Spatial variations and social determinants of life expectancy in China, 2005−2020: A population-based spatial panel modelling study

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Summary

Background Social determinants of health (SDOH) produce a broad range of life expectancy (LE) disparities. In China, limited literatures were found to report association between SDOH and LE at ecological level during a consecutive period of time from the spatial perspectives. This study aimed to determine the existence, quantify the magnitude, and interpret the association between SDOH and LE in China.

Methods Provincial-level LE were estimated from mortality records during 2005−2020 from National Mortality Surveillance System in China. A spatial panel Durbin model was used to investigate LE associated SDOH proxies. Spatial spillover effects were introduced to interpret direct and indirect effects caused by SDOH during long-term and short-term period on LE disparities.

Findings Nationwide, LE increased from 73.1 (95% confidence interval (CI): 71.3, 74.4) years to 77.7 (95%CI: 76.5, 78.7) years from 2005 to 2020. Unequally spatial distribution of LE with High-High clustering in coastal areas and Low-Low clustering in western regions were observed. Locally, it was estimated that SDOH proxies statistically significant related to an increase of LE, including GDP (coefficient: 0.02, 95%CI: 0.00, 0.03), Gini index (coefficient: 2.35, 95%CI: 1.82, 2.88), number of beds in health care institutions (coefficient: 0.02, 95%CI: 0.00, 0.05) and natural growth rate of resident population (coefficient: 0.02, 95%CI: 0.01, 0.02). Direct and indirect effects decomposition during long-term and short-term of LE associated SDOH proxies demonstrated that GDP, urbanization rate, unemployment rate, education attainment, Gini index, number of beds in health care institutions, sex ratio, gross dependence ratio and natural growth rate of resident population not only affected local LE, but also exerted spatial spillover effects towards geographical neighbors.

Interpretation Spatial variations of LE existed at provincial-level in China. SDOH regarding socioeconomic development and equity, healthcare resources, as well as population characteristics not only affected LE disparities at local scale but also among nearby provinces. Externalities of policy of those SDOH proxies should be took into consideration to promote health equity nationally. Comprehensive approaches on the basis of population strategy should be consolidated to optimize supportive socioeconomic environment and narrow the regional gap to reduce health disparities and increase LE.

Abbreviations: LE, life expectancy; SDOH, social determinants of health; NMSS, National Mortality Surveillance System; DSPs, Disease Surveillance Points system; OLS, ordinary least square; SPAR, spatial panel autoregressive regression model; SPEM, spatial panel error model; SPDM, spatial panel Durbin model; LM test, Lagrange Multiplier test; LR, Likelihood ratio; AIC, Akaike Information Criterion; SBIC, Schwarz's Bayesian Information Criterion; CI, confidence interval; SD, standard deviation

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Keywords: Life expectancy; China; Spatial variations; Social determinants of health; Spatial spillover effects; Population strategy

Research in context

Evidence before this study

We used both separate and combined key words of "life expectancy", "China", "spatial distribution", "spatial variations", "social determinants of health", "socioeconomic development and equity", "healthcare resource" and "population characteristics", "spatial panel data models", "spatial spillover effects" to search PubMed, MEDLINE, Science Direct, Web of Science and the official websites of the Chinese Government, China National Knowledge Infrastructure (CNKI) and other institutions for studies and reports on spatial variations of life expectancy (LE) and its associated social determinants of health (SDOH) in China published in English or Chinese until June 30, 2021. Although some of the studies reported the spatial variations of LE and explored its socioeconomic or environmental factors, they failed to propose a rationale SDOH framework in variables selection, results interpretation and policy implications from spatial perspective by using timely and consecutive change of LE and its SDOH.

Added value of this study

National Mortality Surveillance System (NMSS) is the most populous mortality surveillance system worldwide and the only one with provincial representativeness which covers over 300 million individuals from 31 provinces in mainland China. By using data from NMSS, this study comprehensively presented the LE distribution at provincial-level, developed a proxy diagram framework to demonstrate the relationship between selected SDOH proxies and LE, quantified the association between SDOH proxies and LE disparities on the basis of framework, and interpreted direct and indirect effects caused by SDOH during long-term and short-term period on LE disparities. SDOH proxies regarding socioeconomic development and equity, healthcare resources, as well as population characteristics were associated factors of LE disparities, and they not only directly affected LE at local scale but also exerted spatial spillover effects on geographical neighbors.

Implications of all the available evidence

Evidence from our study indicated that, first, the existed provincial variations of LE are making the requests of tailoring regional-specific strategies to bridge the gap of LE between areas. Second, the externalities of policy derived from spatial spillover effects of those SDOH proxies should be took into consideration to promote health equity among proximity provinces, including economy-facilitated effects and resource deprivation. Third, compensation in involvement of healthcare and medical resources allocation should be delivered towards those provinces with lower LE to avoid growing gap between rich and poor areas. Last, comprehensive approaches on the basis of population strategy should be consolidated to optimize supportive socioeconomic environment to reduce health disparities and increase LE.

Introduction

Life expectancy (LE) is the total number of years that a group of people at birth (0-year-old) can expect to live given an existing age-specific mortality rate.[1] Currently, LE has been selected as an indicator of performance and integrated into several national programmatic document by Chinese government.[2–4] It is not only an index reflects mortality level, but also a comprehensive measure widely used in the evaluation of population health status, quality-of-life and allows for tracking geographically health disparities and assessing factors related to these disparities.[5,6] Social determinants of health (SDOH) are the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks, and they embody the consequences of multifaceted societal processes and norms that shape living conditions and produce a broad range of health disparities.[7,8] Therefore, describing the spatial variations of LE and identifying SDOH of LE would be of great necessity to examine the effects of SDOH on LE to unveil disparate health outcomes and interpret how SDOH influence LE disparities in China.

Overseas, previous studies have adopted SDOH framework to measure the association between SDOH and LE. It has proved that much of the variations of LE could be explained by the interplay of race/ethnicity,[7,8] occupation,[8] economic status,[9,10] education,[7,11] and health care sectors.[8,11,12] Besides, in the consideration of spatial autocorrelation which refers to degree to which one province is similar to other nearby provinces in LE and SDOH, some studies have also found that SDOH were not only affected local LE directly but also exerted indirect effects towards LE of nearby areas when incorporated with spatial perspectives.[6,13,14] In China, Luo and Xie,[15] Wu et al.,[16] Wang et al.[17,18] and Jiang et al.[19] have exhibited spatial variations of LE at regional-level and explored its socioeconomic or environmental factors by using data from 1990, 2000 and 2010 Census in the consideration of spatial characteristics. Yet, they failed to propose a rationale SDOH framework in variables selection, results interpretation and policy implications from spatial perspectives. Besides, Census data would not be able to provide timely and consecutive change of LE and its SDOH.

Therefore, in this population-based study, by using LE estimated from National Mortality Surveillance System (NMSS) in China during 2005–2020, we presented findings from the spatial perspectives and aimed to (i) describe the spatial variations of LE at provincial-level in China; (ii) propose a proxy framework for LE associated SDOH exploration; (iii) quantify the association between SDOH and LE on the basis of proxy framework; and (iv) interpret how SDOH influence LE. The results of this study would help to identify SDOH drivers of LE disparities and facilitate the evidence of implementing regional-specific policies to increase LE and improve overall health in China.

Methods

Data source

Mortality and population data. Data for LE estimation was derived from NMSS housed in Chinese Center for Disease Control and Prevention (China CDC). Initiated in 1978 with 2 polit surveillance points in Beijing, the Disease Surveillance Point system (DSPs) was subsequently established in 1990 with 79 points covering 10 million population and expanded in 2004 with 161 points covering 73 million population. In 2013, the National Health and Family Planning Commission (previously known as Ministry of Health) combined the DSPs in China CDC and Vital Registration (VR) System hosted previously by Ministry of Health to create an integrated NMSS. As the most populous mortality surveillance system with provincially representativeness worldwide and the only one with nationally representativeness in China, NMSS covers over 300 million individuals from 605 surveillance points among population from 31 provincial-level administrative divisions (PLADs, excluding Hong Kong Special Administrative Region, Macau Special Administrative Region and Taiwan province) in mainland China, and routinely collects individual details of death information in real time through an internet-based approach.[20] Detailed descriptions of NMSS stratification methods, surveillance points selection, representativeness determination, death information collection and certificate, coding and determining underlying cause-of-death (COD) and quality control procedures, have been reported elsewhere.[21] Data for under-reporting adjustment were obtained from NMSS under-reporting field surveys conducted in 2009, 2012, 2015 and 2018 separately, which collected under-reporting data from 2006 to 2017.[22] Under-5 Mortality Rate (U5MR) were extracted from a combination estimation of data derived from census, national surveys, Intra-Census Surveys, Maternal and Child Health Surveillance System (MCHS) and NMSS in main analysis.[23] Data for surveillance population across 31 provinces in mainland China which collected population number at mid-time of the year was obtained from National Bureau of Statistics of China regardless of internal migration.[24]

Social determinants of health. On the basis of ecological model of health determinants developed by Dahlgren and Whitehead,[25] the health determinants of LE could be attributed to direct causes (or proximal factors, downstream determinants) like disease-specific causes or individual risk factors, and indirect causes (or distant factors, upstream determinants) like social determinants or environment factors.[7,25] In this study, we do not analyze the medical causes, but rather focus on SDOH at ecological level.[7,8] However, since the vague definition and limited accessibility of SDOH, the common approach is to find proxies and thus to establish a statistical relationship between dependent variable and proxies. In this way, proxies should meet two conditions: First, they are as closely related to the direct factors as possible, and can be qualitatively judged based on the physical mechanism or quantitatively selected based on correlation analysis; Second, those proxies should have a full coverage of the study area and study period.[26]

Accordingly, we searched PubMed, MEDLINE and China National Knowledge Infrastructure (CNKI) database by June 2021, to identify relevant studies on different domains of SDOH of LE in China, which including socioeconomic development and equity, healthcare resource, population characteristics. We also included environmental and meteorological factors as potential confounders in the analysis. In PubMed and MEDLINE, we adopted a combination of MeSH terms and free text keywords to improve retrieving sensitivity. Meanwhile, we used similar strategy to include literature published in Chinese from CNKI.[27] Afterwards, we summarized the SDOH and their proxies that might influence LE in China at provincial-level. Detailed methods of literature searching and summary of SDOH proxies related to LE in China were reported in supplementary material (Supplementary Material Part 3).

In the light of ecological model of health determinants, proxy constitution, literature evidence summary, data availability and data quality, we constructed proxy diagram for each component of SDOH to replace indirect factors (Figure 1).[26] During the data curation process, we evaluated the data quality of SDOH proxies and utilized multiple imputation with predictive mean matching approach to deal with the missing data of each proxy. Detailed description of data source for LE and SDOH, along with their data curation process were reported in supplementary material (Supplementary Material Parts 4 and 5).

Socioeconomic development and equity

Numerous studies reported education attainment and urban development that are associated with disparate LE.[10,13] In this component, we summarized that income and income equity, employment, education attainment, urban construction and environment might affect LE disparities and defined "socioeconomic development and equity" as "regional socioeconomic condition and its consequent equity". Therefore, we included 8 proxies: (i) Nighttime light data (NLT), which is usually used for research involving human social activities and urban expansion, socioeconomic factors estimation, and other fields such as environment, disaster, fishery and energy.[28] (ii) Per capita gross domestic product (GDP, 10,000 yuan per person), which reflects to each resident's economic contribution or value creation of his country or region. (iii) Engel's Coefficient (ENGEL), which reflects to the living standard and affluence of focused areas on any account. (iv) Urbanization rate (UR, %), which is the measure of urbanization within the area. (v) Unemployment rate in urban area (UER, %), which reflects to the employment status of working population.[24] (vi) Average years of education attainment (EDU, years), which reflects to the average level of education attainment in contemporary population. (vii) Per capita public green areas (PGA, square meter per person), which reflects to the living environment and quality of life among citizens.[8,24,25] (viii) Gini index (GINI), which is commonly used to reflect the income gap of residents in a country or region.

Healthcare resource

For the commission, each aspect of the economy, government and healthcare policy has the potential to affect population health.[8,25] The health care system and, in particular, the unfair distribution of health care, is itself a SDOH, influenced by and influencing the effects of other social determinants.[7,8,25] In this component, we summarized that health capacity, health expenditure and health quality might influence LE disparities and. Since our study did not take medical factors into consideration, we thus defined "healthcare resource" as "health capacity". Therefore, we included 2 proxies: (i) Number of medical technical personnel in health care institutions per 10,000 persons (NMTP, persons) and (ii) Number of beds in health care institutions per 10,000 persons (NB, units).[24] Those two proxies were commonly used in domestic research with reliable data quality.

Population characteristics

Family structure and household composition could have both positive and negative impacts on health.[6,8] In this component, we summarized that sex, race/ethnicity, family structure and household composition might influence LE disparities. Since most of individuals in China are Han population, we thus excluded race/ethnicity and defined "population characteristics" as "sex-age population structure and population mortality". Therefore, we included 4 proxies: (i) Sex ratio (SR), which reflects to the sex composition. (ii) Mortality rate (MR), which reflects to the level of population mortality. (iii) Gross dependency ratio (GDR, %), which reflects to the basic relation between population and economic development from the demographic perspectives. (iv) Natural growth rate of resident population (NGRRP, ‰), which reflects to the natural trend and speed of the population growth. [24]

Environmental and meteorological factors

In this component, we summarized that the environmental and meteorological factors like particulate matters emission, NOX nitrous oxides emission, temperature, humidity might have impacts on LE.[29,30] We thus included annual average temperature (°C), temperature variability (°C), annual average relative humidity (%) as confounders in main analysis.[24,31]

Statistical methods

Spatial panel data models

Spatial analysis facilitates the investigation of geographic patterns in spatial data and institutes a relationship between ecological factors and health outcomes.[32,33] It is a typical feature of spatial data that attributes of adjacent spatial neighbors are correlated, and those correlations violate the assumptions of statistical independence in conventional (nonspatial) statistical methods.[6] Hence, the estimates of conventional methods may be inefficient and biased which might lead to incorrect inference on the relationship between attributes. In contrast, in the consideration of spatial interactions, spatial models explicitly model non-independence by using spatially weighted dependent variable, independent variables and an error term, which account for "spatially embedded social processes" and

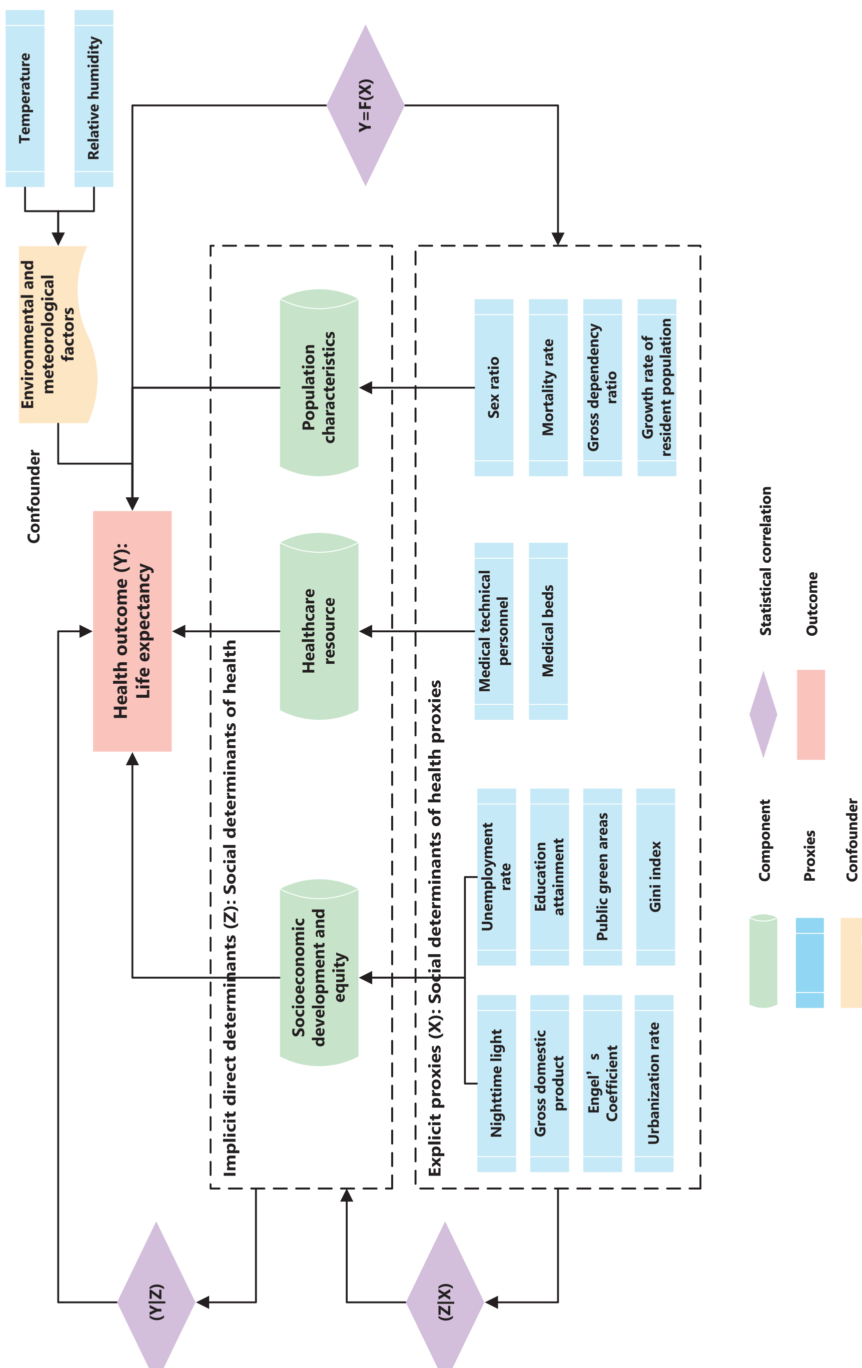

Figure 1. SDOH and their proxies of LE.

the flow of people, resources, ideas, goods and services within and between neighboring places.[13,34,35]

We used spatial panel data models to investigate the association between SDOH proxies and LE at provincial-level in China during 2005–2020. Referred to model specification in this study, we constructed spatial panel data models with common or varying intercept, fixed or random effects concerning spatial (individual) effects and/or time effects, as well as different composition of each component. For details, first, we used Shapiro-Wilk (SW) test to examine the normality of dependent variable, LE. Afterwards, on the basis of ordinary least square (OLS) regression, we constructed spatial panel autoregressive regression model (SPAR) by adding the spatially lagged dependent variable, spatial panel error model (SPEM) by adding the spatially lagged error term, and spatial panel Durbin model (SPDM) by adding both spatially lagged dependent variable and spatially lagged independent variables. Additionally, in order to further explore the time and space-time joint effects of association between SDOH proxies and LE, we introduced dynamic spatial panel data models in the main analysis, namely, dynamic SPDM, which included SPDM adding by time lagged dependent variable (SPDMLAG1), SPDM adding by space-time lagged dependent variable (SPDMLAG1), and SPDM adding by both time and space-time lagged dependent variable (SPDMLAG3) in the regressors with a 1-year time interval.[36,37] Detailed methods of spatial panel modelling specification and estimation were reported in supplementary material (Supplementary Material Part 6).

For models incorporating spatially lagged dependent variable, like SPAR and SPDM, we introduced spatial spillover effects to interpret how the distribution of SDOH proxies influence LE disparities, which are defined as measurements to capture influences SDOH proxies exert on LE from both local area and geographical neighbors, and they refer to equidirectional change between SDOH proxies and LE in the target unit and its neighbors. Specifically, spatial spillover effects include a direct impact on LE from the unit itself, and an indirect impact on LE of geographic proximity and eventually affect the unit in reverse.[36,38–40] Therefore, as spatial spillover effects could be able to tailor public health policies from both local and global scales in narrowing the gaps and coordinating harmonious development across provinces, we examined estimates for direct, indirect, and total effects for each proxy. Essentially, the direct effects represent local impacts and the indirect effect represent impacts on neighbors, which derive from the relationship of neighboring SDOH values to local LE values.[6,36,39,40] For dynamic models, a time and/or space-time lagged terms could be used to motivate the models as the long-run steady state equilibrium of a process and a short-interval time required for the effects delay to occur. In this way, we defined long-term as the whole study period of 16 years, and defined short-term as a specific year in contrast to another. Afterwards, we decomposed the effects estimated by dynamic models to long-term direct/indirect effects and short-term direct/indirect effects to further explore the how SDOH proxies influenced LE in specific space-time specification.[36,37] Detailed methods of spatial panel modelling decomposition were reported in supplementary material (Supplementary Material Part 6).

Statistical analysis

LE estimation. We first calculated under-reporting rate (URR) annually during 2006–2017 for each age-sex stratum among all surveillance points as the proportion of missed deaths among the total number of deaths identified in under-reporting field surveys. We used splines regression to predict URR in each stratum in 2005 and 2018–2020. We then derived under-reporting-adjusted all-cause mortality rate by sex and age group at provincial-level during 2005–2020.[41] Then we used locally weighted regression through a tricube weight function by time and space to handle with the discontinuity for each location-year. Afterwards, we applied a new relational model life table system with flexible standard (MLTFS) based on two parameters of probability of death among children under 5 years and probability of death among adults aged 15–60 yeas to generate a full set of age-specific mortality rate.[42,43] At last, we adopted abridged current life table to calculate LE for 31 provinces during 2005–2020. Restrictive maximum likelihood approach was used to estimate 95% confidence interval (CI) for probability of death among children and adults, and those parameters were subsequently passed into MLTFS to implement CI estimation based on the number of matching parameters and the number of modules 1000 repeated iterations.[41–43]

LE associated SDOH analysis. We used different spatial panels models to quantify the association between SDOH proxies and LE, which including nighttime light (NTL), per capita gross domestic product (GDP), Engel's coefficient (ENGEL), urbanization rate (UR), unemployment rate in urban area (UER), average years of education attainment (EDU), per capita public green areas (PGA), Gini index (GINI), number of medical technical personnel in health care institutions (NMTP), number of bed in health care institutions (NB), sex ratio (SR), mortality rate (MR), gross dependency ratio (GDR), natural growth rate of resident population (NGRRP), and we also took annual average temperature (TEMP), temperature variability (TV), annual average relative humidity (HUMID) as potential confounders. For the first step, the variance inflation factor (VIF) was tested for multicollinearity between potential SDOH proxies (Supplementary Material Part 11). Second, we linked LE, SDOH proxies, China map at provincial-level across 31 provinces and carried out diagnostic tests for spatial dependence in OLS regression with first-order Queen contiguity spatial weight matrix. Detailed information of spatial weight matrix construct was reported in supplementary material (Supplementary Material Part 8). Third, we performed Lagrange Multiplier test (LM) and Robust Lagrange Multiplier test (Robust LM) to ensure the rationality of spatial panel data model construction, including SPAR, SPEM and SPDM, and subsequently performed Wald test, Likelihood Ratio test (LR) to conduct model fit evaluation. Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBIC) were also used in model selection. Afterwards, we performed Hausman test to identify the optimal specification of fixed or random effects of spatial (individual) and time effects for the selected model.[34,39,44,45] In this study, apart from statistical evidence of model selection, we also incorporated professional knowledge from research practice to improve model performance.[6,13,14] Therefore, we constructed SPDM with unstructured covariance matrices that assumed the spatial dependency of LE among adjacent units which used spatially lagged dependent variable in the regressors. Afterwards, we decomposed the effects estimated by dynamic SPDM concerning long-term (16 years of study period) during direct/indirect effects and short-term (adjacent study year) direct/indirect effects to further explore how SDOH influenced LE in different space-time specification.[36,37] Detailed methods of spatial panel modelling procedures were reported in supplementary material (Supplementary Material Part 7).

In this study, a *P* value<0.05 was considered statistically significant and all tests were two sided. We also conducted sensitivity analysis by constructing different spatial weight matrix to examine potential influences it caused on modelling estimation in supplementary material (Supplementary Material Part 11). All analysis were performed in SAS version 9.4 (SAS Institute Inc., Cary, North Carolina USA) and StataMP 16 (Stata Cooperation College Station, Texas, USA) by using “xsmle” command. No allowance for multiplicity was made in the analysis.

Role of the funding source

The funders of the study have no role in study design, data collection, data analysis, data interpretation, or writing of the report. The corresponding authors have full access to all the data in the study and have final responsibility for the decision to submit for publication.

Results

Spatial distribution of LE in China

During 2005–2020, nationwide, LE increased from 73.1 (95% CI: 71.3, 74.4) years to 77.7 (95%CI: 76.5, 78.7) years. In 2020, for provincial disparities, LE in Shanghai (83.1, (95%CI:83.1, 83.2) years), Beijing (82.3 (95%CI:80.3, 84.0) years) and Jiangsu (80.5 (95%CI:80.2, 80.8) years) have exceeded 80 years, and most of the provinces reached 75 years, expect for Tibet (70.9 (95%CI:67.0, 74.0) years). During 2005–2020, even though LE arisen steadily in 31 provinces, change of LE varied among regions, with Guizhou (8.0 (95%CI:7.4, 9.2) years with 11.8 (95%CI:11.5, 12.2) % of relative change) and Yunnan (6.3 (95%CI:5.7, 6.8) years with 9.0 (95%CI:8.6, 9.4)% of relative change) increased the most and have exceeded 6 years, while Shanghai (2.8 (95%CI:2.8, 2.8) years with 3.5 (95%CI:3.5, 3.5) % of relative change) and Beijing (2.9 (95%CI:2.3, 3.5) years with 3.7 (95%CI:3.2, 4.1) % of relative change) increased the less (Figure 2). The Moran scatterplot was used to describe spatial uncertainty and detect spatial clustering of mean LE during 2005–2020, which divided the 31 spatial units into four quadrants by standardized value of observed LE and spatially lagged standardized LE (Figure 3). The first quadrant denoted High-High (H-H) positive spatial correlation, which meant provinces with higher LE were encircled by similar higher units, including southeast coastal regions like Shanghai, Beijing, Jiangsu and Zhejiang. Afterwards, the second quadrant denoted Low-High (L-H) negative spatial correlation, which meant lower LE provinces were encircled by higher units, like Hebei, Jiangxi and Guangxi. The third quadrant denoted Low-Low (L-L) positive spatial correlation, which meant lower LE provinces were encircled by lower units, most of them were from west, southwest or midland regions such as Tibet, Xinjiang, Qinghai and Guizhou. The last, the fourth quadrant denotes High-Low (H-L) spatial correlation, which meant higher LE provinces were encircled by lower ones, including Chongqing and Shanxi. Accordingly, spatial clustering of LE was thus detected statistically significant since most of provinces (23 provinces) belonged to H-H and L-L regions.

Association between SDOH and LE in China

Description of SDOH proxies for 31 provinces was presented by mean (standard deviation, SD) and median (Q1, Q3) and was calculated on average for period 2005–2010, 2011–2015 and 2016–2020 separately (Table 1). With VIF of less than 10 (VIF = 6.82), the linearity was not violated and all SDOH proxies were included in the analysis (Supplementary Material Part 11). Then, we performed model diagnostic tests (including LM lag test, LM error test, Robust LM lag test and Robust LM error test) and selected models according to Wald test, LR test and professional knowledge from research practice. It concluded that SPDM could not be simplified to SPAR (Wald test statistics = 96.47, $P < 0.001$; LR test statistics =86.44, $P < 0.001$) or SPEM (Wald test

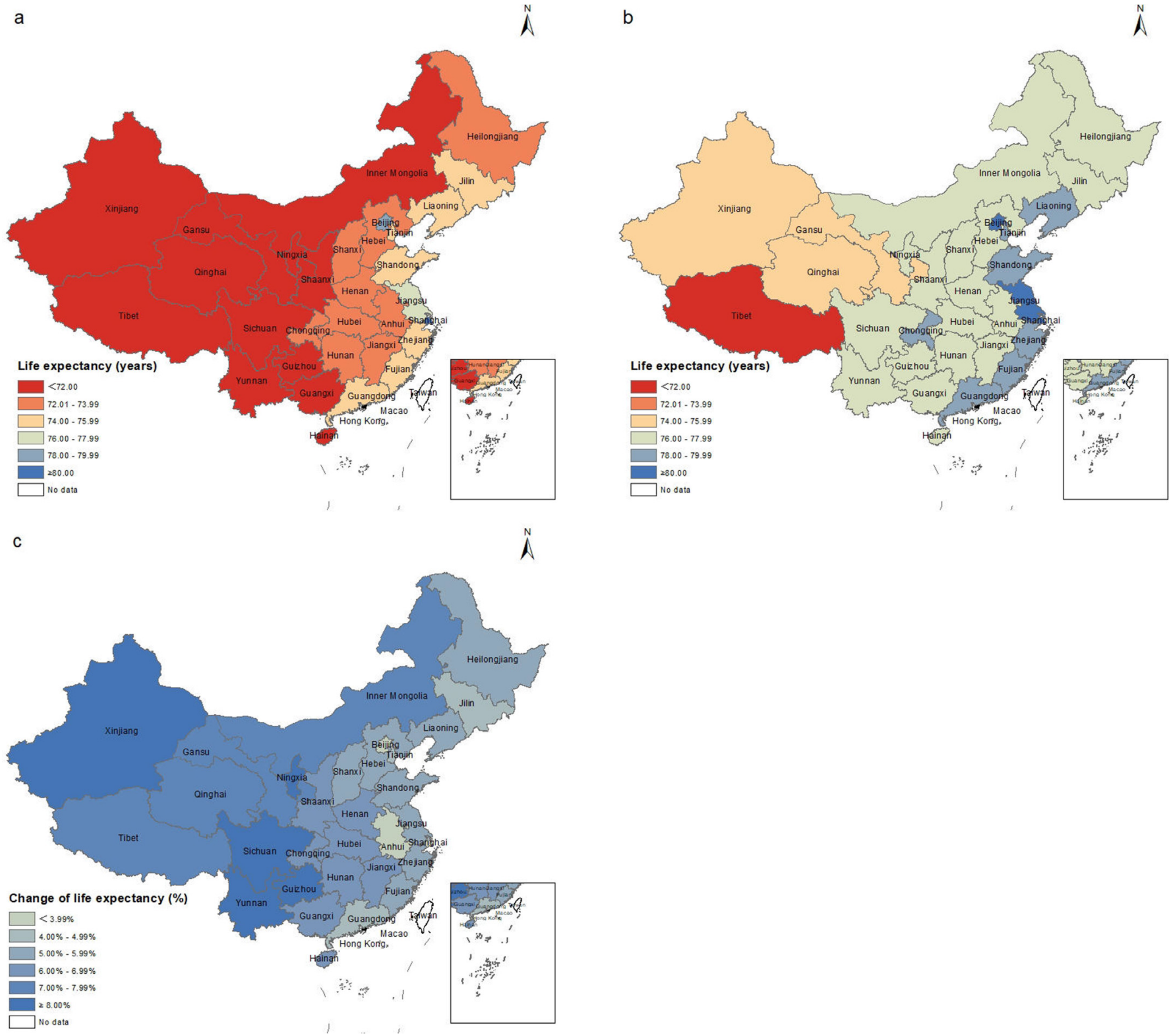

Figure 2. Choropleth map of LE in China in 2005, 2020 and its relative change during 2005−2020
a. LE (years) in 2005; b. LE (years) in 2020; c. relative change (%) of LE between 2005 and 2020.

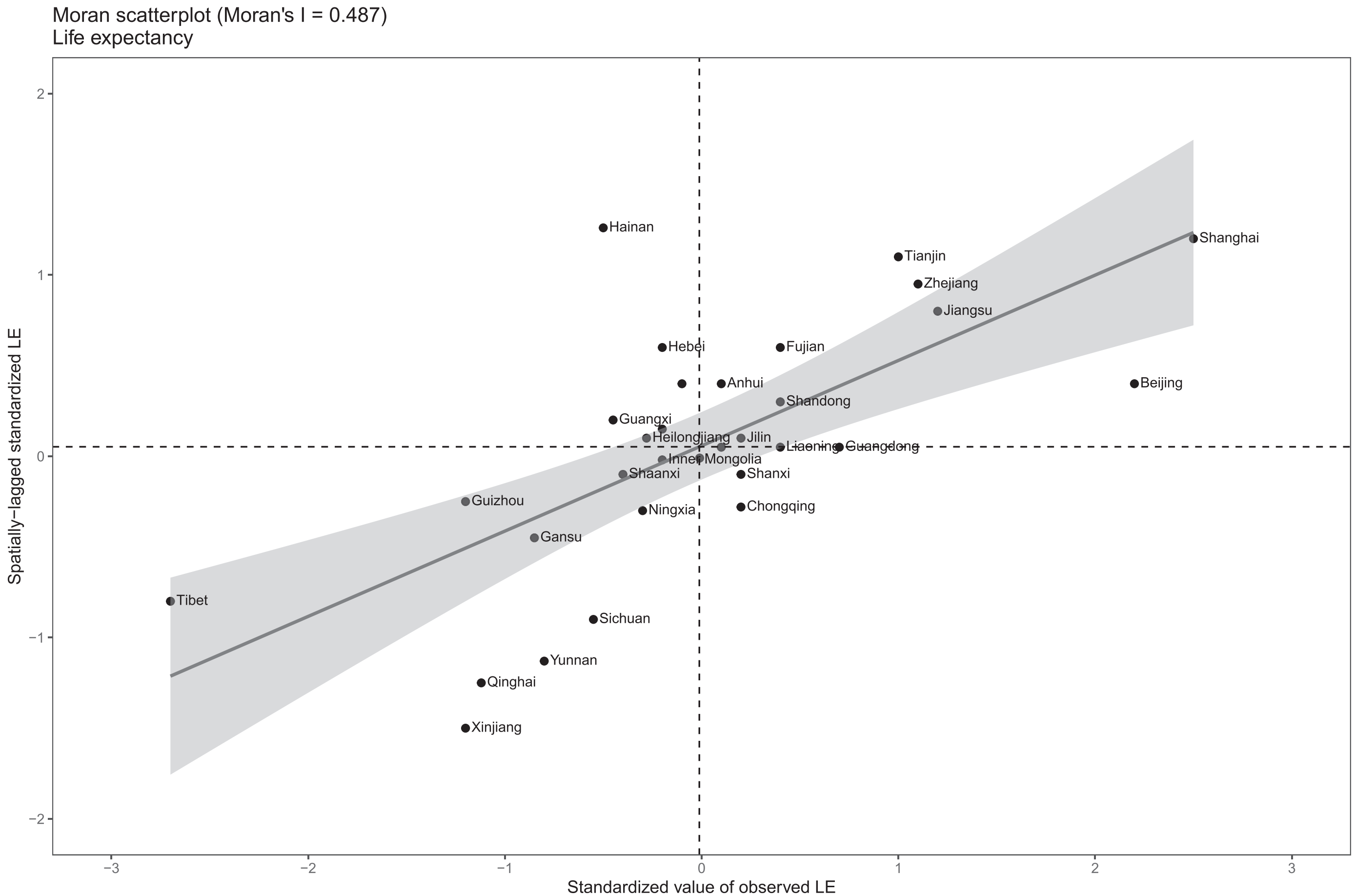

Figure 3. Moran scatterplot of mean LE in China during 2005−2020.

SDOH components	SDOH proxies	Description	2005−2010 on average		2011−2015 on average		2016−2020 on average	
			Mean (SD)[a]	Median (Q1, Q3)[b]	Mean (SD)[a]	Median (Q1, Q3)[b]	Mean (SD)[a]	Median (Q1, Q3)[b]
Socioeconomic development and equity	NTL	Nighttime light	0.66(1.47)	0.14(0.05,0.33)	0.96(1.96)	0.31(0.10,0.62)	1.26(2.38)	0.49(0.23,0.94)
	GDP	Per capita gross domestic product (10 000 yuan per person)	2.29(1.48)	1.81(1.30,2.64)	4.35(2.05)	3.64(3.04,5.07)	6.27(2.98)	5.28(4.30,7.23)
	ENGEL	Engel's Coefficient	40.13(4.74)	39.29(36.40,43.36)	35.52(5.36)	34.73(32.15,38.37)	29.74(4.31)	28.92(26.79,31.95)
	UR	Urbanization rate (%)	47.79(15.04)	44.99(38.50,53.40)	54.45(13.72)	52.43(46.07,60.77)	59.99(11.93)	58.40(53.02,66.50)
	UER	Unemployment rate in urban area (%)	3.74(0.56)	3.86(3.49,4.16)	3.34(0.66)	3.38(3.10,3.70)	3.15(0.61)	3.23(2.73,3.58)
	EDU	Average years of education attainment (years)	8.14(1.15)	8.21(7.63,8.56)	8.93(1.11)	8.98(8.59,9.30)	9.36(1.16)	9.39(8.97,9.75)
	PGA	Per capita public green areas (m^2 per person)	9.11(2.26)	8.73(7.78,10.42)	12.39(2.53)	11.78(10.73,13.96)	13.89(3.05)	13.65(11.88,15.42)
	GINI	Gini index	0.22(0.08)	0.21(0.17,0.25)	0.26(0.08)	0.25(0.21,0.30)	0.30(0.08)	0.29(0.25,0.35)
Healthcare resource	NMTP	Number of medical technical personnel in health care institutions per 10,000 persons (persons)	3.82(1.03)	3.76(3.05,4.46)	5.32(1.17)	5.31(4.52,5.84)	6.85(1.30)	6.73(6.10,7.30)
	NB	Number of beds in health care institutions per 10,000 persons (units)	3.23(1.03)	3.00(2.51,3.68)	4.63(0.92)	4.54(3.97,5.11)	5.95(0.92)	5.92(5.29,6.63)
Population characteristics	SR	Sex ratio	103.09(3.17)	102.94(101.57,104.56)	105.19(3.94)	104.68(102.65,107.54)	104.79(4.24)	103.89(102.03,106.91)
	MR	Mortality rate	5.95(0.65)	6.01(5.59,6.40)	5.98(0.76)	6.08(5.51,6.52)	6.13(0.84)	6.18(5.54,6.93)
	GDR	Gross dependency ratio (%)	37.79(6.82)	37.81(33.00,42.80)	35.02(6.45)	35.90(30.40,39.70)	38.36(6.44)	38.60(32.70,43.50)
	NGRRP	Natural growth rate of resident population (‰)	5.51(2.74)	5.36(3.04,7.24)	5.33(2.75)	5.65(3.51,6.97)	5.21(2.93)	5.43(3.48,7.33)
Environmental and meteorological factors	TEMP	Annual average temperature (°C)	13.60(4.71)	14.14(9.44,16.94)	13.48(4.70)	13.97(9.66,16.69)	13.93(4.60)	14.42(9.82,17.14)
	TV	Temperature variability (°C)	9.34(2.75)	9.26(7.44,11.10)	9.36(2.75)	9.20(7.38,11.05)	9.20(2.70)	8.97(7.35,11.25)
	HUMID	Annual average relative humidity (%)	66.54(8.00)	67.54(59.79,73.61)	66.94(8.64)	67.43(59.44,74.54)	67.91(9.30)	67.74(59.26,76.97)

***Table 1*: Descriptive analysis of SDOH proxies on average of 31 provinces in China, 2005−2020.**

[a] SD: standard deviation.

[b] Q1: 25th percentile; Q3: 75th percentile.

SDOH component	SDOH proxies	PANEL[a,b]	SPDM[a,b]	SPDMLAG1[a,b]	SPDMLAG2[a,b]	SPDMLAG3[a,b]
Main effects						
Socioeconomic development and equity	NTL	0.04(-0.07, 0.16)	0.05(-0.01, 0.11)	0.01(-0.01, 0.02)	0.06(0.01, 0.12)	0.02(0.00,0.04)
	GDP	0.06(-0.03, 0.14)	-0.04(-0.11, 0.03)	0.02(0.00, 0.03)	-0.03(-0.09, 0.04)	0.01(0.00,0.02)
	ENGEL	-0.04(-0.07, -0.02)	-0.02(-0.04, 0.01)	0.00(0.00, 0.00)	-0.02(-0.04, 0.01)	0.00(0.00,0.01)
	UR	0.06(0.02, 0.10)	0.04(0.01, 0.08)	0.00(-0.01, 0.00)	0.05(0.02, 0.08)	0.00(-0.01,0.00)
	UER	0.04(-0.21, 0.30)	0.08(-0.08, 0.24)	0.01(0.00, 0.03)	0.09(-0.04, 0.23)	-0.03(-0.05, -0.02)
	EDU	0.19(-0.11, 0.48)	-0.03(-0.30, 0.23)	-0.03(-0.07, 0.00)	-0.04(-0.28, 0.19)	0.00(-0.04,0.04)
	PGA	0.02(-0.01, 0.06)	0.02(-0.01, 0.04)	0.00(-0.01, 0.00)	0.02(0.00, 0.05)	0.00(-0.01,0.00)
	GINI	0.03(-4.67, 4.73)	-0.69(-4.78, 3.40)	2.35(1.82, 2.88)	-0.70(-4.55, 3.14)	2.60(2.09, 3.12)
Healthcare resource	NMTP	0.14(-0.05, 0.34)	0.02(-0.08, 0.13)	0.00(-0.02, 0.02)	0.02(-0.07, 0.11)	0.00(-0.02,0.03)
	NB	0.28(0.13, 0.42)	0.15(0.01, 0.29)	0.02(0.00, 0.05)	0.13(0.02, 0.23)	0.01(-0.02,0.03)
Population characteristics	SR	0.01(-0.01, 0.02)	0.00(-0.01, 0.01)	0.00(0.00, 0.00)	0.00(-0.01, 0.01)	0.00(0.00,0.00)
	MR	-0.12(-0.31, 0.06)	0.00(-0.10, 0.11)	-0.03(-0.06, 0.01)	0.04(-0.09, 0.17)	-0.03(-0.07, 0.00)
	GDR	-0.02(-0.04, 0.00)	-0.03(-0.04, -0.01)	0.00(0.00, 0.01)	-0.02(-0.04, 0.00)	0.00(0.00,0.00)
	NGRRP	-0.14(-0.20, -0.09)	-0.05(-0.08, -0.02)	0.02(0.01, 0.02)	-0.04(-0.06, -0.02)	0.00(-0.01,0.01)
Constant		70.57(66.20,74.94)	–	–	–	–
$(t-1)\ \times$ LE[c]		–	–	1.05(1.02, 1.08)	–	1.00(0.97, 1.03)
$(t-1)w \times$ LE		–	–	–	0.54(0.27, 0.82)	-0.46(-0.56, -0.36)
Spatially lagged effects[d]						
Socioeconomic development and equity	NTL	–	0.02(-0.09, 0.13)	0.01(-0.02, 0.05)	0.00(-0.12, 0.13)	0.03(0.00,0.07)
	GDP	–	-0.02(-0.16, 0.12)	0.14(0.12, 0.16)	0.03(-0.11, 0.18)	-0.13(-0.16, -0.11)
	ENGEL	–	-0.01(-0.05, 0.04)	0.01(0.00, 0.02)	0.00(-0.04, 0.04)	0.01(0.01,0.02)
	UR	–	-0.06(-0.13, 0.00)	-0.03(-0.04, -0.02)	-0.07(-0.14, 0.00)	-0.04(-0.05, -0.03)
	UER	–	-0.09(-0.46, 0.29)	-0.13(-0.20, -0.06)	-0.08(-0.42, 0.26)	-0.27(-0.32, -0.21)
	EDU	–	0.13(-0.23, 0.48)	-0.09(-0.16, -0.02)	0.15(-0.11, 0.40)	0.00(-0.05,0.04)
	PGA	–	-0.03(-0.07, 0.01)	0.00(0.00, 0.01)	-0.03(-0.08, 0.01)	0.00(-0.01,0.01)
	GINI	–	7.07(-2.46, 16.60)	10.52(9.07, 11.97)	7.07(-2.17, 16.32)	11.18(10.08,12.28)
Healthcare resource	NMTP	–	0.12(-0.09, 0.34)	0.02(-0.01, 0.06)	0.03(-0.13, 0.20)	-0.05(-0.09, -0.02)
	NB	–	-0.08(-0.27, 0.12)	0.03(-0.03, 0.09)	-0.13(-0.32, 0.06)	0.13(0.07,0.19)
Population characteristics	SR	–	-0.01(-0.03, 0.01)	-0.01(-0.01, 0.00)	-0.01(-0.03, 0.01)	0.00(-0.01,0.00)
	MR	–	-0.26(-0.46, -0.06)	0.01(-0.03, 0.05)	-0.24(-0.47, -0.01)	0.01(-0.04,0.05)
	GDR	–	-0.01(-0.06, 0.04)	0.01(0.00, 0.02)	0.00(-0.05, 0.05)	0.02(0.01, 0.02)
	NGRRP	–	-0.03(-0.11, 0.04)	0.06(0.04, 0.08)	-0.01(-0.08, 0.06)	0.02(0.00,0.03)
ρ [e]		–	0.21(0.08, 0.35)	0.29(0.25, 0.32)	0.05(0.02, 0.08)	0.43(0.34, 0.53)
Adjust R^2		0.84	0.73	0.97	0.81	0.98
AIC[a]		166.30	-181.81	-1428.68	-262.33	-1377.41
SBIC[a]		237.81	-51.40	-1304.42	-133.92	-1257.39

***Table 2*: The association between SDOH proxies and LE in China, NMSS 2005−2020: estimated from spatial panel data models.**

[a] PANEL: ordinary panel data model; SPDM: spatial panel Durbin model; SPDMLAG1: spatial panel Durbin model with time lagged LE in regressors; SPDMLAG2: spatial panel Durbin model with space-time lagged LE in the regressors; SPDMLAG3: spatial panel Durbin model with time and space-time lagged LE in the regressors; AIC: Akaike Information Criterion; SBIC: Schwarz's Bayesian Information Criterion.

[b] All models were specified individual (spatial) and time fixed effects, and adjusted for annual temperature, temperature variability and relative humidity.

[c] w referred to Queen first-order contiguity spatial weight matrix at provincial level.

[d] t referred to the observed year 2005-2020.

[e] ρ quantified the spatial autocorrelation magnitude of spatially lagged dependent variable.

statistics = 100.82, $P < 0.001$; LR test statistics = 109.32, $P < 0.001$). Hausman test (Hausman test statistics = 93.75, $P < 0.001$) proved that the rationality of using both spatial (individual) and time fixed effects model. Subsequently, model performance of difference specification of SPDM were evaluated by AIC and SBIC. Although similar performance of SDPMLAG1 and SPDMLAG3 were shown in Table 2, in this study, we were interested in identifying time-lagged LE within the provinces rather than time and space-time lagged LE interactions between spatial units which lack of theoretical supports and overfitting, thus we selected SPDM with time-lagged LE in the following interpretation.

For the first SDOH component socioeconomic development and equity, locally, population in provinces with higher GDP (0.02, 95%CI: 0.00, 0.03), Gini index (2.35, 95%CI: 1.82, 2.88) was associated with an increase in LE. For spatially-lagged effects, namely, the

SDOH component	SDOH proxies	Direct	Indirect	Total
Long-term effects				
Socioeconomic development and equity	NTL	-0.09(-2.76, 2.59)	0.04(-2.64, 2.71)	-0.05(-0.18, 0.07)
	GDP	-0.08(-13.32, 13.17)	0.43(-12.81, 13.67)	0.36(0.28, 0.44)
	ENGEL	0.03(-1.67, 1.72)	-0.05(-1.73, 1.63)	-0.03(-0.15, 0.10)
	UR	0.26(-4.64, 5.17)	-0.16(-5.07, 4.74)	0.10(0.03, 0.17)
	UER	-0.17(-16.85, 16.50)	0.51(-16.16, 17.18)	0.34(0.12, 0.56)
	EDU	0.45(-7.24, 8.14)	-0.09(-7.76, 7.59)	0.36(0.16, 0.56)
	PGA	-0.05(-2.51, 2.41)	0.05(-2.41, 2.51)	0.00(-0.03, 0.03)
	GINI	-44.09(-276.73, 188.56)	5.72(-226.77, 238.21)	-38.37(-44.63, -32.10)
Healthcare resource	NMTP	0.07(-4.75, 4.90)	-0.13(-4.96, 4.69)	-0.06(-0.15, 0.04)
	NB	-0.04(-6.75, 6.66)	-0.12(-6.82, 6.58)	-0.17(-0.35, 0.02)
Population characteristics	SR	0.10(-3.17, 3.38)	-0.09(-3.36, 3.19)	0.02(-0.03, 0.07)
	MR	0.18(-6.01, 6.38)	-0.12(-6.32, 6.08)	0.06(-0.10, 0.21)
	GDR	0.08(-3.15, 3.31)	-0.06(-3.29, 3.17)	0.02(-0.07, 0.12)
	NGRRP	-0.44(-7.44, 6.57)	0.21(-6.79, 7.20)	-0.23(-0.33, -0.13)
Short-term effects				
Socioeconomic development and equity	NTL	0.01(-0.01, 0.03)	0.02(-0.03, 0.07)	0.02(-0.03, 0.08)
	GDP	0.01(-0.01, 0.03)	0.18(0.15, 0.20)	0.19(0.14, 0.23)
	ENGEL	0.00(-0.02, 0.02)	0.01(-0.03, 0.06)	0.01(-0.05, 0.07)
	UR	-0.01(-0.03, 0.02)	-0.04(-0.06, -0.02)	-0.05(-0.08, -0.01)
	UER	0.01(-0.02, 0.03)	-0.17(-0.26, -0.07)	-0.16(-0.26, -0.06)
	EDU	-0.04(-0.07, 0.00)	-0.13(-0.22, -0.05)	-0.17(-0.27, -0.08)
	PGA	0.00(-0.01, 0.00)	0.00(-0.01, 0.02)	0.00(-0.02, 0.01)
	GINI	3.18(2.60, 3.76)	14.92(12.84, 16.99)	18.10(15.64, 20.55)
Healthcare resource	NMTP	0.00(-0.02, 0.02)	0.03(-0.01, 0.07)	0.03(-0.02, 0.07)
	NB	0.03(0.00, 0.06)	0.05(-0.02, 0.13)	0.08(0.00, 0.16)
Population characteristics	SR	0.00(-0.01, 0.02)	-0.01(-0.03, 0.01)	-0.01(-0.03, 0.02)
	MR	-0.03(-0.06, 0.01)	-0.00(-0.06, 0.06)	-0.03(-0.10, 0.04)
	GDR	0.00(-0.03, 0.03)	-0.01(-0.03, 0.00)	-0.01(-0.05, 0.03)
	NGRRP	0.02(0.00, 0.04)	0.09(0.06, 0.12)	0.11(0.06, 0.16)

***Table 3*: Direct and indirect effects decomposition during long-term and short-term of LE associated SDOH proxies in China, NMSS 2005-2020.**[a]

[a] SDPM with time lagged LE were specified individual (spatial) and time fixed effects, and adjusted for annual average temperature, temperature variability and annual average relative humidity.

neighbor effects, GDP (0.14, 95%CI: 0.12, 0.16), Engel's Coefficient (0.01, 95%CI: 0.00, 0.02), urbanization rate (-0.03, 95%CI: -0.04, -0.02), unemployment rate in urban area (-0.13, 95%CI: -0.20, -0.06), average years of education attainment (-0.09, 95%CI: -0.16, -0.02) and Gini index (10.52, 95%CI: 9.07, 11.97) exerted impacts on LE among adjacent proximity. As for healthcare resource, number of beds in health care institutions (0.02, 95%CI: 0.00, 0.05) was associated with LE decrease locally. The rest, for the population characteristics, natural growth rate of resident population was statistically significant predicted local and neighborhood LE, for its every 1‰ increase in a focused province was observed to produce a positive local impact of 0.02 years (95%CI: 0.01, 0.02) and a similar neighbor impact of 0.06 years (95%CI: 0.04, 0.08) of LE. Besides, a statistically significant spatially lagged effect caused by sex ratio (-0.01, 95%CI: -0.01, 0.00) and gross dependency ratio (0.01, 95%CI: 0.00, 0.02) were estimated. In addition to SDOH components, time-lagged LE (1.05, 95%CI: 1.02, 1.08) and spatially lagged LE (0.29, 95%CI: 0.25, 0.32) were positively estimated to affect local LE in a specific year.

On the basis of SPDMLAG1 estimation, we further conducted direct/indirect and long/short-term effects decomposition to interpret how SDOH proxies influence LE disparities (Table 3). For long-term effects, GDP (0.36, 95%CI: 0.28, 0.44), urbanization rate (0.10, 95%CI: 0.03, 0.17), unemployment rate in urban area (0.34, 95%CI: 0.12, 0.56), average years of education attainment (0.36, 95%CI: 0.16, 0.56), Gini index (-38.37, 95%CI: -44.63, -32.10) and natural growth rate of resident population (-0.23, 95%CI: -0.33, -0.13) statistically significant influenced LE disparities in total. For short-term effects, it estimated that there were much more SDOH proxies presented significant influence on

LE disparities (Table 3). In contrast with Table 2, it was inferred that the short-term direct effects occupied the dominant impacts of association between SDOH proxies and LE disparities. It was observed that the average years of education attainment (-0.04, 95%CI: -0.07, 0.00) and Gini index (3.18, 95%CI: 2.60, 3.76) were much different from that estimation shown in Table 2, which attributed to spatial spillover effects, and accounted for 33.33% and 35.32% of main effects, respectively.

Discussion

By using data from NMSS, this study provided comprehensive estimates of LE at subnational level in China and its was observed unequally distributed nationwide. We found LE was a health indicator varied by regions and should be considered in a geographic context with spatial attributes. From the spatial perspectives, this study moved beyond prior researches by identifying significant local and neighbor impacts of SDOH proxies contributed to disparities in local LE from long- and short-term, especially the socioeconomic and urban development proxies.

Spatial variations of LE

During 2005–2020, the overall LE in China have risen steadily and remained at a comparatively high level worldwide, far exceeded than that of India, Brazil, Russia and other BRICS countries, which was closely related to improvement in socioeconomic and medical conditions, press ahead with health care reform and innovation, and universal health coverage.[52] Results of LE estimation in current study were similar to those LE released by National Bureau of Statistics in 2005, 2010 and 2015, which represented the reliability of mortality data and validity of estimation approach. Yet, in some provinces, differences also existed between current study and local results, especially in some developed regions like Shanghai, Beijing and Zhejiang, which could be explained by disparities in data source and estimation procedures.[52] Although LE increased in all provinces across the country, diversity in LE between provinces indicated that health inequities still remained a challenge.

LE associated SDOH

Our results shed light on the domain of socioeconomic development and equity had the largest direct and indirect impacts on provincial-level LE disparities in China. Referring to effects derived from SDOH proxies exerted on LE disparities, GDP and urbanization rate were estimated to be positively with local LE, which was consistent with previous studies.[8,10,46–49] As for indirect effects, the increase of GDP and per capita green areas were associated with neighborhood LE increase, those positive spatial spillover effects reflected the process of driving benefits of economic development from core provinces towards surrounding areas in the aspects of policy incentive, productive factors input, and human capital mobility, thus improved socioeconomic conditions like GDP, and subsequent increased neighborhood LE. On the contrary, urbanization rate, unemployment rate, education attainment and Engel's coefficient showed negative spatial spillover effects towards LE in geographic proximity, which further presented the process of resource deprivation: local economic increase might restrain the development of surrounded provinces and thus generate negative impacts towards influential proxies, then subsequently decrease LE of related provinces.[6,13,37,38] Specifically, the highland of economic development would have the capacity of siphonage to attract first-class social capital, means of production and labor force with exclusion of elements which exerted harmful effects on population health such as industries with environmental pollution. Thus, local improvement SDOH proxies, like above mentioned education attainment, would restrain the socioeconomic development among nearby provinces with inferior conditions and subsequent decreased their LE level. Additionally, it was presented that SDOH proxies measuring inequities in living standards like Gini index, was estimated positively related to LE disparities from both local and adjacent provinces, and were consistent with previous global health disparities and indigenous studies.[8,10,46–49] It was inferred that provinces with higher LE might related to ever larger gap between the poor and the rich, the developed areas were more inclined to suffer from income inequity in current China.[15] Specifically, economic effects exert a profound impact on social cohesion and the perpetuation of socioeconomic inequities in health, and health benefits associated with education attainment may be attributed to employment benefits and higher income.[6,48] For example, urban communities, where decent jobs and education opportunities were often located, may experience positive impacts to local and neighboring LE from increased economic activities.[50]

In reference to healthcare resources, number of beds in healthcare institutions were observed to exert direct influences on local LE. It is argued that health care systems contribute most to health equity when the service provides universal coverage with a well-functioning primary care sector that provides basic care to vulnerable populations, and acts as a pathway to secondary services.[8] For population characteristics proxies, mortality rate had contrasting merely negative impacts on local LE disparities, while gross dependency ratio and natural growth rate of resident population exerted positive spatially lagged impacts on LE disparities. For details, interactions from spatially neighborhoods between gross dependency ratio and LE might be explained by labor-force population outflow from locality to neighboring provinces which rejuvenate proximity population structure and thus increased LE. In reference to natural growth rate of resident population, the increasing of local population might decrease the mortality rate if number of deaths sustained and subsequent resulted in LE increase. Besides, population immigration might also play an important role resulting in LE change through age-specific population structure shifts for resident population, particularly in emerging cities.[6,13,36,38,43,51]

Dynamic SPDM model which incorporated with time lagged LE in the regressors facilitated the effect decomposition of direct and indirect effects during long and short period of time. Limited previous studies have utilized dynamic SPDM model to interpret how SDOH proxies influence LE disparities. While in this study, explanations to interpret how SDOH proxies influence LE were largely based on positive or negative spatial spillover effects, in other words, identification of spatial spillover effects of SDOH proxies on LE may influence both the health of local population and that of the residents nearby. As shown in Table 3, most of SDOH proxies did not observe to be statistically significant associated with LE disparities directly or indirectly. Notably, education attainment and Gini index showed identical direction of both direct and indirect effects during short-term, which was nearly consistent with results in Table 2. Taking education attainment as an example, an around 75% association between education attainment and LE disparities were due to its negative spatial spillover effects, and the estimates was largely greater than its direct effects, 25%.[36,37] Up to this, we speculated that, compared with the association between education attainment improvement and LE increase locality, the increase of education attainment showed much more effects in decreasing LE among geographical provinces through human capacity attraction and resource deprivation. In the consideration of long and short-term effects, taking Gini index as an example, for total effects, its statistically significant negative effects on LE disparities during long-term might be explained by long-term income inequity could related to the deterioration of quality of population health and LE decrease, while positive effects might be explained by the association between income inequity with advanced socioeconomic development, thus increase LE, especially among those developing countries which are experiencing their primary stage of socioeconomic improvement and implementing the policy of "The rich first pushing those being rich later". Therefore, we inferred that, further improvement on SDOH proxies which showed both positive direct effects and spatial spillover effects towards LE disparities, they not only directly promote LE increase in local scale, but also indirectly narrow the gaps between different regions, and maintain the sustainable development in population health. However, on the contrary, for those spatial spillover effects induced by SDOH proxies which turned to be negative, considerations should be extremely emphasized on enhancing involvement and promoting compensation for provinces with lower LE to avoid possible resource outflow to surrounding provinces.[6,13,14,36,38,39,52,53,54] Long and short-term effects should also be considered for the time duration of policy making and implementation.

Implications

Reduce population mortality and improving health equity has long been a government priority, and Healthy China 2030 included justice and equity as one of four core principles.[51] Current characteristics of LE disparities across China might be an interplay between multiple SDOH proxies. Therefore, we suggested that, first, the existed provincial variations of LE are making the requests of tailoring regional-specific strategies to bridge the gap of LE between areas. Second, the externalities of policy derived from spatial spillover effects of those SDOH proxies should be took into consideration to promote health equity among proximity provinces, including economy-facilitated effects and resource deprivation.[36,38,39] Third, compensation in involvement of healthcare and medical resources allocation should be delivered towards those provinces with lower LE to avoid growing gap between rich and poor areas. Last, comprehensive approaches on the basis of population strategy should be consolidated to optimize supportive socioeconomic environment to reduce health disparities and increase LE.[47]

Strengths and limitations

Accordingly, to our knowledge, few studies have attempted to explain the spatial variations of LE disparities and its associated SDOH at subnational-level in China by using a consecutive data with well-designed representativeness. Through introducing ecological model of health determinants, this study not only established enhanced SDOH framework but also made full use of spatial panel data when interpreting the time-varying change of SDOH and LE disparities.

This study was also subjected to several limitations. First, it is important to notice that ecological fallacy may exist when analyzing provincial-level SDOH of LE since it only revealed how drivers of disparate LE operate at the local and neighborhood level but does not establish robust evidence for inferring causation.[13] Second, the components of SDOH may not capture the comprehensive interplay of SDOH processes towards LE disparities, hence omitted variables and potential confounders were inevitable like regional occupation composition, macrolevel events, environmental and metrological metrics, also, inadequate acquisition of long-term cumulative effects of SDOH may left some of the attributions unexplained.[6,14] Third, surveillance population data used in LE estimation did not consider internal migration across rural-urban areas, and did not necessarily obtain the health of population living in an area for their entire lifetime. In particular, under-reporting of death cases might also increase the uncertainty associated with LE estimates or even lead to an underestimation of spatially LE disparities. Hence, cautions should be exercised on those numerator-denominator bias in estimates of the mortality rates when interpreting LE as reflective of more or less healthy places, but rather should be considered as representative of the place-specific health of a population during a time period of certain point.[6,12] Fourth, data quality and missingness of publicly available SDOH proxies might lead to uncertainties of results estimations, and approaches we used to perform multiple imputation might also incompletely reflect the actual situation of original data, such as missingness in some years across 31 provinces. The last, although SDOH framework was relied on literature findings, the mechanism of selected proxy in different domains may spatially interacted with each other actually through mediating and/or moderating effects, thus the linear-based spatial panel modelling approach may insufficiently demonstrate the association between SDOH and LE disparities. In response to those shortcomings, considerations should be given to improve and consolidate a sophisticated theoretical framework of LE associated SDOH proxies with an upstream influencing mechanism in the future. Also, it will be one of our research interests to perform ecological analysis about LE associated SDOH proxies at small-area to unveil health inequities which might be masked by studies at a larger scale. In additional to these, expanding the data accessibility and availability should be enhanced, such as increase the data quality of mortality data collected by NMSS, and methodology for dealing with missing data and non-linear modelling process should also be improved to understand the results more precisely with qualified robustness.[13,55]

Conclusions

In conclusion, we found geographical variations with spatial clustering of LE at provincial-level in China. Under the SDOH framework, we identified that socioeconomic development and equity, healthcare resources, as well as population characteristics associated with LE disparities. Meanwhile, we interpreted how SDOH proxies influence LE through spatial spillover effects from long- and short- term. In this way, the SDOH framework and spatial analysis we applied in this study would also provide a research clue to investigate geographic disparities and measure local and neighborhood health outcomes at ecological level. Exploring SDOH factors affecting LE could play an essential role in optimizing supportive socioeconomic environment and targeting health interventions to reduce local health disparities and increase LE, especially in the country vast in territory with high spatial heterogeneity for locality society development.[6]

Contributors

MZ had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. MZ and WW conceived the study design and analytical plan. WW and YL performed statistical analysis. WW prepared the first draft and finished the draft based on comments from other authors. MZ, WW, PYe, CX, JLi, WS critically revised the manuscript for intellectual content. MZ, LW, PYin, YL, JLiu, JQ, JY, LL acquired the data. MZ, WS, JLi, CX, YQ, YL, PYe provided technical supports in data analysis, manuscript preparation, manuscript editing and manuscript review. All authors had reviewed, provided critical inputs for revision and approved the final manuscript.

Ethics approval and consent participate

All study procedures in current study involving human subjects conformed to the ethical standards of the ethics committee of China CDC and 1964 Helsinki Declaration and its subsequent amendments or similar ethical standards. As mortality data we used in this study was aggregated data derived from NMSS hosted in China CDC, we have no access to information that could identify individual participants, so our research did not involve patients' personal information and written informed consent was waived by the ethics committee of China CDC.

Data and programs sharing statement

For raw data extracted from NMSS and under-reporting surveys used in current study, they were not publicly available due to data sharing regulations established by China CDC, but they were available from the corresponding authors on reasonable request. For raw data extracted from multi-source of SDOH proxies, they were publicly available through National Bureau of Statistics, national or regional statistics yearbook, and specific literatures. Detailed information of data sharing and accessibility was reported in Supplementary Material. In reference to programs both for the analysis of the data and for the derivation of the data, they were not publicly available due to intellectual property for statistical analysis regulations established by China CDC, but they were available from the corresponding authors on reasonable request.

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Declaration of interests

We declare no competing interests.

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Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.lanwpc.2022.100451.

References

1 Shryock HS, Siegel JS. *The Methods and Materials of Demography*. New York: Academic Press; 1976.
2 Central People's Government of the People's Republic of China. The CPC Central Committee and the State Council issued the outline of the healthy China 2030 plan. http://www.gov.cn/xinwen/2016-10/25/content_5124174.htm. Accessed 18 July 2021.
3 Central People's Government of the People's Republic of China. Notice of the State Council on the issuance of the 13th five-year plan for hygiene and health. http://www.gov.cn/zhengce/content/2017-01/10/content_5158488.htm. Accessed 18 July 2021.
4 Central People's Government of the People's Republic of China. Healthy China initiative 2019-2030. http://www.gov.cn/xinwen/2019-07/15/content_5409694.htm. Accessed 18 July 2021.
5 World Health Organization. *World Health Statistics*. Geneva: World Health Organization; 2011.
6 Melix BL, Uejio CK, Kintziger KW, et al. Florida neighborhood analysis of social determinants and their relationship to life expectancy. *BMC Public Health*. 2020;20(1):632.
7 Braveman P, Egerter S, Williams DR. The social determinants of health: coming of age. *Annu Rev Public Health*. 2011;32:381–398.
8 Hauck K, Martin S, Smith PC. Priorities for action on the social determinants of health: empirical evidence on the strongest associations with life expectancy in 54 low-income countries, 1990-2012. *Soc Sci Med*. 2016;167:88–98.
9 Chetty R, Stepner M, Abraham S, et al. The Association Between Income and Life Expectancy in the United States, 2001-2014. *JAMA*. 2016;315(16):1750–1766.
10 Allen RT, Hales NM, Baccarelli A, et al. Countervailing effects of income, air pollution, smoking, and obesity on aging and life expectancy: population-based study of U.S. Counties. *Environ Health*. 2016;15(1):86.
11 Sasson I. Trends in life expectancy and lifespan variation by educational attainment: United States, 1990-2010. *Demography*. 2016;53(2):269–293.
12 Dwyer-Lindgren L, Bertozzi-Villa A, Stubbs RW, et al. Inequalities in life expectancy among US counties, 1980 to 2014: temporal trends and key drivers. *JAMA Intern. Med*. 2017;177(7):1003–1011.
13 Yang TC, Noah A, Shoff C. Exploring geographic variation in US mortality rates using a spatial Durbin approach. *Popul Space Place*. 2015;21(1):18–37.
14 Dobis EA, Stephens HM, Skidmore M, Goetz SJ. Explaining the spatial variation in American life expectancy. *Soc Sci Med*. 2020;246: 112759.
15 Luo W, Xie Y. Economic growth, income inequality and life expectancy in China. *Soc Sci Med*. 2020;256: 113046.
16 Wu Y, Hu K, Han Y, Sheng Q, Fang Y. Spatial characteristics of life expectancy and geographical detection of its influencing factors in China. *Int J Environ Res Public Health*. 2020;17(3).
17 Wang S, Ren Z. Spatial variations and macroeconomic determinants of life expectancy and mortality rate in China: a county-level study based on spatial analysis models. *Int J Public Health*. 2019;64(5):773–783.
18 Wang S, Luo K, Liu Y. Spatio-temporal distribution of human lifespan in China. *Sci Rep*. 2015;5:13844.
19 Jiang J, Luo L, Xu P, Wang P. How does social development influence life expectancy? A geographically weighted regression analysis in China. *Public Health*. 2018;163:95–104.
20 Chinese Center for Disease Control and Prevention, National Health Commission. *China Mortality Surveillance Statistics Yearbook 2019*. Beijing: China Science and Technology Press; 2020.
21 Liu S, Wu X, Lopez AD, et al. An integrated national mortality surveillance system for death registration and mortality surveillance, China. *Bull World Health Organ*. 2016;94(1):46–57.
22 Guo K, Yin P, Wang L, et al. Propensity score weighting for addressing under-reporting in mortality surveillance: a proof-of-concept study using the nationally representative mortality data in China. *Popul Health Metr*. 2015;13:16.
23 Wang Y, Li X, Zhou M, et al. Under-5 mortality in 2851 Chinese counties, 1996-2012: a subnational assessment of achieving MDG 4 goals in China. *Lancet*. 2016;387(10015):273–283.
24 National Bureau of Statistics. National Data. National Bureau of Statistics https://data.stats.gov.cn/english/easyquery.htm?cn=E0103. Accessed 18 July 2021.
25 Dahlgren G, Whitehead M. *Policies and Strategies to Promote Social Equity in Health*. Stockholm: Institute for Future Studies; 1991.
26 Wang JF, Liu X, Christakos G, Liao YL, Gu X, Zheng XY. Assessing local determinants of neural tube defects in the Heshun Region, Shanxi Province, China. *BMC Public Health*. 2010;10:52.
27 Li X, Krumholz HM, Yip W, et al. Quality of primary health care in China: challenges and recommendations. *Lancet*. 2020;395(10239):1802–1812.
28 Chen Z, Yu B, Yang C, et al. An extended time series (2000-2018) of global NPP-VIIRS-like nighttime light data from a cross-sensor calibration. *Earth Syst Sci Data*. 2021;13(3):889–906.
29 Yin Q, Wang J, Ren Z, Li J, Guo Y. Mapping the increased minimum mortality temperatures in the context of global climate change. *Nat Commun*. 2019;10(1):4640.
30 Gasparrini A, Guo Y, Hashizume M, et al. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *Lancet*. 2015;386(9991):369–375.
31 Tian Y, Wu Y, Liu H, et al. The impact of ambient ozone pollution on pneumonia: a nationwide time-series analysis. *Environ Int*. 2020;136: 105498.
32 Nilima PA, Shreenidhi SM, Rai SN. Spatial evaluation of prevalence, pattern and predictors of cervical cancer screening in India. *Public Health*. 2020;178:124–136.
33 Rytkonen MJ. Not all maps are equal: GIS and spatial analysis in epidemiology. *Int J Circumpolar Health*. 2004;63(1):9–24.
34 Anselin L. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geogr Anal*. 1988;1(20):1–17.
35 Dormann CF, Mcpherson JM, Araújo MB, Bivand R, Bolliger J, Carl G. Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography*. 2007;5(30):609–628.
36 Elhorst JP. *Spatial Econometrics from Cross-Sectional Data to Spatial Panels*. Heidelberg: Springer-Verlag Berlin Heidelberg; 2014.
37 Lesage J, Pace RK. *Introduction to Spatial Econometrics*. USA: Chapman and Hall/CRC Press; 2009.
38 Anselin L. Spatial externalities. *Int Reg Sci Rev*. 2003;2(26):147–152.
39 Anselin L. *Econometrics: Methods and Models*. Dordrecht: Kluwer Academic; 1988.
40 Anselin L, Florax R, Rey SJ. *Advances in Spatial Econometrics*. Berlin: Springer; 2004.
41 Wang Y, Li X, Zhou M, et al. Under-5 mortality in 2851 Chinese counties, 1996-2012: a subnational assessment of achieving MDG 4 goals in China. *Lancet*. 2016;387(10015):273–283.
42 Wang H, Dwyer-Lindgren L, Lofgren KT, et al. Age-specific and sex-specific mortality in 187 countries, 1970-2010: a systematic analysis for the Global Burden of Disease Study 2010. *Lancet*. 2012;380(9859):2071–2094.
43 GBD2017 Mortality Collaborators. Global, regional, and national age-sex-specific mortality and life expectancy, 1950-2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet*. 2018;392(10159):1684–1735.
44 Anselin L. *Exploring Spatial Data with GeoDaTM: A Workbook*. Center for Spatially Intergrated Social Science; 2005:198–199.

45 Anselin L, Bera AK, Florax R, Yoon MJ. Simple diagnostic tests for spatial dependence. *Reg Sci Urban Econ*. 1996;26(1).
46 Wang X. *The Spatio-temporal Change of Population Health Distribution and its Influencing Factors in China*. Central China Normal University; 2017.
47 Zhou M, Wang H, Zhu J, et al. Cause-specific mortality for 240 causes in China during 1990-2013: a systematic subnational analysis for the Global Burden of Disease Study 2013. *Lancet*. 2016;387 (10015):251–272.
48 Mujica OJ, Vazquez E, Duarte EC, Cortez-Escalante JJ, Molina J, Barbosa D. Socioeconomic inequalities and mortality trends in BRICS, 1990-2010. *Bull World Health Organ*. 2014;92(6):405–412.
49 Kataoka A, Fukui K, Sato T, et al. Geographical socioeconomic inequalities in healthy life expectancy in Japan, 2010-2014: an ecological study. *Lancet Reg Health Western Pac*. 2021:14.
50 Matheis M. Natural resource extraction and mortality in the United States. *J Environ Manag*. 2019;235:112–123.
51 Zhou M, Wang H, Zeng X, et al. Mortality, morbidity, and risk factors in China and its provinces, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet*. 2019;394 (10204):1145–1158.
52 Institution of Health Metrics and Evaluation. GBD Results Tool. Institution of Health Metrics and Evaluation http://ghdx.healthdata.org/gbd-results-tool. Accessed 18 July 2021.
53 Bloom DE, Canning D. Policy forum: public health. The health and wealth of nations. *Science*. 2000;287(5456):1207. 1209.
54 Olsen MH, Angell SY, et al. A call to action and a lifecourse strategy to address the global burden of raised blood pressure on current and future generations: the Lancet Commission on hypertension. *Lancet*. 2016;388(10060):2665–2712.
55 Wang S, Chen Y, Huang J, Liu Z, Li J, Ma J. Spatial relationships between alcohol outlet densities and drunk driving crashes: an empirical study of Tianjin in China. *J Saf Res*. 2020;74:17–25.