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Transportation, healthcare seeking, and outcomes

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TRANSPORTATION, HEALTHCARE SEEKING, AND OUTCOMES

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Transportation, healthcare seeking, and outcomes

by

Ong Xiao Lin

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Transportation, healthcare seeking, and outcomes

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Transportation, healthcare seeking and outcomes

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Abstract

Advancements in engineering and transportation technology have integrated commuting into modern living. Most studies on transportation infrastructure, such as roads and railways, focus on economic outcomes. This paper examines an overlooked outcome of transportation connectivity: access to medical care. We study the role transportation networks play in determining patients' treatment location choices. Specifically, we aim to study 1) why patients travel to begin with, 2) how do patients choose where to go for treatment, and 3) how travel times can affect patients' travel decisions. To do so, we develop a dynamic discrete choice, spatial model and provide empirical estimates. We find that, firstly, tertiary hospitals are associated with improved outcomes in the form of reduced 30-day in-hospital mortality and readmission rates. Secondly, we estimate a gravity equation via OLS and IV and find that the distance elasticity of healthcare seeking is considerably large at -2.3.

Contents

1 Introduction

By facilitating accessibility to areas outside of where we live, roads and railways are now an integral component of daily living in any modern society. The economic benefits of transportation infrastructure are indisputable – on an aggregate level, transportation connectivity stimulates economic activities and improves economic outcomes such as growth and development. At the individual level, workers can take advantage of employment opportunities; consumers can enjoy amenities, goods, and services (amongst others) offered in connected regions. The non-economic benefits brought about by transportation networks are, however, arguably less direct and apparent.

This paper examines an overlooked outcome of improved connectivity: access to medical care. We study the role transportation networks play in determining patients' treatment location choices. Specifically, we aim to study 1) why patients travel to begin with, 2) how do patients choose where to go for treatment, and 3) how travel times can affect patients' travel decisions. This research question is important for several reasons. First, advancements in engineering technology in the twenty-first century has allowed for more efficient designs of transportation infrastructure. High speed rails, for instance, are being increasingly adopted and enhanced. Much of the developments in transportation infrastructure are seen across Asia and Europe, however plans are underway to build an ambitious rail system in California and Texas in the United States.

Second, the global burden of major diseases is growing. The number of new cancer cases by 2050 from 2022 is predicted to increase by 77%, and the lifetime risk of developing a stroke has increased by 50% over the last two decades.[1] In light of this, we study the role transportation infrastructure plays in influencing healthcare provider (location) choice and outcomes among patients with cancer and cerebro-cardiovascular diseases. Improvements in connectivity allow individuals requiring medical care to travel and seek treatment at better hospitals in newly connected areas. In turn, health outcomes are expected to improve upon receiving higher quality of care.

1.1 Increasing spatial disparity in medical resources

In this section and the next two, we present three motivations behind studying the research question in the context of China. First and foremost, we observe that there exist geographical disparities in access to quality medical care in China. Tertiary hospitals — the best tier of hospitals — are unevenly distributed across China, being largely concentrated in the more developed Eastern regions (Figure 1). In almost all regions of Tibet, tertiary hospitals are virtually absent. This is consistent with other findings on China's uneven spatial allocation of medical resources (Wan et al. (2021); Song et al. (2021); Zheng et al. (2022)). In addition, the disparity in the distribution of hospital

[1] Source: World Health Organisation

beds (across all tiers) at the province level has been increasing over the past decade (Figure 2).

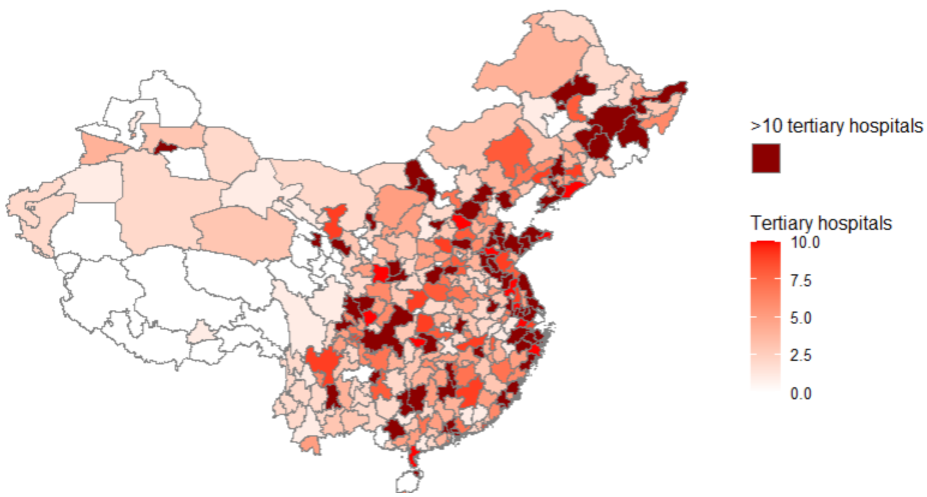

Figure 1: Number of tertiary hospitals (city-level), 2018

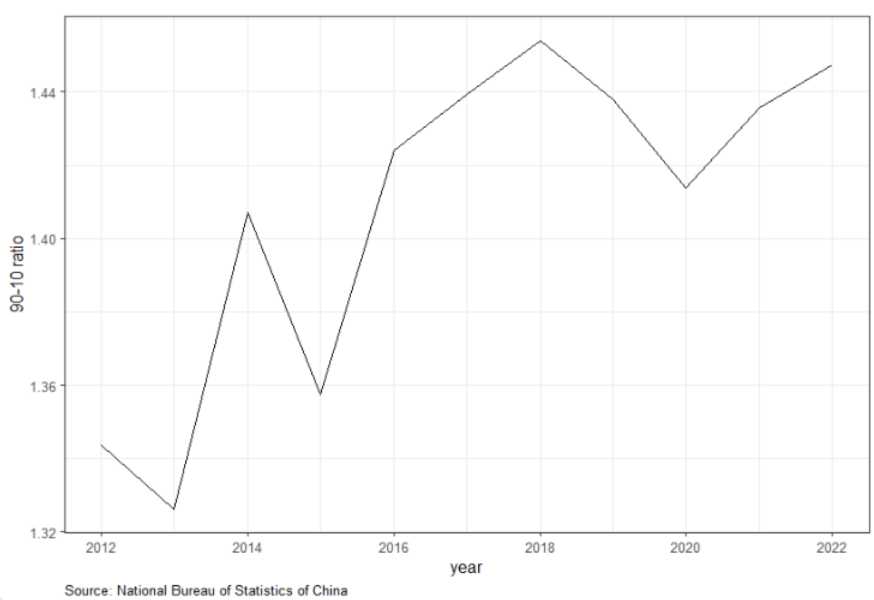

Figure 2: Province-level hospital beds per 10,000 people 90-10 ratio, 2012-2022

1.2 Narrowing spatial disparity in health outcomes

Access to quality medical care is closely tied to health outcomes, evidenced by research on strikes (Friedman et al. (2022); Gruber and Kleiner (2012)) and treatment intensity (Doyle et al. (2015); Almond et al. (2010); Evans and Garthwaite (2012); Chyn et al. (2021); Daysal et al. (2019, 2015)). Accordingly, geographical disparities in health outcomes should arise from spatial disparities in medical resources discussed in the preceding paragraph. This brings us to our next motivation. On the contrary, we find that disparities in medical outcomes are in fact improving. Age-adjusted cancer mortality has reduced across the board between 2005-2020 (Figure 3), reflecting improved drugs and cancer treatment over the years. More importantly, the disparity in cancer mortality has reduced over the same time period (Table 1). For instance, a province at the 80th mortality percentile had a cancer mortality 1.32 times that of a province at the 20th mortality percentile in 2005. By 2020, the figure had dipped to 1.26; the same decline is seen in 90-10 and 70-30 mortality ratios.

year	90/10	80/20	70/30
2005	1.480	1.319	1.163
2020	1.458	1.262	1.109

Table 1: Age-adjusted cancer mortality inequality ratios

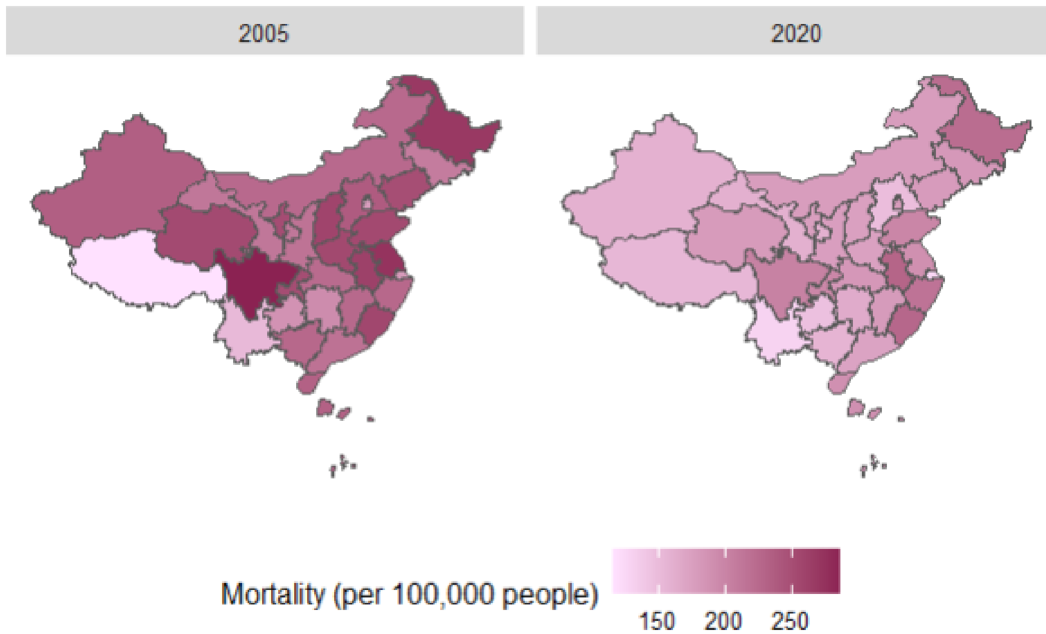

Figure 3: Age-adjusted cancer mortality rates, 2005 and 2020

Source: Qi et al. (2023) National and subnational trends in cancer burden in China, 2005-2020
The Lancet. Public Health, 8(12), e943-e955

1.3 Transportation developments

Our last motivation aims to reconcile the two opposing facts: what explains the increasing spatial disparity in medical resources yet decreasing spatial disparity in health outcomes? We posit that the answer lie in China's massive investments in the transportation sector, which have resulted in tremendous improvements not only in connectivity between regions, but also in the quality of transportation infrastructure. The push for transportation developments can be traced back to China's accession to the World Trade Organisation in December 2001, which enabled China to work with leading HSR firms such as Bombardier and Kawasaki.[2] Between 2000 and 2013, the total length of highways in China as a percentage of the U.S. Interstate Highway System increased remarkably from a mere 64% to 164% (Egger et al. (2023)). At the turn of the 21st century, high speed rails (HSR) had not yet been introduced in China. Today, the total length of HSRs in China is a whopping 45,000km — it is the world's longest, and most extensively used rail network. Figure 4 provides evidence attesting to the rapid transportation infrastructure development in China in the form of marked reductions in average bilateral commuting times.

We hypothesize that transportation networks enable sick individuals to seek treatment in areas that were once impossible or difficult to reach. In improving accessibility to newly connected areas, individuals are now able to enjoy a wider range of healthcare providers at their disposal. They can now choose to travel to a connected city — perhaps with better medical facilities — for treatment. In fact, Liu et al. (2021a) found that the opening of the Cheng–Mian–Le intercity HSR in Sichuan led to patients seeking treatment at better hospitals along the HSR, particularly those located in Chengdu. As a result, health outcomes are now tied less closely with medical resources available in a patients' home city. We believe this is the reason why although medical resources are becoming increasingly unequal, patient outcomes are becoming less unequal.

[2]Source: `https://www.jesus.cam.ac.uk/articles/history-chinas-high-speed-trains`

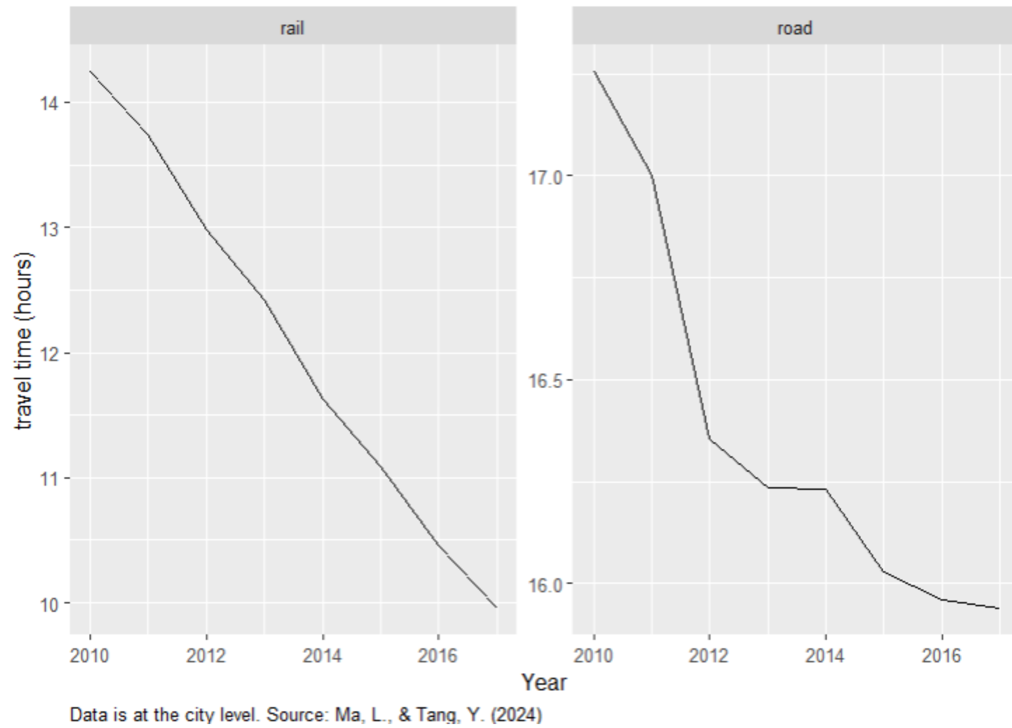

Figure 4: Travel time (hours), 2010-2017

1.4 Background

China's healthcare sector has a long history, having undergone and endured years of rapid change. The country's opening up and reform in 1978 had a profound impact on its healthcare sector, which was privatised, decentralised, and fundamentally reorganised (Wenjuan et al. (2020)). Whilst large public hospitals have traditionally dominated the healthcare sector, the growth of private hospitals over the last decade has led to private hospitals currently outnumbering public hospitals nationwide (Zhang et al. (2023)).

As of 2023, there were 36,570 hospitals in China organized according to a three-tier (primary, secondary, tertiary) system. There were 3,275 tertiary, 10,848 secondary, and 12,649 primary hospitals, with the remainder unclassified (Chen and Liu (2023)). Classification is based on hospital capacity (measured by the number of hospital beds), medical services offered (preventive or specialised care), standard of medical technology and equipment, along with involvement in medical education and research. Of the three tiers, tertiary hospitals are widely regarded as top hospitals in China for several reasons. They are not only the largest hospitals comprising of at least 500 hospital beds; tertiary hospitals also offer the most comprehensive, specialised medical care. Medical equipment used at tertiary hospitals are, furthermore, among the nation's best and most advanced. As most Chinese patients visit tertiary hospitals even for minor illnesses, tertiary hospitals are often overcrowded but primary healthcare facilities remain under-utilised.

1.5 Literature review

This study is related to, firstly, the urban literature on the impact of transportation networks. Transportation infrastructure are primarily recognised in facilitating trade and economic integration, hence are largely studied in the context of economic outcomes. Studies link transportation infrastructure to economic growth (Donaldson and Hornbeck (2016); Banerjee et al. (2020); Donaldson (2018); Faber (2014a)). A large volume of studies associate transportation networks with other economic outcomes, such as changes in population and economic activity (Baum-Snow (2007); Baum-Snow et al. (2017a)), along with labour market demand (Michaels (2008)).

A small but growing literature studies transport connectivity and non-economic outcomes, such as education (Seebacher (2023); Muralidharan and Prakash (2017)). This paper in particular is related to the increasing volume of work studying transportation and health outcomes. On the one hand, transportation networks facilitate the transmission of communicable diseases, increasing mortality rates (Adda (2016); Tang (2017); Djemai (2018)). On the other hand, transportation networks improve patients' access to formal health institutions, leading to improved outcomes evidenced by Adhvaryu and Nyshadham (2015); Aggarwal (2021). Aligned with the latter, we posit a positive relation between transportation networks and health outcomes. We therefore contribute to the relatively limited literature at the intersection of urban and health economics on the impact of transportation infrastructure on medical travel behaviour and consequently, health outcomes.

Next, this research is relevant to the extensive health literature on factors influencing healthcare utilisation. A large volume of studies document the increase in medical demand through health insurance coverage (Manning (1987); Finkelstein et al. (2012); Card et al. (2008)), including reductions in co-payment rates (Shigeoka (2014); Chandra et al. (2014)). In contrast, research on non-monetary factors in medical demand is relatively limited. This is in spite of the fact that large-scale national health insurance programs have substantially reduced out-of-pocket medical costs, and as noted by Acton (1975), individuals will become more responsive to non-pecuniary factors. Non-monetary factors such as wait times, for instance, have been studied to influence medical demand (Tak et al. (2014); Fabbri and Monfardini (2009); Coffey (1983); Óscar D. Lourenço and Ferreira (2005); Phelps and Newhouse (1974); Holtmann and Jr. (1976)). In a similar vein to Elek et al. (2015); Acton (1975); Dor et al. (1987) studying distance and travel costs, this paper contributes to the impact of commuting time on medical demand.

2 Data

We use data from the fifth most populous province in China, Sichuan. Located in the Southwest hinterlands, Sichuan covers a total area of 486,000 square kilometers with approximately 83 million residents as of 2024. Sichuan is a large Province; its population is equivalent to that of Germany — exceeding that of the two largest states combined in the U.S.. Home to 21 cities, Sichuan's capital, Chengdu, is also one of the most densely populated and advanced cities in China. The geography of Sichuan province can be divided into two distinct regions: the East and West. Economically advanced cities are typically located in the East, owing to the Sichuan basin characterized by its flat terrain and fertile soil (and thus able to support a large population). On the contrary, less prosperous cities are located in the Western mountainous regions which are much less accessible. Sichuan province on a whole is landlocked and enclosed by surrounding hills and mountains. As a result, transportation developments have long been bottlenecks in the province before advancements in engineering technology.

2.1 Inpatient dataset

The primary dataset used in this paper is administrative hospital panel data, which comprises yearly inpatient admission records across all hospitals in Sichuan province. This dataset is comprehensive in that it reports a range of patient demographic information such as their age, gender, place of residence and occupation. Medical-related information: diagnosis (ICD9 code), mode of discharge (including deaths), hospital ID and tier are also captured. The latter allows us to identify which patients visited a Tertiary hospital. In order to locate the hospitals visited by each patient, we link hospital IDs to their respective zipcodes using a secondary dataset.

Whilst we are able to retrieve county-level locations of both patients and hospitals, we focus on travel at the city-level. We also focus on within-province healthcare seeking and restrict our sample to patients who reside in Sichuan, as the majority of patients hospitalised in Sichuan are, naturally, Sichuan residents. We exclude the small percentage of patients who are non-Sichuan residents residing in the neighbouring provinces. Additionally, we restrict our attention to two years of data (2017-2018), as the variable for patients' residence is cleaner and more informative in these years.

We also further restrict our sample to patients suffering from two categories of diseases: Cancer and Cerebro-cardiovascular diseases (CCVD). The latter includes patients admitted for either cerebrovascular disease or coronary heart disease; we group them together because 1) the medical literature uses cerebro-cardiovascular disease as an umbrella term of all heart and brain conditions related to vascular diseases (Liu et al. (2021b)) and 2) the sample of patients with coronary heart disease is rather small. We also group patients with lung cancer or esophageal cancer together and simply categorise this group as cancer patients. These categories are chosen because they are consistently among the leading causes of death in China. Stroke, the number one cause of death in China for decades (Cheng et al. (2022)), accounted for 121 and 161 deaths per 100,000 people for females and males respectively in 2019 [3]. Ischaemic (coronary)

[3]Source: World Health Organisation

heart disease comes second, claiming as much as 111 and 134 lives per 100,000 people for Chinese females and males respectively in 2019. Lung and stomach cancers are the most fatal types of cancer, accounting for the largest number of deaths particularly amongst Chinese males. Notably, this is not a recent trend — cerebrocardiovascular diseases and cancer have consistently been among the top five causes of death in China between 2000-2017, alongside respiratory diseases and trauma/toxicosis-related conditions (Zou et al. (2022)). Additionally, deaths attributed to CCVD displayed the steepest increase in the same time period. Cerebro-cardiovascular diseases and lung cancer were reported among the five leading causes of years of lives lost in 2017 (Zhou et al. (2019)).

Excluding non-Sichuan patients and patients with diseases other than the aforementioned leaves us with a total of approximately 800,000 admissions from 600,000 unique patients between 2017 to 2018. Table 2 shows the summary statistics of the main dataset. More patients are admitted for CCVD than for cancer, and the average age of patients with CCVD is also higher. Notably, the majority of patients are admitted to tertiary hospitals — as much as 75% of cancer patients were warded in tertiary hospitals. There are relatively few deaths recorded in the sample, with most deaths being attributed to cancer.

	Disease			
	Cancer		CCVD	
	frequency	percent	frequency	percent
Gender				
Male	145,294	72.65	331,389	54.23
Female	54,708	27.35	279,701	45.77
Age (mean)	65.30279		70.45337	
Hospital Tier				
Primary	1,650	0.94	14,031	2.81
Secondary	31,584	17.90	143,890	28.85
Tertiary	133,236	75.53	295,607	59.26
Ungraded	9,935	5.63	45,295	9.08
Death				
Survived	188,385	94.19	606,285	99.21
Died	11,617	5.81	4,805	0.79
Origin City				
Chengdu	42,027	21.01	121,482	19.88
Zigong	9,632	4.82	18,748	3.07
Panzhihua	2,157	1.08	8,627	1.41
Luzhou	10,132	5.07	30,182	4.94
Deyang	9,542	4.77	16,566	2.71
Mianyang	14,662	7.33	34,765	5.69
Guangyuan	7,532	3.77	21,578	3.53
Suining	11,281	5.64	26,956	4.41
Neijiang	8,433	4.22	30,458	4.98
Leshan	7,739	3.87	22,070	3.61
Nanchong	19,737	9.87	81,124	13.28
Meishan	5,957	2.98	17,412	2.85
Yibin	5,952	2.98	54,041	8.84
Guangan	12,841	6.42	19,964	3.27
Dazhou	12,629	6.31	33,820	5.53
Yaan	2,066	1.03	12,012	1.97
Bazhong	5,754	2.88	19,225	3.15
Ziyang	7,648	3.82	25,250	4.13
Aba	1,090	0.54	2,309	0.38
Ganzi	941	0.47	2,040	0.33
Liangshan	2,250	1.12	12,461	2.04

Table 2: Summary Statistics

2.2 Travel time dataset

The second dataset measures bilateral commuting time (in hours) between Sichuan cities via two possible routes – roads and passenger railways. This is retrieved from Ma and Tang (2023), the first to account for the quality of roads and railroads in China when estimating travel times. The latest year of available data is in 2017, and as such this paper utilises travel matrices for 2016 and 2017 (i.e., a one-year lag from that of the inpatient dataset). Commuting time from 2010-2017 for each of Sichuan's 21 cities is shown in Figure 5. Synonymous with the decline in travel time nationwide (Figure 4), all of Sichuan cities experienced a decline in commuting time by both rail and road.

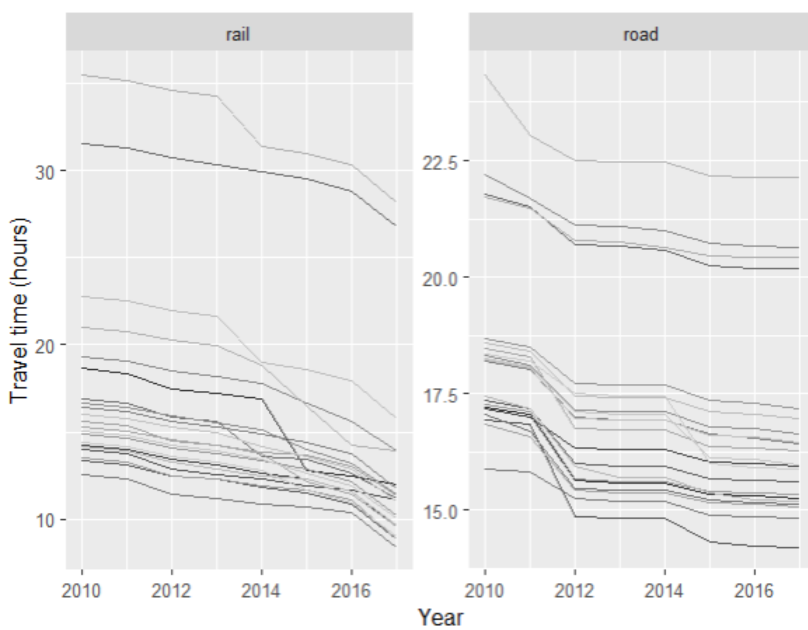

Figure 5: Travel time in all of Sichuan's 21 cities, 2010-2017

3 Empirical Analysis

3.1 Motivating model

We first introduce a simple discrete choice and spatial model of treatment location choices, which motivates the empirical estimation in the next section. This section therefore contributes to a conceptual understanding of how individuals make decisions with respect to medical travel. To our knowledge, there are not many spatial models focusing on healthcare outcomes. Li and Ma (2022) is somewhat most relevant to our motivating model in that they combine a spatial model with a disease transmission framework to show how transportation developments contributed to the spread of COVID-19. Finkelstein et al. (2016); Salm and Wübker (2020); Moura et al. (2019) investigate variation in healthcare utilisation across states by exploiting patient migration. However, these papers develop a demand and supply model instead of a spatial model as we do here.

Time is discrete and indexed as $t = 0, 1, \cdots, \infty$. Consider a country with $k = 1, 2, \cdots, K$ locations. Throughout the paper, we use k and l to index locations, and i and j to index individuals. For simplicity, we do not account for migration, and therefore each location k is occupied by a time-invariant measure of L_k individuals.

An individual i living in location k receives a real wage of ω_{kt} at time t, and discounts the future at the rate of β. An individual is also characterized by his health status at period t, Denoted as S_{it}. The status can take two values, "healthy", denoted as $S_{it} = H$, or "ill", denoted as $S_{it} = I$. Being sick leads to two negative implications: 1) the individual will suffer from a higher mortality rate, and 2) he will also see a reduction in real wage to capture the effect of health status on ones ability to supply labor, as well as, isomorphically, enjoy utility.

All individuals are born healthy. At the end of each period, a healthy individual has a probability of π_I to fall ill. Denote the value function of a healthy individual at location k as v^H_{kt}, and those of an ill individual as v^I_{kt}. A healthy individual does not have to make a decision and his recursive problem is described in equation (1). An individual living in k works and receives a flow utility of $u(\omega_{kt})$. In the next period, there is a probability π_I of an individual falling ill, and a probability 1 - π_I of remaining healthy.

$$v^H_{kt} = u(\omega_{kt}) + \beta \left[(1-\pi_I)\, v^H_{k,t+1} + \pi_I v^I_{k,t+1} \right] \tag{1}$$

We now move to describe the recursive problem of a sick individual. An individual in the state of I receives a cut in real income due to his illness, and therefore only receives a flow utility of $u(\rho\omega_{kt})$. ρ captures the extent to which the illness affects one's ability to supply labor. Clearly, $\rho \in [0,1]$ and a smaller value of ρ indicates that ability to work is greatly impeded by an illness. An ill individual chooses where to seek medical treatment, which affects their recovery probability and mortality rate. Keeping in mind that tertiary hospitals (incidentally also the largest hospitals) offer the most comprehensive medical services, we model health outcomes to vary by hospital capacity. If an individual goes to l for treatment, the probability of recovery is $\pi^H(m_{lt})$ and the mortality rate as $\pi^D(m_{lt})$, where m_{lt} is medical endowment at location l, time t. More details on the mortality and recovery rates are in the Appendix.

An individual seeking long-distance treatment incurs origin-destination specific travel costs that cover both the difficulties of long-distance travel and the potential reduction in out-of-home insurance coverage. If an ill individual in location k seeks medical treatment at location l, he needs to incur travel costs in units of utility denoted as $\lambda_{lkt} \geq 0$. We normalize local treatment costs, $\lambda_{kkt} = 0$. Lastly, we model the medical choice as a dynamic discrete choice by assuming that the cost of treatment is subject to a vector of idiosyncratic preference shocks denoted as ε_l that follows a type-I extreme value distribution with the following CDF where $\bar{\gamma}$ is the Euler's constant:

$$F(\varepsilon) = e^{-e^{-\varepsilon-\bar{\gamma}}} \tag{2}$$

This brings us to the recursive problem of the sick individual in equation (3). A sick individual enjoys a reduction in flow utility $u(\rho\omega_{kt})$. In the next period, he has a probability $\pi^H(m_{lt})$ of recovering and returning to the healthy state, a probability $1-\pi^H(m_{lt})-\pi^D(m_{lt})$ of staying ill, and a probability of death $\pi^D(m_{lt})$. An individual who dies receives zero future utility, and hence the latter term is omitted. κ is the inverse of the distance elasticity of medical treatment, as it will be clear later. The expectation is taken against the realization of the ε_l shocks.

$$v^I_{kt} = u(\rho\omega_{kt}) + \max_l \mathbf{E}\left[\beta\left[\pi^H(m_{lt})v^H_{kt} + \left(1-\pi^H(m_{lt})-\pi^D(m_{lt})\right)v^I_{kt}\right] - \lambda_{lkt} + \kappa\varepsilon_l\right]. \tag{3}$$

Standard results from the discrete choice literature allow us to derive the probability of a sick individual in k seeking treatment in l (for more details, refer to the Appendix):

$$\mu_{lkt} = \frac{\exp\left(\beta y_{lkt} - \lambda_{lkt}\right)^{1/\kappa}}{\sum_{l'=1}^{K}\exp\left(\beta y_{l'kt} - \lambda_{l'kt}\right)^{1/\kappa}} \tag{4}$$

where $1/\kappa$ is the distance elasticity of medical treatments (refer to the Appendix for interpretation). The denominator is denoted as ϕ_{kt}, which captures the medical market access of individuals living in location k. The law of large numbers implies that μ_{lkt} is also the share of patients in k seeking treatment in l among all the patients from k, the direct counterpart of share$_{ijt}$ in the empirical gravity equation (6) below. Taking logs on both sides of equation (4), we arrive at the gravity equation of estimation:

$$\log \mu_{lkt} = \frac{\beta}{\kappa} y_{lkt} - \frac{1}{\kappa} \lambda_{lkt} - \Phi_{kt}. \tag{5}$$

3.2 Tendency to travel

With a conceptual framework in mind, we next move on to present empirical evidence which develops upon the gravity equation, equation (5), further. First, we estimate the following equation which captures patients' tendencies to travel for medical treatment. $Share_{ijt}$ denotes the proportion of patients who travel from their home city i to a hospital in city j in year t among all patients from city i in year t, where t = 2017 or 2018. $Traveltime_{ij(t-1)}$ denotes the shortest commuting time in hours (via road or passenger rail) between city i and city j in year $t-1$. Again, we utilise the one-year lag values for commuting time because the travel time dataset is only available up until the year 2017.

$$Log(Share_{ijt}) = \alpha + \beta Log(Traveltime_{ij(t-1)}) + \mu_{it} + \delta_{jt} + \varepsilon_{ijt} \tag{6}$$

β, the coefficient of interest as shown in Tables 3 and 4, reflects the disutility of travel because a greater distance reduces the likelihood of patients visiting hospitals (Ho and Pakes (2014); Sivey (2012); Joyce et al. (2013)) and travel distance function as prices in discouraging demand for medical services (Acton (1975)).

As noted by Duranton and Turner (2011), endogeneity in route placements present in equation (6) could bias OLS estimates in either direction. On the one hand, planners could connect poorer regions together in a bid to alleviate poverty, as in the case of India's PMGSY (Pradhan Mantri Gram Sadak Yojana) program which provided paved roads to unconnected villages as part of the government's poverty reduction strategy. On the other hand, governments may target regions with higher expected traffic demand or returns to infrastructure investments (Faber (2014b)), such as India's Golden Quadrilateral: a national highway connecting India's four major cities.

Baum-Snow et al. (2017b) and Faber (2014b) present evidence that Chinese transport planners target economically promising cities. The capital of Sichuan, Chengdu, is, for instance, an important historical city economically and politically (Murphey (1970)). Today, Chengdu has an extremely extensive road network comprising 1,902 nodes and 5,943 directed links (Guo et al. (2019)) and is also a station at China's two major railway lines and seven inter-provincial highways.[4] For that reason, we expect OLS estimates of equation (6) to be upward biased: individuals in more prosperous cities have better means of transportation, such as cars, and access to high quality roads and rail, amongst others. Therefore, the omitted variable (prosperous cities) is negatively correlated with the independent variable, travel time. Individuals from richer

[4]Source: South China Morning Post

cities are also less likely to travel out for medical services for two key reasons: they have a higher opportunity cost of time, and they do not have a strong incentive to seek treatment elsewhere given that good hospitals are likely present where they reside in. The omitted variable is also hence negatively correlated with the dependent variable. To address this bias, straight line distance between any two cities is used as an instrument for bilateral commuting time, as in Banerjee et al. (2020); Atack et al. (2010); Faber (2014b).

	(1) Stomach Cancer	(2) Lung Cancer	(3) Diabetes	(4) HBP	(5) CHD
OLS					
Travel time	-1.345***	-1.718***	-1.589***	-1.235***	-1.400***
	(0.213)	(0.217)	(0.206)	(0.269)	(0.231)
IV					
Travel time	-1.654***	-2.049***	-1.758***	-1.391**	-1.310***
	(0.348)	(0.322)	(0.285)	(0.390)	(0.285)
N	282	432	503	244	302

Standard errors in parentheses

HBP: High Blood Pressure. CHD: Coronary Heart Disease

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Gravity equation estimates

The range of β IV estimates range between -2.4 to -1.3 and we make several observations here. Patients with minor conditions, such as Gallstones, Hernia, Hemmorhoid, and Appendicitis are more responsive to increments in travel time since the marginal benefit of traveling to and receiving treatment at a better institution is limited. In con-

	(1) CVD	(2) Hemorhoid	(3) COPD	(4) Appendicitis	(5) Hernia	(6) Gallstones
OLS						
Travel time	-2.033***	-1.618***	-2.055***	-1.597***	-1.620***	-1.912***
	(0.279)	(0.205)	(0.243)	(0.148)	(0.224)	(0.246)
IV						
Travel time	-2.389***	-1.836***	-2.445***	-1.774***	-1.734***	-2.139***
	(0.329)	(0.265)	(0.316)	(0.186)	(0.282)	(0.292)
N	632	539	641	672	489	667

Standard errors in parentheses

CVD: Cerebrovascular disease. COPD: Chronic Obstructive Pulmonary Disease

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Gravity equation estimates (cont.)

trast, quality of care is likely to matter a great deal more for those with severe conditions. Indeed, patients with High Blood Pressure and Coronary Heart Disease — more serious illnesses — are the least responsive to travel time. However, this is not the case for all severe conditions. Patients with serious but time-sensitive conditions, such as those requiring immediate medical attention, are most responsive to travel time. In the event of such emergencies, patients are likely to choose their nearest healthcare provider which can offer assistance within the shortest time possible. Patients with cerebrovascular disease (CVD) and Chronic Obstructive Pulmonary Disease (COPD), for instance, have even larger (absolute) estimates of β than that of minor conditions.

3.3 Health outcomes

Next, we posit that patients engage in healthcare seeking behaviour for an obvious reason: they travel outside of where they live to receive higher quality treatment at better healthcare institutions. This is aligned with evidence that hospitals of higher quality attract more patients (Moscelli et al. (2016); Gutacker et al. (2016); Klemick et al. (2007)). We then estimate equation (7) capturing health outcomes at higher quality hospitals. Better hospitals should bring about improvement in outcomes, otherwise patients would have no incentive to travel and seek treatment there. Our results are expected to be consistent with previous findings that higher quality hospitals/physicians reduce mortality rates (Chandra et al. (2023)) and improve patients' long-run health outcomes (Fadlon and Van Parys (2020)).

$$\mathbb{1}(30 - day\, Y_i) = \alpha + \beta Tertiary + \mu_i + \varepsilon_i \quad (7)$$

We construct three conventional measures of health outcomes Y_i: mortality, recovery, and non-recovery over a 30-day period, as in Chandra et al. (2023) and Gupta (2021). The dependent variable $\mathbb{1}(30 - day\, Y_i)$ is an indicator function that equals 1 if patient i died, recovered, or remained ill either during their hospital stay or within 30 days of discharge. To be more specific, $\mathbb{1}(30 - day\, Mortality_i)$ = 1 if patient i a) died during a current hospitalisation, or b) was discharged, but readmitted again within

30 days and died in that subsequent readmission. We note that this is not a perfect measure of mortality because we only observe in-hospital deaths — it might well be possible that patients die in their homes, which leads to an underestimation of mortality.

Similarly, $\mathbb{1}(30-day\ Recovery_i) = 1$ if patient i was discharged from a hospital, and was not readmitted in the following 30-day period. In all measures, readmission is defined as an unplanned repeat hospitalisation at any hospital. We note that cancer patients are regularly readmitted as part of a treatment plan. As such, we do not consider such planned cases to be a readmission, and only account for unplanned readmission as these are more appropriate outcomes reflecting quality of care (Bjorvatn (2013)). Lastly, $\mathbb{1}(30-day\ Remainedill_i) = 1$ if patient i did not fall into either of the two earlier categories i.e., the length of patient i's current stay exceeded 30 days, or patient i was readmitted in 30 days from a previous discharge. $Tertiary$ is an indicator function which takes the value 1 if a patient was warded in a tertiary hospital, and 0 otherwise.

We are cognisant of the endogeneity inherent in the OLS estimate of β in equation (7): patients who visit tertiary hospitals are simply different from patients who visit non-tertiary hospitals. Patients at tertiary hospitals are perhaps more severely ill, of higher socioeconomic status, or more highly educated. We include μ_i, a vector of patient characteristics to control for such observed traits. Furthermore, we restrict the sample to patients who remain in their own county for medical treatment in order to further account for this selection issue.

Table 5 suggests that tertiary hospitals are associated with improved outcomes for patients with either Cancer or CCVD. In general, visiting a tertiary hospital reduces the probability of death and remaining ill, whilst increasing the chances of recovery.

	(1)	(2)	(3)
	P(30-day mortality)	P(30-day recovery)	P(30-day remained ill)
Cancer			
Tertiary	-0.0344***	0.0771***	-0.0756***
	(0.00449)	(0.00706)	(0.00692)
CCVD			
Tertiary	-0.00320***	0.0140***	-0.0140***
	(0.000716)	(0.00323)	(0.00323)

CCVD: Cerebro-cardiovascular disease
Sample is restricted to only individuals who stayed within their own county.
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Health outcomes from visiting a Tertiary hospital

3.4 Gravity equation

Finally, we take the gravity equation (5) to the data and estimate the empirical equivalent through equation (6). The coefficient of interest, β, measures the elasticity of healthcare seeking to travel time, analogous to $\frac{1}{\kappa}$ in (5). Therefore, from Table 6, we find that κ ranges between -0.44 and -0.42.

	(1) OLS	(2) IV
Cancer		
Travel time	-1.816***	-2.265***
	(0.271)	(0.367)
N	480	480
Cerebro-cardiovascular diseases		
Travel time	-2.031***	-2.362***
	(0.278)	(0.334)
N	653	653

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Gravity equation estimates

3.5 Generalisation

In this section, we present several simple back-of-the-envelope calculations which summarises the above findings. First and foremost from table 5, visiting a tertiary hospital reduces the probability of a patient dying or remaining ill, and increases the probability of recovering within 30 days. Compared to patients who do not visit a tertiary hospital, both cancer and CCVD patients in tertiary hospitals have a 3% reduction in probability of dying. The reduction in the probability of death for patients with cancer is slightly more pronounced (3.4%) compared to patients with CCVD (3.2%). A cancer patient's probability of recovering at a tertiary hospital is also 7% higher than at a non-tertiary hospital, almost 7 folds of the estimate for CCVD (1.4%). Since cancer is a terminal illness requiring regular and prolonged treatment, it is intuitive that cancer outcomes are tied more closely to hospital quality.

We now turn our attention to extrapolating our findings to the whole-of-China and attempt to quantify the role of transportation developments in healthcare seeking nationwide. Liu and Zhang (2018) estimate that the HSR in China reduced bilateral city commuting times by a national average of 45%, or nearly 10 hours. Without China's extensive HSR network servicing more than 3 billion passenger trips annually, there would be an estimated 90% reduction in the share of patients traveling outside of their city for medical treatment. We note that our data is from West China, which is characterised by hostile terrains and longer-than-average commuting times. As noted by Liu and Zhang (2018), the reduction in travel times is more pronounced in these regions, leading to the estimate of 90% likely being an upper bound.

3.6 Limitations

There are several limitations in this paper, which could be improved upon. The first limitation we discuss is data limitation. We utilise pre-pandemic data over 2 years (2017-2018), which might not be reflective of current travel patterns. Travel restrictions and lockdowns implemented during the peak of China's pandemic crisis would have forced individuals to seek treatment in medical facilities around the vicinity of their home. Such habits might persist, and it is possible that individuals may no longer be as responsive to changes in travel time as they were previously. If that is the case, our estimated distance elasticity is likely overestimated.

As noted earlier, we also only observe in-hospital death, and acknowledge this measurement error. In excluding observations where patients experienced an out-of-hospital death, our estimated mortality rates are likely understated. Moreover, because patients with terminal illnesses, such as that studied in this paper, can choose their home as the place of end-of-life care and death, the measurement issue is even more pertinent. The increasing trend of patients choosing to die at their homes instead of hospitals globally raises the question of whether in-hospital deaths are an accurate reflection of actual mortality rates.

Because our inpatient dataset encompasses the universe of admissions into Sichuan hospitals, Sichuan residents who seek treatment outside of Sichuan province are excluded. Major cities like Beijing and Shanghai are widely known to offer the best healthcare in the whole of China and it is certainly plausible for Sichuan residents to seek treatment in these cities even though they are significantly further away. That would also mean that our sample excludes individuals who can afford the time and cost of traveling to a different province. However, based on our current sample, less than 2% of patients at Sichuan hospitals are from neighbouring provinces such as Yunan, Chongqing, and Gansu. This suggests that the excluded segment of the dataset — patients traveling to a different province — is rather limited, and that our sample is a representative one.

In interpreting our empirical results, one should also be cautious about generalising them to the whole of China. Sichuan province is ranked fifth in China by nominal GDP in 2023, and is on a whole of higher income. According to the Sichuan Provincial People's Government, Sichuan is ranked ninth where China's richest reside in 2020. As a result, the same set of findings may not hold true for poorer provinces lacking resources, or with a different resident demography.

The next limitation pertains to model specifics. First, the cut to income as a result of illness, ρ, is not severity specific. The condition of patients admitted to a hospital, however, can vary even between patients with the same illness. For instance, the degree of coronary stenosis in cases of coronary heart disease can differ from patient to patient. Allowing ρ to vary by severity would be a more realistic reflection of the impediments to work caused by an illness. Second, we do not account for congestion in the model. Equations (8) and (9) in the Appendix imply that health outcomes, measured by the probability of recovering and death, improve indefinitely at an institution with more medical resources. Yet there exists an issue of overcrowding at heavily endowed hospitals, such as tertiary hospitals. This is especially significant in China, where patients prefer visiting tertiary hospitals even for primary care (Wu and Lam (2016)). The over-utilisation of tertiary hospitals which has led to prolonged overcrowding and enormous workload on medical staff is widely noted a chronic issue in China's multi-tiered healthcare system (Jiang et al. (2020)). However, there is evidence that hospital volume do not have a causal effect on health outcomes in other settings (Rachet-Jacquet et al. (2021)).

4 Conclusion

Most of the existing literature on the impact of transportation networks has been studied with regards to predominantly economic outcomes. Transportation has been widely documented to impact trade flows in the form of factor mobility and prices as well as economic productivity, development and growth, both positively and adversely. What is less known is how transportation infrastructure can impact non-economic outcomes. This paper therefore contributes to the gap in the literature intersecting urban and health economics by studying how transportation networks affect healthcare seeking behaviour and health outcomes of patients who require medical care.

We ask a straightforward question of why and where ill individuals seek medical treatment. Our setting is ideal: we utilise data from a province in the world's largest developing country, which has experienced remarkable advancements in transportation development. Focusing on patients with some of the most prevalent illnesses in the world today — cancer and cerebro-cardiovascular diseases, we first argue that better hospitals are associated with improved health outcomes. This, we believe, is what motivates healthcare seeking. Next, we empirically estimate sick individuals' tendency to travel and find that a 1% increase in bilateral commuting time reduces the share of patients traveling to the corresponding city pair by approximately 2.3%, which is a considerably large distance elasticity. It is unimaginable that a 10% increase in commuting time, say, from 1 hour to 1 hour and 6 minutes, would deter patients from traveling to such a large extent. To further elucidate what drives healthcare seeking, we develop a motivating structural model that reflects individuals' treatment location choices.

Finally, this paper highlights the importance of transportation infrastructure in allowing individuals to attain better medical care. In the face of limited resources especially in the healthcare sector where the construction of more hospitals or deployment of more healthcare staff is simply infeasible, central planners could leverage on patients' inherent healthcare seeking tendencies. If health outcomes can be improved through medical travel, developing and improving transportation infrastructure is key. Planners can even go further to improve healthcare equity by ensuring that all regions are sufficiently connected to one another, so that all individuals have reasonable access to quality medical care.

5 Appendix

5.1 Recovery and mortality rates

$$\frac{\partial \pi^H(m_{lt})}{\partial m_{lt}} \geq 0 \tag{8}$$

$$\frac{\partial \pi^D(m_{lt})}{\partial m_{lt}} \leq 0, \tag{9}$$

Locations with better medical resources would increase the chance of recovery and decrease one's chance of dying. Hence, the derivatives of π^H and π^D are described by equations (8) and (9).

5.2 Solution details

Note that for all $\{k,t\}$, $v_{kt}^H \geq v_{kt}^I$ due to the negative impacts of disease on both flow utility and mortality rates. In the limit case of $\rho = 1$ and $\pi^D(\cdot) = 0$, the disease is no longer detrimental to one's utility, and therefore the model collapses back to a standard dynamic representative agent model. Denote the outcome of medical treatment of those ill in k and treated in l as:

$$y_{lkt} = \pi^H(m_{lt})v_{kt}^H + \left(1 - \pi^H(m_{lt}) - \pi^D(m_{lt})\right) v_{kt}^I \tag{10}$$

$$= \pi^H(m_{lt})\left(v_{kt}^H - v_{kt}^I\right) + \left(1 - \pi^D(m_{lt})\right) v_{kt}^I \tag{11}$$

From the properties specified in equations (8) and (9), it is also straightforward to verify that $\partial y_{lkt}/\partial m_{lt} \geq 0$ so that the expected medical return is higher in locations with better endowments.

Next, define ζ_{lkt} as:

$$\zeta_{lkt} = \beta y_{lkt} - \lambda_{lkt} + \kappa \varepsilon_l.$$

ε_l follows a GEV-I distribution with location parameter $\bar{\gamma}$ and a scale parameter of 1. ζ_{lkt} is a linear transformation of ε_l, and therefore it also follows a type-I distribution with location parameter $\beta y_{lkt} - \lambda_{lkt} + \kappa\bar{\gamma}$ and a scale parameter of κ. The results come from the fact that GEV-I distributions are closed under linear transformations.

5.3 Distance elasticity

This section explains the interpretation of the distance elasticity, $1/\kappa$, of equation (4). As $1/\kappa \to 0$, $\mu_{lkt} \to 1/K$ i.e., an individual faces equal probability of choosing any of the K treatment locations; the choice is completely random. On the flip side, as $1/\kappa \to \infty$, $\mu_{lkt} \to 1$ at the smallest value of λ_{lkt}. In this case, individuals do not travel and stay in their home city k, where $\lambda_{kkt} = 0$. Hence, a smaller (absolute) elasticity suggests that individuals are less responsive to the impediments implied in λ_{lkt} and therefore more likely to engage in long-distance medical treatments.

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