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DISCUSSION PAPER SERIES

IZA DP No. 16332

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JULY 2023

ISSN: 2365-9793

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ABSTRACT

Do Primary Healthcare Facilities in More Remote Areas Provide More Medical Services? Spatial Evidence from Rural Western China

Primary healthcare institutions (PHIs) in China have experienced a sizable decline in medical services in recent years. Despite the large regional disparities in China, there is a lack of evidence on the differential patterns of medical services offered by PHIs, especially from a spatial perspective. This study examines whether residents in more remote areas use more medical services offered by township healthcare centers (THCs), a main type of PHIs. Linking medical visits to 923 THCs in a western Chinese province in 2020 with the driving time and geographic coordinates from the Gaode map, a leading map navigation provider in China, we applied a multilevel linear model and a geographically weighted regression to examine spatial heterogeneity in medical service utilization. We showed that a one-hour increase in the shortest driving time between THCs and the local county hospitals was associated with an average 6% increase in THCs outpatient visits and a 0.6% increase in THCs inpatient visits. Our findings suggest that THCs located in more remote areas provided more medical services, especially outpatient services.

JEL Classification: I11, I14, I18, R53

Keywords: primary healthcare institutions, spatial accessibility, disparities, medical service, China

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Introduction

Primary healthcare institutions (PHIs) in China have experienced a significant decline in medical services over the past few years, with the proportion of outpatient services provided by PHIs decreasing from 58.5% to 54.1% from 2015 to 2019, and the proportion of inpatient services decreasing from 20.1% to 16.9% (National Health Commission of the People' s Republic of China 2020). One of the main concerns is whether all PHIs in China suffered from the same level of reduction in medical services.

An important backdrop to the shrinking of medical services in PHIs in China is the new healthcare reform that began in 2009. In this reform, three major policies were applied to PHIs: increased government investment, elimination of drug markup as a source of funding, and provision of basic public health services (Meng *et al.* 2019). Studies have explored the reasons why PHIs have suffered significant declines in medical services. Li *et al.* (2017) argued that a policy that increases government investment created incentives similar to the so-called iron rice bowl policy (occupations with job security and benefits) and left PHIs in a low productivity state. Shen *et al.* (2021) also found that township healthcare centers, a form of PHIs in China with large government subsidies, reduced the volume of medical services after 2011. Ma *et al.* (2019) pointed out that the declining use of primary healthcare as a proportion of total healthcare was an unintended consequence of the reforms because the performance-based salary system did not link with quality to ensure adequate compensation for primary healthcare professionals in China. Yip *et al.* (2019) noted that aligning the incentives and governance of primary healthcare systems through the establishment of an integrated delivery system based on primary healthcare would improve the quantity and quality of primary healthcare providers in China. Despite the large regional differences in China, there have been gaps in the literature that aims to understand the heterogeneity of medical services and its decline in PHIs, especially from a spatial perspective.

Spatial factors have been found to play an important role in health systems around the world. We summarized the impact of spatial factors on health sectors into two areas: health-seeking behavior and healthcare utilization; and health outcomes. In terms of health-seeking behavior and healthcare utilization, suburban Chinese with poor access to high-grade hospitals are more likely to perform self-treatment compared with urban residents (Shen & Tao 2022). A survey study conducted in northern China found that the rate of receiving hypertension management services for people living closer to PHIs was about 10 times (OR = 10.360, 95% CI 2.090 to 51.343) as high as those living closer to higher-level hospitals (Liu *et al.* 2019). Jiang *et al.* (2020) explain that the preference for seeking healthcare services nearby is as important as being driven by price or seeking higher quality of care. Even in online healthcare utilization, geographic distance between physician and patient is negatively correlated with the use of online medical services, although this effect is 40% to 50% of the size for offline medical services (Chen *et al.* 2022). The same pattern has been observed in the United States; in the Texas Coastal Bend, older adults with poorer access to general practices but easier access to hospitals had a higher rate of ambulatory care-sensitive conditions in the emergency department (Huang *et al.* 2018). Similarly, in low-middle income countries like Ghana, Haiti, and Kenya, spatial accessibility to healthcare facilities played a significant role in birthing and maternal services. An increase in distance by one kilometer was associated with a 6.7% significant reduction in the prevalence of women giving birth in health facilities in eastern Ghana (Dotse-Gborgbortsi *et al.* 2020). In rural Haiti and Kenya, lower level use of maternity services was observed in some areas with longer distances to facilities and low quality of care (Gao & Kelley 2019).

In terms of health outcomes, large-scale road construction programs in rural India have improved access to medical facilities and led to better care for pregnant women and subsequently better health outcomes such as lower rates of delivery complications (Aggarwal 2021). For elderly people, the low accessibility to healthcare services due to limited public transport service widens health inequalities between older adults living in urban and rural areas (Chen *et al.* 2020), and promoting active travel modes among the older population and community-level health facility planning to reduce travel time can improve the use and satisfaction of older adults with primary care visits (Li, Zhang, *et al.* 2020).

As discussed above, spatial accessibility to PHIs and hospitals and socioeconomic factors may shape residents' health-seeking behavior and thus generate different healthcare utilization in different institutions. Therefore, this study examines whether residents in more remote areas use more medical services offered by PHIs. Remote areas in this study are defined as townships with long travel time between their PHIs and local county hospitals. We hypothesize that health-seeking behavior in western rural China tends to be spatial dependent, i.e., residents in remote areas rely more on PHIs for basic medical services due to a lack of accessibility to higher-level health facilities and therefore fewer health-seeking choices.

In general, five types of medical institutions are classified as PHIs in China, which are township healthcare centers (THCs), community healthcare centers (CHCs), outpatient departments, private clinics, and village clinics (National Health Commission of the People' s Republic of China 2021a), CHCs and THCs are the core primary-care providers (Yip *et al.* 2010). THCs and CHCs are similar in function but different in distribution, THCs is usually built in rural areas of China, while CHCs is usually built in urban areas of China. THCs and CHCs typically provide a wide range of basic medical services to local residents, including preventive care, diagnosis and treatment of minor illnesses, health education, and medication management. Compared to healthcare systems in other countries such as the UK and US, THCs and CHCs in China typically offer a more extensive range of healthcare services and are considered more accessible to the general population due to their location and coverage areas. The primary goal of these healthcare centers is to provide quality healthcare services that address the needs of the local population in a manner that is efficient, effective, and accessible to all. According to the China Health Statistical Yearbook in 2021, there were 1.03 million physicians in PHIs in 2020, with CHCs and THCs accounting for 14.4% and 30.5%, respectively (National Health Commission of the People' s Republic of China 2021b). As this study focused on PHIs in rural China, we selected THCs as research sample.

We linked a dataset of medical utilizations in 923 PHIs in 2020 with drive time and geographic coordinates downloaded from the Gaode map (one of the leading map navigation providers in China) on July 4, 2020, and applied multilevel linear model and geographically weighted regression to examine the spatial dependency of health-seeking behavior in western China. This study may enrich our understanding of spatial disparity in medical service capacity and utilization of township healthcare centers in western China, and attempt to fill the gap in understanding the factors that influence utilization of primary healthcare services in low- and middle-income countries. Our findings highlight the urgency of improving primary medical service capabilities in underdeveloped areas and further promoting a hierarchical medical system in developed areas.

Materials and methods

Sample selection and data sources

Shaanxi Province, a developing province located in western China, was chosen as our study site. There are two parts of data sources used in this study. First, we collected healthcare service workload, workforce, and resource of PHIs and county-level hospital from Annual Report on Health Statistics (ARHS) of Shaanxi Province in 2020. ARHS generates from health resources and medical services statistical survey that is an annual administrative affair for all level Chinese health administration departments. This census survey covers all types of public and private healthcare institutions and is designed to collect basic information on healthcare institutions, including but not limited to operational status and resource allocation (National Bureau of Statistics 2021). Of the 1535 THCs from 78 counties and county-level cities in Shaanxi Province in 2020, a total of 923 THCs were included in this study based on availability of information on key variables, the flow chart of THCs selection can be found in Figure A1 in Supplementary. The spatial distribution of 923 THCs is shown in Figure A2 in Supplementary.

Second, another essential part of data in this study is a measure of the remoteness of THCs. We used the shortest driving time between THCs and local county hospitals to measure this remoteness. The data about shortest driving time was downloaded from route direction Application Programming Interface (API) of Gaode Map (https://lbs.amap.com/api/webservice/guide/api/direction/), one of the leading map navigation providers in China, and the data collection process was done by a self-developed crawler written in Python. The detail process of the data collection is described in our previous study (Shen *et al.* 2020). The data collection strategy was that 1) we firstly used the geocoding function provided by the geocoding API of Gaode Map to obtain the geographic coordinates of THCs based on their institution name, 2) the latitude and longitude of THCs and the local county hospitals were set as the starting and ending points, respectively, 3) Gaode Map offered the shortest driving time with a strategy that navigation speed priority but not take the highway, 4) we conducted two crawls on July 3, 2020 in the morning（Start at 10:17 AM, end at 11:54 AM）and afternoon (Start at 15:38 PM, end at 15:57 PM), respectively. Finally, a total of 1846 (923 multiply by 2 times) shortest driving time in minute was collected for 923 THCs, we used a histogram to show the distribution of 1846 shortest driving time (see Figure A3 in Supplementary).

The reason why we did not choose the road map in ArcGIS to calculate the travel time, such as (Pan *et al.* 2016, Wang *et al.* 2018), is because real-time travel cost metrics base on network map navigation is more accurate when considering traffic lights and traffic congestions (Chen *et al.* 2020). Moreover, it is appropriate to use the real-time travel time between PHIs in a town and county level hospital to evaluate the remoteness, because we define the remote area at township level in our study, and PHIs are located almost in the economic and population center of towns in rural China, which can reflect the average degree of remoteness of each village or household in the township.

Variable measures

As this study focuses on the relationship between the remoteness of the location of THCs and the workload of medical services, we chose outpatient visit and inpatient visit to measure the workload, which are also the dependent variables in our study. It is a common and widely used practice to apply outpatient and inpatient visit to reflect the workload of medical services in a healthcare facility.

In order to mitigate the biases that may affect outpatient and inpatient visit of THCs other than remoteness of location, we controlled for a range of features of THCs, such as number of physicians, number of served population, percentage of served population aged 65 and above, government subsidies as a percentage of revenue (Shen *et al.* 2021), and type of THCs. Moreover, considering the possible crowding-out effect of local county hospitals on THCs (Jia *et al.* 2021, Wu, Tu, *et al.* 2021, Yuan *et al.* 2022), we included the number of available bed days in local county hospital and county category in regression models. For better presentation, we summarized the details about values and attributes of above variables in Table 1. Descriptive statistics of variables is presented in Table 2.

[Insert Table 1 and Table 2 at here]

Empirical strategy

Three parts of empirical strategies were used in this study. First, our baseline model uses an ordinary least squares (OLS) regression to estimate the impact of remoteness on the medical service workload of THCs. The model is shown as follows:

$$\log(Y_{ij}) = \beta Remoteness_{ij} + \delta X_{ij} + \gamma Z_j + \varepsilon_{ij}$$

where Y_{ij} is a measure of medical workload, the number of outpatient visit and inpatient visit, in THCs i in county j. $Remoteness_{ij}$ denotes the shortest driving time from THCs i to county j. X_{ij} is a set of THCs-level variables listed in Table 1. Z_j is a set of county-level variables that account for county characteristics, such as county category and number of hospital bed, and ε_{ij} is the error term. The coefficient β identifies our interested effect.

However, in terms of health management, county governments in China have a certain degree of decision-making autonomy in health policies such as resource allocation and market regulation, which leads to a situation where THCs follow the similar pattern within the same county. This means that THCs from a same county maybe correlated and are nested within county. Then, considering to eliminate the bias caused by the correlation, we also used a two-levels multilevel linear model (MLM) to estimate the coefficient β in the equation above. The first level in our data is THCs and secondary level is counties. We used intra-class correlation (ICC), calculated from an 'empty' MLM model (only intercept, no predictors), to measure the correlation between pairs of THCs located in the same county. The ICCs for outpatient and inpatient services were 0.534 and 0.328, respectively, indicating that MLM was an appropriate choice in this study.

Further, both OLS and MLM so far assume homogeneous effects for each unit, regardless of geographic location, while the relationship between remoteness and THCs medical workload can be spatially heterogeneous that varies by location of the THCs (Wang *et al.* 2016, Thomas *et al.* 2020, Wang & Wu 2020). To account for this spatial heterogeneity in THCs, we used geographically weighted regression (GWR), a derivative of OLS, to fit a series of locally OLS models for subsets of 923 THCs within a given bandwidth of each THCs' location instead of fitting a unique model to the entire 923 THCs. The subsets of 923 THCs were constructed based on the moving window method (Wu, He, *et al.* 2021), which simply means that a search window (bandwidth) is used to cover the available THCs, moving from one THC location to another, and all other THCs around it and within the search window are identified as a subset. The equation of GWR in this study is shown as follows:

$$\log(Y_i) = \alpha_0(u_i, v_i) + \sum_k \alpha_k(u_i, v_i) X_{ik} + \varepsilon_i$$

Where Y_i is a measure of the number of outpatient visit and inpatient visit of THCs, i devotes the THCs, k devotes the number of independent variables and X_{ik} means independent variables. (u_i, v_i) are the spatial coordinates of THCs i, α_k is the spatial weights kernal and $\alpha_k(u_i, v_i)$ is the weight matrix of THCs i based on (u_i, v_i) and α_k. We used adaptive bisquare as spatial weights kernel and select the optimal bandwidth by cross-validation. Fotheringham *et al.* (2002) provided a comprehensive description of GWR.

Data manipulation and visualization were performed by Python 3.8.5, and MLMs were performed using *lme4* (Bates *et al.* 2015) package in R 4.0.5 (R Core Team 2021). Standard errors of coefficients in OLS models are clustered at the county level. GWR was performed in *mgwr* (Oshan *et al.* 2019) module in Python.

Results

Exploratory analysis

First, we mapped the outpatient visit and inpatient per service population of 923 THCs in scatter charts in geographic coordinates (Figure 1), which shows that THCs located near city boundaries had more outpatient visit and inpatient visit per service population than THCs in other locations. To clearly observe this characteristic, we aggregated outpatient visit and inpatient visit per service population of 923 THCs by 78 counties or county-level cities and plotted them in a geographic map. As illustrated in Figure 2, the average number of outpatient visit and inpatient visit per service population is greater in counties or county-level cities near the border of Shaanxi Province than in counties or county-level cities located in the center of Shaanxi province. In general, central areas in Shaanxi Province where the capital city is located are the transportation, economic and population center and have low degree of geographic remoteness. In addition, we drew a scatter plot at the level of THCs with the shortest driving time on the horizontal axis and medical workload on the vertical axis to explore the relationship between these two variables, and then we obtained a slope that slopes upward to the right (see Figure A4 in Supplementary).

[Insert Figure 1 and Figure 2 at here]

Regression analysis

The exploratory analysis indicated us that the THCs located in remote areas of Shaanxi Province appeared to provide more medical services, and regression models quantified this effect while controlling for confounding factors. As shown in Table 3, the OLS coefficients of shortest driving time are consistent with or without controlling for covariates, which indicates that each 1-minute (1-hour) increase in shortest driving time between THCs and the local county hospitals was associated with an average 0.2% (12%) and 0.01% (0.6%) increase in outpatient and inpatient visit of THCs, separately.

[Insert Table 3 at here]

As illustrated in Table 4, the MLM coefficients of the shortest driving time for outpatient visit of THCs are half their OLS coefficients after eliminating the bias caused by intra-county correlations, but there was no change in the coefficient for inpatient visit, which supports that each 1-minute (1-hour) increase in shortest driving time between THCs and the local county hospitals was associated with an average 0.1% (6%) and 0.01% (0.6%) increase in outpatient and inpatient visit of THCs, separately.

[Insert Table 4 at here]

The basic information of the GWR models can be found in Table A1 in Supplementary, only the significant variables in OLS and MLM were included as control variables in GWR, such as Number of physicians in THCs, Service population, Percentage of population over 65, Share of subsidy on revenue, Number of available bed days in local county hospital. As presented in Table A1, the AICs of GWR are smaller than that of OLS and MLM, which indicates GWR removes the effect of spatial heterogeneity on regression coefficient estimates. Typically, the local coefficients for each unit in the GWR are presented as a map, as shown in Figure 3, where the coefficient for the shortest driving time for each THCs is marked in red (coefficient positive) and blue (coefficient negative) colors. A positive coefficient indicates that the longer the driving time or the more remote the THCs, the more outpatient and inpatient visits the THCs will have, and vice versa. We can clearly find that most THCs located in southern and norther Shaanxi Province where are mountainous and developing areas had positive coefficients, and this finding was more obviously in outpatient visits than that of inpatient visits.

[Insert Figure 3 at here]

Robustness analysis

Considering that the 2020 Covid-19 pandemic shocked urban and suburban areas of China more than rural areas, this leads to possible differential impact of the 2020 Covid-19 pandemic on medical services in THCs, which would make the less outpatient and inpatient visits in the THCs with less remoteness was confounded by the 2020 Covid-19 pandemic (Xu *et al.* 2021). Therefore, we performed the same analysis using the 2018 data described above to check the robustness of our findings and presented only the results of MLM in 2018 here, the rest of results can be found in Table A2 in Supplementary. As shown in Table 5, the same findings can be observed in our 2018 sample, and the results are in line with the main analysis based on data in 2020.

[Insert Table 5 at here]

Discussion

This study aims to examine the hypothesis that PHIs located in remote areas serviced more patients in China, and our findings support this hypothesis. Results of OLS, MLM, and GWR all point to spatial disparity in medical service capacity of THCs in western China. Specifically, a one-hour increase in the shortest driving time between the THC and the local county hospitals was associated with an average increase of 6% and 0.6% in outpatient and inpatient admissions to THCs, respectively. This suggests that THCs located in remote areas provided more medical services, especially outpatient services.

Our findings are partly in line with some previous studies that found that inpatient healthcare needs of patients in rural China were significantly influenced by the distance to the hospital; as the distance to the hospital increased, patients' utilization of visits to that hospital decreased (Li *et al.* 2014). PHIs in areas with higher spatial accessibility of hospitals had lower capacity of medical services, and residents were more likely to utilize inpatient services in hospitals (Zhang *et al.* 2018). Chinese patients prefer not to go to a primary care facility for outpatient services when they have the same spatial accessibility to hospitals and primary care facilities (Li & Xing 2020). However, our study provides more insights into the impact of spatial factors on health-seeking behavior in Chinese residents. Specifically, patients in western China prefer to go to a primary care facility for outpatient services when they have less access to higher-level hospitals. In previous studies (Yip et al. 2012, Tang et al. 2014, Xu et al. 2020), concerns were raised about the lack of popularity of primary care in China. However, our findings highlight the possibility that these studies may have overlooked the geographical heterogeneity underlying this phenomenon. Although both urban and rural residents in China tend to seek medical treatment at large hospitals, residents living in remote rural areas in China are more likely to seek outpatient medical services at primary healthcare facilities due to restrictions imposed by their geographical environment. Although our study cannot distinguish whether this tendency is voluntary or forced, it is a fact.

We interpret the "spatial dependence effect of health-seeking behavior" in rural China by three effects. The first we call the substitution effect. It is well known that China has a regional disparity of health resource allocation between rural and urban areas; in terms of all kinds of health resources, urban areas are rich and rural areas are poor (Li *et al.* 2018, Fu *et al.* 2021, Chen, Lin, *et al.* 2021, Dong *et al.* 2021). For residents in resource-rich areas, there are sufficient substitutions of healthcare facilities when residents are seeking medical care, and they are more willing to seek medical services in hospitals rather than PHIs (Ta *et al.* 2020). However, remote areas in rural China are far away from public resource centers and have limited health resources. Consequently, there are insufficient substitutions of healthcare facilities for residents seeking medical care, and they have to rely on THCs that are of relatively high quality compared to village clinics.

The second effect we call the income effect, as income is another key factor affecting residents' health-seeking behavior. In remote areas of China, residents have lower income and a higher incidence of catastrophic health expenditures and are more sensitive to healthcare spending (Wang & Zhang 2021). In addition, the price of medical care in PHIs is the lowest in China's healthcare delivery system; therefore, residents in remote areas used more medical services in THCs.

Third is the residential self-selection effect. Several studies have revealed that the neighborhood and built environment can impact residents' travel (Lin *et al.* 2017, Zang *et al.* 2019) and physical activity behaviors (Wang *et al.* 2022), and even unsafe walking circumstances due to high daytime and nighttime crime rates lead to higher diabetes incidence (Dendup *et al.* 2019, p. 2019). The same is true for health-seeking behaviors, where the transportation conditions and allocation of health facilities within a community may influence residents' decisions to seek healthcare.

However, the above interpretations can only account for the fact that THCs in remote areas provide more medical services, but they cannot explain the difference between outpatient and inpatient services and why the effect on inpatient services is only one-tenth that of outpatient services. We think this difference can be explained by traditional Chinese culture. The Chinese traditionally believe that "if you have green hills, you will not be afraid to burn wood," which means that the Chinese value life or health so much that when a life-threatening illness requires hospitalization, the sensitivity to expenses no longer has the highest priority. Although seeking inpatient care in high-level hospitals costs more in medical care, travel, and lost wages, it provides a higher quality of care than hospitalization in THCs with cheap but lower quality care. Compared to reduce spending, life is much more important, and regaining health and the ability to work as soon as possible are primary concerns.

Several policy implications can be drawn from our findings. First, more attention should be paid to improving the quality of THCs in remote areas of China when constructing the capacity system of primary healthcare. Widespread gaps in the quality of primary healthcare are a long-term challenge for Chinese health policy makers. Building a primary healthcare-based integrated delivery system and strengthening the coordination between PHIs and hospitals to improve the quality of primary healthcare in China is a consensus (Yip *et al.* 2019, p. 2019, Li, Krumholz, *et al.* 2020). Our study suggests that remote areas deserve more attention and priority in the process of improving the quality of primary healthcare since the poor and vulnerable residents in remote areas rely more on primary care services. Specifically, the government can utilize telemedicine technology to connect remote communities with health care providers, and provide professional development opportunities and mentoring programs to primary health care workers in remote regions to enhance their skills and knowledge. Second, health policy makers should take into account the influence of geographic factors in residents' healthcare utilization and the supply of medical institutions and pay attention to the promotion function of infrastructure construction of public transportation, such as high-speed railway, on individuals' health status, healthcare utilization, and household income (Wang *et al.* 2020, Liu *et al.* 2021, Chen, Hao, *et al.* 2021).

Moreover, with the rapid development of telehealth in China—the 2021 China E-hospital Development Report showed that 1,004 internet hospitals had been built in China by the end of 2020 (National Telemedicine and Connected HealthCare Center) —the impact of telehealth on residents' health-seeking behaviors cannot be ignored. Telehealth may weaken the effect of spatial factors on outpatient visits in THCs in China as telehealth could break through the limits of spatial distance. Further research should investigate the long-term effects of telehealth on the relationship between spatial factors and health-seeking behavior.

This study has the following limitations. First, there is a lack of demand-side data to manifest comprehensive health-seeking behaviors, this prevents us from exploring in depth and explaining the mechanisms by which PHIs located in remote areas serviced more patients in China, our findings need to be tested and supported by further future research by surveying residents in remote areas to obtain comprehensive information on their healthcare preferences, choices, and experiences. Second, we focus not only on the quantity but also on the quality of care at THCs in remote areas; however, due to the lack of data related to quality of care, our study could not go deeper to explain whether the increased outpatient and inpatient services of remote THCs led to better quality of care or whether residents in remote areas received better quality primary care services. Third, our sample was limited to THCs, one of five types of PHIs in China, although THCs are the main primary care provider in rural China, our findings do not cover all medical services. Fourth, 612 THCs were dropped from our sample due to missing key variables, which resulted in our findings not reflecting the overall situation in Shaanxi Province and threatened the external validity of our findings, so relative caution should be exercised in extending our findings. Fifth, although the variation in travel time collected by one mode of transportation is sufficient to capture the variation in the remoteness of an area, different modes of transportation may have an impact on the variation in travel time and thus on the measurement of variation in remoteness, further studies are needed to explore this impact.

Conclusions

Our findings suggest that THCs located in remote areas provided more medical services, especially outpatient services, which indicates that patients in western China prefer to go to a primary care facility for outpatient services when they have less access to higher-level hospitals. We suggest that more attention should be paid to enhance the quality of THCs in remote areas, which deserve a higher priority in the process of improving the quality of primary healthcare since the poor and vulnerable residents in remote areas rely more on primary care services. The provision of medical services in more remote areas could be improved through targeted Telehealth interventions that address geographical and socioeconomic inequalities. Prioritizing greater investment in Telehealth construction in remote areas may be an effective solution to promote the quality of primary healthcare and residents' access to high-quality medical service. Health policy making in developing regions like western China should take geographic factors into account.

Supplementary Materials

Supplementary Table A1: Geographically weighted regression model results

Supplementary Table A2: OLS model results of outpatient and inpatient visit per service population of THCs in 2018

Supplementary Figure A1: Flow chart of data clean

Supplementary Figure A2: Geographic distribution of 923 THCs in Shaanxi Province

Supplementary Figure A3: Histogram of shortest driving time from 923 THCs to local county hospital

Supplementary Figure A4: Relationship between shortest driving time and outpatient and inpatient visit per service population

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Declarations and ethics statements

Acknowledgements

We thank the National Natural Science Foundation of China and Health Commission of Shaanxi Province for providing fund and data support. We also thank China Scholarship Council for providing financial support to Chi Shen to visit Yale University.

Funding

This research was funded by National Natural Science Foundation of China (72104195), National Natural Science Foundation of China (71874137), China Postdoctoral Science Foundation (2021M702577), China Scholarship Council (201906280175), Career Development Award (K01AG053408), and a major research grant (R01AG077529) from the National Institute on Aging.

Competing interests

The authors declare no conflicts of interest.

Data availability statement for Basic Data Sharing Policy

Restrictions on the availability of this data and therefore it is not publicly available, but it is available from the corresponding authors on reasonable request.

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Tables

Table 1 Summary of variables in regression models

Variables	Value	Data Sources
Dependent variables		
Outpatient visit of THCs	Numeric, logarithmic conversion	ARHS of Shaanxi Province
Inpatient visit of THCs	Numeric, logarithmic conversion	in 2020
Explanatory variables		
Shortest driving time	Numeric, minute	Gaode Maps
Control variables		
Number of physicians in THCs	Numeric, person	
Service population	Numeric, 10 thousand	
Percentage of population over 65	Numeric, %	
Share of subsidy on revenue	Numeric, %	ARHS of Shaanxi Province
Type of THCs	Three categories (General THCs, Central THCs, Street THCs) *, dummy conversion in models.	in 2020
County category	Two categories (County and County-level city) †	
Number of available bed days in local county hospital ‡	Numeric, day	

Note:

* In China, General THCs (township healthcare centers), Central THCs and Street THCs are the three types of THCs. The difference between them is in size and location, with General THCs being basic and common, and Central THCs being larger than General THCs but smaller than secondary hospitals.

† Both county and county-level city are part of the county-level administrative region in China.

‡ The number of available bed days is equal to the total number of daily available beds in a year.

Table 2 Descriptive statistics of variables

Variables	Overall(N=923)
Shortest driving time (minute)	
Mean (SD)	43.0 (30.3)
Median [Min, Max]	34.6 [1.75, 178]
No. of Physician in THCs	
Mean (SD)	4.99 (5.11)
Median [Min, Max]	4.00 [1.00, 54.0]
Missing	1 (0.1%)
Service Population (10 thousand)	
Mean (SD)	1.90 (1.55)
Median [Min, Max]	1.56 [0.0589, 19.8]
Missing	4 (0.4%)
Percentage of population over 65 (%)	
Mean (SD)	12.2 (6.42)
Median [Min, Max]	11.2 [0, 62.4]
Missing	5 (0.5%)
Share of subsidy on revenue (%)	
Mean (SD)	67.7 (18.3)
Median [Min, Max]	69.4 [0, 100]
Missing	2 (0.2%)
Type of THCs	
Street THCs	2 (0.2%)
General THCs	424 (45.9%)
Central THCs	497 (53.8%)
County category	
County	859 (93.1%)
County-level city	64 (6.9%)
Number of available bed days in local county hospital	
Mean (SD)	194000 (77200)

Median [Min, Max]	187000 [38400, 362000]

Note: SD refers to standard deviation, THCs refers to township healthcare centers.

Table 3 OLS model results of outpatient and inpatient visit per service population of THCs in 2020

Variables	log(outpatient visit per service population)				log(inpatient visit per service population)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Shortest driving time (minute)	0.002***	0.002***	0.002***	0.002***	0.0001**	0.0001**	0.0001**	0.0001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Number of physicians in THCs	0.007**	0.008**	0.008**	0.009***	0.001***	0.001***	0.001***	0.001***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Service population (10 thousand)	-0.058***	-0.058***	-0.059***	-0.052***	-0.002**	-0.002**	-0.002**	-0.002**
	(0.014)	(0.014)	(0.014)	(0.013)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of population over 65	0.017***	0.018***	0.017***	0.019***	0.0002	0.0002	0.0001	0.0002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of subsidy on revenue	-0.009***	-0.009***	-0.009***	-0.009***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Type of THCs: Central THCs	0.155***	0.162***	0.164***	0.158***	0.012**	0.012**	0.013**	0.012**
	(0.053)	(0.056)	(0.057)	(0.046)	(0.005)	(0.006)	(0.005)	(0.006)
Type of THCs: General THCs	0.096*	0.107*	0.109*	0.111**	0.005	0.005	0.006	0.005
	(0.054)	(0.058)	(0.059)	(0.047)	(0.005)	(0.005)	(0.005)	(0.006)
County category: County-level city		-0.143**	-0.244**	-0.136**		0.001	-0.015**	0.001
		(0.068)	(0.106)	(0.068)		(0.005)	(0.007)	(0.005)
Duration * County-level city			0.003				0.0004**	
			(0.002)				(0.0002)	
Number of available bed days in local county hospital				<-0.0001				<-0.0001
				(<0.0001)				(<0.0001)
Constant	0.896***	0.855***	0.874***	0.915***	0.053***	0.053***	0.056***	0.053***
	(0.126)	(0.130)	(0.128)	(0.142)	(0.011)	(0.011)	(0.011)	(0.012)
Observations	915	915	915	915	854	854	854	854
R^2	0.459	0.467	0.469	0.473	0.305	0.305	0.314	0.306
Adjusted R^2	0.455	0.463	0.464	0.468	0.300	0.299	0.306	0.298

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, standard errors are clustered on THCs (listed in parentheses), THCs refers to township healthcare centers.

Table 4 MLM results of outpatient and inpatient visit per service population of THCs in 2020

Variables	log(outpatient visit per service population)				log(inpatient visit per service population)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Shortest driving time (minute)	0.001***	0.001***	0.001***	0.001***	0.0001**	0.0001**	0.0001*	0.0001**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Number of physicians in THCs	0.008***	0.008***	0.008***	0.008***	0.001***	0.001***	0.001***	0.001***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Service population (10 thousand)	-0.048***	-0.048***	-0.049***	-0.047***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of population over 65	0.013***	0.014***	0.013***	0.014***	0.0002	0.0002	0.0002	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share of subsidy on revenue	-0.007***	-0.007***	-0.007***	-0.007***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Type of THCs: Central THCs	-0.009	-0.007	-0.004	-0.007	0.011	0.011	0.011	0.011
	(0.165)	(0.165)	(0.165)	(0.165)	(0.015)	(0.015)	(0.015)	(0.015)
Type of THCs: General THCs	-0.062	-0.059	-0.057	-0.057	0.005	0.005	0.005	0.005
	(0.165)	(0.165)	(0.165)	(0.165)	(0.015)	(0.015)	(0.015)	(0.015)
County category: County-level city		-0.185**	-0.286***	-0.170**		-0.001	-0.016*	-0.001
		(0.086)	(0.107)	(0.086)		(0.006)	(0.008)	(0.006)
Duration * County-level city			0.003				0.0004**	
			(0.002)				(0.0002)	
Number of available bed days in local county hospital				<-0.0001*				<0.0001
				(<0.0001)				(<0.0001)
Constant	0.970***	0.975***	0.982***	1.057***	0.051***	0.050***	0.052***	0.049***
	(0.175)	(0.174)	(0.174)	(0.181)	(0.016)	(0.016)	(0.016)	(0.017)
Observations	915	915	915	915	854	854	854	854
Akaike Inf. Crit.	109.74	110.24	120.54	137.67	-3,939.60	-3,929.23	-3,918.20	-3,893.87
Bayesian Inf. Crit.	157.93	163.25	178.36	195.49	-3,892.10	-3,876.98	-3,861.20	-3,836.87

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, standard errors are clustered on THCs (listed in parentheses), THCs refers to township healthcare centers.

Table 5 MLM results of outpatient and inpatient visit per service population of THCs in 2018

Variables	log(outpatient visit per service population)				log(inpatient visit per service population)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Shortest driving time (minute)	0.002***	0.002***	0.002***	0.002***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Number of physicians in THCs	0.012***	0.012***	0.012***	0.012***	0.001***	0.001***	0.001***	0.001***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Service population (10 thousand)	-0.054***	-0.054***	-0.054***	-0.052***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of population over 65	0.011***	0.011***	0.011***	0.011***	0.001***	0.001***	0.001***	0.0005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of subsidy on revenue	-0.007***	-0.007***	-0.007***	-0.007***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Type of THCs: Central THCs	-0.109	-0.105	-0.103	-0.105	0.013	0.013	0.013	0.013
	(0.165)	(0.165)	(0.165)	(0.165)	(0.017)	(0.017)	(0.017)	(0.017)
Type of THCs: General THCs	-0.185	-0.180	-0.178	-0.177	0.004	0.004	0.004	0.004
	(0.166)	(0.166)	(0.166)	(0.166)	(0.018)	(0.018)	(0.018)	(0.018)
County category: County-level city		-0.190**	-0.249**	-0.176**		-0.004	-0.002	-0.005
		(0.086)	(0.107)	(0.085)		(0.008)	(0.010)	(0.008)
Duration * County-level city			0.002				-0.0001	
			(0.002)				(0.0002)	
Number of available bed days in local county hospital				<-0.0001*				<0.0001
				(<0.0001)				(<0.0001)
Constant	1.065***	1.069***	1.070***	1.161***	0.076***	0.076***	0.076***	0.072***
	(0.174)	(0.174)	(0.174)	(0.180)	(0.018)	(0.018)	(0.018)	(0.019)
Observations	905	905	905	905	905	905	905	905
Akaike Inf. Crit.	110.59	110.85	122.81	137.30	-3,946.48	-3,936.92	-3,919.71	-3,902.92
Bayesian Inf. Crit.	158.67	163.74	180.51	195.00	-3,898.40	-3,884.03	-3,862.02	-3,845.23

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$, standard errors are clustered on THCs (listed in parentheses), THCs refers to township healthcare centers.

Figures

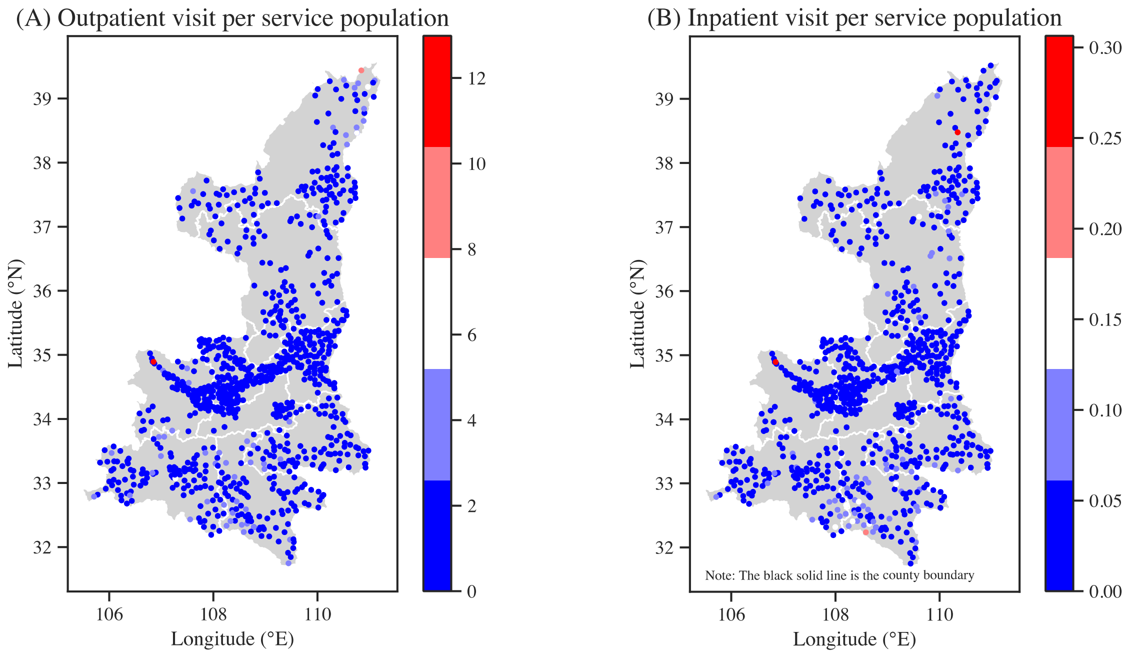


Figure 1 Geographic distribution of outpatient and inpatient visit per service population of 923 THCs in Shaanxi Province in 2020

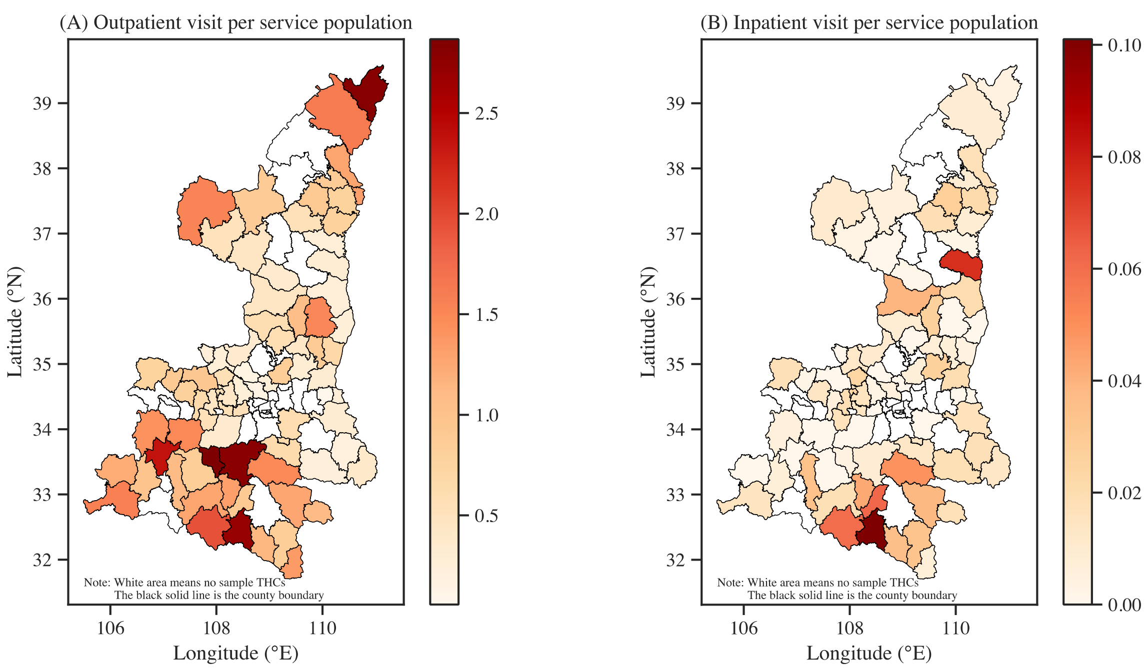


Figure 2 Geographic distribution of average number of outpatient and inpatient visit per service population of 78 counties aggregated from 923 THCs in Shaanxi Province in 2020

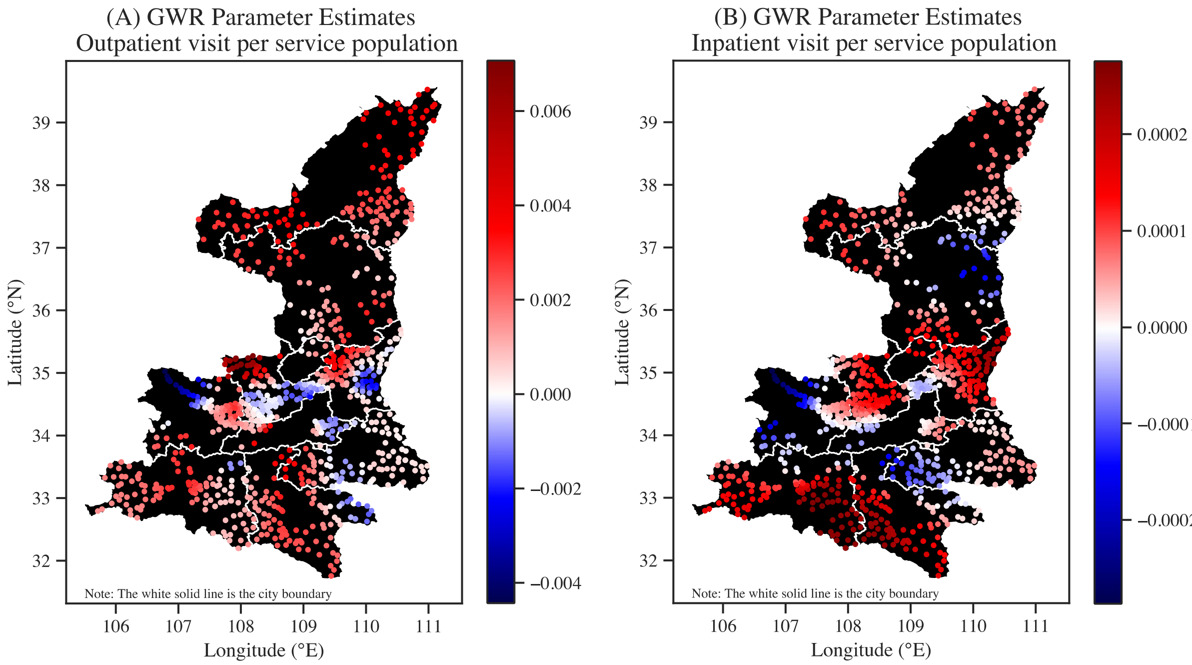


Figure 3 GWR coefficients map of 923 THCs in Shaanxi Province in 2020

Supplementary Materials

Table A1 Geographically weighted regression model results

Parameters	log(outpatient visit per service population)	log(inpatient visit per service population)
Spatial kernel	Adaptive bisquare	Adaptive bisquare
Bandwidth used	103	171
Residual sum of squares	35.587	0.347
Effective number of parameters (trace(S))	126.270	80.199
Degree of freedom (n - trace(S))	727.730	773.801
Sigma estimate	0.221	0.021
Log-likelihood	145.315	2122.288
AIC	-36.090	-4082.177
AICc	8.900	-4064.882
BIC	568.436	-3696.488
R^2	0.716	0.506
Adjusted R^2	0.666	0.455
Adj. alpha (95%)	0.003	0.004
Adj. critical t value (95%)	3.001	2.858

Note: only the significant variables in OLS and MLM were included as control variables in GWR, such as Number of physicians in THCs, Service population, Percentage of population over 65, Share of subsidy on revenue, Number of available bed days in local county hospital.

Table A2 OLS model results of outpatient and inpatient visit per service population of THCs in 2018

Variables	log(outpatient visit per service population)				log(inpatient visit per service population)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Shortest driving time (minute)	0.002***	0.002***	0.002***	0.002***	0.0002***	0.0002***	0.0002**	0.0002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of physicians in THCs	0.013***	0.014***	0.014***	0.014***	0.001***	0.001***	0.001***	0.001***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Service population (10 thousand)	-0.064***	-0.064***	-0.064***	-0.059***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)
Percentage of population over 65	0.013***	0.014***	0.014***	0.015***	0.001***	0.001***	0.001***	0.001***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Share of subsidy on revenue	-0.007***	-0.007***	-0.007***	-0.007***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Type of THCs: Central THCs	0.164***	0.179***	0.179***	0.176***	0.014	0.015	0.015	0.015
	(0.058)	(0.060)	(0.061)	(0.045)	(0.012)	(0.012)	(0.012)	(0.012)
Type of THCs: General THCs	0.079	0.099	0.099	0.105**	0.006	0.007	0.007	0.007
	(0.061)	(0.063)	(0.063)	(0.049)	(0.012)	(0.012)	(0.012)	(0.011)
County category: County-level city		-0.170**	-0.192	-0.165**		-0.006	-0.005	-0.006
		(0.074)	(0.150)	(0.073)		(0.005)	(0.010)	(0.005)
Duration * County-level city			0.001				-0.00003	
			(0.003)				(0.0002)	
Number of available bed days in local county hospital				<-0.0001				<0.0001
				(<0.0001)				(<0.0001)
Constant	0.769***	0.722***	0.725***	0.770***	0.076***	0.075***	0.074***	0.073***
	(0.095)	(0.100)	(0.101)	(0.104)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	905	905	905	905	905	905	905	905
R^2	0.379	0.393	0.393	0.397	0.445	0.447	0.447	0.447
Adjusted R^2	0.374	0.387	0.387	0.391	0.441	0.442	0.441	0.442

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, standard errors are clustered on THCs (listed in parentheses).

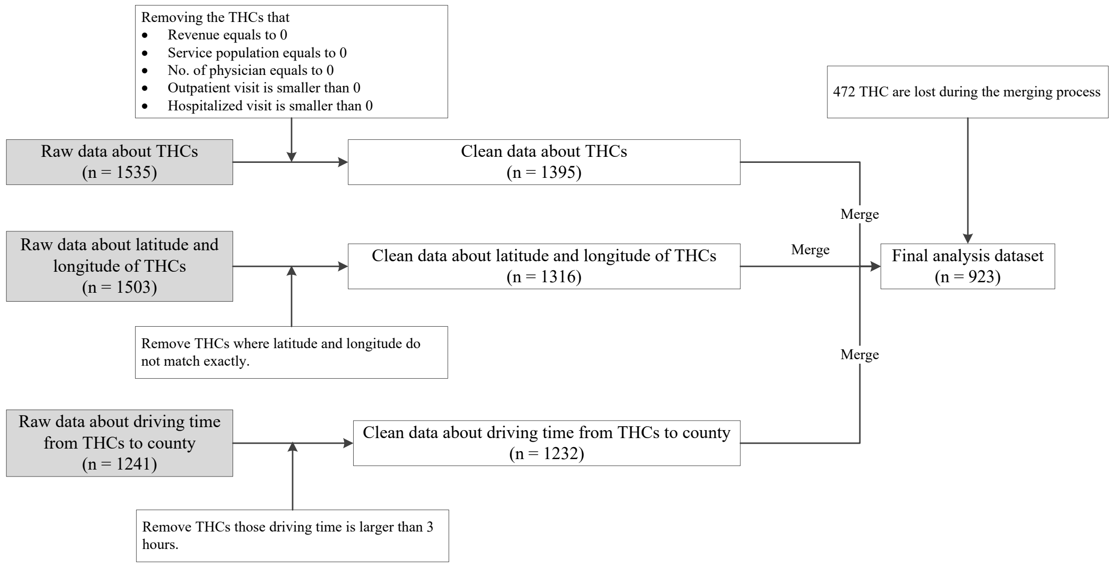
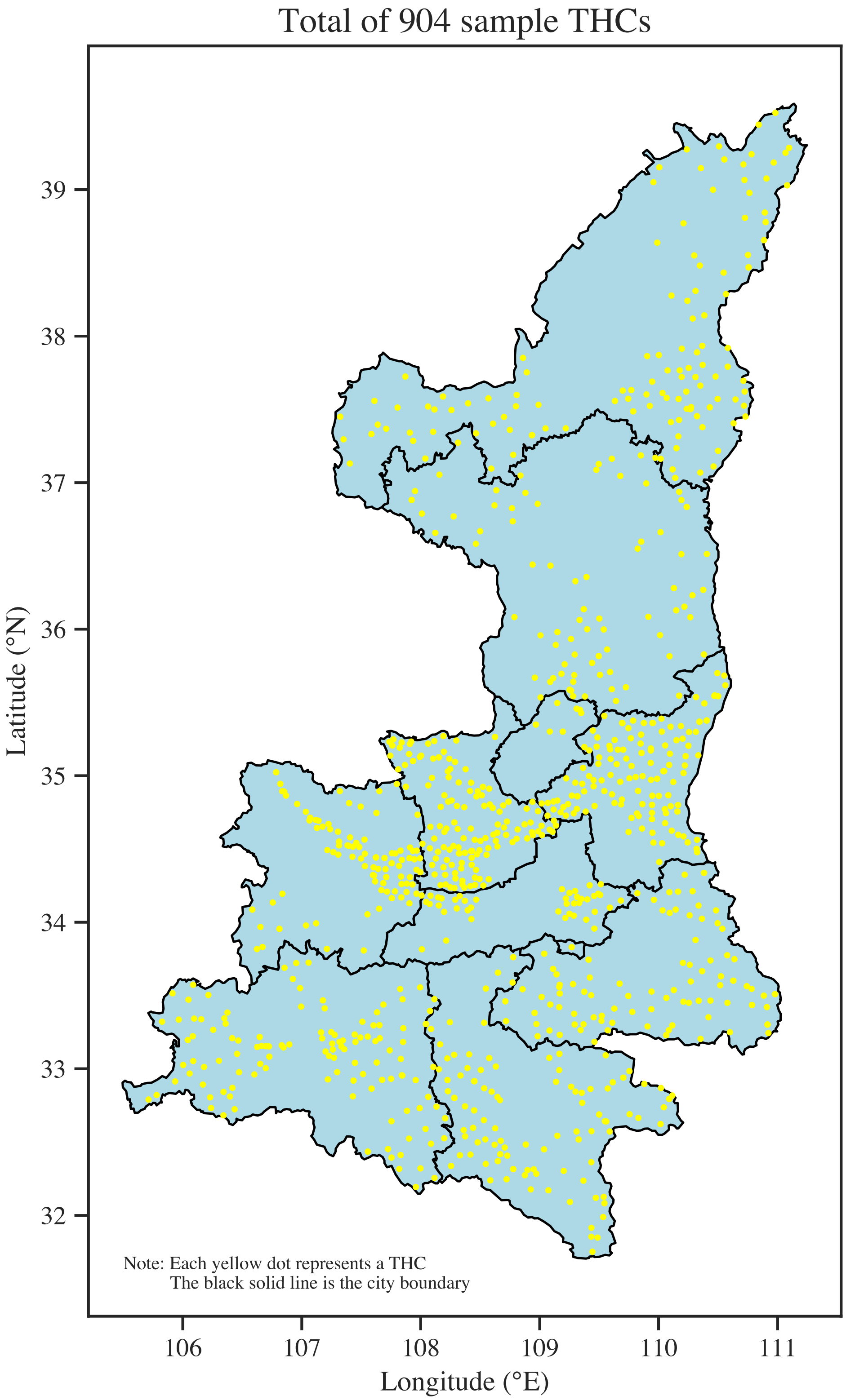
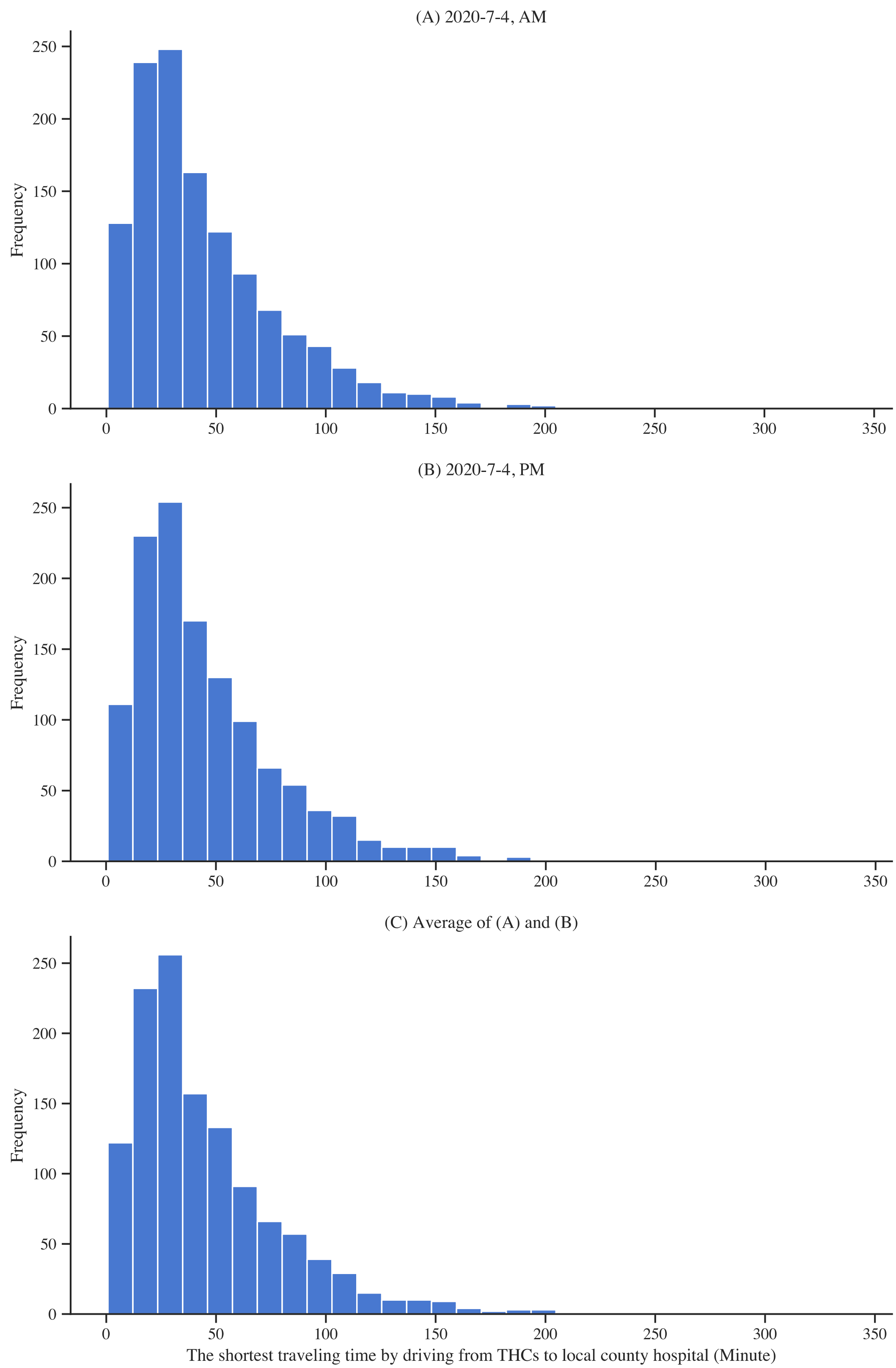
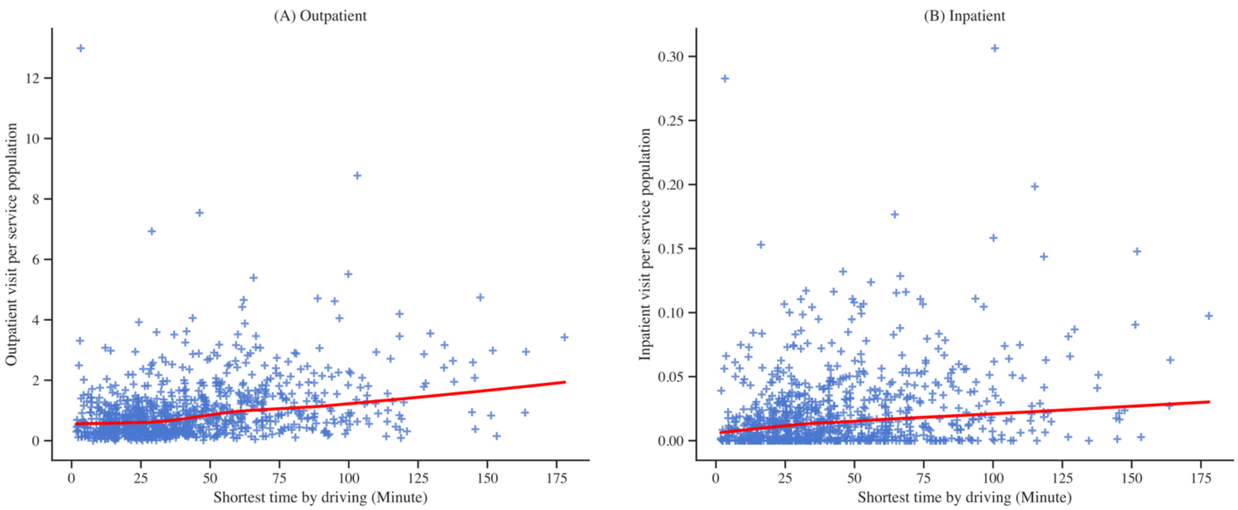


Figure A1 Flow chart of data clean


Total of 904 sample THCs
39
38
37
36
35
34
33
32
Latitude (°N)
106
107
108
109
110
111
Longitude (°E)
Note: Each yellow dot represents a THC
The black solid line is the city boundary



(A) 2020-7-4, AM
(B) 2020-7-4, PM
(C) Average of (A) and (B)
Frequency
0
50
100
150
200
250
300
350
The shortest traveling time by driving from THCs to local county hospital (Minute)



(A) Outpatient
Outpatient visit per service population
0
2
4
6
8
10
12
0
25
50
75
100
125
150
175
Shortest time by driving (Minute)
(B) Inpatient
Inpatient visit per service population
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
25
50
75
100
125
150
175
Shortest time by driving (Minute)