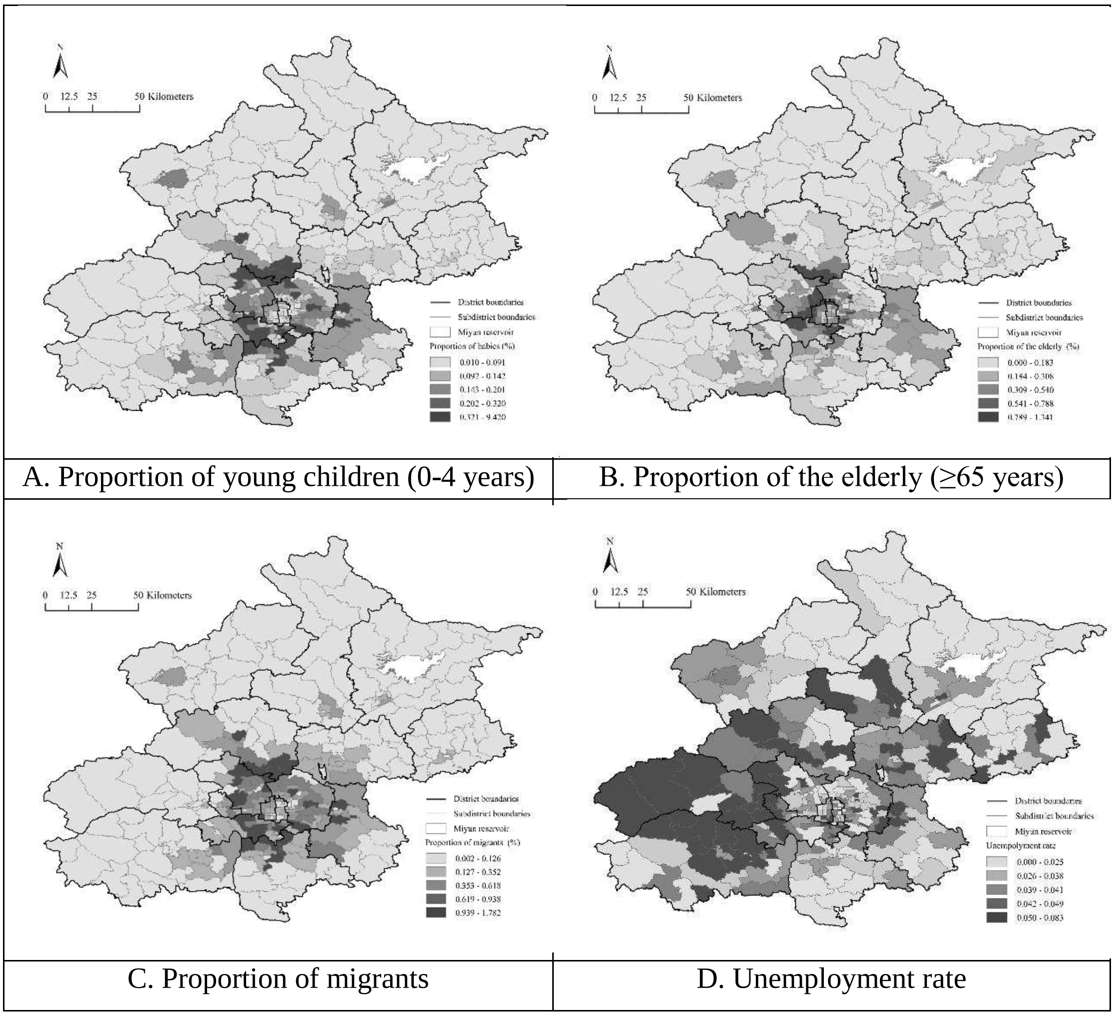


(a) 2000



(b) 2010

Figure 1. Spatial distribution of the annual average $PM_{2.5}$ concentration of Beijing's sub-districts in 2000 and 2010.



A. Proportion of young children (0-4 years)

B. Proportion of the elderly (≥65 years)

C. Proportion of migrants

D. Unemployment rate

Figure 2. Spatial distribution of social-economic groups across sub-districts in Beijing, 2010.

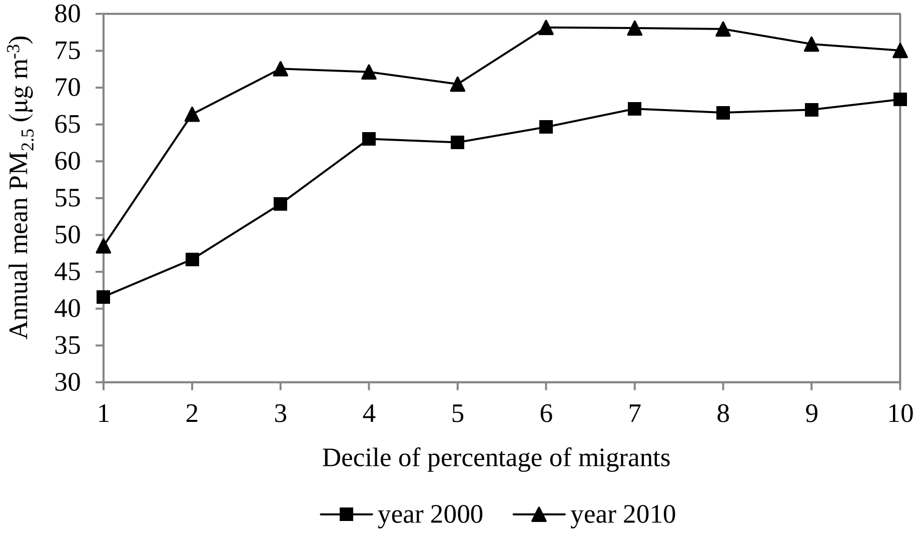


Figure 3. Annual average $PM_{2.5}$ by decile of percentage of migrants for 2000 and 2010. Percentage of migrants is sorted in ascending order.

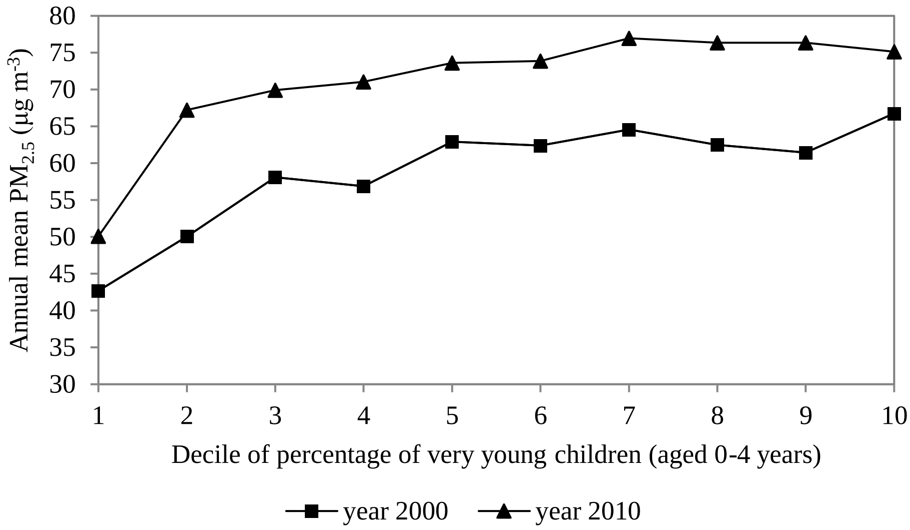


Figure 4. Annual average $PM_{2.5}$ by decile of percentage of very young children (0-4 years) for 2000 and 2010. Percentage of children is sorted in ascending order.

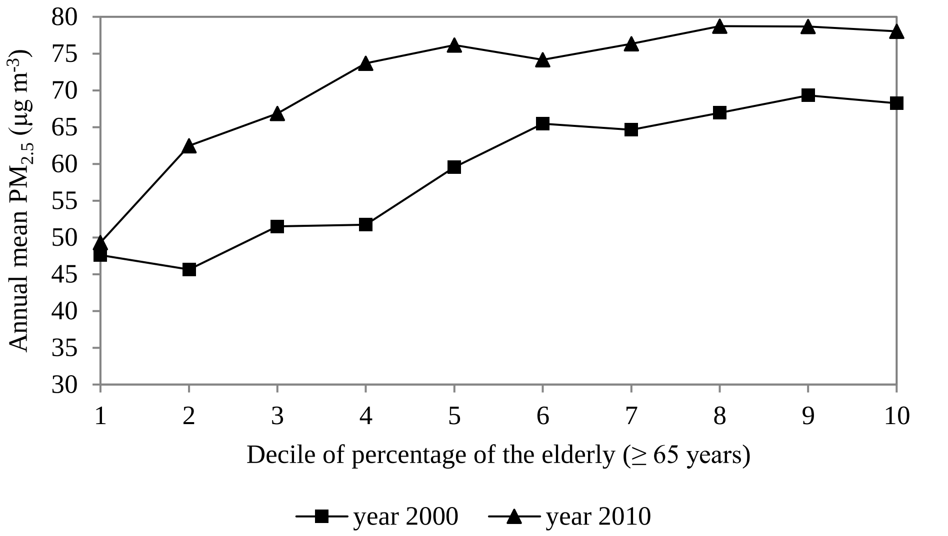


Figure 5. Annual average $PM_{2.5}$ by decile of percentage of the elderly (≥ 65 years) for 2000 and 2010. Percentage of the elderly is sorted in ascending order.

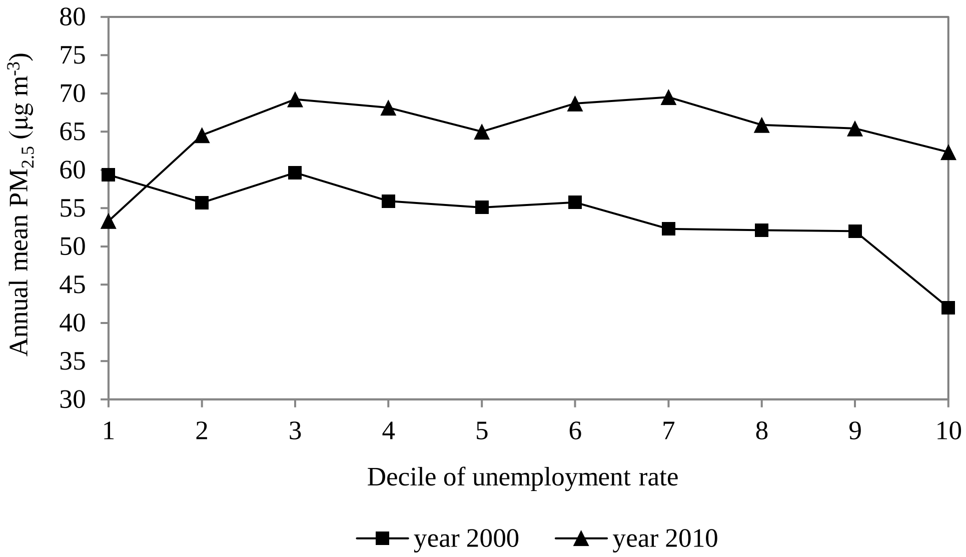


Figure 6. Annual mean $PM_{2.5}$ by decile of unemployment rate. Unemployment rate is sorted in ascending order.